Available online at www.sciencedirect.com
ScienceDirect
Computers, Environment and Urban Systems
31 (2007) 481–501
Computers, Environment and Urban Systems
www.elsevier.com/locate/compenvurbsys

Movement beyond the snapshot – Dynamic analysis of geospatial lifelines ☆

Patrick Laube [a,*], Todd Dennis [b], Pip Forer [a], Mike Walker [b]

[a] *School of Geography and Environmental Science, University of Auckland, 10 Symonds Street, Auckland, New Zealand*
[b] *School of Biological Science, University of Auckland, 3 Symonds Street, Auckland, New Zealand*

Accepted in revised form 31 July 2007

Abstract

Geographical Information Science is challenged by an unprecedented increase in the availability of tracking data related to human and animal movement, typically captured through location-aware portable devices such as GPS receivers. Capture of trajectory data at fine temporal and spatial granularities has allowed with the representation of detailed geospatial lifelines, opening new options for analysis. In this respect we propose a dynamic perspective to analysis which, in contrast to summary trajectory statistics on speed, motion azimuth or sinuosity, that refers to the variability of motion properties throughout the developing lifeline. Four specific lifeline context operators are identified in this paper: 'instantaneous', 'interval', 'episodal' and 'total'. Using this framework, we discuss standardisations that integrate the extended set of motion descriptors within various temporal and spatial frames of reference and the proposed lifeline context operators and standardisations are illustrated using high resolution trajectory data obtained from homing pigeons carrying miniature global positioning devices.

Keywords: Geospatial lifelines; Mobile trajectories; Movement; Context operators; Time geography

☆ This paper is an enhanced and fully reviewed version of a paper that initially appeared in *Proceedings of the ICA Workshop on Geospatial Analysis and Modelling, 8 July, Vienna, Austria.*

* Corresponding author. Current address: Department of Geomatics, The University of Melbourne, Victoria 3010, Australia. Tel.: +61 3 8344 9185.

E-mail addresses: plaube@unimelb.edu.au (P. Laube), t.dennis@auckland.ac.nz (T. Dennis), p.forer@auckland.ac.nz (P. Forer), m.walker@auckland.ac.nz (M. Walker).

0198-9715/$ - see front matter © 2007 Published by Elsevier Ltd.
doi:10.1016/j.compenvurbsys.2007.08.002

1. Introduction

Opportunities to trace individual movement have grown in tandem with the development of electronic transaction networks, location-aware devices and surveillance systems, all capable of tracking people (Mountain & Raper, 2001b), animals (Hulbert, 2001) or vehicles (Wolfson, Sistla, Chamberlain, & Yesha, 1999). Generically, this development has offered an opportunity to move 'beyond the snapshot' (Chrisman, 1998) with respect to our understanding of processes involving individual movement. Specifically, the recent arrival of devices capable of the low cost capture of high resolution locational data now allows the widespread construction of individually-based *geospatial lifelines* (Mark, 1998). Such individual lifelines presage a new era of movement analysis (Eagle & Pentland, 2005) in which scientists from various research fields previously hampered by sparse and random movement observations can now be hard on the heels of their subjects as they move in space and time.

Yet while there is a growing commitment of resources to the large-scale recording of paths, the analysis commonly conducted with trajectory data remains fairly limited in scope and sophistication (Wolfer, Madani, Valenti, & Lipp, 2001). In disciplines outside of geography which do not commonly use geospatial methods or theory this may be due to a lack of awareness and understanding of the power of spatial analysis and GISystems, and within geography GIScience's' fetish for the static may be a factor (Raper, 2002). What ever the cause, GIScience faces a challenge to develop sophisticated analytical tools that integrate geography's spatial awareness with its long-term experience in processing large spatio-temporal data bases. This paper discusses opportunities and shortcomings of analysing lifeline data from a GIScience perspective, specifically in the situation where three spatial dimensions are involved and where movement is largely unfettered.

Clearly, the representation and analysis of geospatial lifelines challenge the GIScience community with respect to procedures for aggregation, generalisation, uncertainty and interpolation. Aggregation and generalisation of lifeline data can be considered to be important tools for coping with the voluminous outputs of movement-related agent-based simulations, for example with respect to emergency planning (Batty, Desyllas, & Duxbury, 2003) or transportation planning (Nagel, Esser, & Rickert, 2000). Uncertainty and generalisation of lifeline data is of interest for designers of location based services (LBS) analysing the lifelines of people tracked by location aware devices (Duckham, Kulik, & Worboys, 2003; Mountain & Raper, 2001a; Smyth, 2001). The more basic derivation of actual motion descriptors, such as speed, motion azimuth, or path sinuosity, also merits attention. Such descriptors build, the underlying basis for attempts to investigate the similarity of trajectories (Sinha & Mark, 2005), which is an important task in spatio-temporal data mining and geographic knowledge discovery (Miller & Han, 2001), and may well pay dividends in the fields of spatialisation (Skupin & Fabrikant, 2003), eye-movement analysis (Fabrikant, 2005) and the evolution of semantic relationships in cognitive spaces (Pike & Gahegan, 2003).

Lifeline data analysis is also relevant to a range of applied research fields outside of geography itself or in cognate areas, such as animal biology and biogeography. In behavioural ecology, the key factors in avian navigation are still not completely understood (Bonadonna et al., 2005; Wiltschko & Wiltschko, 2003), but Steiner et al. (2000) identify the analysis of the homing routes of racing pigeons as the optimal method for almost any study in this field. Advanced path analysis is furthermore considered to be a crucial obligation for the interpretation of behavioural experiments conducted with genetically modified animals, for example for water maze experiments with mice exploring spatial learning (Wolfer et al., 2001). Similar analysis is also of increasing interest in agricultural science, contributing to the development, for example, of optimal grazing strategies for cattle with respect to livestock management (Ganskopp, 2001). Research involving video surveillance (Ng, 2001; Porikli, 2004; Shim & Chang, 2003) or sports scene analysis (Moore, Whigham, Holt, Aldridge, & Hodge, 2003) are further examples where disciplines exhibit deep interests in individual trajectories.

The distinctive feature of high resolution tracking data is that they allow the tracking of individuals along an actual movement path, leaving little need for interpretation between sparse observation points. Thus, at almost every instant along the lifeline we can robustly determine the individual's current movement properties, such as speed, acceleration, motion azimuth, path sinuosity, as well as generate even more complex motion properties. Section 2 reviews work in this area, and elaborates the nature of the existing analytical tool set. In Section 3.1 we propose lifeline context operators to derive motion descriptors along dense trajectories, and adopt a dynamic analysis perspective for this. Section 3.2 rehearses a number of well known motion descriptors such as speed or motion azimuth, and introduces additional measures before discussing their computation as lifeline context operators. Section 3.3 explores the wide variety of analytical options that can be deployed by applying various standardisations for statistical analysis or using different aggregations of the tracking data. To illustrate these possibilities the trajectories of homing pigeons are identified as a research milieu (Section 4), and data from this area are utilised to demonstrate and critique the techniques (Section 5). The paper concludes in Section 6 with a brief review of prospects.

2. Related work

There is ample research on deriving overall descriptors of movement trajectories, such as *time total*, *flying time*, *airline distance*, *net displacement*, *flight path*, *flight speed*, *bias from airline* (e.g. Berger, Wagner, & Wolff, 1999; Steiner et al., 2000; Turchin, 1998; Wolfer et al., 2001). In avian navigation research, where detailed tracking was impossible until recently, the recording of the vanishing bearing of homing pigeons was used as a 'whole flight' indicator, since this direction was believed to be closely related to their loft's direction (Steiner et al., 2000; Wiltschko & Wiltschko, 2003). Further summary trajectory descriptors are the various measures describing the sinuosity or tortuosity of trajectories (Benhamou, 2004; Claussen, Finkler, & Smith, 1997).

Much less work has been done on describing movement with respect to instantaneous or ongoing characteristics of the trajectory, although the database community, especially people working on Moving Object Databases (MOD), have contributed with specific data models and query languages designed to return the state of a moving object at a given time, with 'state' referring to location, speed, or even direction (Sistla, Wolfson, Chamberlain, & Dao, 1997; Wolfson & Mena, 2004). Yet it is only recently that the need to move further beyond summary trajectory measures, and to dynamically explore the detailed information stored in individual lifelines, has been acknowledged in the behavioural ecology literature (Benhamou, 2004; Bonadonna et al., 2005). Benhamou (2004) for instance is exploring in-path variations of turning angles by using a window moving along the trajectory to derive the mean turning angle of the segments within that window. However, while a moving window is a straightforward device for deriving a range of motion properties along a trajectory, it fails to address the full complexity of dense spatio-temporal data. Mennis, Viger, and Tomlin (2005, p. 18) echo this situation in respect of the potential for additional approaches, noting that, it is very surprising that 'despite the growing volume of research on spatio-temporal data models over the past dozen or so years, the extension of map algebra to the temporal dimension has been largely ignored by the spatio-temporal GIS research community'. These authors propose 'cube functions' as an extension of map algebra for three dimensional spatio-temporal snapshot data (Mennis, Viger, et al., 2005) or even multidimensional data (Mennis, Leong, & Khanna, 2005), an approach also developed and critiqued in the context of movement and possible presence by Huisman (2006).

This paper seeks to explore the ground between the simple global analysis of movement paths and the more complex creation of spatio-temporal algebras by extending the dynamic analysis tools that combine aggregation, generalisation and information on sequence to generate new movement descriptors. In doing this we acknowledge both power and danger of using multiple temporal granularities and temporal zooming in the process of spatio-temporal knowledge representation. Theoretically recognised (Hornsby, 2001; Hornsby & Egenhofer, 2002), the actual algorithmic challenges of handling variable temporal granularities are sparsely addressed and the impact of different granularities on analyses is, as ever, a complex issue and under-researched. Dutton's (1999) work is one of a small number of exceptions by addressing line sinuosity as a way to investigate scale-specificity and characteristic points for line generalisation.

While more general approaches to derive procedural motion properties are also relatively few, a number of initiatives have encountered the issue of movement description. Dykes and Mountain refer to lifeline segments primarily for visualisation and exploratory analysis (2003), and propose the notion of episodes as well as a number of episode summaries and indices of movement, including absolute speed, direction, sinuosity and measurements of their variations. Mountain and Raper (2001a) also address summaries of point data histories for tailoring the information returned to a user from LBS. They also propose using rapid changes in speed and motion direction to identify breakpoints in lifelines, ultimately in order to sequence lifelines into episodes. Smyth (2001) presents knowledge discovery algorithms based on motion descriptors to design better LBS. These data mining algorithms attempt to assign predefined activities to segments of trajectories by analysing their measurable motion descriptors (such as speed, heading, acceleration). Brillinger, Preisler, Ager, and Kie (2004) also address motion descriptors for exploratory purposes. They compute speed and predominant motion azimuth of moving elk and deer at various sub-lifeline granularities, analysing diurnal and seasonal motion patterns. Ng (2001) proposes an algorithms to detect outliers from a set of trajectories recorded with surveillance video footage. One of his algorithms detects outliers with respect to their motion speed characteristics. Finally, Laube, Imfeld, and Weibel (2005) use motion descriptors in order to detect predefined motion patterns. They propose 'detached attribute functions', a technique to derive motion descriptors of lifelines at arbitrary given times irrespective of fix times.

Fundamental to all these ideas is aggregation and the simplified representation of the lifeline. Having defined a specific measure, the next step in the analytical process is to superimpose structure on the tracking data to comply with that measure's needs, since each parameter may require different approaches to aggregating the recorded fixes (Wolfer et al., 2001). The most fundamental analytical context for tracking data is the single fix, with its most important feature being the location in the embedding geography. Referring location to the fix's encompassing zone, its proximity to a facility, or position on a linear feature is commonplace in mobile applications related to fleet management, vehicle guidance, prisoner monitoring or LBS.

The most obvious and embracing aggregation is the global one, grouping fixes into individual trajectories. Analytical tasks on individual trajectories range from visualisation (Kraak & Koussoulakou, 2004; Zhao, 2003) to the identification of behavioural episodes (Dykes & Mountain, 2003) to quite complex exploratory analysis approaches seeking to identify repetitive patterns (Imfeld, 2000). A standardised measure of the distance or time travelled in-path may furthermore be of interest in investigating the navigational strategy 'path integration' or 'dead reckoning' respectively, i.e. the integration of walking speed and angular variation along an outbound path in order to construct a homing vector (Merkle, Rost, & Alt, 2006).

The most complex level of aggregation is required for the analysis of the lifelines of an entire population of n individuals. Occupancy maps (Steiner et al., 2000; Wolfer et al., 2001) or continuous density surfaces (Dykes & Mountain, 2003; Kwan, 2000) give a summary overview of the recorded space–time activity, not only of populations of moving objects but also of individuals. Brillinger et al. (2004) use a two-dimensional spatial frame of reference to explore a continuous field of movement properties, in their case the diurnal variation of movement azimuth of deer. Kwan (2000) introduced another means of imposing structure to a population of lifelines. Their method for lifeline standardisation aligns all lifelines along a semantic axis, for example 'work location-home location' in order to uncover distinctive outliers with respect to the commuting pattern of the whole population. Finally, coming back to geography, the flow metaphor has been used to aggregate the movement of large numbers of tourists with respect to two-dimensional and three-dimensional mapping and exploratory analysis (Forer, Chen, & Zhao, 2004; Forer & Simmons, 2000).

3. Methods

This section introduces a set of analytical approaches for lifeline data. Mark (1998, p. 12) defines a geospatial lifeline as a "continuous set of positions occupied in space over some time period. Geospatial lifeline data consists of discrete space–time observations of a geospatial lifeline, describing an individual's location in geographic space at regular or irregular intervals". All methods introduced in this section apply for a data set consisting of n individuals, m_n fixes of the form $(x, y, (z), t)$ per lifeline, and a total of p fixes per population. The individual trajectories need not be equal in length nor start or end at the

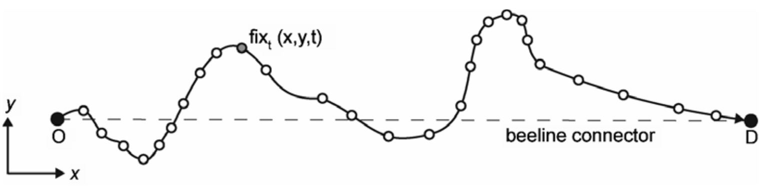

Fig. 1. A typical high-resolution geospatial lifeline.

same time. The straight line connector between two consecutive fixes is referred to as step. The steps of a trajectory can be of equal or unequal lengths. If the tracking device samples at constant sampling intervals and the object moves at variable speeds, the step lengths are unequal. If, by contrast, the device records a fix only after having travelled a certain distance, step lengths may be equal. Fig. 1 illustrates a typical geospatial lifeline connecting an origin O with a destination D.

3.1. Lifeline context operators

Individual lifelines allow a dynamic perception of movement, providing the detailed data to investigate movement properties at arbitrary instantaneous times along given lifelines. Analysis of lifelines normally involves use of movement descriptors such as speed, acceleration, movement azimuth, and sinuosity. An analogy to spatial analysis may help to illustrate the analytical opportunities inherent in individual lifelines. Spatial variables may be investigated using local, focal, zonal, or global context operators (DeMers, 2002; Tomlin, 1990; Worboys & Duckham, 2004). Individual lifelines permit modelling of the movement descriptors described above as one-dimensional continuous streams, very much like two-dimensional continuous fields. Thus, in derivation of movement descriptor measures d along a lifeline, the two-dimensional context operators can be adopted for one-dimensional lifelines (Fig. 2).

- *instantaneous ("local")*. Derive $d_t = d(t)$ at an infinitesimal instant in time.
- *interval ("focal")*. Use a moving interval (moving temporal window) to investigating a fixed length segment of the lifeline, computing $d_{\text{int}} = d(t \pm \delta t)$ respectively.

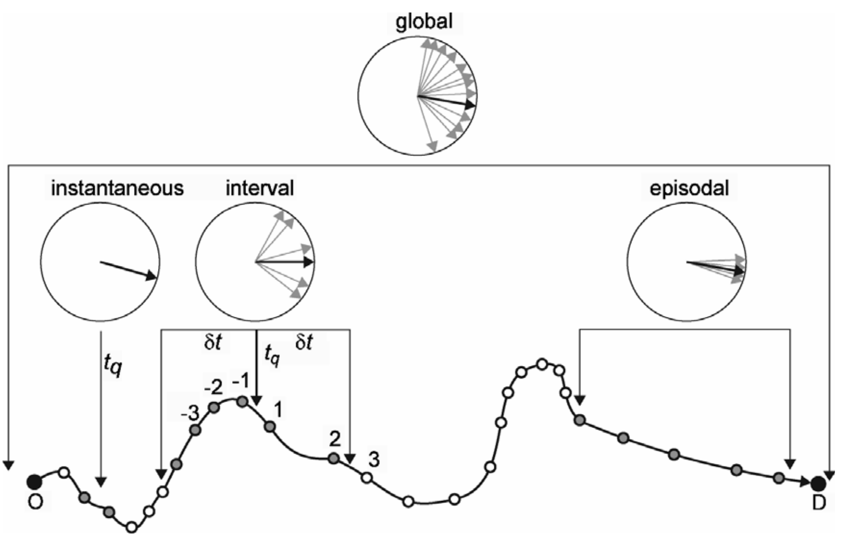

Fig. 2. Four different perspectives to derive the movement descriptor azimuth from a lifeline (top). In many cases also instantaneous measures require the inclusion of at least two fixes. Which fixes are included for interval measures may depend on the way the interval is defined. The temporal interval $\pm\delta t$ includes different fixes than using a fixed number of fixes.

- *episodal ("zonal").* Preliminary analysis may result in a partition of the lifeline in delimited episodes, each represented by a movement descriptor $d_{\text{eps}} = d[t_{\text{begin}}, \ldots, t_{\text{end}}]$.
- *total ("global").* Movement descriptors can be computed for whole trajectories as $d_{\text{tot}} = d[t_0, \ldots, t_{\text{m}}]$. This is the traditional static perspective of lifelines.

Computing instantaneous movement descriptors often requires in practice the inclusion of at least two consecutive fixes or a short segment of the lifeline. Deriving speed and azimuth from given fixes requires at least two consecutive fixes, acceleration three. A measure such as sinuosity is intrinsically an interval measure, requiring a certain number of fixes or a segment of certain length to produce reasonable results. However, the concept of a smoothing moving window of an interval function moving along a lifeline may be adopted for the derivation of all movement descriptors listed above, for example, in the case of noisy or fragmentary data.

The length of the segment for interval analysis can be delimited in various ways, depending on the given tracking data and the research question. The interval can be given as a fixed time interval $d_{\text{int}} = d(t \pm \delta t)$. This procedure may include variable numbers of fixes if the fix sampling is irregular. The same is true if the length of the segment is held constant. If the computation of the movement descriptor at that time requires a fixed number of variables, the number of included fixes can be used to define the segment $d_{\text{int}} = d(\text{fix}(t) \pm \text{i}\, \textit{fixes})$ (Fig. 2).

The sampling times at which d is computed, need not to be restricted to the sampling times of the fixes. Many analytical techniques require for instance equal step lengths (Benhamou, 2004), a feature that is hardly found in tracking data that often feature a constant sampling time. Thus, interval functions may be used to interpolate between known fixes (referred to as 're-discretisation' in the biological literature (Claussen et al., 1997)) or to aggregate a set of fixes.

3.2. Computing selected lifeline context operators

Just as with spatial-context operators, the variability of possible lifeline-context operators seems to be unlimited. It is not the intention of this work to provide an all-inclusive overview of lifeline context operators. In contrast, this section discusses the potential of lifeline context operators, referring to both well known and new movement descriptors. Whereas some movement descriptors (e.g. speed, acceleration, and movement azimuth) can be computed using instantaneous, interval or episodal operators, others intrinsically require at least interval operators (e.g., sinuosity).

Location. At a first glance it may come as a surprise to classify 'location' as a movement descriptor. However, keeping in mind that analysis of movement descriptors may be performed independently from the recorded fixes, lifeline-context operators may be used to interpolate a hypothetical location of an object at a time it had not been fixed in the first instance. Such an interpolation may use a simple interval average or an interval mean of x and y of the involved fixes. Furthermore, using distance-weighted averages it is possible to underline the importance of proximal over distal fixes. An episodal or even total representation of location may refer to the centroid of an episode or the entire trajectory.

Speed and acceleration. In kinematics the average velocity v_{av} is defined to be the vector quantity equal to the displacement divided by the time interval (Sears, Zemansky, & Young, 1987). The instantaneous velocity of a moving object at a specific point in the path, or at a specific instant of time, is called the instantaneous velocity. This parameter is defined in magnitude and direction to be the limit approached by the average velocity as the two specified fixes near each other. However, most applications use the notion of speed as the scalar magnitude of the instantaneous velocity, computing it from the two closest fixes to query time q_t.

$$v = \delta d/\mathrm{d}t \tag{1}$$

whereas δd represents the distance travelled between the two fixes and $\mathrm{d}t$ refers to the elapsed time. Quite similarly, instantaneous acceleration has a scalar and a vector component. However, the simplest computation of instantaneous acceleration considers the change of speed of two consecutive steps δv, three consecutive fixes respectively.

$$a = \delta v/\mathrm{d}t \tag{2}$$

Speed and acceleration are well suited for interval and episodal operators such as average, weighted average or median functions.

Movement azimuth. The simplest computation of an instantaneous movement azimuth computes the straight-line vector of two consecutive fixes. Interval, episodal and total azimuth operators must consider a given number of movement azimuth indications, originating from a set of successive steps. Movement azimuth can be conceptualized as a vector or a scalar. The use of the summary vector connecting the first and the last fix of an interval is a straightforward vector representation for azimuth. Directional statistics allow the computation of an average movement azimuth as a scalar (Mardia & Jupp, 2000). The azimuth summary vector and the azimuth mean scalar may substantially vary since the latter does not consider the lengths of the included steps (Fig. 3b).

Sinuosity. The terms *tortuosity*, *sinuosity*, *straightness*, and *path entropy* all refer to the degree of windingness of a trajectory. In this paper we list the most frequent concepts and refer to the literature for more detailed information. *Tortuosity* is normally calculated as the ratio represented by the greatest distance between any two points on the trajectory divided by the length of the path (Benhamou, 2004; Claussen et al., 1997). Sinuosity is normally computed from an equal step length rediscretized path, considering the standard deviation of the directional changes and the rediscretisation step length (Bovet & Benhamou, 1988; Claussen et al., 1997). The *straightness index* is given as the ratio of the beeline

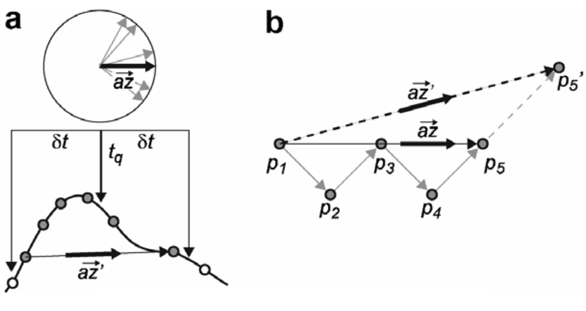

Fig. 3. Interval operator for *movement azimuth*. (a) Movement azimuth at query time q_t can be computed as the average direction of all involved step azimuths ($\vec{az}$), or as the azimuth of the summary vector of the interval ($\vec{az}'$) and (b) whereas the first approach considers only directions, the latter considers also the lengths of the involved vectors, thus the direction of the summary vector of (p_1p_5) is not equal (p_1p_5').

connector distance and the travelled path length (Benhamou, 2004; Weimerskirch et al., 2002). Other authors use a *fractal dimension* of trajectories (Bovet & Benhamou, 1988), or an indication for *path entropy* (Guilford, Roberts, Biro, & Rezek, 2004; Roberts, Guilford, Rezek, & Biro, 2004). Even though these sinuosity measures are mainly applied as total operators, in effect they are perfectly suited for interval and episodal operators.

Navigational displacement. The navigational displacement refers to the deviation of a trajectory to the direct beeline to the destination (see Fig. 4). We propose to evaluate the homing direction at every fix and use this azimuth to compute a dynamic measure of navigational displacement (Fig. 4). The navigational displacement can be assessed as a directed measure ranging from $-\pi$ to π, or as an undirected absolute value ranging form 0 to π.

Approaching rate. The approaching rate is a measure that describes whether and how intensively a moving object approaches its destination D (Fig. 5). We propose an absolute and a standardised approaching rate. The *absolute approaching rate* expresses a speed at which the object approaches D. It is given as the fraction of the approaching distance travelled towards D during an interval $d(t \pm \delta t)$ over the temporal extent of the interval $2\delta t$. Since it is a speed indication, it is expressed in appropriate units (e.g., m/s). The *standardised approaching rate* expresses the fraction of the distance d_a actually travelled towards D and the total distance travelled during that interval δd. This measure ranges from 1 (straight home), through 0 (perpendicular to home) to -1 (straight away form home).

First derivatives. A further opportunity we only start to explore is the investigation of first derivatives of movement descriptors. Rates of change of speed, azimuth or sinuosity may for instance be used for algorithms that automatically delimit different movement episodes in lifelines. Different behavioural episodes express different movement trajectories,

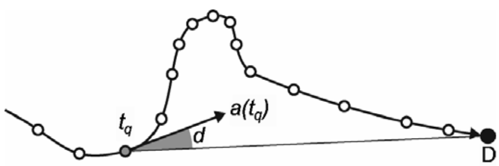

Fig. 4. The *navigational displacement* at query time t_q is computed as the angle between the current homing direction towards D and the current motion azimuth $a(t_q)$.

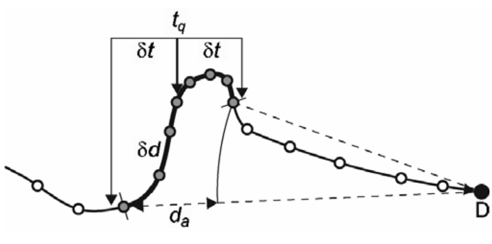

Fig. 5. Interval operator for *approaching rate*. The approaching rate at query time t_q can be expressed as an absolute measure $d_a/(2\delta t)$ (m/s) or as a standardised measure $d_a/\delta d$, producing values from -1 to 1.

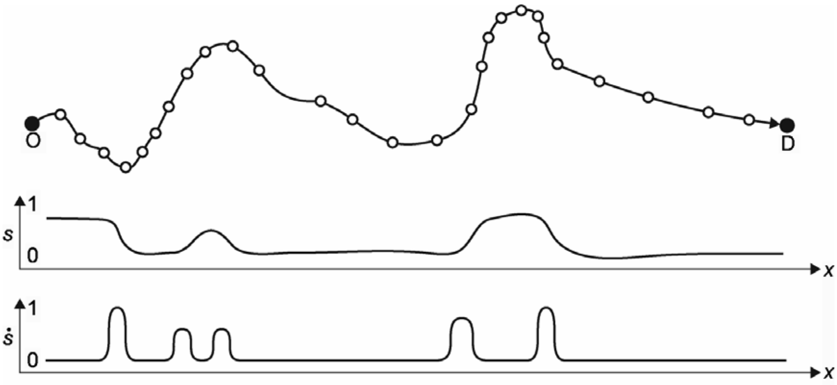

Fig. 6. Analysing the first derivative of trajectory sinuosity. The upper graph provides a sketch of the sinuosity of the plotted lifeline as it develops, derived for example using an interval sinuosity operator. The lower graph sketches the first derivative of the sinuosity. The emergent change events may thereafter be used to delimit episodes of the lifeline.

and peaks in the first derivatives of the movement properties plots may help to delimit such episodes. In Fig. 6, for example, the final episode of fast and direct movement towards the end is indicated by a sudden drop in the trajectories' rate of change of azimuth as well as a drop in sinuosity and an increase of speed.

Interval standard deviation of a movement descriptor. Finally, in certain cases one may want to investigate the distribution of a movement property within a moving interval. Using an interval function to derive the movement descriptor, the computation of its distribution introduces a second moving window, assigning, for example, the observed standard deviation of the movement descriptor under study to the central query time of the interval. Such a procedure results in a framed interval–interval measure, with the outer frame delimiting the interval used to compute the standard deviation and the inner frame delimiting the interval used to compute the movement descriptor (Fig. 7).

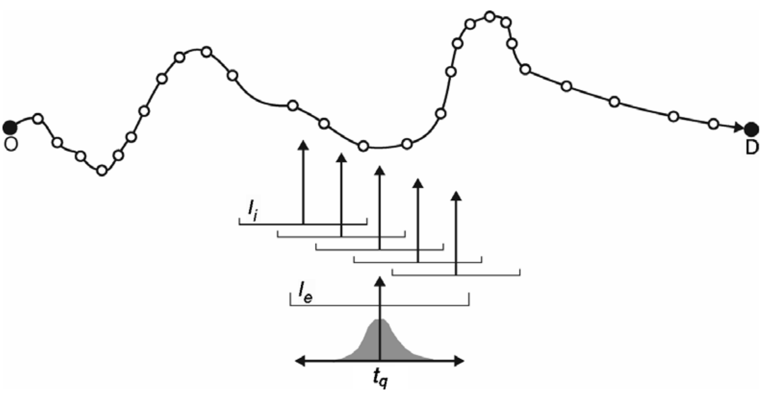

Fig. 7. The standard deviation of a movement descriptor computed as an interval operator at query time t_q. The rate of change of a movement descriptor can be investigated using a framed interval–interval measure, assessing the standard deviation in an external interval I_e for a focal movement descriptor of a set of internal intervals I_i.

3.3. Lifeline standardisation

Whereas mapping and visualisation of high-resolution geospatial lifelines provides useful first impressions of the richness of tracking data, for many scientific applications it is necessary to impose some degree of structure to the data before analysing it, in other words, to aggregate the movement descriptors in order to perform some type of statistical analysis. Lifelines extend both in space and time. Depending on the research question at hand, one may want to conduct analysis on movement descriptors using different frames of reference. A farmer may be interested in the spatial distribution of the grazing speed of cattle, an ethologist studying animal navigation, in contrast, may want to investigate sinuosity along standardised trajectories as a time-series analysis. Despite the differences in objectives, however, both analytical tasks require the computation of movement descriptors at given points in space and time, the only differences being the standardisation of the trajectory data.

The quantitative analysis and comparison of a set of *n* trajectories bears a number of methodological challenges. Firstly, trajectories of tracked entities are rarely of equal length. Be it tracked animals, people or vehicles, moving in an unrestricted space intrinsically produce variable solutions with respect to trajectory lengths. Moreover, it is very likely that at least some of the trajectories feature variable starting or ending times, or both. Thus, analytical efforts to compare trajectories adopting a dynamic perspective, that is concurrently moving along a set of *n* trajectories and comparing movement properties with respect to equal 'in path times' or 'equal travel distances from start', must first adopt a strategy of standardisation.

Different standardisations may aggregate along spatial (s) or temporal (t) dimensions, or combinations of the two (Fig. 8).

- *time series analysis (1t).* Movement descriptors can be analysed in time series analysis, where a single temporal axis is the frame of reference (A).

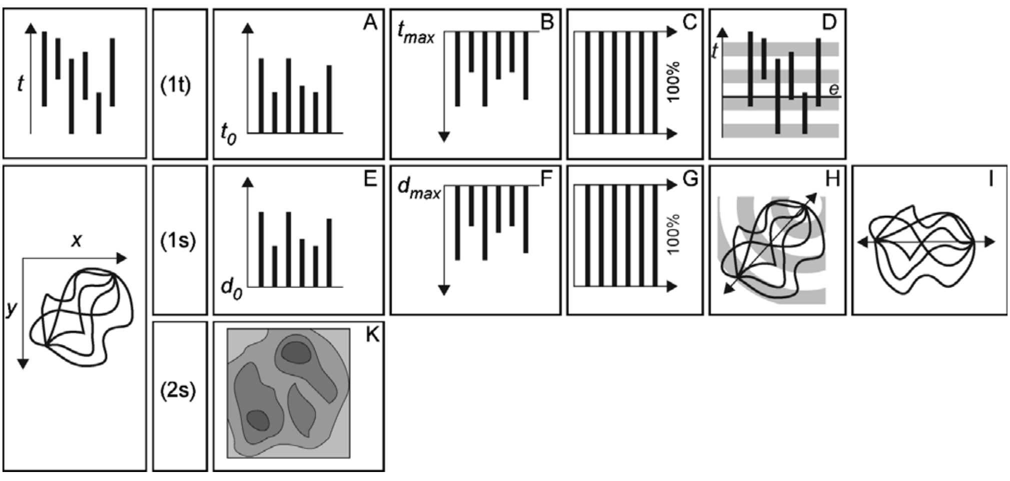

Fig. 8. Temporal and spatial standardisation approaches for lifeline data. The given lifelines have a temporal extent (top left) and a spatial extent (bottom left). Standardisations may be performed along one temporal dimension (t) and two spatial dimensions (s). A to K all represent a form of lifeline standardisation.

- *path time (1t) or path distance (1s) analysis.* For some applications it may be relevant to investigate the variance of movement properties with respect to time or path already travelled in a trajectory (A and E), or vice versa, time to go or distance ahead in a trajectory (B and F).
- *equal duration (1t) or equal track (1s) wrapping.* Trajectories of unequal lengths can be 'wrapped' so that all trajectories correspond to a given duration or track (C and G). Such an approach is adequate if one wishes to investigate, for example, whether a set of moving entities all increase speed in the last quarter of their journey.
- *spatial distance (1s) or temporal distance analysis (1t).* Trajectories relating to specific locations in space (such as a nest, release site, origin or destination) can be analysed with respect to distance to or from that specific location (H). Such an approach permits statistical analysis of movement properties such as speed, azimuth or sinuosity in distance classes (for example, in box-and-whisker plots). Similar aggregations can be used on a single temporal axis with respect to an event e (D). Event e separates all fixes furthermore in the two aggregations before e and after e.
- *bipolar analysis (1s).* Other trajectories may be aligned along a bipolar set of two locations (I), such as origin–destination, release site-loft, work-home, and summer habitat–winter habitat. The two poles may or may not be fixed in space. Using semantic poles with variable locations, such as 'home-work' or variable 'release sites' and 'loft sites', a preliminary standardisation may align the trajectories for the bipolar analysis.
- *spatial variance analysis (2s).* Having a dense and potentially disperse cloud of fixes from either a single or a set of trajectories one can finally investigate two-dimensional variance of movement descriptors (K) (Guilford et al., 2004).

4. Examples

This section illustrates the methodology introduced above using data emerging from an interdisciplinary study in behavioural ecology, investigating the navigation of homing pigeons. Given a data set of a total of approximately $m_n = 30{,}000$ fixes of $n = 54$ individual pigeon flight trajectories (Guilbert, Dennis, & Walker, unpublished).

4.1. Applying lifeline context operators

Example 1. The sinuosity of the trajectories of homing pigeons is considered to express navigational uncertainty: the more variance in path direction, the greater the uncertainty (Roberts et al., 2004). Following the biological hypothesis that the homing trajectory of a pigeon consists of different navigational episodes, dynamic analysis is preferred over a global approach (Benhamou, 2004; Claussen et al., 1997). A first exploratory approach is to map the sinuosity patterns as they develop along the trajectories (Fig. 9).

Example 2. The second example illustrates the analysis of first derivatives of movement descriptors. Fig. 10 describes the rate of change of trajectory sinuosity of pigeon 22. For research of the navigational abilities and mechanisms of pigeons, it would be of great interest if one could quantitatively identify an event when an individual pigeon enters the

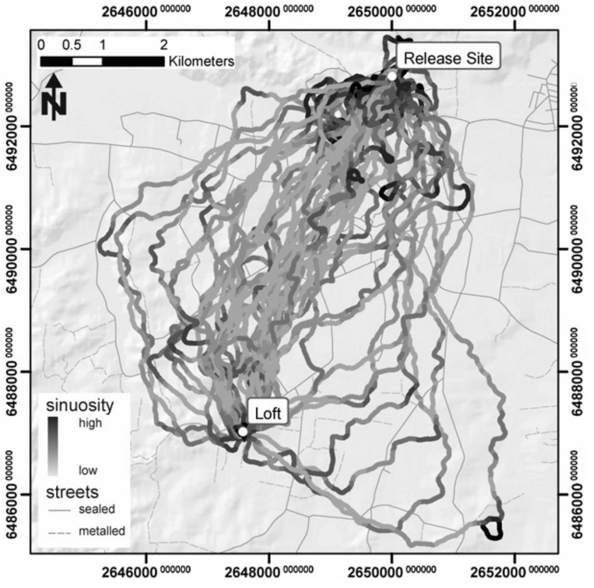

Fig. 9. Map of local sinuosity of 54 homing pigeon trajectories, the sampling rate is 1 s; the interval to derive the sinuosity is ±30 s.

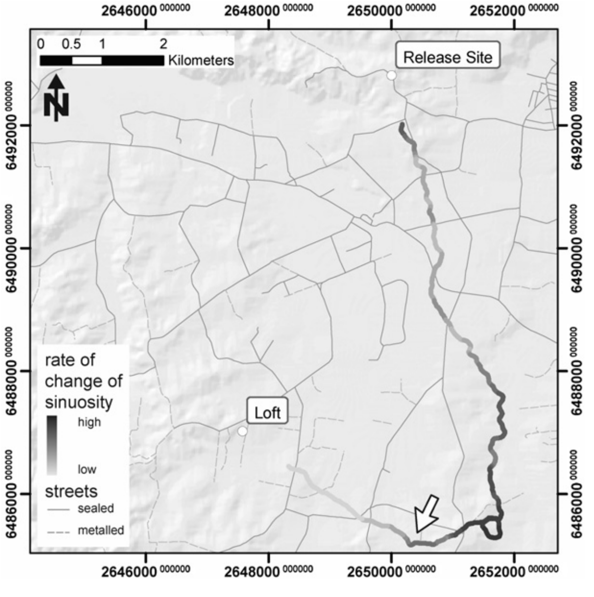

Fig. 10. Rate of change of movement sinuosity of pigeon 22. The darker the fixes, the higher is the rate of change. The high rates of change around the last turn in the path may indicate the event, when the pigeon finally figured out where it was and started to fly straight home (arrow). Please note that the fixes close to the release site and the loft have been excluded to remove noise introduced by starting and landing behaviour.

familiar area near the loft (Burt, Holland, & Guilford, 1997). This event may be characterised by a sudden increase in speed and a parallel decrease of path sinuosity. In the mapped track in Fig. 10, the sudden colour at the last change of direction towards loft (arrow) may indicate such an event.

4.2. Applying lifeline standardisations

Example 3. Standardisation of homing trajectories emerging from different homing experiments but equal 'release site-loft configurations' allows generation of large populations of comparable trajectories. Therefore one might shift all trajectories in time so that they all arrive at loft at the same time, in order to potentially reveal interesting temporal patterns. Fig. 11 illustrates the navigational displacement of five such harmonised trajectories. Such a time-series analysis may help to identify different navigational states. Pigeon 22 for example expresses very distinct navigational 'episodes', illustrated as rather plateau-shaped sections of the plot, with intermittent events of sudden change of the direction (and therefore navigational displacement).

Example 4. Distance to loft is a very relevant reference for the analysis of flight trajectories of homing pigeons. In avian navigation research it may be of interest to quantify differences in the trajectory sinuosity with respect to distance to loft (Fig. 8H). Fig. 12 illustrates this relation. From the figure it is very obvious that the sinuosity of the trajectories is high near the loft (0–500 m, 500–1000 m) and the release site (5500–6000 m, 6000–6500 m). This pattern may be explained by specific take-off, position determination and landing behaviours around the loft and the release site.

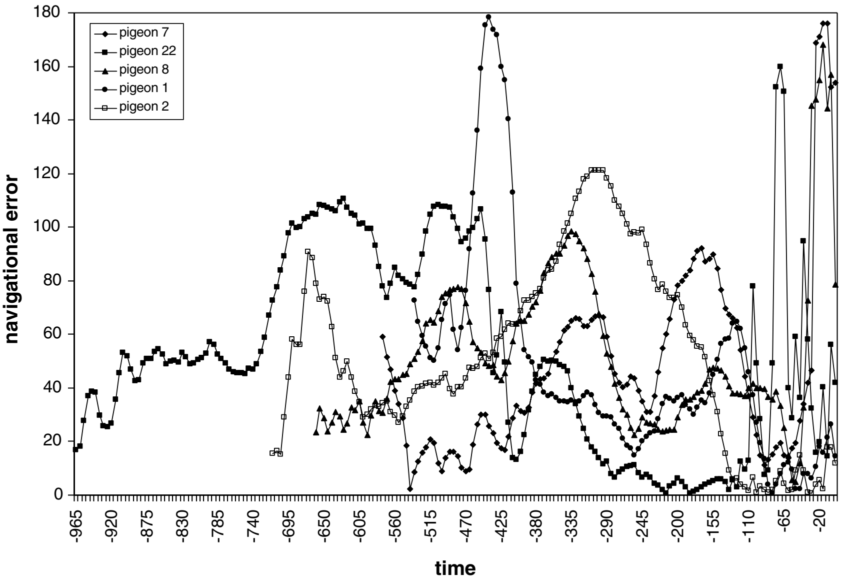

Fig. 11. Navigational displacement of five pigeons, absolute values, standardised with respect to their arrival at the loft ($t = 0$). The sampling rate is 5 s; the interval to derive the displacement as an interval measure is ± 30 s.

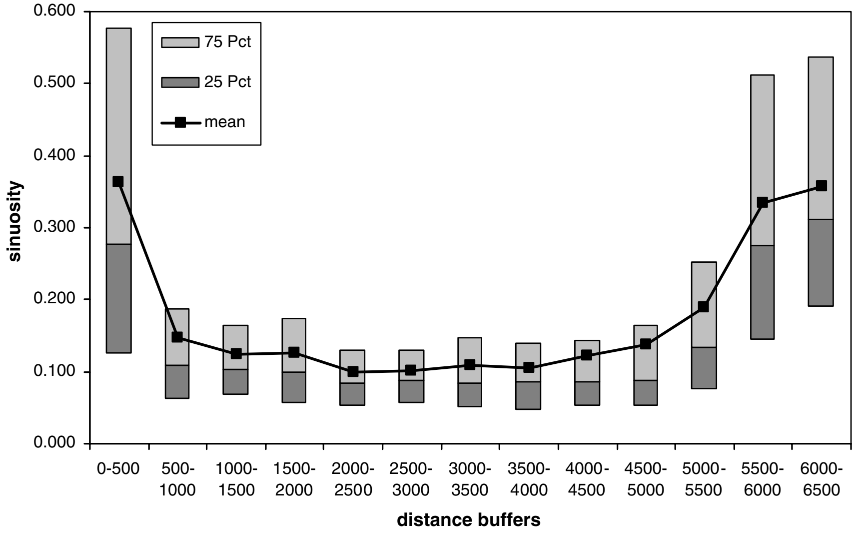

Fig. 12. Trajectory sinuosity of 54 pigeons, aggregated in 13 concentric rings around the loft to express the relation between distance to loft and flight sinuosity.

Example 5. Sinuosity can also be mapped as a two-dimensional spatial field (Fig. 13). We used kriging with a rather coarse cell size (100 m) and clipped the resulting surface with the convex hull of all fixes in order to minimise edge effects. We are well aware that the data present are not optimal for the interpolation of a continuous surface. However,

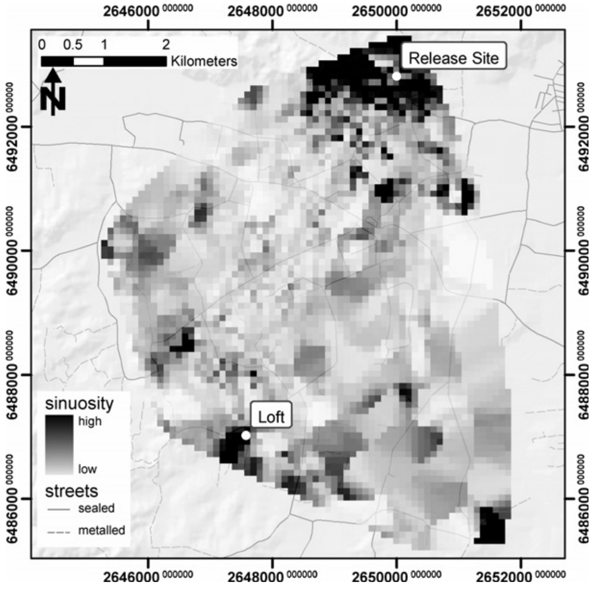

Fig. 13. Trajectory sinuosity mapped spatially using density surfaces basing on kriging. The darker the grid cell, the higher the local sinuosity of this interpolated trend surface.

interpreting with care, we may derive some spatial characteristics of the computed trajectory sinuosity surface. On the one hand we find low sinuosity corridors oriented along the direct beeline connector between release site and loft. On the other we see very distinct high sinuosity spots around the release site and the loft. This general pattern correspond with the findings of Guilford et al. (2004).

5. Discussion

This paper has identified a framework for enriching the toolset available for analysing densely sampled lifelines, and has explored ways to implement a growing range of movement parameters within that broad framework. These have covered movement properties of lifelines already deployed in other research, such as speed, movement azimuth, turning angles, or sinuosity, as well as additional measures and standardisations. In Section 3 we showed that there are, for many movement descriptors, more than one means of computation, including varying parameters such as interval lengths or weight factors. The choice of these naturally has impacts on the final analysis. For example the length of the analytical interval may be as influential as the dimension of a moving window in other focal operators: an important parameter for analysis but also a major influence as a smoothing filter. This observation is significant in movement research in that often little information is provided about lifeline data models and algorithms employed in computing movement descriptors in a particular study. In order to increase the transparency and the repeatability of analysis of movement trajectories, we suggest that researchers report more detail about how their lifeline descriptors are computed.

Our experience with pigeon flight data suggests that the selection of the algorithms used to compute lifeline context operators needs some care because not all algorithms are suitable for all data models or data-capture procedures. The interplay of the data of interest and the applied context operator algorithms may produce artefacts that are, once introduced, hard to recognize. One example of this is the impact of coarse position fix sampling rates on length estimates. Coarse sampling generally results in an inaccurate representation of the actual path of a moving object, and ultimately underestimates the distance travelled (Estevez & Christman, 2006; Turchin, 1998), leading to an underestimation of derived speed parameters. As another example, the detection of directional change is very sensitive to variable sampling rates along a trajectory. The last curve towards D in Fig. 1 illustrates this problem. The moving object slows down making a curve. Having a fixed temporal sampling rate thus leads to a finer sampling in the curved area of the trajectory. This finer local sampling rate results in smaller directional changes occurring per unit time, and ultimately introduces an artefact because the curve itself is over sampled and over-partitioned. In that ‘high resolution’ or ‘dense’ lifelines nonetheless cover a range of sampling frequencies it is also clear that the spatiotemporal resolution of the data comprising a movement trajectory limits the applicability of the various lifeline context operators.

Many authors also identify general difficulties in comparing lifelines of unequal length employing only total trajectory descriptors. Solutions sought include deploying fractal dimensions (Claussen et al., 1997; Dicke & Burrough, 1988) or path entropy (Guilford et al., 2004; Roberts et al., 2004) as measures which are scale independent and free from the effects of variable sampling rates. The very same idea has also been adopted in order to assess lifeline similarity. Porikli (2004) uses, for example, a trajectory distance metric based on Hidden Markov Models when assessing the similarity of the models representing the individual lifelines. These techniques are helpful but rely on total context (global) operators and thus exclude the detailed dynamic perspective of the line. In this paper, in contrast, we argue that applying standardisations such as wrapping or shifting to equalise the start and end times offers an alternative way to address the problem of unequal lifelines without excluding the dynamic view. For example a joint exploration of a harmonised series of temporal graphs as in Fig. 11 may reveal detailed interrelation patterns that unfold in the developing trajectories.

Some issues (such as the navigational displacement or the approaching rate) might be considered as specific to studies of animal navigation or movement. However, although lifelines produced by GPS tracked-animals which unrestrictedly move in heterogeneous space may be quite different from humans acting in a normally constrained geography, some elements of the methods presented in this paper are of generic nature and thus of general interest for a wider GIScience audience. We might expect tracking information from people to be manifest in several forms. Typically, people move on network structures, be it an urban street network or the network of a public transport system, and movement representation may be constrained to these. In the future, trajectories may one day be available from telecommunication providers that model the individual's movement on a network consisting of antenna cells. Since the data model underlying these kinds of trajectories may be very different from animals carrying GPS collars, context operators for network bound movement may look somewhat different. Since directions and the shapes of paths on a network are restricted, measures such as bearing or sinuosity make less sense and may need substantial reformulating. However, context operators relating distance and time, such as speed or acceleration, may be more easily transposed. One might even think of proposing operators that consider network constraints such as speed limits. Such a measure could, for instance, compute speeding values of individuals for each segment used on a certain travel path, and just as with the homing pigeons one might think of context operators that are specifically tailored for a specific LBS application utilising to trajectories on an antenna cell network. Such a measure could quantify the time spent in the cells along a trajectory, considering the current cell and some defined context or neighbourhood.

Finally, the analogy of the lifeline context operators and the field operators associated with Tomlin's map algebra could be discussed in more detail. Considering the GIScience community's growing interest in spatio-temporal phenomena, exploring possible extensions of two-dimensional field operations into the spatio-temporal realm appears worthy of exploration. Mennis, Viger, et al. (2005), for example, propose a cubic map algebra for spatio-temporal analysis and explore the utility of this through a case study on spatio-temporal variability of remotely-sensed data on the 'El Nino' phenomenon. In an urban context, Huisman (2006) used three-dimensional context operators to analyse geospatial lifelines of commuting students. Both examples show that the approach has merit, but the very different nature of spatial and temporal dimensions adds complexity and sometimes a degree of ambiguity when we try to integrate three-dimensional neighbourhood operators into analysis. Consequently this paper focuses simply on the adoption of local operators, neighbourhood effects and chlorplethic zoning for a one-dimensional data stream describing a geospatial lifeline and leave any integration of the spatial and temporal dimension of operators to the future.

6. Conclusions and outlook

Acknowledging the emerging opportunities for the mass analysis of individual movement data, an eclectic set of disciplines interested in movement have recently shown a growing interest in dynamic spatio-temporal analytical methods for trajectory data. These disciplines include geography, GIScience, data base research, animal behaviour research, surveillance and security analysis, transport analysis and market research.

In this paper we have adopted the concept of spatial context operators, often associated with Tomlin's map algebra to create a framework for the computation of descriptive measures of lifeline data. We have proposed instantaneous, interval, episodal, and total context operators applicable to a continuous stream of movement descriptors along a trajectory. We have illustrated this conceptual framework by applying it to some well known existing movement properties such as speed, sinuosity, and movement azimuth, and we additionally propose some new movement descriptors which we believe show value. We have consequently proposed a set of standardisations to harmonise lifelines of differing length or chronology so as to allow statistical analysis.

Even though the contributions of this research are conceptual, our research is to a large degree closely coupled applied contexts where we are involved in a dialectic between data sets and the techniques for their analysis. This dialectic reveals several avenues for further research. The most straightforward is broadening our experience by deploying different data sets from different contexts. Existing or on-stream data bases portraying terrestrial animal and human movement represent an immediate opportunity. In this paper we argued that the quantitative analysis of movement is very sensitive to the data capture procedures being deployed, to the data models representing the moving object and to the algorithms which derive descriptive measures from the trajectories. Exploring the unlimited variety of lifeline context operators reveals that there is not just one natural way of computing variables such as 'speed' or 'movement direction'. Clearly there is room to examine the performance characteristics of various movement indicators relative to different algorithms or parameters for analysis. A related issue is undoubtedly that of granularity and scale in revealing patterns. High resolution lifeline data open up nice opportunities for sensitivity experiments with systematically varied granularities of lifelines. All interval context operators used in Section 4 are based on an interval width of ± 30 s in order to maintain comparability throughout the paper. However, we will perform numerical experiments quantifying the sensitivity of the similarity measures to lifeline granularity. For instance, using different measures of sinuosity or tortuosity.

These however are somewhat technical issues, a more fundamental issue needs to dominate the ongoing agenda. That is the investigation of how lifeline properties relate to, and perhaps can draw definition from, the underlying (or surrounding) geography and the spatial processes that the individual is engaged in. This is not just a challenge in describing the nature of movement but an important foundation for gaining a greater knowledge of movement as a manifestation of process and structuration. Since we know from the literature that homing pigeons also use landmark features such as rivers or streets (Guilford et al., 2004; Lau et al., 2006), one could try to quantify the relation of the obvious alignment of the west-most two trajectories with the underlying street network in Fig. 9. With different fauna, and especially with humans, different and even richer challenges emerge. In this respect such movement research is likely to be one of the major driving forces in the field of behavioural ecology research, where geography's strong spatial awareness can empower behavioural ecology by linking movement data to their geographical context. The quantification of how moving objects, be they animals or people, react to their environment will ultimately help us to better understand their space–time use and a range of spatio-temporal processes. One important aspect of this movement/environment relationship is the degree to which the environment imposes highly differentiated spaces on the individual moving entity (for instance restricting movement to highways or gorges or differentially enabling individuals' mobility, as in a varied terrain).

In the end movement can be represented in many spaces, and we might expect each one might offer different opportunities for the representation of movement "beyond the snapshot".

Acknowledgements

Author's current work is funded by the Swiss National Science Foundation, grant no. PBZH2-110315. The authors wish to thank David O'Sullivan who provided valuable comments on the presented research and previous drafts of the manuscript.

References

Batty, M., Desyllas, J., & Duxbury, E. (2003). The discrete dynamics of small-scale spatial events: Agent-based models of mobility in carnivals and street parades. *International Journal of Geographical Information Science, 17*, 673–697.

Benhamou, S. (2004). How to reliably estimate the tortuosity of an animal's path: Straightness, sinuosity, or fractal dimension? *Journal of Theoretical Biology, 229*, 209–220.

Berger, U., Wagner, G., & Wolff, W. F. (1999). Virtual biologists observe virtual grasshoppers: An assessment of different mobility parameters for the analysis of movement patterns. *Ecological Modelling, 115*, 119–127.

Bonadonna, F., Bajzak, C., Benhamou, S., Igloi, K., Jouventin, P., Lipp, H. P., et al. (2005). Orientation in the wandering albatross: Interfering with magnetic perception does not affect orientation performance. *Proceedings of the Royal Society B, 272*, 489–495.

Bovet, P., & Benhamou, S. (1988). Spatial-analysis of animals movements using a correlated random-walk model. *Journal of Theoretical Biology, 131*, 419–433.

Brillinger, D. R., Preisler, H. K., Ager, A. A., & Kie, J. G. (2004). An exploratory data analysis (EDA) of the paths of moving animals. *Journal of Statistical Planning and Inference, 122*, 43–63.

Burt, T., Holland, R., & Guilford, T. (1997). Further evidence for visual landmark involvement in the pigeon's familiar area map. *Animal Behaviour, 53*, 1203–1209.

Chrisman, N. R. (1998). Beyond the snapshot: changing the approach to change, error, and process. In M. J. Egenhofer & R. G. Golledge (Eds.), *Spatial and temporal reasoning in geographic information systems* (pp. 85–93). Oxford, UK: Oxford University Press.

Claussen, D. L., Finkler, M. S., & Smith, M. M. (1997). Thread trailing of turtles: Methods for evaluating spatial movements and pathway structure. *Canadian Journal of Zoology – Revue Canadienne De Zoologie, 75*, 2120–2128.

DeMers, M. N. (2002). *GIS modeling in raster*. Chichester: John Wiley and Sons.

Dicke, M., & Burrough, P. A. (1988). Using fractal dimensions for characterizing tortuosity of animal trails. *Physiological Entomology, 13*, 393–398.

Duckham, M., Kulik, L., & Worboys, M. (2003). Imprecise navigation. *GeoInformatica, 7*, 79–94.

Dutton, G. (1999). Scale, sinuosity and point selection in digital line generalisation. *Cartography and Geographic Information Systems, 26*, 33–53.

Dykes, J. A., & Mountain, D. M. (2003). Seeking structure in records of spatio-temporal behaviour: Visualization issues, efforts and application. *Computational Statistics and Data Analysis, 43*, 581–603.

Eagle, N., & Pentland, A. (2005). Reality mining: Sensing complex social systems. *Journal of Personal and Ubiquitous Computing.*

Estevez, I., & Christman, M. C. (2006). Analysis of the movement and use of space of animals in confinement: The effect of sampling effort. *Applied Animal Behaviour Science, 97*(2–4), 221–240.

Fabrikant, S. I., (2005). Towards an understanding of geovisualization with dynamic displays: Issues and Prospects. In *American Association for Artificial Intelligence (AAAI) 2005 spring symposium series: Reasoning with mental and external diagrams: computational modeling and spatial assistance* (pp. 6–11). Stanford University, Stanford, CA.

Forer, P., Chen, H. F., & Zhao, J. F. (2004). Building, unpacking and visualising human flows with GIS. In *Proceedings of the GIS research UK 12th annual conference* (pp. 334–336). Norwich, UK: University of East Anglia.

Forer, P., & Simmons, D. G. (2000). *Analysing and mapping tourist flows*. Tourism, Recreation Research and Education Centre, Lincoln University, NZ.

Ganskopp, D. (2001). Manipulating cattle distribution with salt and water in large arid-land pastures: A GPS/GIS assessment. *Applied Animal Behaviour Science, 73*, 251–262.

Guilbert, T., Dennis, & Walker, M. (Unpublished). University of Auckland.

Guilford, T., Roberts, S., Biro, D., & Rezek, L. (2004). Positional entropy during pigeon homing II: Navigational interpretation of Bayesian latent state models. *Journal of Theoretical Biology, 227*, 25–38.

Hornsby, K. (2001). Temporal zooming. *Transactions in GIS, 5*, 255–272.

Hornsby, K., & Egenhofer, M. J. (2002). Modeling moving objects over multiple granularities. *Annals of Mathematics and Artificial Intelligence, 36*, 177–194.

Huisman, O. (2006). *The application of time-geographic concepts to urban micro-process*. PhD thesis, University of Auckland.

Hulbert, I. A. R. (2001). GPS and its use in animal telemetry: The next five years. In A. M. Sibbald & I. J. Gordon (Eds.), *Conference on tracking animals with GPS* (pp. 51–60). Aberdeen, UK: Macaulay Institute.

Imfeld, S. (2000). *Time, points and space: Towards a better analysis of wildlife data in GIS*. University of Zurich.

Kraak, M. J., & Koussoulakou, A. (2004). A visualization environment for the space–time-cube. In P. F. Fisher (Ed.), *Developments in spatial data handling. Proceedings of the 11th international symposium on spatial data handling* (pp. 189–200). Berlin Heidelberg, DE: Springer.

Kwan, M. P. (2000). Interactive geovisualization of activity-travel patterns using three dimensional geographical information systems: a methodological exploration with a large data set. *Transportation Research Part C, 8*, 185–203.

Lau, K.-K., Stephen, R., Dora, B., Robin, F., Jessica, M., & Tim, G. (2006). An edge-detection approach to investigating pigeon navigation. *Journal of Theoretical Biology, 239*, 71–78.

Laube, P., Imfeld, S., & Weibel, R. (2005). Discovering relative motion patterns in groups of moving point objects. *International Journal of Geographical Information Science, 19*, 639–668.

Mardia, K. V., & Jupp, P. E. (2000). *Directional statistics*. New York, NY: John Wiley and Sons.

Mark, D. M., (1998). Geospatial lifelines. In *Integrating spatial and temporal databases*, Vol. 98471, Dagstuhl Seminars.

Mennis, J., Leong, J., & Khanna, R. (2005). Multidimensional map algebra. In *8th International Conference on GeoComputation*. Ann Arbor, MI.

Mennis, J., Viger, R., & Tomlin, C. D. (2005). Cubic map algebra functions for spatio-temporal analysis. *Cartography and Geographic Information Science, 32*, 17–36.

Merkle, T., Rost, M., & Alt, W. (2006). Egocentric path integration models and their application to desert arthropods. *Journal of Theoretical Biology, 240*(3), 385–399.

Miller, H. J., & Han, J. (2001). Geographic data mining and knowledge discovery: An overview. In H. J. Miller & J. Han (Eds.), *Geographic data mining and knowledge discovery* (pp. 3–32). London, UK: Taylor and Francis.

Moore, A. B., Whigham, P., Holt, A., Aldridge, C., & Hodge, K. (2003). A system for video-based spatiotemporal data capture, query and visualisation: The case of team games. In *7th International conference on geocomputation*. University of Southampton, United Kingdom: GeoComputation CD-ROM.

Mountain, D., & Raper, J. (2001a). Modelling human spatio-temporal behaviour: A challenge for location-based services. In *6th International conference of geocomputation: geocomputation CD-ROM*.

Mountain, D., & Raper, J. (2001b). Spatio-temporal representations of individual human movement for personalising location based services. In D. B. Kidner & G. Higgs (Eds.), *GIS research UK, 9th annual conference, GISRUK 2001* (pp. 579–582). University of Glamorgan, UK.

Nagel, K., Esser, J., & Rickert, M. (2000). Large-scale traffic simulations for transportation planning. *Annual Reviews of Computational Physics, VII*, 151–202.

Ng, R. T. (2001). Detecting outliers from large datasets. In H. J. Miller & J. Han (Eds.), *Geographic data mining and knowledge discovery* (pp. 218–235). London, UK: Taylor and Francis.

Pike, W., & Gahegan, M. (2003). Constructing semantically scalable cognitive spaces. In *Spatial information theory, proceedings*, Vol. 2825, (pp. 332–348). Lecture Notes in Computer Science. Berlin: Springer-Verlag.

Porikli, F. (2004). Trajectory distance metric using hidden Markov model based representation. In *IEEE European conference on computer vision, workshop on PETS*. Prague.

Raper, J. (2002). The dimensions of GIScience. In *Second international conference of geographic information science, GIScience 2002*. Retrieved 22 March, 2006. (http://www.soi.city.ac.uk/~raper/research/GIScience2002-OHs-pub.ppt).

Roberts, S., Guilford, T., Rezek, I., & Biro, D. (2004). Positional entropy during pigeon homing I: Application of Bayesian latent state modelling. *Journal of Theoretical Biology, 227*, 39–50.

Sears, F. W., Zemansky, M. W., & Young, H. D. (1987). *University physics*. Reading, MA: Addison-Wesley.

Shim, C. B., & Chang, J.W. (2003). Efficient similar trajectory-based retrieval for moving objects in video databases. In *Image and video retrieval, proceedings*, Vol. 2728 (pp. 163–173). Lecture Notes in Computer Science.

Sinha, G., & Mark, D. M. (2005). Measuring similarity between geospatial lifelines in studies of environmental health. *Journal of Geographical Systems, 7*, 115–136.

Sistla, A. P., Wolfson, O., Chamberlain, S., & Dao, S. (1997). Modeling and querying moving objects. In *13th international conference on data engineering (ICDE13)*.

Skupin, A., & Fabrikant, S. (2003). Spatialization methods: A cartographic research agenda for non-geographic information visualization. *Cartography and Geographic Information Science, 30*, 95–115.

Smyth, C. S. (2001). Mining mobile trajectories. In H. J. Miller & J. Han (Eds.), *Geographic data mining and knowledge discovery* (pp. 337–361). London, UK: Taylor and Francis.

Steiner, I., Burgi, C., Werffeli, S., Dell'Omo, G., Valenti, P., Troster, G., et al. (2000). A GPS logger and software for analysis of homing in pigeons and small mammals. *Physiology and Behavior, 71*, 589–596.

Tomlin, C. D. (1990). *Geographic information systems and cartographic modeling*. Englewood Cliffs: Prentice Hall.

Turchin, P. (1998). *Quantitative analysis of movement: Measuring and modelling population redistribution in animals and plants*. Sunderland, MA: Sinauer Publishers.

Weimerskirch, H., Bonadonna, F., Bailleul, F., Mabille, G., Dell'Omo, G., & Lipp, H. P. (2002). GPS tracking of foraging albatrosses. *Science, 295*, 1259.

Wiltschko, R., & Wiltschko, W. (2003). Avian navigation: From historical to modern concepts. *Animal Behaviour, 65*, 257–272.

Wolfer, D. P., Madani, R., Valenti, P., & Lipp, H. P. (2001). Extended analysis of path data from mutant mice using the public domain software Wintrack. *Physiology and Behavior, 73*, 745–753.

Wolfson, O., & Mena, E. (2004). Applications of moving objects databases. In Y. Manolopoulos, A. Papadopoulos, & M. Vassilakopoulos (Eds.), *Spatial databases: technologies, techniques and trends*. Idea group Co.

Wolfson, O., Sistla, A. P., Chamberlain, S., & Yesha, Y. (1999). Updating and querying databases that track mobile units. *Distributed and Parallel Databases, 7*, 257–287.

Worboys, M., & Duckham, M. (2004). *GIS – A computing perspective*. New York: CRC Press.

Zhao, J. (2003). Representing flows: Unpacking patterns from individual movement data. Master thesis, University of Auckland, Auckland, NZ.