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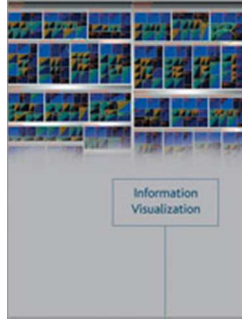
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## Introduction to the special section on Visual Movement Analytics

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**Authors**

Urška Demšar<sup>1</sup>, Aidan Slingsby<sup>2</sup>, Robert Weibel<sup>3</sup>

<sup>1</sup>School of Geography & Sustainable Development, University of St Andrews, Scotland, UK

<sup>2</sup>giCentre, City University London, UK

<sup>3</sup>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](mailto: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 origin-destination flow data, to the more complex trajectory data that represent

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3 geometrical paths through space and time. Further complications come in the form of additional  
4 multivariate information, different sampling rates, different spatio-temporal precisions and  
5 accuracies for individual data points, noise and missing data that require various approaches to  
6 interpolation. Finally, these datasets are typically large and often need specific analytical and  
7 visualisation techniques.  
8

9 In this editorial we first provide a brief review of visual movement analytics methods from across  
10 domain disciplines, grouped according to the movement data type they are intended for (flows,  
11 trajectories and 3D data), then describe how this special section came to be and finish with new  
12 opportunities and open challenges.  
13

### 14 **Visual analytics for movement**

15 Flows are movements between pairs of geographical locations, often also known as origin-  
16 destination data. These are common when considering human mobility and transport, such as  
17 migration flows between a set of census areas, bike movement between docking stations, and  
18 commuting flows between home and work locations. Examples of visual and computational methods  
19 for flow data include the study of bicycle flows [3], flow maps with edge-bundling [4] and the  
20 unusual-looking “kriskograms” for migration [5]. One study [6] introduces a visual analytics system  
21 where flow visualisations are combined with data mining methods, such as clustering. Flow data are  
22 also common in movement ecology, where they can be collected – amongst other techniques – with  
23 RFID systems for terrestrial tracking or by static arrays of underwater acoustic receivers for marine  
24 animals. However, visual analytics tools for animal flows are mostly still lacking, with only a few  
25 recent studies. One study [7] presents a relatively simple system for RFID flows, while another one [8]  
26 introduces a new visualisation for acoustic array data, the so-called activity seascapes, which  
27 combine acoustic array tracking data for sharks with computationally-derived behaviour measures  
28 from accelerometer tags. Flows can also be generalised to any association between pairs of  
29 locations, for example, correlation, similarity or attractiveness, the latter of which can be modelled  
30 with spatial interaction models, which can be further analysed with a visual data mining approach [9,  
31 10].  
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34 Trajectories are a more complex type of movement data: each trajectory is a sequence of locations  
35 with a specific timestamp. Trajectory data can be collected by a range of sensor types including  
36 devices that track their location (e.g. GPS trackers and mobile phones), devices that track the  
37 location of nearby devices (such as Wi-Fi and Bluetooth), and even algorithms that extract  
38 trajectories from video footage common for sports analytics, for example for analysis of football or  
39 ice-hockey matches [11, 12]. Ecological examples of visual analytics for trajectories include spatio-  
40 temporal linked views for bird migration [13-15], and multi-dimensional trajectory analysis  
41 visualisations in the context of environmental data (DynamoVis) [16, 17]. One study [18] developed  
42 a system to identify patterns of dynamic interaction between moving objects and apply their  
43 methods to animal and sports trajectories. In human mobility and transportation studies systems  
44 have been designed to overcome specific problems posed by large real-time data sets [19]. One way  
45 to achieve this is to couple visualisation with efficient data representation and statistical modelling  
46 [20].  
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49 New sensors allow increasingly precise collection of locational and movement data in three physical  
50 dimensions. A typical example are trajectories where location is measured in three geographic  
51 dimensions, which are common in ecology, but present a challenge for visualisation. Biological space  
52 is constrained by the thickness of the atmosphere and the seas and therefore forms a thin layer on  
53 the surface of the Earth – animals that move in this space therefore typically cover much larger  
54 distances on the surface than in elevation. This poses a particularly difficult problem for  
55 visualisation, not only from the perspective of having to show the third dimension on a 2D display,  
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3 but also from having this dimension significantly smaller than the other two dimensions, resulting in  
4 a “pancake” display, a typical example of which are 3D kernel density volumes [21]. This can to some  
5 extent be alleviated through geometric methods [22] or by an alternative hexagonal representation  
6 of the 3D space [23]. Other 3D aspects of movement are captured by accelerometers (3D motion)  
7 and magnetometers (3D orientation) and this information can be used to augment other movement  
8 data. Data from these sensors need to be processed and analysed in different ways. For example,  
9 accelerometer data are hard to interpret in their raw form, but machine-learning techniques can be  
10 used to infer movement type [24]. Magnetometers allow ecologists to analyse animal posture during  
11 movement at very detailed spatial scales – to be able to do this, one study [25] presents an  
12 innovative visualisation of these data that shows the tri-axial magnetic signals on 3D m-spheres and  
13 Dubai plots.  
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### 15 **The workshop and the special section in *Information Visualization***

16 In 2016 we organised a workshop on Visually-supported Movement Analysis at the annual  
17 conference of the Association of the Geographic Laboratories of Europe (AGILE) in Helsinki, Finland.  
18 The aim of the workshop was to demonstrate advances and showcase examples of visually-  
19 supported movement analysis, including best-practice applications in relevant domains. The  
20 workshop called for visual analytics contributions from any discipline where analysis of movement is  
21 important and for any type of movement data, with a goal to reach a wide audience. In addition to  
22 this call we also organised a data challenge using open data from movement ecology, to encourage  
23 participants to develop new methods to explore the foraging and migration patterns of seabirds. The  
24 data we used contains multi-annual GPS trajectories of over 100 lesser black-backed gulls (*Larus*  
25 *fuscus*) and herring gulls (*Larus argentatus*) that nest on the coast of Belgium and migrate as far  
26 south as sub-Saharan Africa. This dataset is also an example of a recent trend in movement ecology  
27 to open the data to other researchers and as such not only remains open, but is updated with new  
28 data every year [26].  
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31 Nine contributions were accepted for presentation at the workshop, including a mix of regular  
32 papers and data challenge entries (all contributions are available at the workshop website  
33 <http://viz.icaci.org/VCMA2016>). Part of the workshop was further reserved for general discussion on  
34 the importance of visual analytics for analysis of movement and in particular on the role that the  
35 interdisciplinarity between the methodological and application disciplines has to play in this  
36 development. We therefore decided to open the discussion to a wider audience through a call for  
37 papers for this special section of the *Information Visualisation* journal. The final result is a section  
38 with three contributions, each of which addresses a different data type reviewed above: GPS  
39 trajectories, flows and 3D data.  
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41 The first contribution [27] is an outcome of the data challenge and presents a visual analytics  
42 methodology for analysis of bird migration trajectories. It is a good example of a traditional  
43 information visualization design study [28], performed in tight collaboration between tool  
44 developers and ecologists. The tools consist of both visual and computational methods. The design  
45 was driven by a set of ecological questions and it allows the analyst to find patterns that are  
46 important in migratory context. These include the identification of stopover sites from GPS  
47 trajectories, building a flow representation of movements between stopovers, performing a  
48 temporal analysis of migratory movements, and identifying similarities and differences between  
49 movement of individuals and groups.  
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52 The second contribution focuses on large flow data [29] and proposes a solution to the inevitable  
53 visual clutter, which is a result of the fixed positions of the origins and destinations of flows. The  
54 paper takes the well-known edge-bundling technique and extends it with a combination of clustering  
55 and force-directed display methods to create a visually clearer flow map. As the new methodology is  
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3 aimed specifically at large flow data, an important driver to the algorithm development was the  
4 need to reduce computational complexity in order to reduce processing time. The approach is  
5 evaluated on a set of different case studies, including traffic flows, bird migration data, human  
6 migration and flights. The method is further compared with more traditional approaches, such as OD  
7 maps [30].  
8

9 The last contribution [31] presents a workflow for emergency evacuation planning. It combines 3D  
10 data on the characteristics of built environment and people's movement in emergency situations.  
11 The workflow they developed combines spatial data science methods with simulation and  
12 visualisation capabilities from 3D gaming software to capture how people move, behave and interact  
13 with the geometry and topology of the built environment during emergency evacuations. This allows  
14 the analyst to simulate and visualise various emergency scenarios, an important factor in  
15 preparedness planning.  
16

### 17 **Conclusions**

18 We conclude this editorial by identifying open challenges and issues that visual movement analytics  
19 could address in the future.  
20

21 The first challenge are new and diverse movement data. As sensor development technology  
22 progresses, new types of motion sensors, such as accelerometers, magnetometers, gyroscopes, and  
23 physiological sensors are becoming commonplace in many domains and in particular in movement  
24 ecology. These new sensors are able to capture complex data at fine spatial and temporal  
25 resolutions. For example, new accelerometers used in animal tracking are capable of measuring  
26 movement at 100Hz, generating complex and precise time series that reduce the need to model the  
27 movement, as everything is measured and observed to an extreme detail. On the other hand, data  
28 coming from these accelerometers data require increasingly complex interactive visual systems for  
29 efficient exploration [32], which are currently rare or non-existent.  
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32 The second challenge is the sheer volume and complexity of the data that these new technologies  
33 bring. This places movement data firmly into the realm of "geospatial big data" and brings a number  
34 of visualisation challenges [33] as well as algorithmic computational complexity problems [34]. This  
35 issue is becoming increasingly recognised as an important research topic in visual movement  
36 analytics [20]. More research and development are needed to overcome the graphical and  
37 algorithmic limitations for efficient displaying and analysis of large movement data sets.  
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40 A third challenge is the access to tools for researchers in the application communities. A particular  
41 challenge for researchers from disciplines that collect movement data but who do not themselves  
42 develop methods for these data, is the accessibility of tools. Many visual analytics tools are research  
43 prototypes from disciplines such as information visualization and are often not freely available in a  
44 form that is easily used by other researchers. As a consequence, they are rarely used by anyone  
45 other than the authors [19]. On the other hand, the movement ecology discipline has a strong  
46 established culture of providing free and open source tools, often in the form of Free and Open  
47 Source Software (FOSS). As well as assisting other researchers, a strong benefit of this culture is that  
48 it can help ensure the reproducibility of both method development and research [35]. Computer  
49 science disciplines, such as information visualisation and visual analytics lag behind and an effort is  
50 needed to introduce and grow this open culture.  
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52 Finally, visual movement analytics is inherently an interdisciplinary discipline. Much of the work in  
53 information visualisation research remains in the information visualisation literature, often with an  
54 arms-length collaboration with the domain experts. This is a problem, since designing a new  
55 analytical methodology requires not only expertise in method development, but also in-depth  
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3 domain knowledge in order to be able to develop informed tools that are appropriate for the  
4 research questions in the domain discipline. This requires a tight collaboration between tool  
5 developers and researchers from application disciplines, which however is not easy – becoming  
6 familiar with each other's terminologies and research requires a lot of motivation, energy and time.  
7 It is still too often the case that information visualisation and visual analytics researchers only focus  
8 on the technical developments of the tools and develop them for their own sake, rather than being  
9 motivated by producing methods that are meaningful and useful for the application discipline.  
10 Conversely, application discipline researchers are often not aware of recent work in information  
11 sciences, consequently ignoring that that visualising and/or analysing their data is in fact not a  
12 problem, but someone else's research challenge. Our workshop, others like it and this special  
13 section are an attempt to cross this interdisciplinary divide and a small part of a general trend in  
14 movement analytics that brings together users and developers [36].  
15

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20

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22 The authors declare that they have no conflicting interests.  
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