# How context influences the segmentation of movement trajectories – an experimental approach for environmental and behavioral context

#### Anna-Katharina Lautenschütz

<sup>1</sup>Department of Geography, University of Zürich, Winterthurerstr. 190, 8057 Zürich, Switzerland a-k.lautenschuetz@geo.uzh.ch

# 1. Introduction

In the digital information age where large amounts of movement data are generated daily through technological devices, such as mobile phones, GPS, and digital navigation aids, the exploration of moving point datasets for identifying movement patterns has become a research focus in GIScience (Dykes and Mountain 2003). Visual analytics (VA) tools, such as GeoVISTA Studio (Gahegan 2001), have been developed to explore large amounts of movement data based on the contention that VA combine computational methods with the outstanding human capabilities for pattern recognition, imagination, association, and reasoning (Andrienko et al. 2008). However, exploring, extracting and understanding the meaning encapsulated in movement data from a user perspective has become a major bottleneck, not only in GIScience, but in all areas of science where this kind of data is collected (Holvoak et al. 2008). Specifically the inherent complex and multidimensional nature of spatio-temporal data has not been sufficiently integrated into visual analytics tools. To ensure the inclusion of cognitive principles for the integration of space-time data, visual analytics has to consider how users conceptualize and understand movement data (Fabrikant et al. 2008). A review on cognitively motivated work exemplifies the urgent need to identify how humans make inferences and derive knowledge from movement data. In order to enhance visual analytics tools by integrating cognitive principles we have to first ask to what extent cognitive factors influence our understanding, reasoning, and analysis of movement pattern extraction. It is especially important to comprehend human knowledge construction and reasoning about spatial and temporal phenomena and processes.

This paper proposes an experimental approach with human subject testing to evaluate the importance of contextual information in visual displays of movement patterns. This research question is part of a larger research project, with two main objectives, namely

- getting a better understanding of how humans process spatio-temporal information
- and empirically validating guidelines to improve the design of visual analytics tools to enhance visual data exploration.

## 2. Background

Recent research has revealed that the visual exploration of movement data is dependent on several factors. From a data perspective, basic movement characteristics, as identified in a taxonomy of movement patterns need to be detectable for an analyst (Dodge, Weibel and Lautenschütz 2008). This taxonomy also reveals a differentiation into generic and behavioral patterns (Dodge, Weibel, Lautenschütz 2008). We contend

that behavioral patterns are highly dependent on context. Context-dependence has been well recognized in computer science, especially for mobile applications. However, context awareness has been limited in the design of visual analytics tools, in particular for space-time data. In order to integrate it, we have to know the effect of contextual information on the exploration and analysis of movement data.

Computational approaches to identify movement patterns have mainly focused on the detection and modeling of (generic) geometric information in movement trajectories (Andersson et al. 2008, Gudmundsson and van Kreveld 2006, Gudmundsson, van Kreveld and Speckmann 2004, Laube and Purves 2006, Laube, Imfeld and Weibel 2005). Recent development suggests a trend to also include semantic information (Schmid, Richter and Laube 2009, Klippel and Li 2009, Yan et al. 2008), especially by looking at the conceptualization of movement patterns as events (Klippel 2009). Event approaches (Worboys and Hornsby 2004, Worboys 2005) are an effort to incorporate cognitive principles into geographic information systems. Worboys and Hornsby (2004) demonstrate that an event approach leads to more powerful modeling of dynamic geospatial phenomena. To enhance the understanding of geographic event conceptualization Klippel (2009) evaluates formal topological models with human subject testing.

Event conceptualization is extensively studied in cognitive science research, (e.g., Zacks and Tversky 2001, Schwartz 2008, Casati and Varzi 2008). Examining categorization and segmentation processes is important, as they are at the core of human cognition to simplify our understanding of complex continuous processes (Zacks and Tversky 2001). This is especially relevant for the understanding of complex dynamic spatio-temporal processes. Event segmentation research in psychology investigates the human identification of breakpoints during animations of moving entities to better understand the underlying mental models and cognitive principles (Shipley and Maguire 2008, Tversky, Zacks 2008, Troje 2008, Zacks 2004). Event segmentation is also applied in computational modeling (Chellappa et al. 2008, Reynolds, Zacks and Braver 2007). While data mining and computational geometry approaches have studied 2D trajectories of movement data (Laube et al. 2007) and visual analytics approaches have developed summarization and aggregation techniques for 2D depictions of movement data (Andrienko et al. 2008), to this date, human event segmentation of continuous behavioral movement patterns shown in static 2D depictions have not yet been investigated. By borrowing sound theory and wellestablished experimental methods from psychology and cognitive science we attempt to close this research gap.

# 3. Methodology

#### 3.1 Experimental Design

We designed a human subject experiment to assess the influence of contextual information on the trajectory segmentation of moving entities depicted on 2D static displays. Human movement data collected for the Mafreina research project (www.mafreina.ch) from the University of Applied Sciences in Wädenswil, Switzerland was used to construct movement trajectories. The data consists of GPS tracks that were recorded during various outdoor activities within and in the vicinity of the Swiss National Park. Participants (N=60) study a single movement trajectory represented by a temporal sequence of GPS fixes (i.e., dots) on a 17-inch sized display. The stimuli are generated by \*.XML-based GPS data that are mapped through Google Maps API. The experiment is set up as a mixed two (environmental context) by two

(behavioral context) by two (trajectory type) factorial design. The variables examined in this experiment are the between-subject factor *environmental context* (a movement trajectory with/without a base map), the within-subject factor *behavioral context* (varying behaviors of the moving entities), as well as *trajectory type* (open or closed paths). The environmental context factor includes a movement trajectory shown on a terrain map or without a map, as shown in Figure 1. To strengthen the environmental context information given in the display, the terrain map also includes cartographic symbols that indicate camping facilities.



Figure 1. Environmental context is differentiated either (a) without a terrain map or (b) with a terrain map.

Behavioral context is manipulated by trajectories generated by either backcountry skiers, or downhill skiers (on groomed slopes). These two outdoor activities (i.e., goal directed behaviors) create distinctly different movement patterns, as shown in Figure 2. Downhill skiers move (rapidly) downhill within a well defined elongated area of groomed slopes, always in the vicinity of existing ski lift infrastructure (slower and mostly straight up hill movement), whereas backcountry skiers hike (slowly) uphill in meandering tracks and (more rapidly) ski downhill, unrestricted by human made infrastructure. The variable, trajectory-shape, contains either open or closed paths, as seen in Figure 3, that have been hypothesized by prior psychological work to be cognitively and perceptually different (Shipley and Maguire 2008).



Figure 2. Behavioral context is generated by two activities, (a) backcountry skiing and (b) downhill skiing.



Figure 3. A closed path (a) and an open path (b) define trajectory type.

### 3.2 Procedure

Participants (N=60) are from the University of Zurich, University of Twente, and University of Munster, and are presented with digital trajectory displays and are asked to intuitively segment the path into the largest units that are natural and meaningful to them. This segmentation task follows prior work by Zacks (2004) where participants segmented animated displays of moving entities. In our study, participants respond by placing circles for the segmentation on the depicted trajectory into the GoogleMap API display. After each segmentation task participants are asked to rate their response confidence on a five-point Likert scale (Tastle and Wierman 2006) ranging from *very confident* to *very unsure*.

# 4. Discussion

We presented an experimental design to evaluate the importance of contextual information for visual displays of movement patterns. Data collection for a series of case studies is currently underway. The analysis of participants' segmentation data focuses on the spatial distribution and the frequency of segmentation points. We hypothesize that the segmentation depends on the amount of contextual information given. For displays with no contextual information, we hypothesize that participants segment trajectories using basic movement parameters, specifically speed and change of direction However, for trajectory displays with a terrain base map, thus adding environmental contextual information, we hypothesize that participants' segmentation will be based on activity changes (Tversky et al. 2008), for instance, slowly hiking uphill, taking a break, and then rapidly skiing downhill with contextual information. We contend that environmental context information is necessary for understanding movement patterns beyond kinematics, which in turn facilitates a better understanding of the behavioral movement processes that underlie observable movement patterns. Additionally, we will analyze participants' response time and confidence ratings to evaluate our hypothesis that the exploration and understanding of complex movement trajectories is easier with environmental context information. For the variable trajectory shape, we assume that closed paths lead to the perception of more events and sub-events, thus creating more segmentation points. We will assess these hypotheses and the effect of environmental context, behavioral context and trajectory type by means of a repeated measure ANOVA on the frequency of breakpoints.

# 5. Conclusions

This paper aims at understanding human conceptualization of spatio-temporal movement patterns by analyzing how humans segment static 2D trajectories of movement data. While prior research in GIScience has emphasized the analysis of generic geometric patterns in movement data, we specifically focus on the human understanding of behavioral movement patterns, and the influence of contextual information for the human segmentation of movement trajectory data.

The results from the experiment will serve as an initial step to gain insight into human's understanding and reasoning of spatio-temporal data with static, 2D visual displays and is a key requirement for the development of cognitively adequate visualization tools. This knowledge can also inform computational (geometry) approaches that have not yet looked at the influence of contextual information on movement trajectory analysis, and especially on behavioral patterns. Experimental findings will be published in a follow-up full-paper.

## Acknowledgements

The author gratefully acknowledges financial support by the Swiss National Science Fund under Grant no 200020-126657/1. I would like to thank Reto Zupf from the ZHAW Wädenswil for the permission to use movement data from the Mafreina Project. I would also like to thank Ramya Venkateswaran for the great programming of the displays, as well as various colleagues from GIS and GIVA for discussing the experiment with me. Finally, I thank Sara Fabrikant and Mary Hegarty for insightful comments and suggestions that substantially improved this research project.

## References

- Andersson, M., P. Laube, T. Wolle & J. Gudmundsson (2008) Reporting leaders and followers among trajectories of moving point objects. *GeoInformatica*, 12, 497-528.
- Andrienko, G., N. Andrienko, J. Dykes, S. I. Fabrikant & M. Wachowicz (2008) Geovisualization of Dynamics, Movement and Change: key issues, and developing approaches in visualization research. *Information Visualization*, Special Issue on Geovisualization of Dynamics, Movement and Change Vol.7, 173-180.
- Casati, R. & A. C. Varzi. 2008. Event Concepts. In *Understanding Events*, eds. T. F. Shipley & J. M. Zacks, 31-53. Oxford: Oxford University Press.
- Chellappa, R., N. P. Cuntoor, S.-W. Joo, V. S. Subrahmanian & P. Turaga. 2008. Computational Vision Approaches for Event Modeling. In *Understanding Events - From Perception to Action*, eds. T. F. Shipley & J. M. Zacks, 473-521. Oxford: Oxford University Press.
- Dodge, S., R. Weibel & A.-K. Lautenschütz (2008) Towards a Taxonomy of Movement Patterns. *Information Visualization*, 7, 240-252.
- Dykes, J. & D. M. Mountain (2003) Seeking structure in records of spatio-temporal behaviour: visualization issues, efforts and applications. *Computational Statistics & Data Analysis*, 43, 581-603.
- Fabrikant, S. I., Rebich-Hespanha, N. Andrienko, G. Andrienko & D. R. Montello (2008) Novem Method to Measure Inference Affordance in Static Small-Multiple Map Displays Representing Dynamic Processes. *The Cartographic Journal*, 45, 201-215.
- Gahegan, M. 2001. Visual exploration in geography: analysis with light. In *Geographic Data Mining* and Knowledge Discovery, eds. H. J. Miller & J. Han, 260-287. London: Taylor & Francis.
- Gudmundsson, J. & M. van Kreveld. 2006. Computing Longest Duration Flocks in Trajectories. In ACM GIS.
- Gudmundsson, J., M. van Kreveld & B. Speckmann. 2004. Efficient Detection of Motion Patterns in Spatio-Temporal Data Sets. In *ACM GIS*, 250-257. New York.
- Holyoak, M., R. Casagrandi, R. Nathan, E. Revilla & O. Spiegel (2008) Trends and missing parts in the study of movement ecology. *Proceedings of the U.S. National Academy of Science*, 105, 19060-19065.

- Klippel, A. (2009) Topologically characterized movement patterns: A cognitive assessment. *Spatial Cognition and Computation*, 9, 233-261.
- Klippel, A. & R. Li. 2009. The Endpoint Hypothesis: A Topological-Cognitive Assessment of Geographic Scale Movement Patterns. In *International Conference on Spatial Information Theory (COSIT)*, eds. K. Hornsby Stewart, C. Claramunt, M. Denis & G. Ligozat, 177-194. Aber Wrac'h, France: Springer LNCS.
- Laube, P., S. Imfeld & R. Weibel (2005) Discovering relative motion patterns in groups of moving point objects. *International Journal of Geographical Information Science*, 19, 639-668.
- Laube, P. & R. S. Purves (2006) An approach to evaluating motion pattern detection techniques in spatio-temporal data. *Computers, Environment and Urban Systems,* 30, 347-374.
- Laube, P., R. S. Purves, S. Imfeld & R. Weibel. 2007. Analysing Point Motion with Geographic Knowledge Discovery Techniques. In *Dynamic and Mobile GIS: Investigating Changes in Space and Time*, eds. J. Drummond, R. Billen, E. Joao & D. Forrest, 263-287. Boca Raton, FL: Taylor and Francis.
- Reynolds, J. R., J. M. Zacks & T. S. Braver (2007) A Computational Model of Event Segmentation From Perceptual Prediction. *Cognitive Science*, 31, 613-643.
- Schmid, F., K.-F. Richter & P. Laube. 2009. Semantic Trajectory Compression. In Advances in Spatial and Temporal Databases - 11th International Symposium, SSTD 2009, eds. N. Mamoulis, T. Seidl, T. B. Pedersen, K. Torp & I. Assent, 411-416. Springer.
- Schwartz, R. 2008. Events Are What We Make Of Them. In *Understanding Events From Perception* to Action, eds. T. F. Shipley & J. M. Zacks, 54-60. Oxford: Oxford University Press.
- Shipley, T. F. & M. J. Maguire. 2008. Geometric Information for Event Segmentation. In Understanding Events - From Perception to Action, eds. T. F. Shipley & J. M. Zacks, 415-435. Oxford: Oxford University Press.
- Tastle, W. J. & M. J. Wierman (2006) An information theoretic measure for the evaluation of ordinal scale data. *Behavior Research Methods*, 38, 487-494.
- Troje, N. F. 2008. Retrieving Information from Human Movement Patterns. In Understanding Events -From Perception to Action, eds. T. F. Shipley & J. M. Zacks, 308-334. Oxford: Oxford University Press.
- Tversky, B., J. M. Zacks & B. Martin Hard. 2008. The Structure of Experience. In Understanding Events - From Perception to Action, eds. T. F. Shipley & J. M. Zacks, 436-464. Oxford: Oxford University Press.
- Worboys, M. (2005) Event-oriented approaches to geographic phenomena. International Journal of Geographical Information Science, 19, 1-28.
- Worboys, M. & K. Hornsby. 2004. From objects to events: GEM, the geospatial event model. In *GIScience*, eds. M. J. Egenhofer, C. Freksa & H. J. Miller, 327-343. Springer.
- Yan, Z., J. Macedo, C. Parent & S. Spaccapietra (2008) Trajectory Ontologies and Queries. *Transactions in GIS*, 12, 75-91.
- Zacks, J. M. (2004) Using movement and intentions to understand simple events. *Cognitive Science*, 28, 979-1008.
- Zacks, J. M. & B. Tversky (2001) Event Structure in Perception and Cognition. *Psychological Bulletin*, 127, 3-21.