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# Real time visual analytics of moving features: A case of vessel movement

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**Abstract:**

A moving feature is described as a rigid body whose location changes over time (Asahara et al., 2015). Fitted with sensor devices, these features often transmit information about their location, coupled with additional attributes that describe their movement characteristics in real time, through data streaming sensor networks. Examples of moving feature datasets include shipping vessels Automatic Identification System (AIS) data, GPS tracked vehicle positions, cycling tracks and many more. Deriving knowledge and understanding behavioural patterns of these moving features has been a subject of research for many years (Andrienko et al, 2013; Krueger et al, 2017; Andrienko et al, 2021; Graser et al, 2021), and several challenges have thus been identified. In this paper we focus on addressing challenges that are pertinent to deriving behavioural patterns of moving features in real time, whilst the movement trajectory is still unfolding. These challenges generally relate to; firstly, the ability to analyse and visualise high velocity observations of multiple moving features, and secondly the ability to understand patterns that evolve because of changes in location and time.

This paper presents a methodology for determining patterns of movement that unfold in real time based on the principles of visual analytics, whilst making use of graph theory to detect the underlying behavioural patterns that may otherwise not be immediately obvious to the human eye. Visual analytics combines the science of analytical reasoning with the support of interactive visual interfaces. This method thus makes extensive use of geographical visual representations at varied spatial and temporal scales, whilst keeping the human in the loop to provide understanding of emerging and retrospective mobility patterns in a data stream of moving features. Graphs are designed to find connections and relations between discrete components. In this study, calculations for movement behaviour attributes are done in segments for the respective temporal windows. For each temporal window, a graph of the segments is created, where the graph nodes are the sub trajectory segments and the edges are defined by the relationships between two pairwise trajectories of different features within the temporal window. The creation of the graph structure is followed by a connected component analysis that considers using distance of nearest approach and vessel behaviour as threshold conditions. The connections that are found define the relationship between sub trajectories of different vessels. Resultantly, graphs are used in this study to detect behavioural relationships of moving features.

The method developed in this study has two parts. The first step is the construction of trajectories of moving features in real time, based on data packets received from a real-time, dynamic data stream. Provided a large real time data stream is used, it is essential to make use of user inputs to decrease the data volume, by providing an estimated area of interest or a feature identifier, such as car registration number, or ship mmsi number, if one is known. The second step involves determining the behaviour of a moving feature. This step thus requires that the movement attributes of a moving feature are extracted from a data stream. Making use of these attributes the behaviour of a moving feature is explored in two ways, 1) the *intrarelationships* between different parts of a voyage of a single moving feature, trajectory segments; and 2) the operations between two trajectory objects, in order to explore *inter-relationships* between voyages of multiple moving features. These are as shown in figure 1 below. To understand the results of the analysis, a visualisation tool geoStreamViewer, based on CesiumJS, developed by the author's was used to visualise the results. The application consists of interactive 2D and 3D visualisation windows, that are connected to a user configuration panel, and a time slider that allows for real-time as well as retrospective views of data and derived patterns.


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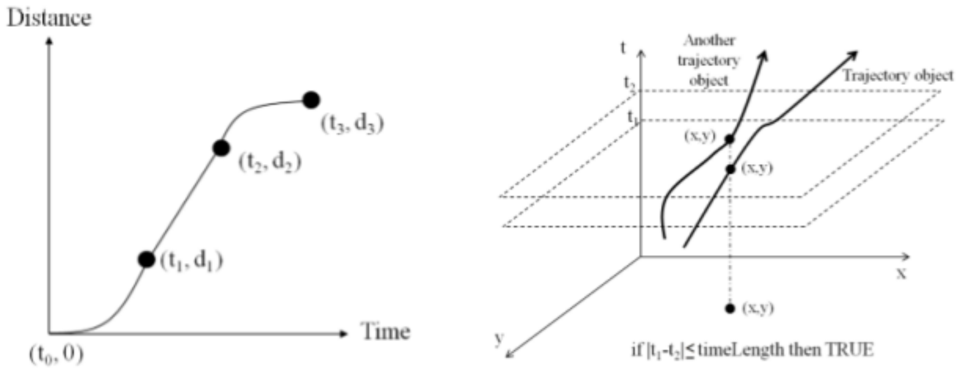


Figure 1. The figure on the left illustrates segments of a trajectory of a single moving feature. the figure on the right shows two trajectories of different features. (OGC moving features, 2016)

This method was tested on an open dataset that consisted of an unlimited number of ship movement data around the coastal areas of the Western Cape, South Africa, over a month for demonstration purposes. The results achieved (figure 2) were able to show changes in rate of speed, acceleration, and deceleration of shipping vessels throughout the trajectories. This is a result that is not immediately visible when looking at large volumes of vessels trajectories. Through the dynamic visualisations it is also possible to view the relationships between movements of several shipping vessels in the same area.

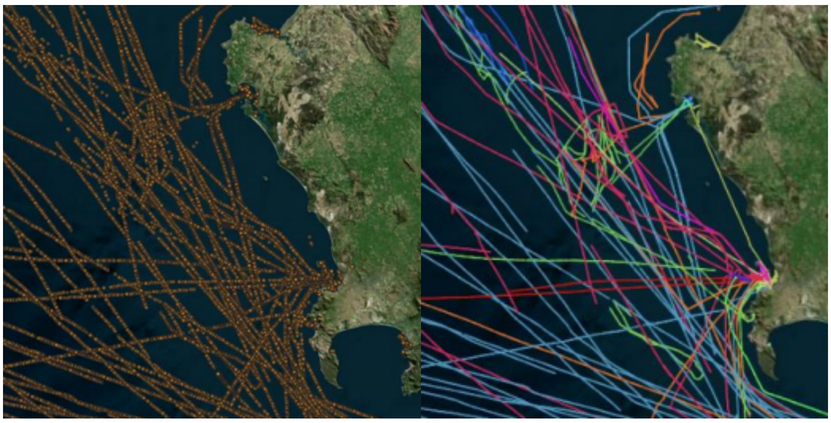

Figure 2.On the left: visualisation of shipping vessels before analysis. On the right: shipping vessels post analysis.

The results obtained from the implementation of this method to ship vessel movement data, confirm that visual analytics-based methods that include, analysis, visualisations and human interaction improve the ability to determine patterns on large volumes of movement data. The use of graph theory had significant impact as it is already geared towards finding patterns in feature data.

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