Visual analytics of movement: an overview of methods, tools, and procedures

Natalia Andrienko and Gennady Andrienko

Abstract

Analysis of movement is currently a hot research topic in visual analytics. A wide variety of methods and tools for analysis of movement data have been developed in recent years. They allow analysts to look at the data from different perspectives and fulfil diverse analytical tasks. Visual displays and interactive techniques are often combined with computational processing, which, in particular, enables analysis of larger amounts of data than it would be possible with purely visual methods. Visual analytics leverages methods and tools developed in other areas related to data analytics, particularly, statistics, machine learning, and geographic information science. We present an illustrated structured survey of the state of the art in visual analytics concerning the analysis of movement data. Besides reviewing the existing works, we demonstrate by examples how different visual analytics techniques can support understanding of various aspects of movement.

1 INTRODUCTION

The main idea of visual analytics is to develop knowledge, methods, technologies and practice that exploit and combine the strengths of human and electronic data processing [33]. Visualization is the means through which humans and computers cooperate using their distinct capabilities for the most effective results. Visualization is particularly essential for analyzing phenomena and processes unfolding in geographical space. Since the heterogeneity of the space and the variety of properties and relationships occurring in it cannot be adequately represented for fully automatic processing, exploration and analysis of geospatial data and the derivation of knowledge from it needs to rely upon the human analyst's sense of the space and place, tacit knowledge of their inherent properties and relationships, and space/place-related experiences [5].

Analysis of movement is currently a hot research topic in visual analytics. The researchers leverage the legacy of cartography, with its established techniques for representing movements of tribes, armies, explorers, hurricanes, etc. [36], time geography, with its revolutionary idea of considering space and time as dimensions of a unified continuum (space-time cube) and representation of behaviours of individuals as paths in this continuum [30], information visualization, with its techniques for user-display interaction supporting exploratory data analysis [20], and geovisualization, with its interactive maps and associated methods enabling exploration of spatial information [23]. To meet the challenges posed by today's data deluge and complexity of the questions to be answered and problems to be solved, the scientists search for the ways to augment the power of human's visual thinking [13] with the power of modern computer technologies.

In this paper we survey the state of the art in visual analytics concerning the analysis of movement data. We limit the scope of the paper to data about movements of discrete objects whose spatial positions can be represented by points. We do not consider movement of fields, such as ocean currents, and spatially extended objects changing their sizes and shapes, such as clouds. These kinds of moving objects have so far been scarcely addressed in visual analytics while the works dealing with discrete objects are abundant.

We divide the relevant works into four categories:

1) <u>Looking at trajectories</u>: The focus is on trajectories of moving objects considered as wholes. The methods support exploration of the spatial and temporal properties of individual trajectories and comparison of several or multiple trajectories.
2) <u>Looking inside trajectories</u>: The focus is on variation of movement characteristics along trajectories. Trajectories are considered at the level of segments and points. The methods support detecting and locating segments with particular movement characteristics and sequences of segments representing particular local patterns of individual movement.
3) <u>Bird's-eye view on movement</u>: The focus is on the distribution of multiple movements in space and time. Individual movements are not of interest; generalization and aggregation are used to uncover overall spatio-temporal patterns.
4) <u>Investigating movement in context</u>: The focus is on relations and interactions between moving objects and the environment (context) in which they move, including various kinds of spatial, temporal, and spatio-temporal objects and phenomena. Movement data are analyzed together with other data describing the context. Computational techniques are used to detect occurrences of specific kinds of relations or interactions and visual methods support overall and detailed exploration of these occurrences.

The structure of the text corresponds to this categorization.

To help the reader better understand the material, we complement the survey of the existing works by illustrated examples showing how different visual analytics techniques can support understanding of various aspects of movement. For the examples, we use a real dataset about movements of ships in the area of North Sea. The Netherlands Coastguard collects data of shipping movements by radar coverage and AIS (Automatic Identification System) base stations. MARIN (Maritime Research Institute Netherlands, www.marin.nl) receives the fused data for use in safety assessment studies with respect to shipping. MARIN has provided an anonymized subset of the data, 8 days duration, for this research. The authors are especially grateful to Y.Koldenhof (MARIN) for describing the analytical tasks in marine safety studies and providing feedback on the application of visual analytics methods. The collection methods and properties of maritime vessel movement data are described in detail by N.Willems in his Ph.D. thesis [57] and papers, e.g., [59][45].

The illustrations have been produced by means of software tools that were available to us, which does not mean superiority of these tools over all other existing tools. The illustrations are also not meant to demonstrate capabilities of particular tools but rather outline possible general approaches, which can be implemented in different ways.

2 LOOKING AT TRAJECTORIES

In this section, we consider, first, the techniques for visual representation of trajectories and interaction with the representations, second, the use of clustering methods for comparative studies of multiple trajectories, and, third, the time transformations supporting exploration of temporal properties of trajectories and comparison of dynamic properties of multiple trajectories.

2.1 Visualizing trajectories

The most common types of display for the visualization of movements of discrete entities are static and animated maps [53][11] and interactive space-time cubes [37][34][32] with linear symbols representing trajectories. These displays as well as some basic interaction techniques are illustrated in Fig. 1.

In Fig. 1A, there is a map with entire trajectories of ships represented by lines drawn with 10% opacity. Small hollow and filled squares mark respectively the start and end positions of

the trajectories. By mouse-pointing on the map, the user accesses detailed information about the trajectories. The lines are distinctly coloured according to the ship types; other attributes of the trajectories can also be represented by colouring or line thickness. The interactive legend on the right serves as a filter to hide some ship types from the view and focus on the other types (the figures in the legend show the counts of trajectories for each ship type). In Fig. 1B, map animation by means of an interactive time filter is demonstrated. The user can select a time window of a desired length (e.g. 3 hours in the screenshot) and move this window forwards and backwards in time by dragging the slider. In response, the map shows only the fragments of the trajectories that were made during the current time window. The figures in the interactive legend show the total counts of trajectories for each ship type and how many of them are visible, at least partly, with the current filter condition.

In C, there is an interactive space-time cube (STC) with all ship trajectories; the colours are the same as in the map. An additional map plane can be interactively moved within the cube to select time moments and separate what was before from what was after. In the figure, the position of the movable plane corresponds to the time 20:00 on 02/01/2009 while the whole time range of the data is from 01/01/2009; 00:00 till 08/01/2009; 23:50. This can be seen at the bottom of the STC display. In D, the STC display represents several interactively selected trajectories (the remaining trajectories have been hidden). The time interval shown in the cube has been limited to 01/01/2009; 20:00 – 03/01/2009; 11:00 (this operation is known as temporal zoom). The position of the movable plane corresponds to 02/01/2009; 15:00. To make the lines more visible, their thickness has been increased to 2 pixels and opacity to 100%.
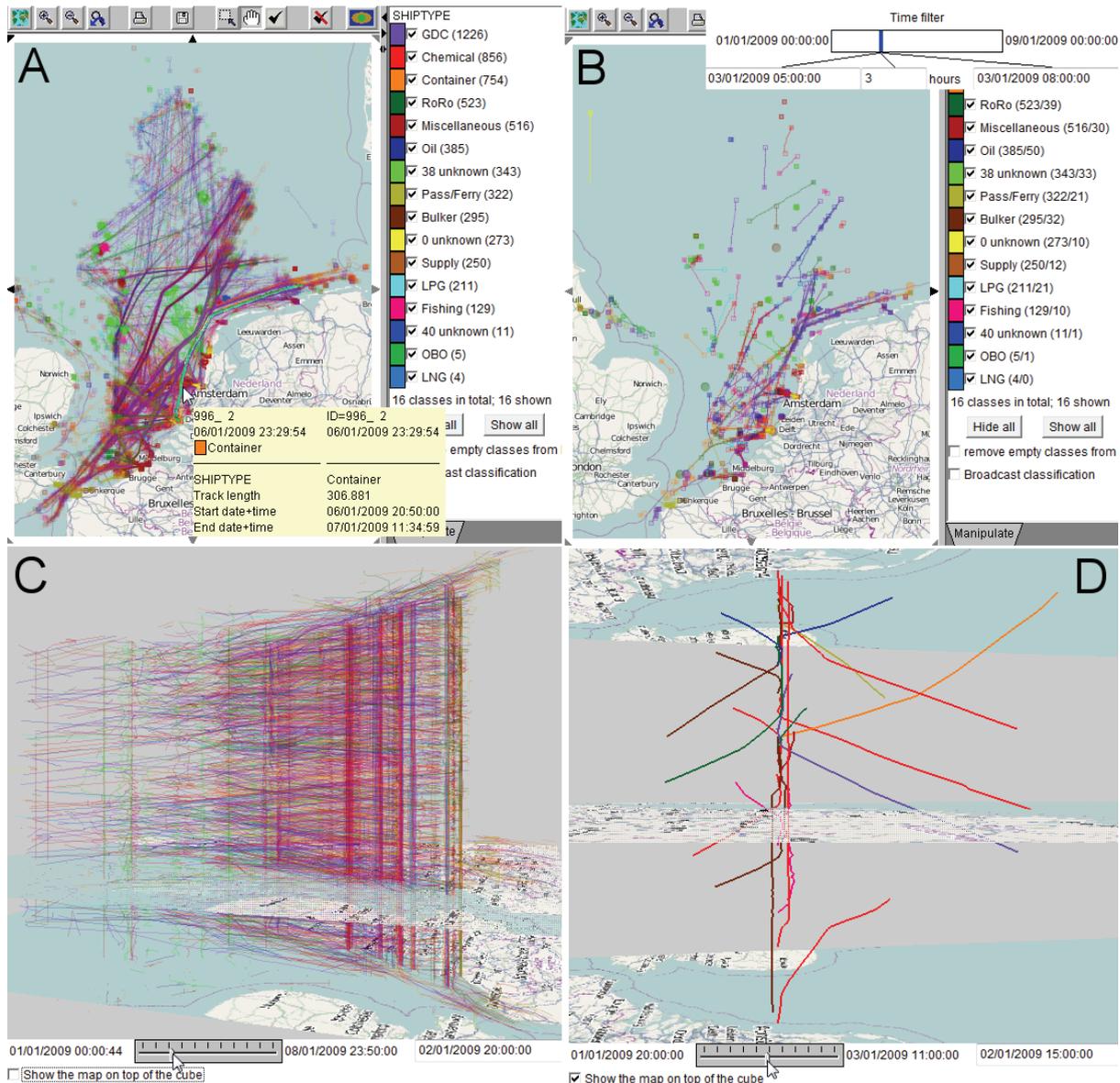
Figure 1. A: An interactive map with trajectories of ships shown as lines with 10% opacity. B: Map animation through a time filter. Positions and movements of ships during a 3-hours time interval are visible. C: An interactive space-time cube (STC) showing all ship trajectories with 20% opacity; the vertical dimension represents time. The cube is seen from the southwest. D: A STC with several selected trajectories is seen from the east.

As can be seen from these examples, displays showing multiple trajectories may suffer from visual clutter and occlusions. The clutter may be reduced by decreasing the opacity of the symbols but the occlusion problem remains. Besides, both displays provide only limited opportunities for representing various characteristics of the movement and their changes over time. The effectiveness of animated displays raises serious doubts [52]. The drawback of STC, besides occlusion, is distortion of both space and time due to projection. It is also quite limited with respect to the length of the time interval that can be effectively studied. To compensate for these limitations, map and STC displays are often complemented with other types of graphs and diagrams. Thus, changes of movement characteristics over time may be represented on a time graph (temporal line plot) (e.g. [34]). Willems et al. [57] suggest a display called Trajectory Contingency Table supporting the exploration of attributes of

trajectories. The rows and columns of the table correspond to different values or value intervals of two selected attributes, either temporal (e.g., date, day of the week, or hour of the day) or thematic (e.g., ship type, ship size, average speed, or destination port). In the table cells there are small maps; each map shows only the trajectories that have the corresponding values of the attributes. The selection of the attributes for the columns and rows can be easily changed by dragging any attribute from a list and dropping it on the top or on the left of the table display.

Movements in three-dimensional space, e.g. in the air or under water, are harder to visualize than movements on a surface. Ware et al. [56] represent a single trajectory of a whale by a three-dimensional ribbon (in a perspective view) with glyphs on its surface showing the direction of the movement. Hurter et al. [31] represent multiple trajectories of aircrafts in horizontal or vertical two-dimensional projections with animated transitions from one projection to another.

Common interaction techniques facilitating visual exploration of trajectories and related data include manipulations of the view (zooming, shifting, rotation, changing the visibility and rendering order of different information layers, changing opacity levels, etc.), manipulations of the data representation (selection of attributes to represent and visual encoding of their values, e.g. by colouring or line thickness), manipulations of the content (selection or filtering of the objects that will be shown), and interactions with display elements (e.g. access to detailed information by mouse pointing, highlighting, selection of objects to explore in other views, etc.). Multiple co-existing displays are visually linked by using consistent visual encodings (e.g. same colours) and exhibit coordinated behaviours by simultaneous consistent reaction to various user interactions. These are generic techniques used for various types of data, not only for movement data. They have become standard in information visualization and visual analytics; most of the existing software tools include them.

In addition to these generic techniques, Guo et al. [29] suggest several interaction techniques specifically designed for trajectories, including selection of trajectories with particular shapes by sketching. Bouvier and Oates [15] suggest original interaction techniques for marking moving objects on an animated display and tracing their movements.

2.2 Clustering trajectories

Clustering is a popular technique used in visual analytics for handling large amounts of data. Usually existing clustering methods are wrapped in interactive visual interfaces supporting not only visual inspection but often also interactive refinement of clustering results.

Trajectories of moving objects are quite complex spatio-temporal constructs. Their potentially relevant characteristics include the geometric shape of the path, its position in space, the life span, and the dynamics, i.e. the way in which the spatial location, speed, direction and other point-related attributes of the movement change over time. Rinzivillo et al. [43] argue for the use of diverse distance functions addressing different properties of trajectories and introduce the procedure of progressive clustering that allows analysts to combine these distance functions in the process of analysis. The analysis is done in a sequence of steps. In each step, clustering with a single distance function is applied either to the whole set of trajectories or to one or more of the clusters obtained in the preceding steps. In this way, the user may (a) refine clustering results, (b) combine several distance functions differing in semantics, and (c) gradually build comprehensive understanding of different aspects of the trajectories. Several distance functions suitable for clustering of trajectories are suggested by Andrienko et al. [9].

The procedure of progressive clustering is illustrated in Fig. 2. First, the density-based clustering algorithm OPTICS with the distance function "common ends" has been applied to the ship trajectories (Fig. 2A). Each of the resulting clusters consists of trajectories with spatially close end points. In this way, the user uncovers the major destinations of the ships. Second, one of the clusters, namely, trajectories ending at Rotterdam, has been interactively selected, i.e., all other clusters hidden (Fig. 2B). Third, the same clustering algorithm with the distance function "route similarity" has been applied to the members of the selected cluster (Fig. 2C). The user can see the typical routes of the ships coming to Rotterdam. In Fig. 2D, the route-based clusters of trajectories are shown in a STC, which is explained in more detail in the next subsection.
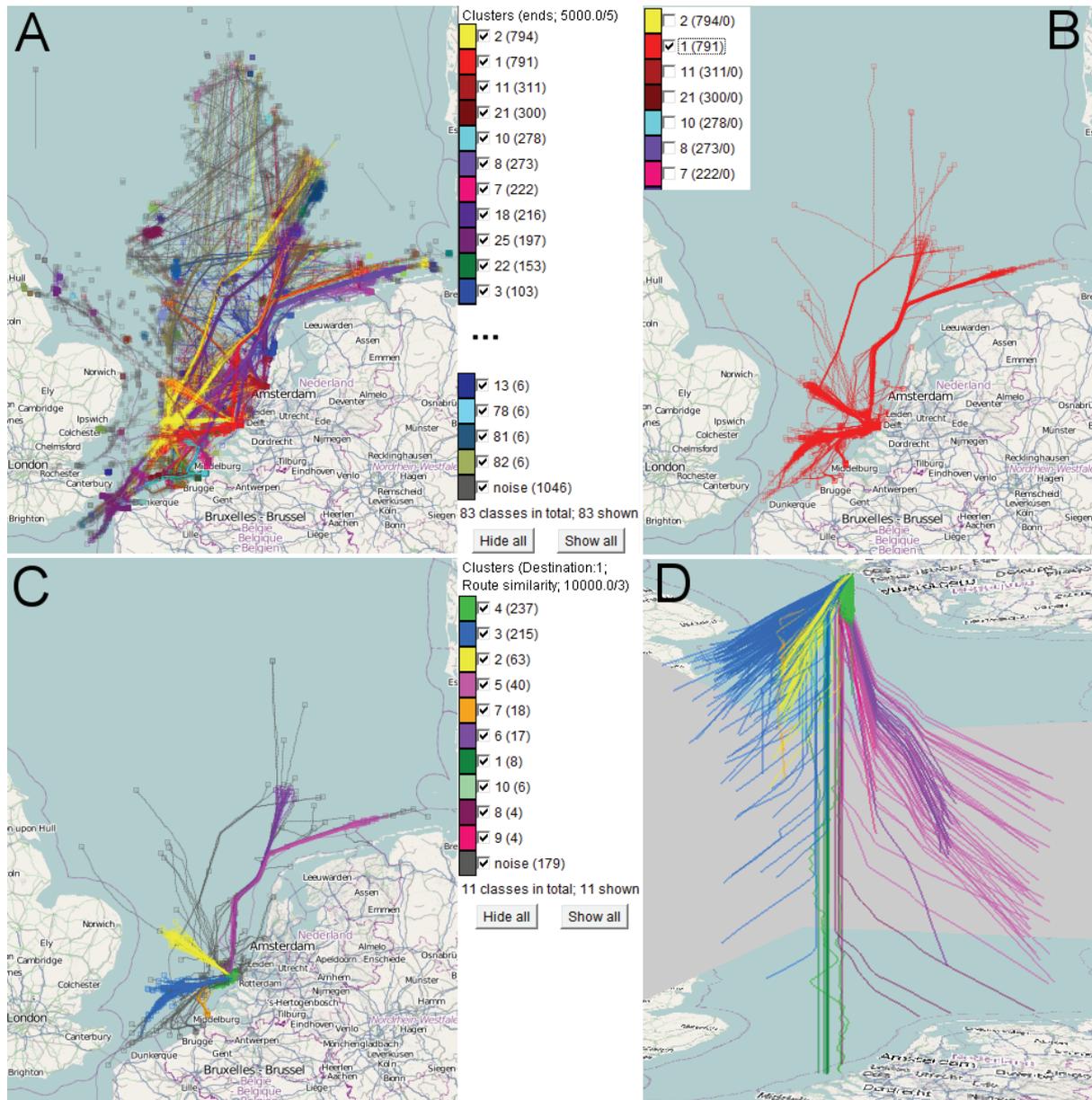

Figure 2. Interactive progressive clustering of trajectories. A: The ship trajectories have been clustered according to the destinations. B: One of the clusters is selected. C: Clustering by route similarity has been applied to the selected cluster. D: The clusters by route similarity are shown in a STC; the noise is excluded.

The majority of the clustering tools can only work with data loaded in the computer RAM and are therefore not scalable to very large datasets. Andrienko et al. [8] suggest a way to overcome the limits of RAM. After defining clusters of trajectories on the basis of a subset (sample) of trajectories, the analyst is supported by interactive visual and computational tools in the process of creating, testing, and refining a classification model for assigning trajectories to the clusters. Then the classifier is used to supplement the clusters with new trajectories, which are loaded from a database by portions fitting in the main memory.

2.3 Transforming times in trajectories

Comparison of dynamic properties of trajectories using STC, time graph, or other temporal displays is difficult when the trajectories are distant in time because their representations are located far from each other in a display. This problem can be solved or alleviated by transforming times in trajectories [2]. Two classes of transformations are suggested:

1. Transformations that reflect the cyclic nature of time. Depending on the data and application, trajectories can be projected in time to a single year / season / month / week / day etc. This allows the user to uncover and study movement patterns related to temporal cycles, e.g., find typical routes taken in the morning and see their differences from the routes taken in the evening.
2. Transformations with respect to the individual lifelines of trajectories. Thus, trajectories can be shifted in time to a common start time or a common end time. This facilitates the comparison of dynamic properties of the trajectories (particularly, spatially similar trajectories), for example, the dynamics of the speed. Aligning both the start and end times supports comparison of internal dynamics in trajectories irrespective of the average movement speed. Particularly, movement patterns of fast and slow movers can be compared in this way.

An example of time-transformed trajectories is shown in Fig. 2D. The STC shows route-based clusters of ship trajectories ending at Rotterdam. The times in the trajectories have been transformed so that all trajectories have a common end time. This allows us to see that, although the routes within each cluster are similar, the dynamics of the movement may differ greatly. The speeds can be judged from the slopes of the lines. Fast movement is manifested by gently sloping lines (which means more distance travelled in less time) while steep lines signify slow movement. Vertical line segments mean staying in the same place. The STC in Fig. 2 shows us that some ships just stayed all the time near Rotterdam, others approached Rotterdam and then stayed close to it for time intervals of different lengths, and the remaining ships moved towards Rotterdam with different speeds without stops. Doing such a comparison is hardly possible when the trajectories are positioned in the STC according to their original times.

3   LOOKING INSIDE TRAJECTORIES: ATTRIBUTES, EVENTS AND PATTERNS

The methods described in the previous section deal with trajectories as wholes, i.e., treat them as atomic objects. Here we consider the methods operating on the level of points and segments of trajectories. They visualize and analyze the variation of movement characteristics and other dynamic attributes associated with trajectory positions or segments. These may be existing (measured) attributes or attributes derived from the position records, i.e., coordinates and times. Derived attributes may express *instant*, *interval*, and *cumulative* characteristics of the movement [7]. Instant movement characteristics include instant speed, direction, acceleration (change of speed), and turn (change of direction). Interval characteristics are computed for time intervals of a chosen constant length before, after, or around a given time moment. They include travelled distance, displacement, average speed,

sinuosity, tortuousity, as well as statistics of the instant characteristics. Cumulative characteristics are computed for the interval from the start of the trajectory to a given time moment or for the remaining interval to the end of the trajectory.

The most obvious way to visualize position-related attributes is by dividing the lines or bands representing trajectories on a map or in a 3D display into segments and varying the appearance of these segments. Attribute values can be represented by colouring or shading of the segments [35][29][48] or by symbols (glyphs) drawn on the segments [56]. Spretke et al. [48] suggest an interactive tool for segmenting trajectories by dividing ranges of one or more position-related attributes into suitable intervals. Furthermore, clustering may be applied to join adjacent segments with similar characteristics. This allows the user to detect and locate different movement behaviours, for example, day migration, night migration, and stopovers of migrating birds. These behaviours are shown by different colouring of line segments on a map.

Kraak and Huisman [35] use STC to visualize not only known spatio-temporal positions of moving objects but also space-time prisms, i.e., sets of positions that could potentially be visited by the objects during the time intervals between the known positions. The space-time prisms are computed taking into account the maximal possible speeds of the objects and visualized as volumes (3D bodies) in the STC.

Representing dynamic attributes of trajectories on a map or in an STC may be ineffective due to display clutter and occlusions, especially when trajectories or their parts overlap in space. Therefore, position-related dynamic attributes are often visualized using additional displays. A time graph, also known as line chart, can be used for visualizing temporal variation of attribute values [34][35]. One dimension (usually horizontal) of such a graph represents time and the other dimension is used for representing attribute values by positions. Each trajectory is represented by a curve or polygonal line. Wörner and Ertl [63] suggest a display which is similar to a time graph except that the base dimension represents space rather than time. This is possible for movements along a standard route, for example, movements of public transport vehicles. The horizontal dimension the route graph represents relative positions along the route and the vertical dimension is used for representing attribute values, such as speeds. Besides the lines representing individual trajectories, the display may include a line showing the variation of the average values along the route and a band with variable thickness representing the standard deviation. The same techniques are possible in a time graph.

A time graph or a "route graph" representing multiple trajectories can suffer from visual clutter and overlapping of lines. To avoid overlapping, the idea of stacking is often used [6][51][63]: trajectories are represented by bars or bands stacked within a temporal or spatial display. The bars or bands are divided into segments, which are coloured according to values of some dynamic attributes. Examples are shown in Fig. 3 A and C.
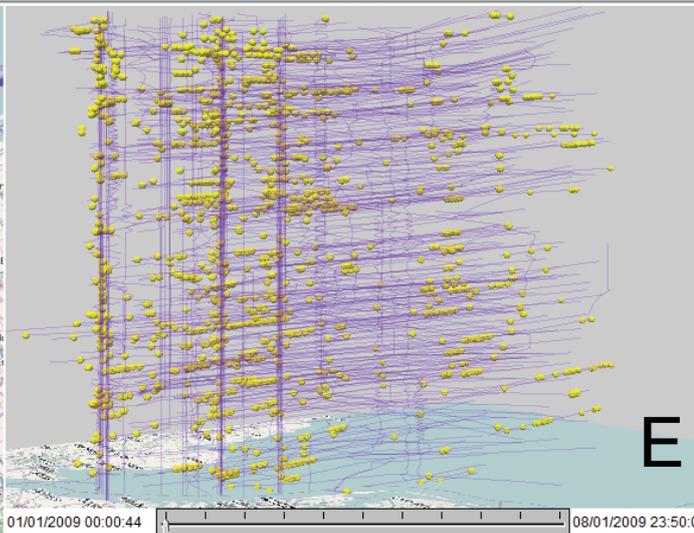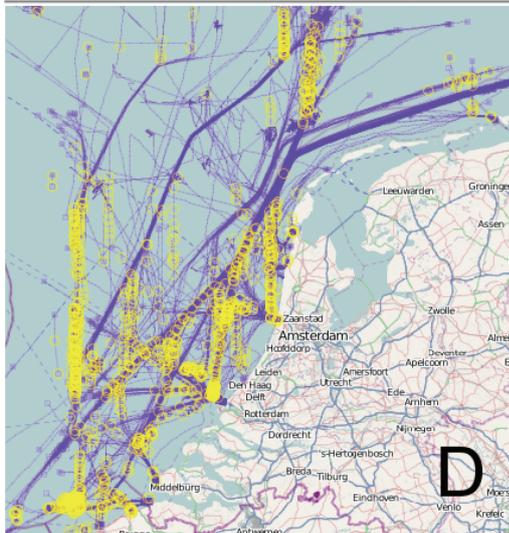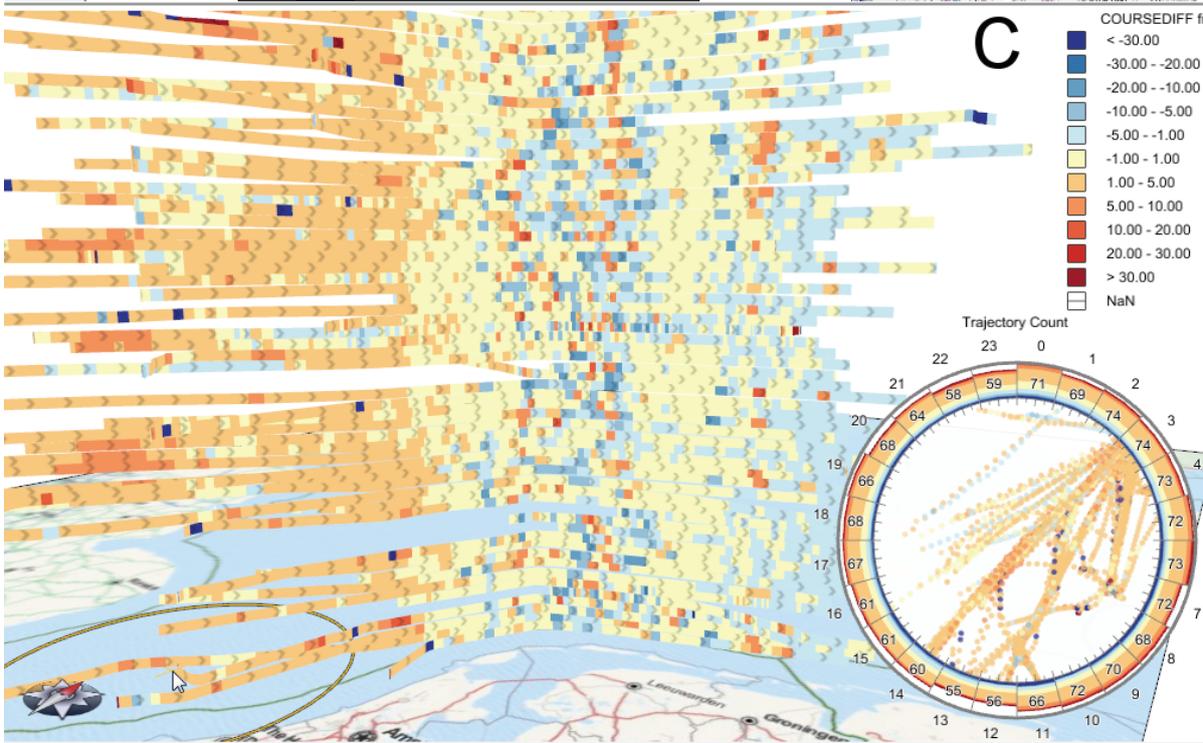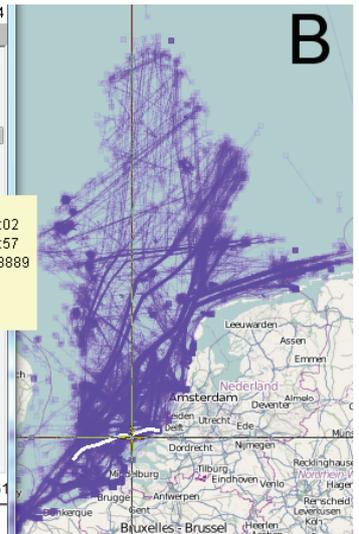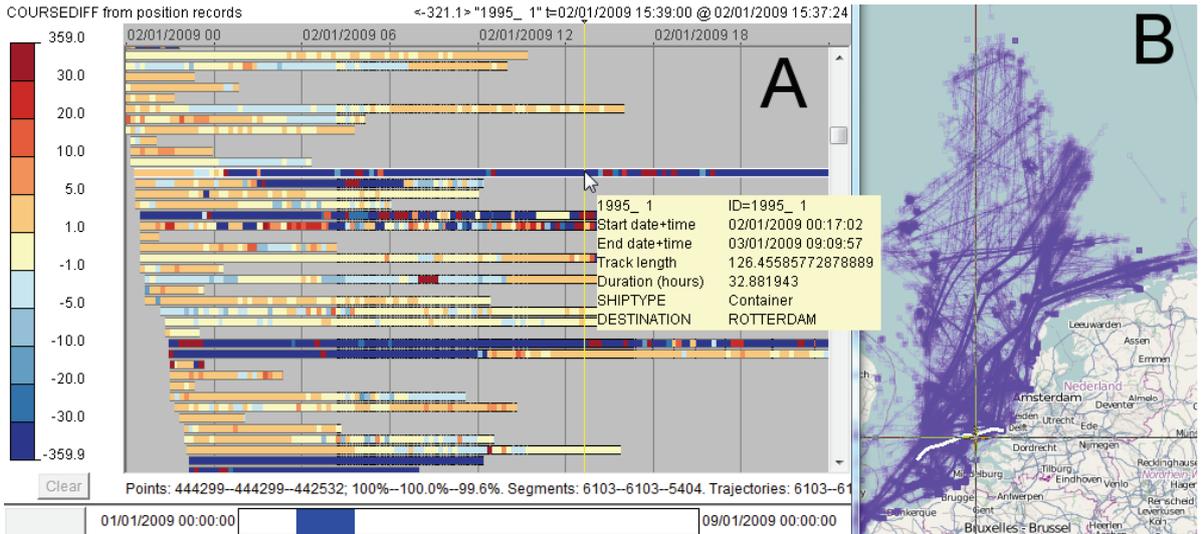
Figure 3. A: A time bars display shows temporal variation of values of a dynamic attribute within trajectories. The bars represent trajectories; the attribute values are colour-coded. B: A trajectory selected in the time bars display is highlighted on a map. The crossing of the vertical and horizontal lines marks the spatial position corresponding to the position of the mouse cursor in the time bars display. C: A trajectory wall represents trajectories by segmented bands stacked on top of a cartographic map. D, E: A map and STC show spatial events extracted from trajectories.

Fig. 3 A demonstrates a time bars display, where the horizontal dimension represents time. Each trajectory is represented by a horizontal bar such that the horizontal position and length of the bar correspond to the start time and duration of the trajectory. The vertical dimension of the display is used to arrange the bars, which can be sorted based on one or more attributes of the trajectories (start time in our example). Colouring of bar segments encodes values of some user-selected dynamic attribute associated with the positions in the trajectories. This may be an existing attribute or an attribute derived "on the fly" from the position records. To represent attribute values by colours, the value range is divided into intervals, and each interval is assigned a distinct colour or shade. The display in Fig. 3A represents the values of the attribute "course difference" expressing the difference between the ship heading and its actual movement direction in each trajectory point. The shades of blue and red represent negative and positive differences, respectively. Darker shades correspond to higher absolute values of the differences. Light yellow is used for values around zero. The legend on the left of the display explains the colour coding.

A disadvantage of temporal displays of trajectory attributes, such as time graph and time bars, is that they lack spatial information. To alleviate this, temporal displays are linked to spatial displays through interactive techniques. An example is shown in Fig. 3 A and B. The mouse cursor in Fig. 3A is positioned on one of the bars. In Fig. 3B, the trajectory represented by the bar is highlighted on a map display. The intersection of the horizontal and vertical lines marks the spatial location corresponding to the position of the mouse cursor in the time bars display. This means that the ship was in this location at the time selected by the mouse cursor.

Such interactive links between displays are useful for exploring in detail one or a few particular trajectories but not suitable for exploration of a large number of trajectories. To show multiple trajectories in their spatial context while avoiding overlapping, the trajectory wall display [51] (Fig. 3C) uses the same idea of stacking as the time bars display. A trajectory wall is a 3D view where the space is represented on a horizontal plane and trajectories are represented by bands stacked in the vertical dimension. The technique is especially suitable for exploration of groups of trajectories with similar shapes. As in a time bars display, the bands representing trajectories are divided into segments, which are coloured according to attribute values. In Fig. 3C, the same attribute and colour-coding are used as in Fig. 3A.

Like a time bars display lacks spatial information, a trajectory wall display by itself lacks temporal information. This is partly compensated by including a display element called time lens, which is visible in the lower right corner of the display in Fig. 3C. The time lens shows temporally aggregated information for an interactively defined spatial query area (a circle of a chosen radius around the mouse cursor position, visible in the lower left corner of Fig. 3C). The interior of the time lens shows the relative spatial positions of the trajectory points within the selected area. The points are represented by dots coloured according to the attribute values. The ring of the time lens represents one of the temporal cycles: 4 quarters of a year, 12 months of a year, 7 days of a week, or 24 hours of a day. In our example, the latter cycle is

chosen. The ring is divided into bins corresponding to the units of the chosen cycle. The fill levels of the time bins visualize temporally aggregated information about the trajectories that intersect with the query. One of the possible aggregates is count of the trajectories, as in our example. The coloured segments show the distribution of attribute values per time unit.

Interactive filtering of trajectory segments according to values of dynamic attributes [6] allows the user to explore the spatio-temporal distribution of particular attribute values or value combinations. The trajectory segments that do not satisfy current filter conditions are hidden from the spatial and temporal displays. For example, the user can set the filter so that only the segments with high deviations of the movement direction from the heading will be visible in the time bars display, map, and trajectory wall. Trajectory segments can also be filtered according to values of two or more attributes. In our example, the user can add a query condition that the movement speed must be at least 5 km/h, to disregard direction deviations in anchored ships.

Furthermore, the points satisfying filter conditions can be extracted from the trajectories into a separate dataset (information layer) consisting of spatial events, i.e., objects located in space and time [6][7]. This dataset can be visualized and analyzed independently of the original trajectories or in combination with them. In Fig. 3 D and E, the yellow circles represent the spatial events constructed from the points of the ship trajectories where the deviation of the movement direction from the heading is either below -30 or above 30 and the speed is not less than 5 km/h. The trajectories in which such events occurred are shown by lines; the filtering of the trajectory segments has been cancelled. It can be seen that high deviations of the direction often occur when ships move in the meridian directions.

Filtering of trajectory segments according to values of two or more attributes allows the analyst to find the segments where all filter conditions are fulfilled simultaneously. To support searching for more complex patterns of movement, in which filter conditions are fulfilled in a particular temporal order (or, more generally, the time intervals on which each of the filter conditions is fulfilled stand in particular temporal relations), Sakr et al. [44] combine interactive visual techniques with queries to a moving object database (MOD). The authors demonstrate finding of complex patterns in aircraft landings such as missed approach (interrupted landing attempt), when an aircraft approaches the airport and descends in order to land but then goes up again. Visual analytics tools are used for an initial exploration of the data, selection of a suitable subset for further analysis by interactive filtering, finding of suitable parameter settings for the MOD queries, and then for viewing and interactive analysis of the query results. The patterns found with the help of the MOD can also be extracted from trajectories as events.

Andrienko et al. [6] introduce a conceptual model where movement is considered as a composition of spatial events of diverse types and extents in space and time. The model gives a ground to a generic approach based on extraction of interesting events from trajectories and treating the events as independent objects. There are many possible ways how events extracted from trajectories can be further analyzed and used, for example, in studies of behaviours of wild animals [6], traffic congestions in a city or connections between airports [7]. The latter paper suggests a generic visual analytics procedure where events are extracted from trajectories and clustered in special ways to detect significant places and investigate the temporal dynamics of the movements within and between these places. The procedure also involves spatio-temporal aggregation, which is the topic of the next section.

4 BIRD'S-EYE VIEW ON MOVEMENT: GENERALIZATION AND AGGREGATION

Generalization and aggregation enables an overall view of the spatial and temporal distribution of multiple movements, which is hard to gain from displays showing individual trajectories. Besides, aggregation is helpful in dealing with large amounts of data. An illustrated survey of the aggregation methods used for movement data and the visualization techniques applicable to the results of the aggregation is given in [1]. These methods and techniques are also presented in a more formal way in [3]. There are two major groups of analysis tasks supported by aggregation:

- Investigation of the presence of moving objects in different locations in space and the temporal variation of the presence.
- Investigation of the flows (aggregate movements) of moving objects between different locations in space and the temporal variation of the flows.

4.1   Analyzing presence and density

Presence of moving objects in a location during some time interval can be characterized in terms of the count of different objects that visited the location, the count of the visits (some objects might visit the location more than once), and the total or average time spent in the location. Besides, statistics of various attributes describing the objects, their movements, or their activities in the location may be of interest. To obtain these measures, movement data are aggregated spatially into continuous density surfaces (fields) [24][59] or discrete grids [26][1]. While the most common approach is to aggregate points of trajectories and point-related attributes, Willems et al. [59] have developed a specific kernel density estimation method for trajectories, which involves interpolation between consecutive trajectory points taking into account the speed and acceleration. Density fields built using kernels with different radii can be combined into one field to expose simultaneously large-scale patterns and fine features (Fig. 5A). Density fields are visualized on a map using colour coding and/or shading by means of an illumination model. A more recent paper [45] suggests a library of methods and a scripting-based architecture for creation, transformation, combination, and enhancement of movement density fields. This approach allows an expert user to involve domain knowledge in the process of building density fields. Mountain [39] further processes density surfaces generated from movement data to extract their topological features: peaks, pits, ridges, saddles, etc.

An example of spatial aggregation using a discrete grid is given in Fig. 5B. The irregular grid has been built according to the spatial distribution of characteristic points from ship trajectories as described in [10]. The darkness of the shading of the grid cells is proportional to the total number of visits. Additionally, each cell contains a circle with the area proportional to the mean duration of a visit. It can be observed that the average duration of staying in the cells with dense traffic (dark shading) is mostly low; longer times are spent in cells that are not intensively visited.

Presence and density maps do not convey information about the movement directions. Brillinger et al. [19] use arrow symbols to represent the prevailing movement directions in cells of a discrete grid. The lengths and widths of the symbols are proportional to the average speed and the number of moving objects, respectively. This approach is suitable when the movement is mostly coherent, i.e., objects moving closely in space tend to have the same direction, which is not always the case. Movements in different directions can be represented by directional diagrams positioned on a map within grid cells [1]. A diagram consists of bars arranged in a radial layout and oriented in different compass directions, as in a wind rose. The lengths of the bars are proportional to the counts of objects that moved in the respective

directions, or to their average speeds, or to any other numeric statistics associated with the directions. This approach combines two kinds of aggregation: by spatial positions and by movement directions.

To combine spatial aggregation with aggregation by several arbitrary attributes, researchers from London City university suggest spatially-ordered treemaps [47][60]. Generally, a treemap [46] is a space-filling hierarchical layout of rectangles, typically labelled, differing in size and, optionally, colouring or shading. Each rectangle represents a group of objects with close values of some attribute so that the size of the rectangle is proportional to the size of the group. The group can be further subdivided according to values of another attribute, and the rectangle representing the group is also partitioned into smaller rectangles.

The method of creating a spatially ordered treemap is illustrated in Fig. 4. The territory is divided into compartments, for example, using a regular grid, as in Fig. 4A (irregular divisions can also be used). Each compartment is represented by a rectangle with the size (area) proportional to the number of trajectory points occurring in the compartment. According to the general idea of treemap, the rectangles are subdivided into sections proportionally to the numbers of trajectory points with different values of a selected attribute; in our example, ship type. In Fig. 4 B, the rectangles are located in the display according to the spatial positions of the respective compartments. To get rid of the occlusions and display clutter, the rectangles are then shifted and reshaped so that each rectangle can receive its individual portion of the display space (Fig. 4 C). This is done in such a way that the relative spatial positions of the rectangles are distorted as little as possible. The transitions between the views shown in Fig. 4 B and C can be animated to help the user understand how the space is transformed. The interpretation of the display requires training but the benefits are the absence of occlusions and the possibility to analyze several attributes simultaneously, e.g., ship type, destination, and average speed. For each additional attribute, the sections of the rectangles representing the compartments are further subdivided.
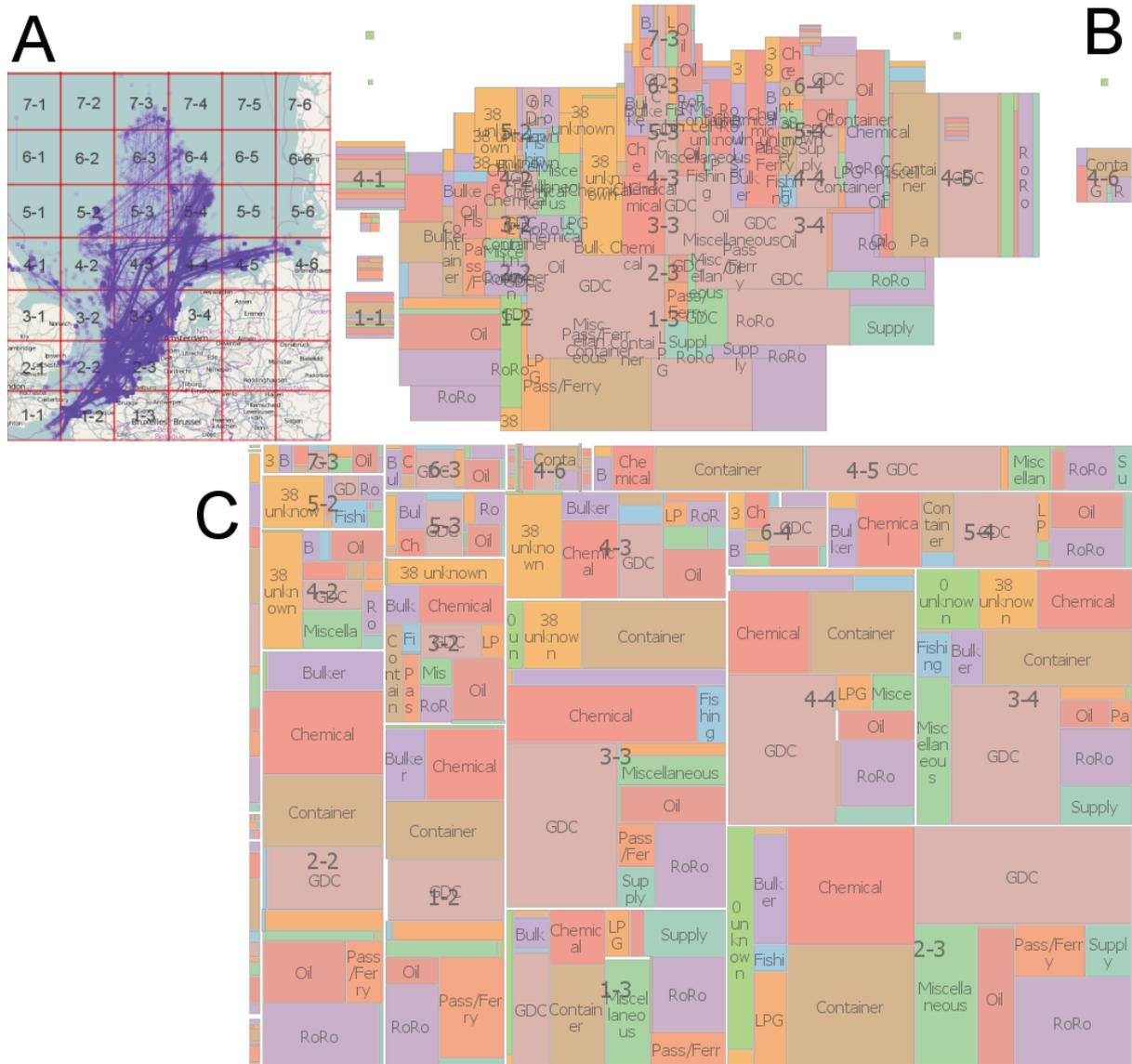
Figure 4. To generate a treemap, the territory has been divided into squares (A). The squares have been scaled proportionally to the number of trajectory points in them and subdivided into sections according to the proportions of different ship types (B). The squares have been shifted in space and reshaped for avoiding overlapping (C). We thank Aidan Slingsby (City University of London) for the help in creating this illustration.
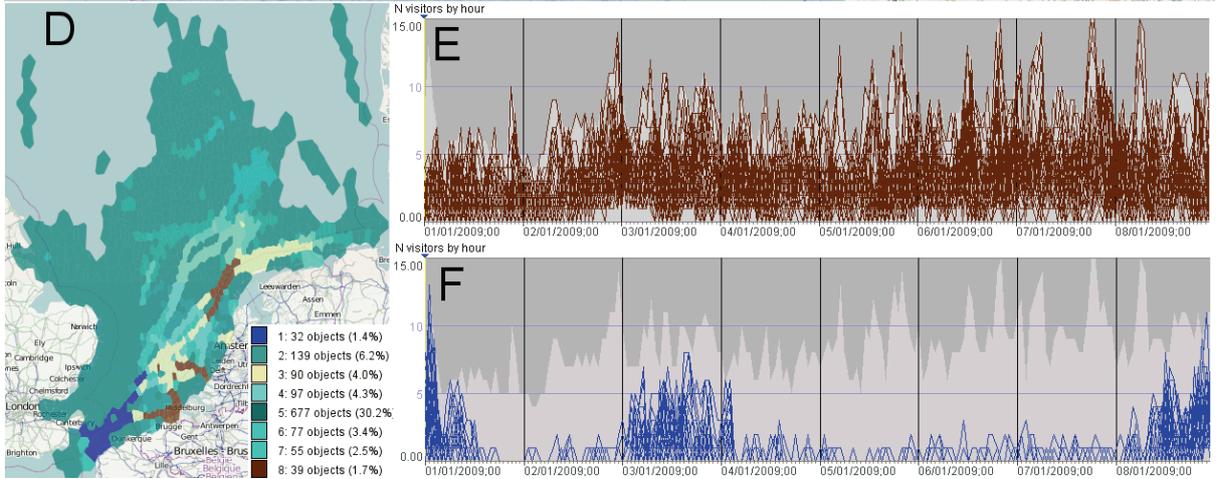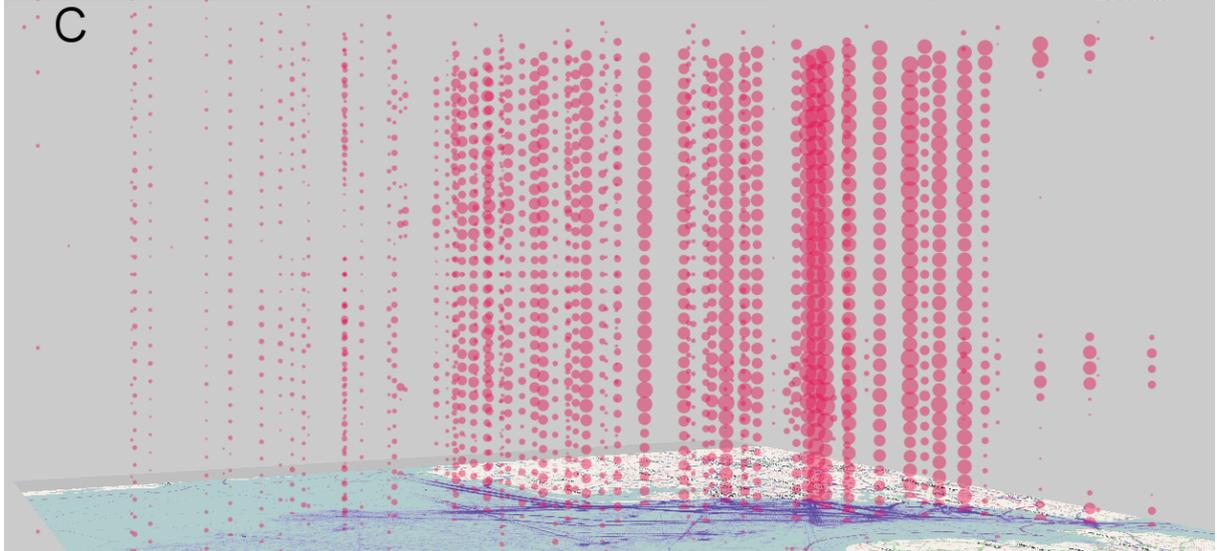
Figure 5. A: Ship movement data aggregated into a continuous density surface (image courtesy of N.Willems). B: Spatial aggregation by cells of a discrete grid: counts of cell visits are shown by shading and mean durations of the visits by areas of circles. C: Time series of cell visits represented by proportionally sized circles in a STC (viewed from the northwest). D: Grid cells clustered according to the time series of visitor counts. E, F: The time series for two selected clusters of cells.

To investigate the temporal variation of object presence and related attributes across the space, spatial aggregation is combined with temporal aggregation, which can also be continuous or discrete. Demšar and Virrantaus [22] extend the idea of spatial density to spatio-temporal density: they aggregate trajectories into density volumes in three-dimensional space-time continuum by generalizing the standard 2D kernel density around 2D point data into 3D density around 3D polyline data. The resulting volumes are represented in a STC.

For discrete temporal aggregation, time is divided into intervals. Depending on the application and analysis goals, the analyst may consider time as a line (i.e. linearly ordered set of moments) or as a cycle, e.g., daily, weekly, or yearly. Accordingly, the time intervals for the aggregation are defined on the line or within the chosen cycle. The combination of discrete temporal aggregation with continuous spatial aggregation gives a sequence of density surfaces, one per each time interval, which can be visualized by animated density maps. It is also possible to compute differences between two surfaces and visualize them on a map, to see changes occurring over time (this technique is known as a change map). The combination of discrete temporal aggregation with discrete spatial aggregation produces one or more aggregate attribute values for each combination of space compartment (e.g., grid cell) and time interval. In other words, each space compartment receives one or more time series of aggregate attribute values. Visualization by animated density/presence maps and change maps is possible as in the case of continuous surfaces. There are also other possibilities. The time series may be shown in a STC by proportionally sized or shaded or coloured symbols, which are vertically aligned above the locations [64]; Fig. 5C gives an example. Occlusion of symbols is often a serious problem in such a display.

It is also possible to combine presence/density maps with time series displays such as a time graph or temporal histogram [39][62]. Zhao et al. [64] build circular temporal histograms to explore the dependency of movement behaviours on temporal cycles. They also suggest a visualization technique called ringmap, a variant of a circular histogram where aggregate values are shown by colouring and shading of ring segments rather than by bar lengths. Multiple concentric rings can represent aggregation according to an additional attribute, for example, activity performed by the moving objects.

When the number of the space compartments is big and time series are long, it may be difficult to explore the spatio-temporal distribution of object presence using only visual and interactive techniques. It is reasonable to cluster the compartments by similarity of the respective time series and analyze the temporal variation cluster-wise, i.e., investigate the attribute dynamics within the clusters and do comparisons between clusters. Andrienko et al. [4] do the clustering using self-organizing maps and create specific visualizations to explore the clustering results; however, other clustering and visualization techniques may be used as well. Fig. 5D demonstrates the outcome of k-means clustering of grid cells according to the time series of presence of different ships computed by hourly time intervals. Distinct colours have been assigned to the clusters and used for painting the cells on the map. The colours are chosen by projecting the cluster centroids onto a two-dimensional continuous colour map; hence, clusters with close centroids receive similar colours and, vice versa, high difference in colours signifies much dissimilarity between the clusters. The analyst can select the clusters one by one or pairs of clusters for comparison and look at the corresponding time series presented on a time graph (Fig. 5 E and F).

In our example, the clusters differ mainly in the value magnitudes and not in the temporal patterns of value variation. Fig. 5E shows the time series of the cluster with the highest values (cluster 8). The variation appears random. The same can be observed for other clusters. However, there is one cluster (cluster 1, located between the coasts of England and continental Europe) that has a particular temporal pattern shown in Fig. 5F. There are three time intervals in which the presence values are quite high and the rest of the time they are close to zero. The three intervals with high values occurring in the area of English Channel are also visible in the STC in Fig. 5C (on the right; note that the aggregation represented in the STC has been done by larger spatial compartments than in Fig. 5D and by 6-hour time intervals). This variation of the ship presence can be, probably, explained by weather conditions, but we have no data to check this.

Spatially referenced time series is one of two possible views on a result of discrete spatio-temporal aggregation [4]. The other possibility is to consider the aggregates as a temporal sequence of *spatial situations* [12]. The term 'spatial situation' denotes spatial distribution of aggregate values of one or more attributes in one time interval. Temporal variation of spatial situations can also be investigated by means of clustering [4][12]. In this case, the spatial situations are considered as feature vectors characterizing different time intervals. The clustering groups the time intervals by similarity of these feature vectors. An example is presented in Fig. 6.

Spatio-temporal aggregation by cells of an irregular grid and hourly time intervals has been applied separately to 322 trajectories of the passenger and ferry boats (for this purpose, the trajectories have been filtered by the ship type). Then k-means clustering method has been applied to 192 spatial situations (8 days times 24 hours) in terms of the presence of the passenger and ferry boats expressed by their visit counts in the grid cells. The results of the clustering are represented on the time mosaic display in the bottom right corner of the figure. The time intervals are represented by squares arranged in 8 columns corresponding to the 8 days and 24 rows corresponding to 24 hours of the day. The squares are painted in the colours assigned to the clusters. After running the clustering tools multiple times with different values of the parameter k (number of clusters), we have chosen the result for k=8 since it produces the most prominent periodic patterns on the time mosaic display. We can see that the morning of the first day (01/01/2009, New Year) differs from the mornings of all other days but starting from 15:00 the pattern becomes similar to the other days. The time mosaic display indicates mostly regular character of the movement of the boats. The multiple maps display summarizes the spatial situations by the time clusters: for each time cluster and each cell, the mean count of visits has been computed from the counts for the time intervals contained in the cluster. The clusters represented by the maps are designated by the coloured captions. It is interesting that the presence situations in the hours 7 and 9-11 on Saturday (day 3) are prominently different than in the same time of the other days. These situations belong to the orange cluster, which is represented by the last map in the bottom row. The map shows that the situations in this cluster are characterized by unusually high presence of boats at Dunkerque and Brugge. This can, probably, be explained by people from England going on the continent for Saturday shopping.
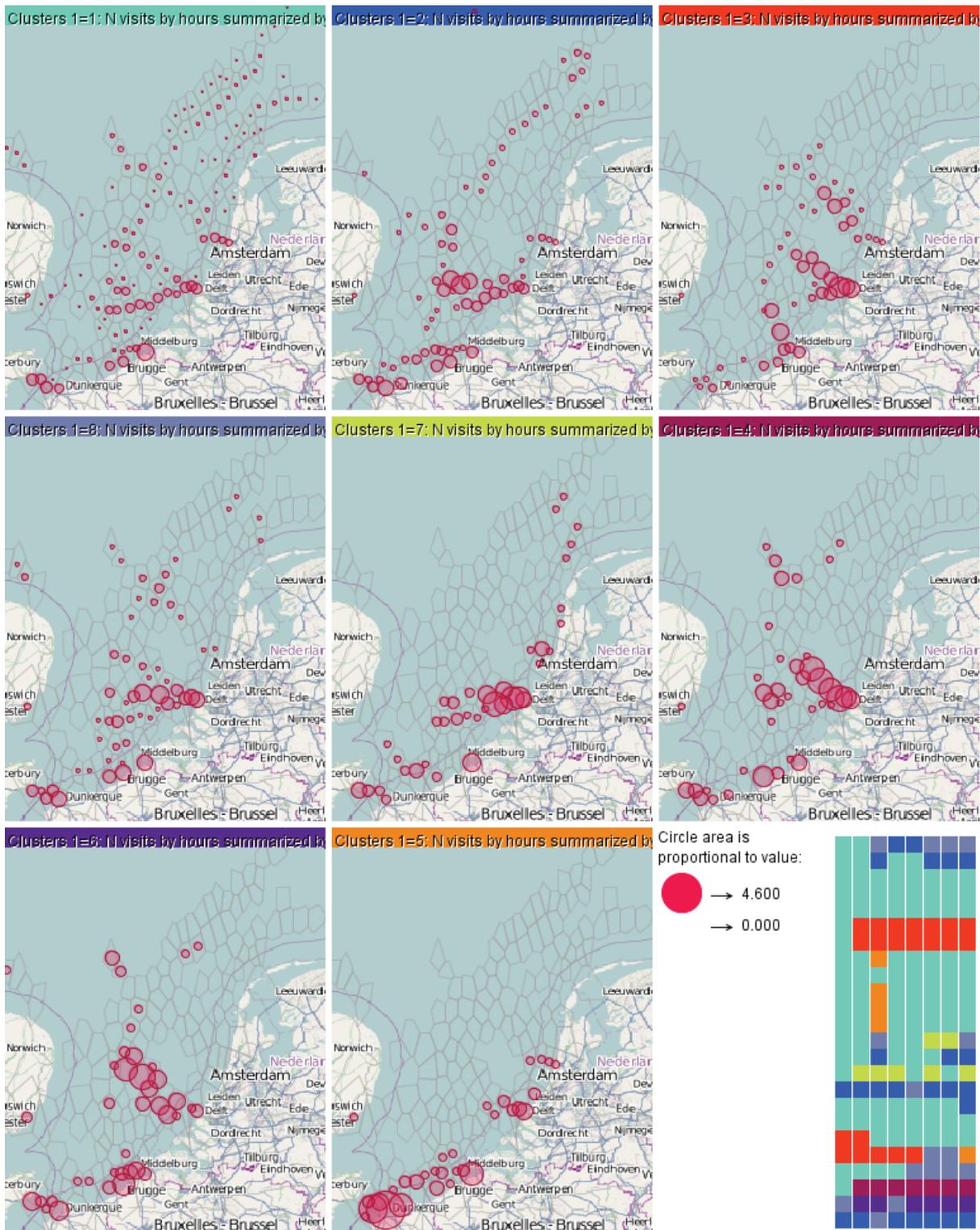
Figure 6. Hourly time intervals have been clustered by similarity of spatial situations in terms of presence of passenger and ferry boats. Bottom right: time mosaic display where the columns, from left to right, correspond to days from 01/01/2009 (Thursday) to 08/01/2009 (Thursday) and rows, from top to bottom, to hours from 0 to 23. The maps summarize the spatial situations by the time clusters by showing the mean presence values in the cells.

Bak et al. [14] represent presence of moving objects at different locations without explicit spatial aggregation. Each visit is represented on a map by a pixel coloured according to the time of the visit or value of some attribute. The pixels are arranged in a spiral layout around

the locations so that identically coloured pixels are placed closely to each other. As a result, a circle emerges around a location in which pixels with same colours form rings; the technique is therefore called Growth Rings. The layout induces perceptual aggregation: the user does not distinguish individual pixels but perceives them all together as one figure. The size of the whole figure shows the total number of visits while the rings show the proportions of occurrences of the attribute values encoded by the colours.

To deal with very large amounts of movement data, possibly, not fitting in RAM, discrete spatio-temporal aggregation can be done within a database [1] or a data warehouse [42]. Only aggregated data are loaded in RAM for visualization and interactive analysis. Using roll-up and drill-down operators of the warehouse, the analyst may vary the level of aggregation.

4.2   Tracing flows

In the previous section, we have considered spatial aggregation of movement data by locations (space compartments). Another way of spatial aggregation is by pairs of locations: for two locations A and B, the moves (transitions) from A to B are summarized. This can result in such aggregate attributes as number of transitions, number of different objects that moved from A to B, statistics of the speed, transition duration, etc. The term "flow" is often used to refer to aggregated movements between locations. The respective amount of movement (i.e., count of moving objects or count of transitions) may be called "flow magnitude".

There are two possible ways to aggregate trajectories into flows. Assuming that each trajectory represents a full trip of a moving object from some origin to some destination, the trajectories can be aggregated by origin-destination pairs, ignoring the intermediate locations. A well-known representation of the resulting aggregates is origin-destination matrix (OD matrix) where the rows and columns correspond to the locations and the cells contain aggregate values. OD matrices are often represented graphically as matrices with shaded or coloured cells. The rows and columns can be automatically or interactively reordered for uncovering connectivity patterns such as clusters of strongly connected locations and "hubs", i.e., locations strongly connected to many others [27]. A disadvantage of the matrix display is the lack of spatial context.

Guo et al. [28] use multiple small maps each showing flows to/from one place by colouring or shading the other places according to the respective flow magnitudes. The maps are arranged similarly to the relative positions of the places in the geographical space. Wood et al. [61][62] devised an algorithm to generate so called OD maps, in which multiple OD matrices are arranged according to the geographic positions of the places.

Another way to visualize flows is flow map where flows are represented by straight or curved lines or arrows connecting locations; the flow magnitudes are represented by proportional widths and/or colouring or shading of the symbols [49][62]. Since lines or arrows may connect not only neighbouring locations but any two locations at any distance, massive intersections and occlusions of the flow symbols may occur, which makes the map illegible. Several approaches have been suggested for reducing the display clutter. The simplest are filtering [49] or reducing the opacity of lesser flows [62], but these involve high information loss. Approaches involving edge bundling [41][54][25] work well only for showing flows from one or two locations or in special cases, e.g., when radial flows from/to one location prevail over all others [25]. Besides, edge bundling on a map representing geographical rather than abstract space introduces undesired geographical artefacts: bundled edges make a misleading impression of arterial roads that do not exist in reality. Boyandin et al. [16] remove the middle parts of the lines connecting the places and colour the remaining starting

and ending segments of the lines in two different colours. This reduces the clutter but the flows may be not easy to trace. Boyandin et al. [17] use a display with two maps and a table between them. Each row in the table corresponds to one place. Lines representing flows are drawn not between places within a map but between places in the maps and rows in the table. The left and right parts of the display show the out- and ingoing flows, respectively. The rows of the table contain visual representations of the time series of the flow magnitudes. The information content of the display is very high, but the spatial patterns of the flows can hardly be perceived. There is currently no universally good solution for visualizing arbitrary origin-destination flows.

Vrotsou et al. [55] consider aggregated movement data as a weighted directed graph where vertices are the places and arcs are the flows. They compute various centrality measures for the graph vertices, which may be a valuable addition to the other place-related statistics such as counts of visits. The measures are visualised on maps, e.g., by colouring or shading of the places, but this does not show the connections between the places.

The other possible way of transforming trajectories to flows is to represent each trajectory as a sequence of transitions between all visited locations along the path and aggregate the transitions from all trajectories. Movement data having sufficiently fine temporal granularity or allowing interpolation between known positions may be aggregated so that only neighbouring locations (adjacent spatial compartments) are linked by flows. Such flows can be represented on a flow map without intersections and occlusions of the flow symbols. When there are no predefined locations or space partitioning, the space can be tessellated into larger or smaller compartments to achieve higher or lower degree of generalization and abstraction [10]. This is illustrated in Fig. 7A and B. The same trajectories of ships have been aggregated into flows using finer (A) and coarser (B) territory tessellations. The flows are represented by "half-arrow" symbols, as suggested by Tobler [49], to distinguish flows between the same locations in the opposite directions. Minor flows (below 20 individual moves) have been hidden to improve the display legibility. The flow maps exhibit the major traffic lanes, which were also visible in the visualization of the original trajectories (Fig.3A) and in the density map (Fig. 5A). However, the movement directions are only visible on the flow maps, and the intensity of the traffic can be judged from the widths of the flow symbols.
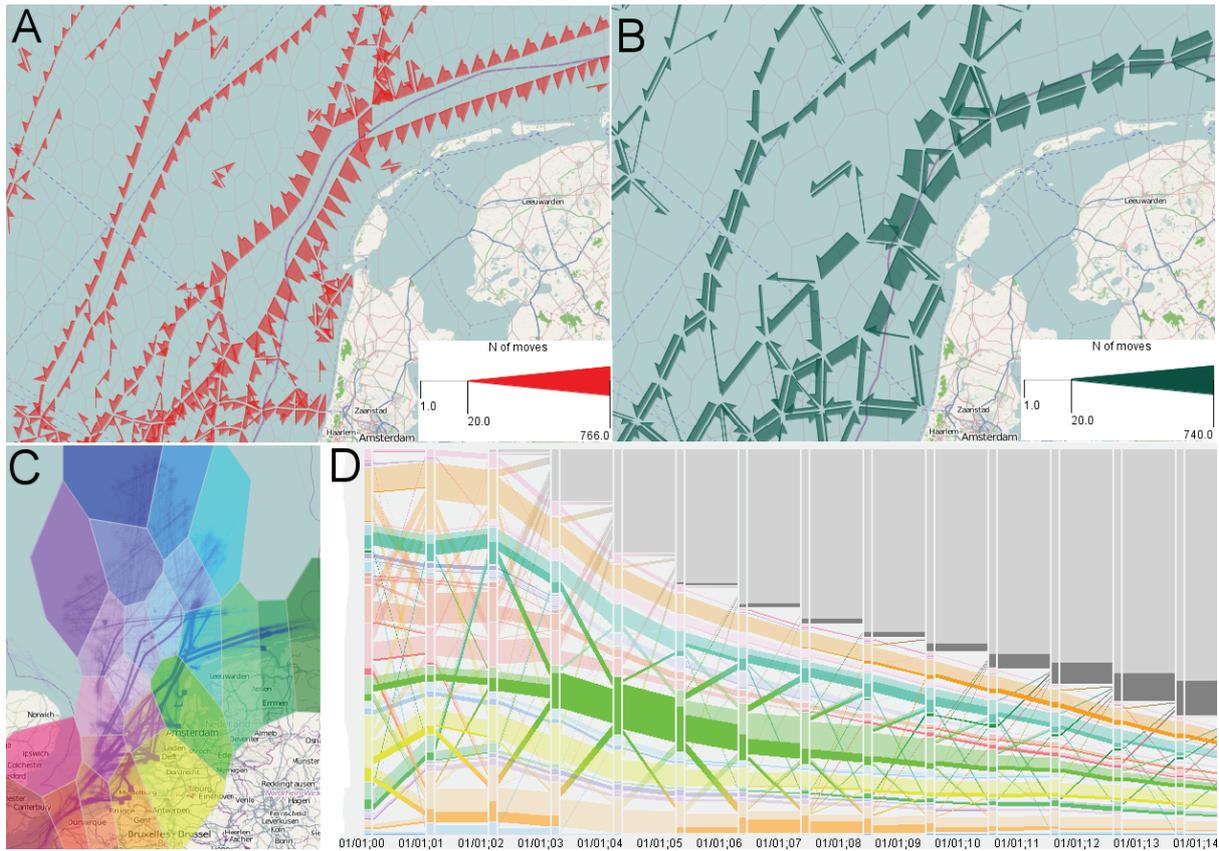
Figure 7. A, B: Flow maps based on finer (A) and coarser (B) territory divisions. C, D: Exploration of sequences of visited areas. C: Colour coding of the areas. D: Presence of ships in the areas and aggregated transitions between the areas by time intervals.

The territory divisions demonstrated in Fig. 7 A and B result from a method that accounts for the spatial distribution of characteristic points extracted from trajectories [10]. It uses a special algorithm for spatial clustering of points that produces clusters of user-specified spatial extent (radius). The geographic or gravity centres of the clusters are then used as generating points for Voronoi tessellation. Depending on the chosen radius, the data can be aggregated at different spatial scales.

When movement data are aggregated into flows by time intervals, the result is time series of flow magnitudes. These can be visualized by animated flow maps or by combining flow maps with temporal displays (e.g. [17]). Flows may be clustered by similarity of the respective time series and the temporal variation analyzed cluster-wise, as was suggested for time series of presence indicators in the previous section. Complementarily, time intervals can be clustered by similarity of the spatial situations in terms of flows [12].

Bremm at al. [18] suggest a visualization technique showing temporal variation of object presence at different locations and flows between the locations on a particular kind of temporal display where the locations are represented by distinct colouring (this can work well for a relatively small number of different locations). The technique is demonstrated in Fig. 7D; the map in Fig. 7C shows the territory division and colours of the areas that are used in Fig. 7D. To build this display, the trajectories of the ships have been aligned in time to a common starting time, as mentioned in section 2.3. Then the transformed time has been divided into hourly intervals. For each time interval, the display contains a bar divided into coloured segments proportionally to the number of moving objects that visited the areas in this interval. Grey is used for unknown positions. In this particular example, grey segments

represent the trajectories that ended before the respective time intervals. Aggregated transitions between the areas are represented by bands drawn between the bars. The widths of the bands are proportional to the counts of the objects that moved. Gradient colouring is applied to the bands so that the left end is painted in the colour of the origin area and the right end in the colour of the destination area, or in grey for the trajectories that ended.

By interacting with the display, it is possible to explore not only direct transitions between areas but also longer sequences of visited areas. When the user clicks on a bar segment, the movements of the corresponding subset of objects are highlighted in the display (i.e., shown by brighter colours). This is illustrated in Fig. 7D. By clicking on the green segment of the fifth bar, the user has selected the subset of ships that were in the area of Amsterdam in the fifth hour since the beginning of their movement. We can see the previous and past locations of the selected ships and when the transitions occurred. Analogously, the user can click on a band connecting segments to select the objects participating in the respective transitions and trace their movements.

5   INVESTIGATION OF MOVEMENT IN CONTEXT

The spatio-temporal context of the movement includes the properties of different places (e.g., land cover or road type) and different times (e.g. day or night, working day or weekend) and various spatial, temporal, and spatio-temporal objects affecting and/or being affected by the movement [6]. Tomaszewski and MacEachren [50] consider the notion of context on a more general level and suggest a conceptual model that encompasses three aspects of context, spatial (geographical), temporal (historical), and conceptual. They describe a prototype software system for analysis of text documents where spatial, temporal, and conceptual context information can be visually represented to facilitate sense-making.

The methods for movement data analysis discussed so far do not address the context in an explicit way. However, movement data are usually visualized using cartographic maps, which serve as very important providers of information about the spatial context. By looking at the maps, the analyst can relate visible spatial patterns to the spatial context, e.g., observe that the highest ship traffic density is near ports. In principle, information about the temporal context can be represented in temporal displays, such as a time graph, together with movement data or their derivatives; however, this is rarely done in practice. It is more usual to represent context information on additional displays, which are linked to displays of movement data by means of visual and/or interactive techniques. Thus, Lundblad et al. [38] use a time graph to visualize weather parameters along the routes of selected ships. Besides, multiple weather parameters for all ships at a selected time moment are shown on a parallel coordinate plot. The links between the displays are established through interactive selection of ships or time moments for the additional displays. The mosaic temporal display in Fig. 6 conveys context information about temporal cycles through special arrangement of display elements (squares). The colouring of the squares visually links the mosaic display to the display of sea traffic situations.

Bouvier and Oates [15] suggest an original interaction technique called "staining", which may be used for exploring emerging relationships between moving objects and elements of the spatial context. The technique is used with an animated map showing object movements. The user can mark some context item such as area or object on the map by painting (staining) it in a particular colour. Several context items may be stained with same or different colours. As moving objects move through a stain, they also become stained, i.e., painted in the colour of the stain. This allows the user to observe easily which objects encountered the marked

item, when it happened, and how these objects behaved after that. Furthermore, it is possible to run the animation backwards in order to see how these objects moved before the encounter.

Besides the context items that are explicitly represented on visual displays, the analyst also takes relevant context information from his/her background knowledge. Visual displays, especially maps, help the analyst in doing this since things that are shown can facilitate recall of related things from analyst's mind. Thus, we noticed in Fig. 5 that the spatial situations that occurred on Saturday are characterized by exceptionally high traffic of passenger and ferry boats between the southeast coast of the UK and the continent. We knew previously from other sources that many residents of the UK go from time to time for shopping to France and Belgium. Based on this knowledge, we concluded that the observed pattern of sea traffic may be related to this shopping.

So far, we have discussed the cases when context information is represented visually and relationships between the movement and the context are established solely by the user through observation of the visual displays and interaction with them. By the current moment, not much has been done in the visual analytics research for involving context information also in computational processing and analysis of movement data. One existing approach is to produce and visualize dynamic attributes representing certain relationships between positions of moving objects and elements of their spatio-temporal context [6]. Many types of relationships can be expressed in terms of spatial and/or temporal distances [6][7]. This includes spatial proximity of moving objects to certain locations or types of locations, spatio-temporal proximity to a spatial event, spatio-temporal proximity between moving objects, etc.

Crnovrsanin et al. [21] compute spatial distances of multiple moving objects to a selected item of spatial context, such as place (point or area) of interest, static object, or moving object, and visualize the resulting dynamic attributes of the moving objects on a time graph. Patterns formed by the lines on the graph not only show the movements in relation to the selected context item and allow the user to observe common behaviours and detect outliers but also indicate various emergent relationships (referred to as "movement patterns") among the moving objects: spatial concentration (congestion), convergence, divergence, meeting, coincidence, concurrence, etc. Interactive tools allow the user to select the objects participating in these patterns and observe their traces on a map. Two or more time graphs enable comparison of movements from different places. Orellana et al. [40] computationally extract occurrences of proximity relationships between moving objects and then visualize them on spatial and temporal displays by means of specially designed techniques.

A more generic method for detection and analysis of various types of relationships that can be expressed in terms of spatial and/or temporal distances is suggested in [6]. The main idea is to compute spatial and/or temporal distances from moving objects to context items and represent them as attributes attached to trajectory positions. Then the user interactively filters the positions according to values of one or more of these attributes and creates spatial events from the points and segments satisfying the filter, as described in section 3. The extracted events can be explored visually and with the use of computational methods. We shall present this approach by an example.

Unfortunately, for our example dataset with ship trajectories, we have no additional datasets describing elements of the movement context, such as the weather conditions, positions of offshore wind farms and oil platforms, protected zones, etc. However, various kinds of secondary data produced in the process of analyzing movement data can also be considered as context data in the further analyses of the movement data [6]. In our previous examples, we have demonstrated derivation of spatial events, event clusters, and classes (clusters) of locations and of time moments. Such derived data can be used as context data. From the

perspective of the presented approach, the origin of the context data makes no difference. Context data coming from external sources are processed in exactly the same way as context data previously derived from movement data.
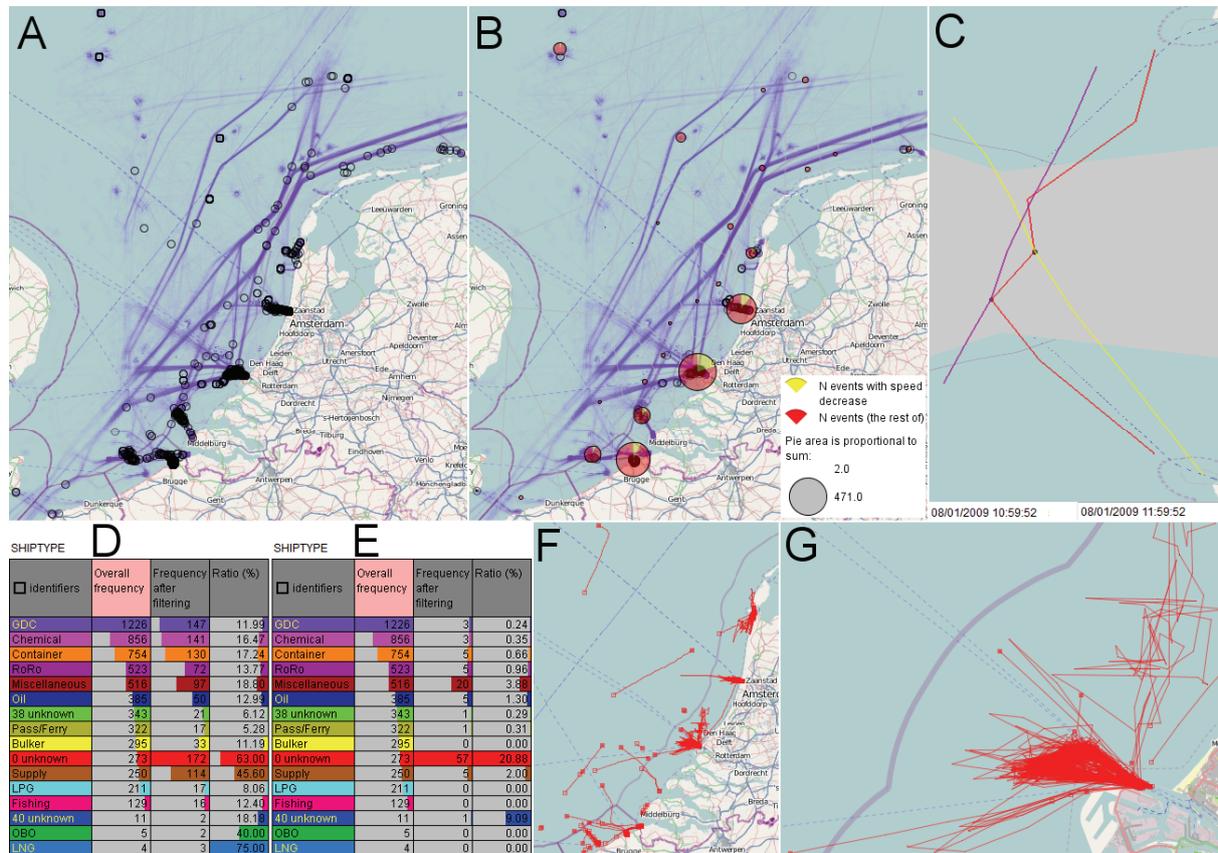

Figure 8. Investigation of near-encounter relationships between ships. A: Extracted events of distance less than 100m to the nearest ship (black circles). B: The events in which at least one of the ships decreased the speed by 10km/h or more. The pie charts show the total counts of events and the counts of events with decreased speed by areas around groups of events. C: Investigation of the spatio-temporal neighbourhood of a selected event in a STC. D, E: Statistics of event occurrence by ship types. D: all events, E: events with speed decrease. F, G: Trajectories of the ships of the "unknown" type.

In our example, the first task is to detect occurrences of near-encounter (close proximity) relationships between ships. We computationally derive a dynamic attribute representing the distance from a ship to the nearest other ship. Then we generate spatial events from the points where this distance is 100m or less. The events are shown as black circles on a map in Fig.8A. Concentrations in areas close to ports are well visible.

The next task is to investigate how the near-encounter events affected the movement behaviours of the ships. We compute the statistics of the changes of the movement speed in the spatio-temporal neighbourhood of the events and apply a filter to see only the events associated with speed decrease by at least 10km/h. Fig. 8B shows these events. For the areas around the event concentrations, the total numbers of the near-encounter events and the proportions of the events with speed decrease are also shown by pie charts. Spatial and temporal filtering allows us to explore any selected event in detail using a space-time cube (Fig. 8C). The traces in the STC are coloured according to the ship types; the meaning of the colours is visible in Fig.8 D and E.

To see which types of ships get most often involved in near-encounter relationships, we apply filtering to the ship trajectories according to the events that had been extracted from them. The table in Fig. 8D shows the frequencies of different ship types among all trajectories (column 2) and among the trajectories in which near-encounter relationships occurred (column 3). It can be seen that the ships of the type "0 unknown" were disproportionally often involved in such relationships (the type "0 unknown" means that the AIS messages sent from these vessels contained zero in the field meant for the ship type code). Fig. 8E shows similar statistics for the subset of near-encounter events accompanied with speed decrease. Again, the relative frequency of the ships of the "0 unknown" type is much higher among the trajectories involved in the events than among all ships. The map in Fig. 8F shows the trajectories of the ships of this category; an enlarged fragment is given in Fig. 8G. It is seen that these ships mostly move closely to ports and the movement looks rather chaotic, which can explain the high involvement in near-encounter relationships.

Sections 2-4 show that movement can be analyzed at different levels: whole trajectories, elements of trajectories (points and segments), and high-level summaries (densities, flows, etc.). In principle, analyzing movement in context can also be done at these levels. However, a comprehensive set of visual analytics methods addressing all these levels and different types of context items does not exist yet, which necessitates further research in this direction.

6 CONCLUSION

Visual analytics has developed a rich palette of methods and tools for analysis of movement data. Visual displays and interactive techniques are often combined with computational processing, which, in particular, allows analysis of larger amounts of data than it would be possible with purely visual methods. Visual analytics leverages methods and tools developed in other areas related to data analytics, particularly, statistics, machine learning, and geographic information science. Close collaboration between visual analytics researchers and scientists from these areas can greatly promote the progress in developing methods for analyzing complex data and solving complex real-world problem. Thus, many of the methods described in this chapter appeared in collaborative projects involving researchers in visual analytics, data mining, and database technologies. Since there is yet ample space for further research in the area of movement analysis, new achievements can be expected from cross-disciplinary cooperation.

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