WhereNext: Towards a Cartographic Framework for Movement

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Keywords: cartography, movement, trajectory, knowledge discovery, information visualization

Introduction

This paper describes an ongoing research towards the development of a cartographic framework for mapping movement. Although research on trajectory data and movement analytics is on the rise (Long *et al.*, 2018), the suitability of cartographic theories for movement as a dynamic phenomenon and the efficacy of current visualization approaches for knowledge discovery using large tracking data sets remain understudied (Griffin, Robinson and Roth, 2017; Demšar, Slingsby and Weibel, 2019). A vast amount of information on trajectories (i.e. time-ordered sets of locations of mobile entities) is now collected at very high spatial and temporal resolutions. These data promise new forms of knowledge about global flows of humans and goods, disease outbreaks, the impact of transportation changes on urban dynamics, or effects of human activity on the behavior of competing species. However, as computational approaches advance our ability to analyze trajectory data, we remain limited in our understanding of how movement patterns should be displayed in accurate and informative ways.

Figure 1 shows the data science paradigm for movement introduced in Dodge (2019). Taking advantage of abundant real tracking data, the model operates on a bottom-up approach for understanding movement processes through data-driven analytics, knowledge discovery and machine learning. Complementary, a top-down approach integrates domain knowledge with analytical outcomes to enhance theory-driven models for more reliable movement modeling and prediction of dynamic systems. Emphasizing the role of *human* in movement data science, visualization is highlighted as a fundamental element of this paradigm (Figure 1).

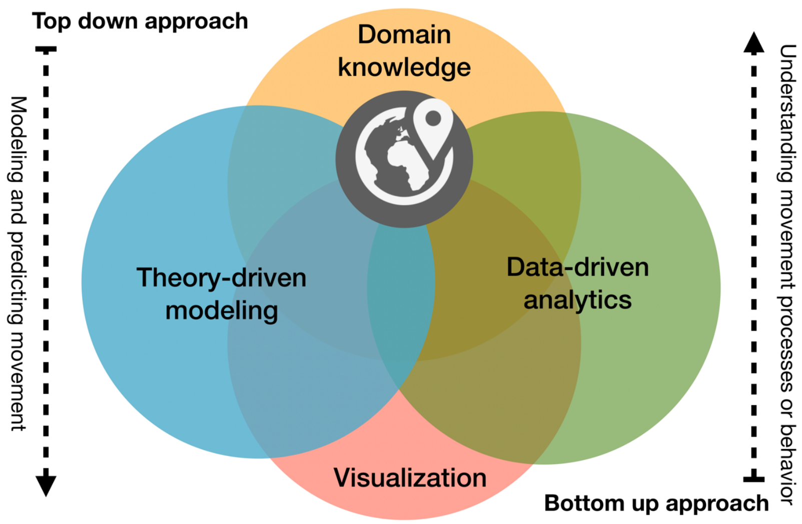

Figure 1 The Data Science Paradigm for Movement (Dodge, 2019)

Proper visualizations grounded in sound cartographic theories can enhance the exploratory analysis of movement data, knowledge communication in cross-disciplinary collaborations with domain experts, and human interpretation of discovered patterns and processes. Inspired by Sacha *et al.* (2018), Figure 2 illustrates a model for human-centered knowledge discovery of movement through data science. In this model, mapping movement is central to data exploration and knowledge generation, and to spark new hypotheses through human visual reasoning. In addition, information visualization supports movement data science in several ways, as follows:

- It enables visual inspection of raw observations to learn about the data and its structures and anomalies (e.g. trends, extents, outliers, etc.).
- It can reveal unexpected or hidden patterns and movement-context dependencies in observations.
- It provides a means to illustrate extracted patterns from models and analytics.
- It supports the method validation process by providing a means to monitor the work process of algorithms and simulations.
- While facilitating communication with domain experts, it supports human visual reasoning to infer and interpret knowledge about underlying processes and behaviors captured in the data.
- It enables the delivery of analytical outcomes and generated knowledge in a form that is easy to perceive and understand (e.g. maps, animations, graphs).

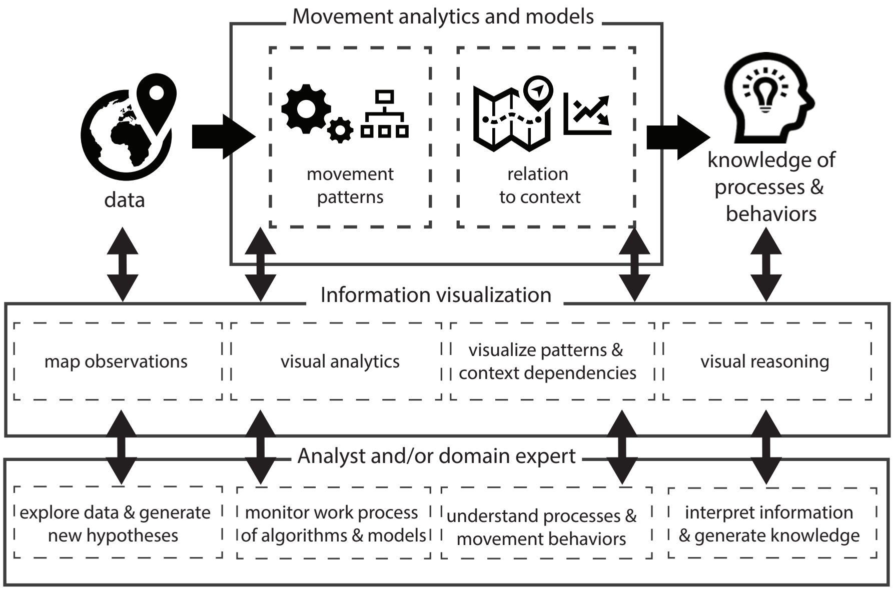

Figure 2 Human-centered knowledge discovery of movement, modified from (Dodge, 2018).

Therefore, to take advantage of the evolution in tracking data and strengthen data science research on movement, we need to advance our cartographic theories and visualization techniques to effectively map movement as a multidimensional dynamic process that involves space, time, and context.

Background

One of the most famous early representations of movement is the Charles Minard's map of Napoleon Russian Campine in mid-nineteenth century. Later, the space-time prism representation of human activity was introduced by Hägerstrand (1970). These handmade graphs illustrate a schematic representation of movement in space over time. Digital cartography of movement took off by mapping flows representing Origin-Destination (O-D) vectors or flowlines (Steiner, 2019). As an example, (Tobler, 1981) mapped the US net population flows and migration trajectories using a field representation of directional vectors (gradient vectors) and directional contour lines. These illustrations of movement flows were based on the concept of *spatial interaction* representing the flows of goods, cash, and population between different geographic regions (Tobler, 1976). In these representation the quantity (represented as the size of vector) is not an attribute of the region but the amount of flow between two different regions (e.g. population origin and destination).

Traditionally, movement is mapped as static representations of points and lines capturing movement trajectories. Other common way to map movement applies aggregation to represent patterns in tracking data or trends in movement parameters (e.g. speed, direction, etc.). The aggregated information is usually overlaid on top of 2D thematic maps as density maps, treemaps, charts or bar graphs (Andrienko *et al.*, 2017) or incorporated in 3D space-time representations (Demšar *et al.*, 2014). In a dynamic representation, Xavier and Dodge (2014) used ribbons and directional vectors to depict the changes and associations in movement and contextual parameters by gradually varying the color and widths of lines representing the trajectories. Although a wealth of studies have offered methods for visual analytics of movement (Demšar, Slingsby and Weibel, 2019), the question is how well these methods capture movement and can facilitate our perception and cognition of complex movement patterns in support of quantitative knowledge discovery of large movement data? As a first step towards answering this question, this ongoing research aims to develop and systematically evaluate a cartographic framework for movement.

A Cartographic Framework for Movement – Preliminary Elements

Movement is realized in a multidimensional space-time-context continuum (represented as a Movement Cube in Figure 3). A trajectory is a manifestation of the footprints of a mobile entity as it traverses this space-time-context continuum. *Space* represents a two or higher dimensional geographic or abstract space in which the entity moves. *Time* represents the temporal duration, start and end time of movement, and the frequency of observations. *Context* encapsulates a multidimensional attribute space representing the circumstances of movement and the characteristics of its embedding environment. The Movement Cube operates across multiple spatial and temporal scales at which movement patterns are observed or studied.

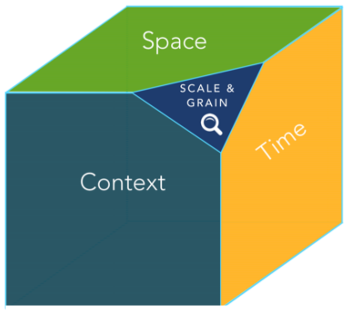

Figure 3 Movement Cube, representing a multidimensional space-time-context continuum

The proposed framework associates cartographic primitives and visual principles to different components of movement (i.e. space, time, context, scale, movement parameters, and movement patterns) as described in (Dodge, Weibel and Lautenschütz, 2008). The framework consists of the following elements:

- **Cartographic space:** describes the environment in which movement is mapped. Examples include time plots, 2D geographic maps, 3D space-time cube, network graphs.
- **Data representation forms:** describes the geographic data model (i.e. vector, raster) used to represent movement.
- **Movement components:** includes information on:
    - Object: represents the moving phenomena that is captured in the visualization (e.g. discrete movement tracks or aggregate flows)
    - Location: represents the geographic location and the extent of movement
    - Time: can be linear or cyclic (Kraak, 2014). It represents temporal information about the start and end time, the duration, and the frequency of movement patterns.
    - Attributes: involve measurable movement parameters (e.g. speed, acceleration, traffic counts, etc.) or other contextual variables setting the circumstances surround movement (e.g. weather conditions, behavioral states, transportation modes, etc.)
- **Visual variables:** describes how Bertin's visual variables (Roth, 2017) can be applied to encode movement using moving points and trajectory lines (see Figure 4).
- **Movement data and visualization perspective:** describes the perspective of movement or view angle in visual representations, which includes *Lagrangian* (when individuals are observed and followed along their movement paths over time) or *Eulerian* (when movement is observed at fixed locations).
- **Visualization techniques:** provides a taxonomy of visualization techniques for movement. These techniques include but not limited to: aggregation, dynamic visualization and animation, flow lines, space-time path representations, multivariate maps, coordinated parallel views, and interactive displays.
- **Interaction:** describes the applicability of *interaction* modalities (e.g. zoom, pan, touch, navigating a time slider, modification) in movement visualization.
- **Granularity:** describes how spatial, temporal, and thematic granularity (Kuhn, 2012) of movement are captured in static and dynamic visualizations.
- **Display forms:** explores the use of static and dynamic, and Virtual Reality displays in mapping movement.

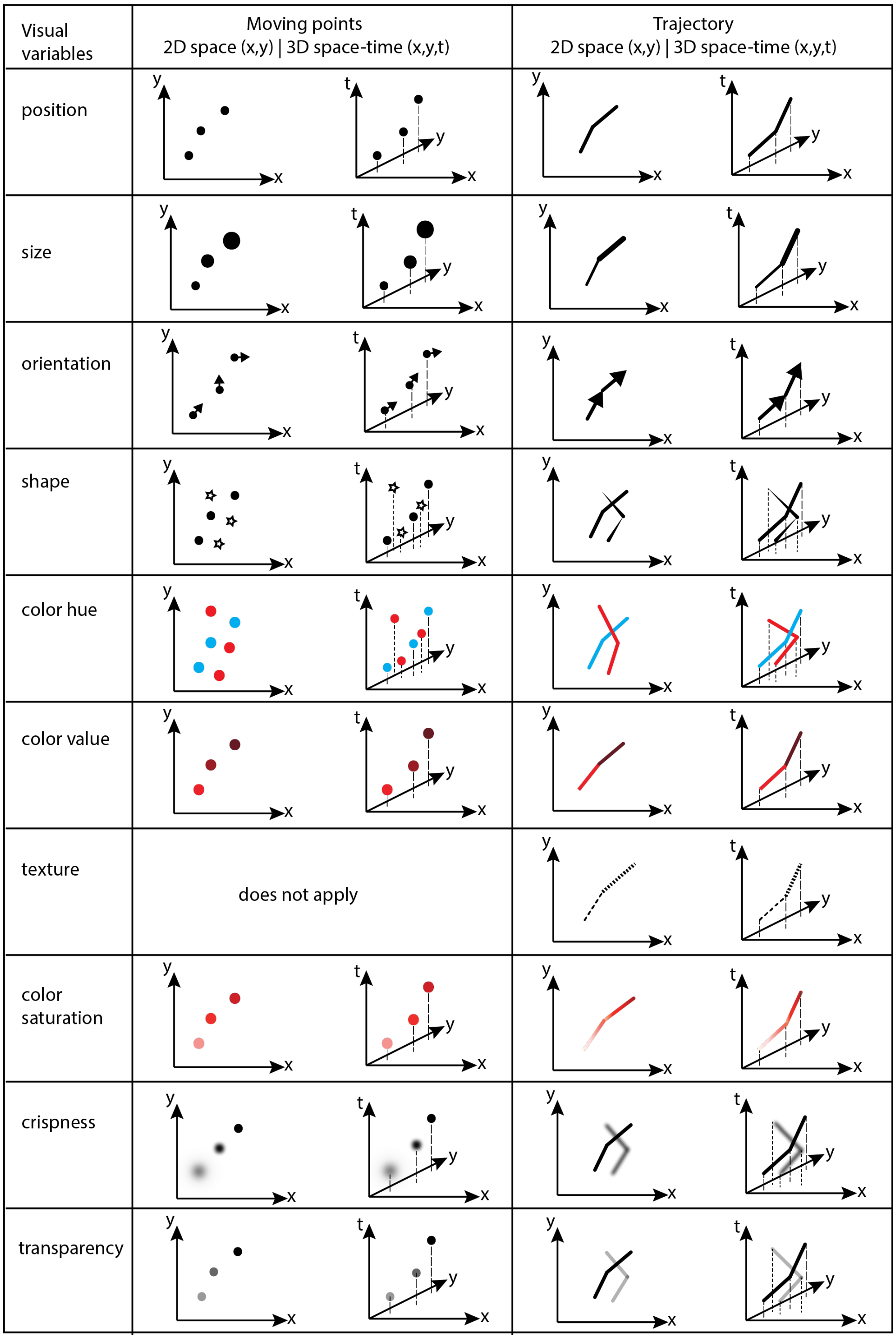

Figure 4 Visual variables and their suitability for mapping movement (preliminary draft)

Conclusion and Future Work

This research conceptualizes a cartographic framework to facilitate the design of more effective, intuitive, and accurate representation of movement within the space-time-context continuum. This extended abstract mainly outlines a preliminary draft of the elements considered in the framework. A taxonomy of movement visualization techniques based on different elements of this framework will be submitted to the special issue of *Cartography and Geographic Information Science (CaGIS)*. As future work, to evaluate the efficacy and the usability of the framework, a series of user study experiments will be conducted.

Acknowledgements:

This research is supported by the National Science Foundation, Award # 1853681. "Visualizing Motion: A Framework for the Cartography of Movement."

References

Andrienko, G. *et al.* (2017) 'Visual analytics of mobility and transportation: State of the art and further research directions', *IEEE Transactions on Intelligent Transportation Systems*. IEEE, 18(8), pp. 2232–2249. doi: 10.1109/TITS.2017.2683539.

Demšar, U. *et al.* (2014) *Stacked space-time densities: a geovisualisation approach to explore dynamics of space use over time*, *GeoInformatica*. doi: 10.1007/s10707-014-0207-5.

Demšar, U., Slingsby, A. and Weibel, R. (2019) 'Introduction to the special section on Visual Movement Analytics', *Information Visualization*, 18(1), pp. 133–137. doi: 10.1177/1473871618810849.

Dodge, S. (2018) 'Embracing visualization as a key element in computational movement analytics', in Freundschuh, S. M. and Sinton, D. (eds) *AutoCarto/UCGIS 2018. The 22nd International Research Symposium on Computer-based Cartography and GIScience*. Cartography and Geographic Information Society (CaGIS), pp. 52–57.

Dodge, S. (2019) 'A Data Science Framework for Movement', *Geographical Analysis*, pp. 1–21. doi: 10.1111/gean.12212.

Dodge, S., Weibel, R. and Lautenschütz, A.-K. (2008) 'Towards a taxonomy of movement patterns', *Information Visualization*, 7(3–4), pp. 240–252. doi: 10.1057/palgrave.ivs.9500182.

Griffin, A. L., Robinson, A. C. and Roth, R. E. (2017) 'Envisioning the future of cartographic research', *International Journal of Cartography*. Taylor & Francis, 9333, pp. 1–8. doi: 10.1080/23729333.2017.1316466.

Hägerstrand, T. (1970) 'What about people in Regional Science?', *Papers of the Regional Science Association*, 24(1), pp. 6–21. doi: 10.1007/BF01936872.

Kraak, M. J. (2014) *Mapping Time: Illustrated by Minard's Map of Napoleon's Russian Campaign of 1812*. Esri Press.

Kuhn, W. (2012) 'Core concepts of spatial information for transdisciplinary research', *International Journal of Geographical Information Science*, 26(12), pp. 2267–2276.

doi: 10.1080/13658816.2012.722637.

Long, J. A. *et al.* (2018) ‘Moving ahead with computational movement analysis’, *International Journal of Geographical Information Science*. Taylor & Francis, 32(7), pp. 1275–1281. doi: 10.1080/13658816.2018.1442974.

Roth, R. E. (2017) ‘Visual Variables’, *International Encyclopedia of Geography: People, the Earth, Environment and Technology*, pp. 1–11. doi: 10.1002/9781118786352.wbieg0761.

Sacha, D. (2018) *Knowledge Generation in Visual Analytics : Integrating Human and Machine Intelligence for Exploration of Big Data*. University of Konstanz. Available at: http://nbn-resolving.de/urn:nbn:de:bsz:352-2-163cdymlht22d9.

Steiner, E. (2019) ‘Flow Maps’, *The Geographic Information Science & Technology Body of Knowledge*. University Consortium for Geographic Information Science, pp. CV–31. doi: 10.22224/gistbok/2019.4.10.

Tobler, W. R. (1976) ‘Spatial Interaction Patterns’, *Journal of Environmental Systems*, 6(4), pp. 271--301. doi: 10.2190/VAKC-3GRF-3XUG-WY4W.

Tobler, W. R. (1981) ‘A Model of Geographical Movement’, *Geographical Analysis*, 13(1), pp. 1–20. doi: 10.1111/j.1538-4632.1981.tb00711.x.

Xavier, G. and Dodge, S. (2014) ‘An Exploratory Visualization Tool for Mapping the Relationships between Animal Movement and the Environment’, in *Proceedings of the 2nd ACM SIGSPATIAL Workshop on MapInteraction*, pp. 36–42.