Exploring mobile trajectories:

An investigation of individual spatial behaviour and geographic filters for information retrieval

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David Mountain, Dec 2005

Thesis Abstract

Two recent trends in the field of mobile computing have been location-aware devices, and the use of handheld devices by mobile users to access information via wireless and cellular networks. It is proposed that knowing a device owner's geographical context, as defined by their present and previous spatial behaviour, could greatly increase the relevance of the information retrieved by that user by utilising this information to define the *geographic footprint* of their query. Existing approaches have considered primarily spatial proximity relationships between the (mobile) user and information sources. This thesis considers other approaches to defining the *geographic context* of mobile individuals such as accessibility (*temporal proximity*), likely future locations and visibility. geoVisualization tools have been developed for the visual analysis of mobile trajectories, to implement an interactive approach to time geography, and for the development of *geographic filters* representing the geographic context of mobile individuals in different scenarios.

Evaluation is both quantitative, including comparison of the characteristics and effectiveness of different approaches to prediction, and qualitative, including large-scale user evaluation of implementations of geographic filters as part of a location-based service. The results of this study suggest that mobile individuals require geographic context for information retrieval, and that spatial proximity is useful as a default filter, but that they are receptive to other notions of geographic context such as temporal proximity, prediction and visibility. When predicting the future locations of moving point objects, a time geography approach using temporal proximity prediction surfaces was found to be the most effective, which analyse a long-term record of previous behaviour. The next most effective approach applied speed-heading prediction surfaces (which analyse a short-term record of previous behaviour), followed by spatial proximity prediction surfaces (which access no record of previous behaviour). This suggests that the most effective predictions can be derived from data mining behaviour from the long-term past.

For those readers pushed for time, or who only require an abridged overview of the aims, context, methodological approach and findings of this study, section abstracts can be found at the start of each chapter.

1. Introduction

Introduction Abstract

This introductory chapter first describes the motivation for the research: the convergence of mobile computing, mobile telephony and position determining technology, and advancement in the field of geographic information retrieval leading to the emergence of a new field of research - location-based services. Next, the aims and objectives are stated, including the need to develop geoVisualization software to analyse mobile trajectories, to develop representation that define the geographic context of the queries made by mobile individuals based upon their previous behaviour, to develop and evaluate prediction surfaces, and to test these notions of geographic context with users of a location-based service. Finally some potential applications for this work are described.

1.1 Motivation

The widespread acceptance and use of the Internet has been hailed variously as the "death of distance" (Cairncross, 1999) and the "death of geography" (Bates, 1999, Bates, 2000) since it allows individuals to access vast reserves of globally distributed digital information, regardless of their proximity to individual sources. As a consequence spatial and temporal constraints upon access to information associated with physical limitations on individual movement (Kwan, 2000, Lenntorp, 1978) have become less important. As predicted by Openshaw and Goddard (1987) nearly twenty years ago, you no longer have to travel to an information source, or wait for it to be sent to you, in order to access it.

Entities and phenomena described within documents however, usually refer to one or more locations within the physical world since entities tend to be found, and events occur, at specific locations (Longley et al., 2001). Despite the wealth of *geographic context* that appears to be implicitly contained within documents (Silva et al., 2004), current Internet information retrieval engines do not handle these *geographic footprints* (Goodchild, 1997) well since they tend to rely on exact matching between terms in the query and those in documents. Until recently possible spatial relationships between the query and document, such as distance and containment have been overlooked (Jones et al., 2002). A field of research known as geographic information retrieval (GIR) has emerged to tackle the problems associated with the "spaceless Internet" focusing upon building geographic ontologies and automated query term expansion to match the spatial properties of documents to the spatial context of the query. It is generally assumed that the user will define the spatial footprint for their query explicitly in some way, either using text such as a city name, address or zip code (Google, 2004) or via map interaction (Jones et al., 2002).

The development of consumer handheld devices such as personal digital assistants (PDAs) and mobile phones has led to a new computing paradigm, that of mobile computing (Helal et al., 1999). Mobile computing constraints include limited screen real estate (Brewster, 2002) and reduced interaction between user and device due to generally less sophisticated input mechanisms and the distractions of the outside world (Passani, 2002). As a result, mobile computing use tends to be characterised by short, frequent, task focused sessions (Ostrem, 2002) and these tasks are often of a fundamentally geographic nature such as routing (Kulju and Kaasinen, 2002), rendezvous (Chincholle et al., 2002), searching around one's location (Kjeldskov, 2002), proximity messaging between acquaintances, tracking of dependents, employees or resources, proximity advertising and location-based tariffs (Brimicombe and Li, 2004). These tasks belong to the emerging field of location-based services – LBS - (Open Geospatial Consortium, 2005b), which have been defined as;

> *"the delivery of data and information services where the content of those services are tailored to the current or some projected location of the user" (Brimicombe and Li, 2004)*

The importance of the *geographic context* of mobile users', combined with their reduced ability to interact with a device whilst on the move, makes a strong case for automated techniques to define the region that is relevant to a user's query at a given time. Previous research in this area has generally considered this context to be invariant and a property of the information sought (Amitay et al., 2004) or space itself (Jose et al., 2003) rather than the behaviour of the individual. Various *geographic filters* may be capable of defining this region that are appropriate in different situations. Such filters could include distance from current location (*spatial proximity*), accessibility in terms of travel time (*temporal proximity*), predictions of future locations, visibility among others. The application of these geographic filters offers the potential to reduce the volume of information delivered, and perform ranking based upon notions of *geographic relevance* (Raper, 2001). One of the main factors influencing the utility of location-based services (LBS) is likely to be the fitness-of-purpose of retrieved information. The existing assumption of spatial proximity is unlikely to satisfy all contexts in which mobile users access information, and geographic filters offer a potential solution to filtering information to the task in hand. When considering prediction and accessibility, the previous spatial behaviour of mobile individuals, as recorded by location-aware devices, may hold the key to generating geographic filters that attempt to rank information based upon both the *subject* sought, and the user's current *situation* (Saracevic, 1996a).

Within the discipline of GI science, a unifying theme of much research is the understanding of geographic entities and phenomena - and many researchers in the field have investigated individual spatio-temporal constraints (Miller, 1991, Forer, 1998, Miller, 2002, Moore et al., 2003, Mountain, 2005b) - hence it is perhaps uniquely suited to the study of information access in mobile environments. There is an opportunity to revisit much existing theory in the light of recent technological developments, and explore the potential for applying these ideas to this emerging area of research.

Within GI science, the temporal dimension has thus far been poorly represented and not used to full potential for analysis (Peuquet, 1999, Imfeld, 2000, Miller, 2003, Laube et al., 2005, Laube, 2005). This has been due in part to a lack of suitable data for modelling dynamic entities such as people at an appropriate scale. Technological developments have led to many new sources of data becoming available such as the Global Navigation Satellite Systems (GNSS) that have replaced less precise, more cumbersome techniques such as travel diaries and personal observation (Pospischil et al., 2002). Given this new supply of spatio-temporal data, there is a need to implement digital representations that allow sophisticated analysis of the entity or phenomena under analysis. Simple forms of analysis may miss the clear but complex patterns displayed by dynamic entities due to a failure to utilise the

temporal dimension appropriately, and through the loss of signal through noise in the data set (Andrienko et al., 2005, Imfeld, 2000). Given the human visual system's unsurpassed capacity to detect patterns in such data (Bruijn and Spence, 2000), new interactive visualization techniques that place equal importance upon spatial and temporal dimensions represent a critical step towards understanding human behaviour, and the development of hypotheses. Following from this, novel approaches to defining the geographic context associated with queries may be developed that may be able to improve the relevance of information accessed in a mobile computing environment by an individual with spatio-temporal constraints.

1.2 Aims and objectives

The broad aims of this research are first, to investigate approaches to improve the understanding of the individual spatial behaviour of people at an appropriate scale of analysis. Second, to consider approaches to making the information retrieved in a mobile environment more relevant to the geographic context of the individual making that query. Third, to test these ideas both through quantitative evaluation, and to generate more qualitative feedback from end users of a functioning mobile information retrieval system.

More specific objectives include:-

1. The collection of a library of mobile trajectories, recording representative spatial behaviour for several individuals, collected over a prolonged period of time;
2. The development of new geoVisualization tools for the exploration of the spatial, temporal and attribute components of those mobile trajectories;
3. The implementation of *time geography* concepts in this interactive geoVisualization environment;
4. The development of tools and algorithms that extract - from mobile trajectories - representations of the *geographic context* of an individual: for example, the region of space that is spatially close, accessible, or likely to be visited in the future based upon previously displayed behaviour;
5. The development of evaluation criteria for surfaces predicting the future location of moving entities, and the use of these criteria to compare the characteristics and effectiveness of different approaches in a variety of situations;
6. The implementation of a geographic filter that ranks information by the likelihood of an individual's future path coinciding with the geographic footprint associated with that information, and test this filter in a location-based service with users of that service;
7. To contrast the mobile and "desktop" Internet, and to get feedback from potential users of the mobile Internet about their information needs.

1.3 Limitations

This study will consider geographic context in terms of the information that can be extracted from the previously displayed spatial behaviour of mobile individuals. It will not consider the use of external data sources such as transportation networks, land-use, surrounding features and will only discuss (but not implement) the possibility of viewsheds extracted from digital terrain models as a potential geographic filter.

This thesis is not attempting to solve any of the problems associated with wayfinding, a discipline concerned with the communication of navigational directions (Nothegger et al., 2004). The information retrieved using the processes described is intended to provide spatially relevant information, commentary and service identification as opposed to orientation or directions.

Issues related to cartographic visualisation on small screen devices will not be considered at length. The thesis will be concerned primarily with the retrieval of features of interest, although there are obvious issues related to map generalisation and data conflation when presenting this information as a two dimensional map on a small screen device (Edwardes, 2004, Edwardes et al., 2003a).

1.4 Potential Applications

The primary application for the research conducted as part of this thesis is the field of location-based services (LBS): the central aim is to consider alternative approaches to the "search around me" spatial proximity search that is the current paradigm for such services (Karimi et al., 2000, Abele et al., 2005). Whilst using distance from present location may be desirable in many situations, the projected future locations of mobile individuals may be equally relevant for geographic queries, particularly for faster moving individuals, since the point at which the query was made may be redundant at the time the information is required or received. This thesis will consider a range of geographic filters that could be of use for mobile information retrieval and location-based services, and will attempt to evaluate different approaches to prediction.

A related area where prediction algorithms could be applied is moving object databases (Xu and Wolfson, 2003), with utility in fleet management, where a centralised command centre tracks the location of a large number of moving vehicles. The application of prediction models has been demonstrated to be a more efficient approach to maintaining a current database of the location of the fleet, than updates that operate at a predefined frequency, or spatial resolution (Wolfson and Yin, 2003). One emerging application area for prediction algorithms developed in the study could be the development of ad hoc mobile networks (Sharma et al., 2005). The recent trend towards mobile devices with wireless network

connections has been a driver for research into mobile, ad hoc networks. Such networks are essentially mobile peer-to-peer networks, characterised by non-static, autonomous nodes that can act as clients or servers as required, where keeping track of the other nodes in the network is required to maintain a network topology based upon spatial proximity.

2 Literature Review:

Literature review abstract

This section aims to place this research in context and is necessarily broad in scope due to the multidisciplinary nature of the research conducted. First, the scene is set by introducing geographic concepts and representations of space and time, prior to discussing the digital representation of these concepts, and approaches to integrating time into GI Systems. Given this context, the historical roots are described, and subsequent developments contrasted, within the field of *time geography*: a technique for modelling individual mobility. Next, correlated random walks, used to simulate movement paths generated by moving objects, are described, along with circular statistics, required to represent associated motion attributes. Next, the subject of prediction is considered with emphasis upon predicting the future location of moving point objects.

GeoVisualization is the next topic covered, as an approach to uncover patterns in large data sets by visual analysis. GeoVisualization is closely related to (and considered again) in the next section, geographic knowledge discovery, which describes data mining in general terms, followed by the specifics of applying these analytical techniques to geographic information. Next, the subject of information retrieval is described, followed by consideration of the literature on geographic information retrieval and approaches to defining geographic footprints for queries and information sources, and techniques to compare the similarity of the two. Finally, mobile computing is described, as the technology by which mobile individuals will make information requests.

2.1 Geographic concepts and representations of space and time

Whilst Geography can be viewed as a distinct academic discipline, geographic concepts relate to virtually everything we experience in everyday life; Couclelis (1999) suggests that this is the "great common denominator for all of us living on the surface of the earth". Human behaviour is constrained within a geographic framework comprised of space and time (Parkes and Thrift, 1980) at the *mesoscopic* scale (Smith and Mark, 1998). The mesoscopic scale is distinct from the atomic and astronomic levels and is appropriate to the human scale of analysis, where the physical entities we perceive and define for ourselves can be identified (Raper, 2000). It is essential for a study of this nature to first investigate geographic concepts, and the nature and representation of two key geographic components, space and time, across a range of disciplines prior to looking at how they can be represented digitally.

Couclelis (1999) proposes two categories of universally held geographic concepts within which human experience of the world can be framed. The first category deals with the tangible entities and phenomena that can be observed at different geographic scales, and that can change over time. Geographers regard *entities* as physical objects that can be identified at the mesoscopic scale, "a physical entity that is recognized in the user's definition of reality" (Lehan, 1986). It is within this class that people as individuals fall, although there is no constraint that entities must be discrete or singular objects. Geographic *phenomena* refer to "things that happen" rather than "things that are" (Couclelis, 1992). Examples of the types of phenomena relating to mobile individuals include traffic congestion and the migration of individuals or groups over a range of spatial and temporal scales.

The second category of geographic concepts identified by Couclelis include concepts of space and time (at different levels of granularity) and the spatial and temporal relationships between entities and phenomena. Conceptualisations of time and space are generally held to be different (NCGIA, 1989), although many authors have identified commonalities between them (Frank, 1998, Raper, 2000). These notions of spatial and temporal dimensions can be defined in different ways according to the context, different notions may be mutually exclusive and not all approaches are appropriate in all situations (Raper, 2000). The nature of space and time has traditionally been the concern of mathematics, physics, philosophy and geography (Couclelis, 1999). There is strong overlap between disciplines and a brief overview of the evolution of the conceptualisation of time and space is given here to provide a framework for discussing the handling of space and time within geographic information science. The evolution of different representations in different disciplines will first be considered to ground this research in the broader academic context.

Mathematics provided early perspectives - on space in particular - and a language with which to describe geographic entities and phenomena (Harvey, 1969). Examples of approaches to understanding space and time can be seen as far back as ancient Egypt and ancient Greece and was formalised by mathematicians such as Pythagoras and Euclid (Raper, 2000). Euclidean geometry remains perhaps the most commonly understood perspective of space, where measurements between points reflect the absolute distance between them. Mathematics also introduced topology, relationships that do not represent scale or absolute distance in the same way as geometry but remain true through a series of transformations. Where Euclidean geometry can describe absolute distance between physical entities, topology can answer questions such as whether two entities are adjacent, overlapping or if one is contained within the other (Alexandroff, 1961).

Physics has offered diverse and often contrary theoretic frameworks with which to describe space and time; in particular the distinction between absolute and relative space (Jammer, 1964). The absolute approach, a precondition of Newtonian physics, regards space as a neutral "container of all material things" (Harvey, 1969) and is described by two or three linear spatial dimensions which can be augmented by the single uni-directional linear dimension of time (Nagel, 1961). Relative space has no external framework to define locations or distances and is an emergent property of physical entities and events (Raper, 2000), hence 'empty space', which may dominate an absolute model, cannot exist (Couclelis, 1999).

The concept of time has been a particular source of discourse within Physics (Raper, 2000). Our common perception of time is that of an invariant linear progression, properties described by Newton in *Principia Mathmatica* in 1687; "Absolute, true and mathematical time, of itself and from its own nature, flows equably without relation to anything else" (Whitrow, 1975). Around the same time as Newton, Barrow considered time to have the same properties as a line in that it has length (duration), and that linear lengths could be added to form a longer durations (Child, 1916). Barrow also acknowledged the cyclical property of time using the example of a circular line. Discrepancies in the Newtonian approach, first raised by Leibnitz, were given empirical support from James Clerk Maxwell's electro-magnetic theory of light. In attempting to reconcile the theory's findings with Newtonian physics, Einstein showed that time is not invariant, but "an aspect of the relationship between the Universe an observer" (Whitrow, 1975).

Whilst the limitations of the Newtonian approach to time have subsequently been identified for processes that operate on the astronomic (macro) and atomic (micro) scales, this has minimal implications for the 'real world' which geographers aspire to model (Couclelis, 1999). At the mesoscopic scale (Smith and Mark, 1998) of human perception within which human spatial behaviour takes place (Golledge and Stimson, 1997), time is still generally considered as a linear, invariant framework that displays circular properties.

2.1.1 Digital representations of space and time

The geographic concepts and notions of space and time described have evolved over considerable periods of time, however the prevalence of digital computing as a primary form of analysis is a relatively recent trend that nevertheless has transformed how we go about representing and analysing data (Longley et al., 1999). The digital representation of space has long been the primary objective for the developers of what have become known as *geographic information systems* (GI Systems) (Burrough, 1994). There are many diverse examples of digital systems developed for the representation of spatial entities and phenomena within different disciplines, often in response to a need. Examples of precursors to modern GI Systems can be found in such diverse fields as cartography, demographics, architecture, agriculture, meteorology and geology (Longley et al., 1999); as such GI Systems are firmly rooted in analysis at the mesoscopic scale. The digital representation of time has its own characteristics and often occurs without reference to space (Peuquet, 1999). Approaching the debate from the perspective of temporal databases, Snodgrass (1992) argues that representing temporal dimensions is inherently more complex than representing spatial ones since they are non-homogenous, although this may be based upon a simplistic view of the potential representations of space - perhaps that such representations are confined to Euclidean geometry.

A commonality between digital representations of time and space is that their definition is often the result of a pragmatic solution to a specific problem (Frank, 1998). Frequently the conceptualisation of time has evolved out of the necessary functionality of the system. Designers of pay roll systems, for example, may employ a conceptualisation of time in order to fulfil this single function with little concern for the broader implications of their implementation (Frank, 1998). When adopting this pragmatic approach, the representation is defined by the process rather than vice-versa, however the representations of space and time adopted can place restrictions on the descriptions and analysis that can be performed.

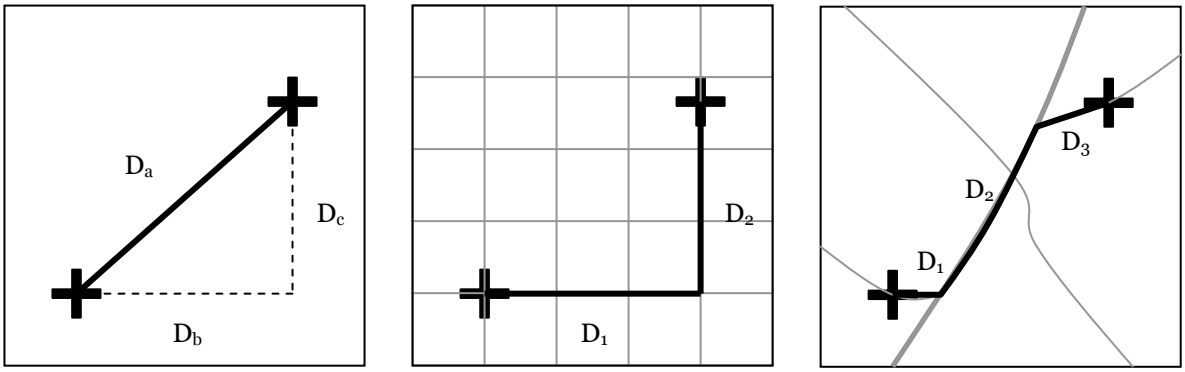
2.1.2 Atemporal GI Systems

GI systems have been criticised for neglecting the temporal dimension due to their *cartographic inheritance* (Couclelis, 1999), the result of them evolving as the digital counterparts to paper-based maps, that by their very nature are static documents poorly suited to representing change (Longley *et al*, 1999). There are many critiques of research that has failed to challenge this static approach. With respect to modelling individual mobility and mobile trajectories, Imfeld (2000) has been critical of the field of animal biology for describing movement using only the shape of a path and neglecting the temporal dimension (Imfeld, 2000). This section will provide a very brief description of the characteristics of these traditional 'atemporal' GI systems; prior to a discussion later on attempts to construct

models using a spatio-temporal framework, both generally within GI Systems and the specific issue of modelling individual movement using the time geography approach.

Figure 1: Three different concepts of distance in GI Systems, demonstrated for two dimensional space (Laurini and Thompson, 1992b)

a: Euclidean distance **b: Manhattan distance** **c: Network distance**



Distance = $D_a = \sqrt{(D_b^2 + D_c^2)}$ Distance = $D_1 + D_2$ Distance = $D_1 + D_2 + D_3$

There are two main paradigms in GI Systems, object and field representations (Cova and Goodchild, 2002). Within the object model, objects can be modelled in a number of different spatial dimensions. In zero-dimensional Euclidean space, an entity can be modelled as a point and the only information that can be known about that entity is whether it exists or not. In one-dimensional space, the distance of a point along a single axis can be measured, for example the distance travelled along a motorway. In two-dimensional space, a point can be plotted on a plane, this representation is familiar from points rendered on paper or flat screens. In three-dimensional (volumetric) space, a point's location can be plotted in terms of location on the two-dimensional plane with the third dimension representing height. It is important to distinguish between the dimension of the modelling *framework* and that of the entity to be modelled. For example, a point object has zero-dimensions (it either exists or not) but its location can be modelled in a zero-, one-, two- or three-dimensional spatial framework. A line object, such as a road, has one dimension (distance along that line) and can be modelled in a one-dimensional spatial framework or higher. An area object (such as a administrative region) has two dimensions (often referred to as x and y) and can be modelled in a planar or volumetric framework. Finally a three-dimensional object, such as an underground oil reserve, must be modelled in three-dimensional framework (Wood, 2003). Despite the fact that in reality, people as individuals, along with the majority of moving objects, occupy a volume in three dimensional space, for the mesoscopic scale of analysis, they are frequently represented as point objects and hence can be modelled in a zero-, one-, two- or three dimensional spatial framework. Tracing a line through a series of point locations creates a representation of where an object has been over a duration in time, which is often modelled in a two- or three-dimensional spatial framework. As will be described in

later sections, in order to model mobility in a meaningful way, it is necessary to incorporate a temporal dimension into this framework.

The distance between two spatial locations is a fundamental element of GI Systems. Laurini and Thompson (1992b) identified many aspects to this fundamental spatial property such as distance as a metric for measurement, as a type of geometry, the number of dimensions, and whether the measurement of distance is isotropic or anisotropic. The distance in a two dimensional isotropic surface is given by the Euclidean distance (Figure 1a). The Manhattan distance assumes movement is restricted to cardinal directions and hence is the sum of the lengths of the sides of a right-angled triangle (Figure 1b). Network distances acknowledge that movement is constrained to transportation networks and calculates the distance between two points along network edges (Figure 1c).

2.1.3 Aspatial temporal systems

There are many distinct approaches to representing time in a digital environment, however for all the "different types of time" that will be discussed here (Frank, 1998), the distinctions are between different conceptual models to represent the temporal dimension as perceived at the mesoscopic scale. Frank (1998) categorised the types of time used in GI Systems, however the descriptions are generic enough to offer a classification scheme for all digital representations of time. First, time can be represented as either a series of *events* of no duration, or as the time *intervals* that occur between events. Langran (1992) used the term event to identify occurrences that "transform one state into the next". An interval on the other hand defines the duration of a state and is represented by two events: a start and an end (Snodgrass, 1992). Second, time can be considered as ordinal, a series of ordered events, or as a continuous temporal axis upon which events can be plotted. Third, time can be subdivided by either linear time where each event follows on from the next, or cyclical, which takes account of the repetition inherent in many naturally and socially constructed phenomena. Adopting Frank's fourth taxonomy, combining two different viewpoints leads to multiple overlapping perspectives that can be partially ordered or compared with a single viewpoint where total order is maintained. Each type of time as identified by Frank (1998) will be considered briefly.

Ordinal time models share the characteristics of the ordinal scale of measurement (Stevens, 1946) and can be represented as a series of *time points* (Frank, 1998), events in a temporal sequence. Events can be ordered according to when they occurred or will occur. This defines a fundamental temporal relation which can be used to identify cause and effect relationships (Frank, 1998), however the actual times of occurrences remain unknown hence duration between two events them cannot be derived. *Continuous time* is analogous to the interval or ratio scales of measurement and hence can be represented with real or integer values. Beyond the temporal topology described for ordinal models, the duration between events can

be calculated for continuous time schema (Peuquet, 1999). A model that employs real numbers can be considered as a continuous stream that is infinitely divisible: time is dense (Snodgrass, 1992) since another event can always be inserted between two existing events. A continuous model can be viewed at different resolutions from fractions of seconds to millennia. The temporal *resolution* can be defined by a tolerance value that reflects the level of uncertainty in measurement. For example global positioning system (GPS) receiver clocks are accurate to 1 part in 10^{10} offering nanosecond precision (Rizos, 1999) allowing almost all events to be ordered correctly, whilst fossil records from the field of geology may only be determined to millennia (Flewelling et al., 1992), hence events several hundred years apart in a geological record may be indistinguishable.

Both processes and temporal measurements can be *cyclical*, for example the agricultural cycle is dependent upon the seasons; it is not possible to say that reaping follows sowing or Summer follows Winter, the cycle repeats indefinitely. The frequency of cycles can be dictated by natural events such as daily and annual solar cycles which control, among other phenomena, animal sleeping habits and growing seasons respectively (Laube, 2001). The cycles can also be defined by socially constructed frameworks (eg days of the week or hours of work), dictating individual regimes and having broader implications for the emergent behaviour of groups of individuals. In many cases the natural and socially constructed cycles interact, for example the seasonal and diurnal movement patterns of wildlife in National Parks in response to the volume of visitors (Haller and Filli, 2001).

2.1.4 Approaches to integrating time into GI Systems

The previous sections have described the evolution of notions of geographic entities, geographic phenomena, concepts of space and time across different disciplines, and approaches to representing these concepts digitally. Following the previous descriptions of digital representations of space and time in isolation of each other, this section will discuss how existing *atemporal* GI systems, designed primarily for representing spatial dimensions (Langran, 1992), have been extended to include time.

Much research investigating time in the field of GI systems has taken the approach of adding a temporal dimension to existing spatial systems. Peuquet (1999) identified two sources of motivation for the inclusion of time in GI Systems. The first considers the need to model both phenomena and the evolution of entities through time. This cannot be achieved with GI Systems that just store static representations of the world as they have a limited capacity for representing process and change. Second, the more pragmatic issue of updating databases with current data and what to do with the 'redundant' data, a problem encapsulated by the phrase "the agony of delete" (Copeland, 1982). Imfeld (2000) argues that to be called temporal GI System, functionality should extend beyond representation to analysis. Justification for this argument comes from the spatial analogy; a system that simply

represents points, lines and polygons and displays them to screen is not referred to as a GI System. Similarly without analysis functionality that includes time, a system is not a true temporal GI System (Imfeld, 2000). A key consideration for integrating time within GI Systems is the retrieval of information in response to queries (Langran, 1992). A key distinction between types of query is whether they wish to find the spatial distribution of some phenomena at a *specific instant in time*, or changes that occurred *over a period of time* (Peuquet, 1999). The first approach is essentially static, answers to queries can be retrieved from a series of time-stamped "snapshots" (Snodgrass, 1992), however it is harder to retrieve information about process. Such a query could reveal for example, the extent of a forest at a certain date. A more dynamic query would consider changes through time, such as areas of deforestation (or reforestation) over the previous decade.

Dynamic modelling requires a closer look at the nature of change and the rates at which it can occur. Peuquet (1999) built upon the definition of an event (Mackaness, 1993) to propose a classification of four types of change based upon the frequency at which change occurs. At one extreme there is continuous change, an unbroken 'event' that occurs constantly. An element of periodicity is implied by two intermediate types, majorative change (occurring most of the time) and sporadic change (occurring some of time). Unique changes, at the other extreme, are those that occur only once. The classification is somewhat subjective and dependent upon the spatial and temporal granularity at which a phenomenon is viewed. When viewed as a whole over a period of many years, the sedimentation of a delta could be viewed as continuous. When considering seasonal variations this may prove to be majorative or sporadic. However if only considering the impact upon the artificial landscape, immediately preceding and following a major flood, the sedimentation process may be seen as a unique event. Events are distinct from the collective term *episode,* which refers to a series of events, typically more prolonged over time (Mackaness, 1993).

There are many different approaches to classifying the research conducted into temporal GI systems. Imfeld (2000) groups research into three topics; database, query and analysis. Spatio-temporal data can be represented in GI systems according to three perspectives depending upon whether the data is ordered by location, by time or by the entity itself (Peuquet, 1999). Location-based representations are closest in nature to traditional GI systems since they can be implemented by simply appending existing data in a GI System with a temporal attribute (Cohn and Hazarika, 2001). This avoids the "agony of delete" by replicating the entire dataset with a temporal attribute to create a series of *sequent snapshots* (Halls and Miller, 1996) through time. Whilst a logical progression from traditional GI Systems this approach has a number of drawbacks. The time of a change can only be identified as between two adjacent snapshots; the time of the change in the real world, even if known, is not stored explicitly. Data volume increases enormously due to redundancy since there is no attempt to identify what has changed between updates; in the extreme case, two or more snapshots may be identical (Peuquet, 1999). In order to identify *changes* rather than

simply report upon the *state* for a given time, two layers must be compared in an inefficient brute force way. A modification to the raster data model to reduce storage and record the time and place of changes was suggested by Peuquet and Qian (1996). By allowing a variable length list of attributes associated with the time, cells of a raster can be updated with new values whilst retaining the old ones storing the time of the change in the database, hence cells that have not changed need not be updated.

Entity-based representation adopts the object-orientated paradigm where entities themselves are encapsulated and amendments recorded for each (Langran, 1992); this contrasts with the first approach where amendments are stored based upon location. This form of representation is most suited to the geometric approach of object representations than the field paradigm; hence it can "track the changes in the geometry of entities through time" (Peuquet, 1999). Using *amendment vectors*, changes to existing features can be stored (Langran, 1992), however this approach has been criticised conceptually for being too simplistic for entities with complex lifecycles (Halls and Miller, 1996) and in practice can lead to severe fragmentation. This notion of life cycle also indicates the problems associated with identity when two existing entities merge or a single one splits.

The third approach to representing spatio-temporal data within GI systems uses time as the organisational framework, creating a timeline of events that store the changes that have occurred between successive states (Peuquet, 1999). Whilst this approach is suitable for the unique, sporadic and majorative forms of change identified previously, it models continuous change poorly, since continuous phenomena must be broken down into episodes of discrete events (Mackaness, 1993).

According to Peuquet (1999), analysis of temporal data can take three forms; quantitative, qualitative and visual. Qualitative approaches have considered temporal logic (Worboys, 1990). Visual analysis has been identified as an essential tool for data exploration, utilising human vision to interpret patterns in data (MacEachren and Kraak, 2001). This will be described in detail under the section geoVisualization. Examples of quantitative analysis include the time geography approaches developed by Hagerstrand (1973) and others (Lenntorp, 1976, Miller, 1991, Forer, 1998), which will be discussed in detail in the following section.

For the research into mobile trajectories conducted in this thesis, it is appropriate to model individuals as *moving point objects* in a framework of two or three spatial dimensions and a single temporal dimension. Imfeld (2000), suggests an ontology of point objects based upon two characteristics of the object type. The first of these is whether the object is static at the desired temporal scale of analysis (such as a mountain when viewed over a period of a few years) or mobile (such as an individual's behaviour over a day). The second characteristic is the duration of the point object, which is also dependent upon the temporal resolution of

analysis. Static points can exist for an instant then vanish. Both mobile and static points can exist for a *period* with defined start and end point (eg an animal over its lifetime), at *intervals* with multiple start and end points (eg the repeated journey to work for an individual), or the duration may be considered *infinite* at the scale of analysis (eg the location of a city, for a study of individual mobility that takes place over a period of weeks) (Imfeld, 2000). The temporal resolution of analysis is frequently dictated by the sampling strategy used for data collection. When considering mobile trajectories, data sources can include travel diaries (Kwan, 2000), that tend to record the start, end and important 'via' points of journeys, animal observation in wildlife studies (Marell et al., 2002), and automated positioning systems such as global navigation satellite systems. Most approaches generate a series of point objects recording at least a two dimensional spatial identifier and time-stamp. The sampling strategy associated with mobile trajectories is typically non-continuous and usually a sequence of snapshots recording the location of the object for a specific instant. In addition the temporal sampling strategy may be regular, for example a point recorded every second, or the approach may result in an irregular temporal sampling such as a point recorded when the object moves more than x metres from the previous observation.

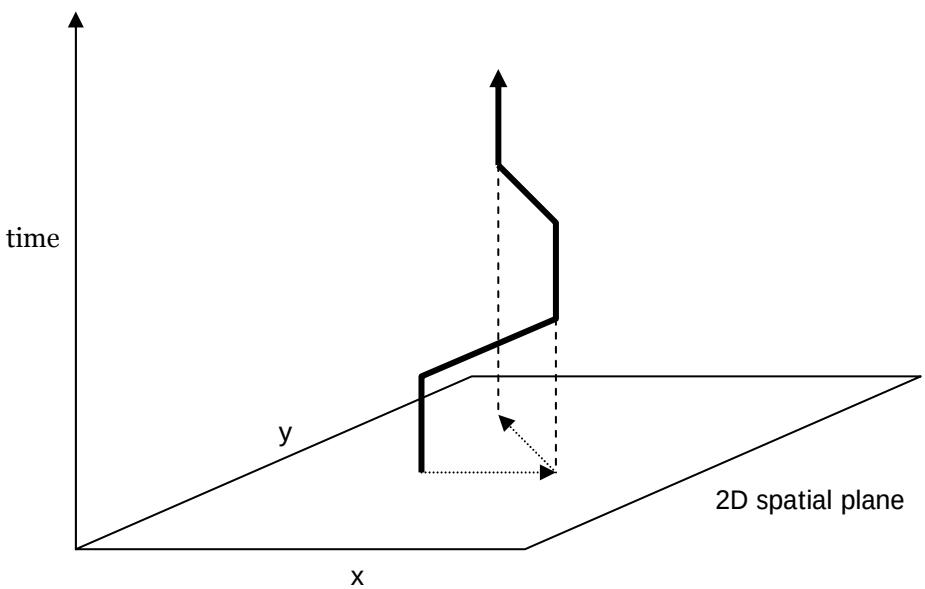
Spatial metaphors are frequently used to describe temporal relations, such as referring to two contemporary events as 'close', or a memory from the long-term past as 'distant' (Raper, 2000). Language describing movement through space also shares commonalities with that describing the progression of time, such as locations that are *ahead*, *coming up*, or *behind* you. When moving, these relations are equivalent, since locations that are in front on you in space, are also those that you will reach in the course of time. Likewise distances are often described using temporal metrics when people refer to the spatial separation of two locations by the time taken to travel between them, for example *its 10 minutes away* (Forer, 1998). Parkes and Thrift (1980) noted that "One of the most common relative space measures combines space with time... Thus in everyday life we consider the time it takes to get somewhere". This notion of travel time or *accessibility*, will be described next.

2.2 Time Geography

All human activities occur coincidentally in time and space (Golledge and Stimson, 1997), hence a framework of two or three spatial dimensions and a single temporal dimension is suitable for modelling individual mobility. As discussed previously, at the mesoscopic scale of analysis it is appropriate to model individual human beings as point objects, although in reality they occupy a volume in three spatial dimensions. At any given point in time then, an individual can be modelled as a point object occupying a unique location in space and time (Snodgrass, 1992). Starting at some spatio-temporal location, such as the place and time at which it came into existence, an entity's movement can be realised as the trajectory of a point through this three-dimensional space-time framework, where a horizontal plane represents two spatial dimensions and the vertical axis represents time elapsing (Golledge and Stimson, 1997). This results in a *space-time path*, or *mobile trajectory* (Smyth, 2000) representing the unique path followed by that entity; such a trajectory is shown in Figure 2.

Figure 2: Schematic representation of the space-time path, after Miller (1991)

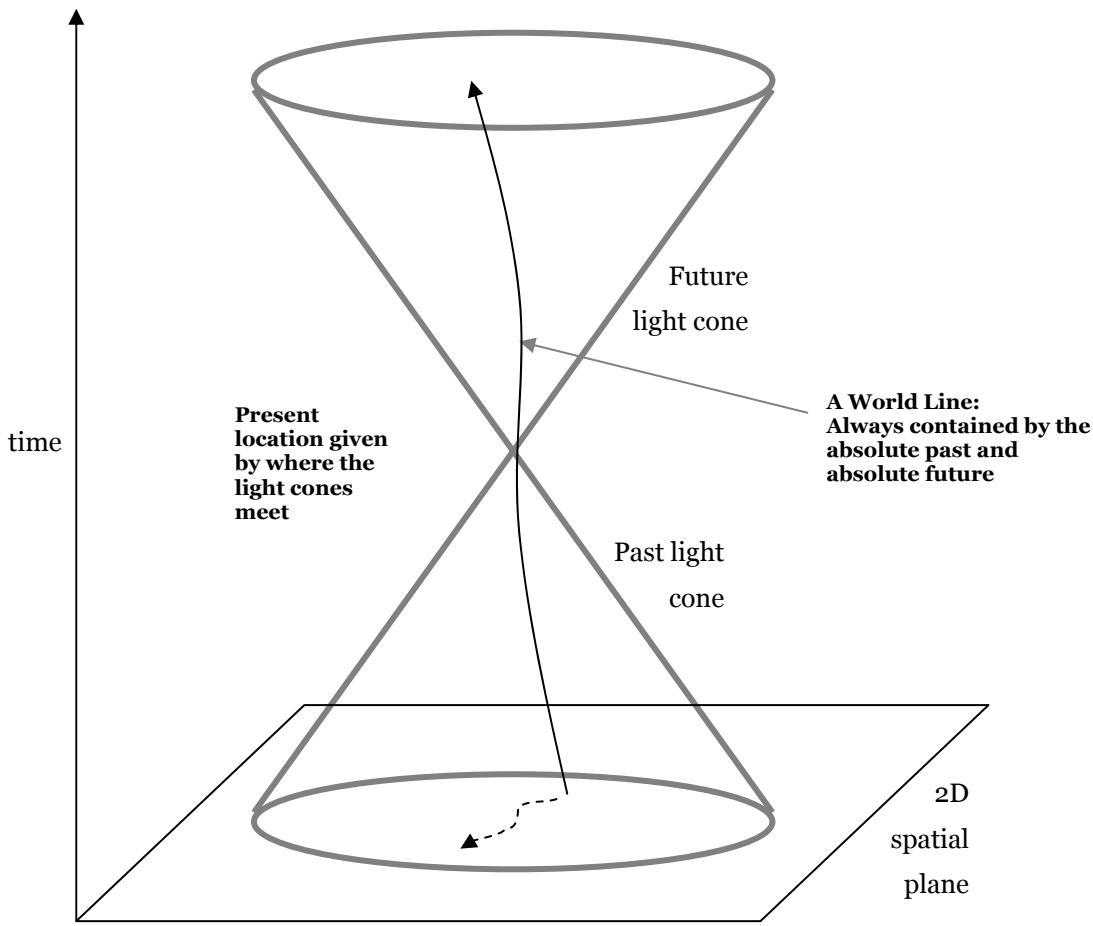
The heavy black line shows the trajectory formed when the movement of a point object is represented in two spatial dimensions (the horizontal plane), and one temporal dimension (the vertical axis).



Many authors have described the use of this space-time framework for modelling individual accessibility (Hagerstrand, 1973, Kwan, 2000, Lenntorp, 1976, Lenntorp, 1978, Miller, 1991, Moore et al., 2003). Forer (1998) describes *space-time* as "a conceptualisation of space (i.e. separation) and time as part of a 3- or 4-D continuum": a framework of two or three spatial dimensions and single temporal one, within which activity can be modelled. Such a framework has been termed an *aquarium* (Moore et al., 2003) because of its appearance. The majority of work in this area has described geometric approaches to combining time and

space in the context of modelling everyday human activities (Hagerstrand, 1973, Miller, 1991, Forer, 1998).

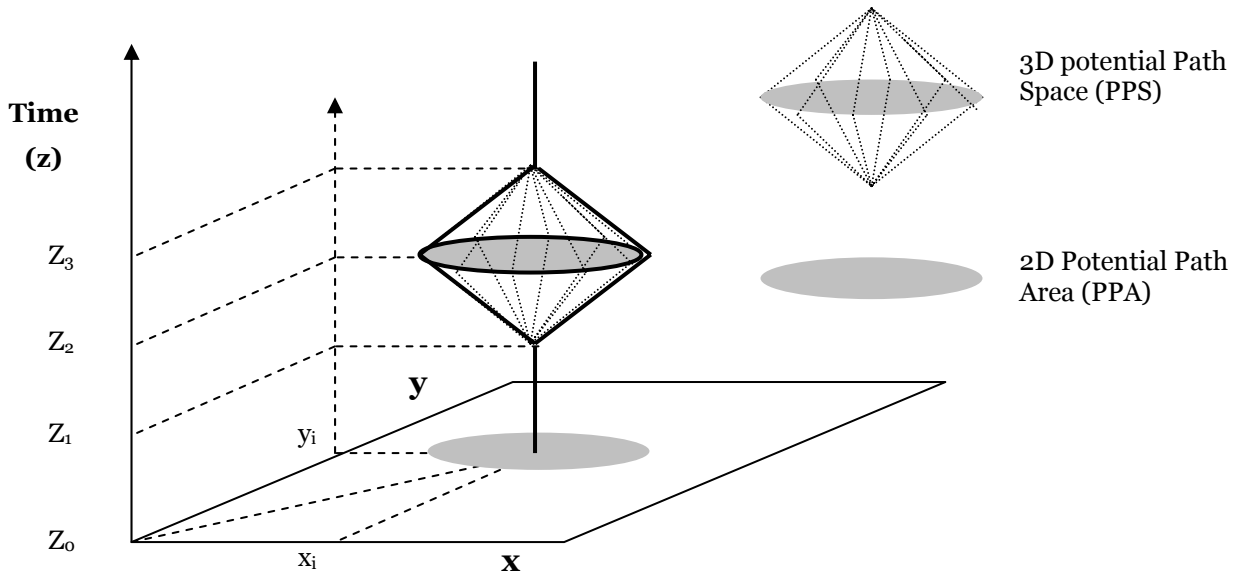
Figure 3: Light Cones and World Lines, after Minkowski (1923)



More recent research attempting to model human behaviour against a spatio-temporal framework owes much to scientists researching the physics of space and time in the first half of the twentieth century. Ideas developed by Minkowski (1923) allowed space and time to be visualised as a light cone. For any location at a specific time, there is a sharply delineated light cone defining a boundary between the accessible locations for the future (see Figure 3) which is defined by light emanating from that point at that time. This is the *absolute future* for that instance of space-time: all movement must be contained within this light cone since nothing can travel faster than the speed of light. Extrapolating the cone back in time define the *absolute past* for that location. World lines, predecessors of the space time-paths previously described in this section, can be plotted within the light cone to describe an object's movement. The gradient of a line on these plots represents velocity across the 2-dimensional surface. A vertical line represents no movement and increasingly horizontally sloped lines show faster velocities. The Lund School of Sweden adapted these earlier ideas to

lay the foundations of *time geography* by attempting to create a spatio-temporal framework against which to model human activity. Hagerstrand (1973) of the Lund School developed the key idea of the space-time path or mobile trajectory for representing movement and activity, an idea the same in essence to world lines.

Figure 4: Schematic representation of the space-time prism, after Miller (1991)



Whilst the light cone defines the absolute physical limit of accessibility, when modelling human activity the constraining cones (or prisms) tend to be defined by more mundane factors. In practice the maximum speed of walking or mechanised transport sets the limit on the potential past and future physical locations, although they may be able to observe or interact with more distant locations. Miller (1991) describes the *space-time prism* as modelling the ability of individuals to travel to and participate in activities at different locations. These prisms will always confine the space-time paths (of where you have been) and define Boolean volumetric regions in space-time indicating places that individuals can and can't get to for a given *time budget*. Beyond physical transportation constraints, the prisms are defined by the individual's present location and commitments to be certain places at certain times in the future. Figure 4 shows a reproduction of Miller's space-time prism (1991). It shows the potential path space (PPS) of an individual leaving the spatial location x_1, y_1 at time z_1 who must return to the same location by time z_3. The prism generated describes the maximum spatial extent the individual can access at any given time (z_2); this two-dimensional spatial extent is referred to as the potential path area (PPA). Speed is a limiting factor on the size of the PPS and PPA hence increasing the maximum speed at which an individual can travel increases their accessibility.

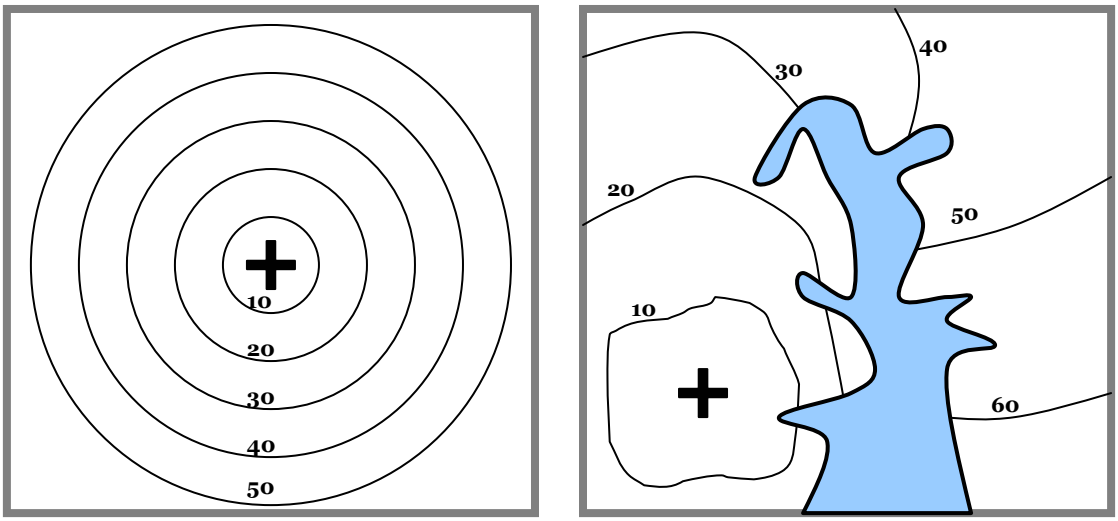
The boundary of the PPA can be referred to as a time travel isoline (Laurini and Thompson, 1992b) or isochrone when projected in two dimensions, since it represents the maximum

distance that can be travelled from starting point, given some time budget. For an isotropic surface where there is no variation in ease of movement for different locations and directions, a series of isochrones with increasing time budgets for the same starting point will form concentric circles around that starting location (Figure 5a). In most real world situations, there are many other constraints than just maximum speed to consider when defining space-time prisms. Some spatial locations will be out of bounds either permanently (such as private land) or intermittently (such as opening hours of facilities) and there will be constraints imposed by physical capabilities such as the transport network and the terrain leading to anisotropic space-time prisms and isochrones (Figure 5b).

Figure 5: Isochrones showing travel times for a point location (Laurini and Thompson, 1992b)

a: For an isotropic surface. The isochrones are concentric hence accessibility mirrors spatial proximity.

b: In this anisotropic surface, movement is impeded by a river estuary leading to a more complex isochrone pattern.



Lenntorp (1976, 1978) attempted to apply these ideas to measure accessibility in urban areas. By configuring the locations to be visited, transport restrictions and schedules of activities, all feasible permutations of the model can be realised. This offers some measure of accessibility, however at that time, computing restrictions could offer only simplistic simulations of the real world. Burns (1979) conducted work along similar lines with particular attention to the variations in accessibility that occur with changes in an individual's speed, however this work was purely theoretical and was never applied to the real world.

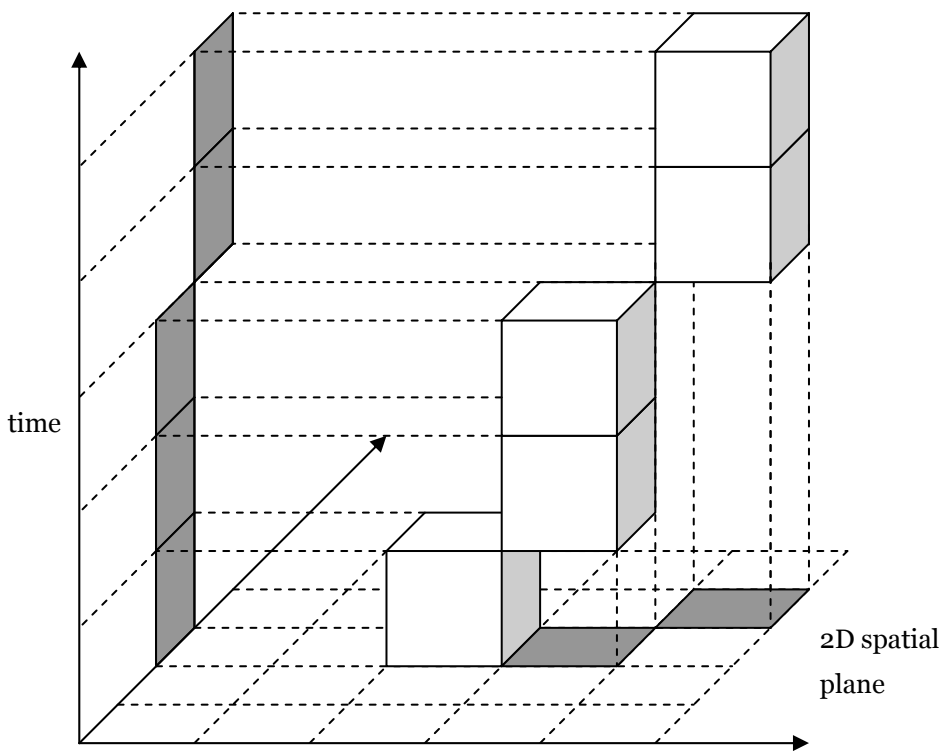
One approach to moving from simple isotropic space-time prisms and isochrones to more realistic models of accessibility is to include links and nodes corresponding to transport infrastructure. Miller (1991) considered approaches to the time geography model, the "punctiform" version considered locations as points in Euclidean space linked by straight lines. A network version linked nodes with a series of arcs and associated travel times corresponding to the transportation network. Although Miller (1991) only implemented this

second model at the level of a simplistic grid structure, it can be seen how this could be extended to a transport network where the class (and hence mean speed) of roads is recorded as an attribute; this allows the development of more complex, and ultimately realistic, space-time prisms.

Another approach to modelling more realistic travel speeds, which do not include simplistic assumptions such as homogenous surfaces, is the use of travel geometry for urban modelling (Hyman and Mayhew, 2004). This approach does not depend upon an accurate or detailed representation of the road network, but instead is based upon the notion that speed of movement is dictated by purely geometric factors. Constraints on speed can be dictated by factors such as the distance from the centre of a city. Template road networks include a *Grid City* where movement is constrained to the ordinal directions which bares similarities to Miller's model (1991). In *Edge City* movement is constrained to either radial or orbital roads which is a good fit for London in the UK, with its major orbital roads such as the M25 and the North and South Circular. *Surf City* considers cities where movement in a particular direction is constrained by a barrier such as the coast. Non-conformal transformations from the two-dimensional spatial plane associated with these template cities produces *time surfaces*, where speed of movement is the same at all points on the surface and in all directions (Hyman and Mayhew, 2004).

Figure 6: An individual's space-time path as the consumption of space-time.

Plotted in a discrete model of space-time where mobile entities consume *taxels* of space-time, after Forer (1998)



Forer (1998) considered two general approaches to describing human behaviour using a space-time framework that attempted to make more realistic assumptions about constraints on movement. One is on a point node basis where an individual's difficulty in travelling between nodes may be used to describe movement. In this case the actual physical distance and direction of separation of the nodes may not be relevant - it is the travel time between two nodes that matters. The other approach is to take full account the physical locations of relevant nodes and describe the physical space in terms of continuous geometry described by Forer (1998) as using space-time as an activity framework. In both cases, however, flow between points is of key importance.

An interesting approach relating to the uniqueness of each position in space and time considers travel to be the consumption of space through time (Forer, 1998). During its existence, an entity always occupies a unique location in space-time that cannot be shared with other entities. For modelling and representing individual movement behaviour Forer (1998) suggested plotting various spatial entities as solid cubic cells occupying space in spatial and temporal dimensions, rather than modelling individuals as point objects after the time geography approach (Figure 6). This shows the individual as a consumer of time space, always occupying some region of space through time. Each cube within the framework is referred to as a taxel: a three dimensional space-time pixel.

Various entities can be represented in this way. Spatially static entities such as buildings will always occupy the same two-dimensional space, although access to services offered within these structures may be continuous (such as one's own home) or intermittent (such as shops with specific opening hours). In the first case the taxels will form a continuous column, in the second these spatial static but temporally dynamic structures will form broken columns. Mobile entities such as individual people, on the other hand, will form a single wandering line of taxels that is constant in size but moves in space through time. An individual's space-time prism (Miller, 1991) will be represented as collections of taxels emanating from single taxel at the present time, widening to a maximum, then contracting through time to a specific spatio-temporal location in the future indicating a commitment to be at that place, at that time.

This section has demonstrated that time geography can be applied to modelling previously displayed spatial behaviour, and also offers an approach to predicting future behaviour, since potential path area is a prediction of the bounds of an individual's accessible space, for a given time budget. A great deal of research has taken place in other areas concerned with the modelling of motion patterns, and the prediction of the future locations of moving point objects, and these will be reviewed in the following sections.

Research in the area of time geography is very much ongoing. A special issue of *Geografiska Annaler* in 2004 had several papers devoted to recent work in this area (Lenntorp, 2004). Of particular interest was the development of the notion of a *pocket of local order* (Ellegard and Vilhelmson, 2004), which extends the idea that resources and opportunities exist in discrete regions of time and place. Ellegard and Vilhelmson argue that the completion of tasks is dependent upon the negotiation of the pockets of such resources, some of which individuals have more control over than others. Making individuals aware of the resources available in the region of space-time accessible to them is clearly compatible with the aims of this thesis. Raubal *et al* (2004) apply the notion of time geography to location-based services (LBS), pointing out that present LBS do not account for individuals' preferences or time constraints. They propose building upon the time geography concept of *affordances*, which can belong to the physical, socio-institutional and mental domains. Their "user centred spatio-temporal theory" approach aims to take more account of individual constraints within the field of LBS, rather than making simplistic assumptions about the services and information that will be of relevance or interest to any one individual, an approach which also has very similar ambition to this thesis.

2.3 Modelling motion patterns

2.3.1 Correlated random walks

The use of correlated random walks (Byers, 2001) is a technique that models the movement paths generated by moving objects and can be applied to make predictions about the future location(s) of some entity or phenomenon, based upon statistical distributions for speed and turning angles (Nams, 1996). The primary application has been simulating the spatial dispersion of animals over time, but the technique has been applied to model human behaviour in applications such as crime modelling (CrimeStat, 2001). Most correlated random walk models take three parameters (Byers, 2001);

- The number of steps that comprise the walk,
- The step size,
- A distribution of turning angles (Byers, 2001), or headings (Nams, 1996)

This model has been very popular in ecology, particularly for modelling foraging patterns of animals, however it has limitations. First fixing the step size so that the moving point object always makes a turn every n metres is an unrealistic simplifying assumption that can generate unnaturally uniform walks. Second, there is no clear consensus about the most suitable statistical distribution to use for turning angles. A uniform random distribution assumes a turn direction is equally likely to the left or right, and that there is no bias in turn magnitude which is equally likely to be any value from 0° indicating no change in heading, to

180° indicating a reversal in heading. Such a model generates Brownian motion (Byers, 2001). A Normal random distribution assumes a bias in the direction and magnitude of turn. Often a mean value of 0° is used, suggesting that there is no left-right bias, and that small turns are more likely than large ones (Marell et al., 2002). Imfeld (2000) criticised approaches that assume that patterns are random – particularly in the field of wildlife biology. This misconception arises from the inability of simple techniques to identify the clear but complex patterns that animals exhibit in their movement (Imfeld, 2000). Finally when using the turning angles approach, correlated random walks are very sensitive to the initial choice of heading from which the first step in the path will deviate, which can make the paths poor for prediction. An alternative approach is to use a distribution of headings, rather than turning angles, so that the heading at each step of a walk projected into the future is not dependent upon the steps that preceded it.

More recently, random walks have been applied as a means of comparing the relative motion of groups of entities over space and time (Laube and Purves, 2005). An individual displays a *constancy* pattern when it retains the same heading for a period of time. A *concurrence* pattern is defined by a number of entities following the same heading. By searching for these patterns, *trend-setters* within a group can be identified, those that follow a given heading and are subsequently joined by other group members. The work has thus far been applied to the deer herds, and movement of electoral units within a two-dimensional spatialisation (Fabrikant, 2000) of voting behaviour. Random walks tend not to account for constraints on movement and work well in some conditions and specific spatial scales, such as the movement of foraging animals in open space (Marell et al., 2002), but may be less applicable in highly constrained environments. There is a parallel between the encapsulation of movement in random walks, and research into agent simulation of individual behaviour using swarming or flocking behaviour (MacGill and Openshaw, 1998). The correlated random walk could be used as the rules which dictate the individual spatial behaviour of agents in a simulation, with applications in a wide range of studies such as crowd control (Batty et al., 2003).

2.3.2 Circular statistics

Of the multitude of publication on statistics, surprisingly little attention is given to directional (or circular) data (Brunsdon and Charlton, 2003). Directional data sets defy the linearity of data assumed by most descriptive statistics models since they can only be described in two (circular), three (spherical) or more dimensions (Brunsdon and Charlton, 2003). Cyclical data has been discussed from the perspective of temporal cycles that can recur at different scales, such as daily, weekly, lunar month and solar year cycles (Frank, 1998). Some attributes of the mobile trajectories (Smyth, 2000) display circular properties. *Heading* (Pfoser and Theodoridis, 2003) can be defined as the direction of movement of some moving object; related terms that do not imply movement include *bearing* between

points (Perkins and Perkins, 1991), *orientation* of an object (Smyth, 2000) and the topological relation *direction* (Mark, 1999). Similarly the vector attribute velocity is described by (scalar) speed and direction (Duncan, 1990). Such data sets are circular and have no clear minimum and maximum, a heading of 0 degrees is very similar to 359 degrees, although these are the extreme values according to linear statistics (Brunsdon and Charlton, 2003), this is shown diagrammatically in Figure 7a.

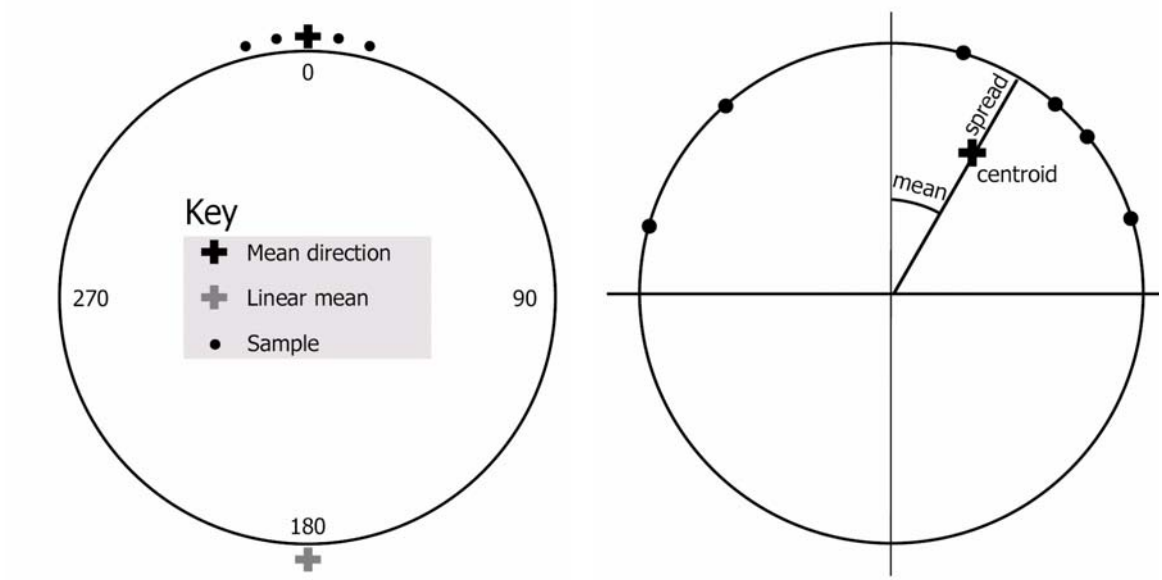
Figure 7: Circular statistics, after Brunsdon and Charlton (2003).

a: The mean direction and linear mean for a sample of four angles.

The diagram shows a sample of four angles, clustered around zero degrees. The linear mean of the sample is 180 degrees, the opposite direction of the required value, given by the directional mean.

b: The mean direction and circular spread for a sample of angles.

The mean direction and measure of spread are both calculated by deriving the centroid of the points on the circumference of the circle (representing angles). The mean is the angle of the centroid from the origin. The spread is the (minimum) distance from the centroid to the circumference.



One approach to deriving measures of central tendency and *spread* for circular data sets is to treat them as points on the unit circle (Brunsdon and Charlton, 2003), a circle whose radius is equal to one, centred on the origin. Although plotted in 2D space, the points are confined to the one-dimensional subset of it defined by this unit circle. Calculating the centroid of these points reveals a point somewhere within the circle. The mean direction is given by the angle from the origin to the centroid of the points. A measure of spread is given by the

minimum distance between the centroid and circumference, a value of 0 suggests complete clustering of all angles upon a single point, a value of one suggests a uniform distribution (Figure 7b).

There are also a number of statistical approaches to the analysis of directional data (Fisher, 1993) which can offer alternative measures of central tendency and spread. Some linear distributions have been *wrapped* (Mardia and Jupp, 1999) to make them suitable for circular data including the wrapped Normal distribution. Others have been developed specifically for circular data such as the Von Mises distribution and the Wrapped Cauchy distribution (Fisher, 1993).

2.4 Prediction

When making predictions, it is typically assumed the present and future will reflect previously displayed patterns of behaviour: in short "the past is the key to understanding the future" (Longley et al., 2005). This concept of temporal autocorrelation is in some ways analogous to spatial autocorrelation; however there are some distinct differences. First time series data is one-dimensional, whereas space is usually modelled in two or three spatial dimensions. Crucially, causality is uni-directional, since past events may influence future event but the opposite is not true. It could be argued that future events effect the present, for example that you are at a particular location because you are en route to another *intended* location in the future. However, until you arrive at that location at a future time it remains an intention (as opposed to an event that has occurred), based upon a decision that was taken in the *past* (J. Wood personal communication, Sept 2005). This uni-directional temporal constraint is not usually applied when considering spatial autocorrelation (Longley et al., 2005).

Before considering the literature concerned with prediction for individual point objects based upon their previous behaviour, it must first be acknowledged that a great deal of research is, and has been, concerned with modelling and predicting the aggregate daily or longer-term migration of large numbers of individuals, between competing commercial centres (Jornsten et al., 2004). This work, with roots in behavioural geography, is often highly theoretical and has traditionally been based upon gravity models and an assumption of distance-deterrence, ie that if all other factors are equal, people will travel to the *closest* location (Jornsten et al., 2004). Such research has informed urban planning, and assisted decision making process when considering changes to the transportation infrastructure. The assumptions and approach of this literature is of limited utility to a study that considers the movement of individuals, without reference to external factors such as the presence or absence of towns or transportation links, hence little reference will be made to this body of work.

When considering the spatial behaviour of individuals, a model of mobility can allow predictions to be made about the future location of that individual moving object. A great deal of research has been focussed upon such prediction based upon mobile trajectories storing a record of known current and previous locations (Schlenoff et al., 2004, Wolfson et al., 2000). Suggested application areas for moving object prediction have included fleet and public transport management (Farhan et al., 2002, Xu and Wolfson, 2003), air traffic control (Tao et al., 2004), collision avoidance for robotics (Elnagar, 1999, Elnagar, 2001, Vasquez and Fraichard, 2004) and unmanned vehicles (Madhavan and Schlenoff, 2003), mobile ad-hoc networks (Sharma et al., 2005), and as a filter to increase the relevance of information for mobile users of personal digital assistants (Brimicombe and Li, 2004, Karimi and Liu, 2003, Wolfson and Yin, 2003).

In the context of the update of a moving objects database, a predictive model has proved to be far more efficient than those updated at a predefined temporal frequency or spatial resolution (Wolfson and Yin, 2003). The approach maintains a model of where a moving object is likely to be at a future time, given its current location, speed and direction, and a transportation network. A deviation policy controls database update by monitoring the degree to which the actual location deviated from the predicted location, and performs an update when some threshold is crossed (Wolfson and Yin, 2003). This model can provide answers to queries relating to when a moving object will reach a known destination (which may be a point location or region) (Xu and Wolfson, 2003), but has not been explicitly designed to provide the possible future locations of a moving point object for a given future time. A critique of the approach applied by Xu and Wolfson (2003) is that it does not account for the individual spatial behaviour of moving point objects, but assumes that all objects will traverse the edges of a transportation network at the same speed; it cannot make predictions about future locations based upon the previous trajectory path of the moving point object alone. Furthermore the prediction can only predict as far ahead as the length of each network edge since there is no approach described to make a decision about which path to take at nodes in the transportation network. This may be acceptable for networks with long edges and relatively few nodes (eg motorways), but is ineffective for networks characterised by high node density, where the prediction model must be updated every time a node is passed.

Another major application area for prediction of future locations, based upon present and past behaviour, has been the field of robotics, specifically autonomous robotic motion control (Vasquez and Fraichard, 2004). The location of moving point objects is typically taken from visual sensors, hence there is overlap with research into video surveillance (Vasquez and Fraichard, 2004). Motivations include the need for robots and unmanned vehicles to navigate through a dynamic environment (Elnagar, 1999, Elnagar, 2001, Madhavan and Schlenoff, 2003) and robotic arms that pick up non–static objects in production line assembly (Payeur et al., 1995). The prediction is often made relative to the location of a motion sensor on a 'robot', so relative location is usually more important than absolute

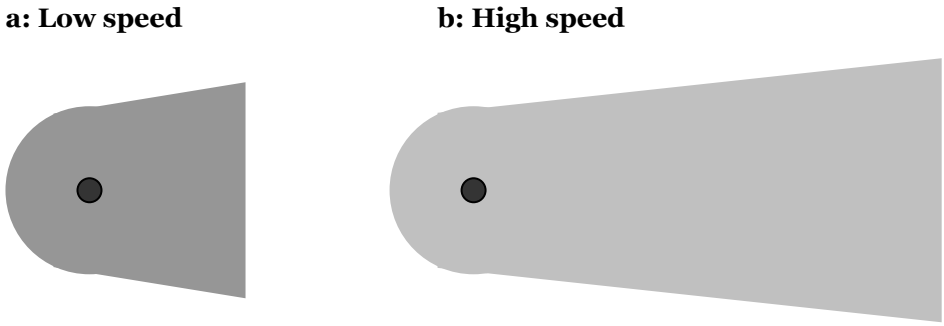
location. The sensor itself may be moving, and the aim is often to control the motion of the robot to either avoid contact (Madhavan and Schlenoff, 2003), or to connect with the another moving object (Payeur et al., 1995). One technique that has been applied quite extensively in this field is the Kalman filter. This is a technique that allows predictions of past, present and future states of an object. Future states are calculated given a current state (eg location) and control (eg speed and heading). Given these input parameters, an *a priori* prediction is made about a location in the future. This prediction can be verified by measurements to assess the error associated with the prediction: the distance between the predicted location, and the actual location at the predicted time. This feedback can be applied to tune the filter to improve future predictions. The Kalman filter, as applied in the field of robotics, provides a point prediction for a future time, with an uncertainty estimate. Research in this area is usually concerned with movement over small time-scales, although it has also been applied to longer-term prediction such as bus travel time prediction (Farhan et al., 2002). A critique of this work has been its failure to consider the longer-term history of individual movement, relying instead on very recent behaviour. In addition, the research is very reliant upon simulated motion data, and very rarely mobile trajectories related to the spatial behaviour of moving objects in the real world.

One general criticism of existing prediction techniques has been that their reliance on linear extrapolation based upon a current position, time, velocity (PVT) vector oversimplifies motion patterns (Tao et al., 2004). This simplification has been justified on the grounds that a series of straight-line interpolations can approximate curved lines, and that the linear model avoids the complications of motion patterns and nevertheless allows much interesting analysis to be performed (Tao et al., 2004). A second criticism has been the cost - in terms of processing overhead and data transfer - associated with maintaining in a database of moving objects since an entry must be frequently updated, for example for every change of direction, speed or when passing a node in transportation network (Wolfson and Yin, 2003). Many of these approaches concentrate on making point predictions of future locations based upon linear extrapolation from the current position at a given heading and speed (Xu and Wolfson, 2003). Others have attempted to define the dynamic regions of space associated with clusters of moving objects by recording a minimum bounding rectangle based upon the speed of movement of the cluster in cardinal directions (Tao et al., 2004).

A promising geometric approach to prediction, developed specifically for information filtering for location-based services, has been suggested by Brimicombe and Li (2004). They suggest the application of *dynamic space-time envelopes* to define the region of space relevant to a mobile individual. These space-time envelopes are dependent upon the speed and heading of the mobile user, hence faster spatial behaviour increases the range of the envelope, and the direction of movement controls the central axis of the envelope. The space-time envelope comprises a core (a circle around the moving point object), extension (a trapezoidal projection in the direction of movement), and limit (cutoff point). The resulting

envelopes resemble torch beams, shining ahead of an individual's current location (see Figure 8). One of the main advantages of this approach is that it provides a *region* (as opposed to a point) in space, and such a region could be applied for mobile information retrieval to identify information sources whose geographic footprint is contained within this region. Whilst this approach is promising, at present it is constrained by some simplistic assumptions. The measures of speed and heading are based upon a very short-term measure, calculated by comparison of the present and previous position only. This makes no attempt to model the distribution of speed and heading over an interval in time, with the result that the envelope does not distinguish between sinuous behaviour and movement in a straight line. Further arbitrary parameters are included in the model, such as a default radius of 1km is used for the radius of the circle, which is unlikely to be appropriate in all situations, and a 'splay' of 15 degrees either side of the extension, which again takes no account of the sinuosity of previous behaviour.

Figure 8: Dynamic space-time envelopes based upon recent speed and heading, after Brimicombe and Li (2004).



2.5 GeoVisualization

The human visual system is very effective at detecting patterns in large volumes of data, and separating complex patterns from background "noise" and outliers (Gahegan et al., 2001). Geovisualization is concerned with the visual representation of geographic information to take advantage of this property of the human visual system, with end goals including understanding, the formation of ideas and concepts, and hypothesis formulation (Andrienko et al., in press) - a process known as *ideation*. Algorithms that analyse geographic data to identify patterns or make predictions will typically be based upon various assumptions about what sort of structures are likely to exist within the dataset. It is therefore of crucial importance when developing algorithms that new forms of data are thoroughly understood prior to development, else existing theory developed from analysis of different data sets may be applied, that is not valid for the particular set in question.

As described in section 2.1.2, traditional Geographic Information (GI) systems have received criticism for being most suited to an inventory role of objects with a spatial reference at a fixed moment in time (Langran, 1992, Wang and Cheng, 2001). Accepting that geographic space is a combination of space, time and attribute (Parkes and Thrift, 1980), then in order to be more than *spatial* information systems, GI systems must include the temporal component and allow the modelling and visualization of dynamic processes. Increasingly the temporal component is also being included in the geoVisualization processes (Wang and Cheng, 2001, Andrienko and Andrienko, 1999, Dykes and Mountain, 2003) and the idea pre-dates the computing era with examples from the nineteenth century on paper (Tufte, 1983) and on the cusp of the digital age using film (Moellering, 1976). In order to develop effective on-screen realisations and interact with the temporal component, the nature of the spatio-temporal processes we aim to represent must be understood.

As discussed in section 2.2, individual spatial behaviour – the focus of this thesis - can be represented by the movement of a *point* abstraction (Erwig et al., 1999) since the space occupied by individuals is negligible for most scales of analysis. Individual mobility is most suited to representation by stepwise change (defined by Wang and Cheng (2001) as an object that is sometimes moving and sometimes static) as opposed the discrete change (static with occasional, instantaneous changes in location) associated with land-use change or continuous change associated with many natural physical processes (Wang and Cheng, 2001).

A number of ideas have been suggested in the literature and implemented in visualization software. For example, geographic traces allow users to define sequences of positions for which local statistics are generated and analysed in geographic data sets (Wills et al., 1989). Traces can be used to detect the geographic distributions of various attributes according to physical features such as rivers (Wilhelm and Sander, 1998). The sequences used in traces can be defined by sections of a mobile trajectory as well as geographic features. Combining spatio-temporal activity with measurements of independent geographic phenomena in this way enables analysts to identify the dominant attributes of any routes taken through time and space. Relationships can be considered, requirements assessed and models generated from any insights that are achieved. Graphical representations of such statistics can be implemented through local parallel co-ordinates plots (Dykes, 1998). Each of these techniques could be used to analyse the variation in attributes across time and space as defined by a spatio-temporal user-profile.

A relatively recent, novel representation that combines user-centred and spatially distributed geographic information is the radial distance function (RDF) plot (Imfeld, 2000). The temporal RDF plots generated from such functions are explicitly designed to focus on sequences of positions in time and space by representing the variation in measured phenomena (such as land-use) at a series of distances from successive locations. The two-

dimensional plots use one axis to represent time and another to represent distance depicting the way in which the environment around a mobile object varies over time. This approach, developed for the study of animal behaviour, is an effective integration of the temporal characteristics of geographic information moving away from a purely space-centred method of analysis. Considerable success is reported in identifying patterns at a range of scales using temporal RDF plots (Imfeld, 2000), suggesting that they may be useful for a series of applications outside those relating to the study of wildlife and habitats such as those associated with mobile trajectories. Present implementations can take several hours to generate on standard workstations, hence such techniques cannot yet be integrated into real-time visualization software.

2.6 Geographic knowledge discovery

The field of knowledge discovery is well established with roots in computer science (Ester et al., 2001), however spatial and temporal dimensions have typically been used in the same way as any other attribute in the dataset, rather than as an organising framework (Gahegan et al., 2001). For this reason, specific fields of data mining have developed to tackle geographic data all of which fall within the realm of *geographic* data mining (Han, 1999a). Within this group *spatial* data mining utilises the (usually 2 or 3 dimensional) spatial reference system as the framework for analysis. Similarly temporal data mining utilises the time that events occurred as a framework. Spatio-temporal data mining attempts to use this combined geographic framework which gives a "when" and "where" by which to analyse real world entities and processes. One of the ambitions of this thesis in to adopt such an approach to extract the geographic context of mobile individuals and to increase the relevance of the information they retrieve. This section will first discuss the general themes of data mining, followed by some specifics of spatial, temporal and spatio-temporal data mining.

Knowledge discovery process, after Han (1999b)

1. Data cleaning: Handling erroneous, missing or irrelevant data
2. Data integration: Combining heterogenous data sources
3. Data selection: Retrieving the data relevant to the task
4. Data transformation: Into forms suitable for data mining
5. Data mining: Extraction of interesting knowledge
6. Pattern evaluation: Identifying the most significant/interesting results
7. Knowledge presentation: Communicating results

According to Han (Han, 1999b), data mining is one part of the process of knowledge discovery in databases. The full knowledge discovery process also includes data preparation and presentation and is described above, however much of the literature considers the data mining process to include all seven steps.

The data mining process (step 5 above) aims to discover significant, previously unknown patterns within large volumes of data, and additionally to explain these patterns (Gahegan et al., 2001). These patterns can then be encapsulated as knowledge in the form of associations, rules, spatio-temporal distributions and other relevant data structures. Data mining is a brute force computational technique which can proceed without the initial development of a hypothesis to test against, as is required for traditional statistical approaches (Longley, 1998). This inductive process can often be more successful in revealing trends then testing the validity of existing hypotheses (Openshaw, 1998a).

Data mining tasks can be subdivided into either descriptive (summary and presentation of trends) or predictive tasks. *Prediction* is the extrapolation of the data into unknown regions, for example constructing models to infer possible future states of an entity based upon previous behaviour. A number of general descriptive data mining tasks have been identified (Han, 1999a). *Class description* is the calculation of summary information about a set of data which can be useful for comparison with other sets; these are are often simple parameters such as the mean, the count of total observations, the set maximum, minimum, range, quartiles, variance and standard deviation which may be used as part of more complex algorithms. Measures of *association* quantify the degree of correlation between the objects (observations) or groups of objects or the attributes associated with objects. *Classification* is the division of the data into meaningful subsets, either through the use of some classification rules, possibly derived from a training dataset, or from finding the natural breakpoints within the set. *Time series analysis* is the use of the time reference to find interesting sequences, periodicities or trends. The general descriptive data mining task of clustering is the classification of a data set into a number of groups according to some algorithm (Fotheringham et al., 2000). This classification is useful since it gives structure to the dataset; new observations can be compared to exisiting classes and assigned to one of them.

2.6.1 Geographic data mining

As discussed in section 2.1, geographic information can be described as a combination of space, time and attribute (Parkes and Thrift, 1980). Geographic data mining refers to techniques that utilise the spatial and temporal reference framework of a data set as well as the attribute values. Some techniques have concentrated upon spatial dimensions only (Han et al., 2001) and others solely upon the temporal dimension (Roddick and Spiliopoulou, 1999), however for the effective analysis and summarisation of real world objects, a combined spatio-temporal (Yuan, 1998) or geographic (Miller and Han, 1999) approach to data mining is required. The application of data mining techniques to geographic data has led to a number of new research areas (Miller and Han, 1999), including the need for better spatio-temporal representations, new geographic data types, the need to handle large

volumes of geographic data and crucially the utilisation of the derived geographic knowledge within GIS operations.

Mobile trajectories have specific characteristics that can be exploited by data mining techniques. Such opportunities include new information types that can be extracted from the mobile trajectories, the potential to simulate future behaviour given previous trends and analysis of group dynamics. Developing these opportunities however presents challenges such as privacy issues (Raper, 2001), and extracting trends from data sets that may be incomplete, or collected at a coarse spatio-temporal resolution (Smyth, 2000).

2.6.2 Integrating Geovisualization and Knowledge Discovery

The International Cartographic Association research agenda has identified the need for closer integration between geoVisualization, knowledge discovery in databases and geocomputation (Gahegan et al., 2001), since the objectives and approaches of these three disciplines overlap to a large degree. An overriding aim of all three is knowledge construction, particularly in new or poorly understood datasets, where existing theory and hypotheses may not be valid (Gahegan et al., 2001). Mobile trajectories are a good example of such datasets, since they are relatively new and have thus far been poorly handled by conventional knowledge discovery processes as mentioned in the previous section. Similarly geocomputation techniques are often atemporal, performed on GI Systems that are burdened with the cartographic inheritance (Couclelis, 1999) of paper maps. This issue is summarised by a research question posed the International Cartographic Association, “To what extent, and for what tasks, must a data mining process consider the spatial and temporal properties along with the other attributes?” (Gahegan et al., 2001). It is the contention of this thesis that in order to extract information about dynamic processes, such as the movement of and interaction between individuals - as recorded in mobile trajectories, the spatial, temporal and motion properties are of paramount importance.

Knowledge discovery and geoVisualization have been discussed in some depth above, however it is worth briefly discussing the aims of geocomputation. This discipline shares some of the objectives of knowledge discovery, such as to uncover previously unknown, interesting and significant patterns within datasets. An overriding aim is to enrich geography with a set of tools to model complex, frequently non-deterministic datasets (Gahegan et al., 2001). However frequently geocomputation techniques aim to provide solutions to *known* problems, rather than uncover unknown structure, hence they perform poorly on new data types.

A question that is being asked increasingly in this research frontier is how geoVisualization techniques can inform the knowledge discovery process. This process can be seen to utilise three modes of reasoning at distinctive stages of investigation; abduction, induction and

deduction (Gahegan et al., 2001). *Abduction* tends to take place at the initial exploratory stage of scientific investigation where no theory has yet been developed or hypotheses formed. When the geoVisualization process is applied to abduction the aim is to promote thinking about the data in order to generate ideas and hypotheses that can be tested later. It is a very flexible approach since it does not enforce existing structures on the dataset, whose structure is often poorly understood. *Induction* requires that some structure has been identified within a dataset, which may be applied to new instances of similar data types. Induction is the perhaps the most reliable tool in knowledge discovery (Gahegan et al., 2001), where often rules of association, classification, dependency and description are learned from a training dataset, and then applies to new situations. The role of geoVisualization at this stage is further investigate and develop initial theories, and to provide a platform upon which hypotheses may be tested and either confirmed or rejected. *Deduction* is applied when rules are well established, for example encapsulating the knowledge and deductive processes of practitioners in expert systems. This is addressed by a further research question asked by the International Cartographic Association, "What effect does the visual environment have upon the knowledge discovery process?" (Gahegan et al., 2001). In the context of this thesis, the visual environment has been important at the abduction stage of hypothesis formulation, and as an evaluation tool to assess the effectiveness of predictions based upon knowledge extracted from previous experience and applied in new situations.

2.7 Information Retrieval

2.7.1 Information retrieval and relevance

Criteria for judging the relevance of information has been central to the discipline of Information Retrieval (IR) for nearly forty years (Cleverdon and Keen, 1966). The central aim of IR has been stated as the retrieval of information (such as textual documents or multimedia) relevant to some query that represents a person's information needs arising as a result of some particular task or problem at hand (Spink et al., 1998). Traditionally the different IR algorithms have been evaluated primarily at a system level with little reference to the user (Vakkari and Hakala, 2000), however relevance has been acknowledged to be;

- multidimensional, in that it can be measured on a number of different levels (Spink et al., 1998),
- dynamic, in that a user's information needs are mental constructs that vary through time (Ingwersen, 1996), and,
- complex, but inherently measurable (Borlund and Ingwersen, 1997).

This discrepancy has led to criticism of the IR community for relying on traditional relevance criteria that are solely objective, considering only the relationship between retrieved documents and the query from a computing perspective, rather than considering subjective

dimensions of relevance related to the person who's individual information needs led to the query being conducted (Borlund and Ingwersen, 1997).

A system of five distinct but interrelated manifestations or *levels* of relevance has been suggested (Saracevic, 1996b) which aims to integrate the different frameworks for defining relevance that have emerged in different disciplines. *Algorithmic (1)* relevance considers the relationship between the query definition and retrieved information sources based upon a system's internal relevance criteria. It can be assessed by a user in terms of the effectiveness of different algorithms when inferring which documents were relevant. S*ubject (2)* relevance considers the topic defined by the query and the topic covered by information sources. It can be assessed in terms of the relationship between the query definition and retrieved information sources and can be assessed in isolation of a user. In the algorithmic case, methods make some assumption about what is relevant and are measured by their effectiveness. For subject relevance, it is assumed that the subjects covered by both the query and information sources are known. *Cognitive (3)* relevance (or pertinence) considers the relationship of the user's state of knowledge and information needs allowing retrieved sources to be measured subjectively in terms such as informativeness, novelty and quality. *Situational (4)* relevance (or utility) considers the relationship between the user's context in terms of task or problem in hand and their situation, such as their activity or environment. It can be measured in terms of appropriateness (with respect to the user's problem), usefulness (in decision making) and reduction in uncertainty. The geographic component of relevance can be seen as a subset of situational relevance, filtering information according to the surrounding environment and their relationship to it – ie their geographic context. *Motivational (5)* relevance relates the user's goals and intentions to the retrieved sources and can be measured in terms of satisfaction and accomplishment (Saracevic, 1996a).

A second related criticism of IR evaluation has been the reliance of a Boolean classification of relevance (results are either relevant or not) (Spink et al., 1998), in part due to the legacy from only conducting evaluation IR at a system level. It is increasingly argued that this Boolean approach is inappropriate for evaluating the complex, multidimensional concept of relevance and that user relevance judgements should be graded on a continuum (Kekalainen and Jarvelin, 2003). It has been found that since user's information needs evolve through subsequent searches, that sources classified as 'partially relevant' are often associated with a change in the user's problem definition and subsequent information seeking (Spink et al., 1998). These 'fuzzy middle' sources can therefore have more influence than documents initially considered highly relevant, which may simply act to confirm, rather than modify or augment, the user's current knowledge state.

2.7.2 Geographic Information retrieval

"Geographic information is pervasive on the web" (Silva et al., 2004)

Individuals performing natural language searches of information sources, for example using a web search engine, often require information that is geographically specific and will include *toponyms* (placenames) in the query to define its spatial focus (Sanderson and Kohler, 2004). Traditional approaches to natural language searches focus upon the exact matching of terms in the query and documents. When applied to geographic query terms, this approach can only retrieve exact matches and fails to consider documents containing nearby place names, alternative spellings and names, or placenames that refer to the same location at a different spatial resolution (Sanderson and Kohler, 2004). Studies suggest that nearly 20 percent of Internet queries contain a geographic term (Sanderson and Kohler, 2004), and to counter the lack of geographic intelligence of existing search engines, the new research field of Geographic Information Retrieval has emerged.

In order to ensure that retrieved information is *geographically relevant*, the geographic extent of the query and individual records in the dataset must be known. The geographic extent of the query may be determined by including a toponym in a natural language search (Nissim et al., 2004), by defining an extent on a map (Gey and Carl, 2004), or by determining an individual's current location using some positioning determining technology (Goker et al., 2004). There are many approaches to determining the geographic extent of the candidate results of a query, which have developed to take account of the nature of the individual datasets to be searched. First, many features / points of interest (FOI / POI) datasets exist, designed to associate some spatial reference with features. Many of these come from the commercial field, *geocoding* features – with particular emphasis on services - by giving them a point reference which can be derived from address fields in a database (Sagara and Kitsuregawa, 2004). Other examples include content extracted from geographic databases from which spatially referenced multimedia documents can be created (Edwardes et al., 2003b). For the majority of natural language documents that comprise the World Wide Web however, there is no one clear solution to assigning reliable spatial references to individual sources, and many approaches to extracting geographic information from unstructured text have been suggested (Hill et al., 2004).

Geographic information is found throughout Internet resources. A study by Silva et al. (2004) suggests that web documents contain an average 2.17 references to geographic entities. The first stage of geographic information retrieval – geoparsing - is to recognise these geographic references or toponyms within the free text. The most commonly accepted approach is to compare components of the free text to those stored in a gazetteer, which may

additionally store some spatial reference for those terms (Hill et al., 2004). Once relevant toponyms have been identified, the geographic scope should be expanded beyond the individual terms. It has been suggested that the link structure between pages could reveal their *geographic scope*; since a link between two documents suggests they share a common theme and possible a geographic location (Silva et al., 2004). Such links can assist in identifying the true *geographic focus* of the document, by eliminating spatial locations and other entities that have the same toponym, such as "London, UK", London, Otario" and the author "Jack London" (Amitay et al., 2004).

Geographic ontologies can be constructed which provide a model of geographic terminology and structure of space (Jones et al., 2004). Such ontologies can be applied to associate spatial footprints with individual toponyms, and hence queries and web resources. Once geographic ontologies have been constructed, geographic knowledge bases can define the relationships between toponyms, such as whether two locations are adjacent, or one is contained within the other (Silva et al., 2004). This has been done not only for formal placenames with known administrative boundaries, but also imprecise regions with no formally defined spatial extent such as "The Mid-West" or "The Black Country" (Arampatzis et al., 2004).

Once the geographic extent of both query and records in the dataset have been defined, the two can be compared to give spatial similarity score that allows records to be ranked according to their relevance to the query (Larson and Frontiera, 2004). In the simplest case this may be a Boolean classification, according to whether the extents of query and record overlap or not. Various authors have attempted definitions of spatial similarity, which is usually based upon the degree of overlap of two extents and assumes that the spatial extent of both query and record can be precisely defined (Larson and Frontiera, 2004).

As discussed in the following section, the convergence of computing and mobile telephony is leading to increasingly sophisticated handheld computers that have wireless network access. Increasingly these devices are location-aware, utilising terrestrial and satellite-based position determining technologies (Mountain and Raper, 2001b). This enabling technology is promoting the growth of context aware computing (Jose and Downes, 2005), and of particular interest to this thesis, information retrieval systems that are able to take account of the location and behaviour of the user and apply this as a filter to improve the *situational relevance* of the information received by the user. It is within the situational level that mobile computing may be able to make the greatest contribution by informing the geographic context of the user and modifying the query using spatial and temporal parameters. This could take account of the user's spatial location, the time at which they conduct the query, the accessibility of the surrounding locations, available means of transport, level of visibility and likelihood of them visiting different locations in the future (Brimicombe and Li, 2004).

Several systems have already been developed that are able to filter information according to the user's location. A variety of technologies have been employed such as dedicated wireless hotspots at specified locations, serving information to about local features to suitably equipped mobile devices in the area (Goker et al., 2004). Other systems have attempted a more generic solution where location-aware mobile devices access bespoke georeferenced datasets via a wireless connection and filter information according to the user's current context (WebPark, 2003). No systems thus far have succeeded in using the user's geographic context to permit the retrieval of geographically relevant information from unstructured web sources.

2.8 Mobile computing

This section will consider the key characteristics of mobile computing, in particular as an environment for the mobile Internet, location-based services and mobile GIS. The evolution of Internet computing had a profound impact upon application development, forcing a change from a stand-alone desktop architecture, to a more flexible, client-server architecture (Peng and Tsou, 2003). Developments in mobile computing are currently having a similar impact, forcing the development of web resources and applications that can be run on a wider range of devices than traditional desktop machines. According to Peng and Tsou (2003), mobile computing environment have three defining characteristics:

- mobile clients that have limited processing capacity (personal digital assistants (PDAs), and smart phones);
- non-stationary users who may use their devices whilst on the move;
- wireless connections that are often more volatile, and have more constrained bandwidth, compared to the 'fixed' Internet.

2.8.1 Mobile telecommunications infrastructure and hardware

Wireless networks are comprised of a series of network *cells*: areas on the ground served by one single base station (Swedberg, 1999). Widescale (ie nationwide) construction of these networks of base stations first occurred in the early 1980s, particularly in the USA and Europe. These *first generation* (1G) networks characterised by unencrypted analogue signals broadcasting voice data between the mobile phone and a nearby base station – evolved into second generation (2G) wireless networks in the late 1980s (IMT-2000, 2005). These 2G networks transmitted voice data as digital signals and this key distinction saw the functionality of the *phone* increase to that of a mobile computer, capable of exchanging and processing digital data. Devices on 2G networks are characterised by slow network

connections (since they were developed to handle voice data), and very limited processing capability. It was nevertheless at this stage that there was a mass consumer take-up of mobile phones, and as a result, the price of devices and call charges dropped significantly.

Second generation networks were the environment in which the first attempts were made to bring fixed Internet content to mobile device. These mobile web services depended upon gateway servers, which acted as a bridge between the wireless networks and the fixed Internet upon which web servers reside. The bandwidth restrictions associated with the 2G systems were addressed by so called two and half generation (2.5G), networks. The data transfer rate of 2G systems was typically 9.6 kilobits per second (kbps), which resulted in long download times for large datasets. 2.5G networks, such as the General Packet Radio Service (GPRS), have increased data transfer speeds to over 50kbps. The state of the art in wireless communications, are now *third generation* (3G) networks, developed to the International Telecommunication Union's (ITU) standard (IMT-2000, 2005). By 2005, many mobile operators offer a 3G service. The bandwidth associated with 3G networks (over 300kbps), comparable with a broadband connection to the fixed Internet, makes them highly suitable for the exchange of digital data. These new networks, combined with modern mobile devices, offer a very suitable environment in which to deploy location-services processing and serving GI data. This, combined with the large potential audience of 3G services compared to the traditional GIS specialist niche market, suggests that mobile GIS applications, in the form of location-based services, may now be primed for widespread take-up (Ericsson Mobility World, 2005).

However, despite all these advancements, wireless networks are likely to remain, for the foreseeable future, a more challenging environment to work in than the fixed Internet. Specific challenges for mobile GI include dealing with (Peng and Tsou, 2003);

- restricted bandwidth;
- latency in the time taken to transfer content;
- more unstable connections, including variation in bandwidth and dropped connections.

Hardware clients for mobile GIS form a continuum in terms of the ability to display information, perform processing tasks, and store and handle large volumes of data (Peng and Tsou, 2003). At one end of the spectrum, standard mobile phones, and smart phones, have small screens, typically 208x320 pixels, with limited processing capabilities and data storage. The user interacts via touch screen or keypad. Personal digital assistants (PDAs), and handheld computers, tend to have larger screens (up to 640 by 480 pixels), and faster processors, in the range of 500MHz; most PDAs have touch sensitive screens as the primary input device. Tablet PCs bridge the gap between PDAs and PCs: they can be as powerful as laptops, but are smaller and have touch sensitive screens. Finally laptops can be as powerful as desktop machines with large displays and 10s of gigabytes of storage capacity (Peng and

Tsou, 2003). For this reason, smart phones and PDAs tend to be more suitable for *thin client* applications, where application logic and data reside on the server, and tablet PCs and laptops more suitable for *thick client* applications, where logic and data are handled on the client device. However this is not hard and fast rule and careful application design can allow a smartPhone to act as a thick client (Krug et al., 2003).

2.8.2 Positioning technologies

The hardware and software required to identify the location of a mobile client in real time is collectively known as the *position determining technology* component in mobile computing. This may operate entirely on the mobile client itself, such as the Global Positioning System (Enge and Misra, 1999), on a wireless network server, such as Cell-ID, or a hybrid client-server solution, such as network assisted GPS (Ericsson Mobility World, 2005). The telcommunications literature tends to classify these techniques according to whether processing takes place on the client device or on the server (Swedberg, 1999), however an alternative distinction is whether the positioning systems are satellite or terrestrial (Mountain and Raper, 2001b)

Global Navigation Satellite Systems

The Global Positioning System (GPS) has become synonymous with positioning systems, however it is in fact a specific type of Global Navigation Satellite System (GNSS). GPS was developed by the US Dept of Defense (DoD) from 1978 becoming operational in the 1980's (Enge and Misra, 1999); by the 1990's the price of commercial handheld GPS receivers had fallen to a level that saw mass consumer take-up as GPS chipsets became small enough to be installed in a variety of devices such as in-car navigation systems and mobile phones. The GPS signal is available to anyone for the cost of the receiver alone, but the constellation of satellites remains the property of the US Military who have in the past chosen to degrade the accuracy of the signal in the interests of national security (The White House: Office of the Press Secretary, 2000). The other implemented GNSS system is the Russian Federation's GLONASS (GLObalnaya Navigatsionnay Sputnikovaya Sistema). This was developed around the same time as GPS, however in recent years this has declined operationally as failing satellites have not been maintained or replaced, leading to only about half of 21 operational satellites functioning at any one time (Börjesson et al., 1999).

Acknowledgement of the global reliance on a single, military-owned system (GPS) has led to the development of a European Union funded system, Galileo, the first GNSS designed primarily for civilian use. Galileo is planned to become operational by 2012 (House of Commons Transport Committee, 2004). Galileo plans to offer five services designed for different user groups. The two services most relevant for mobile computing and location-based services are the freely available open service for mass market applications (which will

be comparable to the existing GPS system) and the commercial service, which will target a similar target audience but offering improved accuracy and a guarantee of service at a cost. Interoperable receivers capable of calculating position using GPS, GLONASS and Galileo are expected that will take advantage of the constellation of over 75 satellites eventually planned. Coverage is likely to likely to improve substantially with this much larger constellation of satellites.

Terrestrial positioning systems based on the mobile telecommunications infrastructure

Network positioning systems exploit the existing telecommunications network infrastructure to calculate the position of a mobile device. There are many different techniques, each with its own characteristics in terms of accuracy and precision (Mountain and Raper, 2001b). Some require adjustments to the network whilst others can exploit the network as it stands. The cell global identity (cell-ID) identifies within which network cell (the area surrounding one of the base stations that comprise the network) the mobile client is located. This is one of the most widely available techniques, since it is required for call routing, and also one of the least precise since this is dictated by the size of network cell (Mountain and Raper, 2001b). There is variation between urban areas, where the density of base stations is high, and the size of network cells correspondingly small (perhaps a few hundred metres radius) and rural area areas where network cells may have a radius of 20km or more. This technique can be improved using timing advance information, to identify how far (within roughly 500metres) the device is from a base station (Swedberg, 1999).

By triangulating the signals from multiple base stations, the location of a mobile device may be narrowed to the much smaller area (Swedberg, 1999). Using the enhanced observed time difference (E-OTD) approach, a mobile device can calculate its distance from a base transceiver station from the observed time difference between the transmission and arrival of information 'bursts', providing an estimation of position to 100 metres accuracy or better (Cursor, 2005). A similar approach, the uplink time difference of arrival (UL TOA) method can achieve accuracy of between 50 to 150 metres (Swedberg, 1999), although some have claimed 5 metre accuracy (Cell-loc, 2005)

Network assisted GPS (A-GPS) is a hybrid approach that improves the time to first fix by using the telecommunications network to transfer almanac and ephemeris information: the improvement is die in the main to the relative stability and greater bandwidth of the network, as opposed to the communications link between satellite and receiver (Swedberg, 1999). Recent improvements in the algorithms that interpret the GPS signal and decrease in the size and cost of GPS chip sets have made it the preferred technology for mobile geolocation. This is the system adopted by the 3 locate platform (3, 2005) and it is available in many consumer PDAa and phones such as the HP ipaq hw6515 and the Panasonic A920.

An additional benefit of A-GPS is that when no GPS signal is available (for example, in doors), the terminal can fall back on less precise positioning technologies such as cell-ID, to ensure that some positional information is available.

2.8.3 Location-based services

Within this environment of location-aware mobile computing, a new field of applications have begun to emerge, commonly referred to *location-based services*. A classification of location-based services has been developed by the Open Geospatial Consortium's Open Location Services initiative (Open Geospatial Consortium, 2005b). Each of the identified services can take the user location and contextual geographic information as input, and aim to provide a service either to a user directly, or as input to another process. The definition of these services is in keeping with the ambition of interoperability in GI Systems more generally (Open Geospatial Consortium, 2005a) to define standards in the GIS industry that allow developers to integrate geospatial data and geoprocessing resources into their location services. Five core services have been defined for mobile users: gateway services, directory services, route determination services, geocode services and map/feature display services (Mabrouk et al., 2004).

Location gateway services are utility services designed to act as the interface to the position determining technology component and are intended for use by other services, rather than by an end user directly. They are concerned with providing information about the position of a mobile device to an agreed standard. Geocoding services are also utility services that allow conversion from toponyms or other textual spatial identifier, to spatial coordinates (geocoding) and the vice versa (reverse-geocoding) (Mabrouk et al., 2004)

Directory services allow users to find a specific place, product or service according to its location, from a georeferenced online directory. The user formulates a query by specifying the spatial and subject criteria in some user friendly way. The spatial criterion may be specified by the user's current location, as calculated by the position determining technology component. Alternatively the user may specify the spatial criterion via a visual interface (such as a map click) or by specifying a placename or other textual description of location. The subject may be specified by categories, for example a drop-down box or series of "click through" screens, or a natural language in the same way as Internet search engines (Google, 2005, Yell Group, 2005a).

Route determination services provide navigation assistance to mobile users (Mabrouk et al., 2004). Given a start and end location, and a specific criterion such as fastest or shortest, a route can be determined and directions given en route (Vodafone, 2005a). Map and feature display services render geographic information ready for display on a mobile device. The service may be used by the end user, or other location services, to create a map of a desired

area (Mabrouk et al., 2004). This map may be raster backdrop map imagery, or be comprised of a series of feature layers displaying, for example, features of interest, transportation or utility networks, routes and directions or polygonal geographic features such as water bodies or land use types.

3 Methodology

Methodology Abstract

This methodology chapter first considers the data collection exercise conducted as part of this project, where mobile trajectories representing the spatial behaviour of a small number of volunteers were recorded using global positioning system receivers over periods of up to one year. The next subject considered is the development and functionality of a geoVisualization tool (the Spatial History Explorer) written specifically for this research for the analysis of mobile trajectories, using the java programming language. The next section describes the mobile platform and test bed that acted as a driver for some of this research and was the environment in which implemented mobile information retrieval tools were evaluated with end users.

The subsequent section introduces the concept of geographic filters for information retrieval as surfaces that in some way encapsulate the region of space that is relevant to an individual at some time and place. Several geographic filters are described both at the conceptual and implementation level: these include spatial proximity (closeness in space), temporal proximity (accessibility in terms of travel time) and predictions based upon previously exhibited speed and heading.

Following the discussion of geographic filters, the prediction surface is described (which models the likely future locations of a moving point object), as are generic evaluation criteria that describe and assess the performance of prediction surfaces by comparison with a known *verification* point collected at the predicted time. Finally, the application of geographic filters to the task of sorting geographic (and georeferenced) information is discussed, building upon existing literature in this area.

3.1 Data collection

The techniques described later in this chapter rely upon large volumes of data describing the mobile trajectories of individuals over prolonged periods of time. There are various possible sources of this data as discussed in section 2.8.2 (Positioning technologies). One possible source are the records of data exchanged - such as voice calls, SMS texts, data transfer, and network information such as hand-offs and SIM updates - between phone terminals and base stations. This would provide a vast and rich dataset, potentially comprising millions of individuals over a period of months or years (Briggs, 2006). Whilst a dataset of this size is desirable, it remains unsuitable for a number of reasons. First, this data is stored for the purposes of billing and network traffic analysis and is not stored in a format suitable for the extraction of mobile trajectories of individual users (Hulls, 2004). Next, as described in section 2.8.2, the spatial resolution of this data is very coarse, and does not permit the fine grained analysis of individual spatial behaviour that is required for a study of this kind. In addition, the temporal sampling strategy is coarse and ad hoc, occurring when the user transfers data in some way or crosses the boundary between the regions served by base stations, which cannot represent individual spatial behaviour at the desired *temporal* resolution. Finally, conversations with executives at mobile operators suggested that the privacy issues surrounding the release of positional information representing the movements of customers without their explicit consent was an insurmountable barrier to this type of wide scale analysis at the time of writing (Hulls, 2004). Nevertheless, with the integration of GPS chipsets into mobile terminals, and an increasing number of mobile services becoming available, the release of anonymised positional information may be a concession which customers are prepared to make in future, in return for an improved service or a reduction in monthly tariff.

Having ruled out the possibility of analysing mobile trajectories derived from the records stored by the mobile telecommunications operators, a repository of trajectories was generated by volunteers carrying global positioning system (GPS) receivers describing their spatial behaviour for periods of up to one year. The three main contributors to this repository were Pete Boyd, Jonathan Raper and David Mountain, all members of staff at City University. Various GPS receivers were used for the data collection process including the Garmin GPS12, the Garmin GPS IIIplus (Garmin, 2005), the emtac BTGPS (Emtac, 2005) and the pharos iGPS-BT (Pharos Science and Applications, 2005), the latter two connected to ArcPad installed on a Windows mobile PDA as the data collection tool.

The spatial and temporal resolution of the collected data sets was dependent upon the configuration of individual units, however the units would either record a point every 10 seconds (ArcPad), or every 20metres, with a higher spatial resolution for sinuous movement, and lower resolution for relatively straight movement (Garmin devices). The data sets were

collected after May 2000, hence the GPS signal could be assumed to be accurate to approximately 25 metres (The White House: Office of the Press Secretary, 2000). The data sets were recorded using the latitude, longitude World Geodetic System 1984 (WGS84) coordinate system, and subsequently converted to the Ordnance Survey British Grid coordinate system (OSGB), by applying an appropriate projection and datum conversion (Ordnance Survey, 2005b).

The data collection exercises attempted to represent all of the movement of the individual carrying the device for a given period of time. GPS receivers struggle to get a positional fix indoors, hence there is a bias in the mobile trajectories to recording moving, but not static behaviour. Tools were developed to interpolate static behaviour, where a mobile trajectory ceases at a location, then begins again from the same location at a later point, however none of these interpolated trajectories have been used in this study. The GPS receiver sometimes had difficulty achieving a positional fix in *urban canyons*, where tall buildings can shield the receiver and promote multipath errors (where signals reflect from objects), leading to the potential for systematic data paucity and errors associated with certain locations. The receivers also can struggle to achieve a positional fix on certain types of transport, notably trains due to the reinforced safety glass, leading to some bias in the transport use observed. In the data collected, there was a systematic attempt to position the receiver to get the best possible GPS signal.

The stated objective of data collection was to record datasets recording *representative* behaviour for participating individuals, however it has been suggested that the very act of tracking volunteers may modify their behaviour (Briggs, 2006). This could occur in at least two distinct ways. First, participants may modify their behaviour to present what they perceive is a better impression of their movements, for example travelling to more wide ranging locations via a broader choice of routes to suggest variety in their spatial behaviour (Briggs, 2006), ceasing to visit certain locations that may be regarded as undesirable, or conversely attending longer hours at locations which they wish to be associated with. The second influence is that by carrying a positioning system that stores contextual information such as street data, participating individuals may be encouraged to explore alternative routes with the aim of discovering new locations or finding shorter or faster routes between locations. Whilst each of these components may have some influence over individual behaviour, neither can have any influence over the constraints identified by the Time Geography School, such as the need to attend certain locations at certain times. Hence the resulting datasets were found to contain a rich record of spatial behaviour, which can be considered representative and is suitable for a study of this nature.

3.2 GeoVisualization

This methodology is heavily influenced by the principles of geoVisualization (described in section 2.5), where the interactive manipulation of graphic realisations of data sets can lead to the discovery of hidden structure, and ultimately the formation of new idea and concepts - a process known as *ideation* (Andrienko et al., 2005). Following the process of data collection, a highly interactive visual development environment was developed to allow visual analysis of mobile trajectories. The development process was iterative, with visual analysis providing insight into the data models that should be developed, methodologies that would be suitable given the form of the data set, and the algorithms that were developed.

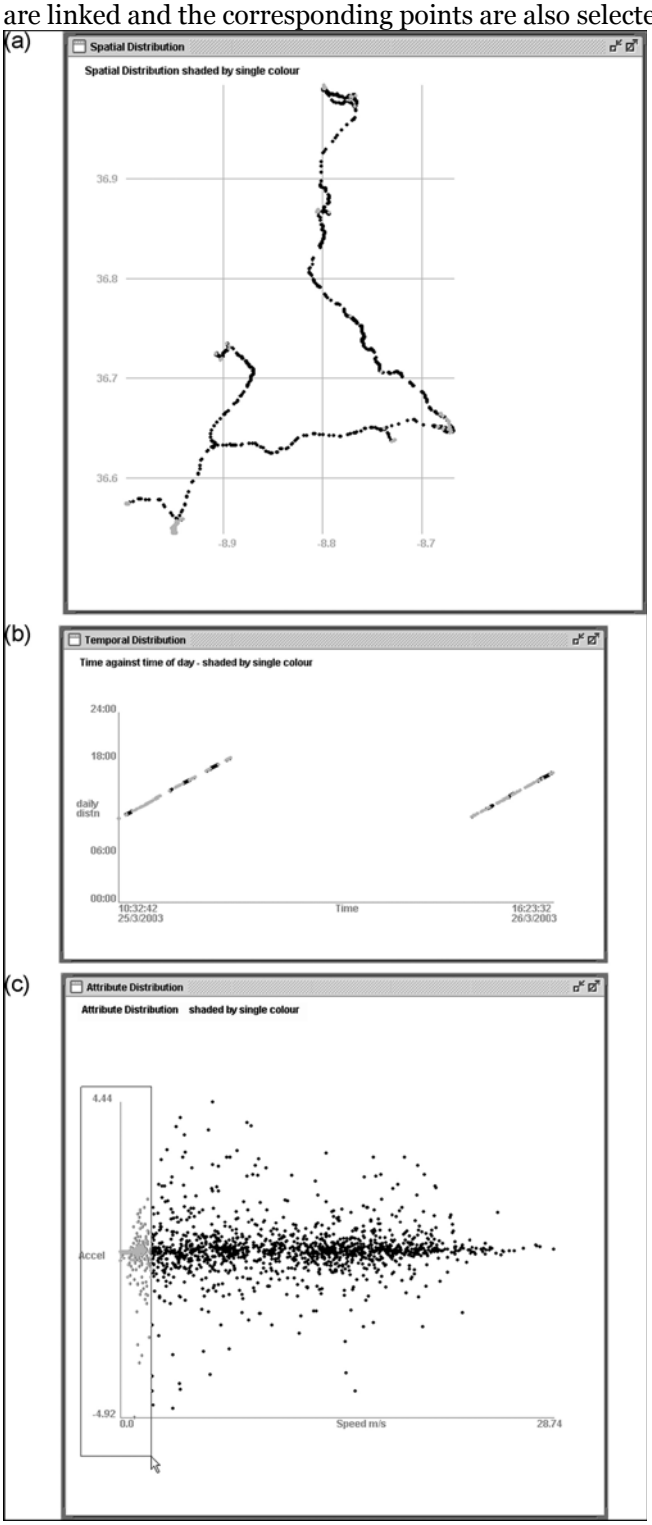
The spatial history explorer (SHE) is an application that has been developed to interpret spatio-temporal point data representing the movement of individuals or entities across space through time. It has been designed to be used at the exploration and confirmation stage of analysis (DiBiase, 1995), thus to promote visual thinking in the private domain (MacEachren, 1994). Initial objectives of the software include;

- simultaneous on-screen realization of spatial, temporal and attribute dimensions;
- representation of alternative temporal views to consider cyclical trends on a range of scales;
- facilitate interactive spatio-temporal querying, and
- promote visual thinking about the mobile trajectory in order to conceptualise the types of information that might be generated from it.

The software provides a traditional planimetric *map view* (Figure 9a) of the spatial information contained in a mobile trajectory; alone this approach is inherently static in nature (Wang and Cheng, 2001). A reciprocal *time view* (Figure 9b) displays absolute time plotted along the x-axis, to retain order for the data set, whilst the temporal y-axis can display different temporal attributes representing *cyclical trends* for a range of temporal scales. A third panel, the *attribute view*, has axes configurable by the user and hence can display a combination of spatial, temporal and attribute parameters; (Figure 9c) shows the relationship between speed and acceleration (Mountain, 2005b).

Figure 9: The spatial history explorer Map View, Time View and Attribute View

The data set shown is focused spatially upon South-West tip of Portugal and extends in time over two days in March, 2003. The points are not shaded by any attribute but low speed points (less than 2 metres per second) have been highlighted in the attribute view; the views are linked and the corresponding points are also selected in the spatial and temporal views.



a: Map View (spatial distribution)
Although no contextual background data is shown, the data set extends from Monchique in the North, Sagres in the South-West and Lagos (the temporary home location) in the South-East; the view is about 30 km wide. Notable hubs can be detected at the aforementioned locations and also at Aljezur, North of Sagres. These hubs tend to be associated with low-speed behaviour (as indicated by the lighter highlighted shade); the links between them are associated with high-speed behaviour.

b: Time View (temporal distribution)
The time view shows absolute time (from 10:32 25 March to 16:23 26 March) on the x-axis and time of day on the y-axis. Each day elapses from midnight (at the bottom of the y axis) to midnight (at the top of the y axis); hence the daily trajectory from the bottom of the graph to the top is repeated every 24 hours. Blank areas represent a lack of data collection associated with a lack of positional fix on the GPS receiver. It can be seen that most time is spent at low speed (the lighter highlighted shade) rather than at higher speeds travelling between destinations.

c: Attribute View (attribute distribution)
This view can display a range of attributes on the axes however in this case speed in metres per second is plotted on the x axis and acceleration in metres per second per second on the y axis. The cursor and dragged box indicated that the user has highlighted all points where speed is less than 2 metres per second.

3.2.1 Representing motion attributes

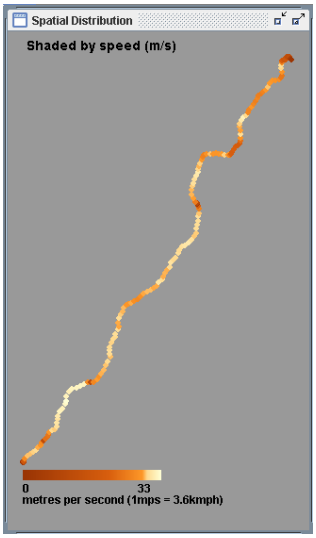
The shading of points in the linked spatial, temporal and attribute views can represent either spatial and temporal variables or other attributes that can be associated with motion. Speed can offer an immediate overview of an individual's mobility at different locations and times as shown in Figure 10a. Locations associated with low speeds or no movement tend to highlight *destinations*, such as places of home, work or leisure pursuits, whereas sections of the mobile trajectory with higher speeds show the *routes* between those destinations. Shading by acceleration offers an opportunity to represent natural breakpoints in an individual's spatial history, since the start and end of journeys tend to be associated with acceleration and deceleration respectively. Acceleration can also display the characteristics of journeys, whether they are smooth or involve a series of stops and starts, as shown in Figure 10b. Shading by heading (Figure 10c) helps identify 'to' and 'from' routes and asynchronous journeys (Mountain, 2005b).

Circular attributes (as described in the Literature Review section 2.3.2) can be represented either by shading or plotting on circular axes. Figure 10c shows points plotted in the map view, shaded by heading using a continuous colour wheel to represent the direction of movement. For large volumes of data this can reveal repeated patterns of behaviour that may be based upon authority constraints, such as one way streets, or a capability constraints when traversing a circuit; for example, a journey consisting of leaving home by car, dropping children at school then travelling on to work, is likely to be a repeated morning pattern for many parents. Within the spatial history explorer environment, circular attributes can also be plotted on circular axes in the attribute view as shown in Figure 10d and Figure 10e. Beyond heading, turning angle (Figure 10e) provides a visual representation of sinuosity and can give insight into the nature of different activities. For example, motorway driving tends to be predominantly straight, whilst browsing shops on foot is likely to see far more sharp turns. Bias in left or right turns can also be revealed. This visual analysis allows various hypotheses about the attribute signature of different activities to be revealed, and offers an opportunity for data mining classification rules, based upon the attribute signature of different activities (Dykes and Mountain, 2003). Shading points by point density allows magnitude to be added to the display that may be lost from over-plotting; SHE also allows the generation of point density surfaces for the same purpose. Point density gives an indication of an individual's *familiarity* with specific areas; whether it is their first time in a specific location, or a well frequented route or destination. Points can also be shaded by distance from a selected location to show patterns of return periods for that location in the temporal panel (Mountain, 2005b).

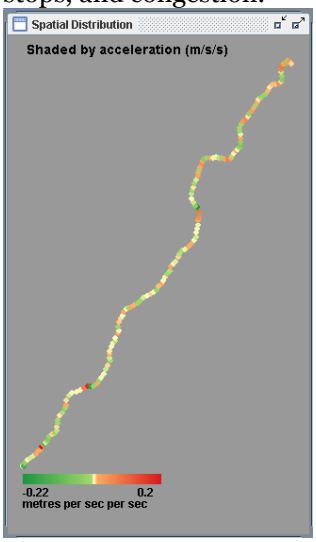
Figure 10: Representing motion attributes
The data set shown represents a journey from Nottingham, via the A42 and M42, then past Birmingham on the M6 and South past Bristol, finally following the M5 to Exeter

a – c: Map View: Nottingham is in the North-East, Exeter the South-West

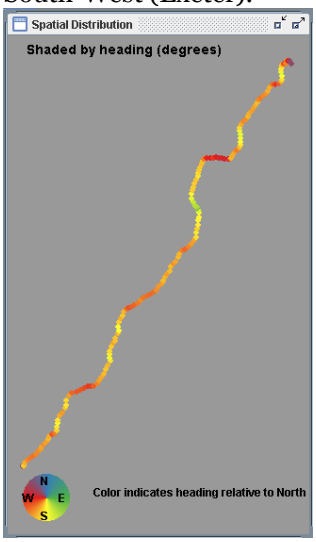
a: Shaded by speed
Slower speeds are shown in darker brown, faster speeds in lighter brown. Faster speeds can be seen on sections of motorway, slowing on A-road and around cities.



b: Shaded by acceleration
Acceleration is shown in red, deceleration in green, no change in speed is shown in white. Changes in speed can be seen at various points along the route, corresponding to rest stops, and congestion.

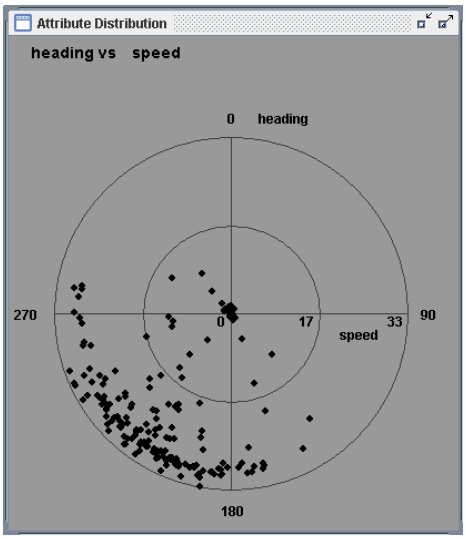


c: Shaded by heading
Heading is represented as blue (heading North), yellow (South), green (East), and red (West). It can be seen that this journey was from the North-East (Nottingham) to the South-West (Exeter).

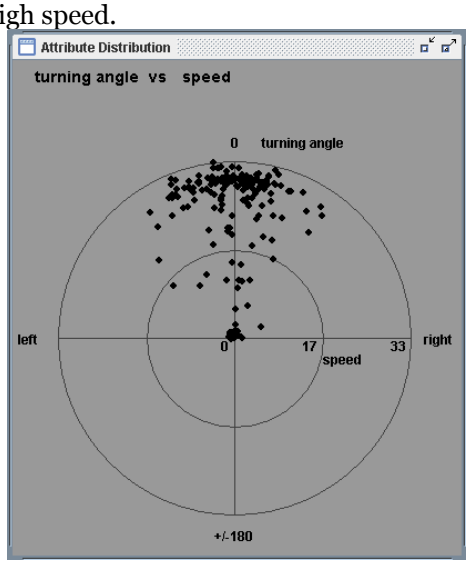


d and e: Attribute View

d: Shaded by heading
Plotting heading against speed clearly reiterates that heading over the course of this journey was to the South-West



e: Shaded by Turning Angle
Plotting turning angle against speed shows that there is little bias in left or right turns. Few U-turns were taken on this journey, and none at high speed.



Data collected by David Mountain, Jun 2004.
Images produced using the spatial history explorer.

3.2.2 Emphasising the temporal component

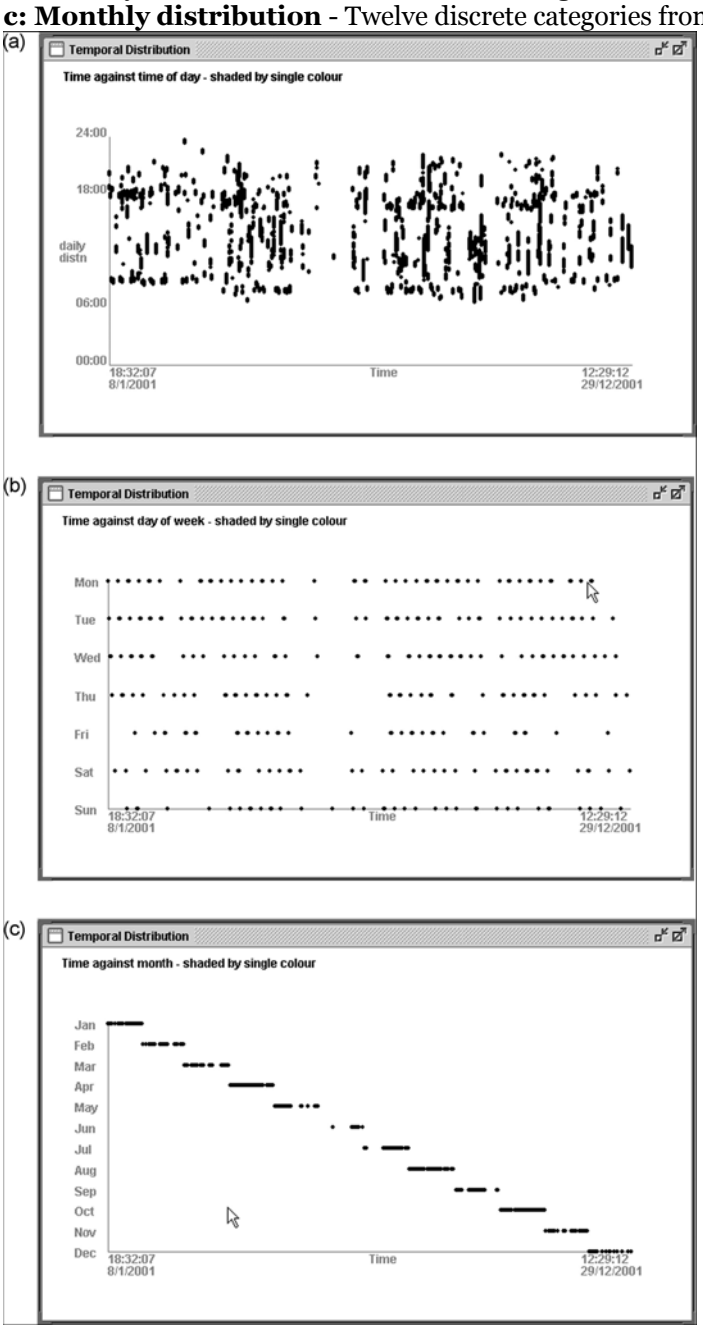
The inescapably linear nature of our experience of time (Hazelton, 1998) is an additional factor that must be considered for representations of individual spatial behaviour. *When* places were visited is important, as prior knowledge affects our behaviour considerably. By plotting absolute time along the x-axis of the temporal view (Figure 11), the spatial history explorer allows us to assess the way in which a user's behaviour changes as their experience of a new region increases. If detected, such information on changing behaviour could be used to predict future responses to visiting new areas (which are likely to be locations in which users have high information needs) and to determine likely information requirements (Mountain, 2005b).

Beyond representing the ordering of the spatial history by absolute time of collection, further temporal attributes can be represented to explore cyclical temporal patterns (Hazelton, 1998) that occur on a range of scales. As mentioned previously, the x-axis of the temporal view plots absolute time, however the y-axis can represent additional temporal variables such as time of day (Figure 11a), day of the week (Figure 11b) or the month (Figure 11c) to look for cyclical patterns at different temporal resolutions. When visualizing time of day, a complete dataset will show patterns of movement and static periods; the repetition of these patterns suggests that individual mobility is (to a degree) predictable for single individuals (Mountain, 2005b).

Figure 11: The 'temporal view' with the y-axis representing different temporal measures.

Different temporal measures can be displayed on the y axis of the temporal view. When brushing with linked views this can give insight into differences in behaviour at different times of day, variation on a weekly temporal scale and seasonal patterns.

a: Daily distribution - Start of day (midnight) to end of day (midnight) from bottom to top.
b: Weekly distribution - Seven discrete categories from Monday (top) to Sunday (bottom).
c: Monthly distribution - Twelve discrete categories from January (top) to December (bottom).



Data collected by David Mountain, 2001 - 2002
Images produced using the spatial history explorer.

3.2.3 Spatio-temporal querying

Interactive techniques can be extremely useful in reducing the complete dataset to a meaningful subset (Becker et al., 1987). In SHE linked *brushing* between views is supported, where the interactive selection of objects in one view leads to them changing their visual characteristics not only in that view (for example, highlighting those objects), but also in other views (Becker et al., 1987). Views can be re-configured so that a subset can be derived by interactively selecting either from particular temporal limits (Hornsby, 2001) or defining a subset from spatial limits. In each case the selection updates the new spatial history for both spatial and temporal views. This familiar concept of spatial focus or zoom (from a click and drag operation) can be extended for temporal focusing. Beyond selecting all data between two absolute start and end times, the y-axis of the temporal view can also be used to develop a more complex spatio-temporal query that restricts the selection according to the time of day, day of the week or for a range of months. For example a single interactive click and drag function return and display the result of the query

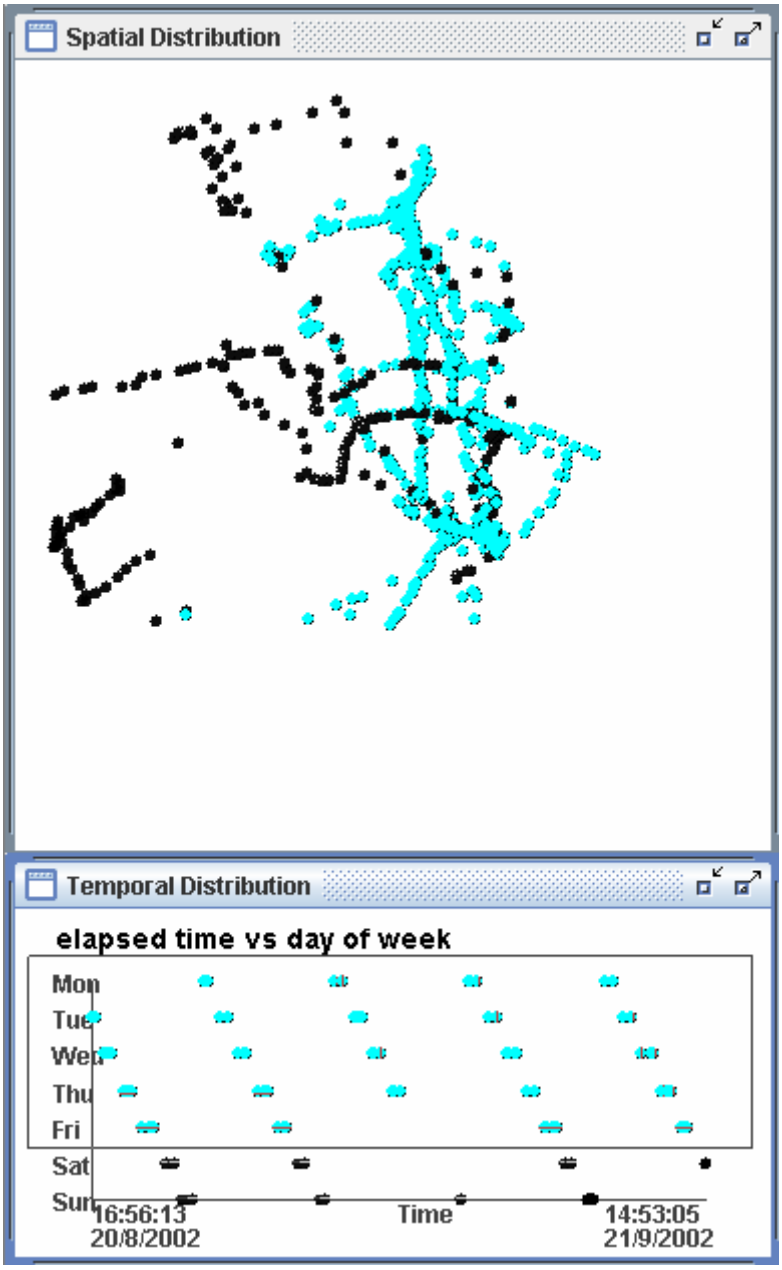
```
SUBSET
BETWEEN ‘12:52 29/06/2001’ AND ‘14:43 08/09/2001’
FOR dayOfWeek={”Fri”, “Sat”, “Sun”}
```

This interactive selection, taking seconds to perform, will return weekend results for the specified time period. By altering the y-axis parameter the above query can be modified for selections according to time of day (eg restricting the subset to morning or afternoon behaviour) or month (eg seasonal distributions) (Mountain, 2005b).

Figure 12: Comparing weekday and weekend behaviour

The image below shows a dataset collected over a period of five weeks by one individual and clipped to central London: the curving banks of the Thames between Westminster and Waterloo can be seen in the centre of the image. In the time view, all weekdays have been selected by brushing; these are highlighted in light blue in both the time view (bottom) and map view (top). It can be seen in the map view that for weekdays, repeated journeys - via slightly different routes between the North and South of the study area - stand out. This corresponds to the commute to and from work.

The unselected dark black points represent weekend behaviour. It can be seen that this is unconstrained by the commute of the working week, and is far more likely to be associated with wider ranging, less restricted movement.



Data collected by David Mountain, Aug - Sep 2002.
Images produced using the spatial history explorer.

The weekly cycle is a human construct rather than a natural phenomenon but can place greater constraints than any naturally occurring cycle on individual accessibility. A comparison of weekdays and weekends reveals that weekdays exhibit a far more restricted distribution associated with the schedule restrictions enforced by employment (focused upon the home and work locations and routes between them). Interactive highlighting of the weekend demonstrates far less restricted movement and more longer distance travel away from the home location, as shown in Figure 12 (Mountain, 2005b).

Dealing with data interactively in this graphical and user-centred manner allows the analyst to gain an appreciation of any periodicity or pattern in the data and the temporal and spatial scales at which these forms occur through a process of visualization. Several subsetting operations of each type may be required to reduce a large data set in order to extract significant episodes and higher level information such as familiar and unfamiliar locations, ranges of movement, repeat and periodic behaviour (Mountain, 2005b).

A subset operation has the disadvantage of not displaying the selected data in the context of the entire dataset, however the same interactive technique of brushing can be used to highlight selected points. The views are linked so a simple enclosing rectangle selecting a (highlighted) set of points in the spatial view will also highlight these points in the temporal view. Being interactive this technique can select and unselect points by dragging with the mouse in real time, so can answer queries such as;

- "what was the direction of travel along this route?" (by advancing the selection through time)
- "when did this individual visit this area" (by making a spatial selection)
- "in what areas does this individual spend their evenings" (by restricted a temporal selection to a specific time of day)

Beyond allowing the exploration of mobile trajectories, the SHE software has acted as a development environment, allowing algorithms to be developed and tested, and the results visualised, prior to implementation in other systems such as the WebPark architecture (Mountain and Raper, 2002, WebPark, 2005). All of the geographic filters described in the remainder of this chapter, were developed as part of the SHE software. In particular, it has allowed an interactive approach to time geography to be developed, as discussed later.

3.2.4 Design and implementation

The spatial history explorer was developed using the standard edition of the java programming language, J2SE (Sun Microsystems, 2005b). A variety of development environments were used, notably the open source Eclipse SDK (The Eclipse Foundation, 2005). All development was the work of the author, including the definition of data models, implementation of algorithms and the front-end to the application that allowed the considerable visual analysis, configuration and interaction described above. A full list of the java *packages* that comprise the software can be found in appendix 2. Appendix 2 also provides summary java documentation on a small number of these packages and selected java classes and interfaces. The purpose of this section is to provide a very brief overview of the class design of the spatial history explorer, as a means of demonstrating how the geoVisualization described above, and data models and algorithms described in the following sections, was implemented in the java language.

The classes in the geometry package (edu.cu.gi.dmm.she.geometry) provide the data model for the representation of multidimensional points, the storage of the mobile trajectory itself, and the handling of exceptions. The Point3D, Point3DT, and PointID classes extend the existing java two-dimensional point representation to include (respectively) a third spatial dimension, time, and a unique identifier. Next, the SpatialHistory class provides a representation of the mobile trajectory, including the list of time-stamped points that comprise the trajectory, and associated motion attributes such as speed, acceleration and heading. Both linear and circular attributes can be stored in the SpatialHistory, using the LinearAttribute and CircularAttribute classes found in the attribute package (edu.cu.gi.dmm.she.attribute). The raw values for a particular dataset are stored along with summary statistics such as measures of central tendency and spread. The main purpose of the attribute package is to store *motion* attributes associated with the mobile trajectory, although the associated classes are not restricted to this use.

The grids package (edu.cu.gi.dmm.she.grids) provides a mechanism for the storage and analysis of field based representations (Cova and Goodchild, 2002). Of particular relevance to this thesis is the PredictionGrid class, which is a field-based representation used to store the likely future locations of an individual at a future time, and is used when adopting the speed-heading approach to prediction (see section 3.4.3); this class implements the Prediction interface in the prediction package (edu.cu.gi.dmm.she.prediction). The Prediction interface has methods for storing the configuration parameters for a prediction, and the actual location at a predicted time if known, which can act as a verification point (see section 3.5). The PpaPrediction and SpatialBufferPrediction store the predictions associated with two other approaches to prediction that are described later in this section (see sections 3.4.1 and 3.4.2).

The time geography package (edu.cu.gi.dmm.she.timeGeog) stores all of the data models for representing the concepts of the time geography school implemented as part of this research (as described in section 2.2) using the java language. This included the space-time path (SpaceTimePath) and potential path area (PotentialPathArea) described in section 2.2. In addition, further classes extended some of these concepts specifically for the purpose of generating time geography representations based upon the previously exhibited spatial behaviour of individuals, as described in the following sections (see section 3.4.2).

There are many more classes that are not described at all in this thesis. This includes 15 packages for the visual representation of mobile trajectories on the screen (edu.cu.gi.dmm.she.screen.*), including handling user interaction (edu.cu.gi.dmm.she.screen.interaction), and generating and storing the colours associated with attribute shading (edu.cu.gi.dmm.she.screen.color). Various other packages were designed to fulfil specific functions, such as the storage and analysis of *sets* of points (edu.cu.gi.dmm.she.sets), handling spatial reference systems and the transformation between them (edu.cu.gi.dmm.she.srs), and statistical analysis (edu.cu.gi.dmm.she.stats).

The full detailed java documentation for all classes can be found on the attached CD ROM, and downloaded from the website associated with thesis (http://www.soi.city.ac.uk/~dmm/phd), (Mountain, 2005a)

3.3 Mobile platform and testbed

Some of the work described in this thesis was either inspired by or developed as part of the WebPark project, a collaboration of six European partners funded by the EU 5th framework (WebPark, 2005) whose primary aim was to develop a mobile information system providing geographically relevant information for visitors to outdoor recreational areas. At the close of the WebPark project in October 2004, one project member launched a commercial spin-off company – Camineo (2005) – trading shares in the company for the intellectual properties rights (IPR) of the other project partners. The links between the WebPark project, Camineo and the spatial history explorer will be explained in the next section.

The main test-bed for the WebPark project was the Swiss National Park, which hosted user needs assessments early in the development cycle, and subsequent user evaluation of the prototypes developed during the project's three-year lifetime. The user needs studies from the beginning of the project are of interest at this stage in the thesis since they assisted in defining the notion of geographically relevant information (Krug et al., 2002). Various user needs studies were conducted in attempt to discover and categorise the information needs of mobile individuals. Several strategies were employed including a formal questionnaire with

1600 respondents, and sessions of user shadowing in the field, and these are discussed in the following sections.

3.3.1 The WebPark project, the Camineo spin-off and the Spatial History Explorer Intellectual Property Rights

As described in section 3.2, the spatial history explorer was developed as a geoVisualization tool for the analysis of mobile trajectories. Whilst the spatial history explorer existed as a tool in its own right prior to the WebPark project, the functionality of SHE evolved during the course of the project to satisfy the needs of the WebPark project, primarily the development and evaluation (both visual and quantitative) of geographic filters designed for mobile information retrieval. As a result, the SHE API also describes data models and algorithms for the analysis of mobile trajectories (see section 3.2.4). During the development of the WebPark project, a subset of SHE classes was reengineered to run alongside the WebPark platform on mobile devices running the personalJava API, part of the Java Micro Edition, J2ME (Sun Microsystems, 2005a). This reengineered subset of classes was extended to implement some of the *geographic filters* – including the "search ahead" algorithm based upon a speed-heading prediction (see section 3.4.3) – which are described at length in the later sections of this methodology, within the WebPark architecture.

At the close of the WebPark project in October 2004, the spin-off company, Camineo, was launched by a project partner based in Toulouse. Camineo bought the intellectual property rights (IPR) to all of the code required to run the WebPark platform from the five other partners, trading shares in the company or service contracts, for each partner's IPR. Thus some of the geographic filters developed as part of this research are now part of a commercial location-based service with implementations for clients in the Swiss Alps (The Swiss National Park), the Dutch Coast (EcoMare) and the French Pyrenees (Pyrenees National Park).

Camineo has given permission to publish work describing and evaluating the algorithms developed by the author whose IPR is now owned by Camineo. Furthermore, permission has been granted to publish the java documentation associated with these algorithms. The only restriction placed upon the author is that the java code itself should not be published. The IPR associated with the classes developed for geoVisualization was not transferred, so the spatial history explorer is not owned by Camineo.

3.3.2 User needs questionnaire

As part of the WebPark project (WebPark, 2005), a user needs study was conducted within the Swiss National Park. A questionnaire was disseminated by various channels including the

National Park visitor information centre, by post to subscribers to the park magazine, and to other identified contacts with an interest in the park (Krug et al., 2002). Of particular interest to this thesis are questions relating to the existing sources of information that people employ when visiting the park, and their willingness to use a mobile information guide in place of those established sources.

Table 1: Media used when preparing of a visit to the SNP (Krug et al., 2002)

	Rank	*% responses*
Internet	1	64
Maps	2	61
Brochures	3	48
Books	4	43
Friends / relatives	5	25
CD Rom	6	24
Other	-	3

Based upon 1520 valid responses

In an attempt to ascertain the means by which visitors currently satisfy their information needs, respondents were asked which media they used when preparing a visit to the National Park, and their primary means of information provision in the field; in both cases they were allowed to choose more than one option (Krug et al., 2002). When planning a visit, visitors' most used media were the Internet (used by 64% of respondents) and maps (used by 61% of respondents) as shown in Table 1. This implies the need for location-aware mobile information systems: people preferentially access online information, and there is strong geographical component to their information needs. Below this, brochures and books were used, then word of mouth and finally information in CD-ROM form. The results of this question led to two design decisions for the WebPark system: that it should use the familiar web browser as the Interface, and that geography should be used as a way of organising information.

Table 2: Present information provision when hiking through the SNP.

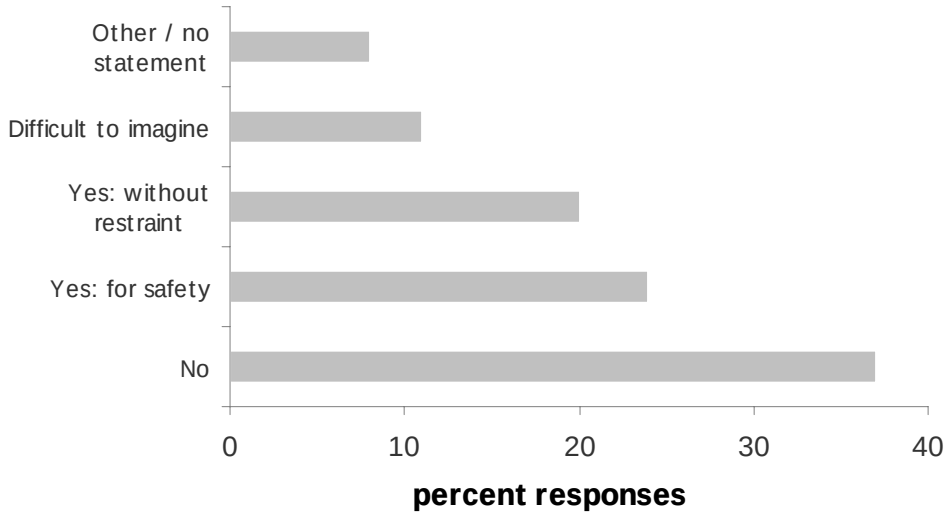
	Rank	*% responses*
Information boards	1	66
Literature	2	51
Nature trail	3	41
Personal contact with staff	4	40
No info	5	19
Knowing SNP well	6	19
Guided tour	7	14

Based upon 1579 valid responses

When respondents were asked how they accessed information when in the Park, two thirds used the information boards located in the field (see Table 2). This suggests that visitors display an interest in information that is relevant to specific locations, and informed another WebPark design decision, that the system should attempt to provide tools to allow the user to retrieve information that is geographically relevant. People also relied on literature, nature trails set up the Park and contact with park staff, suggesting that people prefer authoritative sources of information (Krug et al., 2002).

Figure 13: Intention to use a mobile information system

Derived from 1597 responses to the WebPark user needs questionnaire (Krug et al., 2002)



Users were asked whether they would use such a system in the field; at this point in the development cycle, no system had been developed hence the respondents had only descriptions of how such a system might work. 37% replied with a straight "no", suggesting user scepticism could act a barrier to take up of mobile information systems. 44% replied "yes", although 24% of these would only use it as a safety feature (see Figure 13). The remainder either did not reply, or would not express a preference since they could not imagine such a system, suggesting that the novelty of a system may itself act as a barrier to take-up.

3.3.3 Visitor shadowing

The second study undertaken to assess user needs comprised two visitor shadowing exercises. In these exercises, visitors were accompanied on their trip by a member of the WebPark team who recorded the questions they raised and problems they experienced. They acted as a "human LBS", recording and responding to queries, but not prompting the visitor

for information. The intention was to assess mobile information needs and anticipate potential scenarios of use of the system (Krug et al., 2002).

During the two user shadowing exercises, a total of 90 questions were recorded, of which 53 had some spatial reference related to the question. Of the 53 questions with a spatial reference, 15 were related to navigation (eg "Where is the trail leading to Munt La Schera", "Where are we?") or landscape (eg "Is this the Lake of Livigno?"). Of the remaining questions with a spatial reference, 9 were related to park fauna (eg "Are there any marmots here?"), 12 to flora (eg "At what elevation is the timberline? Will we pass it on our way?"), and 8 to the geomorphology (eg "Is this a moraine?") (Krug et al., 2002). In many the spatial component of the query was implicit as the question referred to the current location (eg "... around here ... "), a visible location (eg "Which mountain is ... ") or a future location on the route (eg "Will we pass ..."). A full list of the 53 questions with a spatial reference can be found in Appendix 1.

This implication that roughly 60% of queries have a spatial component is an interesting result that is at odds with existing literature in this area which suggests that only about 20% of queries have a spatial component (Sanderson and Kohler, 2004, Spink et al., 2002). There are key differences between this particular user needs study and those in literature: this study was conducted in an outdoor environment; the participants were mobile unlike those in the literature; and user needs were recorded from comments and questions made by the participant, rather formulating queries that were submitted to, and logged by, an Internet search engine. The limited size of this user needs study means that care must be taken in interpreting results, however one interpretation is that the discrepancy with the literature could be due to mobile and outdoor individuals being more likely to have a spatial component to their query, since their information needs are more likely to be influenced by their surroundings. An alternative interpretation is that static users of Internet search engines are as likely to have a spatial component to their information needs, but they do not include a toponym or spatial relation in the query having learned from experience that this spatial component is poorly handled by search engines (Sanderson and Kohler, 2004).

It was clear from this study that the information needs of mobile individuals frequently contained a geographic component, that many queries would be meaningless without this geographic context, and that the majority of such queries could not be satisfied by existing information systems. The results of this study led to contemplation about the geographic filters that could be applied to increase the relevance of retrieved information. It was clear that users of mobile information systems engage with their surroundings, which provide a dynamic backdrop likely to prompt questions, far more than their static counterparts whose backdrop will be a more familiar predictable location, such as a workplace or the home (Krug et al., 2002).

3.4 Geographic filters for information retrieval

The following sections propose various *geographic filters* that attempt to increase the relevance of the information retrieved by users of mobile information systems: this area of work is closely related to the concept of *geographic relevance* (Raper et al., 2002). These measures are represented as surfaces or geographic features that define regions of space that are relevant for an individual, at some time, based upon some quantifiable geographic criterion. Various assumptions are made about how information can be processed to be made more relevant to the geographic context of the user. The first is *spatial proximity*, where the closer an information source is to an individual, the more relevant it is. The concept of spatial proximity can be represented with a (spatial) buffer around a point location, a bounding box, or by generating a spatial proximity surface which can not only define a region in space that is relevant, but differentiate within that space, based upon distance from the user's position or some other location. A more sophisticated assumption is that of *temporal proximity*: regions that can be reached in a shorter period of time are more relevant than those that are temporally distant. This concept can be defined by time geography concepts such as potential path areas, and derived surfaces such as accessibility surfaces. Another related assumption is that information that coincides with an individual's likely future locations is more relevant than that located in places they are unlikely to visit. This can be modelled using *speed-heading prediction surfaces*, that provide an estimate of the likelihood of an individual visiting different locations, based upon their recent spatial behaviour. Other measures of geographic relevance are also suggested but not implemented including those based upon visibility, making the assumption that people's information needs are inspired by what they see around them.

3.4.1 Spatial proximity

Perhaps the simplest and most intuitive measure to consider when attempting to define geographic relevance is spatial proximity (Laurini and Thompson, 1992a): the key assumption here is that locations that are closer in space to some feature, are more relevant than those that are distant. This relates closely to what has been defined as the first law of Geography, "everything is related to everything else, but near things are more closely related than distant things" (Tobler, 1970). Different measures of spatial proximity can be defined with distinct characteristics.

Buffer

A simple and familiar filter for defining a region of space representing an individual's geographic context is a buffer, which can be described by a circle of radius r, centred on the location of an individual at a specific time (see Figure 14a). This buffer can be used within the field of geographic information retrieval to retrieve all features within a specified distance of an individual. The spatial buffer is a Boolean representation, where the region inside the

circle is considered to be relevant, and the region outside the circle, not relevant. By employing this Boolean approach it is not possible to distinguish between results that fall within the circle; all that can be said is that these results are relevant, not *how* relevant. The radius of the circle must be defined accord to some criterion and rules must be defined to specify how areal features qualify for inclusion in a search. Some geographic search engines allow people to define this sharp cut-off distance for themselves, for example "search within 500 metres of present location" (WebPark, 2005). A more sophisticated approach is to define the cut-off automatically, using some criterion related to the user's behaviour, such as the present speed.

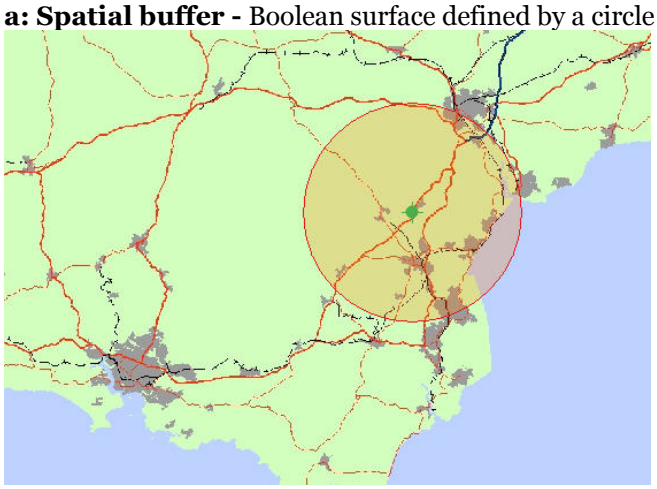
The minimum bounding rectangle (MBR) is similar to the spatial buffer in that a Boolean region of space is defined that is deemed to be geographically relevant to a particular point in space, however for a MBR the region is defined by a specified width and height, rather than a circle of fixed radius r. An artefact of using a MBR is that two points that are the same distance from the target location may be classified differently (one relevant, one not). Nevertheless, the bounding box is frequently used as a heuristic within GIS and for geographic information retrieval, since candidate features can be assessed to see whether they are within the bounds very quickly, often prior to a more sophisticated and time consuming procedure (Jones, 1997).

Spatial proximity surface

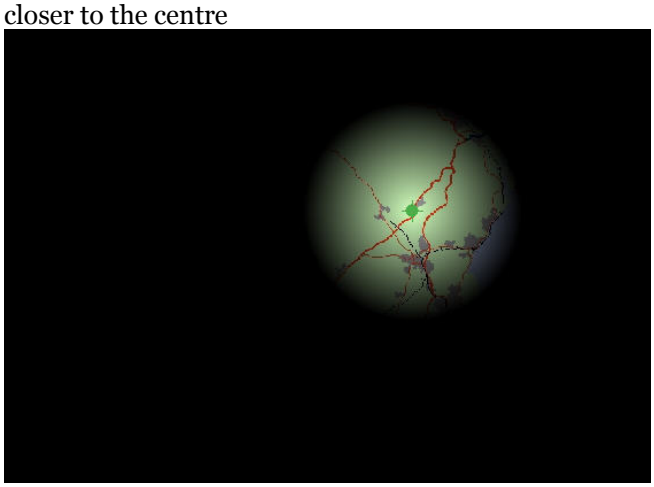
Buffers and MBRs both define Boolean regions centred on a point. It is also possible to define a regular grid of cells (a raster) where values vary across the grid based upon distance from some focal point, such as the centre: such a raster can be referred to as a *spatial proximity surface* (see Figure 14b). This raster grid can also have a cut-off, defined by the range where it is assumed that further increases in distance will have no further influence over the values, ie beyond that point, all information is considered to be not relevant (Burrough and McDonnell, 1998). This distance-weighting requires some decay function to be applied. A Boolean spatial buffer assumes that no decay has been applied, and all locations closer than the cut-off distance have the same value (see Figure 15a). Longley et al (2005) describe three distance decay functions: linear distance decay, negative power distance decay and negative exponential distance decay (Figure 15b - Figure 15d). Linear decay is a less extreme decay function, where values on the surface are calculated according to a linear relationship from the highest at the centre, to zero at and beyond the cut-off (Figure 15b). The negative power distance decay function can provide a more extreme peak at the centre of the surface, decaying faster to low values (Figure 15c); the size of the central peak and rate of decay can be configured by manipulating the exponent, where higher exponents provide a more extreme peak and faster decay. The negative exponential distance decay function acts in a similar way to the power function, and can provide a more extreme peak and faster decay than the linear function (see Figure 15d).

Figure 14: Spatial proximity surfaces

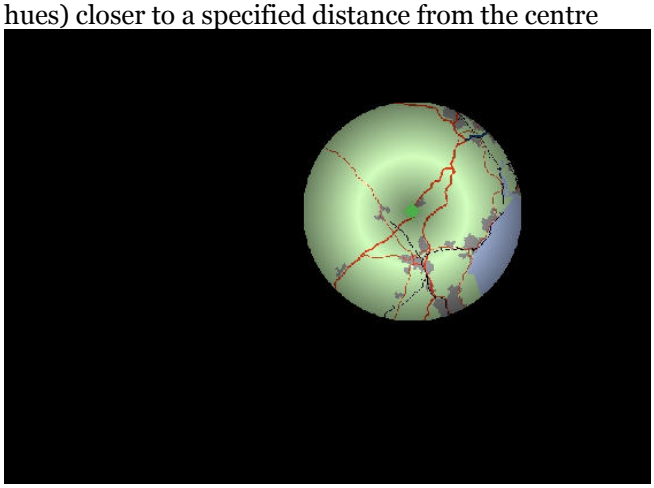
a: Spatial buffer - Boolean surface defined by a circle of radius r, centred on a point



b: Spatial proximity surface - graded surface, with higher values (shown in lighter hues) closer to the centre



c: Offset spatial proximity surface - graded surface, with higher values (shown in lighter hues) closer to a specified distance from the centre



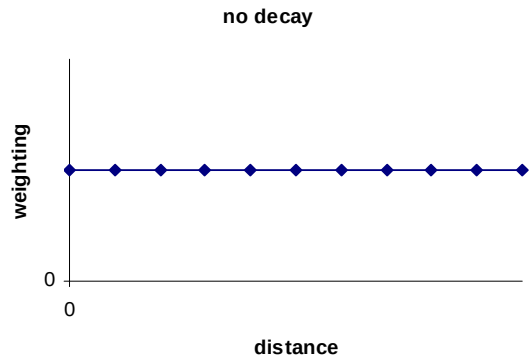
Data collected by David Mountain, Jun 2004
Images produced using the spatial history explorer.

Distance decay functions - from Longley et al (2005)

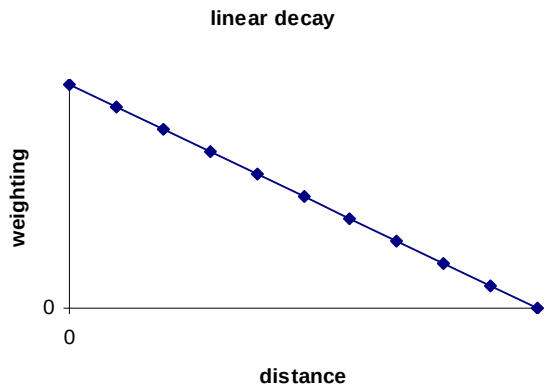
Equation 1: Linear distance decay	Equation 2: Negative power distance decay	Equation 3: Negative exponential distance decay
$W = a - bd$	$W = d^{-b}$	$W = \exp(-bd)$

Figure 15: Distance decay functions: adapted from Longley et al (2005).

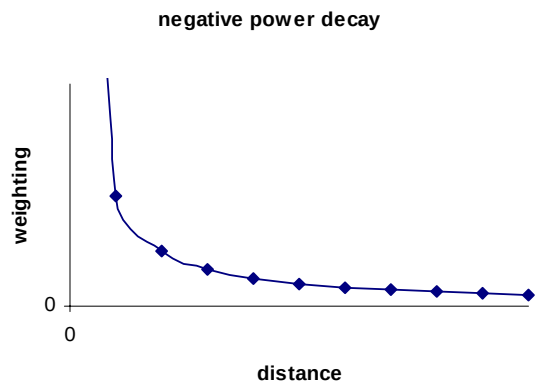
a: No decay



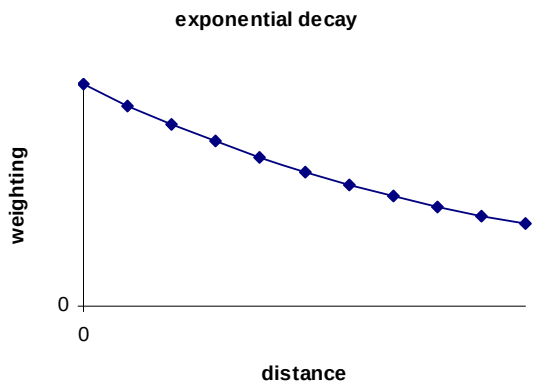
b: Linear distance decay



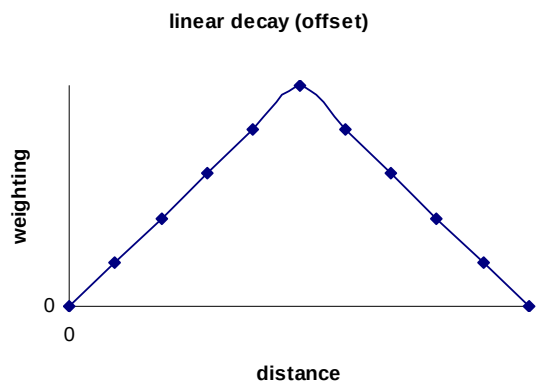
c: Negative power distance decay



d: Negative exponential distance decay



e: Offset linear distance decay



An alternative to the assumption that locations closer to the centre of the circle receive a higher weighting that those elsewhere within the surface, is to choose some offset distance, at which the maximum values are found (see Figure 15e). This creates a torus or donut shape; values increase from a minimum at the centre of the surface to a maximum at the offset distance, then decrease again to a minimum at the cut-off distance (see Figure 14c). The same distance decay functions can be applied, for example offset linear distance decay functions. This surface could be useful for predicting the future locations of moving point objects when we have some idea of the distance that they are likely to cover, but are unsure about in which direction they may travel. The spatial proximity surfaces can be normalised (Sarle, 2002), where each cell value is divided by the mean cell value. Following normalisation, the mean cell value is 1, with values below 1 reflecting more locations further from the target, and values greater than 1, close locations.

3.4.2 Time Geography and temporal proximity

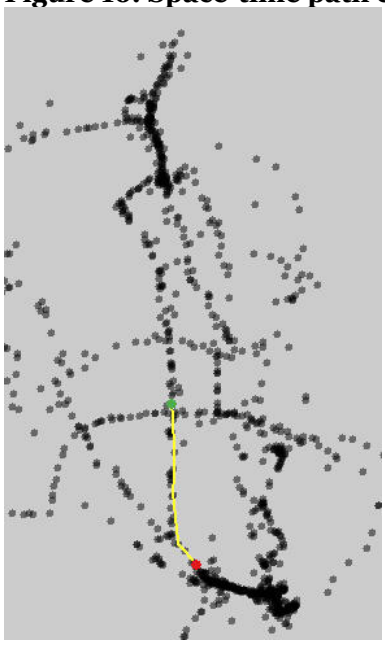
"The past is the key to the present" (Longley et al., 2005)

As discussed in the literature review, the emergence of time geography had a profound effect upon notions of accessibility in the 1970s, placing emphasis upon modelling the behaviour of *individuals* rather than groups of people (Hagerstrand, 1973). This approach has offered considerable insight into the constraints faced in personal accessibility in terms of physical capabilities, availability (of individuals and services) and authority restrictions. Implemented models, however, have often made unrealistic simplifying assumptions such as ease of movement in all directions (Lenntorp, 1976), since they have lacked fine-resolution spatio-temporal data describing the behaviour of individuals, relying instead on travel diaries (Kwan, 2000) . The visual representation of time geography concepts has traditionally been a laborious process often undertaken by a dedicated graphics unit over a period of hours or days; the final images were intended to communicate ideas to a mass audience, rather than for exploration of the model or data itself.

Two key technological advancements have allowed time geography concepts to be implemented in an interactive environment. The first is the increased processing speed and memory of modern computers (Raymond, 2000), permitting the interactive analysis of large volumes of quantitative data. The second is the availability of handheld GPS receivers that can record the mobile trajectories at a much finer spatio-temporal resolution than travel diaries (see section 3.1). This section describes how time geography techniques have been implemented in an interactive environment, following this the concept of temporal proximity will be explained, and how this may represent the geographic context of a mobile individual in certain circumstances.

The space-time path

Figure 16: Space-time path created interactively in the spatial history explorer



The image below shows a space-time path created interactively using the spatial history explorer software. The black points show the parent dataset from which the space-time path was extracted: one month's spatial behaviour recorded in central London. The coloured points show the path; the green point represents the start of the path, yellow line shows the path itself and the red point represents the end of the path.

Data collected by David Mountain, Aug - Sep 2002
Images produced using the spatial history explorer.

As described in the Literature review (section 2.2), one of the most fundamental time geography concepts is that of the space-time path (Miller, 1991) also known as the life path (Hagerstrand, 1973) or mobile trajectory (Smyth, 2000). Temporal subsets of this complete path can reveal a moving point object's spatial behaviour over a week, a day or some other temporally bounded period. In this section, the conventions will be adopted of using the term 'mobile trajectory' to refer to the parent data set, and 'space-time path' to refer to temporally bounded subsets. An interactive approach to the space-time path has been implemented in the spatial history explorer (SHE) software, where given a temporal duration (or time budget) and origin (a spatial point location), the corresponding space-time path is rendered in multiple views that can represent spatial, temporal and attribute dimensions (see Figure 16). The time budget of the space-time path must be specified in advance. The origin point can be defined by clicking in a panel in SHE and selecting the *nearest* point in the parent set. The nearest point may be defined by a spatial, temporal or attribute metric depending upon the panel in which the click occurred.

The potential path area (PPA) or temporal proximity surface

Any one space-time path reveals the previous behaviour of a single moving point object over a specific period of time. It is possible to aggregate a number of space-time paths, all of which came close to the same spatial origin, to reveal the region of space that is accessible for a

given time budget, based upon the previous behaviour of a single or multiple moving point objects (see Figure 17). This is analogous to the time geography concept of the potential path area (Lenntorp, 1976), the two-dimensional spatial extent within which an individual can travel in a specified time budget. Rather than using simplifying assumptions about ease of travel in all directions (Lenntorp, 1976) or using contextual data such as transportation networks (Miller, 1991) which may only address one component of accessibility, this approach is informed by previous behaviour and represents the region that actually *was* accessible given the previously displayed spatial behaviour. For small datasets, this approach will provide quite conservative PPAs since it represents only the locations previously visited and does not account for exploration to new areas, even if those unvisited are accessible.

Defining a potential path area (PPA)

This process takes as input;

- One or more mobile trajectories (parent dataset) describing the spatial behaviour of one or more moving point objects.
- A time budget for the potential path area.
- An origin point for the PPA (O).
- The number of paths that will be used to define the PPA (n).

The procedure is;

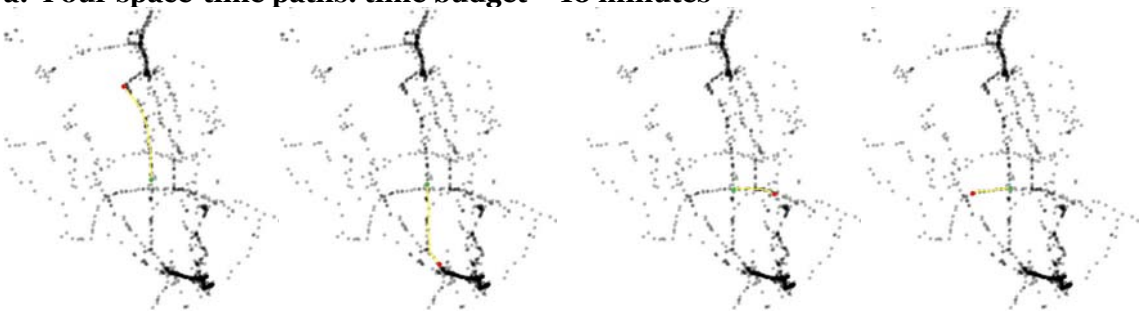
1. Select the n points in the parent set that are closest in space to the origin (O) to be the starting points of n space-time paths.
2. From each starting point, follow the parent set mobile trajectory for the duration specified by the time budget to define n space-time paths.
3. The potential path area is defined by performing some transformation to enclose all of the points that comprise the n space-time paths, for example a convex hull around the points, or buffer around the space-time paths themselves.

As described in step 3 of the defining a potential path area (ppa) process (above), the ppa is defined by performing some GIS operation to enclose all of the points in the space-time paths emanating from the origin point. The convex hull approach seems more in keeping with the time geography tradition, where accessible regions of space are defined, however one drawback of this approach is that it can lead to the inclusion of regions of space that were not visited. In Figure 17b it can be seen that the convex hull has included a great deal of space that was not visited, and hence may be inaccessible, including a bridge across the Thames, that was never crossed in the previous trajectory; for example Southwark Bridge in Figure 17b and Tower Bridge (the most Easterly Bridge shown) in Figure 18. Such an approach could include private inaccessible regions in the PPA, as well as areas that cannot be reached due to travel time constraints.

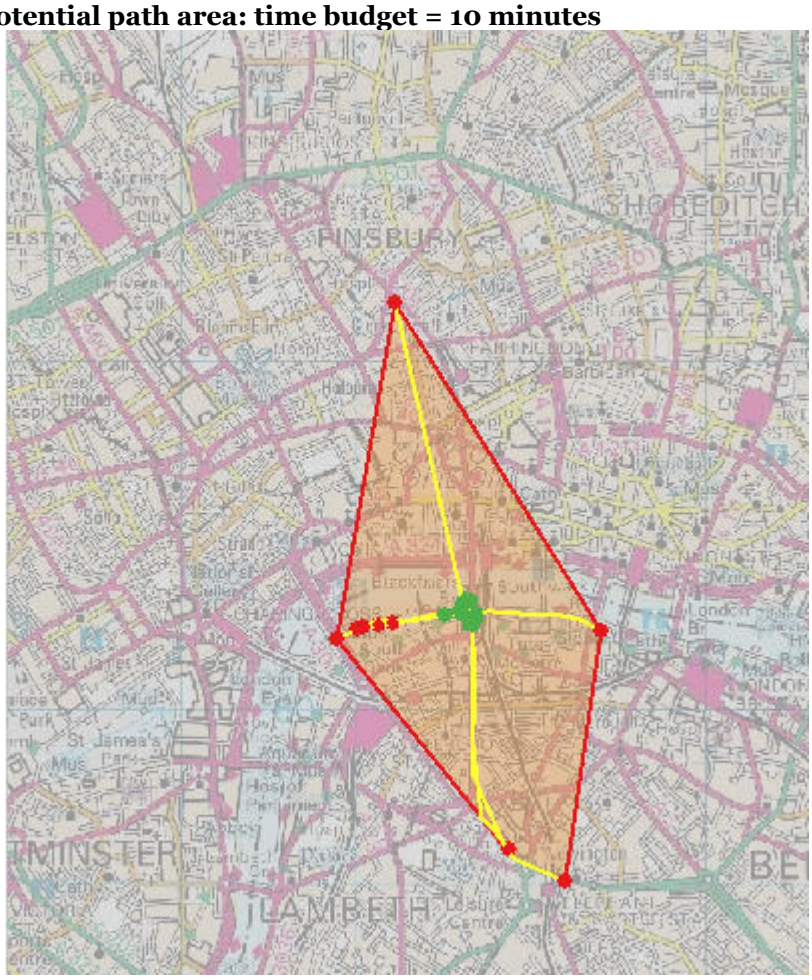
Figure 17: Using space-time paths to define a potential path area:

In a, four space-time paths (shown in yellow with green and red endpoints) have been extracted from the parent mobile trajectory (shown as transparent black points), using four origin points close to a user defined starting point; they demonstrate that in the past, movement to the North, South, East and West has been displayed from this location. In b, 12 space-time paths have been enclosed using a convex hull, to define a potential path area representing the region of space accessible within 10 minutes.

a: Four space-time paths: time budget = 10 minutes



b: Potential path area: time budget = 10 minutes



Data collected by David Mountain, Aug - Sep 2002
Images produced using the spatial history explorer.

An alternative approach is to use a buffer around the space-time paths themselves, which results in a region that is more spatially constrained, and with less opportunity for overlap

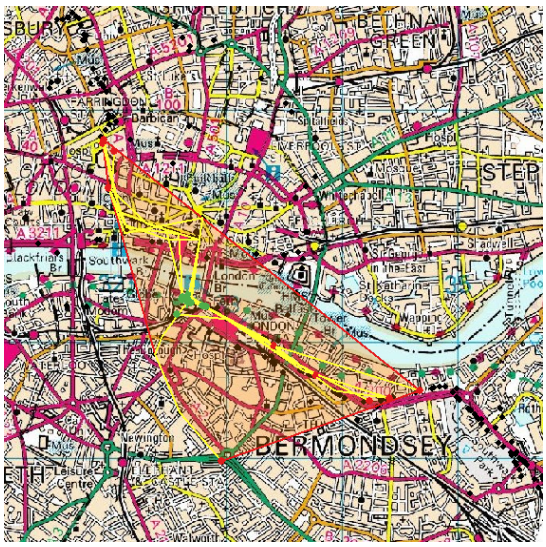
into regions that were not visited. An appropriate buffer distance should be selected: for GPS data the reported accuracy since the ending of deliberate signal degradation due to selective availability (The White House: Office of the Press Secretary, 2000) is between 10 to 25 metres, depending upon the type of receiver and environmental conditions (Enge and Misra, 1999, Porcino, 2001). Such a small buffer distance may be appropriate if there is sufficient data density, however for smaller datasets, larger buffer distances may be required to prevent the potential path areas being unrealistically small. In the study, a buffer distance of 250 metres has been applied around the space-time paths. The resulting regions of space form accessibility corridors, and are generally more precise than the convex hull approach.

The potential path area is a crisply delineated, homogenous area that defines what region of space is accessible for a given time budget, no distinction is made about how accessible one region of the ppa is relative to another. Such information, however, is stored implicitly within mobile trajectories and the next two sections will consider ways of extracting and representing accessibility as a phenomenon with indeterminate boundaries. The potential path area acts as *temporal proximity surface*, analogous to the spatial proximity surfaces described in section 3.4.1. Whereas a spatial proximity surface can define the region of space within x metres of the present location, the potential path area can define the region of space accessible within t minutes of the present location, based upon previously displayed behaviour.

Figure 18: Alternative approaches to bounding the sections of the mobile trajectory, accessible with a given time budget

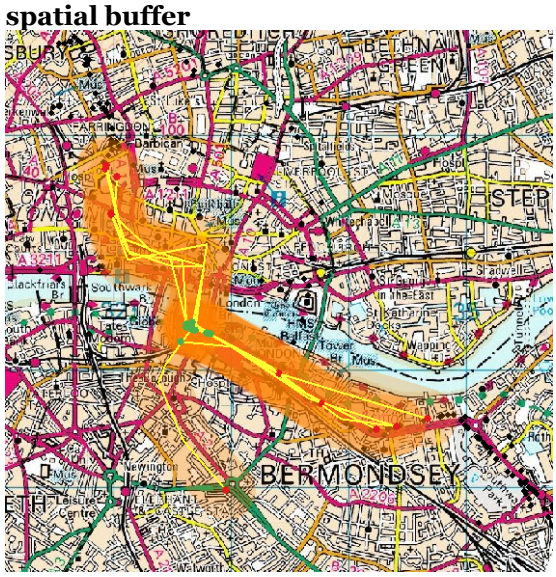
Based upon the previous behaviour of a single individual in Central London during Dec 2003

a: bounding points with a convex hull



The hull is shown as a transparent orange region with a red boundary, generated around a series of origin points (in green). The yellow paths show the sections of the mobile trajectory that had been traversed from the origin points, within 5 minutes.

b: bounding points with a 250 metre spatial buffer



The buffer is shown as a transparent orange region, generated around a series of origin points (in green). The yellow paths show the sections of the track log that had been traversed from the origin points, within 5 minutes. The intensity of the orange colour represents the density of space-time paths, so darker orange regions were visited many times, lighter orange visited infrequently.

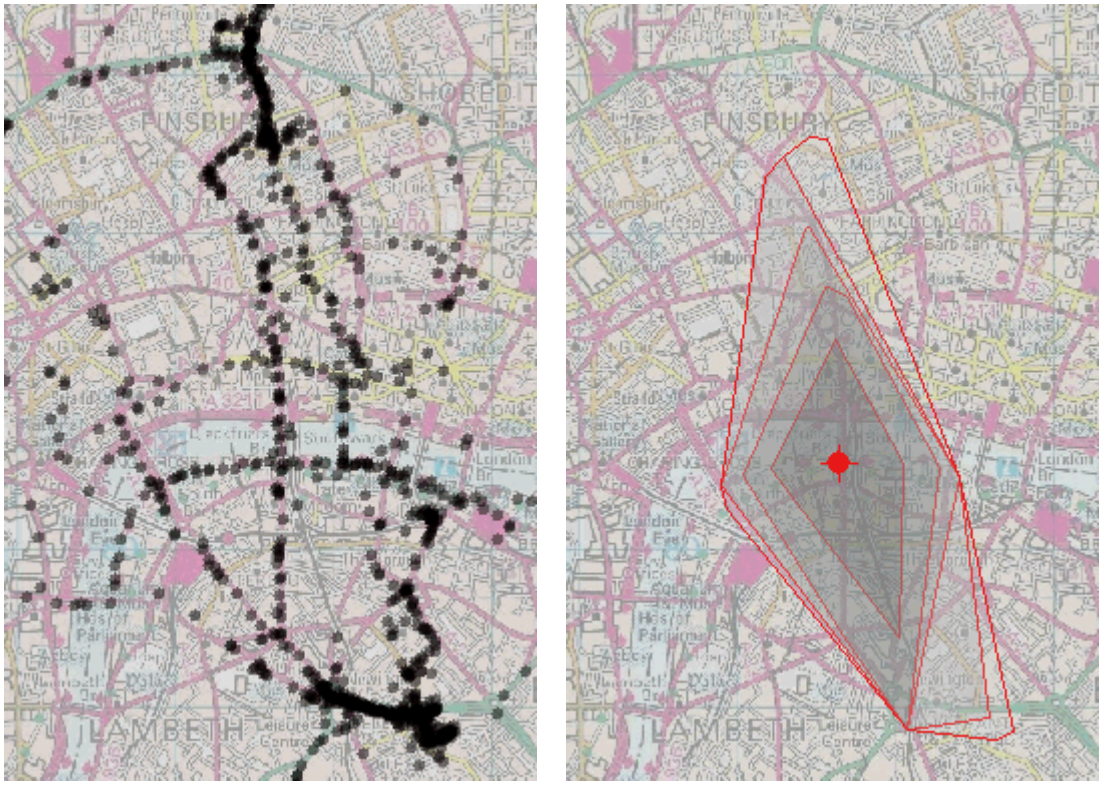
Data collected by Pete Boyd, Dec 2003
Images produced using the spatial history explorer.

Isochrone surfaces

An *isochrone surface* can be derived from a series of potential path areas all of which have the same origin but different time budgets. It is a graded surface comprised of a series of concentric polygons, centred on an origin point (see Figure 19). Travel time increases as you cross a boundary between two polygons, moving away from the origin. This introduces heterogeneity into the concept of accessibility; some locations within the surface are *temporally* closer to the origin than others, which is not the case for locations within the potential path area.

Figure 19: Isochrones surfaces: regions accessible from Blackfriars bridge in 15 minutes or less.

The spatial behaviour of one individual, recorded over a one month duration and clipped to Central London, has been analysed to generate the isochones shown in the right panel. Each successive red polygon, heading out from the central red point, shows the area accessible within an additional 3 minutes. The largest enclosing red polygon, the 5th isochrones, therefore represents the region accessible within 15 minutes. It can be seen, that for this particular individual, speed of travel is faster in a North-South direction than in an East-West direction.



Data collected by David Mountain, Aug - Sep 2002
Images produced using the spatial history explorer.

Accessibility surfaces

An accessibility surface is a raster grid where each cell represents the travel time from a spatial location (the origin). Representing accessibility in this way avoids the inclusion of inaccessible areas and homogeneity that is associated with potential path areas and isochrones surfaces. Raster modelling does not place the constraint on accessibility that time travel can only increase with distance from the surface origin as unlike the isochrone surface, it does not reply upon concentric polygons.

There are many parameters that can influence this surface. The size of cells in the output grid represents the spatial resolution of the surface. Using a larger grid cell size reduces the processing time associated with calculating the surface, however the associated decrease in spatial resolution may lead different components of the transportation network, with very

different characteristics, falling into the same set of cells (for example, a railway line running alongside a canal). When calculating the travel time to each cell in the raster, a distance weighted mean can be used, or an alternative is to use the minimum travel time value of those points that fall within the search buffer since people are often interested in how fast they can travel to different locations. Accessibility surfaces are similar to the approach of Forer, who implemented time geography concepts using a raster model of space (see section 2.2).

Temporal Proximity Summary

For this study, the potential path area will be used to model temporal proximity since it is considered to be the most appropriate representation and conceptually closest to the original work of the time geography school. The justification for adopting this representation, above all those described is that, unlike the space-time path, it represents the *region* of space (areal representation as described in section 2.1.2 of the Literature Review) associated with a particular time budget. Furthermore, it is an object (vector) representation as opposed to a field (raster) representation (this distinction is also described in section 2.1.2). As described in the Literature Review (section 2.2), the original time geographers applied object representations of accessible areas and field representations, such as the accessible surface described above, have accounted for only a small percentage of this research.

3.4.3 Speed-heading predictions

Of the existing approaches for predicting the future locations of moving point objects, many have been criticised for assuming that those objects move according to simple linear functions and for failing to capture the complexity of motion patterns (Tao et al., 2004). Of the methods available for predicting the future location of moving point objects, the idea of using speed and either turning angle or heading from correlated random walk analysis (Byers, 2001) was identified as a useful approach, particularly since this has been applied for modelling the future locations of moving point objects (often animals), based upon their previous behaviour. As discussed in section 2.3.1 implementations of correlated random walks frequently lack the volume of data required to generate valid statistical distributions for input parameters to the model. The spatial and temporal resolution of the data repository collected as part of this study is sufficiently fine to permit the calculation of statistical distributions for parameters such as speed, heading, turning angle and step size. The following sections describe the influence of different parameters when making predictions about future behaviour, and how the ideas from correlated random walk analysis were adapted to use a moving point object's mobile trajectory to create a *prediction surface*.

Whilst this form of prediction is closely related to correlated random walk analysis, it considers only heading and not turning angle when predicting future locations. The

justification for this is that we wish to predict the destination of the moving object, rather than construct a model of recent movement that could describe the motion pattern seen when travelling to that destination. When making a prediction based upon turning angle, the initial starting direction used in correlated random walk analysis can be crucial, and may result in a good model of motion pattern that heads initially in an arbitrary direction. By using heading, the model of motion is less effective, but the prediction will continue on the heading described by previous behaviour, and be less affected by very recent deviations away from the overall direction of movement. For this reason, these predictions will be referred to as *speed-heading predictions*, to indicate that they are based upon an extrapolation from the current location given values to describe speed and heading, and to differentiate this approach from correlated random walks. This is a new approach to this problem.

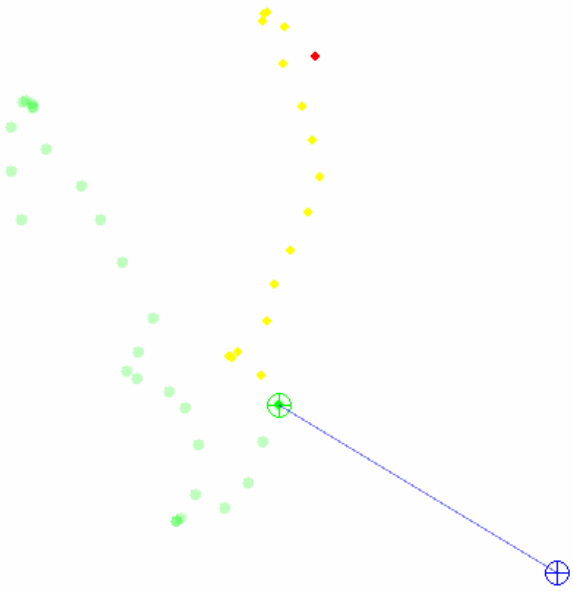
Several new terms will be used when discussing predictions. The two- (or three-) dimensional spatial point location from which the prediction is being made is referred to as the *prediction origin*, and the time at which a prediction is being made, the *prediction start time (t)* the prediction spatial origin and start time are typically defined by the most recent point in a mobile trajectory, or the time and place where a mobile user has an information need and performs a search for geographically relevant information. One issue to consider is what period into the past should be considered, when predicting a moving object's future location. In this discussion, the period of time elapsed since the start time for which a prediction will be made is referred to as the *prediction period*: this is the "20 minutes" parameter predicting where an object will be "20 minutes from now", hence a *long-term prediction* will use a greater value for prediction period than a *short-term prediction*. In the context of testing a prediction, a *verification point or destination point* refers to the actual known location of the moving point object at the time for which the prediction is made. The term *recent behaviour* is used to define the spatial behaviour of a moving point object (as described by its mobile trajectory) from some specified period of time in the past until the prediction start time. The principle behind the application of correlated walk analysis in this context is therefore to predict the future location of some moving point object, from the analysis of its recent spatial behaviour.

Point predictions

Wolfson and Yin (2003) provide a definition for predicting the future location of a moving point object, based upon linear extrapolation from a known location along a straight line at a constant speed. Given these assumptions, a single, future point location can be calculated using the arithmetic mean of speed and the circular mean of heading for a moving point object's *recent behaviour*. An example of this is shown in Figure 20.

Figure 20: A deterministic point prediction using mean speed and heading

In the image to the right a point prediction (the blue cross hair) has been made from an origin location (the green cross hair), given a moving point object's recent spatial behaviour (the pale green points). The prediction is made for 15 minutes into the future, given the behaviour over the previous 15 minutes. The object is predicted to move 372 metres from the starting location, at a heading of 124 degrees (the blue line). The actual behaviour, shown by the yellow points, deviates considerably from the prediction. The predicted location was 684 metres away from the actual location 15 minutes later (the red point).



Source data: A GPS tracklog representing a walk in a semi-natural setting, Kolymbari, Crete, March 2004 Images produced using the spatial history explorer.

The general algorithm for generating point predictions is given below.

Generating point predictions

1. Specify the *prediction period*: the period of time into the future at which to predict the location of a moving point object (eg 20 minutes from now).
2. Retrieve the mobile trajectory that defines the object's *recent behaviour*, from the period of time prior to the *prediction start time* to be considered for this prediction.
3. Calculate speed, heading and sinuosity† values, given this recent behaviour.
4. Calculate the distance over the ground that the point object will have travelled by the predicted time given that speed, using the equation.

   distance (covered over ground) = speed* time

5. Calculate the straight-line distance that the point object would travel by dividing the distance covered over the ground by the object's sinuosity index†;

   straight-line distance = distance covered over ground / sinuosity index

6. Given this straight-line distance and a heading value, calculate the predicted location by extrapolation from the given *prediction origin*.

† the inverse heading spread function can be used as a substitute for sinuosity

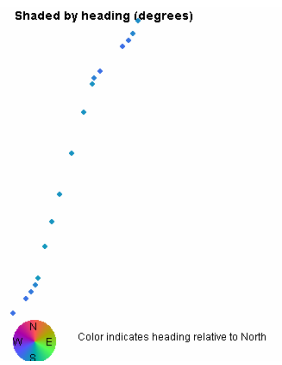
Sinuosity and the inverse heading spread function

As step 5 demonstrates, the predictions should also take account of the sinuosity of recent behaviour. The sinuosity index is defined as the distance travelled over the ground between two points, divided by the straight line distance between those points (Laube, 2005). At one extreme, the sinuosity index of a straight line is equal to one. At the other extreme, a circuit that starts and ends in the same place has a sinuosity index equal to infinity (since the straight line distance between start and end points is zero). For short periods of time such as those shown in Figure 21, the sinuosity index is useful descriptor of behaviour. For mobile trajectories recorded over long periods of time such as hours, days or weeks, sinuosity is a less effective descriptive statistic, since with time it can increase to very high values, reflecting the repetitive journeys that tend to be made as part of everyday life, for example the daily repeated circuit from home to work and back again.

Figure 21: Comparison of sinuosity and heading for three different tracks

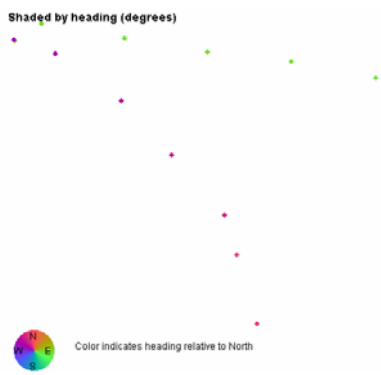
a: Straight track

Sinuosity index = 1.019
Heading spread = 0.018
Inverse heading spread = 1.018



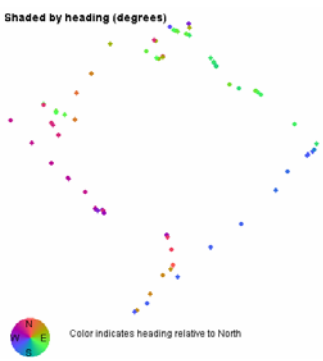
b: Sinuous track

Sinuosity index = 2.792
Heading spread = 0.611
Inverse heading spread = 2.571



c: Circuitous track

Sinuosity index = 20.89
Heading spread = 0.923
Inverse heading spread = 13.09



Images produced using the spatial history explorer

The sinuosity index is inversely proportional to the heading *spread* parameter (a circular statistic that can be used in place of the standard deviation, see section 2.3.2), since both reflect the degree of variation in heading for a specified section of a mobile trajectory. Figure 21a illustrates that for a relatively straight track, the sinuosity index is close to one, and the heading spread is close to zero, both parameters indicating very little deviation in heading. As sinuosity increases in Figure 21b and Figure 21c, the heading spread decreases correspondingly. The inverse function of the heading spread:

$$\text{Inverse heading spread function} = \frac{1}{(1 - \text{heading spread})}$$

Equation 4: Inverse heading spread function

provides a statistic that is similar in magnitude to the sinuosity. It is this parameter that is used in step 5 of the calculating point prediction process, since whilst sinuosity can only give a single figure to describe the sinuosity for all spatial behaviour that is defined as recent, the inverse spread function can be weighted by *temporal* distance to allow the most recent behaviour to have a greater influence than that in the more distant past (see Equation 1 - Equation 3 and Figure 15), a process described in more detail in the following section.

Recent behaviour and time weighted statistics

The problem posed by the increasing sinuosity index raises a wider question of what period of time should be used to define recent behaviour. Wolfson and Yin (2003) provide a definition for predicting the future location of a moving point object, based upon linear extrapolation from a known location along a straight line at a constant speed. Given these assumptions, a single, future point location can be calculated using the arithmetic mean of speed and the circular mean of heading for a moving point object's recent behaviour. An example of this is shown in Figure 20. In Figure 20, *recent* is taken to mean all spatial behaviour displayed over the previous 15 minutes, hence the values for sinuosity (or inverse heading spread function), mean speed and mean heading used for the prediction are based upon the previous 15 minutes of the mobile trajectory: the cut-off is sharp between points that are included in analysis (<15 mins), and those that are not (>15 mins).

Given the assumption that more recent behaviour is more indicative of what an individual will do in the immediate future, than behaviour in the more distant past, it is appropriate to calculate a *weighted mean* for speed and heading in step 3 of the algorithm to generate point predictions, where greater significance is given to more recent points. This is similar to the inverse distance-weighted approach described for spatial proximity surfaces, but instead of using *spatial* separation to define distance, points are weighted according to their separation in *time* from the most recent point in the set. The separation in time for each point in the set is given by the number of seconds (or some other temporal interval) by which it precedes the prediction start time. These values are then rescaled in a linear fashion from zero to one so that the earliest point has the largest 'distance' separation (1) and the most recent point the least (0).

Given these rescaled separation values, different inverse-distance weighted functions can be applied to provide a weight for each point in the set. Linear distance decay is illustrated in Figure 15b and is characterised by giving relatively high weightings to the earlier points in the set. Negative power and negative exponential distance decay give relatively higher weightings to more recent points in the set, and the rate of decay can be controlled by the distance-decay parameter, b (see Equation 1, Equation 2 and Equation 3 on p77).

Given these distance decay functions, weighted statistics can be calculated for speed and heading that are more influenced by the most recent behaviour. The weighted mean is calculated using the equation;

$$\text{Weighted mean} = \frac{\sum wx}{\sum w}$$

Equation 5: Weighted mean

Where ∑wx is the sum of all weighted values and ∑w is the sum of all weights (Shaw and Wheeler, 1985). When calculating speed, the value of x is the speed value itself in metres per second or some other appropriate measurement unit. In the case of heading, the circular angle value (in degrees, radians or some other circular measure) cannot be used directly. The mean for heading is calculated by plotting each point on the unit circle according to its heading value and calculating the centroid of the points which will always fall on or within the unit circle (described in section 2.3.2).

The weighted standard deviation for speed can be calculated in a similar way;

$$\text{Weighted standard deviation} = \sqrt{\left(\frac{\sum w(x - xMean)}{\sum w} \right)}$$

Equation 6: Weighted standard deviation

For heading, the weighted spread is used instead of standard deviation (Brunsdon and Charlton, 2003, Cox, in press, Fisher, 1993, Mardia and Jupp, 1999). Since the spread value can be weighted, the inverse heading spread function can also be weighted to reflect the sinuosity of more recent behaviour, and not simply the sinuosity index of the entire mobile trajectory.

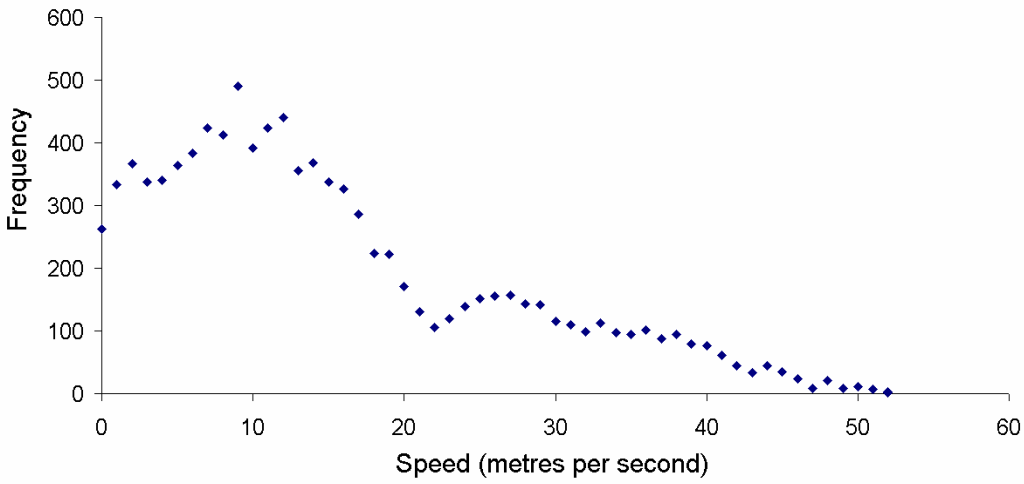
Stochastic predictions

Regardless of whether the mean is weighted or not, a single point prediction is of limited use for defining the geographic footprint of a query based upon where a moving point object is likely to be in the future in the context of mobile information retrieval. Retrieved search results may be ranked by distance from the prediction, but this is not a significant improvement upon the simple proximity searches that are the current paradigm in location-based services, such as the “Find nearest” service from UK mobile phone operator Orange (Orange, 2005) which operates on strict linear distance. Applying a deterministic approach (Burrough, 1998) that uses only the mean of speed and heading fails to consider the distribution of the data set that comprises recent behaviour; the prediction will always be in the same place given the same recent behaviour. One criticism of existing approaches to

prediction has been the simplification associated with linear extrapolation (Tao et al., 2004). Such approaches take no account of the complexity or degree of variation in the previous trajectory used to calculate the speed and heading values.

Figure 22: Frequency distribution of speed for 9870 GPS points collected in the UK in March and April 2004

Whilst for this dataset, the distribution displays some bimodal characteristics, with peaks at 10 and 27 metres per second suggesting two different primary means of transport, the Normal distribution still provides a reasonable fit for this data set using a mean = 15.2, standard deviation = 11.3.



Knowing the standard deviation of speed and heading, and assuming a Normal distribution (or a wrapped Normal distribution for heading), a random element can be introduced to derive a series of non identical point predictions, based upon the same previous behaviour. Analysis of nearly 10,000 data points collected over one month (Mar – Apr 2004) suggests that the motion attributes associated with mobile trajectory appear to be Normally distributed (see Figure 22). You may expect to see bi- or multi-modal distributions for larger volumes of this kind which reflect the presence of many different examples of activity within the same data set; for example a peak associated with walking behaviour, another associated with driving and so on. Such a trend is evident to a certain extent in Figure 22. It is likely that the Normal distribution will be a better model when a single activity is represented in the data (for example, just driving behaviour), than when multiple activities are represented.

Using this stochastic approach, the process to calculate the speed and heading values in step 2 of the generating point predictions algorithm is a little more complex. First a pseudo-random number between zero and one is generated; this number is taken to represent an area under the Normal curve, between -∞ and some upper zed score. Transforming the standard (z) score to a value for the data set (x) is a basic statistical technique and can be achieved by using the equation;

$$x = (z * \sigma) + \mu$$

Equation 7: Transforming zed scores

given that the mean (μ) and standard deviation (σ) of the dataset are known. Applying this technique allows a prediction of a future location to be made, which incorporates a random element based upon the distribution of speed and heading.

The predictions described above for both the deterministic and stochastic approaches are modelled as single steps from the origin location to the final predicted destination. This is a valid heuristic if the intermediate behaviour is not required, and the distance travelled takes account of the sinuosity of the dataset (step 5 of generating point predictions algorithm). It is also possible to calculate a multistep prediction by calculating a series of predictions for the duration of the prediction.

The speed-heading prediction surface

By adopting this stochastic approach (Burrough, 1998) a Monte Carlo simulation (Openshaw, 1998b) can be run where a number of predictions are made over a range of locations, which may be more versatile than the single deterministic point prediction for two main reasons. First, placing a bounding box around the predictions produces an two-dimensional area footprint, which moves from the simple proximity spatial relation to that of containment; candidate result features can be examined to see if they fall within the prediction surface bounding box, not just by measuring their distance from some point location. Second, creating a point density surface of the point predictions gives variation within the bounding box; cells with high values represent locations the moving point object is likely to be, cells with low values are less likely to be visited, based upon the moving point object's recent behaviour.

Figure 23: Generating a surface based upon a series of stochastic predictions.

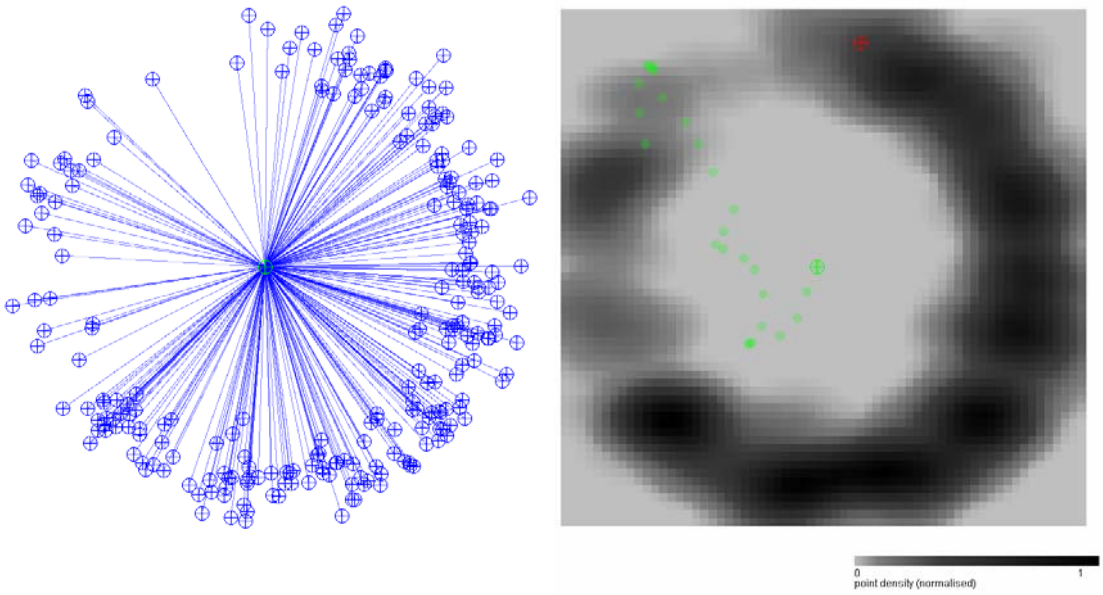
The torus shape in the prediction (b) is determined by the previous behaviour, shown by the pale green points. Previous movement is very sinuous and meanders to the East, however speed is quite consistent suggesting that the object is unlikely to remain in the same location. The surface performs well when compared to the object's known future location.

a: Multiple point predictions

250 point predictions (the blue crosshairs) of the future location of a moving point object 15 minutes into the future, are shown for the same origin location (the green cross hair). The predictions are based upon the object's behaviour over the previous 15 minutes.

b: Speed-heading prediction surface

A point density surface (720 metres width) generated for the 250 prediction points in a. The surface values have been rescaled to between zero (unlikely to be visited - lighter) and one (most likely to be visited - dark). The red cross hair shows the point object's actual location 15 minutes later, where the surface has a value of 0.36.



Source data: A GPS tracklog representing a walk in a semi-natural setting, Kolymbari, Crete, March 2004
Images produced using the spatial history explorer.

Differentiation within surfaces

The value of each cell in the grid surface is point density, measured in points per unit area. By normalising (Sarle, 2002) the cell value by the mean cell value, a *relative* point density value is given, where the mean value of all cells is equal to one.

$$\text{Relative point density} = \text{cell point density} / \text{mean surface point density}$$

Equation 8: Relative point density

These relative point density cell values offer an effective way of assessing which regions of the grid are more likely to be visited (greater than one) and which are less likely to be visited (less than one). The area outside the grid has a value of zero, since point density outside the

grid is zero. Relative point density is a dimensionless measure, since it is the ratio of point density at a particular location, to the average point density over a region. Such a grid can be used to rank candidate query results, as discussed later in section 3.6.

Instant vs interval predictions

As discussed in section 2.1.3, there is a distinction between events that occur at some exact instant in time, and intervals which have a duration in time (Langran, 1992). It is possible to predict future locations at an instant in time, or for an interval with a specified temporal duration. Both may be useful in the context for mobile information retrieval. In the first instance, you may have a need for a specific service at a known time in the future, for example, a restaurant to stop at a time that is agreeable for lunch. Interval predictions can be applied to retrieve features that are likely to be passed in the future, for example, an ornithologist walking in a National Park, wishing to know the locations of rare birds' habitat that they are likely to pass over the course of the next hour.

When generating a prediction surface that describes the likely position of a moving point object at an instant in the future, the prediction period is fixed to the specified value for all the point predictions that are used to generate the prediction surface. This will tend to produce prediction surfaces that are smaller and more focussed and, for longer prediction periods, that are further from the prediction origin. When generating surfaces for an interval, the prediction period should be varied, through the introduction of a random element, from 0 to twice the prediction period. This tends to produce surfaces that resemble a torch beam shining out from the prediction origin in the direction of movement as defined by the recent behaviour.

3.5 Prediction surfaces

In the previous sections, various approaches to defining the geographic context of a mobile individual have been proposed. In the context of spatial and mobile information retrieval, these can be seen as geographic filters performing a post query filter, allowing a further ranking of candidate results identified as being relevant on the *subject level* (Saracevic, 1996b). The aim of these geographic filters is to include a measure of situational relevance (Saracevic, 1996b), based upon an individual's location and previously displayed spatial behaviour. One key assumption to be investigated is that for mobile individuals, the future location - as opposed to current location - could be used as an alternative means of assessing geographic relevance, or as the focus for retrieving location-based information (Brimicombe and Li, 2004). There are various contexts in which this may true. First, mobile individuals requesting specific services (such as foods, shops, accommodation, fuel, leisure facilities) or location-based *information* (with no assumption that this information must relate to a

specific service) are likely to be more interested in those that are ahead of them than those around or behind them. This is demonstrated effectively by people requesting current travel information from a moving car on a motorway. The travel information closest in space may be behind them, hence no longer relevant to them, or else on surrounding roads, that are actually quite distant from them in terms of the distance over the transport network and travel time. In this context, a geographic filter gives a higher ranking to information whose geographic footprint is related to places that are ahead of the car than that based solely on spatial proximity. In another context, visitors to an outdoor recreational area such as a National Park may be interested in the flora and fauna that they are likely to encounter during a walk. Once the walker has passed a point on a walk, they are less likely to wish to turn back on themselves to visit it again. Again information related to the areas they are *likely* to visit can have greater situational relevance than the past or present location.

Of the three approaches described in section 3.4 (spatial proximity, temporal proximity, speed-heading predictions), all could be applied to predict the future location of a moving point object.

- **Spatial proximity prediction surfaces:** Any of the spatial proximity surfaces described in section 3.4.1 could be used for prediction, making the assumption that the current position, or some offset from it, is a good estimate of future location.

- **Temporal proximity prediction surfaces:** The potential path area described in section 3.4.2 could be used as temporal proximity surface, predicting future locations on the assumption that future movement will be subject to the same authority and capability constraints as that displayed in the past.

- **Speed-heading prediction surfaces:** These can be used for prediction, on the basis that immediate future spatial behaviour will be correlated to recent behaviour.

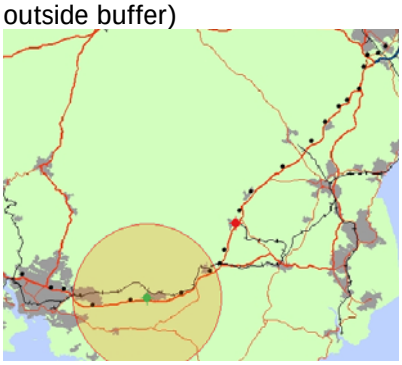
Given these three approaches to prediction we need unbiased evaluation criteria to compare the performance of these different approaches. We can assume that the each prediction will be a surface, which may be homogenous within its boundaries (eg spatial buffer, potential path area), or display internal variation where higher values represent the locations that the moving point object is more likely to go (eg spatial proximity surface, speed-heading prediction surface). Each prediction will have an origin (usually the last known position of the moving point object), a start time (t), and a prediction period. Given these common characteristics of prediction surfaces, the following section describes the development of criteria that could evaluate, in an unbiased manner, the effectiveness of different approaches to prediction.

3.5.1 Evaluation criteria for prediction surfaces

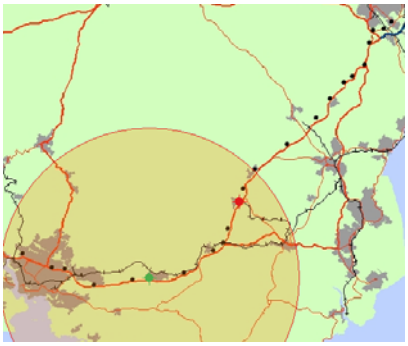
According to Stockwell and Peters (1999) "there are two main ways of evaluating predictive modelling systems": demonstrating validity on a theoretical basis, or the use of "empirical trials and comparisons with alternative systems". The mobile trajectories used in this study are represented by a series of time-stamped point locations, so the future sections of those mobile trajectories can be used to find the actual destination of a moving point object at the predicted time, and these *verification points* used to evaluate the effectiveness of any given prediction (see Figure 24). The datasets collected as part of this research were recorded at a sufficiently fine spatio-temporal resolution to allow an empirical approach to be adopted. This design was intended to test these prediction surfaces against observed reality – the actual spatial behaviour as displayed by individuals - as opposed to simulations based upon assumptions about how individuals move over space through time, which will always display some element of bias and hence the results of which will always be more open to interpretation. Various approaches to prediction will be tested, and compared using the same evaluation criteria.

Figure 24: Evaluation criteria to compare the effectiveness of three individual prediction surfaces, illustrated using spatial buffers.

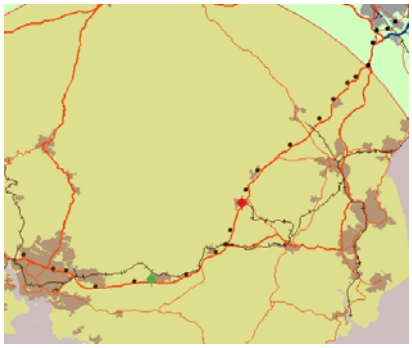
a: 10km buffer predicting location in 10mins (verification point falls outside buffer)



b: 20km buffer predicting location in 10mins (verification point falls inside buffer)



c: 40km buffer predicting location in 10mins (verification point falls inside buffer)



The buffer is shown as a yellow region with a red boundary, generated around an origin point (in green) and compared to a verification point (in red).
Extent of images is about 70km width from Plymouth (SW) to Exeter (NE) in the UK.

Data collected by David Mountain, 9 Jun 2004
Images produced using the spatial history explorer.

Prediction surface effectiveness criteria

For 10km spatial buffer	For 20km spatial buffer	For 40km spatial buffer
Verification value = 0 (outside buffer)	Verification value = 1 (inside buffer)	Verification value = 1 (inside buffer)
Surface area = pi * 10000^2 = 314,159,265 m^2	Surface area = pi * 20000^2 = 1,256,637,061m^2	Surface area = pi * 40000^2 = 5,026,548,245 m^2
Prediction surface effectiveness = Verification value / surface area = 0	Prediction surface effectiveness = Verification value / surface area = $8.0*10^{-10}$	Prediction surface effectiveness = Verification value / surface area = $2.0*10^{-10}$

In some situations no verification points may be available, for example when the GPS receiver loses a positional fix, or when the end of a trajectory is reached. When no verification points are available, the prediction cannot be evaluated and is excluded from analysis. The sampling frequency of the positioning system means that there may not always be a verification point recorded at the exact required instant that coincides with the prediction time. For this study, the point temporally closest to the prediction time is used for verification, as long as it occurs within one minute of the predicted time. If there is no verification point within one minute of the required time, the prediction is again excluded from analysis. For predictions that estimate the location of a moving point object for an instant in time (eg exactly 10 minutes from now), a single verification point is used. When making a prediction over an interval in time (eg during the next 10 minutes), a series of verification points can be used. For ease of description, the following discussion describes the case for predictions made for an instant in time, however it should be noted that these evaluation criteria can be extended to consider predictions made over an interval in time.

Tests that attempt to assess the effectiveness of predictions of future locations of moving points objects typically measure the distance between the predicted destination, and the actual destination at the predicted time. Sharma et al (2005) use the term *prediction accuracy*, to describe the absolute distance (in two-dimensional space) between the predicted and actual point location. Vasquez and Fraichard (2004) use the *estimation error* to describe the performance of their predictions: this is the measure of the distance between a predicted and actual *trajectory*, hence is a measure of dissimilarity. While these definitions of prediction error and accuracy are useful, they cannot be directly applied to the case where a surface, representing a region of space, has been used to predict a point location, describing the future location of a moving object. When considering individual predictions of this kind, two factors are important: the location of the verification point relative to the prediction surface, and the area of the prediction surface.

An independent evaluative test is required to compare the effectiveness of different prediction surfaces in an unbiased manner. For effective prediction surfaces, the verification point will fall within the surface, and – if the surface is heterogeneous – coincide with cells that have relatively high values. An added criterion is that these surfaces should be small in spatial extent, reflecting the fact that they are precise, not “scattergun” predictions that cover a large area and are therefore much more likely to coincide with the verification point. An additional requirement is that our evaluation should be able to compare not just individual prediction surfaces, generated for a single point in time, but how well one *approach* performs in comparison to another in different situations. Hence the evaluation criteria should consider the performance of a particular approach over a period of time where many prediction surfaces are generated in an iterative manner, one for each point in a mobile trajectory representing spatial behaviour in some situation.

Given the need to ensure that the evaluation testing is fair and unbiased, the evaluation criteria themselves have been subjected to a series of tests to assess how they perform in different situations. It was decided to test the evaluation criteria by using buffers of different radii (described in section 3.4.1) to assess the characteristics of different candidate evaluation criteria when comparing individual surfaces, and to see how they perform when applied iteratively for an entire trajectory. Spatial buffers were chosen as a control since they are a basic and well-understood transformation within GIS, and since this type of geographic filter is widely used in LBS when retrieving location-based information.

Normalisation of prediction surfaces

As described in section 3.4.1, buffers are Boolean surfaces, where the area inside the cutoff can be given a value of one, and the area outside a value of zero. The same principle applies to the potential path areas (temporal proximity surfaces) described in section 3.4.2. As mentioned in sections 3.4.1 and 3.4.3, spatial proximity surfaces and speed-heading surfaces can be normalised (Sarle, 2002), to ensure that the mean value within the surface is one. In this way we can ensure that there is no systematic variation in the surface values between approaches, since the mean value within all prediction surfaces is equal to one.

3.5.2 Evaluation of individual prediction surfaces

We will first consider evaluation criteria that allow the characteristics of individual prediction surfaces to be described, and their effectiveness compared, before moving on to describe evaluation criteria that describe characteristics and account for the consistency of an approach in a particular situation, over a series of predictions.

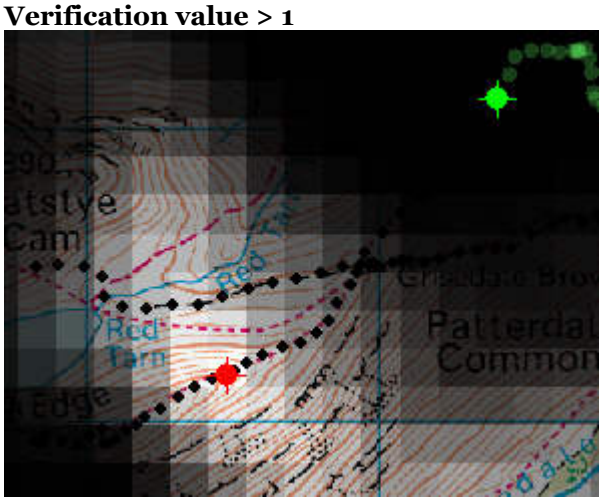
Verification value

The first criterion that can be used for evaluation is the verification value: this is the value of the surface at the point that coincides with the *verification point* (the actual destination at the predicted time). For all surfaces, this value is zero outside the surface bounds. For Boolean surfaces (buffers, and potential path areas) this verification value will be one if the point falls within the surface bounds. For continuous surfaces (spatial proximity surfaces and speed-heading surfaces) the verification value will be the value of the cell that coincides with the verification point. This value can tell us, therefore, whether the surface coincided with the actual destination at all, in the first instance, and in the second instance - for continuous surfaces - whether it coincided with high or low values. Large surfaces will perform well according to this criterion, since they are more likely to coincide with the actual destination. Since we do not wish to reward scattergun predictions, that are large in extent, we must also take account of the surface area.

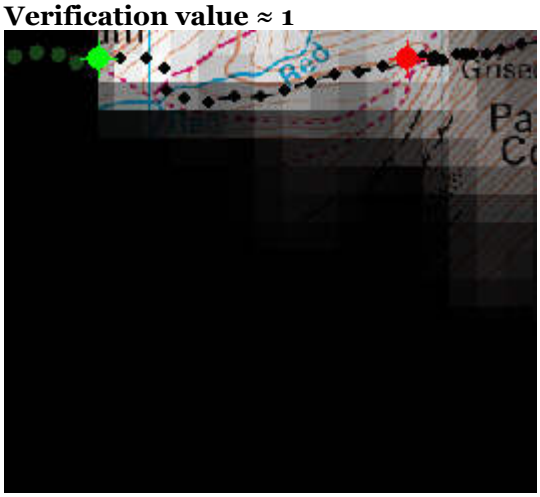
Figure 25: Verification value

The green point is the prediction origin and the red the verification point. The verification value is given by the value of the cell in which the verification point falls. Where the verification point falls outside the grid, a value of zero is recorded.

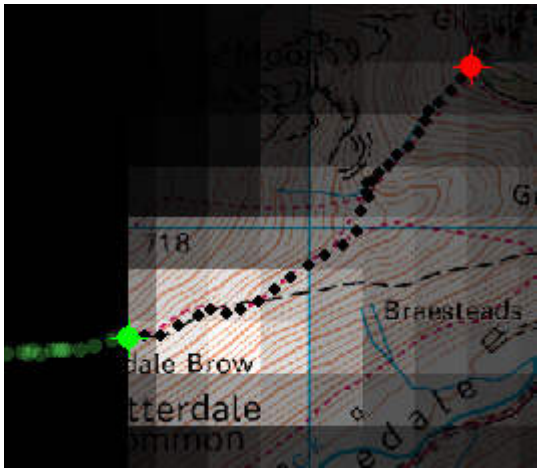
Verification value > 1



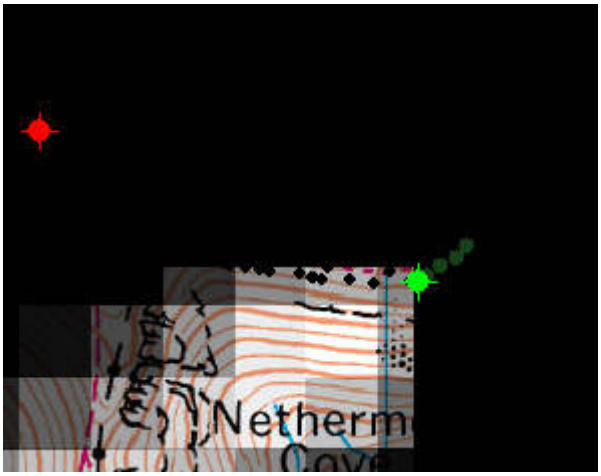
Verification value ≈ 1



Verification value < 1



Verification value = 0



Images produced using the spatial history explorer

Surface area

This is a measure of the spatial extent of the surface. An assumption is that effective prediction surfaces will generally be smaller in extent, hence this criterion provides an opportunity to assess how that extent varies for different approaches in different scenarios.

Prediction surface effectiveness

It is assumed that for effective prediction surfaces:

The verification point will be higher than for ineffective ones
The surface area will be smaller than for ineffective ones.

Hence our measure of the effectiveness for individual prediction surfaces can be given by:

$$\text{Prediction surface effectiveness} = \frac{\text{verification value}}{\text{surface area}}$$

Equation 9: Prediction surface effectiveness

This measure appears upon first consideration to offer a complete approach to assessing the effectiveness of prediction surfaces, and also the effectiveness of a particular approach over the course of an entire trajectory. Surfaces where the verification point coincides with high grid values, and where the overall extent of the surface is small, will perform well according to this criterion. The units of measurement are m^{-2}, which are the same as the relative point density (per metre^2) measure used for the speed-heading predictions.

When this evaluation criterion is applied to a spatial buffer prediction, for a point on a mobile trajectory collected in Devon (see Figure 24), the characteristics of this evaluation criterion can be assessed. For a 10km buffer, the verification point falls outside of the buffer (a value of zero), so the prediction surface effectiveness will also be zero. For a 20km buffer, the verification point falls inside the buffer, so the prediction surface effectiveness measure is $8.0*10^{-10}$. For a 40km buffer, the verification point again falls inside the buffer, and the final prediction surface effectiveness measure is $2.0*10^{-10}$. This demonstrates that the prediction surface effectiveness of the 40km buffer is just ¼ that of the 20km, due to their relative surface areas. The 10km has a value of zero, as it did not coincide with the verification point. This approach appears to give a reasonable approach to comparing the effectiveness of individual surfaces, since it is sensitive to both the value at the verification point and the surface area.

3.5.3 Evaluation of a prediction approach

Measures are also required that can describe the characteristics and assess the performance of one prediction approach, where multiple predictions are generated for all the points in a

particular mobile trajectory, to get a longer-term view of how it performs in a particular situation. This is a measure of the *consistency* of an approach, how effective it was in a particular scenario over a period of time, as opposed to for a single prediction. Various potential evaluation criteria were considered. The average (mean or median) verification value and surface area can be used for description, but for a comparison of effectiveness, other measures are required.

Success rate

The *success rate* is a common concept that describes the effectiveness of predictions, forecasts, and systems generally (Vasquez and Fraichard, 2004), for a series of predictions, given by the ratio of successes to total attempts made. Xu and Wolfson (2003) use a similar measure that they refer to as *precision* - the ratio of correct predictions to the total number of predictions - to evaluate the effectiveness of their approach. For this study the success rate will be defined as;

$$\text{Success rate} = \frac{\text{n successes}}{\text{n attempts}}$$

Equation 10: Success rate

A success occurs when the prediction surface overlaps with the verification point, regardless of where on the surface the point falls. A failure occurs when the point falls outside the prediction surface. The total number of attempts is given by the total of successes and failures. A success rate of zero indicates that the surface never coincided with the actual destination. A success rate of one indicates that it always coincides with the destination. This measure is closely related to the verification value for comparing individual surfaces. For Boolean surfaces, the mean verification value will be the same as the success rate (since both are the ratio of successes to total attempts). It also shares the key drawback of the verification value, that larger surfaces tend to perform better, since it cannot differentiate between those appropriately sized surfaces that consistently just coincide with the destination, and those scattergun approaches that achieve high success rates because the surfaces cover a very large spatial extent. An approach is required that can reflect the effectiveness of surfaces (in terms of having a small spatial extent, and having high verification values) *and* the consistency of an approach.

Average prediction surface effectiveness

The prediction surface effectiveness (PSE) can assess the effectiveness of a single prediction, and the success rate can assess the consistency of an approach over a series of prediction surfaces. Whilst these are both useful measures, a single evaluation criterion is desirable that can compare how two approaches perform in the same situation. This has led to the definition of the average prediction surface effectiveness. Two measures of central tendency are described below, and their strengths and weaknesses contrasted.

Mean prediction surface effectiveness

The first measure that was investigated was to use the *mean* value over the series of prediction surfaces: the prediction surface effectiveness is calculated for each prediction in a particular situation, and the mean used to describe the effectiveness of that approach in that particular situation. Despite the attractiveness of this method, testing conducted with buffers was found give counter-intuitive results. A small number of very effective surfaces (buffers with small surface areas), could skew the overall mean so that very inconsistent approaches with low success rates appeared to perform well. This can be best illustrated with an example. This evaluation criterion was tested for a driving journey from St Austell in Cornwall to St Albans in Hertfordshire (see section 4.1.1 for a full description); several buffer sizes were tried to see which were effective in predicting location 10 minutes ahead. The overall result, when applying this evaluation criterion, was that very small spatial buffers that hardly ever coincided with the verification point performed very well, due to their very small surface area. However buffers of a size that frequently *just* coincided with the verification point, that one would intuitively consider to be the most effective for predicting future location, performed less well. Of all buffers tested, the most effective according to this evaluation criterion was the 1000m buffer, however this only coincided with the verification point 1% of the time over the duration of the journey. The 15km buffer, which coincided with the verification point 71% of the time, and 20km buffer (coincided 99% of the time) on the other hand, achieved lower mean prediction surface effectiveness scores.

> ***"Even a stopped clock tells the right time twice a day"***
> from the film, "Withnail and I" (Robinson, 1987)

These approaches, that achieved high mean prediction surface effectiveness values from the performance of a small proportion of predictions were labelled "stopped clocks", since although they were almost always poor (failing to coincide with the verification point), very occasionally the approach achieved extremely high prediction surface effectiveness scores. A stopped clock, by way of analogy, usually tells the wrong time, but twice a day is exactly correct. A clock that is a few minutes slow, by contrast, always tells approximately the right time – and most would argue more useful to the wearer - but is never so precisely correct.

It was found, following investigation of spatial proximity surfaces, that this effect can be exacerbated when using very fast decay functions that result in extreme peaks at the centre of a spatial proximity surface (as mentioned in section 3.4.1). Due to the sensitivity of the this approach to extreme values, an alternative measure of central tendency was investigated, which is less sensitive to outliers (Pagano, 1999).

Median prediction surface effectiveness

The median prediction surface effectiveness was investigated as an alternative to reduce the influence of a small number of extreme values. This approach reduces the influence of the extreme values and rewarded surfaces that are both consistent and effective. Table 3 shows that for the journey from St Austell to St Albans, the 1000m buffer achieves a median prediction surface effectiveness score of 0, reflecting its inconsistent approach. The 15km buffer, which is spatially constrained and has a success rate of 71%, achieves the highest score, followed by 20km buffer.

Table 3: Comparison of different measures of prediction surface effectiveness:

Tested using three spatial proximity buffers, for a driving journey from St Austell to St Albans.

Buffer size (metres)	***1000***	***15000***	***20000***
Surface area (m^2)	3.1E+06	7.1E+08	1.3E+09
Success rate	1%	71%	99%
Mean prediction surface effectiveness (m^{-2})	3.2E-09	1.0E-09	7.9E-10
Median prediction surface effectiveness (m^{-2})	0.0E+00	1.4E-09	8.0E-10

This approach also has a key limitation which is much more evident for Boolean surfaces than for prediction surfaces with internal variation (such as the spatial proximity surfaces and speed-heading predictions). An approach that achieves a success rate of 49% will get a median prediction surface effectiveness score of zero (since the median verification value = 0), however an approach which achieves a success rate of 51%, will achieve high PSE score (since the median verification value = 1). This is a drawback, however it is tolerable, since it is far less evident in continuous surfaces, and is a minor disadvantage compared to the sensitivity to outliers seen when using the mean PSE.

3.5.4 Prediction approach: evaluation criteria summary

The objective of these evaluation criteria was to be able to describe the characteristics, and assess the performance, of different approaches to motion prediction, in a range of different scenarios. The criteria therefore had to be effective over a series of predictions, made in a

particular scenario. It was decided that a combination of evaluation criteria would be useful in describing the characteristics of prediction surfaces: these are described below. The median values were used, to reduce the influence of the "stopped clocks" described above.

Median verification value: An assessment of the degree to which the surface coincided with the actual destination, and whether it coincided with high values on the surface, or low ones. It is useful as a descriptive statistic, but rewards large surfaces, hence should not be used as a measure of effectiveness.

Median surface area: The spatial extent of the prediction surface with the assumption that smaller prediction surfaces are more effective than larger ones.

Median prediction surface effectiveness: A measure of the effectiveness and consistency of an approach. This value was used to compare the effectiveness of different approaches.

Success rate: A measure of the consistency of an approach, which tended to reward larger surfaces. It was found to be useful as a descriptive statistic.

3.5.5 Implementation of prediction surface tests

Within the interactive geoVisualization software application, the spatial history explorer, the procedures to generate the prediction surfaces described above, and perform the evaluative tests to assess their performance, have been implemented. Different approaches to prediction can be applied, including spatial proximity, temporal proximity, and speed-heading predictions. The tests are described in more detail in the Results section (section 4.1) however they are based upon the criteria described above, and are performed by proceeding through a given mobile trajectory in an iterative manner, generating a single prediction surface for each point in the set, then generating aggregate results for overall performance over the entire set. Input parameters, such as the period of time to predict into the future, the period of time to use as "recent behaviour", and the temporal weighting to be applied, can be modified for each test. Results include the quantitative evaluation criteria described above, and qualitative visual output, in the form of an animated film, where each frame of the film shows the prediction surface generated for a single point in the dataset. Although these animations, by their very nature, cannot be included in a paper thesis, they communicate very useful feedback about the conditions in which particular approaches and configurations perform well or poorly. This information has in turn informed the design process. Selected animations are available on the CD ROM that accompanies this thesis, and can also be downloaded from the associated website at http://www.soi.city.ac.uk/~dmm/phd (Mountain, 2005a).

3.6 Sorting results using geographic filters

Having developed an approach to generate surfaces of values between zero and one that represents, in some way, the geographic context of a query - such a speed-heading prediction surface, spatial proximity surface, or temporal proximity surface - results that match the query at the subject level can also be ranked according to the degree to which they are relevant geographically. This is an attempt to quantify the situational relevance (Saracevic, 1996a) based upon specific geographic criteria. As part of the WebPark mobile information system described in section 3.3, a speed-heading prediction filter was implemented that allowed users of the system to search based upon where they were likely to be in the future: the tools was referred to as the "search ahead" filter.

In the WebPark implementation, the geographic footprints associated with location-based information could have point, line or area geometry: these information sources were referred to as *features* of interest (FOIs), as opposed to *points* of interest (POIs), to reflect this. A process has also been defined that allows a geographic relevance score to be assigned to these features of interest.

Calculating a geographic relevance score for features of interest

This process takes as input;

- a *feature* with a spatial footprint that represents a candidate query result,
- a *geographic filter*: a surface of value, scaled between zero and one, that defines in some way the geographic characteristics of the query.

The procedure is;

1. Intersect the feature footprint and geographic filter,
2. Calculate the mean value of the grid cells within the intersect,
3. Weight the mean value given in 2. by the degree to which the feature's spatial footprint is contained within the geographic filter.

This is summarised in the equation below;

$$\text{Geographic relevance score} = \text{Mean cell value in feature-surface intersect} * \frac{\text{Intersect size}}{\text{Feature size}}$$

Equation 11: Geographic relevance score

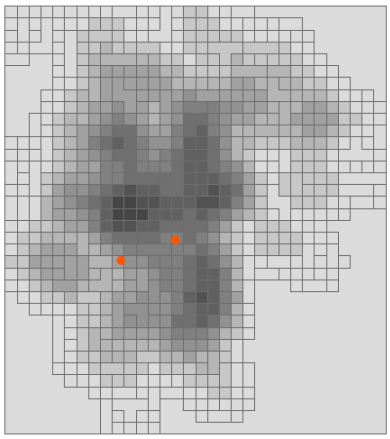
Equation 11 demonstrates that there are two distinct aspects to the score. First, the mean value of the cells in the geographic filter that intersect with the feature. Second, the degree to which the feature is contained within the geographic filter, the aim being to improve the ranking of results that area relevant *locally*. This is a technique that has been adapted from

existing measures of spatial similarity (Larson and Frontiera, 2004). The principle behind this approach is that features with large spatial extents tend to less be relevant *in any one place* than features with small, well-defined spatial extents.

3.6.1 Point features

Points represent the simplest case since they have no spatial extent. The first step is to intersect features with the relevance grid, points will either fall entirely inside the grid and should be retained, or entirely outside and should be disregarded. The geographic relevance score is given by the value of the grid cell within which the point feature falls. There is no need to apply the final weighting since in effect, the feature size and intersect size are the same.

Figure 26: Geographic relevance scores for point features



In the example shown to the left, five red point features represent five candidate results. The greyscale surface is a rescaled grid that represents the spatial extent of the query, where dark cells are more relevant (close to one) and light cells are less relevant (close to zero).

The three red points to the South and South East of the surface can be dismissed since they do not intersect with the grid. Of the two points that fall within the grid, the more central one falls within a cell with a higher value, hence has higher geographic relevance score than the point feature to the West.

3.6.2 Line features

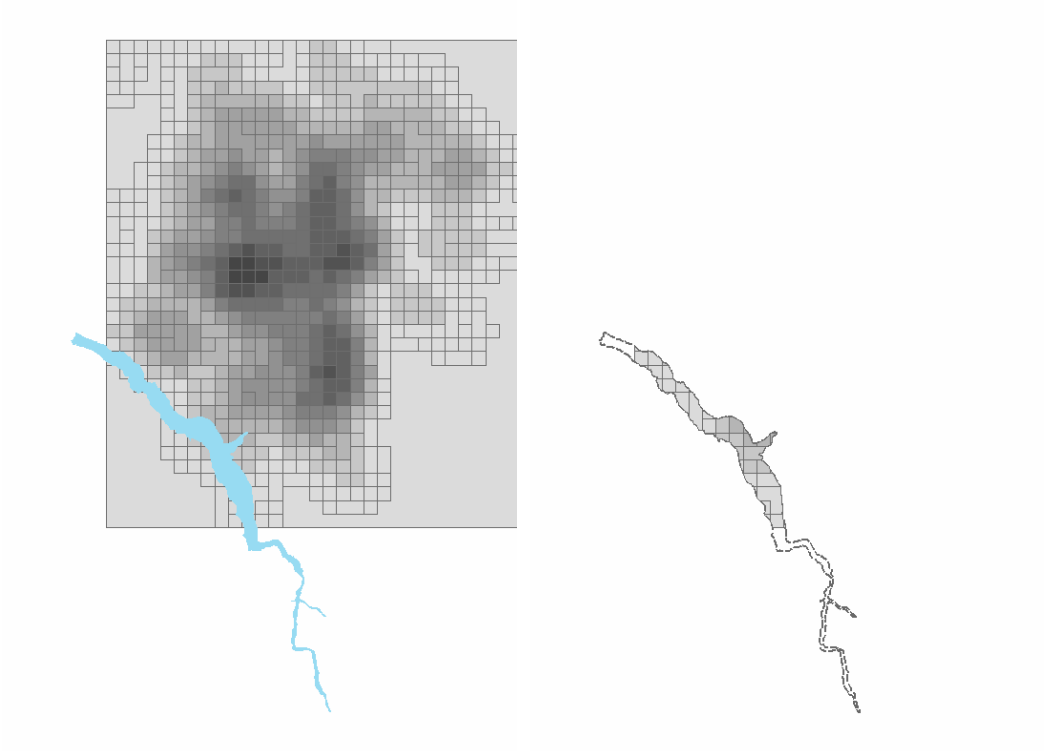
For candidate results represented by a line feature, for example roads, rivers, walking routes or boundaries, the line should again be intersected with the geographic filter grid and the mean cell value along the intersection calculated. The mean value of the intersected cells should then be weighted by the ratio of the length of the intersection to the total length of the line feature.

3.6.3 Area features

First an intersect operation should be performed for the feature and the geographic filter grid. If there is no overlap then the result can be disregarded as not geographically relevant based upon the current criteria. If there is overlap, then the mean value of the cells in the intersection should be calculated. In the case where the feature is wholly contained within the geographic filter, this mean cell value is the result. Where the overlap is only partial, it is weighted by the ratio of the intersect area to the feature area.

Figure 27: Geographic relevance scores for area features

a: Relevance surface (greyscale) and area feature (blue) **b: Intersection (shaded grey scale) and original feature (broken line)**



In the above example the feature (a lake shown in blue in the left panel) is intersected with a surface that defines the geographic footprint of a query; in this case the surface is a prediction of the places that the individual making the query is likely to be in 30 minutes time (shown in grey scale in the left panel). The values of cells vary from 0 in light grey (least likely to be visited) to 1 in black (most likely to be visited); the width of the grid is 3250 metres. The resulting intersection (shown in greyscale to the right) has a mean cell value of 0.097 (≈10%). This should be weighted by the ratio of the intersection area (254679m^2) to the feature area (351233m^2). The final geographic relevance of the lake, based upon a prediction of where the user is likely to be in 30 minutes time, is

Geographic relevance score = mean cell value within intersect * (intersect area/lake area)

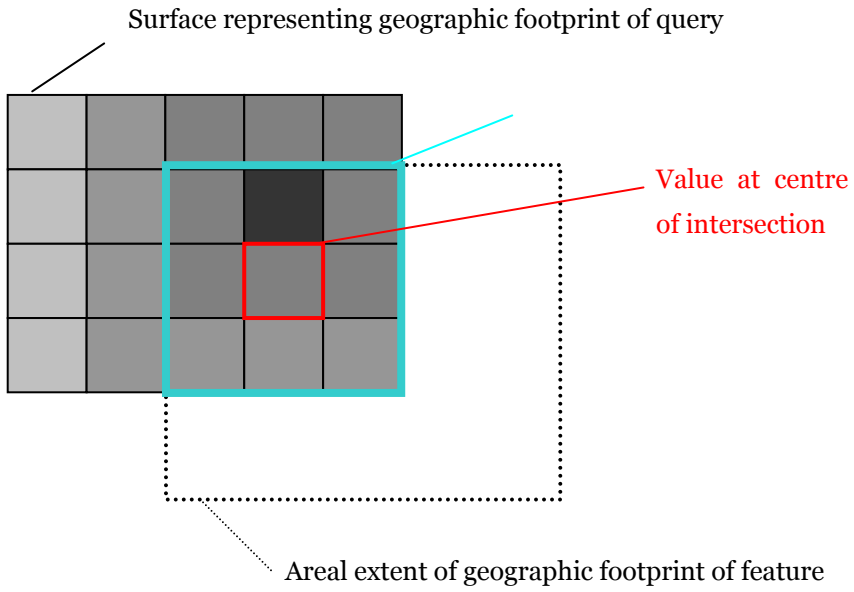
Geographic relevance score = 0.097 * (254679 / 351233)

Geographic relevance score = 0.0703346

Therefore, the geographic relevance score for the lake is **7%**

Bounding box heuristic

Figure 28: The bounding box heuristic



Calculating the geographic relevance scores for feature with area and line geometry was found to be very computationally demanding. A bounding box heuristic was adopted, to reduce the complexity of the procedure and allow results to be returned in real-time. A bounding box was place over the features and this box intersected with the query footprint. Rather than taking the mean of all of the points in the surface, the value of the cell at the centroid of the intersection was used, and this multiplied by the ratio of the intersection extent to the feature extent. This offers can approach of scaling this approach to allow large volumes of results to be ranked according to geographic context.

3.6.4 Geographic Information ranking implementation

These approaches to sorting geographic information based upon geographic filters as described above have been implemented as part of the WebPark platform, described in section 3.3. In an implementation developed for the Swiss National Park, three spatial filters were available. These were:

Search whole park: where no spatial filter was applied;

Search around me: where a spatial proximity filter was applied;

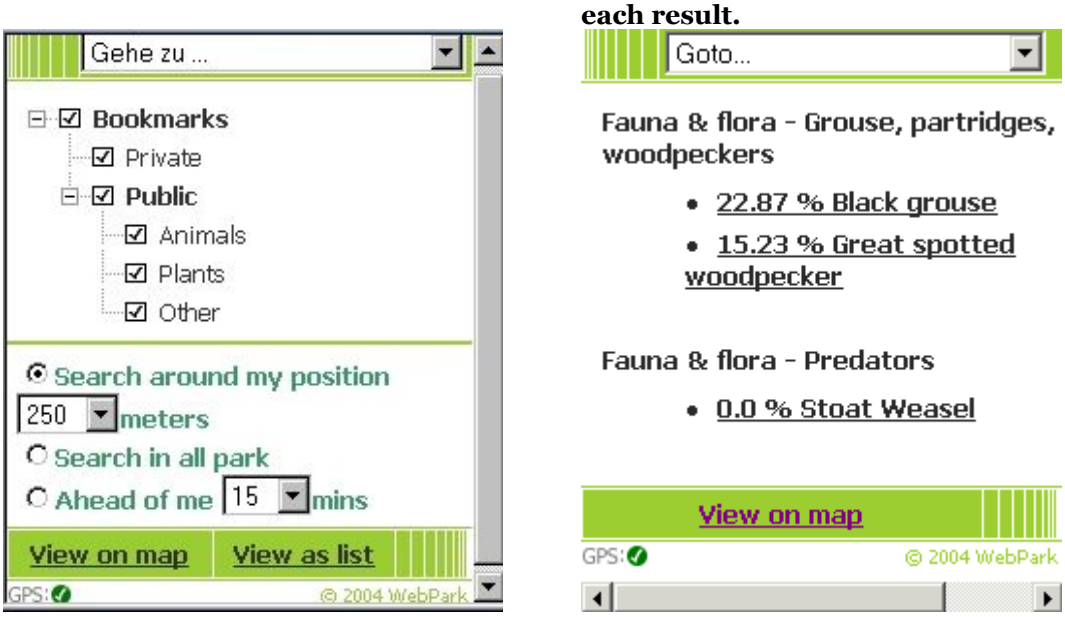
Search ahead: where a speed-heading prediction based upon recently observed behaviour was applied.

The user controlled which filter they wished to apply at the query formulation stage by selecting the desired filter using a radio button on a web page in browser on the mobile device. The user could specify the semantic component of the query either by selecting checkboxes associated with a list of pre-defined topics, or using a natural language search interface. The interface to this location-based search tool is shown in Figure 29. The results from user evaluation of these geographic filters are analysed in section 4.4.

Figure 29: Geographic filters implemented in the WebPark system

a: the selection of the filter at the query formulation stage.

b: ranking by the likelihood of an individual coinciding with the geographic footprint associated with each result.



Images generated using the WebPark platform, for a specific implementation in the Swiss National Park

3.7 Methodology Summary

This Methodology section first described the collection of data about the movement of individuals, and the development of a geoVisualization tool – the spatial history explorer – to analyse these mobile trajectories. Next a mobile platform and test best were described for a mobile information retrieval application, built upon the WebPark architecture. The development of *geographic filters* for information retrieval then described various approaches to modelling individual accessibility, and detailed ways in which these concepts can be applied to generate prediction surfaces of the likely future locations of an individual,

based upon their previous behaviour. The definition of evaluation criteria for these prediction surfaces were then described, and the implementation of procedures in the spatial history explorer to generate predictions and evaluative their effectiveness for a larger number of points. Finally, approaches that apply the surfaces to the task of retrieval geographic information have been defined.

The next section (Results) will first describe various test scenarios, and test configurations, before applying the evaluation criteria to both describe and assess the performance of different approaches in different conditions.

4 Results

Results Abstract

This section presents both quantitative results, related to the performance of prediction surfaces according to the evaluation criteria described in section 3.5, and qualitative results, based upon testing geographic filters for information retrieval in an outdoor mobile computing environment as part of a major user evaluation study in the Swiss National Park, in the Summer of 2004.

The chapter begins with quantitative evaluation, where three test scenarios are described (walking, driving and daily migration), followed by a description of the systematic variation in the temporal component of prediction, designed to compare short-term (10 minutes) and long-term (60 minutes) predictions into future. Next, three geographic filters described in the methodology are introduced as prediction surfaces. The three filters are spatial proximity, temporal proximity and speed-heading predictions. For each approach, the prediction input parameters were varied in a systematic way to uncover the impact of buffer size and distance decay functions (for spatial proximity prediction surfaces), the 'recent behaviour period', temporal weighting and decay function (for speed-heading prediction surfaces) and the time budget and enclosing function (for temporal proximity prediction surfaces). Next, the results are presented and analysed to describe, explain and contrast the characteristics of each prediction approach. This is followed by a brief assessment of the suitability of each approach to the scenarios in which it was tested.

Overall, predictions based upon temporal proximity are found to be more effective than speed-heading predictions, which in turn out are more effective than predictions based upon spatial proximity.

Finally, the chapter concludes with the results of the user evaluation study, which suggests that users of mobile information retrieval tools found the implemented "search ahead" filter useful, are receptive to the idea of other geographic filters, and benefit from the use of personalised geographic information with a spatial and temporal component.

4.1 Prediction testing framework

> **"It is difficult to make predictions, especially about the future"**
> Unattributed saying, from Wikipedia (2005), variously attributed to Confucius, Mark Twain, Benjamin Disraeli, Albert Einstein, Sir George Bernard Shaw, Winston Churchill, Niels Bohr, Cecil B. DeMille, Woody Allen, etc...

As discussed in section 2.4, there are a great many potential approaches for predicting the future location of moving point objects, and more specifically people. A testing framework has been devised that allows the characteristics of different approaches to be described, and assess how each approach performs in different situations, when configuration parameters are systematically varied. Three approaches to prediction are compared: speed-heading prediction surfaces, spatial proximity prediction surfaces, and temporal proximity prediction surfaces. Three different scenarios of human behaviour have been tested: walking, driving, and a 'daily migration' scenario. Both short-term (10 minute) and long-term (60-minute) predictions have been made for the walking and driving scenarios. Various configuration parameters have been tested in a systematic and repeatable way, which are described for each of the three approaches in the following sections. In all, 528 individual tests were run. The results of all tests are included in tabular form in appendix 3, and graphical representations of these figures are given within each section.

4.1.1 Behaviour scenarios

It is possible, to some degree, to distinguish classes of human spatial behaviour - such as sitting, walking, or moving in a vehicle such as a car, bus, train or plane – where each class of behaviour has distinct characteristics (Golledge and Stimson, 1997). Movement on foot tends to be relatively unconstrained in the direction of travel, but more constrained in terms of the distance that can be covered, due to the slow maximum speed of movement. Movement by mechanised transport tends to be less constrained in terms of speed, but more constrained by transportation networks which can restrict the freedom to change direction (Dykes and Mountain, 2003). For these tests three scenarios were tested: a walking scenario, a driving scenario, and the 'daily migration' pattern described by the round trip from home to work and back. All datasets were derived from GPS data collected as described in section 3.1.

For each scenario, a section of mobile trajectory has been extracted that represents a particular class of spatial behaviour. As part of the analysis, prediction surfaces will be generated – and their characteristics described and effectiveness assessed - for each of the n points that comprise this section of the trajectory; this set of points will be referred to as the

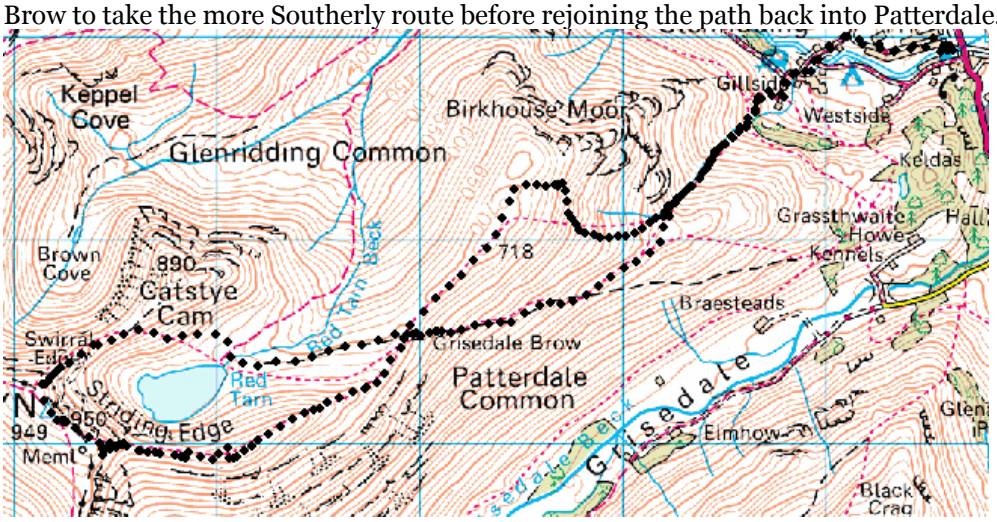
mobile trajectory testing set or the *testing set*. The testing set for each scenario was extracted from a longer *parent mobile trajectory*, which describes the spatial behaviour of that individual prior and subsequent to the test set. This parent trajectory can provide verification points, for predictions close to the end of the test trajectory, and can contribute to the recent behaviour, particularly for points closer to the start of the test trajectory, and tests that use a long time period to define recent behaviour. The use of the parent set in this way avoids the 'edge effects' apparent at the start of the test, when no or limited previous behaviour would otherwise be available from which to determine the speed and heading of predictions, and at the end of the set, when no verification points would be available to assess the effectiveness of the predictions.

Walking scenario

For the walking scenario, a section of mobile trajectory was extracted that described the ascent and descent of a mountain (Helvellyn), starting and finishing in Patterdale in the English Lake District (see Figure 30). The walking scenario test trajectory itself consisted of 226 unique, time-stamped point locations. The walking route took about 4hrs to complete and was characterised by a slow average speed (2.8 kmph) and highly sinuous behaviour. The route describes a steep profile ascending 900 metres in height from Patterdale to Helvellyn, returning by an alternative route to describe a circuit that resembles a figure of eight. The slope was generally steep and the terrain often rough underfoot, particularly near the summit. The downhill sections of the mobile trajectory were generally faster than those ascending and at the summit (see Figure 31). The parent mobile trajectory displays driving and walking behaviour, as described in Figure 32.

Figure 30: Walking scenario: Mobile trajectory test set

The track log shows a circuitous route around Helvellyn (South West Corner) starting from Patterdale (in the North East). The ascent begins on paths common to ascent and descent before diverging to take a more Northerly course closer to Birkhouse Moor, then heading South West over Grisedale Brow to ascend Helvellyn via Striding Edge. The return route completes the figure of eight, first descending North East via Swirral Edge, before crossing the ascending track at Grisedale Brow to take the more Southerly route before rejoining the path back into Patterdale.



Data collected by David Mountain, 9 Nov 2004, from 10:53 – 14:53
Image produced using the spatial history explorer.

Figure 31: Time vs elevation plot for Helvellyn walking behaviour

The plot below shows the time of day plotted against elevation (using the WGS84 vertical datum), for the track log displayed in Figure 30. The points are shaded using a sequential colour scheme from dark (slow) to light brown (fast) (Brewer, 2005). It can be seen that the slowest section of the route was at the summit, where the terrain is both steep and rough. Downhill and flat sections away from the summit are generally characterised by faster speeds; uphill sections on average show slow speeds. Note the unadjusted height values from the GPS, that describe the vertical height above the WGS84 ellipsoid, not height above sea level in the UK.

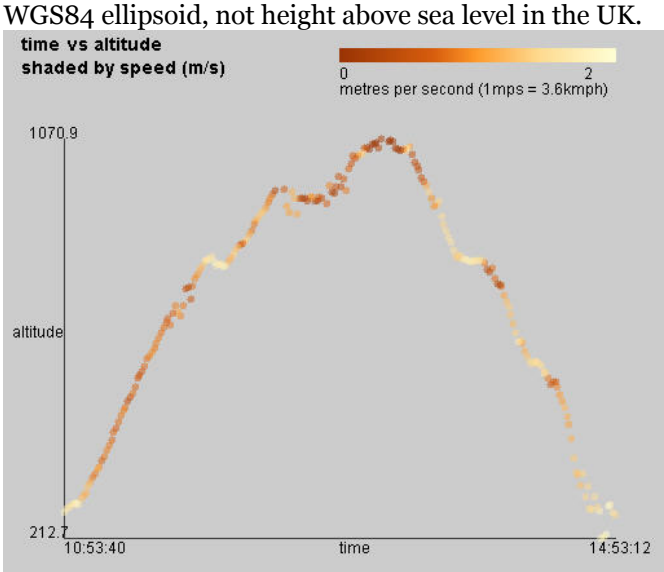


Image produced using the spatial history explorer.

Figure 32: Walking scenario parent set

The testing set for the walking scenario was preceded by 2 days of walking in the Scottish Highlands, with travel by car between the walks. The 24 hours immediately preceding the test set is characterised by a walk in the Scottish Highlands the previous day, followed by a drive South to Settle in Yorkshire, an overnight stay, then a 1hr30 drive to Patterdale. Immediately after the test set, the parent set records a period of no movement (resting in a café), followed by a journey South by car. This parent set was used to compare predictions to the actual location at the predicted time and available of a source of 'recent behaviour' for speed-heading predictions.

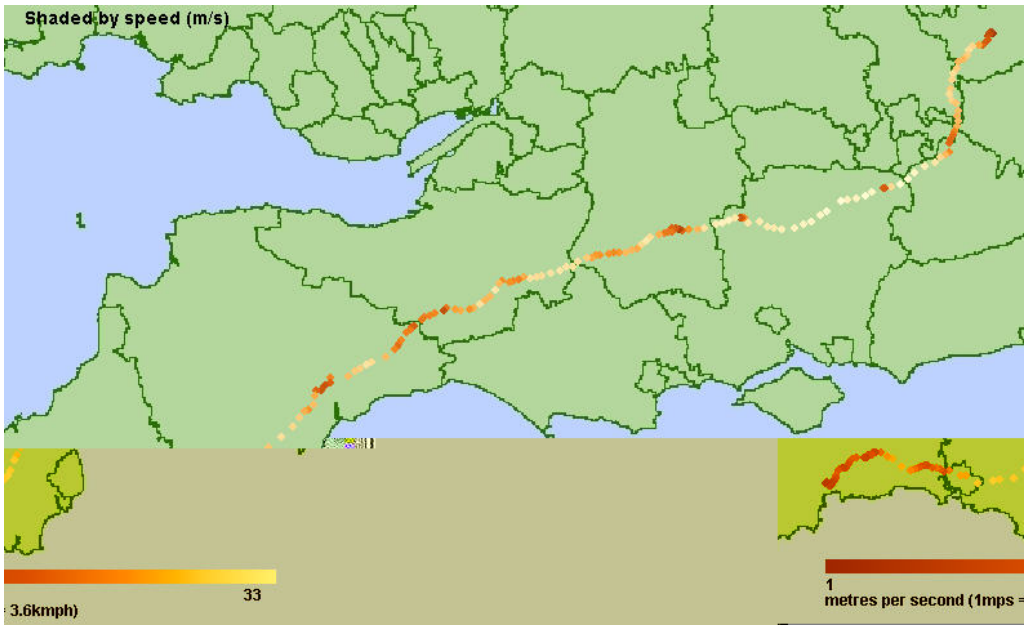
Data collected by David Mountain, 06-10 Nov 2004.
Image produced using the spatial history explorer.

Driving scenario

The driving scenario describes a car journey from St Austell in Cornwall, to St Albans in Hertfordshire, UK, via fast A-roads and motorways (see Figure 33). The journey was a generally high speed event (mean 80kmph), with slower speeds on the more minor roads at the start of the journey, and a number of stops for fuel and refreshment. The route is relatively straight following a heading towards the East-North-East as indicated by both the sinuosity index (1.16) and the inverse heading spread function (1.15) (Figure 34). The driving scenario mobile trajectory test set consists of 195 unique, time-stamped point locations. The parent set contains 4 days of predominantly driving behaviour, with some walking behaviour displayed.

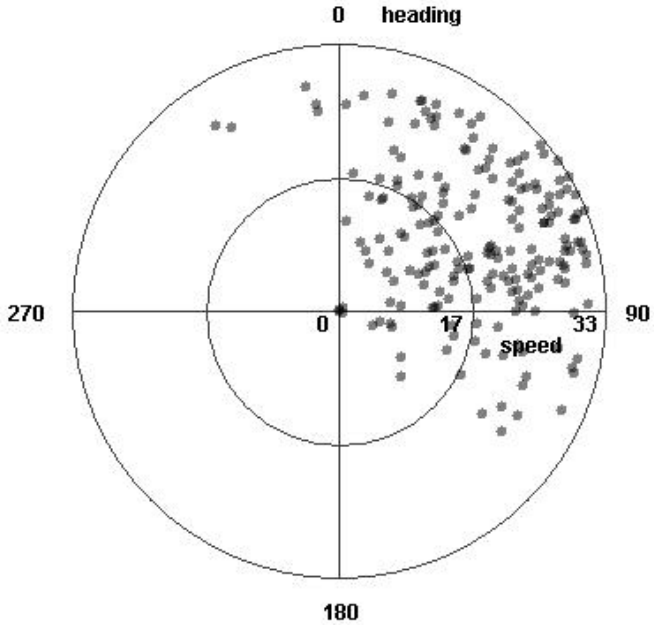
Figure 33: Driving scenario: Mobile trajectory test set

Car journey from St Austell (South West of the map) to St Albans (North East) driving along A-roads and motorways. Points are shaded by speed from relatively slow (dark brown) to fast (light brown).



Data collected by David Mountain, 9 Jun 2004, from 13:55 – 20:12
Image produced using the spatial history explorer.

Figure 34: Driving scenario test set: characteristics of speed and heading

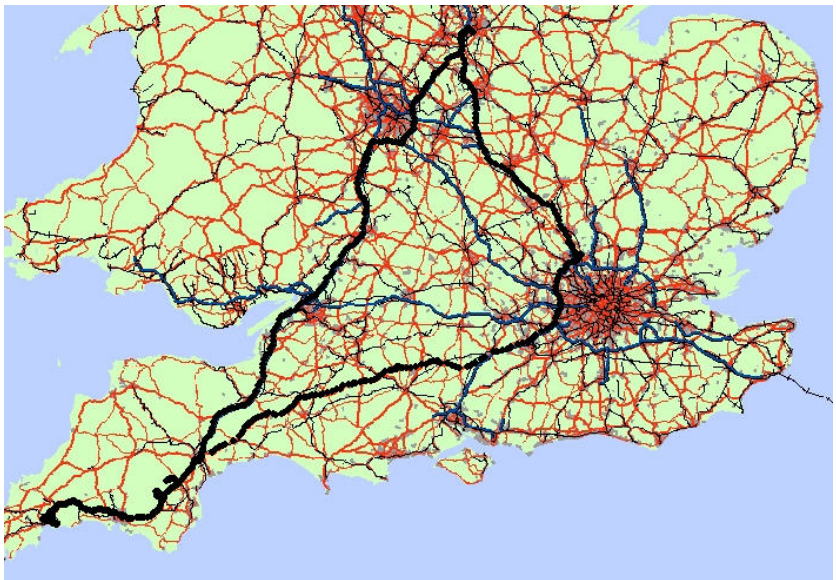


The mobile trajectory test set describing the car journey from St Austell to St Albans is characterised by generally high speed behaviour (mean 22 m/sec or 80 kmph). There is limited variation in heading, with travel generally heading towards the North East.

Data collected by David Mountain, 9 Jun 2004, from 13:55 – 20:12
Image produced using the spatial history explorer.

Figure 35: Driving scenario: Parent mobile trajectory

The parent set for the driving scenario included journeys by car from St Albans to Nottingham, then on to the South West in the preceding days. The previous 24 hours was characterised by a journey by car from Dartmoor to St Austell, an overnight stay, a short car journey in the morning, followed by the test set itself. The parent set ends at the same time as the test set, hence some of the later predictions in the test set could not be compared to the actual location at the predicted time.



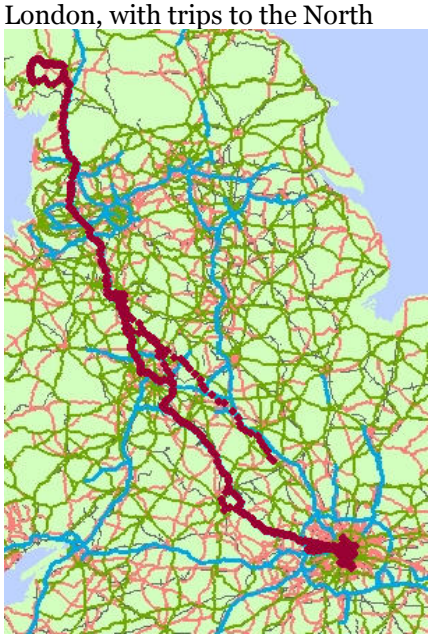
Data collected by David Mountain, 9 Jun 2004, from 05 -09 Jun 2004
Image produced using the spatial history explorer.

Daily migration scenario

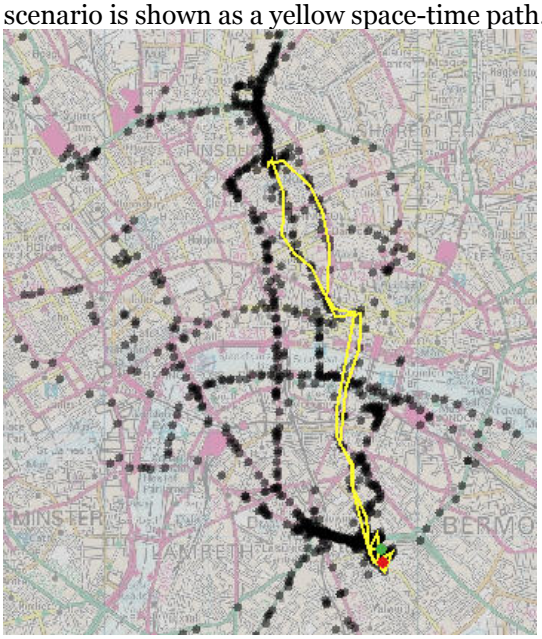
Figure 36: "Daily migration" scenario: parent mobile trajectory

The parent mobile trajectory for the daily migration scenario was collected over the duration of 5 weeks. It included walking behaviour, cycling, driving, and travel on buses, trains and the London underground. Most time was spent within Greater London, however journeys were also taken to the English Lake District, and Stoke-on-Trent in the Midlands.

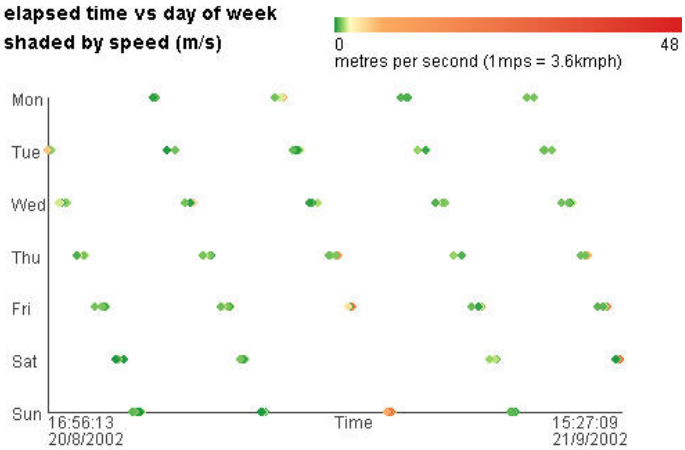
a) The full parent set for the daily migration scenario - showing a concentration of behaviour around London, with trips to the North



b) The parent set for the daily migration scenario, zoomed in to Central London - the mobile trajectory representing the daily migration scenario is shown as a yellow space-time path.



c: Temporal distribution - the plot below shows absolute time on the x axis vs day of the week on the y axis. This shows that data was collected almost every day for 5 weeks, and that the majority of movement occurred at low speed (green colours), with infrequent high speed events.



Data collected by David Mountain, 16:56:13 20/08/2002 to 15:27:09 21/09/2002
Image produced using the spatial history explorer.

The daily migration scenario test set consists of 35 points describing two journeys across central London by bicycle: from home to work in the morning, and the return journey in the evening (see Figure 36b). The parent mobile trajectory was collected by one individual between 20 Aug and 21 Sept 2002, and includes movement on foot, by bicycle, by bus, underground, train and car (see Figure 36a). This previously exhibited spatial behaviour was available to the temporal proximity algorithm to predict where this individual was likely to be in the future, based upon the area accessible to them in the past from that location.

4.1.2 Long-term and short-term predictions

In order to test the effectiveness of different approaches at making both long-term predictions into the distant future, or a short-term predictions into the near future, two prediction periods have been tested;

t + 10 minutes: to represent a short-term prediction
t + 60 minutes: to represent a long-term prediction

For the walking and driving scenarios, both short-term and long-term predictions have been made. For the daily migration scenario, only short-term behaviour has been tested, since sections of the mobile trajectory associated with the journey to work are themselves less than one hour in duration.

4.1.3 Prediction configuration parameters

Three approaches to prediction were tested in all; speed-heading predictions, spatial proximity prediction surfaces, and temporal proximity predictions surfaces. Each approach has configuration parameters which have been varied systematically to assess their influence, and to see which configurations are suited to which scenarios.

Figure 37: Running prediction surface tests.

A single test consists of the generation of one prediction surface grid for each point in the trajectory test set. The images below show the prediction surfaces generated for 8 of the 262 points that comprised the walking scenario test set. In this particular case, a short-term (10 mins), interval, prediction was generated using recent behaviour from the previous 60 minutes, weighted using an inverse square temporal decay function.

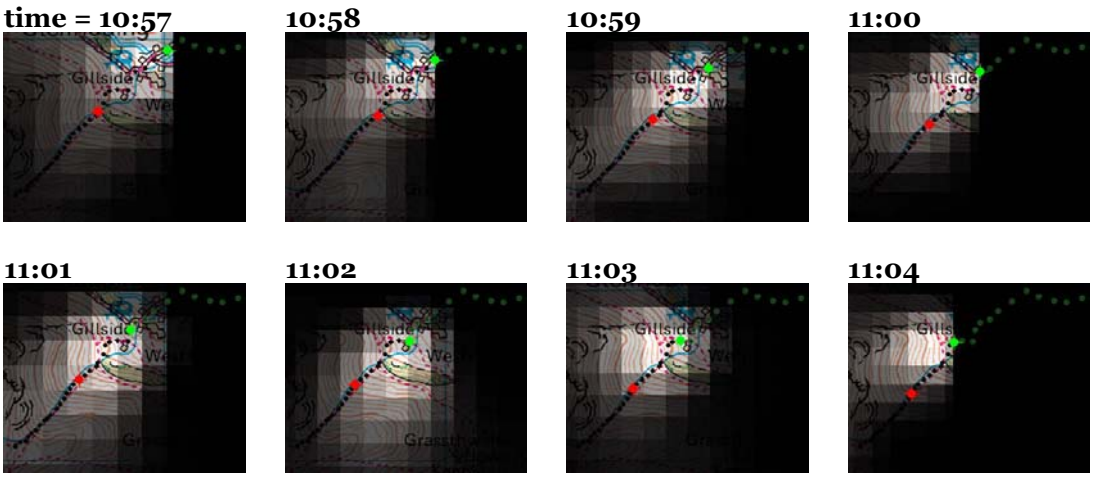


Image produced using the spatial history explorer.

Speed-heading prediction surface tests

In order to account for every possible configuration a total of 200 tests were run for speed-heading predictions. Each test consisted of one prediction surface being generated *for every point in the mobile trajectory test set*, and median values being recorded for each test that reflect the performance of this approach using those specific parameters, in that situation. As described in section 3.4.3, there several different parameters which may be configured for speed-heading predictions surfaces. The first parameter is the period of time used to define the recent behaviour. In all, 8 cut-off time periods have been used to define recent behaviour. These are;

5mins; 15mins; 30mins; 1hr; 3hrs; 6hrs; 12hrs; 24hrs.

The aim in systematically varying this parameter is to see how far one must look into the past, in order to predict the future.

The second parameter that was tested was the temporal weighting and decay function applied to the recent behaviour, to increase the influence of more recent points, as described in section 3.4.3. Several different weightings and decay functions have been systematically tested and these are shown below in

Table 4.

Table 4: Temporal weightings and decay functions

Weighting	*Decay function*	*Description*
None	None	All recent behaviour (up to the cut-off) has the same influence
Temporal	Linear	Influence of less recent behaviour diminishes by a linear inverse distance-decay function, up to a cut-off (see Figure 15: Distance decay functions: adapted from Longley et al (2005).Figure 15 and Equation 1).
Temporal	Negative power	Influence of less recent behaviour diminishes by a negative power decay function, up to a cut-off, where points cease to have an influence (see Figure 15 and Equation 2). Temporal decay parameters that have been tested are 1.5, 2, 3.

For the walking and driving scenarios, a total of 160 tests were run: this accounted for the 2 scenarios, 2 prediction periods, 5 decay functions for temporal decay, and 8 periods of recent behaviour (see Table 5).

Table 5: Situations and configurable parameters for which the speed-heading prediction surfaces were tested

Scenario	N prediction periods	N recent behaviour periods	N temporal weightings / decay functions	N configurations tested
Walking	2	8	5	80
Driving	2	8	5	80
Daily migration	1	8	5	40
Total	-	-	-	200

A further 40 tests were run for the daily migration, where short-term predictions were made, for the 8 periods of recent behaviour, and 5 temporal weighting and decay functions.

Each prediction surface itself was generated as described in section 3.4.3 by generating 200 random point predictions (based on the distributions for speed and heading), and calculating

the normalised point density for a grid of 32 columns width, placed over the point predictions. The process of generating a series of prediction surfaces is described in Figure 37. After each test, four values recording the evaluation criteria described in section 3.5.4 were recorded: the median verification value; the median surface area; the median prediction surface effectiveness; and the success rate.

Spatial proximity prediction surface tests

Whilst this surface was not designed explicitly as a prediction surface, it acts as a useful control against which to compare the other approaches. The main assumption with this surface is that where you are now provides a good prediction of where you are likely to be in the future. In the absence of any further information, this is a reasonable heuristic to adopt and can reduce a search space from the global (everywhere on earth), to the local (the immediate vicinity of this individual).

In all, 318 tests were conducted for the spatial proximity prediction surfaces. The tests were performed for 3 scenarios: walking, driving and daily migration. The first configuration parameter for spatial proximity prediction surfaces that was systematically tested was the buffer distance employed. For the walking and daily migration scenarios 11 buffer distances were tested (distances are in metres);

100; 250; 500; 750; 1,000; 1,500; 2,000; 3,000; 5,000; 7,500; 10,000

For the driving scenario 10 buffer distances were tested;

250; 500; 1,000; 5,000; 10,000; 15,000; 25,000; 50,000; 100,000; 250,000.

It is worthy of note that these distances were selected with the scenario in mind - smaller buffer distances for walking and commuting behaviour, greater distances for driving - in order to avoid testing buffer sizes that are very unlikely to be effective, such as a 250km buffer for short-term walking prediction. The effectiveness of this approach is highly dependent upon buffer size, and without some information indicating an individual's spatial behaviour, such as current speed, wholly inappropriate buffer sizes could be used.

The second parameter that was tested was the distance weighting and decay function applied. As described in the methodology, this has the effect of producing higher values around some target point (or points), usually the prediction origin, decreasing as you move away from the target. Six distance weighting and decay functions were tested: no weighting; linear decay; linear-offset; power(1.5), power(2) and power(3) - see section 3.4.1 for an explanation of these decay functions.

Table 6: Distance weightings and decay functions

Weighting	*Decay function*	*Description*
None	None	Surface values are homogenous within the buffer distance.
Distance	Linear	Surface values diminish by a linear inverse distance-decay function. Two approaches were tested: linear and linear-offset.
Distance	Negative power	Surface values diminishes by a negative power decay function. Distance decay parameters that have been tested are 1.5, 2, 3.

In all 318 spatial proximity surface prediction tests were run for the three different scenarios, systematically varying the prediction period, buffer size and distance weighting and decay function.

Table 7: Scenarios and configurable parameters for which the spatial proximity prediction surfaces were tested

Scenario	N prediction periods	N buffer sizes	N distance weightings / decay functions	N configurations tested
Walking	2	11	6	132
Driving	2	10	6	120
Daily migration	1	11	6	66
Total	-	-	-	318

Each prediction surface was realised as a grid of 32 columns width, where the value of each cell was calculated using the appropriate function as described in the methodology (see section 3.4.1). After each test, four values recording the evaluation criteria described in section 3.5.4 are recorded: the median verification value; the median surface area; the median prediction surface effectiveness, and the success rate.

Temporal proximity prediction surface tests

This surface is intended to represent the region of space accessible to an individual, as opposed to simply predict the future locations of that individual. However, given that patterns of human spatial behaviour tend to be repeated over a range of temporal scales (Golledge and Stimson, 1997), the region of space that has been accessible to someone in the past from a particular location provides a good indication of where they are likely to go in future.

In all just 10 tests were conducted for the spatial proximity prediction surfaces. Only one scenario (daily migration) had the required long-term mobile trajectory required to data mine accessible regions. Only short-term (t+10mins) predictions were made since the journey to work takes less than one hour. The first parameter that was systematically varied was the time budget used when calculating the accessible region. 5 time budgets were tested;

5mins; 10mins; 15mins; 20mins; 25mins; 30mins.

The second parameter that was configured was the function used to enclose the space-time paths to form the potential path area. Two approaches were employed: a convex hull around all of the points that comprise the space-time paths, and a spatial buffer of 250metres around each space-time path.

Table 8: Scenarios and configurable parameters for which the temporal proximity prediction surfaces were tested

Scenario	N prediction periods	N time budgets	N enclosing functions	N configurations tested
Daily migration	1	5	2	10
Total	-	-	-	10

4.2 Approach characteristics

4.2.1 Speed-heading prediction surfaces

As described in the Speed-heading predictions section in the methodology, these are generated by selecting a section of mobile trajectory that immediately precedes the time for which a prediction is made (the recent behaviour period), and using the distribution of speed and heading within that trajectory to make predictions about the possible future locations of the moving point object. The controlling factors for this approach are therefore, the period of time used to define 'recent' and whether a temporal weighting has be applied to increase the influence of more recent points: these parameters are both concerned with the degree to which one must look to the past when predicting the future. In order to analyse the characteristics of this type of prediction, and to assess the influence of different configurations of recent behaviour periods and temporal decay functions, each of the evaluation criteria will be considered in turn. The characteristics of this approach will be assessed by considering performance in the walking and driving scenarios.

Median verification value

An immediately obvious trend, evident for both scenarios and long-term and short-term predictions, is that for very short recent behaviour periods, the median verification value is very low, typically less than one (see Figure 38a to Figure 38d). By using short periods to define the recent period, the recent behaviour lacks variation, leading to small, very focussed surfaces, that are unlikely to coincide with the verification point (see Figure 40). As the recent behaviour period increases, the median verification value increases, since there is increased heterogeneity in the recent behaviour, leading to larger, less focussed surfaces. This increases to a maximum that occurs for a recent behaviour period of about three hours for both scenarios, and both long-term and short-term predictions. In the case of the walking scenario, the verification value levels at off at this point and for further increases in the recent behaviour period there is little change in the verification value. This gives the impression that in this particular scenario, after three hours, all examples of spatial behaviour in the parent set have been displayed, hence subsequent increases beyond this point will have minimal further impact. In the case of the driving scenario, the median verification value also reaches a maximum for a recent behaviour period of roughly three hours, but then subsequently declines slightly for further increases in the recent behaviour period. This is likely to reflect that by extending the recent behaviour period to over three hours, a different type of behaviour is seen in the parent set, which acts as a poor predictor for the driving behaviour.

Figure 38: Median verification value against recent behaviour period for a series of speed-heading prediction surfaces

All figures a to d show the median verifiction value for a series of speed-heading prediction surfaces on the y axis, against the period of time used to define the recent behaviour (in minutes) on the x axis.

Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

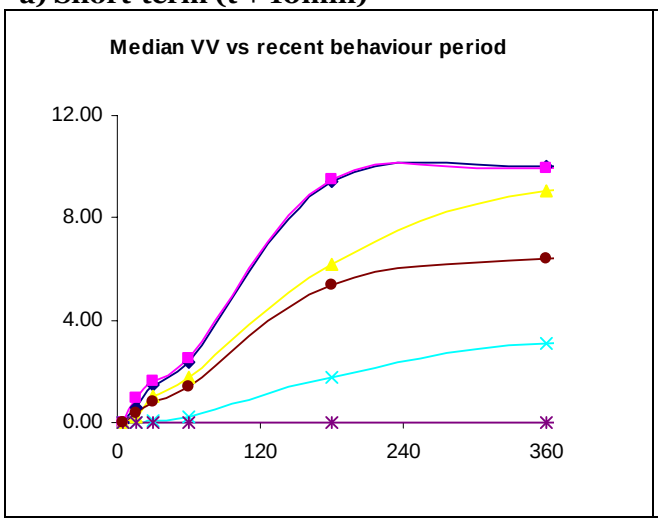
Various approaches to temporal weighting have been tested including no weighting, temporal weighting with linear decay, and temporal weighting with various examples of decay using power functions (1.5, 2 and 3).

Key to temporal decay functions

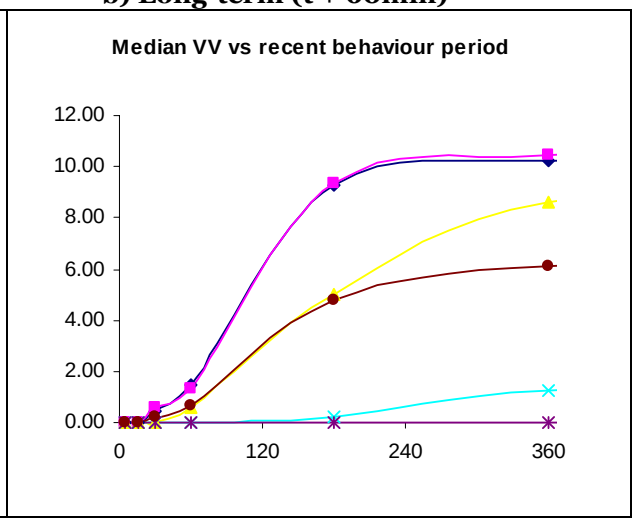
- no weight
- linear
- power (1.5)
- power (2)
- power (3)
- mean

Walking behaviour

a) Short-term (t + 10min)

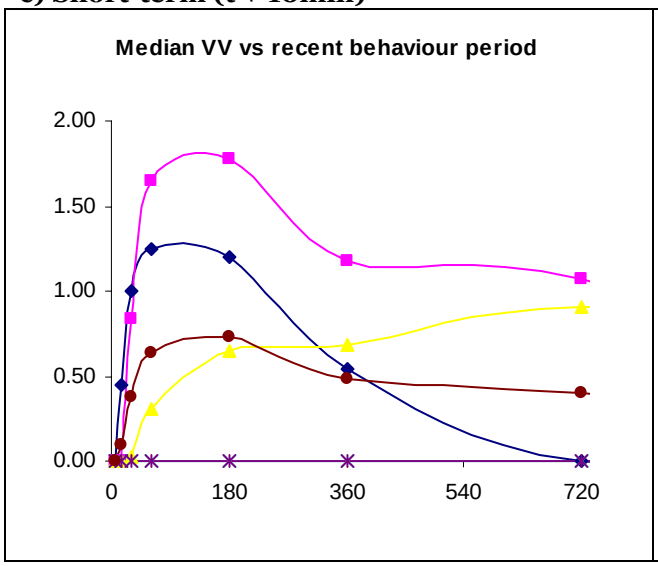


b) Long-term (t + 60min)

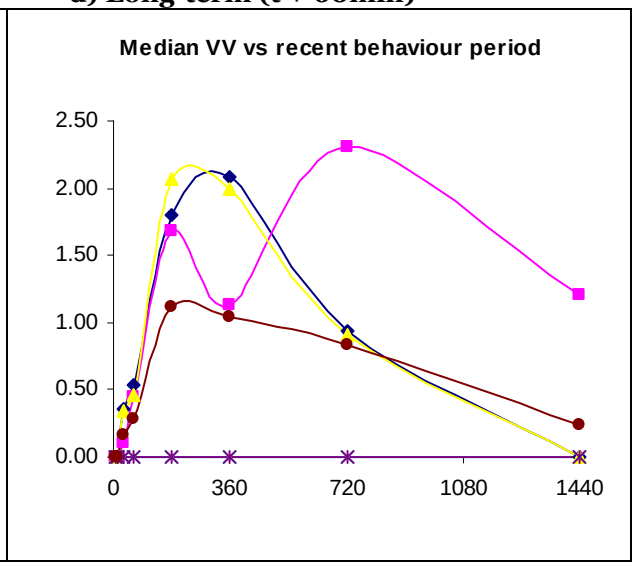


Driving behaviour

c) Short-term (t + 10min)



d) Long-term (t + 60min)



Median surface area

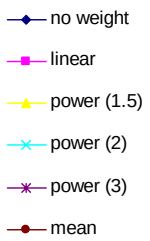
Figure 39: Median surface area against recent behaviour period for a series of speed-heading prediction surfaces

All figures a to d show the median surface area (in m²) for a series of speed-heading prediction surfaces on the y axis, against the period of time used to define the recent behaviour (in minutes) on the x axis.

Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

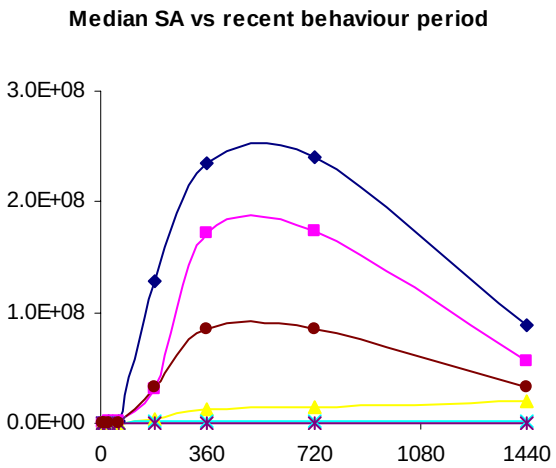
Various approaches to temporal weighting have been tested including no weighting, temporal weighting with linear decay, and temporal weighting with various examples of decay using power functions (1.5, 2 and 3).

Key to temporal decay functions

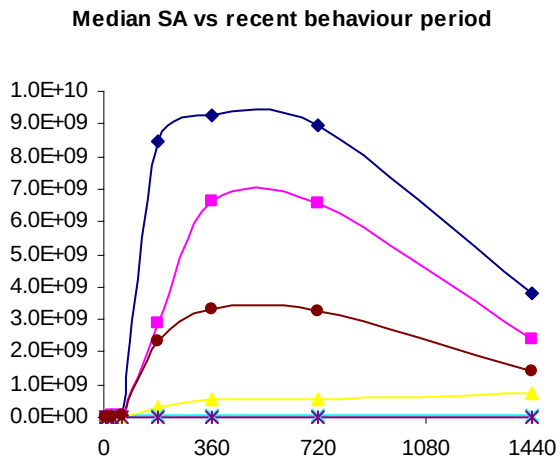


Walking behaviour

a: Short-term (t + 10min)

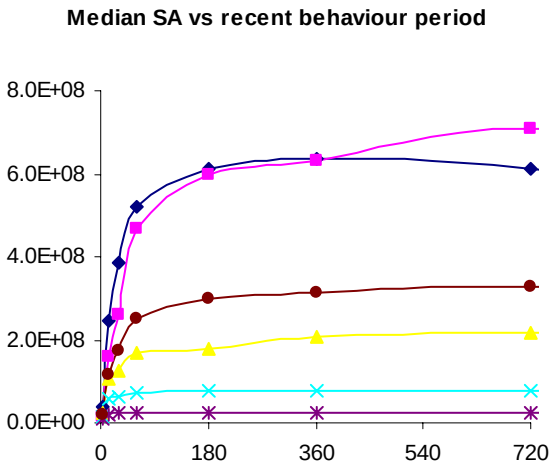


b: Long-term (t + 60min)

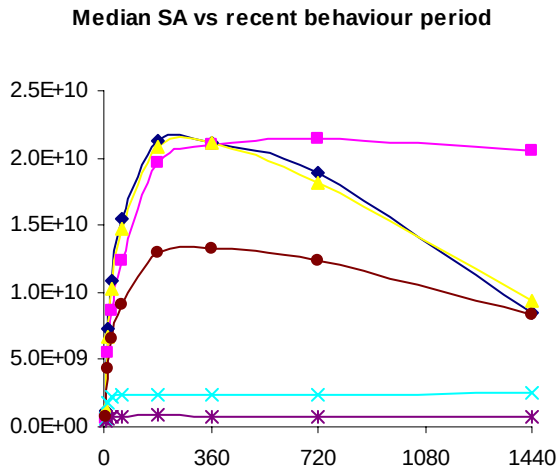


Driving behaviour

c: Short-term (t + 10min)



d: Long-term (t + 60min)



The trend with median surface area was closely related to that seen for median verification value. Surface area tends to start low in all cases, associated with the limited heterogeneity in the recent behaviour, then increase to a maximum between three and twelve hours, when most examples of spatial behaviour have been exhibited. The median surface area then levels off (in the case of driving behaviour) or decreases (in the case of walking behaviour) for subsequent increases in the recent behaviour period. For walking behaviour in particular, there is a clear and smooth trend of increase to a maximum, associated with a recent behaviour period between 6 and 12 hours, before beginning to decrease again for further increases in the period used to define recent behaviour. In this particular example, the dramatic increase is associated with inclusion of driving behaviour, both on the morning of the example and the previous day. This rises to a peak once this behaviour has been included, and then begins to tail off once the recent behaviour period is increased further to include examples of walking behaviour from the previous day. This has the effect to decrease the range of the prediction overall, since the recent behaviour is now representing relatively more walking behaviour, associated with slower speeds, and hence a smaller area that is likely to be accessible.

It can be seen that the approaches that use no temporal weighting, or a temporal decay function that results in a slow decrease in the influence of behaviour with time (such as a linear decay function), are more affected by the trend for surface area to decrease for further increases in the recent behaviour period. This is as you would expect since for these approaches, points from the distant past still have considerable influence upon the overall set (see Figure 39b). For approaches that use faster decay functions – such as negative power decay functions - surface area tends to level off at the maximum, but not decrease for further increases in the recent behaviour period. This is since the influence of these points from the distant past is negligible compared to the influence of more recent points. Generally surface area is also much greater for approaches that adopt no temporal weighting, or a linear decay function, than for those points that adopt a faster temporal decay function. This reflects the rapid temporal decay function providing a similar effect to decreasing the period of time used to define recent behaviour: by giving very low weights to points from the past, the heterogeneity of the recent behaviour is decreased resulting in much more focused, smaller predictions surfaces, based upon the most immediate behaviour. The surface area for driving behaviour is consistently larger than for walking behaviour, reflecting the increased range of mechanised transport. The long-term predictions also have larger surface area, since with more time, there are a greater region of space where you could possibly be.

Figure 40: Speed-heading prediction surfaces: influence of the recent behaviour period

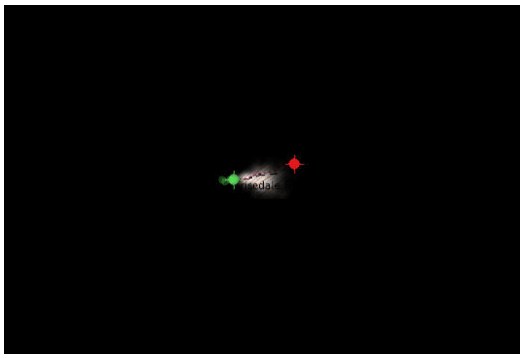
In the figures below, short-term (t+10min) speed-heading prediction surfaces have been generated for the walking scenario. The prediction origin is shown as a green crosshair, and the actual destination 10 minutes later is shown as a red cross-hair. The points that are included in the recent behaviour period are shown in light green.

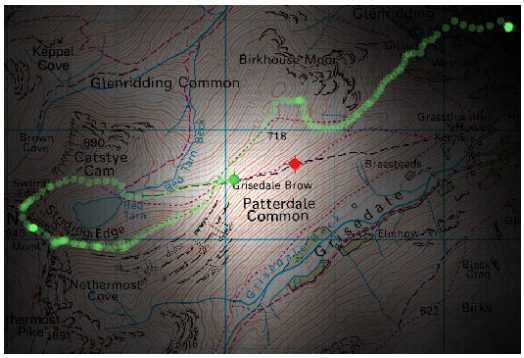
a: 5mins recent behaviour period

Using only 5 minutes to define the recent behaviour period, the prediction surface is very focussed in extent and direction. The surface area is very small, hence the surface is unlikely to coincide with the actual destination at the predicted time. For this reason the median verification value (and success rate) will be very low using this approach, resulting in low median prediction surface effectiveness values, despite the small surface area.

b: 24hrs recent behaviour period

Using the last 24 hours to define the recent behaviour period, a scattergun prediction surface results that is sprawling in extent and displays very little directionality. The surface area is very large, and the median verification value (and success rate) for this approach will be high, since the surface coincides consistently with the destination point. The excessively large surface areas result in low median prediction surface effectiveness, despite the high median verification values.





Images produced using the spatial history explorer

Median prediction surface effectiveness

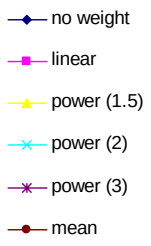
Figure 41: Median prediction surface effectiveness against recent behaviour period for a series of speed-heading prediction surfaces

All figures a to d show the median prediction surface effectiveness for a series of speed-heading prediction surfaces on the y axis, against the period of time used to define the recent behaviour (in minutes) on the x axis.

Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

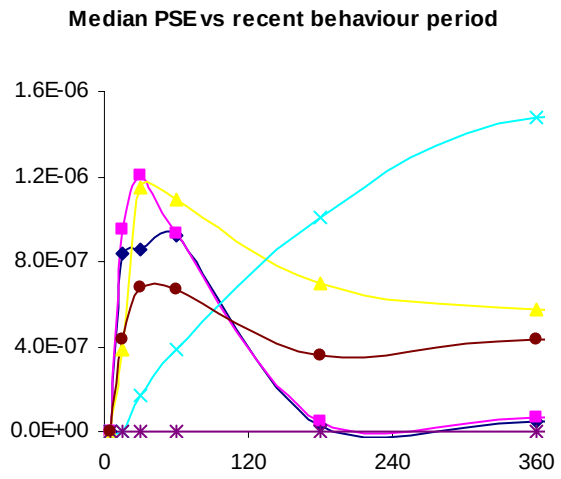
Various approaches to temporal weighting have been tested including no weighting, temporal weighting with linear decay, and temporal weighting with various examples of decay using power functions (1.5, 2 and 3).

Key to temporal decay functions

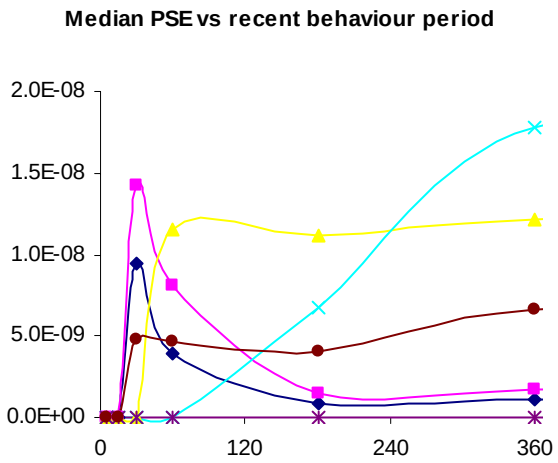


Walking behaviour

a: Short-term (t + 10min)

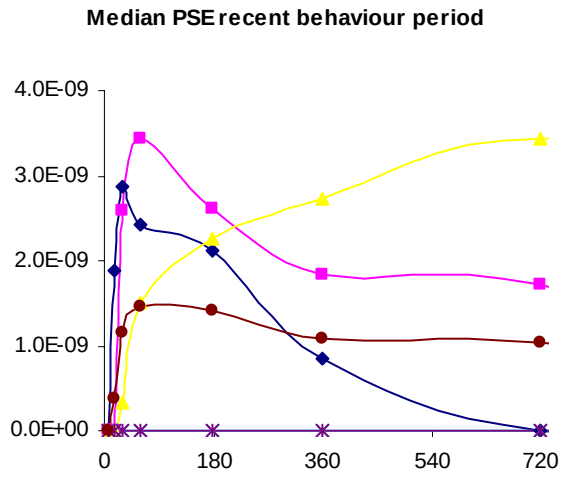


b: Long-term (t + 60min)

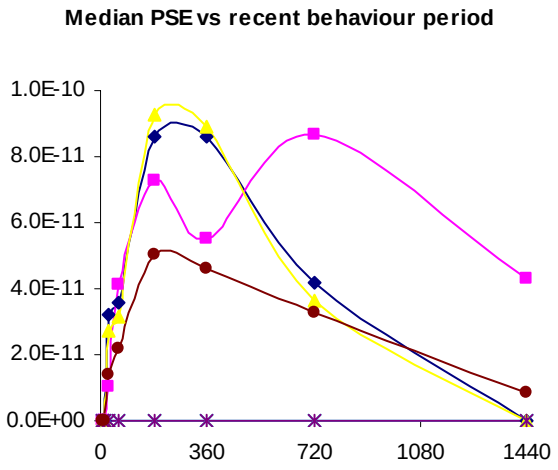


Driving behaviour

c: Short-term (t + 10min)



d: Long-term (t + 60min)



Prediction surface effectiveness tends to increase with an increasing recent behaviour period up to some maximum value, then decrease for further increases in the recent behaviour period. The small, highly focused prediction surfaces associated with very small periods of recent behaviour tend to only rarely coincide with verification point, leading to very low median verification values, and hence low median prediction surface effectiveness, despite the small surface size. The prediction surface effectiveness increases to a peak where the median verification value is generally higher, but the prediction surface size is still quite small. For subsequent increases in the recent behaviour period, the prediction surface effectiveness begins to decrease, since the median verification value levels off, but the surface area continues to rise, leading to "scattergun" predictions that are less spatially constrained.

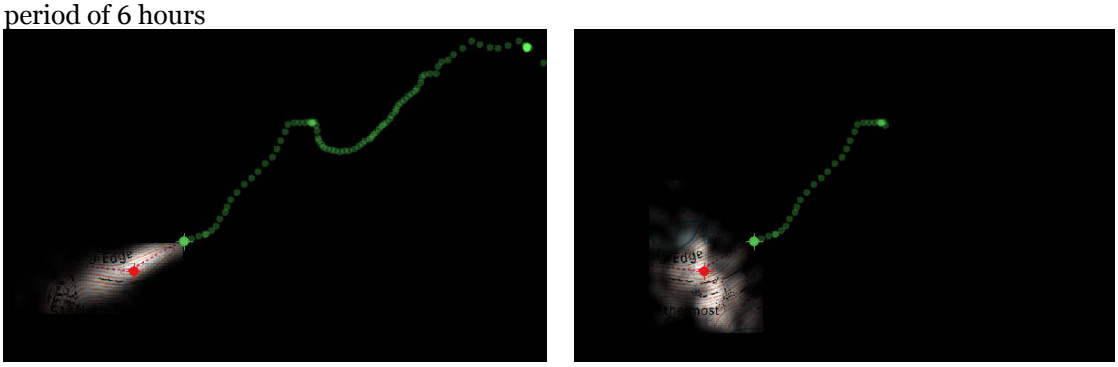
For short-term predictions for both walking and driving scenarios, this maximum value tends to occur after 30-60 minutes. In both scenarios (and notably for the driving example) the peak in median prediction surface effectiveness occurs for a longer recent behaviour period than for the long-term then for short-term predictions, suggesting that it may be appropriate to look to the more distant past when making predictions into the more distant future.

Approaches that adopted either a slow temporal weighting decay function (eg negative linear), or no temporal decay at all tend to have a very pronounced peak and subsequent drop off, hence when employing these approaches, selecting an appropriate recent behaviour period is very important. Approaches which use a faster temporal decay function (eg negative power functions), tend to peak later and experience a less dramatic drop off. The late peak effect is particular evident for the negative power decay when the exponent '2' is used. In this particular scenario, long recent behaviour periods and the negative square temporal decay functions appear to act as a very good predictor of future behaviour (see Figure 41). This approach includes a wide variety of speed values in the recent behaviour and hence to produce a prediction surface with more variation in the potential distance than could be covered, leading to more of a "torch-beam" effect emanating from the prediction origin (see Figure 42a). Another approach that performed well for the short-term walking scenario was using a 30 minute recent behaviour period with a linear temporal decay function. This approach tended to result in less variation in the distance that could be covered for each prediction, leading "crescent moon" predictions, reflecting heterogeneity in the heading in the recent behaviour, but homogeneity of speed (see Figure 42b).

Figure 42: Speed-heading prediction surfaces, predicting the location of the moving object displaying walking behaviour, 10 minutes into the future

a: Negative power temporal decay function (exponent = 2), using a recent behaviour period of 6 hours

b: Linear temporal decay function, using a recent behaviour period of 30 minutes



Images produced using the spatial history explorer

Success rate

The overall trend in success rate is to have a lowest success rate for shortest periods of recent behaviour, with success rate increasing with the recent behaviour period up to some maximum. For short-term predictions, this levelling off occurs for recent periods of between 30 minutes (for driving) and 60 minutes (for walking). For long-term predictions, the levelling off in success rate tends to occur for recent behaviour periods of about 60 minutes. As seen from the median surface area, predictions made using a very short recent behaviour period have very little heterogeneity in the recent behaviour and tend to be very small and focused, hence are less likely to coincide with the verification point. By using a longer duration, there is more heterogeneity in recent behaviour, and the resulting predictions tend be larger. This trend also impacts upon the success rate: larger surfaces are more likely to coincide with the verification point. Even though surface area tails off beyond a point for further increases in the recent behaviour period, the success rate of the prediction remains level, still capturing the verification point with the same frequency.

Since fast temporal decay functions effectively decrease the heterogeneity of the recent behaviour, resulting in smaller surfaces, they tend to have lower success rates than slow temporal decay functions (eg linear), or speed-heading predictions that employ no temporal weighting at all. It can be seen that this evaluation criterion rewards larger, scattergun predictions, which are more consistent because their larger size makes them more likely to coincide with the verification point.

Figure 43: Success rate against recent behaviour period for a series of speed-heading prediction surfaces

All figures a to d show the success rate for a series of speed-heading prediction surfaces on the y axis, against the period of time used to define the recent behaviour (in minutes) on the x axis.

Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

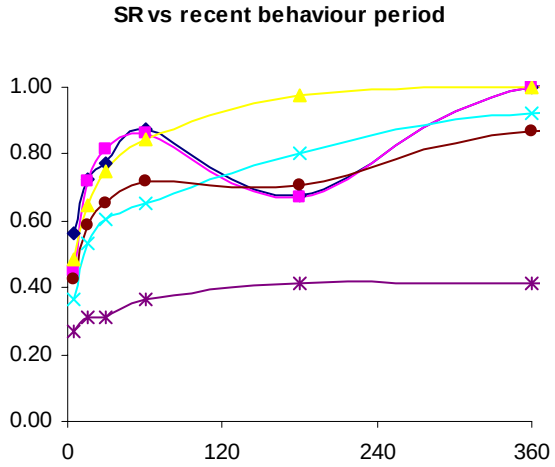
Various approaches to temporal weighting have been tested including no weighting, temporal weighting with linear decay, and temporal weighting with various examples of decay using power functions (1.5, 2 and 3).

Key to temporal decay functions

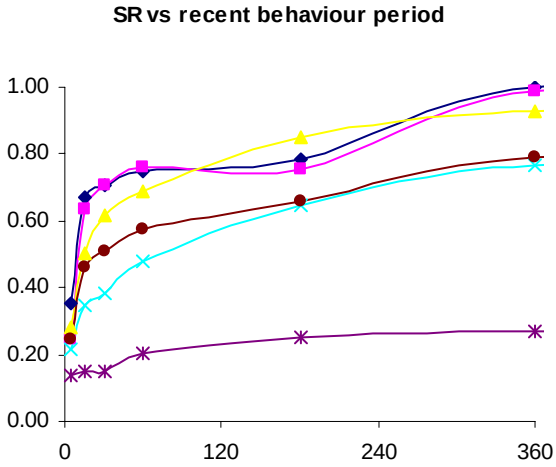
- no weight
- linear
- power (1.5)
- power (2)
- power (3)
- mean

Walking behaviour

a: Short-term (t + 10min)

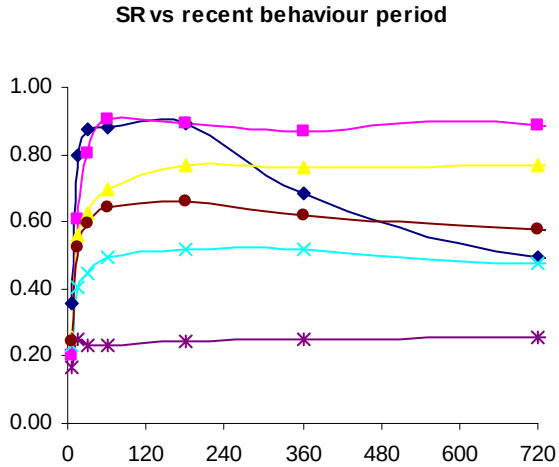


b: Long-term (t + 60min)

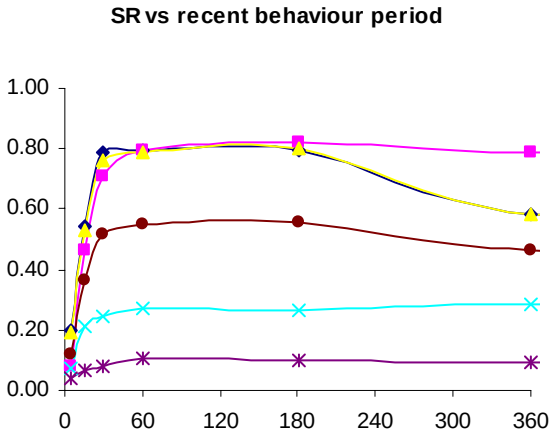


Driving behaviour

c: Short-term (t + 10min)



d: Long-term (t + 60min)

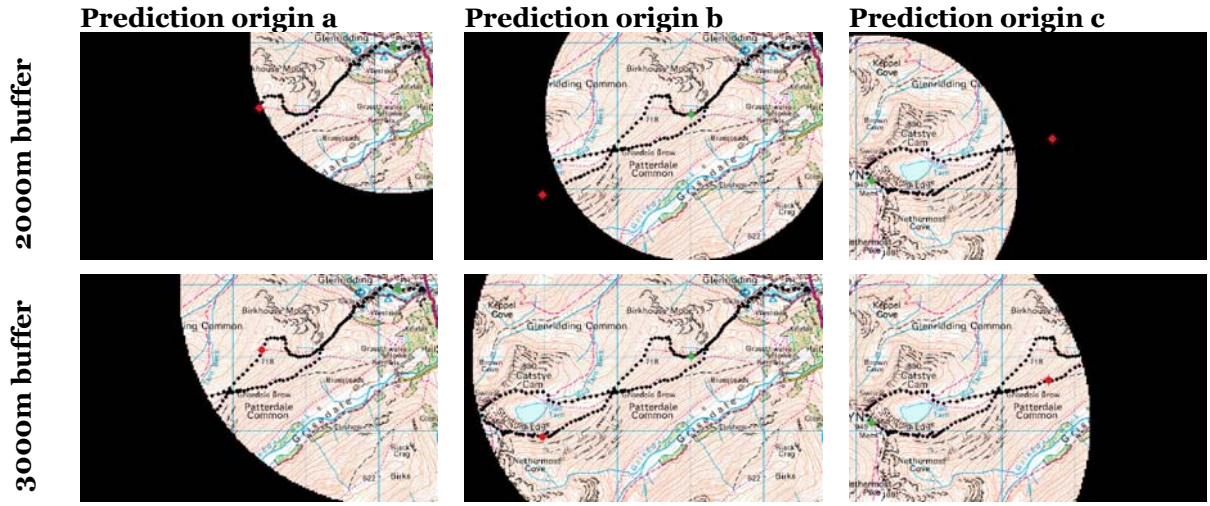


4.2.2 Spatial proximity prediction surfaces

These tests systematically vary the buffer distance and distance decay functions, to assess the characteristics of these prediction surfaces. The characteristics of these spatial proximity prediction surfaces will be assessed by comparing different configurations for two scenarios (walking and driving), and for short-term (t + 10min) and long-term (t + 60min) predictions. The evaluation criteria discussed in section 3.5 will be used to allow the comparison of these different approaches.

Figure 44: The effects of the buffer distance on spatial proximity surfaces

Six long-term (t + 60min) predictions are shown for the walking scenario. The predictions have been made for three different spatial origins, using two different buffer sizes (2000 metres and 3000 metres). It can be seen that whilst the 2000 metre buffer consistently fails to coincide with the destination point, using the 3000 metre buffer, the surface captures the destination point consistently. This explains the dramatic increase in the median verification value and median prediction surface effectiveness at a threshold buffer size: spatial proximity surfaces that consistently just coincide with the verification point perform well because they are not unnecessarily spatially extensive, but those with a slightly smaller buffer distance can fail to coincide with the destination point at all.



Images produced using the spatial history explorer

Median verification value

The general trend for the median verification value is to have very low values for very small buffer distances and to stay low until some threshold buffer distance is crossed. At this point median verification value increases exponentially for increases in buffer distance. Finally, with further increases in the buffer distance, the rate of increase of median verification value either levels off, or decreases. This threshold buffer distance is the distance at which the spatial proximity surface first begins to coincide with destination point for the given spatial behaviour: for smaller buffer sizes the surface is too small to consistently "capture" the verification point. For this threshold buffer size, the median verification point increases dramatically from values close to zero, the very high values very quickly (Figure 44). For unweighted spatial proximity surfaces, the median verification value then tails off for

subsequent increases in the buffer distance, since there is no variation in the values within the buffer. The linear-offset spatial proximity behaviour demonstrates very similar behaviour to the unweighted spatial proximity surface in all situations.

For spatial proximity prediction surfaces which apply a distance decay function, the median verification value continues to increase for further increases in the buffer size. This can be explained by the considering the characteristics of these surfaces: spatial proximity surfaces that apply rapidly decaying functions are characterised by high peaks at the centre surrounded by low values as you move to the edge of the surface. As the buffer increases in size the higher values close to the centre of the surface cover a bigger area, the destination point is more likely to increase with these points near the centre. For the linear-offset prediction surface, the maximum values are found in a circle around the centre. For this decay function, the median verification value increases with increases in buffer size until the destination is most likely to coincide with high regions on the surface, before decreasing for subsequent increases in the buffer size, as the destination point is more likely to coincide with the lower values close to the centre of the prediction surface.

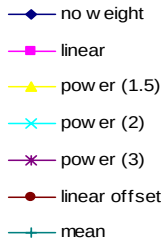
Figure 45: Median verification value against buffer distance for a series of spatial proximity prediction surfaces

All figures a to d show the median verification value for a series of spatial proximity prediction surfaces on the y axis, against buffer distance (in metres) on the x axis.

Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

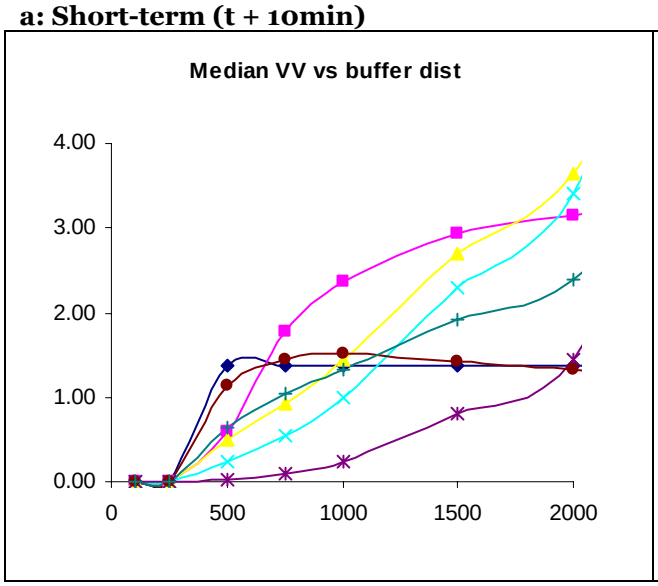
Various approaches to distance weighting have been tested including no weighting, distance weighting with linear decay, and distance weighting with various examples of decay using power functions (1.5, 2 and 3).

Key to distance decay functions

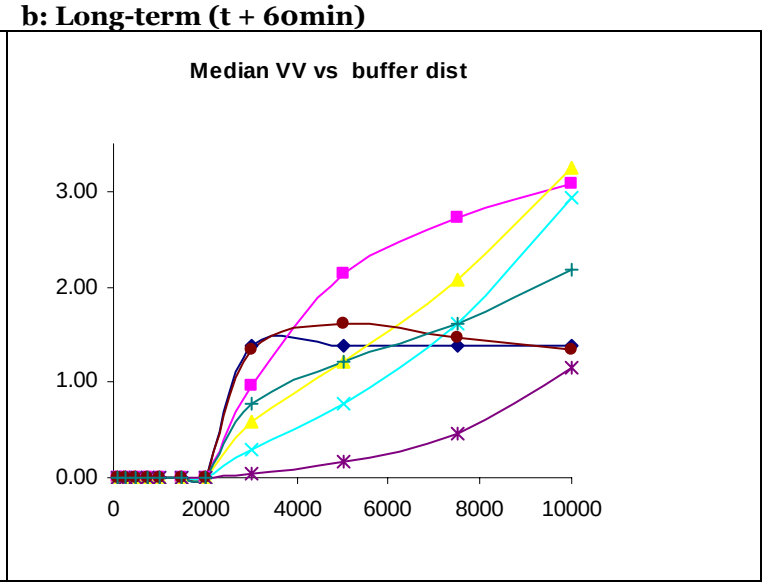


Walking behaviour

a: Short-term (t + 10min)

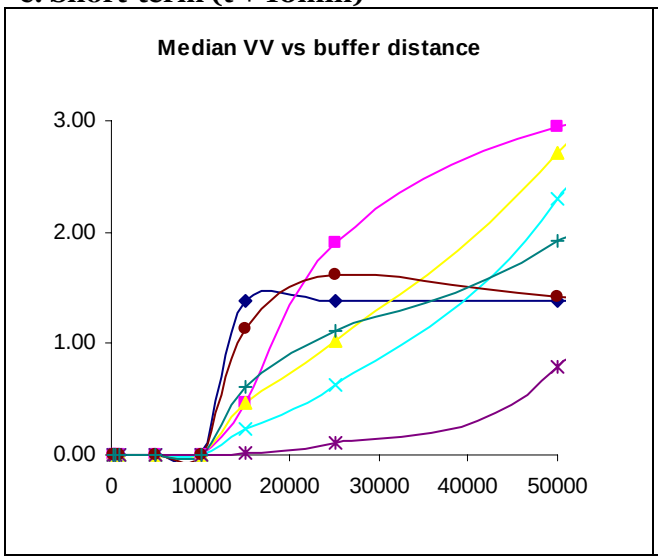


b: Long-term (t + 60min)

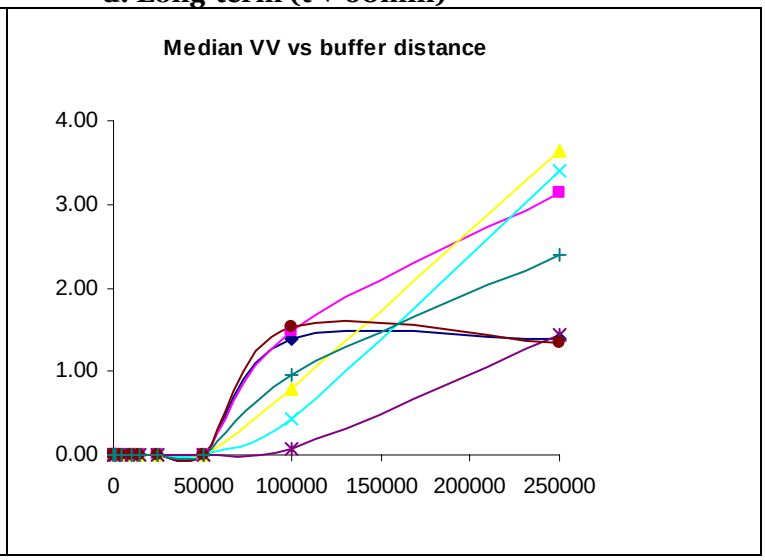


Driving behaviour

c: Short-term (t + 10min)



d: Long-term (t + 60min)



Median surface area

Figure 46: Median surface area against buffer distance for a series of spatial proximity prediction surfaces

All figures a to d show the median surface area (in m²) for a series of spatial proximity prediction surfaces on the y axis, against the buffer distance (in metres) on the x axis.

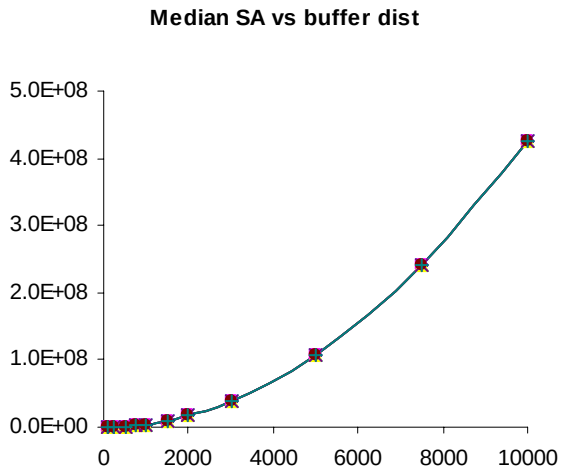
Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

Various approaches to distance weighting have been tested including no weighting, distance weighting with linear decay, and distance weighting with various examples of decay using power functions (1.5, 2 and 3).

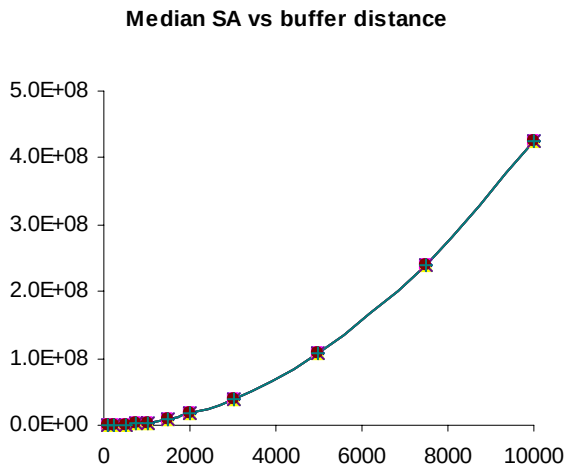
Key to distance decay functions

Walking behaviour

a: Short-term (t + 10min)

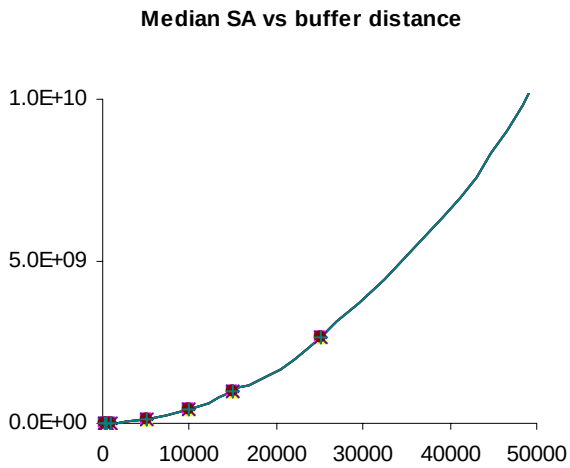


b: Long-term (t + 60min)

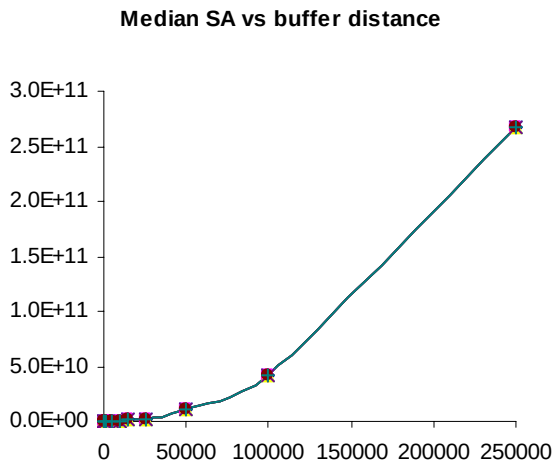


Driving behaviour

c: Short-term (t + 10min)



d: Long-term (t + 60min)



The surface area increases exponentially with increases in buffer distance, as dictated by the equation for the surface area of a circle. The spatial proximity surface places an enclosing rectangle around the buffer region, however the relationship between buffer size and surface area follows the same trend. The distance decay function has no impact on median surface area.

Median prediction surface effectiveness

Median prediction surface effectiveness is low for small buffer sizes, since these small surfaces do not consistently coincide with the verification point. In most cases there is a rapid increase in median prediction surface effectiveness for the threshold buffer distance, as the surface begins to coincide consistently with destination, but surface area is still small. This threshold value varies depending upon scenario and the length of the prediction period. Table 9 shows the threshold buffer distances for alternative scenarios and prediction periods. It can be seen that larger threshold buffer distances are associated with faster moving transportation, and for longer prediction periods, since both these increase the potential spatial extent of movement.

Table 9: Threshold buffer distances for alternative scenarios and prediction periods

		Prediction period	
		t+10 mins	**t+60 mins**
Scenario	**Walking**	≈ 0.25 km	≈ 2 km
	Driving	≈ 15 km	≈ 100 km

Where extreme decay functions have been applied, a secondary peak can be seen for very large buffer sizes. The secondary peak reflects the coincidence of the destination with these very high values close to the centre. Since the surface area increases by an exponent of 2, but the decay functions can apply an exponent of greater than 2, this can result in a high prediction surface effectiveness values. This is a limitation of the evaluation criterion that should be considered when assessing performance and scepticism should be expressed at the seemingly strong performance of surfaces employing extreme decay functions. Intuitively these surfaces with very large surface areas are poor predictors of future behaviour, however applying extreme decay functions can lead to high prediction surface effectiveness values (see results in appendix 3).

Figure 47: Median prediction surface effectiveness against buffer distance for a series of spatial proximity prediction surfaces

All figures a to d show the prediction surface effectiveness for a series of spatial proximity prediction surfaces on the y axis, against buffer distance (in metres) on the x axis.

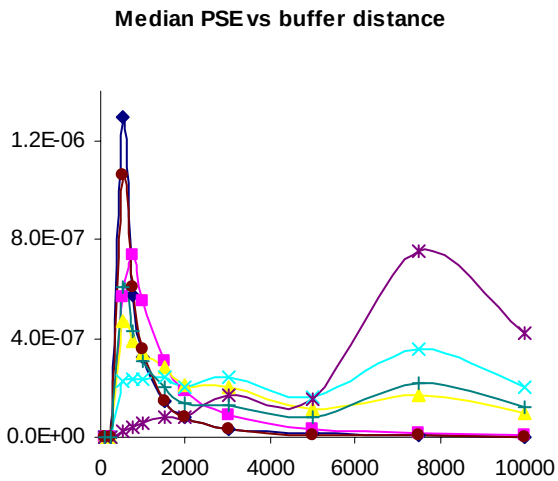
Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

Various approaches to distance weighting have been tested including no weighting, distance weighting with linear decay, and distance weighting with various examples of decay using power functions (1.5, 2 and 3).

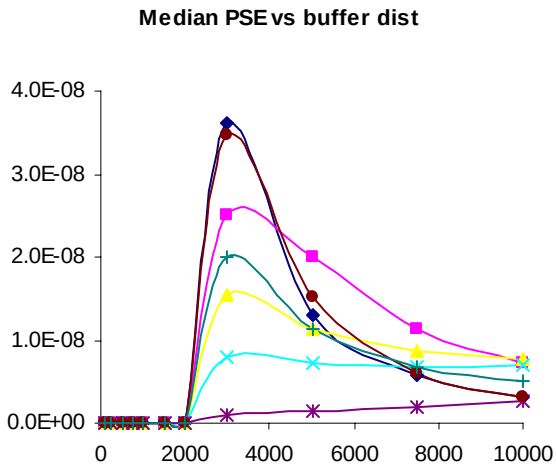
Key to distance decay functions

Walking behaviour

a: Short-term (t + 10min)

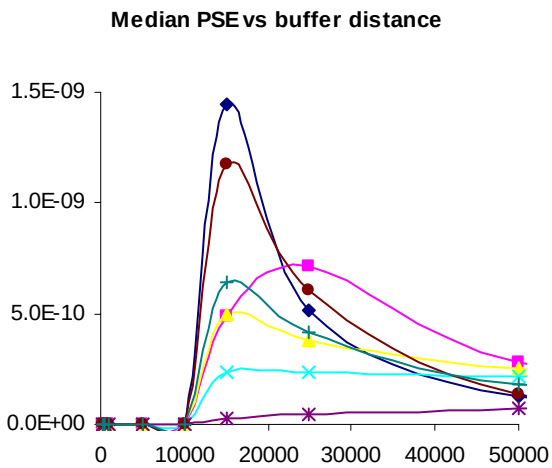


b: Long-term (t + 60min)

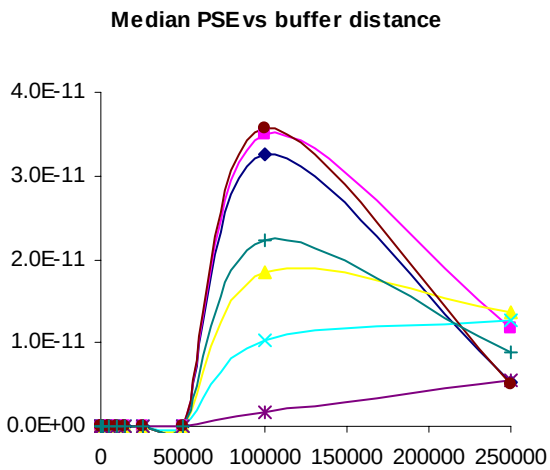


Driving behaviour

c: Short-term (t + 10min)



d: Long-term (t + 60min)



Success rate

Figure 48: Success rate against buffer distance for a series of spatial proximity prediction surfaces

All figures a to d show the success rate for a series of spatial proximity prediction surfaces on the y axis, against buffer distance (in metres) on the x axis.

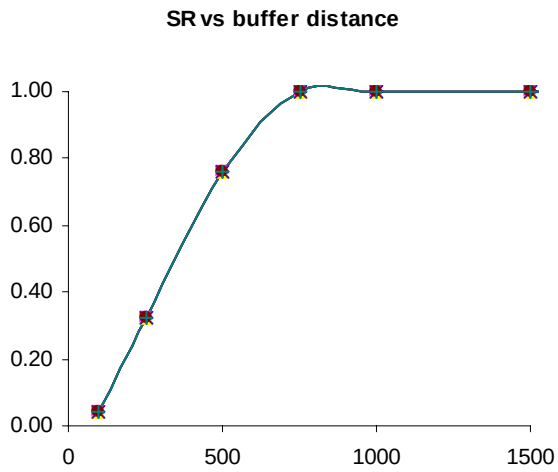
Two scenarios are represented - walking and driving - and both short-term (t + 10 min) and long-term (t + 60 min) predictions have been generated for each scenario.

Various approaches to distance weighting have been tested including no weighting, distance weighting with linear decay, and distance weighting with various examples of decay using power functions (1.5, 2 and 3).

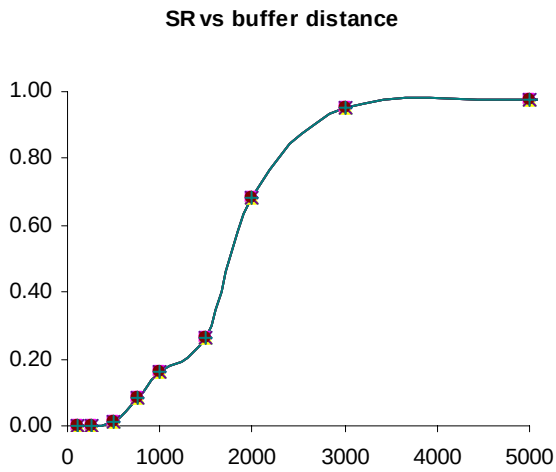
Key to distance decay functions

Walking behaviour

a: Short-term (t + 10min)

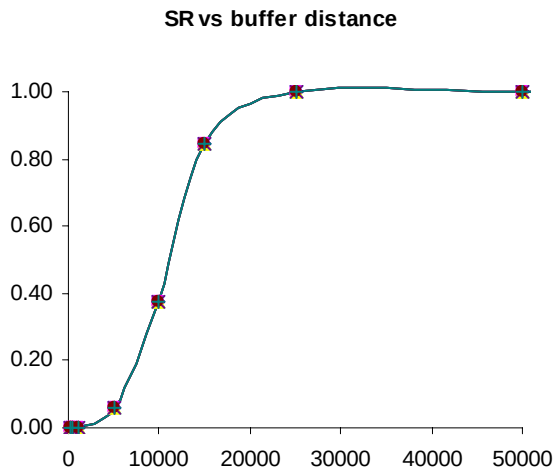


b: Long-term (t + 60min)

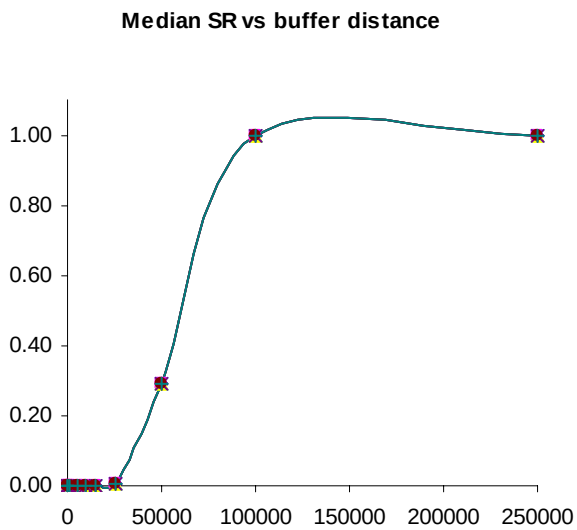


Driving behaviour

c: Short-term (t + 10min)



d: Long-term (t + 60min)



Success rate is only dependent upon buffer size, and not the decay function, since success rate records simply whether the prediction surface coincides with the destination point, and is not influenced by the internal variation within the surface. Success rate starts low for small buffer distances, and increases rapidly as the threshold buffer distance is reached, where the surface reaches a size where it is likely to overlap with the destination point given the behaviour and prediction period. For further increases in the buffer size, the success rate increases rapidly to a maximum of 1, indicating that for these buffer sizes, the surface always coincides with the destination point.

4.2.3 Temporal proximity prediction surfaces

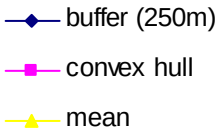
The temporal proximity prediction surfaces were tested in just one scenario, daily migration, for a commute to and from work via bicycle. The temporal proximity prediction surfaces could not be tested in the walking and driving scenarios since they need a mobile trajectory collected over a long period of time (weeks or more), which can mined to discover which regions of space are accessible from different locations, based upon repeated behaviour displayed over the coarse of multiple temporal cycles. These tests systematically varied the time budget used to calculate the potential path area from a minimum of five minutes to a maximum of 30 minutes. Two approaches to enclosing the selected space-time paths were tested: a convex hull and a 250metre buffer around the paths.

Median verification value

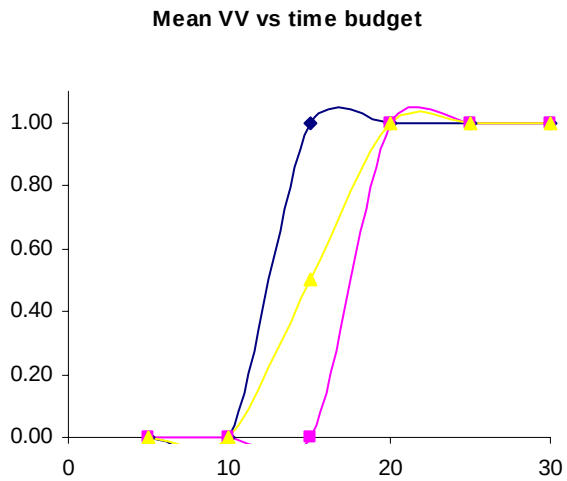
The median verification value sees an increase from zero to one between 10 and 20 minutes. This reflects the poor performance of surfaces with short time budgets, since they have very constrained spatial extent and are less likely to coincide with the verification value. The jump from zero to one is a reflection of the median value being used for a Boolean surface (see section 3.5.3).

Figure 49: Temporal proximity predictions for the daily migration scenario

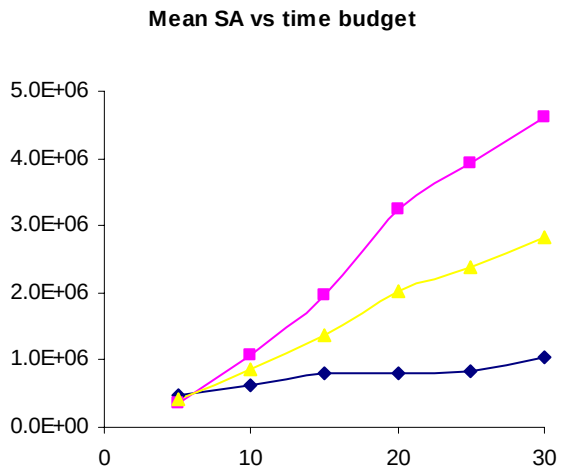
Key to space-time path bounding function



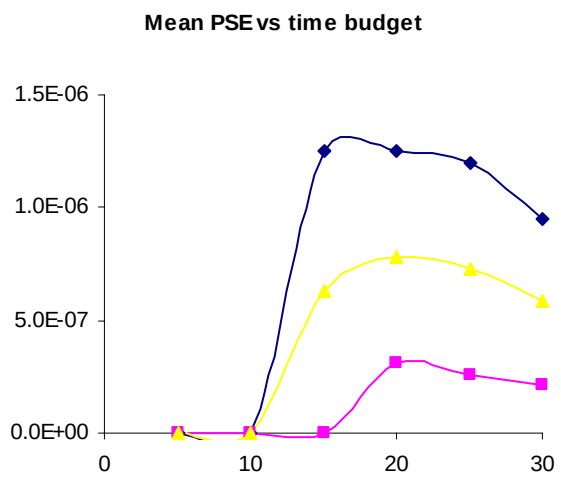
a: Median verification value



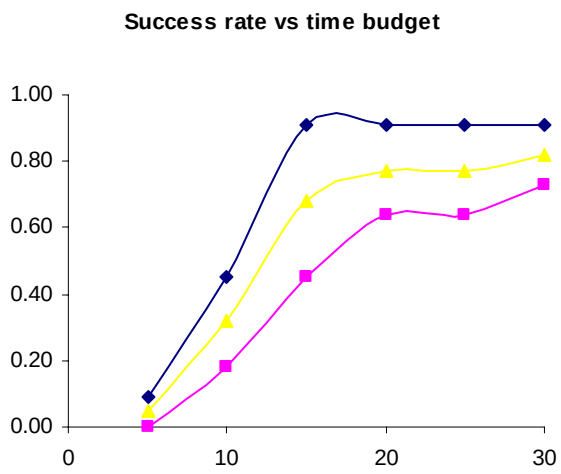
b: Median surface area



c: Median prediction surface effectiveness



d: Success rate



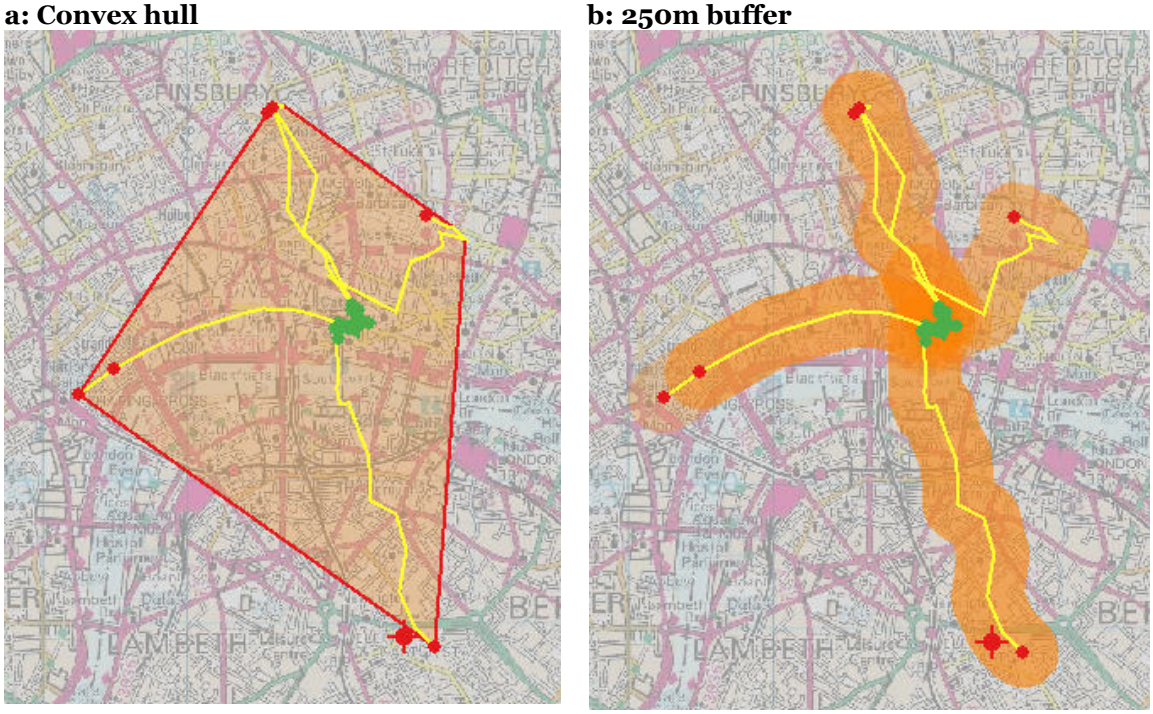
Median surface area

The overall trend is for the surface area to increase at a linear rate for increases in the time budget: given a greater time budget, a greater region of space is accessible to you. It can be seen that by using the convex hull to enclose the space-time paths, the surface area is up to four times greater than when the spatial buffer around paths is used. This is since the convex hull encloses larger regions of space between paths that was actually never visited during the previous exhibited spatial behaviour. The spatial buffer approach is far more focused, leading to accessibility corridors that are a better representation of the locations that were accessible (see Figure 50).

Figure 50: Temporal proximity prediction surface: convex hull vs buffer

Two short-term temporal proximity predictions are shown for the daily migration scenario. For each prediction, the selected space-time paths can be seen (yellow lines bounded by green and red points), as can the actual destination at the predicted time (a red cross hair in the bottom right of both figures). In a, all selected space-time paths are enclosed using a convex hull (bounded by a red edge). In b, the space time paths are enclosed using a 250 metre buffer. It can be seen that the buffer has a smaller surface area, and encloses less unvisited space, notably several bridges across the Thames that are included in the potential path area defined by the convex hull. A further interesting feature is that by buffering beyond the points, the temporal proximity surface defined by the buffer coincides with the destination point (red crosshair), however the convex hull, which provides a tight fit around the points, fails to coincide with the destination point.

a: Convex hull **b: 250m buffer**



Images produced using the spatial history explorer

The buffer approach also extends the potential path area beyond the space-time paths, however this only occurs around the points that comprise the space-time paths themselves, and not the space between space-time paths (see Figure 50). Using both methods, the potential path area extends beyond the area that was accessible based upon previous experience, however there is more control over this extrapolation using the buffer than the convex hull, since the buffer size can be manipulated.

Median prediction surface effectiveness

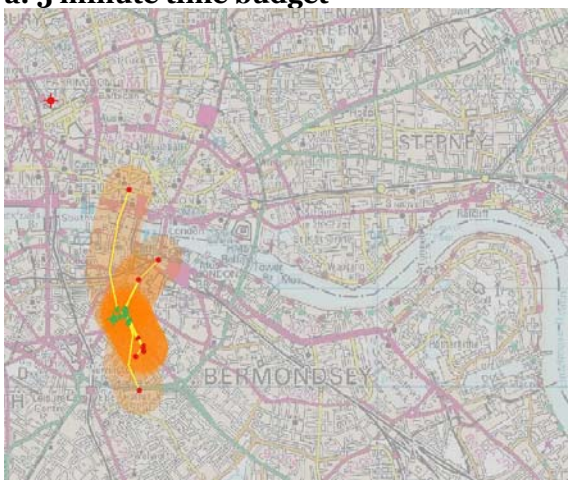
For both the buffer and convex hull approaches, the median prediction surface effectiveness is zero for time budgets of less than 10 minutes, reflecting median verification values of zero for these time budgets. Beyond this point, median PSE tends to increase rapidly for increases in the time budget, up to some maximum, then decreases for further increases in the time budget (see Figure 49c). The initial increase is associated with the increase in the mean verification value as discussed above and seen in Figure 49a. At a threshold value (about 20 minutes), the median verification value levels off, however the surface area continues to rise. The peak is found just before this point, and for subsequent increases in surface area, associated with increases in the time budget, the median prediction surface effectiveness begins to decrease.

In this example, a time budget slightly in excess of the prediction period results in the most effective temporal proximity prediction surfaces: time budget of 15 and 20 minutes work well for a prediction of t+10mins. It can be seen that the buffer approach to enclosing the space-time paths is far more effective than the convex hull approach, due in the main to the smaller surface area of the resulting surfaces.

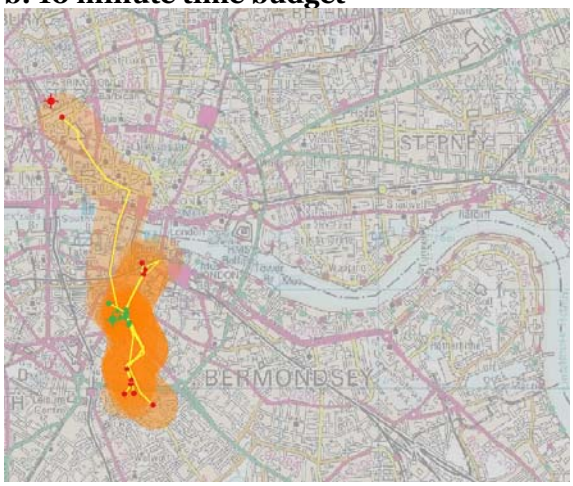
Figure 51: Temporal proximity prediction surface: influence of the time budget on the surface area

Four short-term temporal proximity prediction surfaces are shown below for the daily migration scenario. A 250metre buffer has been used to define the potential path area shown in orange. It can be seen that the surface area increases with the available time budget. The surface does not coincide with the destination for the 5 minute time budget, but does for time budgets 10, 20 and 30 minutes.

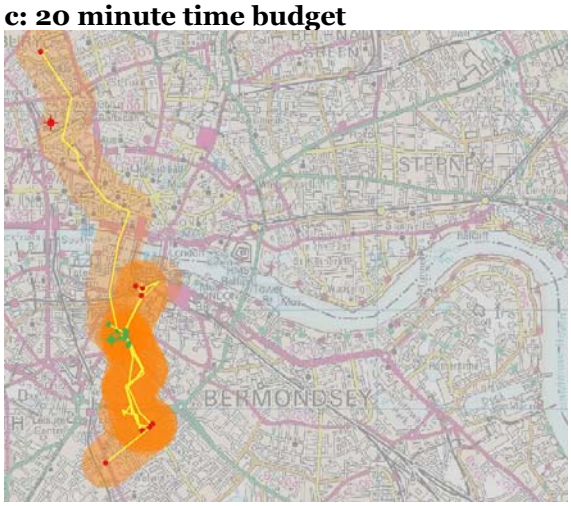
a: 5 minute time budget



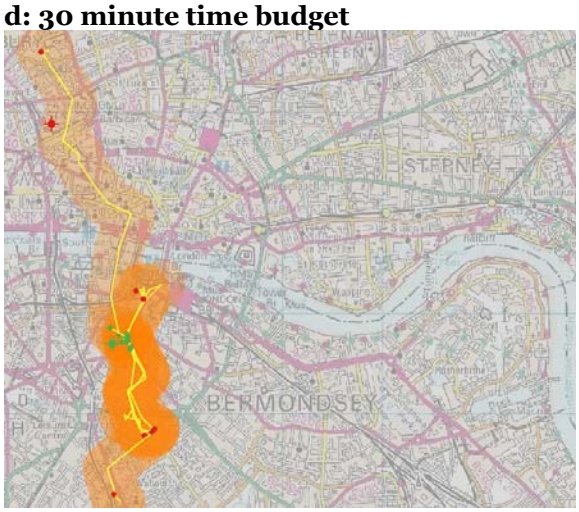
b: 10 minute time budget



c: 20 minute time budget



d: 30 minute time budget



Images produced using the spatial history explorer

Success rate

The overall trend here is for the success rate to increase rapidly for increases in the time budget, then to level off for further increases (see Figure 49d). Using a time budget of less than the prediction period (eg a time budget of 5 minutes to predict location in 10 minutes), leads to very low success rates since the surface is unlikely to coincide with the individual's actual destination unless they display unusually fast behaviour on that particular day. A threshold is reached for a time budget of around 20 minutes and success rate begins to level

off, suggesting that a temporal proximity prediction surface using a time budget of 30 minutes is not more likely to coincide with the verification point. This is most evident for the tests conducted using a 250 metre buffer to enclose the space-time paths, however a similar result can be seen when a convex hull is used. The increase of surface area for increases in the time budget is shown in Figure 49b. Using a 250 metre buffer to enclose the space-time paths results in consistently higher success rates than using a convex hull to enclose the points. This is since whilst the convex hull fits tightly around all the points that comprise the space-time paths, the buffer extends a further 250metres at the end of the paths (Figure 50).

4.3 Suitability of approaches for scenarios

Having considered the characteristics of each of the three approaches to prediction, we will now compare how the different approaches performed in different situations. In all, five situations are considered: short-term and long-term predictions for the walking scenario, short-term and long-term predictions for the driving scenario, and short-term predictions for the daily migration scenario.

Overall, speed-heading predictions outperformed the spatial proximity approach in four of the five situations in which it was tested (see Table 10). The temporal proximity approach outperformed both the speed-heading approach and spatial proximity approach in the one situation in which it was tested.

Table 10: Most effective configuration for each prediction approach, in each situation.

The most effective approach in each situation is shown in bold

		Prediction approach		
		Speed-heading (recent behaviour period, decay function)	**Spatial proximity (buffer size, decay function)**	**Temporal proximity (time budget, bounding function)**
Situation	**Walking: short-term**	**6 hours, power (2) decay**	500 metres, no decay	-
	Walking: long-term	24 hours, power (2) decay	**3km, no decay**	-
	Driving: short-term	**1hr linear decay**	15km, no decay	-
	Driving: long-term	**3hrs, power (1.5) decay**	100km linear decay	-
	Daily migration: short-term	3 hrs, power (2) decay	3km, no decay	**15 (or 20) min time budget, 250 metre buffer**

Table 11: Prediction surface effectiveness (of the most effective configuration) for each prediction approach, in each situation.

The most effective approach in each situation is shown in bold

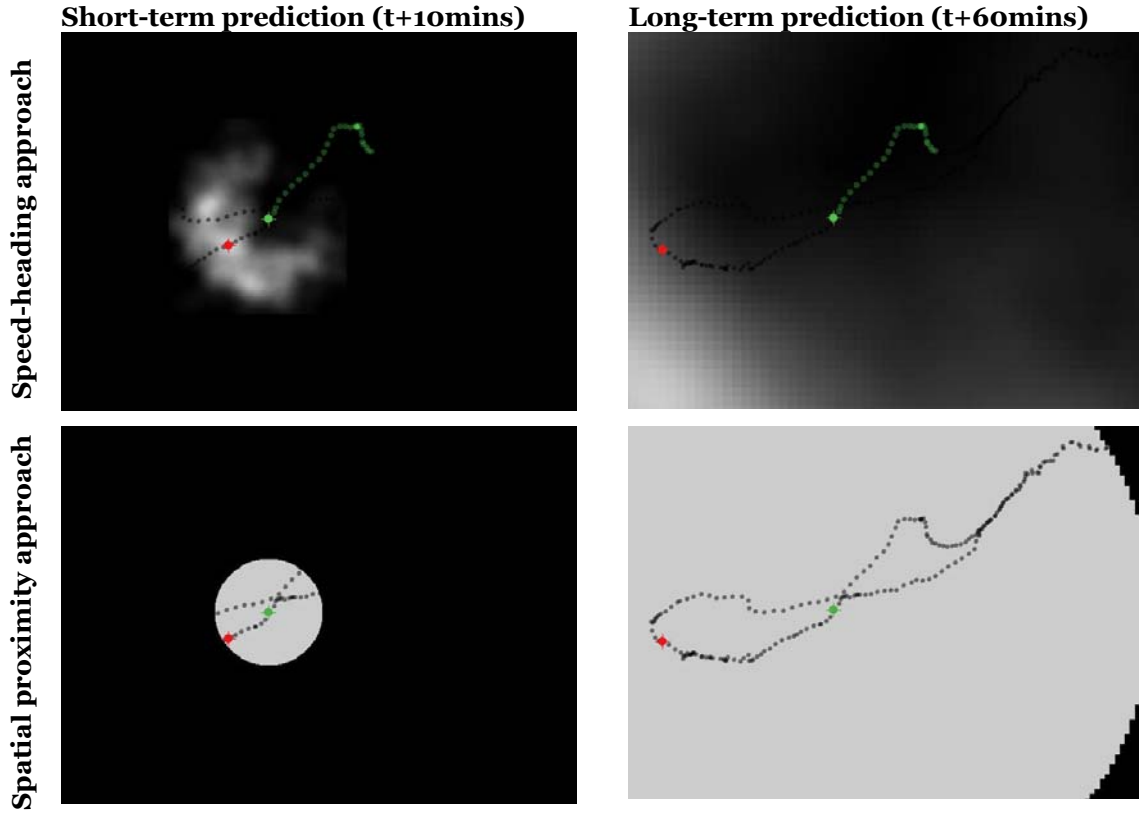
		Prediction approach		
		Speed-heading	**Spatial proximity**	**Temporal proximity**
Situation	**Walking: short-term**	**$1.5*10^{-06}$**	$1.3*10^{-06}$	-
	Walking: long-term	$1.9*10^{-08}$	**$3.6*10^{-08}$**	-
	Driving: short-term	**$3.4*10^{-09}$**	$1.4*10^{-09}$	-
	Driving: long-term	**$9.3*10^{-11}$**	$3.5*10^{-11}$	-
	Daily migration: short-term	$1.8*10^{-07}$	$3.6*10^{-08}$	**$1.3*10^{-06}$**

4.3.1 Walking scenario: short-term prediction (t+10mins)

Only the speed-heading and spatial proximity approaches were tested for this situation.

Figure 52: Successful approaches for the walking scenario

Spatial behaviour was highly sinuous for the walking scenario. For short-term predictions, the speed-heading approach was most effective, since in the short-term, heading is a quite effective predictor of future direction of movement. For long-term predictions, the spatial proximity approach outperformed the speed-heading approach, reflecting the fact that heading is a less effective predictor variable in the long-term for sinuous behaviour.



Images produced using the spatial history explorer

The single most effective approach overall was a speed-heading prediction surface using a recent behaviour period of 6 hours, and temporal weighting with power (2) decay function, however less extreme decay functions saw a peak in the prediction surface effectiveness for a recent behaviour period of about 30 minutes (see Table A1.3 in appendix 3 and Figure 41). The most effective spatial proximity surface used a 500metre buffer, and no distance weighting (see Table A1.7 in appendix 3). There is very little difference between the highest recorded prediction surface effectiveness scores for the speed-heading approach ($1.5*10^{-6}$) and the spatial proximity surface ($1.3*10^{-06}$), suggesting that the speed-heading approach offers only minor advantages over an appropriate spatial proximity surface in this situation. This is likely to be due to the highly sinuous nature of this scenario, which describes a figure of eight over a period of four hours. Nevertheless, when making short-term predictions,

recently exhibited speed and heading can result in a more effective prediction surface than the most appropriately sized spatial proximity surface (see Figure 52).

4.3.2 Walking scenario: long-term prediction (t+60mins)

Only the speed-heading and spatial proximity approaches were tested for this situation.

The single most effective approach in this situation was a spatial proximity prediction surface, employing a 3km buffer size with no weighting, suggesting that in this situation, the speed-heading approach offers no advantage over spatial proximity surface using an appropriate buffer size. Again the reason for this is likely to be the sinuous nature of the walking scenario: whilst previous heading was of use as a predictor variable for short-term (t+10min) predictions, it can tell us little about the direction of movement in the longer-term (see Figure 52).

It is notably that the spatial proximity surfaces are more sensitive to buffer size, than the speed-heading prediction surfaces are to recent behaviour period (Figure 52 and Figure 53). There are very pronounced peaks around the threshold buffer size, for which the spatial proximity surface begins to consistently coincide with the actual destination at the predicted time; the spatial buffer sizes were selected with the scenario in mind, whereas the same recent behaviour periods were tested for all scenarios. This suggests that speed-heading predictions may be a more robust approach, if the choice of buffer size is not obvious for spatial proximity prediction surfaces. Alternatively, recently displayed speed could be used to define the buffer distance for spatial proximity surfaces for highly sinuous behaviour.

4.3.3 Driving scenario: short-term prediction (t+10mins)

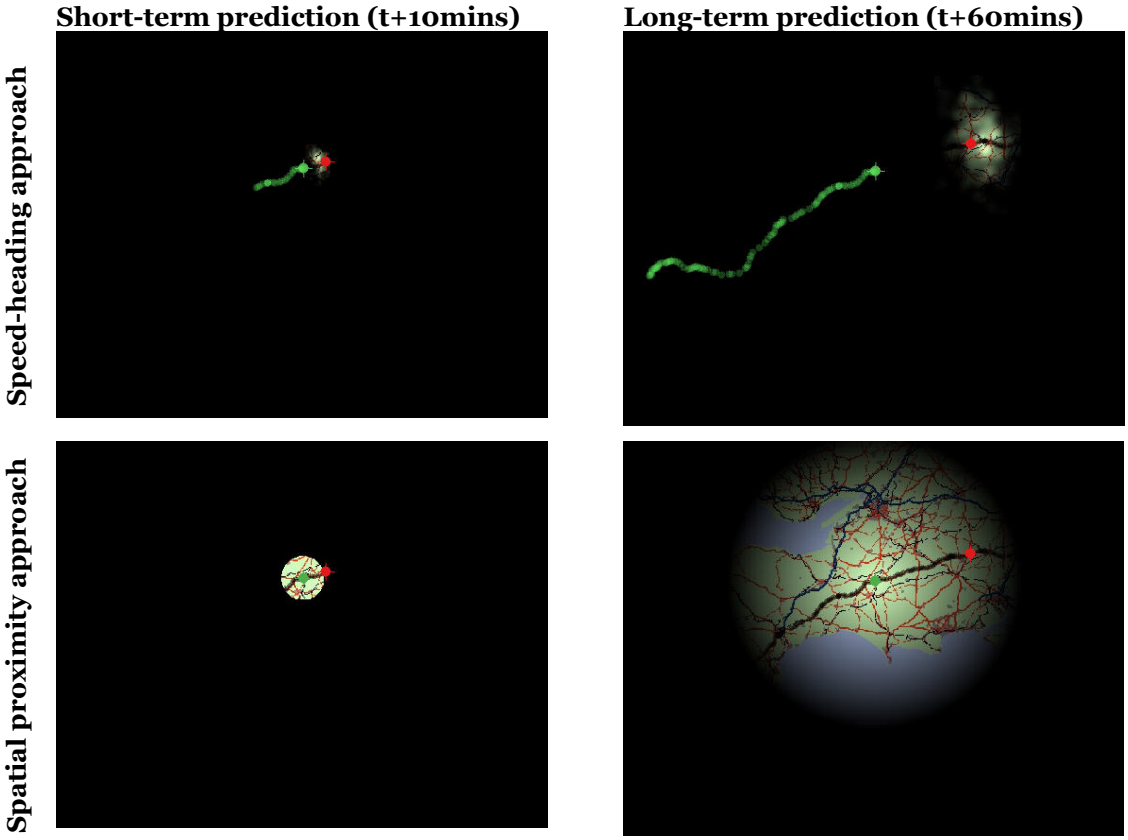
Only the speed-heading and spatial proximity approaches were tested for this situation.

In this situation, a speed-heading approach employing a 60min recent behaviour period with a temporal weighting and linear decay function records the highest prediction surface effectiveness (PSE) score (PSE = $3.4*10^{-09}$). The most effective spatial proximity approach is a 15km buffer with no spatial weighting (PSE = $1.4*10^{-09}$). The success of the speed-heading approach in this situation is due to the more directed, and less sinuous behaviour displayed in the driving scenario (see Figure 53); behaviour for which speed and heading act as good predictor variables in the short-term.

4.3.4 Driving scenario: long-term prediction (t+60mins)

Figure 53: Successful approaches for the driving scenario

Spatial behaviour was quite directed for the driving scenario, hence the speed-heading approach performed well for both short-term and long-term predictions. The speed-heading approach was successful in reducing the size of the surface, whilst still consistently coinciding with the actual destination at the predicted time. The spatial proximity surfaces that performed well employed either no spatial weighting, or slow decay functions, such as linear decay.



Images produced using the spatial history explorer

The speed-heading approach is also a good predictor for long-term predictions in the driving scenario, again reflecting the forced direction and consistent speed displayed. The most effective speed-heading approach, employing a 180min recent behaviour period and temporal weighting with a power (1.5) decay function, is almost three times more effective (PSE = $9.3*10^{-11}$) then the most effective spatial proximity approach, employing a 100km buffer and spatial weighting with a linear decay function (PSE $=3.5*10^{-11}$). Speed-heading predictions appear to perform well for this type of scenario – where consistent behaviour is displayed.

4.3.5 Daily migration scenario: short-term prediction (t+10mins)

This was the only scenario in which all three prediction approaches (speed-heading, spatial proximity and temporal proximity) were compared directly against each other. The temporal

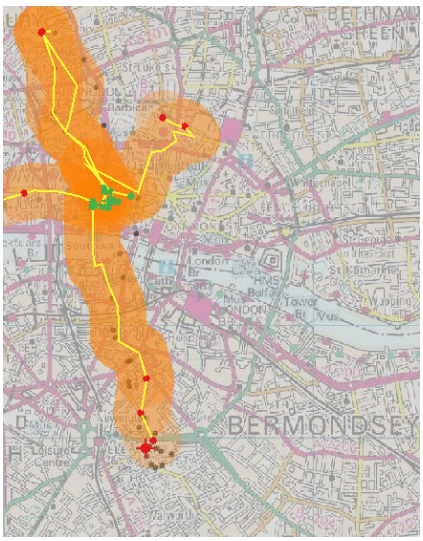
proximity approach was by the far the most effective approach in this situation, followed by the speed-heading approach, then the spatial proximity approach. The success of the temporal proximity approach is due to the long-term history of personal data recording the movements of this individual. Behaviour is clearly cyclical, and many journeys, such as the journey to work, will take similar routes at similar times. When potential path areas are generated from this data, they act as exceptionally good predictors of future location. It should be noted that if potential path areas were generated for aggregate data, ie the area accessible to a large number of users over the same period, then the surface area of the potential path area would be much greater, with the result that this approach would have a smaller prediction surface effectiveness score.

The speed-heading prediction approach also outperforms the spatial proximity approach by an order of magnitude in this scenario. This is since the journeys to and from work display a clear directional trend, which can result in more focussed predictions using the speed-heading approach that consistently coincide with the destination at the predicted time. By comparison, the spatial proximity surfaces are very large in spatial extent, and perform badly in this situation. The trend for the temporal proximity approach to outperform the speed-heading approach, and for both to be more effective than the spatial proximity approach, implies that in this situation at least, the further into the past that you look, the more effective the prediction will be.

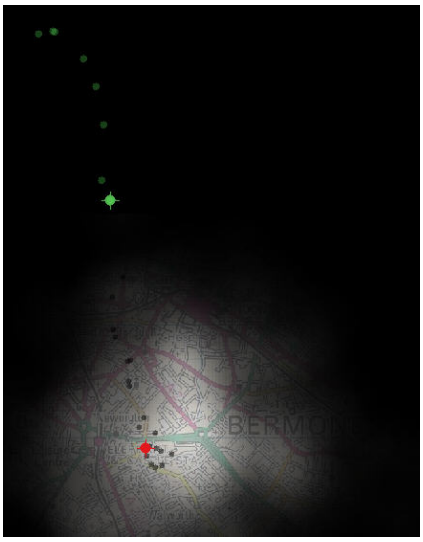
It is important to keep in mind that these conclusions are based upon a relatively small set of scenarios and data collected by a small number of individuals, all of whom live and work in, or close to, London, UK. Whilst it is possible to generalise these findings to a certain degree, care must be taken in extrapolating these results to the wider population. Future work could include repeating this analysis for larger datasets, containing the multiple users, to see if the same results can derived.

Figure 54: Successful approaches for the daily migration scenario

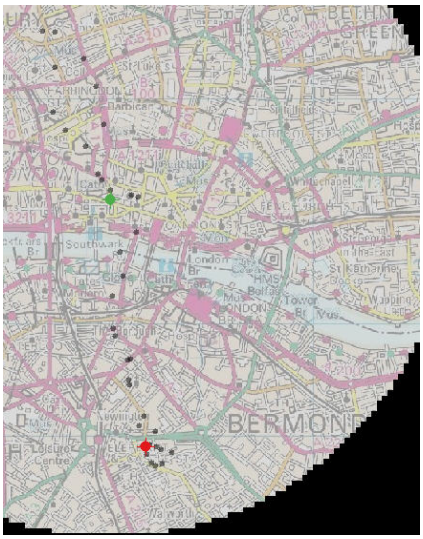
Temporal proximity approach



Speed-heading approach



Spatial-proximity approach



For the daily migration scenario, a temporal proximity prediction surface using a 15 minute time budget and 250 metre buffer was by far the most effective approach (PSE = **$1.1*10^{-06}$**). The next most effective approach was the speed-heading approach, using a 6hr recent behaviour period with a power (1.5) temporal decay function (PSE = $1.8*10^{-07}$). This was an order of magnitude more effective than the most effective spatial proximity approach, using a 3km buffer and no distance weighting (PSE = $3.6*10^{-08}$).

4.4 User evaluation

At the end of the WebPark project, a formal period of user evaluation was conducted using the Swiss National Park as a testbed. All project members, including the development team had an input into the user testing strategy, and all (including the author of this thesis) attended the week-long user test sessions, held annually for three years in the Swiss National Park. Over 100 individuals participated in these tests and a total of 87 feedback questionnaires were completed (Krug and Abderhalden, 2004). Test participants were given a brief introduction to the system at the National Park House, then left to use the device unaccompanied in the field for the duration of the day. Upon return, they were asked to complete a feedback questionnaire. In this less formal testing scenario, it could not be guaranteed that all users would utilise all of the system functionality, hence the response rate to some questions was low. Questions relevant to this thesis, discussed below, relate to the performance of alternative geographic filters for mobile information retrieval, and a trekking application that built on some of the time geography concepts developed in this thesis to estimate time to completion for known walking routes. The WebPark system allows the user to specify the subject and geographic component of their query separately. The subject can be specified either by selecting categories from an ontology specified by the Park managers, or by a keyword search, similar to Internet search engine. The geographic component can be specified by selecting one of three options (see Figure 29): search whole park (no geographic filter), search around me (spatial proximity surface filter), search ahead (speed-heading prediction surface filter).

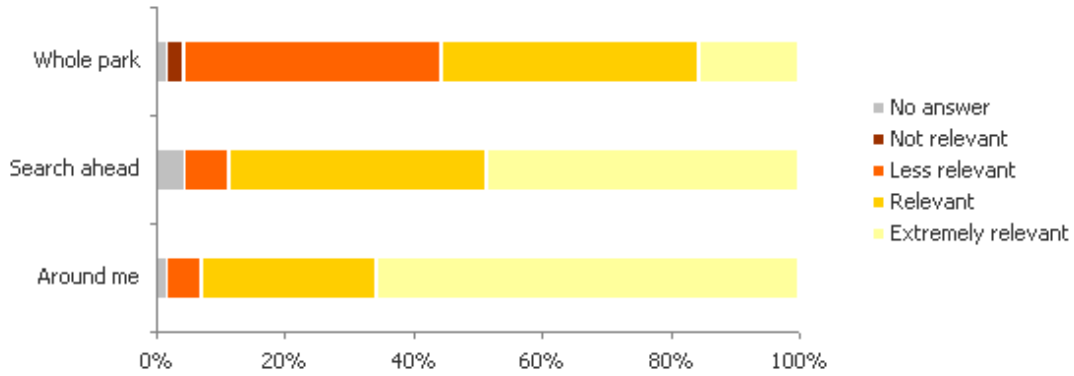
For the spatial proximity filter, the buffer size can be specified from a drop down menu. For the search ahead filter, the time to predict ahead can similarly be specified from a drop down menu (see Figure 29). This allowed users to tailor the geographic component of their filter according to their needs. The speed-heading prediction surface employed a 10 minute recent behaviour period and no temporal weighting, hence the prediction reflects the user's behaviour from the recent past. No accessibility or visibility filters were implemented as part of the WebPark system.

The feedback from users about the geographic filters can be seen in Figure 55. The search around me filter was considered to provide the most relevant information with two thirds of the respondents saying that this provided "extremely relevant" results, and over 90% claiming that results were either "extremely relevant" or "relevant". The search ahead filter also performs well, with a similar number (89%) claiming that results were either "extremely relevant" or "relevant", and half claiming that the results were "extremely relevant". The geographic filters clearly outperform the "search whole park" option, where 43% of respondents claimed that the information provided using this option was either "less relevant", or "not relevant" (Krug and Abderhalden, 2004). Considering the geographic

component of the user questions identified in the visitor shadowing study (see Appendix 1) it is unsurprising that the spatial proximity filter was considered to provide the most relevant results, since the majority of the questions referred to the user's current location for geographic context. The good performance of the "search ahead" filter suggests that this can also perform well, and that people are receptive to the idea of alternative notions of geographic context when making queries from mobile devices.

Figure 55: Relevance of results using different geographic filters

Responses to the question "How relevant did you find the results using the following search functions?", from WebPark Summer testing 2004, in the Swiss National Park. The questionnaire was completed by 87 respondents.



Visitors were also asked about further geographic filters which were not implemented in the WebPark system (see Figure 56). These were;

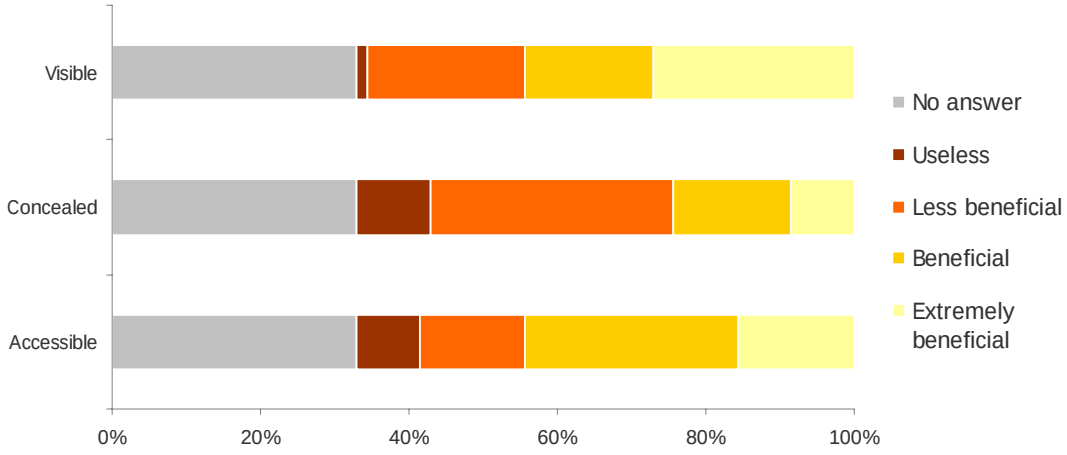
A "visible" filter: retrieving only results which are visible to the user;

A "concealed" filter: retrieving results which are close by, but concealed from view by the terrain;

A "travel time" filter: ranking results by the time taken to travel to the associated location, hence results are ranked by temporal proximity, as opposed to spatial proximity.

Figure 56: Perceived benefit of alternative geographic filters

Responses to the question "How beneficial would you find the following search options?" from WebPark Summer testing 2004, in the Swiss National Park. The questionnaire was completed by 87 respondents.



Responses suggest that the visibility filter would provide the greatest benefit to mobile users, with one quarter of respondents finding this "extremely beneficial", and 44% considering it "extremely beneficial" or "beneficial". A travel time (temporal proximity) filter is also considered to be of use, with a similar number (45%) considering this "extremely beneficial" or "beneficial", although fewer (16%) chose the top category. The concealed option is considered to be of the least benefit with only 25% considering this "extremely beneficial" or "beneficial" and one third thinking it would be "less beneficial" (Krug and Abderhalden, 2004). Interestingly one third of respondents did not answer this question, suggesting that the use of these geographic filters may still be difficult to imagine, and hence difficult to express an opinion about.

The final application relevant to this thesis which was evaluated as part of the WebPark Summer testing 2004 was the trekking application. This application plots the long profile of known walking routes, with distance along the route on the x-axis against elevation on the y-axis (see Figure 57a). Anecdotal evidence suggested that this application was extremely useful, providing an immediate visual representation of the progress through a route in terms of distance on the ground, and the elevation left to climb. Using the principles of the time geography school, the time taken to travel along the route was also calculated, making the assumption that speed along the ground would vary according to the steepness of the terrain. The first version of the application used speeds dictated by Naismith's rules (Fritz and Carver, 1999, Langmuir, 1995, Scarf, 1998). Subsequent versions used the mobile trajectories collected by previous users to data mine speed rules. As a result estimates could be provided about the time remaining for the traversal of a route, based upon previous

experience (see Figure 57b), hence this application used the same principle as the accessibility filter, however it was applied in only one dimension, distance along the route.

Figure 57: User interface for the trekking application

The trekking application was developed as part of the WebPark project, and provided information about progress along a known route in a National Park or outdoor recreational area. The application displays elevation against distance along the route (a), or the travel time along the route (b), based upon established speed rules, or previously displayed behaviour. For the travel time route profile, it can be seen that the uphill sections are more drawn out (reflecting slower ascent), and the downhill sections steeper (reflecting faster descent).

a: Distance along route vs elevation **b: Travel time vs elevation**

Figure 58: Benefit of the trekking application

Responses to the question "How beneficial did you find the Trekking Application?", from WebPark Summer testing 2004, in the Swiss National Park. The questionnaire was completed by 87 respondents.

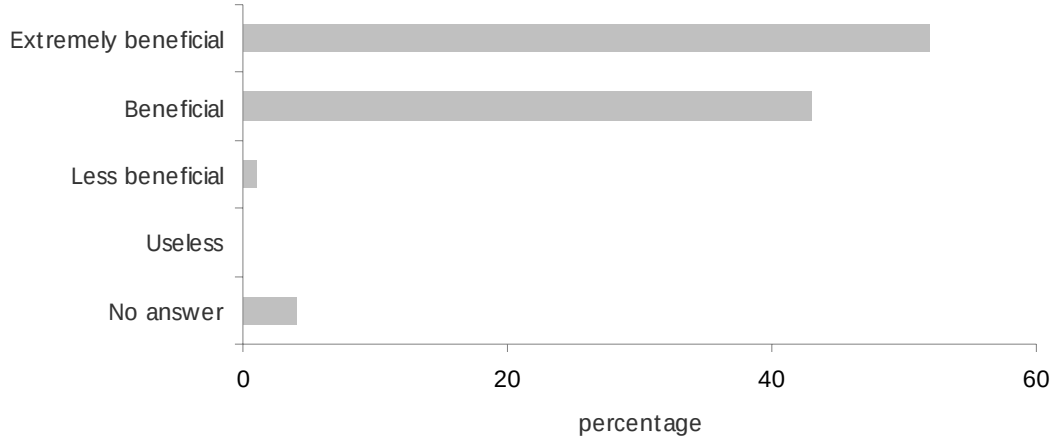
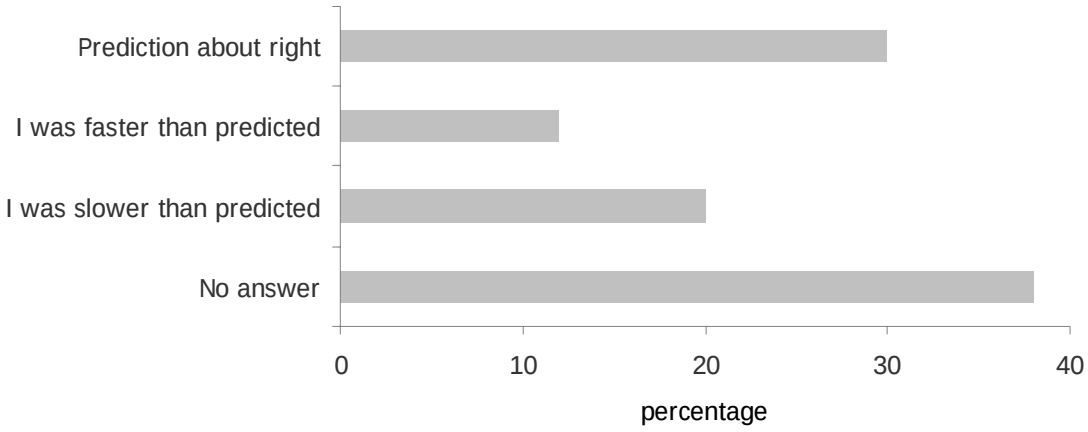


Figure 59: Accuracy of the trekking application travel time predictions

Responses to the question "How did the travel time predictions made by the Trekking Application compare to your progress?", from WebPark Summer testing 2004, in the Swiss National Park. The questionnaire was completed by 87 respondents.



Respondents were first asked how beneficial they found the trekking application (Krug and Abderhalden, 2004). 90% of respondents replied that it was either "extremely beneficial" (52%), or "beneficial" (43%), suggesting that information related to travel times and accessibility is of great importance to mobile users. As a follow-up question, users were asked how their progress compared to the travel time predictions made by the trekking application. 38% of respondents did not answer this question suggesting that they either did not use this functionality, or did not remember using it. Of the remainder, just under one third (30%) replied that the prediction was about right, one fifth (20%) replied that they were slower than

the prediction, and about one eighth (12%) said that they were faster than the prediction. This suggests that whilst there is no systematic error with the travel time predictions in this particular context, there is a need to personalise the travel times to reflect individual behaviour, since there is evidently variation in the time taken to complete walking routes. Data mining personalised speed rules is quite possible, however, it requires a large volume of data about that individual to be generated, providing examples of walking behaviour in a variety of different conditions.

5 Discussion

Discussion Abstract

This chapter commences with a discussion of *geographic context* for mobile information retrieval, and suggests that by concentrating on providing information related to the *spatial proximity* of available *services*, location-based service providers have missed an opportunity to consider the more general problem of providing generic information sources that are *geographically relevant* (based on a range of criteria) to mobile users of handheld devices. The contrast between the expected take-up of location-based services and the current reality is presented as motivation to create more sophisticated mobile information retrieval tools. The utility of four potential geographic filters, that have been introduced at various points in this thesis are then discussed: the "search around me" filter; the accessibility filter; the "search ahead" filter and the visibility filter.

Next, the effectiveness of different geographic filters as prediction surfaces is considered. The assumptions underlying the evaluation criteria are restated (that effective prediction surfaces tend to coincide with the verification point, that the surfaces are spatially constrained, and that they are consistent over a series of predictions). The characteristics of different prediction approaches are then contrasted.

Next, the utility of geoVisualization and interactive time geography for the exploration and analysis of mobile trajectories is discussed, and some insights gained from visual analysis are described.

5.1 Geographic context for mobile information retrieval

Within the field of mobile telecommunications, the focus for information retrieval on mobile devices has thus far been the emerging field of location-based services (LBS). LBS are, by definition, concerned with providing information about the services that are in some way geographically relevant to your current location: an implication of this approach is that you wish to purchase some service, be it consumables from a nearby store, or geographically relevant information from a service provider. In a taxonomy of mobile location services, Giaglis (2003) identified six broad categories of services: emergency, navigation, information, advertising, tracking and billing. The commercial aspect of the majority of these services is clear, even in the need to commodify information services, where the subclasses "travel services", "mobile yellow pages" and "infotainment services" were identified. There has been far less attention to searching for freely available information sources using the mobile Internet, or attempts to compare the similarity of the geographic footprint of free text web documents with the geographic footprint associated with a user's query. This is at odds with the experience of the "static" Internet, where search engines rank web documents according to the relevance to the user query: the emphasis here is on providing relevant *information* (which may contain information about services), hence people are accustomed to accessing information sources without the barrier of cost. In the world of mobile information retrieval, we are in danger of only providing information about this subset of information – services – and not tackling the larger problem of providing geographically relevant information from freely available web documents.

There are several possible reasons why mobile information retrieval has thus far been primarily concerned with services rather than information sources. First, it has proved easier to identify the geographic footprint of many services than information sources generally: so called "service-scopes". Many databases already exist detailing available services, with spatial information linking that service to an unambiguous location in the physical world (upmystreet.com, 2005, Yell Group, 2005a, Google, 2005). Many such databases existed in paper form for decades prior to the existence of the World Wide Web (Yell Group, 2005b), all requiring a significant investment in terms of initial creation and subsequent maintenance and curation to ensure the currency and accuracy of the information listed. Established geocoding processes (Raper et al., 1992) have allowed toponyms and addresses to be converted into spatial coordinates, creating point of interest databases allowing these resources to be processed by conventional GI Systems. Usually these services are associated with a single point location, specified by the address listed for a given service. The availability of an unambiguous point location associated with every service has made the development of location-based services much easier. The notion of geographic relevance is then based upon

spatial proximity – which could be Euclidean or network distance - between a point location defining the user query (for example a toponym or postcode), and the point location representing the location of the required services (Jones et al., 2004).

Geographic information is also found in web resources: as mentioned in the literature review (see section 2.7.2) Silva et al (2004), in a study of Portuguese resources, found references to administrative areas alone could be found with a frequency of over 2 references per document. The research conducted within the emerging field of Geographic Information Retrieval suggests that the geographic footprints associated with web resources are far more ambiguous and complex than those associated with services in point of interest databases. Web documents may refer to several, geographically distributed, toponymns, identifying the broad geographic scope that the document may refer to (Silva et al., 2004). Moreover, toponyms are rarely unique: the word "Newcastle" forms part of at least 12 toponyms in the UK alone (Ordnance Survey, 2005a). Disambiguating this plethora of spatial information to identify the geographic focus of a document is a non-trivial procedure, for which research is ongoing to find a robust solution (Amitay et al., 2004). The application of gazetteers and construction of geographic ontologies has allowed progress to be made in this area, however the complexity of the geographic footprint associated with web resources is still likely to be far more complex than those associated with the services listed in custom FOI databases.

The main reason cited for the complexity of the geographic footprints associated with web resources is that documents will frequently refer to more than one toponym in the text (Amitay et al., 2004). Where these multiple toponyms display clustering in space, this may assist in identifying the geographic focus of these resources, however when they are geographically distant, the presence of multiple toponyms becomes problematic. A further complicating factor, that has received less attention amongst the geographic information retrieval community, is that whilst gazetteers and geocoding tools can assist us in identifying the locations to which toponyms and addresses refer to in spatial coordinates, many natural features are not stored in gazetteers and hence cannot be processed in the same way. The process of identifying the geographic footprint of natural feature is more complex, since many geographic phenomena, such as mountains and forests, do not have discrete boundaries but can display the characteristics of continuous phenomena on the one hand, or there may be no true defensible consensus as to what constitutes certain geographic concepts on the other (Fisher and Wood, 1998, Fisher et al., 2004). All these factors have made the identification of the geographic footprint associated with a web document very problematic.

A further reason for the focus of services in mobile information retrieval is likely to be related to the more commercial nature of mobile telecommunications when compared to the fixed Internet. The physical infrastructure of the Internet is not owned by any one single organisation, but is a network of networks, run collaboratively by a large number of public and private organisations (Berners-Lee and Fischetti, 1999). The majority of mobile

telecommunications networks, however, are designed to run independently and are owned privately by profit making organisations (3, 2005, O2, 2005, Orange, 2005, T-Mobile, 2005, Vodafone, 2005b). These organisations have made significant investment in both the network infrastructure, and the license to build third generation networks (VisionGain, 2003). Given this context it is perhaps unsurprising that the mobile Internet, accessed via the networks of privately owned organisations, has concentrated on services that can be purchased at a price, as opposed to information that can be accessed for free.

Nevertheless, this promotion of location-based services has failed to see the take-up anticipated when they were first proclaimed as the "killer app" of the mobile Internet (Berg Insight AB, 2005). Various reasons have been suggested as to why these services have failed to perform as expected, including slow and imprecise positioning technology, and lack of processing power and functionality in client handsets, however the primary reason for the slow take up identified in a market report by Berg Insight AB (2005) was:

"... the services offered up until today have simply been too slow and complicated to use." (Berg Insight AB, 2005)

Unlike desktop users, who can devote their full attention to a task with limited external distraction, mobile usage tends to take place in an environment where the cognitive load on the user from external sources is higher: rather than a blank wall behind their screen there is a dynamic world, within which they are moving and interacting. Research by Palm (Ostrem, 2002) has suggested distinct differences in usage behaviour between desktop and handheld computing, with handheld usage being characterised by multiple, short sessions, as opposed, to the few, long sessions displayed in desktop usage. This suggests that mobile users may be more in need of filters to ensure the relevance of the information that they receive, than their static counterparts, since they have neither the time, nor the same level of attention, to manually refine information searches themselves, in the way that users accessing the Internet over static desktop devices have become accustomed to. A variety of geographic filters, deployed in different situations, may assist in increasing the relevance of retrieved information, and may possibly lead to the anticipated take-up of mobile information retrieval and mobile location services.

In order to retrieve geographically relevant information, relevance ranking based upon the similarity of the geographic footprints of Internet resources (or services), and the geographic footprint associated with a user's query must occur. Users of static machines, with mouse interfaces and keyboard interfaces may define the spatial extent of their query in a number of ways, for example clicking on a map (Jones et al., 2002), or typing a toponym or postcode (Yell Group, 2005a). Alternatively, a linear feature, such as a road or river, could be selected from a map – or "heads-up" digitised manually - and used as the geographic footprint of a query. Finally an areal geographic footprint may be defined, either by specifying a spatial

extent on a map (Google, 2005) , or by entering a toponym associated with an areal feature (such as “Greater London”, or “England”). Whilst these options are also available to mobile users, as this thesis has suggested, there may be more automated and intuitive ways of identifying the geographic extent of their query.

5.1.1 The “Search around me” filter

This is the current paradigm in LBS, where results are ranked according their distance from the user’s current location. This is a reasonably unsophisticated filter that may not take account of network distances, speed of travel, or the spatial behaviour of the individual making the query. Some services allow users to vary to spatial extent of their query by changing the buffer size (WebPark, 2005)

One usage scenario that is not currently handled is spatial proximity alerts for Internet resources. A historian, on their day-to-day movements about their home town of London, may wish to be alerted to resources related to the Great Plague, as they pass the locations associated with those resources. This requires a dedicated agent working in the background, searching for resources linked to an individual’s declared interests, filtering those results by spatial proximity filter (Mountain et al., 2003), and providing an alert when a resource is identified as being relevant on the subject and situational level (Saracevic, 1996a). Such a system is likely to require a great deal of tuning, to ensure that it provides novel information, and that the frequency of information is not too overwhelming on one hand, or too infrequent on the other. Push services based upon agent technology such as these could offer one novel approach to accessing resources on the mobile Internet, however the spatial proximity filter described here is only one of the potential geographic filters that could be applied to increase the relevance of retrieved information.

5.1.2 The accessibility filter

Whilst the current paradigm of LBS has been proximity in space, we have also considered the case of proximity in terms of travel time. This is sensitive to that fact that accessibility is rarely homogenous in all directions; transportation networks, and physical and administrative barriers, result in a complex geographic footprint for the region of space that is accessible within 20 minutes. In addition certain regions may be restricted due to authority constraints (Hagerstrand, 1973), either at specific times or permanently, and these regions could be masked out. This could include private property, live firing ranges in outdoor recreational areas (Dartmoor National Park Authority, 2005), or public access land closed temporarily under a temporary prohibition order from the land owner (1999).

An example of a query using a temporal proximity filter that is currently unsatisfied using existing search engines might be a parent, searching for child care services within 20 minutes

drive of their home. Such a query requires the geographic location associated with web documents to be known, and an algorithm to calculate the region of space accessible to a person, within 20 minutes from a given location. Queries such as these are likely to be of use to users of both the static and mobile Internet.

5.1.3 The "Search ahead" filter

A problem that has been identified with the spatial proximity "search around me" filters is that for fast moving mobile users, by the time the results have been received, they are no longer relevant since the user has moved on. Even at slow speeds, users may wish to receive information that will be relevant for a longer period of time than the immediate future. One can imagine at least two scenarios: providing information relevant to where the user will be at an instant in the future (for example a passenger in a car searching for places to stop and eat in one hour's time) and results relevant to an interval in time (in the same scenario, searching for the restaurants they are likely to pass in the next hour).

One scenario of use can be drawn from the WebPark project (Krug et al., 2003). A visitor to a National Park may be interested in finding the areas where wild orchids are likely to found over the course of the next hour of their walk. Such a query requires some prediction algorithm, to calculate the region of space they are likely to pass during the next hour, and an approach to defining the geographic footprint associated with the distribution of wild orchids. In the WebPark project a search ahead algorithm was implemented that allowed the user to search for results that were ahead of them, and allowed them to specify the cut-off time period for the prediction. A species application modelled the distribution of different animal and plant species, based upon elevation and land cover, defining the geographic footprint associated with each species depending upon their habitat preferences (WebPark, 2005). The combination of these components has allowed such queries to be satisfied for visitors to the Swiss National Park.

5.1.4 The visibility filter

The final suggested geographic filter is based upon the region visible to an individual, and can be calculated knowing an individual's location (and ideally height) with a Digital Elevation Model in a GI System. Testing in the Swiss National Park has suggested that mobile users tend to be more engaged in the world around them than static users, and more inspired by the things they see. In a region of extreme terrain, an individual may be motivated to find out more about a distinctive distant peak that is omnipresent on the skyline, and less interested in the closer landforms that are hidden by foreshortening.

In a scenario that combines a visibility filter with newswire resources, an individual may witness an established fire in a factory from a distance, and wish to search for any up-to-date

news reports that may have already covered this story. This requires a viewshed to be calculated to refine the search to the region that the user can see, and the geographic footprint associated with the newswire documents to be extracted, stored and indexed in a scalable way, to allow relevance ranking to occur on the basis of the query and documents' footprints.

5.1.5 Combining filters

Beyond the individual application of these filters, there is the possibility of combining them together, or with external sources of information, to generate yet more sophisticated filters. For example, an accessibility filter could be combined with a "search ahead" filter to produce a surface that represented the locations that were both accessible, and likely to be visited. External sources of information could include network and land-use to model constraints. A Boolean mask of private land could be used to exclude areas that are known to be inaccessible. Similarly, network-based routing algorithms, such as the Djikstra shortest path algorithm, could be combined with these filters as a means of combining the deterministic network-based routing with more personalised information related to the previous behaviour of an individual or individuals.

5.1.6 *Mobile* information retrieval based upon historical *spatial* data

One alternative use of positional data not discussed at length in this thesis is to analyse historical records of *spatial* behaviour to evaluate how information provision itself influenced user behaviour, and possibly use this information in 'page ranking' algorithms. There is a clear parallel here with the patent filed by Google Inc - *Information retrieval based on historical data* - (Acharya et al., 2003), where the length of time a user visits a particular page, following a search on the fixed Internet, can be used to assess the relevance of that page, with one interpretation being that information seekers will dwell for longer on more relevant results.

In mobile information retrieval, each result has a spatial footprint associated with it. Following a search for mobile information, the user's location can be tracked to see which, if any, of the suggested results were visited and how long was spent at that location, and whether they subsequently visited further results from the list (Briggs, 2006). This information could then be used to influence the 'rank' of the information sources associated with those locations. Just as with the fixed Internet case, care must be taken when interpreting results. In the fixed Internet, a short dwell time does not necessarily imply a less relevant site – on the contrary it could indicate a well organised page that allows an information seeker to resolve their anomalous state of knowledge quickly. Similarly, a very

relevant feature in the physical world may not be visited for a long duration, but may provide an individual with the service or information that they require: an opportunity to buy a product, a place to park a car, or a successful rendezvous at an agreed location are all examples where relevant information was provided but an individual need not dwell for long at the location associated with that information source. Similarly, subsequently visiting other locations on a list does not imply that the information source associated with previously visited locations is less relevant or previous information sources failed in themselves to resolve an anomalous state of knowledge. There is clear opportunity for further research in this area.

5.2 Geographic filters for prediction

Given the potential for geographic filters for mobile information retrieval, the geographic filters implemented as part of this study will now be reassessed. A stated objective of this thesis is to implement a geographic filter that ranks information by the likelihood of an individual going to the location associated with that information. An interesting counterpoint to this approach is that relevant information could itself be the motivation to change your spatial behaviour. For example, discovering that a site of great interest to you is located along a path that doubles back on your current heading, may be the motivation to take that path. The geographic context of an individual is complex, dynamic, and inherently uncertain. This thesis has attempted to widen the scope of what is considered to be “spatially relevant”, and tailor this context based upon personal spatial behaviour. Three geographic filters have been developed as part of this thesis (spatial proximity, temporal proximity, speed-heading prediction) and all have been tested for their ability to predict the future location of moving point objects. In the following sections, the evaluation criteria used to describe the characteristics and effectiveness of the prediction surfaces will be assessed. Next each filter will be discussed in turn, to see how well it met its objectives, and how it could be used for mobile information retrieval.

5.2.1 Prediction Evaluation criteria

The prediction surfaces evaluation criteria were based upon three key assumptions about effective prediction surfaces:

1. Effective prediction surfaces coincide with the actual destination at the predicted time; where a surface has internal variation, the destination point coincides with high values;
2. Effective prediction surfaces are spatially constrained;
3. Effective prediction surfaces are consistent when making a series of predictions

Based upon these assumptions, four criteria were defined that could describe the characteristics of the approaches to prediction in different situations. The aim of these criteria was to be able to describe the characteristics of different approaches to prediction, in a range of situations, and to allow direct comparison of the effectiveness of these different approaches in a clear and unbiased manner. Of the four criteria, three were predominantly descriptive, attempting to assess how changes in input parameters influenced the character of the resulting surface. Only one of the criteria – prediction surface effectiveness – was used to compare the effectiveness of different approaches.

Median prediction surface effectiveness

Prediction surface effectiveness (PSE) is defined by verification value divided by surface area, and used to compare the performance of any two prediction surfaces in the same situation. Median PSE was used to compare the performance of a particular approach in a particular situation, measured over a series of predictions. Using the median prediction surface effectiveness reduced the influence of the small number of surfaces with extreme scores, which could skew results to give high *mean* verification values for inconsistent approaches.

Another limitation to using the median value for Boolean surfaces, is that there is the sudden jump in the median verification value, and hence also the PSE, as described above. When using this measure with Boolean surfaces, it is wise to also consider the success rate, to distinguish those approaches which are reasonably consistent (eg 51% success rate) from those which are very consistent (eg success rate = 100%).

5.2.2 Spatial proximity

This thesis has considered only Euclidean distance, but network distance can also be used rank information on the basis of proximity. Spatial proximity was included primarily as a control as a prediction surface: it operates on the assumption your current future location will be correlated to your current location, which can reduce search spaces down from the global to the local. The most effective surfaces tended to be those with either no spatial decay (see Table 10), or slow decay functions. This is unsurprising since all tests were conducted in scenarios in which the point object was moving, hence a peak in values at the current location - associated with fast decay functions - is less likely to coincide with the location of the object in the future. Offset linear spatial proximity functions were developed specifically to account for anticipated movement from the current location. These offset spatial proximity surfaces tended to perform better than fast decaying functions, but not as well as those with no decay.

Spatial proximity surfaces performed much better when highly sinuous behaviour was displayed - relative to speed-heading predictions - than when continuous movement in a

particular direction was displayed. In the absence of any other information, proximity in space to the last known position is a reasonably effective approach to predicting future location, however an appropriately sized cut-off distance should be selected. Such a distance could be calculated from current speed, but in an absence of this information and choosing arbitrary buffer distance, the prediction surface is likely to be either much too big (eg for slow moving objects) incorporating a great deal of space that is unlikely to be visited, or much too small (eg for fast moving objects), and unlikely to coincide with the actual destination. There is also no way to prevent the selection of inaccessible and invisible information resources with this filter, and thus it should best be used with filters to exclude results with subfilters.

5.2.3 Temporal Proximity

Temporal proximity prediction surfaces built directly upon the principles of time geography, and the potential path area, dictating the region accessible given time restrictions. Increasing the time budget increases the region of space available to an individual. The most effective temporal proximity prediction surfaces used a time budget slightly longer than the prediction period. A buffer around the space-time paths that comprise the potential path area was found to be a more effective way of defining the surface than a convex hull, which was more likely to include previously unvisited space. This approach defined accessibility corridors, based upon previous experience, and was found to be the most effective approach to predicting future location for the “daily migration” scenario in which it was tested.

Of the measures of temporal proximity developed and described in section 3.4.2, only the potential path area was used to define temporal proximity; these define the region of space accessible within a specified time budget, but provide no indication about which is the more accessible of two locations within the surface boundary. Using isochrone surfaces and graded accessibility surfaces provides variation within the surface, giving an indication of the degree of separation in time. This could be a fruitful area for future research. Isochrone surfaces can be used to create space-time prisms (Forer, 1998, Lenntorp, 1978, Miller, 1991, Mountain et al., 2003) that are based upon previous experience, rather than simplistic assumptions about movement.

In this thesis, when defining the region accessible to an individual in a given time budget, this was always based upon the previous behaviour of that same individual. Forer (1998) argued that many of the constraints (such as economic or mobility) experienced by individuals are in fact generic and can be applied to others. By contrast the original principles of Hagerstrand (1973) considered the movements of individuals and made conclusions form these. Forer suggested that the anonymous approach is the correct one since it retains individual privacy. There is the opportunity to data mine the behaviour of many individuals, to define the region of space accessible in new locations, or using routes that are unvisited by this individual. Recent technological developments, such as the

convergence of positioning and mobile telephony technologies (Camara, 2003, Goker et al., 2004, Pinpoint Faraday, 2005, Swedberg, 1999) allow mobile trajectories to be gathered on a large scale, and this data could be used to define temporal proximity surfaces (Ratti et al., 2005) based upon such aggregate behaviour.

Given larger volumes of data, there will be an increased need to classify the spatial behaviour into different categories (Blythe et al., 1999, Laube, 2001). Temporal proximity surfaces could be defined for different types of transport (eg walking, private car, public bus); an individual's current behaviour, or transport preferences, could then be matched to these classes. As described in section 4.4, work has already been undertaken in developed personalised speed rules based upon previous experience. This could be extended to develop personalised accessibility networks, based upon transportation preferences, where travel times are mined from the aggregate behaviour of large numbers of users. Transportation networks tend to display diurnal variation in congestion and speed of movement that is to some degree predictable. Temporal proximity surfaces could be developed, based upon aggregate behaviour, that model accessibility at different times of day, days of the week, or for specific events such as sunny bank holidays, or a football match (Ratti et al., 2005). The aggregate behaviour of large numbers of individuals is also likely to be of interest to urban planners, who could use information about the numbers of people moving at different times, and the speed of movement, when planning transportation networks and services (Ratti et al., 2005). Thus there is the opportunity to filter information based upon personal experience, the aggregate experience of all other users, or the experience of others who display similar patterns of spatial behaviour.

5.2.4 Speed-heading predictions

Speed-heading predictions were found to be most effective in situations where movement was reasonably consistent in terms of speed and heading, such as journeys where the intention is to travel between two locations by the shortest route, as displayed in the driving and daily migration scenarios. They performed less well for highly sinuous behaviour, such as the walking scenario. There is a compromise in specifying a recent behaviour period, between including too much "irrelevant" behaviour from the distant past, and including sufficient variation to account for the individual's unpredictable future behaviour. It was found that relatively long periods of recent behaviour, with relatively fast decay functions, were most effective in predicting future location. This appears to offer a compromise between using appropriate mean values for speed and heading, and ensuring that there is also sufficient variation displayed.

Predictions may be improved by identifying breakpoints in the mobile trajectory associated with changes in spatial behaviour, for example getting off a train and onto a bus, or getting into a car following a walk. One hypothesis that could be tested in the future is that a more

effective prediction may be achieved if only the behaviour after the last breakpoint is considered. There is inherent uncertainty when making predictions, and this may be best represented through the inclusion of a noise component to the prediction, to avoid situations where very uniform previous behaviour leads to very precise predictions. Kalman filters discussed in section 2.4 use a noise and prediction component, and vary the influence of noise depending upon feedback from previous predictions (Elnagar, 2001, Vasquez and Fraichard, 2004). Kalman filters have mostly been applied for prediction periods of a few seconds (Vasquez and Fraichard, 2004), however some studies have attempted to use them to predict the future location of moving objects in the longer-term future (Li, 2002). Such an adaptive approach, that could systematically assess which configurations have been most effective in the past, could be useful for defining which parameters to apply for subsequent predictions.

Finally this approach has predicted likely future locations based upon speed and heading: the distribution of turning angles is not considered in the prediction. Future work could include modelling spatial behaviour using speed and turning angles. This could be applied to the task of classifying spatial behaviour (Blythe et al., 1999), identifying breakpoints in the mobile trajectory, and uncovering relationships between the spatial interactions of two or more entities (Laube and Purves, 2005).

5.3 GeoVisualization and Interactive Time Geography

Forer (1998) identified two key research questions relevant to time geography: what approaches, that have been previously constrained by technology, look likely to yield suitable results, and what existing models of space-time may be suitable for implementing the concepts developed by time geography. When time geography first emerged, researchers were more limited in terms of the data and computing resources available. In an attempt to reassess how these concepts could be applied to real data as part of this thesis, first mobile trajectories were collected at a fine spatio-temporal resolution, describing the spatial behaviour of several individuals, over a prolonged period of time, and in a variety of representative situations. Next, the time geography concepts were implemented in an interactive environment, the spatial history explorer, which allows space-time paths and potential path areas to be extracted, that are based on the previous behaviour of mobile individuals. This development was necessary due to the poor handling of the temporal dimensions within existing GI Systems (Peuquet, 1999). Analysis of mobile trajectories within this environment has led to considerable insight into individual patterns of movement. These insights include:

- Individuals tend to display very repetitive motion patterns, that recur on a variety of temporal scales;

- Future behaviour is to some degree predictable, based upon short-term and long-term previous behaviour;
- For the datasets collected, distinct classes of behaviour can be discerned, that reflect alternative transport preferences and tasks.

These insights led directly to the development of speed-heading prediction and accessibility filters described in this thesis.

Applying a traditional spatial approach to modelling movement, Forer (1998) has suggested that distance and travel time are interchangeable entities with travel time often being a more relevant parameter for modelling human behaviour. By creating potential path areas base in an interactive environment, the notion of a temporal proximity (eg within 5 mins) could be contrasted to spatial proximity (eg within 500 metres). This approach has allowed comparison between the spatial behaviour of different individuals, and the complex temporal characteristics of temporal proximity which arise as a result of predictable events. Whilst the distance in space between two locations is a fixed variable, travel time is dynamic, changing on a range of temporal scales from the short (e.g. daily rush hours) to longer periods of time (e.g. evolution of the transportation infrastructure).
There is much further research that could be conducted in the area. As mentioned in section 5.2.3, aggregate analysis could yield information that would be extremely useful to those planning public services such as transportation networks, and used as the geographic context for mobile information retrieval. Furthermore most researchers have considered the space-time prism as a Binary region with an infinitely sharp boundary dividing the accessible and inaccessible. The more realistic case of a graded boundary between the two would add another level of complexity to the derivation of the spaces and has not been attempted to date. Isochrone surfaces and accessibility surfaces described in section 4.2.3 demonstrate how internal variation could be included into the time geography concepts, to describe not only whether a location was accessible within a given time budget, but how long it would take to get there.

6. Conclusions

Conclusions Abstract

This section first restates the original aims and objectives, and assesses the degree to which they have been satisfied. Following this, the main findings of this research are presented.

6.1 Research aims

One of the broad aims of this thesis has been to consider new approaches to understanding the individual spatial behaviour of people. This has been approached from the perspective of geoVisualization, and in particular by bringing some of the ideas of the time geography school to an interactive environment. The next overriding aim has been to consider ways of making the information retrieved in a mobile environment more relevant to the *geographic context* of the individual making that query. This has been approached from the perspective of various *geographic filters* that operate on different assumptions, for example that relevant information will be that which is closest in space, the most accessible, related to the locations which an individual is most likely to coincide with in the future, or that which is visible. The final overriding aim of the thesis was a formal evaluation strategy which took into account both quantitative testing of prediction surfaces, and the reaction of users of a mobile information retrieval system which implemented some of the ideas developed as part of this research.

6.2 Revisiting specific objectives

Given the broad aims and the approaches adopted in tackling them as described above, the full list of stated objectives from section 1.2 will be revisited to assess the degree to which each objective has been satisfied.

1. **The collection of a library of mobile trajectories, displaying representative behaviour for several individuals, collected over a prolonged period of time;**

This objective has been satisfied by the data collection process described in the methodology, section 3.1. Three individuals carried global positioning units recording their spatial behaviour over periods of up to one year. This has provided a rich data set for exploration, analysis and testing, upon which many of the remaining objectives have been dependent.

2. **The development of new geoVisualization tools for the exploration of the spatial, temporal and attribute components of those mobile trajectories;**

The interactive geoVisualization application, the spatial history explorer (SHE), has been developed specifically to meet this objective (Mountain, 2005b). As described in detail in section 3.2, this tool allows the visual exploration of mobile trajectories, and aims to promote abductive reasoning (Gahegan, 2001), where hypotheses are formulated as a result of

exploration of the data. The restrictive "map view" associated with atemporal GI Systems (see section 2.1.2) is rigorously avoided, with equal emphasis placed on the spatial, temporal and attribute components of mobile trajectories. The development of this software has been a major deliverable in this research, as evidenced by the associated publications in the academic domain (Mountain and Raper, 2001c, Mountain and Raper, 2001a, Mountain and Dykes, 2002, Mountain et al., 2003, Dykes and Mountain, 2003, Mountain, 2005b, Andrienko et al., 2005).

3. **The implementation of *time geography* concepts in this interactive geoVisualization environment;**

The spatial history explorer (SHE) application implements various time geography concepts as described in sections 3.2 and 3.4.2. First, space-time paths (Hagerstrand, 1973) can be extracted from a parent mobile trajectory and this path plotted against spatial, temporal and attribute dimensions (Dykes and Mountain, 2003). Next, the concept of the potential path area is extended - beyond the simplifying assumption of ease of movement in all directions associated with the homogenous surface - to generate potential path areas based upon previously exhibited individual spatial behaviour. Further extensions to the time geography approach include isochrones surfaces (Laurini and Thompson, 1992b), a series of potential path areas with varying time budgets, which generate a surface representing travel time from a particular location, and the accessibility surface, a field-based approach to time geography, with similarities to Forer (1998).

4. **The development of tools and algorithms that extract - from mobile trajectories - representations of the *geographic context* of an individual: for example, the region of space that is spatially close, accessible, or likely to be visited in the future based upon previous displayed behaviour;**

This objective has been thoroughly investigated in various sections (see sections 3.4, 3.6, 4.3 and 5.1) through the development of geographic filters that attempt to encapsulate the geographic context of an individual at some point in time based upon various assumptions. This approach, described in detail in this thesis, has aroused interest in both the academic and commercial domains. First, the concept has been presented to an academic audience at conferences (Mountain et al., 2003) and to a technical audience via industry journals (Krug et al., 2003). The "search ahead" algorithm was implemented in a functioning mobile information system, which has since launched as a commercial entity (see objective 6 below).

5. **The development of evaluation criteria for surfaces predicting the future location of moving entities, and the use of these criteria to compare the**

characteristics and effectiveness of different approaches in a variety of situations;

The development of evaluation criteria for prediction surfaces is discussed at length in section 3.5, and results based upon these criteria are described and analysed in sections 4.2 and 4.3. These criteria have allowed different approaches to prediction to be described and compared, and the effectiveness of different approaches evaluated.

6. **The implementation of a geographic filter that ranks information by the likelihood of an individual's future path coinciding with the geographic footprint associated with that information, and test this filter in a location-based service with users of that service;**

The "search ahead" algorithm, a prediction surface based upon recent exhibited speed and heading (see sections 3.4.3, 4.2.1 and 5.1.3) has been developed by the author as part of this research, implemented in the WebPark mobile information retrieval system (WebPark, 2005) and subsequently evaluated in a large-scale user study during the Summer of 2004. Beyond the initial satisfaction of this objective, there has also been interest from the commercial sector in this new approach to searching for information whilst on the move. As described in section 3.3.1, in 2005, the Intellectual Property Rights of the java code associated with the search ahead algorithm were transferred from City University to a commercial spin-off company – Camineo (2005). The algorithm is now being deployed on location-based services across Europe, the first of which was a commercial service for visitors to the Swiss National Park. The implementation of this algorithm, and its transfer to the commercial sector, can be seen as another major deliverable of this thesis.

7. **To contrast the mobile and "desktop" Internet, and to get feedback from potential users of the mobile Internet about their information needs.**

The information needs of mobile individuals were surveyed as part of the WebPark project and are discussed in section 3.3. The implemented mobile information retrieval system was tested extensively with end users and the results are discussed and analysed by the author in section 4.4.

6.2 Main findings

The main findings of this thesis are both qualitative and quantitative, and span a range of disciplines; the research is likely to be of particular interest within the emerging field of location-based services and also mobile computing, mobile human computer interaction and the established discipline of information retrieval. The first main finding is the notion that there are distinct classes of *geographic context* associated with the information needs of

mobile individuals. This thesis has built upon this idea and suggests that this context can be encapsulated by geographic filters, which can then be used to rank georeferenced information. Four such geographic filters are proposed: the "search around me" filter; the accessibility filter; the "search ahead" filter and the visibility filter.

The effectiveness of different geographic filters as prediction surfaces has been evaluated. This first required an investigation into, and subsequent definition of, a range of both descriptive and evaluative criteria, based upon three central assumptions: that effective prediction surfaces tend to coincide with the location of a moving point object at the predicted time; that the surfaces are spatially constrained; and that they are consistent over a series of predictions. These evaluation criteria have been used to test different approaches to prediction in different scenarios, using alternative configurations by systematically varying input parameters to predictions. The main findings in this area are listed below.

- Predictions based upon spatial proximity reduce the size of a prediction from the global to the local, but take no detailed account of the behaviour of the user, although varying the radius of the spatial proximity buffer, perhaps to reflect recently displayed speed, can dramatically improve results. The most effective surfaces tended to employ either slow distance decay functions, or no decay function at all, and perform best in situations where highly sinuous behaviour is observed (such as walking).
- Predictions based upon temporal proximity build upon the principles of time geography and require a long-term history of previous spatial behaviour to be known. This approach encapsulates the region of space accessible by an individual, for a given time budget, based upon the locations that have previously been shown to be accessible from that location given the available time. An approach which encapsulates previously visited locations using a *buffer* around paths was found to be more effective than a *convex hull* around all visited locations, which tended to enclose a greater proportion of unvisited, and hence possibly inaccessible, space. This approach was found to be most effective when predicting the location of individuals based upon their own long-term previously exhibited behaviour in a region.
- Predictions based upon *recently* exhibited speed and heading were found to be most effective in situations where movement was reasonably consistent. When predicting into the future, a dilemma is faced about how far into the past it is necessary to look in order to preserve a high degree of diversity within the set, but not include behaviour from the more distant past which is no longer indicative of current or likely future behaviour. Using relatively long periods of recent behaviour, but applying fast temporal decay functions (so recent behaviour has a greater influence over the prediction than spatial behaviour in the more distant past) was found to be an effective strategy.

The comparison between filters showed that the temporal proximity approach (using a long-term record of previous behaviour) was the most effective overall, followed by speed-heading

predictions (using a short-term record), followed by spatial proximity predictions (using no record of previous behaviour). This result suggests that more effective predictions can be generated by looking further into the past to analyse a larger dataset, which would be a validation of the inductive approach.

In testing the "search ahead" filter with visitors to the Swiss National Park as part of an extensive user evaluation study, it was found to perform well when compared to the default filters, but was not favoured over the more familiar "search around me" filter. Nevertheless the study suggests that users are receptive to the idea of alternative geographic filters for mobile information retrieval. More general testing in the user evaluation study corroborates this general principle, suggesting that mobile users benefit from accessing *personalised* geographic information with a *spatial* and *temporal* component.

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Glossary

The descriptions in this glossary are the author's own unless otherwise stated.

2G: Second generation mobile telecommunication systems. These were the first digital cellular networks introduced in the late 1980s, designed primarily for the exchange of voice data, and characterised by low bandwidths (IMT-2000, 2005).

2.5G: So called two and half generation mobile telecommunication systems – such as General Packet Radio Service - the successor to 2G networks with increased data transfer speeds of over 50kbps (IMT-2000, 2005)

3G: Third generation mobile telecommunication systems, launched in the early 2000s, and characterised by high bandwidths of over 300kbps, comparable with a high speed connection to the fixed Internet (IMT-2000, 2005).

Accessibility filter: A specific type of *geographic filter* that can eliminate, rank or provide a relevance score for information sources on the basis of the time taken to reach those sources from a specific location. Such a filter can be based upon a *temporal proximity surface*.

Brushing: An interactive visualization term where dragging a cursor on a screen to define a region leads to all objects within that region changing their visual characteristics in some way, for example, highlighting those objects (Becker et al., 1987). In applications with linked views, brushing in one view may highlight the same objects in associated views.

Feature of Interest: some entity with a definable *geographic footprint*. It is a more generic term for a point of interest, without the restriction that the entity must adopt a point representation.

FOI: see *feature of interest*.

Geographic context: In this thesis, some encapsulation of the region of space and time that is in some way relevant to an individual. See *geographic relevance* and *geographic filter*.

Geographic filter: A procedure for eliminating, ranking or sorting information retrieved as the result of a user query, on the basis of some geographic criterion, for example, spatial proximity, accessibility, features that lie ahead, or those that are visible.

Geographic footprint: An encapsulation of the geographic extent (in space and additionally in time) of some particular feature (Goodchild, 1997).

Geographic relevance: A measure of the degree to which information is relevant to an individual given well defined spatial *and* temporal metrics. For example services that are close in space and available now may be considered more geographically relevant than those that are spatially distant and unavailable.

Geographic relevance score: Value that communicates the degree to which some information source is geographically relevant, according to some criteria. In the context of this thesis, this score can be calculated on the basis of *spatial proximity*, *temporal proximity*, likelihood of being at a future location (*search ahead*) or *visibility*. See *Geographic relevance*.

GIS: This can refer to either *GI Systems* or *GI Science* depending upon context. To avoid confusion, in this thesis either one of these terms will be used rather than the potentially confusing "GIS" acronym.

GI Sci/Science: Geographic (or Geographical) Information Science: The scientific discipline concerned with research on the generic issues that surround the use of *Geographic Information* (from Clarke 1997).

GI Systems: Geographic (or Geographical) Information Systems: Software systems designed for handling *Geographic Information*.

GNSS: Global Navigation Satellite System.

GPS: The Global Positioning System, currently the most widely used example of a *GNSS*.

Inverse heading spread function: A value that can act as proxy for the sinuosity index. As the name suggests, it is inversely related to the *spread* parameter.

LBS: See Location-based services

Location-based services (LBS): "the delivery of data and information services where the content of those services are tailored to the current or some projected location of the user", from (Brimicombe and Li, 2004)

Mobile trajectory: Also known as a 'space-time path' within time geography, this is some representation of the movement of some mobile entity through space over time. It can be represented as a series of time-stamped point locations from which further motion attributes such as speed, heading and acceleration can be derived.

Mobile trajectory testing set: In the context of this thesis, a relatively short *mobile trajectory* that is used to generate predictions of the likely future locations of a moving point object. This testing set is typically extracted from larger *parent mobile trajectory*.

Parent mobile trajectory: In the context of this thesis, a more complete mobile trajectory, describing the spatial behaviour of an individual over a relatively long period of time. From this parent set, *mobile trajectory testing sets* may be extracted. The *parent set* will often be used to provide *verification points*, with which to evaluate the effectiveness of predictions made based upon the *testing set*.

Parent set: See *parent mobile trajectory*.

Potential path area: The set of spatial locations accessible to an individual within a given *time budget*. The defining work in time geography often modelled the potential path area as a circle or ellipse (Lenntorp, 1976).

PPA: See *potential path area*.

Prediction origin: In the context of this thesis, the spatial location – represented as a two- or three-dimensional point - of a moving point object at the point at which a prediction of likely future locations is made for that object.

Prediction surface: A continuous surface of some kind (for example a raster grid, surface based upon a function or isoline) whose values provide an estimation of the likelihood of a moving point object visiting the locations on that surface at some predicted time in the future.

Prediction surface effectiveness: A measure developed as part of this thesis which describes the effectiveness and consistency of a prediction approach. It is defined as the *verification value* divided by the surface area of the prediction surface. This value can be used to compare the effectiveness of different approaches.

Previous behaviour: In the context of this thesis, this refers to the motion patterns of one or more individuals that can be represented as a *mobile trajectory*.

Recent behaviour: The most recent period of *previous behaviour*. In the context of this thesis it refers to one or more *mobile trajectories*, from some previous point in time until the present.

Search ahead filter: A specific type of *geographic filter*, proposed in this thesis, which sorts information on the basis of how likely it is that a moving individual will coincide with the geographic footprint associated with that information, at some defined point in the future. An implementation of this filter was based upon a speed-heading prediction surface.

Search around me filter: A specific type of *geographic filter* can sort georeferneced information on the basis of spatial proximity to an individual.

SHE: See *spatial history explorer*

Space-time: In time geography, the framework of two or three spatial dimensions and a single temporal dimension within which individual accessibility can be modelled.

Space-time path: See mobile trajectory. This thesis has adopted the convention of using the phrase 'space-time path' to refer to temporally bounded subsets of a moving point object's entire duration. A full mobile trajectory may describe the behaviour of some moving point object from birth to death; a space-time path extracted from this parent set may describe behaviour on a single day.

Space-time prism: The region of *space-time* within which an individual is constrained. Constraints fall into three categories (Hagerstrand, 1973). The concept of the space-time prism is from time geography.

Spatial history explorer: Software application developed as part of this research for the interactive visual analysis of mobile trajectories.

Spatial proximity prediction surface: A specific type of *prediction surface* for a moving point object, based upon the spatial proximity from the known location of that point object.

Spatial relevance: A measure of the degree to which information is relevant to an individual given well defined spatial metrics. For example services that are close in space may be considered more geographically relevant than those that are spatially distant (see *geographic relevance*).

Speed-heading prediction: A (point) prediction of the future location of a moving point object, given the recently exhibited spatial behaviour of that object.

Speed-heading prediction surfaces: A specific type of *prediction surface* for a moving point object, based upon a point density surface generated from a series of *speed-heading predictions* based upon the recent exhibited behaviour of that point object.

Spread: A measure of the deviation of circular data. A value of 0 suggest a very clustered data set, a value of 1 represents an evenly distributed circular distribution (Brunsdon and Charlton, 2003).

Success rate: Describes the effectiveness of predictions, forecasts, and systems generally (Vasquez and Fraichard, 2004), for a series of predictions, given by the ratio of successes to total attempts made.

Temporal proximity prediction surfaces: A specific type of *prediction surface* for a moving point object, based upon the accessibility of locations from the known location of that point object.

Testing set: See *mobile trajectory testing set*

Time budget: The amount of time that an individual has available to perform some activity. This is a constraint in *time geography*, and given this time budget and a spatial origin, a potential path area can be calculated by mapping the temporal constraints in the spatial dimension.

Time geography: The field of geography, developed in the second half of the twentieth century concerned with modelling the accessibility of individuals using a *space-time* framework .

Verification point: The point in a mobile trajectory that represents the actual location of a moving point object at a predicted time (see *verification value*).

Verification value: The value of a *prediction surface* at the point of coincidence with a *verification point*. It is used in evaluation criteria that aim to assess the performance of a particular prediction, or an approach to prediction. The value reports whether or not the point coincided with a *prediction surface*, and if so whether it coincided with high values on the surface, or low ones. It is useful as a descriptive statistic, but rewards large surfaces, hence should not be used as a measure of effectiveness on its own.

Visibility filter: A specific type of geographic filter, proposed in this thesis, that sorts information on the basis of how visible it is to an observer.