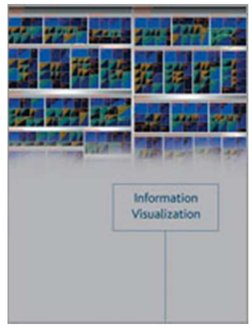
Citation: Demsar, U., Slingsby, A. ORCID: 0000-0003-3941-553X and Weibel, R. (2019). Introduction to the special section on Visual Movement Analytics. Information Visualization, 18(1), pp. 133-137. doi: 10.1177/1473871618810849



Introduction to the special section on Visual Movement Analytics

Journal:	*Information Visualization*
Manuscript ID	Draft
Manuscript Type:	Original Manuscript
Keywords:	movement analytics, visual analytics, movement data, geographic information science, spatio-temporal visualization
Abstract:	/

Article type: Special Section Editorial

Article title: Introduction to the special section on Visual Movement Analytics

Authors
Urška Demšar[1], Aidan Slingsby[2], Robert Weibel[3]

[1] School of Geography & Sustainable Development, University of St Andrews, Scotland, UK
[2] giCentre, City University London, UK
[3] Department of Geography, University of Zurich, Switzerland

Corresponding Author:
Urška Demšar, School of Geography & Sustainable Development, University of St Andrews, Irvine Building, North Street, KY16 9AL St Andrews, Scotland, UK
Email: urska.demsar@st-andrews.ac.uk

Introduction

Information visualisation plays an important role in both presenting the results of analysis and facilitating exploratory analysis on data. But when combined in a more directed and structured way with analytical techniques, it can go beyond exploratory analysis. This concept is formalised in Visual Analytics [1], an approach to analysis that involves iteratively allowing the computer to do what computers are good at (identifying structure in large amounts of data and presenting these as interactive and rich visual summaries of results) and allowing human analysts to do what human analysts are good at (interpreting and interacting with rich visual summaries of results to interpret the results in the light of domain knowledge and their analytical goals, using the information gleaned to further the analytical process). The interactive visual displays that result from analytical outputs may be summaries of data aggregated in different ways and using different visual variables to encode different data variables to convey different aspects of the data. They may instead represent analytical outputs from the data, along with details of the parameters used. Analytical methods may include those that are statistical or those based on data mining or machine-learning techniques. Visual analysis provides the opportunity for analysts to distinguish between patterns that may be worth investigating further from those that are simply known artefacts not worthy of further investigation. It also provides the opportunity for analysts to run analyses on different subsets of data and with different parameters. This is typically done through an iterative process of interpreting and interacting with visual displays that show data from different perspectives and making decisions about the next analytical step. A good example is the iterative use of statistical clustering to identify "similar" movements, where appropriate movement characteristics and parameters are determined through an iterative visual analytics approach. Such a combination of computational and visual methods leads to the ultimate goal of visual analytics, which is to assist the human analyst in building a cognitive model representing a piece of reality and through this improve the understanding and/or support forecasting of a specific phenomenon [2].

This editorial addresses the current state of the art in visual analytics for movement data. Data depicting movement are increasingly commonly collected in many different disciplines: ecologists tag animals with GPS tags to explore animals' responses to changing environmental conditions, transportation researchers track vehicles to monitor traffic developments in real-time, spatial planners need to know how, when and where commuters move in order to be able to plan improvements in the infrastructure and public transport. What all these different disciplines have in common is that the data they create can be mathematically represented in the same way. Movement data typically contain abundant data points that have both location and time, and range from the simpler original-destination flow data, to the more complex trajectory data that represent geometrical paths through space and time. Further complications come in the form of additional multivariate information, different sampling rates, different spatio-temporal precisions and accuracies for individual data points, noise and missing data that require various approaches to interpolation. Finally, these datasets are typically large and often need specific analytical and visualisation techniques.

In this editorial we first provide a brief review of visual movement analytics methods from across domain disciplines, grouped according to the movement data type they are intended for (flows, trajectories and 3D data), then describe how this special section came to be and finish with new opportunities and open challenges.

Visual analytics for movement

Flows are movements between pairs of geographical locations, often also known as origin-destination data. These are common when considering human mobility and transport, such as migration flows between as set of census areas, bike movement between docking stations, and commuting flows between home and work locations. Examples of visual and computational methods for flow data include the study of bicycle flows [3], flow maps with edge-bundling [4] and the unusual-looking "kriskograms" for migration [5]. One study [6] introduces a visual analytics system where flow visualisations are combined with data mining methods, such as clustering. Flow data are also common in movement ecology, where they can be collected – amongst other techniques – with RFID systems for terrestrial tracking or by static arrays of underwater acoustic receivers for marine animals. However, visual analytics tools for animal flows are mostly still lacking, with only a few recent studies. One study [7] present a relatively simple system for RFID flows, while another one [8] introduces a new visualisation for acoustic array data, the so-called activity seascapes, which combine acoustic array tracking data for sharks with computationally-derived behaviour measures from accelerometer tags. Flows can also be generalised to any association between pairs of locations, for example, correlation, similarity or attractiveness, the latter of which can be modelled with spatial interaction models, which can be further analysed with a visual data mining approach [9, 10].

Trajectories are a more complex type of movement data: each trajectory is a sequence of locations with a specific timestamp. Trajectory data can be collected by a range of sensor types including devices that track their location (e.g. GPS trackers and mobile phones), devices that track the location of nearby devices (such as Wi-Fi and Bluetooth), and even algorithms that extract trajectories from video footage common for sports analytics, for example for analysis of football or ice-hockey matches [11, 12]. Ecological examples of visual analytics for trajectories include spatio-temporal linked views for bird migration [13-15], and multi-dimensional trajectory analysis visualisations in the context of environmental data (DynamoVis) [16, 17]. One study [18] developed a system to identify patterns of dynamic interaction between moving objects and apply their methods to animal and sports trajectories. In human mobility and transportation studies systems have been designed to overcome specific problems posed by large real-time data sets [19]. One way to achieve this is to couple visualisation with efficient data representation and statistical modelling [20].

New sensors allow increasingly precise collection of locational and movement data in three physical dimensions. A typical example are trajectories where location is measured in three geographic dimensions, which are common in ecology, but present a challenge for visualisation. Biological space is constrained by the thickness of the atmosphere and the seas and therefore forms a thin layer on the surface of the Earth – animals that move in this space therefore typically cover much larger distances on the surface than in elevation. This poses a particularly difficult problem for visualisation, not only from the perspective of having to show the third dimension on a 2D display, but also from having this dimension significantly smaller than the other two dimensions, resulting in a "pancake" display, a typical example of which are 3D kernel density volumes [21]. This can to some extent be alleviated through geometric methods [22] or by an alternative hexagonal representation of the 3D space [23]. Other 3D aspects of movement are captured by accelerometers (3D motion) and magnetometers (3D orientation) and this information can be used to augment other movement data. Data from these sensors need to be processed and analysed in different ways. For example, accelerometer data are hard to interpret in their raw form, but machine-learning techniques can be used to infer movement type [24]. Magnetometers allow ecologists to analyse animal posture during movement at very detailed spatial scales – to be able to do this, one study [25] presents an innovative visualisation of these data that shows the tri-axial magnetic signals on 3D m-spheres and Dubai plots.

The workshop and the special section in *Information Visualization*

In 2016 we organised a workshop on Visually-supported Movement Analysis at the annual conference of the Association of the Geographic Laboratories of Europe (AGILE) in Helsinki, Finland. The aim of the workshop was to demonstrate advances and showcase examples of visually-supported movement analysis, including best-practice applications in relevant domains. The workshop called for visual analytics contributions from any discipline where analysis of movement is important and for any type of movement data, with a goal to reach a wide audience. In addition to this call we also organised a data challenge using open data from movement ecology, to encourage participants to develop new methods to explore the foraging and migration patterns of seabirds. The data we used contains multi-annual GPS trajectories of over 100 lesser black-backed gulls (*Larus fuscus*) and herring gulls (*Larus argentatus*) that nest on the coast of Belgium and migrate as far south as sub-Saharan Africa. This dataset is also an example of a recent trend in movement ecology to open the data to other researchers and as such not only remains open, but is updated with new data every year [26].

Nine contributions were accepted for presentation at the workshop, including a mix of regular papers and data challenge entries (all contributions are available at the workshop website http://viz.icaci.org/VCMA2016). Part of the workshop was further reserved for general discussion on the importance of visual analytics for analysis of movement and in particular on the role that the interdisciplinarity between the methodological and application disciplines has to play in this development. We therefore decided to open the discussion to a wider audience through a call for papers for this special section of the *Information Visualisation* journal. The final result is a section with three contributions, each of which addresses a different data type reviewed above: GPS trajectories, flows and 3D data.

The first contribution [27] is an outcome of the data challenge and presents a visual analytics methodology for analysis of bird migration trajectories. It is a good example of a traditional information visualization design study [28], performed in tight collaboration between tool developers and ecologists. The tools consist of both visual and computational methods. The design was driven by a set of ecological questions and it allows the analyst to find patterns that are important in migratory context. These include the identification of stopover sites from GPS trajectories, building a flow representation of movements between stopovers, performing a temporal analysis of migratory movements, and identifying similarities and differences between movement of individuals and groups.

The second contribution focuses on large flow data [29] and proposes a solution to the inevitable visual clutter, which is a result of the fixed positions of the origins and destinations of flows. The paper takes the well-known edge-bundling technique and extends it with a combination of clustering and force-directed display methods to create a visually clearer flow map. As the new methodology is aimed specifically at large flow data, an important driver to the algorithm development was the need to reduce computational complexity in order to reduce processing time. The approach is evaluated on a set of different case studies, including traffic flows, bird migration data, human migration and flights. The method is further compared with more traditional approaches, such as OD maps [30].

The last contribution [31] presents a workflow for emergency evacuation planning. It combines 3D data on the characteristics of built environment and people's movement in emergency situations. The workflow they developed combines spatial data science methods with simulation and visualisation capabilities from 3D gaming software to capture how people move, behave and interact with the geometry and topology of the built environment during emergency evacuations. This allows the analyst to simulate and visualise various emergency scenarios, an important factor in preparedness planning.

Conclusions

We conclude this editorial by identifying open challenges and issues that visual movement analytics could address in the future.

The first challenge are new and diverse movement data. As sensor development technology progresses, new types of motion sensors, such as accelerometers, magnetometers, gyroscopes, and physiological sensors are becoming commonplace in many domains and in particular in movement ecology. These new sensors are able to capture complex data at fine spatial and temporal resolutions. For example, new accelerometers used in animal tracking are capable of measuring movement at 100Hz, generating complex and precise time series that reduce the need to model the movement, as everything is measured and observed to an extreme detail. On the other hand, data coming from these accelerometers data require increasingly complex interactive visual systems for efficient exploration [32], which are currently rare or non-existent.

The second challenge is the sheer volume and complexity of the data that these new technologies bring. This places movement data firmly into the realm of "geospatial big data" and brings a number of visualisation challenges [33] as well as algorithmic computational complexity problems [34]. This issue is becoming increasingly recognised as an important research topic in visual movement analytics [20]. More research and development are needed to overcome the graphical and algorithmic limitations for efficient displaying and analysis of large movement data sets.

A third challenge is the access to tools for researchers in the application communities. A particular challenge for researchers from disciplines that collect movement data but who do not themselves develop methods for these data, is the accessibility of tools. Many visual analytics tools are research prototypes from disciplines such as information visualization and are often not freely available in a form that is easily used by other researchers. As a consequence, they are rarely used by anyone other than the authors [19]. On the other hand, the movement ecology discipline has a strong established culture of providing free and open source tools, often in the form of Free and Open Source Software (FOSS). As well as assisting other researchers, a strong benefit of this culture is that is can help ensure the reproducibility of both method development and research [35]. Computer science disciplines, such as information visualisation and visual analytics lag behind and an effort is needed to introduce and grow this open culture.

Finally, visual movement analytics is inherently an interdisciplinary discipline. Much of the work in information visualisation research remains in the information visualisation literature, often with an arms-length collaboration with the domain experts. This is a problem, since designing a new analytical methodology requires not only expertise in method development, but also in-depth domain knowledge in order to be able to develop informed tools that are appropriate for the research questions in the domain discipline. This requires a tight collaboration between tool developers and researchers from application disciplines, which however is not easy – becoming familiar with each other's terminologies and research requires a lot of motivation, energy and time. It is still too often the case that information visualisation and visual analytics researchers only focus on the technical developments of the tools and develop them for their own sake, rather than being motivated by producing methods that are meaningful and useful for the application discipline. Conversely, application discipline researchers are often not aware of recent work in information sciences, consequently ignoring that that visualising and/or analysing their data is in fact not a problem, but someone else's research challenge. Our workshop, others like it and this special section are an attempt to cross this interdisciplinary divide and a small part of a general trend in movement analytics that brings together users and developers [36].

Acknowledgements

The VCMA2016 workshop that led to this special issue was organised as an activity of the Commission on Visual Analytics of the International Cartographic Association (ICA). We would like to thank all participants of the workshop for their contributions.

Declaration of conflicting interests

The authors declare that they have no conflicting interests.

References

1. Thomas JJ and Cook KA. *Illuminating the path: The research and development agenda for visual analytics*. Los Alamitos, CA: IEEE Computer Society, 2005.
2. Andrienko N, Lammarsch T, Andrienko G, et al. Viewing Visual Analytics as Model Building. *Comput Graph Forum* 2018; 37(6):275-299.
3. Beecham R and Wood J. Characterising group-cycling journeys using interactive graphics. *Transp Res Part C* 2014; 47:194–206.
4. Verbeek K, Buchin K and Speckmann B. Flow Map Layout via Spiral Trees. *IEEE Trans Vis Comput Graph* 2011; 17(12): 2536-2544.
5. Xiao N and Chun Y. Visualising Migration Flows Using Kriskograms. *Cartogr Geogr Inf Sci* 2009; 36(2): 183-191.
6. Andrienko G, Andrienko N, Fuchs G et al. Revealing Patterns and Trends of Mass Mobility Through Spatial and Temporal Abstraction of Origin-Destination Movement Data. *IEEE Trans Vis Comput Graph* 2017; 23(9):2120-2136.
7. LaZerte SE, Reudink MW, Otter KA, et al. feedr and animalnexus.ca: A paired R package and user-friendly Web application for transforming and visualizing animal movement data from static stations. *Ecol Evol* 2017; 7:7884–7896.
8. Papastamatiou YP, Watanabe YY, Demšar U, et al. Activity seascapes highlight central place refuging strategies in marine predators that never stop swimming. *Mov Ecol* 2018; 6:9.
9. Guo D. Visual analytics of spatial interaction patterns for pandemic decision support. *Int J Geogr Inf Sci* 2007; 21(8): 859-877.
10. Guo D. Flow Mapping and Multivariate Visualization of Large Spatial Interaction Data. *IEEE Trans Vis Comput Graph* 2009; 15(6): 1041-1047.
11. Stein M, Janetzko H, Lamprecht A, et al. Bring it to the Pitch: Combining Video and Movement Data to Enhance Team Sport Analysis. *IEEE Trans Vis Comput Graph* 2018; 24(1):13-22.
12. Pileggi H, Stolper CD, Boyle JM, et al. SnapShot: Visualization to Propel Ice Hockey Analytics. *IEEE Trans Vis Comput Graph* 2012; 18(12):2819-2828.
13. Slingsby A and van Loon EE. Exploratory Visual Analysis for Animal Movement Ecology. *Comput Graph Forum* 2016; 35(3):471-480.

14. Slingsby A and van Loon EE. Characterisation of Temporal Occupancy for Movement Ecology. *Workshop on Visualisation in Environmental Sciences (EnvirVis)*, 12-13 Jun 2017, Barcelona, Spain. http://openaccess.city.ac.uk/18270/
15. Slingsby A and van Loon EE. Temporal tile-maps for characterising the temporal occupancy of places: A seabird case study. In: *Proceedings of the Geographical Information Science Research UK Conference (GISRUK 2017)*, 18 - 21 Apr 2017, Manchester, UK. http://openaccess.city.ac.uk/17398/
16. Xavier G and Dodge S. An Exploratory Visualization Tool for Mapping the Relationships between Animal Movement and the Environment. In *Proceedings of ACM MapInteract'14*, 4-7 Nov 2014, Dallas/Fort Worth, TX, USA. http://dx.doi.org/10.1145/2677068.2677071
17. Dodge S, Xavier G and Wong WY. DynamoVis - Dynamic Visualization of Animal Movement Data. 2018. Retrieved from the *Data Repository for the University of Minnesota*, https://dx.doi.org/10.13020/D6PH49.
18. Konzack M, McKetterick T, Ophelders T, et al. Visual analytics of delays and interaction in movement data. *Int J Geogr Inf Sci* 2017; 31(2): 320-345.
19. Andrienko G, Andrienko N, Chen W, et al. Visual Analytics of Mobility and Transportation: State of the Art and Further Research Directions. *IEEE Trans Intell Transp Syst* 2017, 18(8):2232-2249.
20. Graser A and Widhalm P. Modelling massive AIS streams with quad trees and Gaussian Mixtures. In *Proceedings of the AGILE 2018 conference*, Lund, Sweden, 12-15 June 2018.
21. Tracey JA, Sheppard JK, Zhu J et al. Movement-Based Estimation and Visualization of Space Use in 3D for Wildlife Ecology and Conservation. *PloS One* 2014; 9(7):e101205.
22. Demšar U and Long JA, 2016, Time-Geography in Four Dimensions: Potential Path Volumes around 3D Trajectories. In *Proceedings of GIScience 2016,* Montreal, Canada, 27-30 Sept 2016. http://dx.doi.org/10.21433/B3117gc866qs
23. Ferrarini A, Giglio G, Pellegrino SP, et al. A new methodology for computing birds' 3D home ranges. *Avian Research* 2018; 9:19.
24. Ramasamy Ramamurthy S and Roy N. Recent trends in machine learning for human activity recognition—A survey. *WIRES Data Min Knowl Disc*, 2018; 8:e1254.
25. Williams H, Holton MD, Shepard ELC, et al. Identification of animal movement patterns using tri-axial magnetometry. *Mov Ecol* 2017; 5:6.
26. Stienen E, Desmet P, Aelterman B, et al. GPS tracking data of Lesser Black-backed Gulls and Herring Gulls breeding at the southern North Sea coast, *ZooKeys* 2016; 555: 115-124.
27. Konzack M, Gijsbers P, Timmers F, et al. Visual exploration of migration patterns in gull data. *Information Visualisation* 2018; 1-15. https://doi.org/10.1177/1473871617751245
28. Sedlmair M, Meyer M and Munzner T. Design Study Methodology: Reflections from the Trenches and the Stacks. *IEEE Trans Vis Comput Graph* 2012; 18(12):2431-2440.
29. Graser A, Schmidt J, Roth F, et al. Untangling origin-destination flows in geographic information systems. *Information Visualization* 2018; 1-20. http://dx.doi.org/10.1177/1473871617738122.
30. Wood J, Dykes J and Slingsby A. Visualisation of Origins, Destinations and Flows with OD Maps. *Cartogr J* 2010; 47(2): 117-129
31. Lochhead IM and Hedley N. Modeling evacuation in institutional space: Linking three-dimensional data capture, simulation, analysis, and visualization workflows for risk assessment and communication. *Information Visualization* 2017; 1-20. http://dx.doi.org/ 10.1177/1473871617720811.
32. Walker JS, Jones MW, Laramee RS et al. TimeClassifier: a visual analytic system for the classification of multi-dimensional time series data. *Vis Comput* 2015; 31:1067–1078
33. Robinson AC, Demšar U, Moore AB et al. Geospatial big data and cartography: research challenges and opportunities for making maps that matter. *International Journal of Cartography* 2017; 3(1):32-60.

34. Li S, Dragicevic S, Castro FA, Sester M, et al. Geospatial big data handling theory and methods: A review and research challenges. I*SPRS J Photogramm Remote Sens* 2016; 115:119-133.
35. Hampton SE, Anderson SS, Bagby SC, et al. The Tao of open science for ecology. *Ecosphere* 2015; 6(7), Article 120.
36. Long JA, Weibel R, Dodge S et al. Moving ahead with computational movement analysis, *Int J Geogr Inf Sci* 2018; 32(7):1275-1281.