SpatioTemporal Helixes for Event Modeling

Anthony Stefanidis, Peggy Agouris, Panos Partsinevelos
Department of Spatial Information Science & Engineering
National Center for Geographic Information and Analysis
348 Boardman Hall, University of Maine
Orono, ME 04469-5711
{tony, peggy, panos}@spatial.maine.edu
http://www.spatial.maine.edu/~peggy/dgi.html

Abstract

This paper defines a framework for the spatio-temporal analysis of motion imagery (MI) datasets depicting two-dimensional phenomena evolving in time. More specifically, we introduce the concept of a spatiotemporal helix as a concise representation of spatiotemporal events, modeling their path in space and the variations of their outline. We also present in some detail the automated algorithms developed to support the automated generation of spatiotemporal helixes and discuss their comparison to support spatiotemporal analysis.

1. Introduction

In modern geospatial applications the aspect of time is becoming increasingly important. The information that analysts seek often resides not in a single image or a map but rather in a multitemporal collection of images and maps. Various parallel advances in sensor technology have resulted in the wide availability of multitemporal geospatial datasets. Considering imagery in particular, these datasets may comprise a video segment or a sequence of static images that differ by seconds, minutes, or even days. We use the term motion imagery (MI) to refer to these multitemporal image datasets. The processing and analysis of spatiotemporal datasets is introducing interesting data handling challenges, mostly associated with the large volumes of datasets, the corresponding processing times, and the diverse nature of information contained in them.

The efficient modeling of spatiotemporal events is a major research challenge and an important step towards the analysis and management of large spatiotemporal datasets. Relevant research includes the work of (Smith & Kanadae, 1995) on the analysis of visual and speech properties to construct "skim" video synopses by merging select segments of the original video. The extraction of select key frames for the generation of video summaries has also been addressed in (Yeung & Yeo, 1997). (Pfoser and Theodoridis, 2000) provide a spatio-temporal synthetic dataset generator to simulate movement trajectories, analyze novel index schemes for moving points using tree structures. The indexing and querying of moving points is also addressed in (Vazirgiannis & Wolfosn, 2001), while (Sistla et al., 1997; Wolfson et al., 1999) discuss the use of future temporal logic for modeling and querying moving objects. Work on indexing animated objects is reported in (Kollios et al., 2001), while (Tao & Papadias, 2001) propose a framework for indexing and querying spatiotemporal data by constructing new tree structures.

In (Stefanidis et al., 2001) we introduced a general framework for the summarization of spatiotemporal trajectories considering point datasets (a point changing its position over time). This was in accordance to the above mentioned relevant works, where moving objects are reduced to a point representation, ignoring spatial extent of objects and the variations of their outlines. In this paper we move beyond this simplification, extending the framework introduced in (Stefanidis et al., 2001) to accommodate the spatial extent of objects. This allows us to consider not only the movement but also the deformation of spatial objects, introducing a more comprehensive spatiotemporal model than the currently existing ones. At the core of our work is the concept of the *spatiotemporal helix*, a novel spatiotemporal object model. It allows us to model object movements and deformations, supporting complex spatiotemporal analysis.

This is a key development to support the analysis of spatiotemporal phenomena that have certain spatial extent and change their position and/or extent over time. Such phenomena can be slowly moving (e.g. urbanization trends depicted in a series of monthly satellite images) or rapidly evolving (e.g. hurricanes depicted in hourly or daily datasets), and they take place over a fixed area (e.g. flooding) or may be constantly changing their location (e.g. a moving fire front).

The rest of the paper is organized as follows: In the second section we introduce the concept of the spatiotemporal helix as a concise representation of spatiotemporal events. The automated generation of spatiotemporal helixes makes use of two automated techniques we have developed: a technique based on self-organizing maps for the generalization of point trajectories (presented in extent in dg.o 2001) and differential snakes, an extension of the model of deformable contour models to perform outline comparison (Section 3). Section 4 addresses spatiotemporal analysis issues using helixes, with final comments following in section 5.

2. Spatiotemporal Helix

The spatiotemporal domain of a scene comprises two *(x,y)* spatial dimensions and one *(t)* temporal dimension. Object movement is identified by tracing objects in this 3-dimensional *(x,y,t)* space. We introduce the spatiotemporal helix (*STH*) is a compact description of an object's spatiotemporal behavior. It comprises a central spine and annotated prongs (Fig. 1). More specifically:

- The central **spine** models the spatiotemporal trajectory described by the center of the object as it moves over a temporal interval.
- The protruding **prongs** express expansion or collapse of the object's outline at a specific time instance.

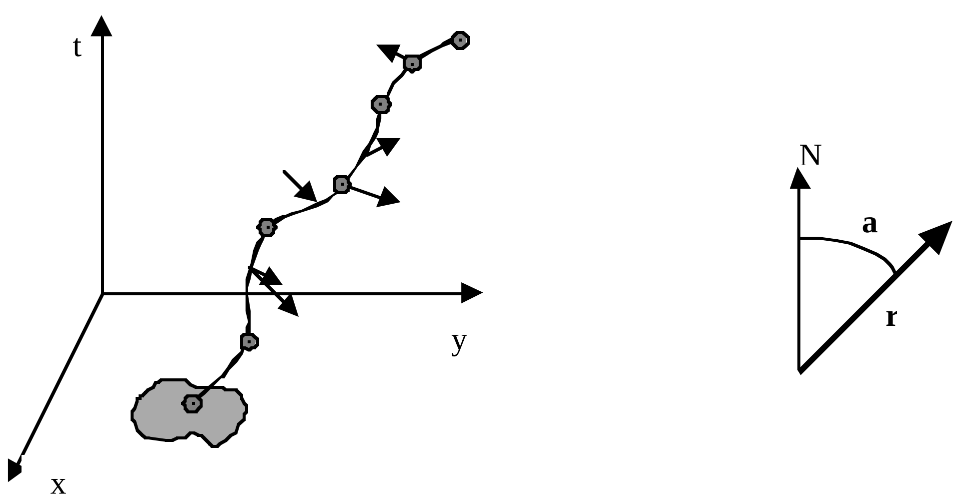

Fig 1: A spatiotemporal helix (left) and a detail showing the azimuth of a prong (right)

Fig. 1(left) is a visualization of the concept of spatiotemporal helix. The spine is the vertical line connecting the nodes (marked as white circles), and the prongs are shown as arrows protruding from the spine, pointing away from or towards it. The gray blob at the base of the spine is the initial outline of the monitored object. The helix describes a movement of the object whereby the object's center follows the spine, and the outline is modified by the amounts indicated by the prongs at the corresponding time instances.

As a spatiotemporal trajectory, a *spine* is a sequence of (x,y,t) coordinates. It can be expressed in a concise manner as a sequence of spatiotemporal nodes $S(n^1,\ldots n^n)$. The nodes correspond to breakpoints along this trajectory, namely points where the object accelerated/decelerated and/or changed its orientation.. Accordingly, each node n^i is modeled as $n^i(x,y,t,q)$, where:

- *(x,y,t)* are the spatiotemporal coordinates of the node, and
- *q* is a qualifier classifying the node as an *acceleration* (q^a), *deceleration* (q^d), or *rotation* (q^r) node.

Each prong is a model of the local expansion or collapse of the outline at a specific time instance, and is represented in Fig 1 by a horizontal arrow pointing away from (expansion) or towards (collapse) the spine. It is modeled as $p^i(t,r,a_1,a_2)$ where:

- *t* is the corresponding temporal instance (intersection of the prong and the spine in Fig. 1 left),
- *r* is the magnitude of this outline modification, expressed as a percentage of the distance between the center of the object and the outline, with positive numbers expressing expansion (corresponding arrows pointing *away from* the spine) and negative numbers indicating collapse (arrows pointing *towards* the spine),
- a_1, a_2 is the range of azimuths where this modification occurs; with each azimuth measured as a left-handle angle from the North (y) axis (Fig. 1 right).

As shown in Fig 1 we can have more than one prongs at a single instance, as it is possible for an object to be expanding in one direction while shrinking in another at the same time. While in general prongs correspond to small ranges over an outline, by properly assigning values to the azimuth parameters of a prong we can also model global expansion/collapse (a_1=0, a_2=360).

Combined, spine and prongs comprise a concise signature of an object's spatiotemporal behavior. They express external (spine) and internal (prongs) processes affecting an object's position and shape, and allow efficient spatiotemporal modeling to support complex analysis. We have developed automated techniques to collect the information required to create spatiotemporal helixes. The generalization of point trajectories is accomplished using a variation of self-organized maps (SOM), a class of artificial neural networks. Trajectories can be perceived as paths in the spatiotemporal space, and as such they are generalized with SOM using a nonlinear and nonparametric regression solution. This abstraction uses as input clouds of points in the (x.y,t) spatiotemporal domain and produces a generalized description of the spatiotemporal trajectory through a set of distributed nodes (spine of Fig. 1). Our work in this topic was presented in last year's Digital Government conference and the reader is referred to (Stefanidis et al., 2001) for further details. In the next section we will present a novel approach developed by our group to track variations of object outlines, to provide the remaining information necessary to produce a spatiotemporal helix.

3. Tracking Outline Deformations with Differential Snakes

Tracking changes in the outline of an event involves the comparison of the event's outline at an instance to the same outline at another instance, to identify the points where this outline has expanded or collapsed. The model of deformable contour models (a.k.a. snakes) provides a theoretical foundation for the delineation of an outline (Kass et al., 1987). It proceeds by establishing a theoretical model of an ideal outline as it is expressed by radiometric and geometric criteria. These criteria are formulated as energy functions that describe geometric and radiometric constraints to be satisfied by the extracted outline. During solution iterations they act as forces that deform an outline to comply to the local image content while optimizing the total energy metrics.

In a traditional snake model the total energy of each snake point is expressed as:

$$E_{snake} = \alpha \cdot E_{cont} + \beta \cdot E_{curv} + \gamma \cdot E_{edge} \qquad (1)$$

where : E_{cont} , E_{curv} are energy terms expressing first and second order continuity constraints (forcing the outline to be as smooth as possible); E_{edge} is an energy term expressing edge strength (forcing the outline to describe locations where gray values differ significantly from their neighbors); and α, β, γ are (relative) positive weights of each energy term, describing which part we emphasize most.

In order to detect changes in an object's outline we proceed by comparing the content of an image (time *T+dt*) to the last record of this outline (time *T*). The outline extracted through Eq. 1 is stochastic in nature, as varying image conditions affect our ability to differentiate between an object and its neighbors. To take this information into account we extended the traditional snake model by introducing an additional energy term (and corresponding weight coefficient) to express a buffer zone in the area of each snake node, expressing the local fuzziness effect of uncertainty. The new model of differntial snakes is expressed as:

$$E_{snake} = \alpha \cdot E_{cont} + \beta \cdot E_{curv} + \gamma \cdot E_{edge} + \gamma \cdot E_{edge} + \delta \cdot E_{unc} \qquad (2)$$

Furthermore, as our objective is to detect major trends in an outline's variations, we mark as such the locations where the outline has moved the beyond the buffer zone more than a pre-specified threshold (typically selected to be 3 times the buffer zone). Prongs (as they were described in Section 2 of this paper) correspond to such instances. A detailed description of our differential snakes model may be found in (Agouris et al., 2001).

Fig. 2 shows an example of the application of our technique. The two outlines show an event's evolution from instance *T* to *T+dt*. Thee arrows mark the points where we detected major variations with our differential snakes method. These results produce 4 prongs for the vent's helix at time *T+dt*, with their size and azimuth corresponding to the size and azimuths of the arrows of Fig. 2.

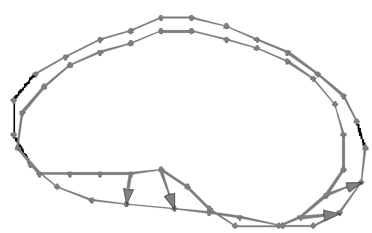

Fig 2: Major object outline variations detected with a differential snake.

4. Spatiotemporal Analysis Using Helixes

A description of the integration of SOM and snakes techniques to automatically generate spatiotemporal helixes is shown in Fig. 3. It should be noted that for practical purposes SOM-based trajectory generalization takes place first. Using this information we register all outlines to the same center and proceed with differential snakes. This cycle of processes allows us to extract all necessary information to construct a spatiotemporal helix describing a spatiotemporal event.

Spatiotemporal analysis commonly involves the comparison of events, to identify similarities, establish causalities, and thus identify interrelationships among them. Spatiotemporal helixes are valuable tools towards this goal. They serve as signatures of spatiotemporal events and, drawing upon the obvious parallelism, helix similarity analysis resembles DNA hybridization: it proceeds by comparing nodes and prongs to establish links between helix pairs (Fig. 4). This involves the comparison of their corresponding records as they were presented in Section 2. Similarities can be identified in instances where the corresponding records (e.g. azimuth values or positions) differ less than an acceptable threshold (see e.g. the buffer zones in Fig. 5). A similarity metric *S* is then provided as a coincidence percentage:

S = (duration of coincidence)/(duration of event) (2)

Where duration coincidence is the aggregate time during which the two events were displaying similar properties (e.g. both were pointing North). In order to support this comparison, the range of values of each property may be tessellated in few subsets. For example, azimuth information may be presented as 4 (N, W, S, and E) or even 8 (adding NE, SE, SW, NW) discrete directions as opposed to 360 discrete degrees.

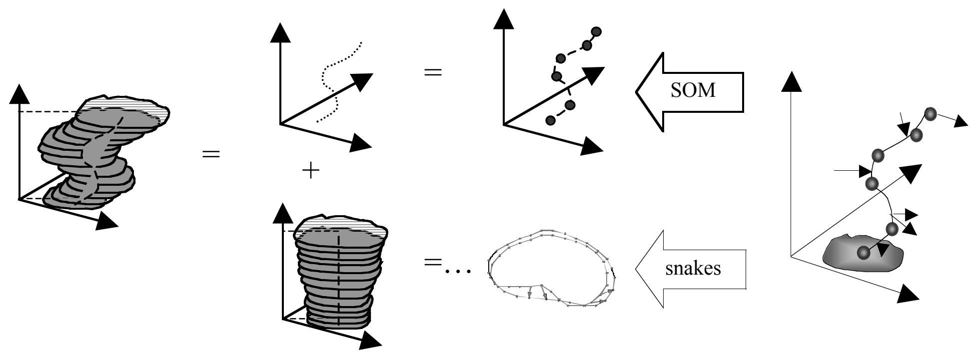

Fig. 3: Overview of helix modeling

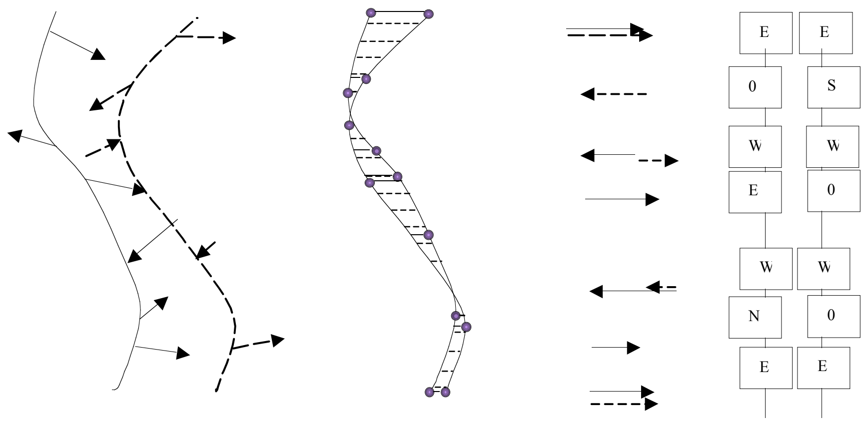

Fig. 4: Comparison of spatiotemporal helixes

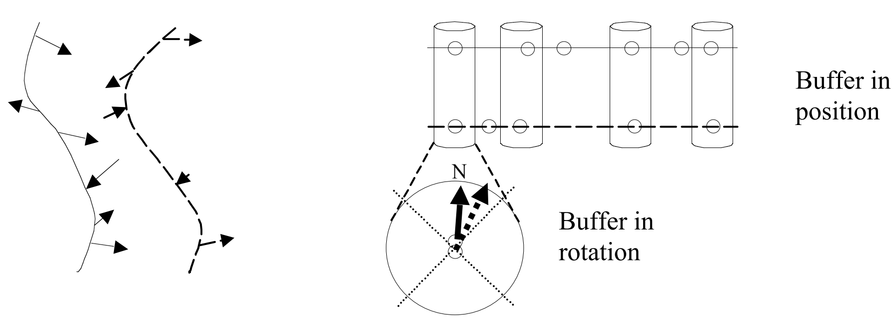

Fig 5: The effect of buffering in spatiotemporal helix comparison when comparing two spatiotemporal helixes (one represented by a continuous line, the other by a dashed line).

5. Comments

In this paper we introduced the concept of spatiotemporal helix as a model of spatiotemporal events. It allows us to model efficiently changes in the location and extent of a phenomenon, and supports the comparison of events to identify similarities and complex relationships among them. This comparison of spatiotemporal helixes allows us to produce meaningful qualitative metrics to what up to this point have been considered as quantitative queries. While our motivation is the analysis of events as they are captured in motion imagery datasets, the concept of the spatiotemporal helix can be applied to any type of multitemporal datasets with spatially-registered information (e.g. land use patterns as they are depicted in a multitemporal sequence of maps, disease spread as it is recorded in a GIS etc.).

Acknowledgements

This work was supported by the National Science Foundation under Award number DG-9983445. We would like to thank Mr. Gyftakis for providing Figure 2.

6. References

Agouris P., A. Stefanidis & S. Gyftakis, 2001. Differential Snakes for Change Detection in Road Segments, *Photogrammetric Engineering & Remote Sensing*, 67(12), pp. 1391-1399.

Kass M., A. Witkin, & D. Terzopoulos, 1987. Snakes: Active contour models, in *Proceedings of the 1st Int. Conf. on Computer Vision*, London, pp. 259-268

Kollios G., V. Tsotras, D. Gunopulos, A. Delis, & M. Hadjieleftheriou, 2001. Indexing Animated Objects Using Spatiotemporal Access Methods, *IEEE TKDE*, 13(5): 758-777.

Partsinevelos P., A. Stefanidis & P. Agouris, 2001. Automated Spatiotemporal Scaling for Video Generalization, IEEE-ICIP01 (International Conference on Image Processing), Thessaloniki, Vol. 1, pp.177-180.

Pfoser D., & Y. Theodoridis, 2000. Generating Semantics-Based Trajectories of Moving Objects, *Intern. Workshop on Emerging Technologies for Geo-Based Applications*, Ascona.

Smith M. & T. Kanade, 1995. Video Skimming for Quick Browsing based on Audio and Image Characterization, *Tech. report CMU-CS-95-186*, Carnegie Mellon University.

Stefanidis A., P. Partsinevelos & P. Agouris, 2001. Using Lifelines for Spatiotemporal Sumaries, *DG.O 2001 Proceedings*, pp. 1-8, Los Angeles, CA.

Sistla A.P., O. Wolfson, S. Chamberlain, & S. Dao, 1997. Modeling and Querying Moving Objects. *ICDE*, pp. 422-432

Tao Y., & D. Papadias: 2001. MV3R-Tree: A Spatio-Temporal Access Method for Timestamp and Interval Queries. *VLDB 2001*: 431-440.

Vazirgiannis M., & O. Wolfson, 2001. A Spatiotemporal Query Language for Moving Point Objects, *SSTD '01*, Los Angeles, pp. 20-35.

Wolfson O., A.P.Sistla, B. Xu, J. Zhou, & S. Chamberlain: DOMINO: Databases fOr MovINg Object tracking. *SIGMOD Conference 1999*, pp. 547-549.

Yeung M., & B.L. Yeo, 1997. Video Visualization for Compact Presentation and Fast Browsing of Pictorial Content, *IEEE Trans. on CSVT*, 7(5), pp. 771-785.