Stacking-Based Visualization of Trajectory Attribute Data

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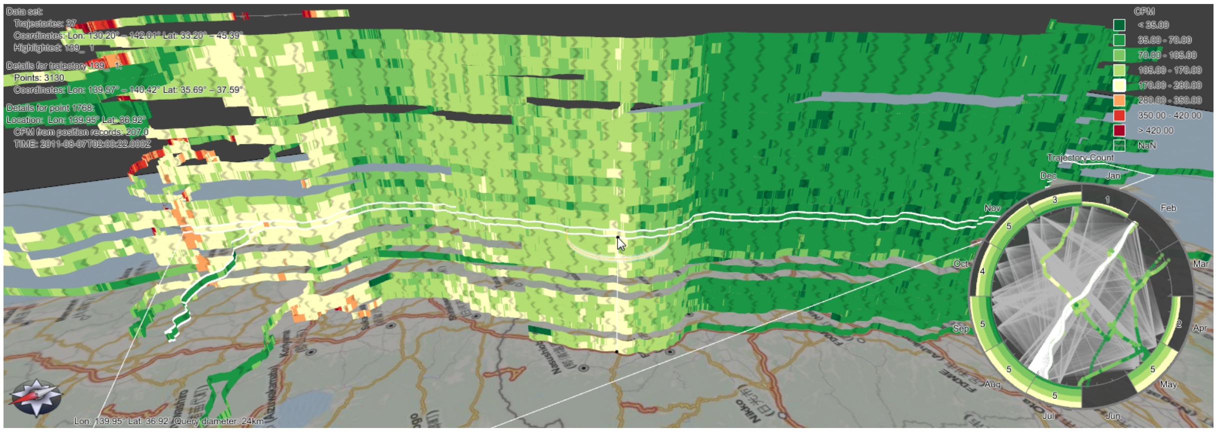

Fig. 1. Visualization of radiation (CPM values) along the Tokio-Fukushima highway.

Abstract—Visualizing trajectory attribute data is challenging because it involves showing the trajectories in their spatio-temporal context as well as the attribute values associated with the individual points of trajectories. Previous work on trajectory visualization addresses selected aspects of this problem, but not all of them. We present a novel approach to visualizing trajectory attribute data. Our solution covers space, time, and attribute values. Based on an analysis of relevant visualization tasks, we designed the visualization solution around the principle of stacking trajectory bands. The core of our approach is a hybrid 2D/3D display. A 2D map serves as a reference for the spatial context, and the trajectories are visualized as stacked 3D trajectory bands along which attribute values are encoded by color. Time is integrated through appropriate ordering of bands and through a dynamic query mechanism that feeds temporally aggregated information to a circular time display. An additional 2D time graph shows temporal information in full detail by stacking 2D trajectory bands. Our solution is equipped with analytical and interactive mechanisms for selecting and ordering of trajectories, and adjusting the color mapping, as well as coordinated highlighting and dedicated 3D navigation. We demonstrate the usefulness of our novel visualization by three examples related to radiation surveillance, traffic analysis, and maritime navigation. User feedback obtained in a small experiment indicates that our hybrid 2D/3D solution can be operated quite well.

Index Terms—Visualization, interaction, exploratory analysis, trajectory attribute data, spatio-temporal data.

1 Introduction

Exploring trajectories of moving objects is relevant to people in a number of application domains. Examples are traffic planners who need to find bottlenecks in traffic networks, physicists who seek to understand particle movements, or sociologists who analyze the behavior of human individuals. For these scientists, trajectories are valuable sources of information because they encompass spatial and temporal aspects of the movement of objects and additional quantitative and qualitative attributes about the movement and the environment or context in which the movement took place.

The three components *space*, *time*, and *attributes* lead to an information richness that makes analyzing trajectories a profitable task. But understanding spatio-temporal trajectory attributes is also difficult, because it involves a variety of aspects. One needs to assess spatial and temporal dependencies, which need to be set into relation to gain insight into the spatio-temporal dynamics of attributes. Trajectory data might contain interesting facts not only at the level of individual trajectories, but also at the level of sets of trajectories (e.g., trajectories that cross specific regions in space and/or that cover particular spans in time). For larger data sets it is usually unclear where interesting facts can be found and which trajectories needs to be looked at in detail.

In consequence of the complex interplay of different data aspects and analysis tasks, providing appropriate support for interactive exploration of trajectory attribute data is challenging. Hence, existing visualization methods usually focus on one or two particular aspects, but not all of them. According to our research, none of the existing methods provides sufficient support for investigating individual trajectories *and* sets of trajectories with regard to space *and* time *and* attributes.

With this work, we develop a novel solution that covers all facets involved in the analysis of trajectory attribute data. According to the nature of the data and based on a study of relevant analysis tasks, we suggest the following general visualization design: Attribute data of individual trajectories are visualized as *color-coded bands* and sets of trajectories are visualized by *stacking* the bands.

Because showing all data aspects in full detail at all times regardless of the analysis task is infeasible, we provide complementary visual representations. The hybrid 2D/3D *trajectory wall* visualizes trajectory attribute data by stacking 3D color-coded bands on a 2D map.

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The association to time is established through temporal ordering and through the *time lens*, a circular time display that is connected to a dynamic query mechanism. Additionally, the 2D *time graph* shows trajectories as horizontal bands along which the time-dependency of an attribute is encoded by color. All representations are coordinated, enabling analysts to link temporal and spatial aspects in order to make spatio-temporal discoveries.

This basic visualization solution is further equipped with supplemental components, including construction of meaningful subsets of trajectories based on interactive selection and analytical calculations, interactive adjustment of the color-coding based on statistical properties of the data, and dedicated navigation mechanisms.

In summary, our contribution is a novel approach that (1) integrates space, time, and attributes, (2) considers relevant analysis tasks, and (3) combines visual, analytical, and interactive components to facilitate trajectory attribute exploration.

We derive our novel approach and describe its individual components in detail in Section 3. To demonstrate the usefulness of the proposed solution, we apply it in Section 4 to visualize several interesting data sets, including the radiation around Fukushima Daiichi nuclear power plant, the taxi traffic at San Francisco airport, and vessel movement in the harbor of Brest. The usability of our solution has been evaluated in a small experiment. The generally positive feedback of the participants and their constructive suggestions for improvements are briefly discussed in Section 5. This article ends in Section 6 with a conclusion and ideas for future work.

2 Data, Tasks, and Related Work

Next, we start with introductory comments on the data we are concerned with, study the questions that analysts might ask about such data, and take a look at related work.

2.1 Data

The general goal of our work is to explore dynamic attributes along trajectories in space and time – for individual trajectories as well as across sets of trajectories. Achieving this goal is becoming increasingly relevant, because new sensors and data collection infrastructures support the acquisition of contextual attributes of movement better and better.

For example, GPS devices used by runners annotate position records with attributes representing physical conditions such as heart rate or body temperature. Web sites like `movebank.org` provide the infrastructure for enriching trajectories with environmental attributes reflecting weather, land cover, and other phenomena.

Moreover, attributes can be derived directly from raw trajectory data. Examples are speed, direction, acceleration, turn, sinuosity, and distance to selected places or trajectories. A classification of potentially interesting attributes is provided in [4].

Trajectory data D that are associated with attributes can be formally defined as follows. A trajectory $\mathbf{d} \in D$ is an ordered set of data points $\mathbf{d} = \langle d_1, \ldots, d_{l_\mathbf{d}} \rangle$. Each data point $d_k : 1 \leq k \leq l_\mathbf{d}$ is of the form $d_k \in (S^n \times T \times A_1 \times \cdots \times A_m)$, where S^n defines the spatial coordinates of the point (e.g., geographical latitude and longitude if $n = 2$, plus elevation if $n = 3$), T defines time, and $A_i : 1 \leq i \leq m$ are the value ranges of quantitative or qualitative attributes. This definition shows the complexity of the problem we face: The data encompass spatial and temporal aspects as well as numerical and/or categorical data.

Here we consider trajectories in 2D space with a moderate number of attributes. The number of trajectories and the number of points per trajectory varies between a few dozens and several thousands, resulting in data sets with about a million individual measurements. Furthermore, we consider domains with hard-constrained (e.g., road traffic or indoor movement of people) or soft-constrained (e.g., seasonal migration of animals or traffic lanes in sea or sky) trajectories. An essential aspect of such constrained trajectory data is that there are large subsets of trajectories with similar geometry. This similar geometry is crucial for our approach.

2.2 Tasks

In exploratory trajectory analysis the analyst aims at understanding the interrelations between the data components, in particular, between the spatial (S), temporal (T), and attributive (A) components in trajectories of moving objects. Based on distinguishing between *independent* dimensions and *dependent* attributes, exploratory data analysis can be viewed as analogous to the investigation of the *behavior* of a mathematical function, i.e., the way in which the values of the dependent variable(s) vary with respect to the independent variable(s) [7]. For trajectory data, the main goal is to understand the functional dependency $S \times T \rightarrow A$, i.e., the *behavior* of the attributes with respect to space and time.

Depending on the focus of the investigation, the analyst may pursue the following behavior-related objectives:

Behavior characterization Observe the value distribution of A over the whole S and T or selected parts of S and T and characterize, mentally or explicitly, the behavior of A. It can be characterized as constant or piecewise constant in regions in space or periods in time or as having gradual or abrupt changes, temporal or spatial trends, repetitions in space and time, periodicities in time, local or global outliers, and so forth. An example is to characterize the behavior of the vehicle speed along a highway over a day.

Behavior search Detect occurrences of a particular behavior of interest and locate them in S and T. An example is to find out in which parts of the highway and during which times of the day traffic congestions occurred, i.e., low speeds of multiple cars.

Behavior comparison Compare the behaviors of A in different regions of S or in different intervals of T or in different subsets of the trajectory data D. Examples are to compare the behaviors of the vehicle speeds on different highway segments, or on different days (e.g., work days vs. weekend), or in the subsets of trajectories going in opposite directions.

Since the investigation of the overall behavior $S \times T \rightarrow A$ is a complex task, the analyst may decompose it into simpler subtasks. One type of subtask is to focus on selected places $s \in S$ and consider the corresponding behavior of A over T: $T \rightarrow A$ for $s = const$. An example is to consider the temporal variation of the speed over the day at a selected crossing. This kind of behavior can be called *local* with respect to space.

Another subtask type is to focus on selected times $t \in T$ and consider the corresponding behavior of A over S: $S \rightarrow A$ for $t = const$. An example is to consider the variation of the speed along the highway at around 8AM. This kind of behavior may be called *local* with respect to time. In both cases, one of the dimensions T or S is handled at an *elementary level*.

After exploring the local behaviors in different places and times, the analysis is lifted to a *synoptic level*, where the goal is to understand the overall behavior $S \times T \rightarrow A$. The term *synoptic level* combines Bertin's [9] overall and intermediate reading levels (as opposed to the elementary reading level).

Hence, visualization tools for exploring trajectory attribute data should provide appropriate support for the characterization, search, and comparison of local behaviors $T \rightarrow A$ and $S \rightarrow A$ and overall behaviors $S \times T \rightarrow A$ for the whole S, T, and D and subsets thereof.

2.3 Related Work

A recent review [6] indicates that the analysis of movement data in general is still one of the most important topics in many fields of research, including data mining, GIScience, and visual analytics (see for example [12, 2, 13]). The majority of the existing works concentrate on (1) analyzing spatial and temporal aspects of trajectory shapes (in 2D for space and 3D for space-time), (2) detecting stops, interactions between trajectories, and other types of events, or (3) aggregating trajectories in space and time. However, only little has been done so far on analyzing trajectory attributes.

Among the first attempts to visualize attributes of trajectory data are Charles Minard's maps (see [29] for a review of Minard's work). A classic example is his famous map of Napoleon's Russian Campaign. The map depicts the size of the French army by the width of a band on the map, and air temperature by a visually connected time graph.

At present, trajectories are often represented in a space-time cube, which combines time and space in a single display [20, 17]. In principle, it is possible to show also attributes in this display, but this approach is quite limited in respect to the number of trajectories.

Contemporary works on visualizing trajectory attributes confirm that plotting attributes in geographic space (2D or 3D) is beneficial for their analysis. For instance, Ware et al. [35] developed the GeoZui4D system to display multiple attributes along 3D trajectories of underwater movement of whales using color, texture, and glyphs.

Kraak and Huisman [21] use a combination of time graphs for two attributes (speed and heart rate), a map, and a space-time cube (representing a selected attribute by coloring trajectory segments) for identifying interesting events. However, this approach considers only single trajectories and not sets of them.

Spretke et al. [33] apply color-coding to the segments of multiple trajectories on a 2D map for showing different classes of segments based on multiple attributes. This facilitates separating day flights of migratory birds from night flights and from stops, as well as showing footprints of different classes on the map. However, overplotting hinders detecting spatial behavior along individual trajectories.

Crnovrsanin et al. [10] use a time graph together with a trajectory map for displaying the dynamics of distances to selected places (e.g., forest roads or exits from a building). To compensate for overplotting on the map, the authors transformed the geography using so-called proximity PCA. This approach works for multiple trajectories, but overplotting on maps and in time graphs remains a critical issue.

Andrienko et al. [3] also use a combination of a time graph display with a map for multiple trajectories. To resolve overplotting in the time graph, they use a so-called time band display (similar to [18, 24]) with coloring based on class intervals.

The reviewed approaches work well for basic tasks. Depending on the focus of the visualization design, $S \to A$ and $T \to A$ tasks can be accomplished. Arguably, some approaches (e.g., those based on the space-time cube) can be useful to support $S \times T \to A$ tasks, but as described earlier such tasks remain complicated anyway. The idea of splitting this complex analysis task into more focused and easier to accomplish subtasks is not explicitly supported by existing solutions, neither at an elementary level nor at a synoptic level.

As a result of the review of the related work, we can summarize that the distribution and the dynamics of attribute values in space and time remain difficult to analyze, especially, when analysts are interested not only in individual trajectories, but also in collections of trajectories.

3 Trajectory Attribute Visualization

In order to support analysts in exploring trajectory attribute data, we have to address the complex data characteristics and the tasks as described in Sections 2.1 and 2.2. We propose a novel approach that deals with these challenges by combining visual, analytical, and interactive means.

3.1 Solution Overview

Inspired by Tuan Nhon Dang et al.'s [25] stacking of graphic elements, our solution visualizes attribute values along stacked trajectory bands. Individual color-coded bands support elementary $* \to A$ tasks and the stack of the bands as a whole supports synoptic $* \to A$ tasks. The utility of this approach depends on appropriate color-coding, and appropriate grouping, selection, and stacking of trajectories, which will be discussed in Section 3.2.

Because time and space differ in their intrinsic properties and also in terms of how humans perceive them and reason about them, the general visualization design needs to be adapted to space and time. The flexibility of trajectory bands and the generality of the stacking concept enables such an adaptation. As a result, we provide two complementary displays:

- The hybrid 2D/3D *trajectory wall* focuses on the spatial behavior $S \to A$ by embedding 3D bands into a virtual map space. The temporal information cannot be displayed in full detail in this view. A part of the temporal information, namely, temporal ordering, can be conveyed through ordering of the bands. Additionally, an integrated dynamic query tool, called the *time lens*, allows the analyst to access temporally aggregated information.
- The 2D *time graph* focuses on the temporal behavior $T \to A$ by showing attribute values along horizontal 2D bands.

Understanding the spatio-temporal behavior $S \times T \to A$ for individual trajectories and across sets of trajectories requires switching frequently between space and time, and between elementary and synoptic tasks. The full potential of our approach lies in applying the provided visual representations, interactive mechanisms, and analytical tools in a linked and coordinated way.

3.2 General Visualization Issues

As indicated before, our approach requires an appropriate color-coding of attribute values and an appropriate selection and ordering of the trajectories to be visualized as stacked trajectory bands.

Color-coding of attribute values Because we use the spatial coordinates on the screen for showing the dimensions of time and space, attribute values must be encoded using another visual variable. We rely on color because it is a widely accepted approach, it fits well with the trajectory band design, and it is both selective and associative [9] and therefore can support very well elementary and synoptic tasks.

To make $* \to A$ behavior of attribute values easily detectable and interpretable, an appropriate mapping of the values to colors is required. There is a long standing discourse in the visualization community about whether to use isomorphic vs. segmented color scales [8]. In cartography, this topic corresponds to the discussion about unclassified vs. classified thematic maps. According to cartographers, classified thematic maps (i.e., maps using segmented color scales) can represent behavior better [23]. However, this requires not only an appropriate color scale, but also an appropriate definition of class intervals used for the mapping of data values to colors.

In terms of the color scale, we rely on the ColorBrewer [14], which provides evaluated color scales for different numbers of classes. We give the user the freedom to choose one of the ColorBrewer scales according to his/her preferences or domain-specific conventions.

The definition of appropriate class intervals is intricate because there is no perfect method that produces a single "best" partition of an attribute's value range into classes [23]. The partitioning can be based on different criteria [32]. The cartographic literature recommends choosing class breaks according to the statistical distribution of the values so that similar data values are placed in the same class and dissimilar in different classes [32].

Our tools support this recommended strategy in two ways. First, the division can be done fully automatically using the algorithm for statistically optimal classification [16, 32]. Second, the user can interactively set class breaks according to "natural breaks" in the data, which can be detected visually by means of a dot plot or a cumulative curve display [7]. The classification tools also support the divisions into equal intervals and by quantiles, which also have certain advantages [32]. Furthermore, the user can arbitrarily set the breaks according to his/her understanding of the data or according to domain-specific standards or conventions.

Irrespectively of the criteria and strategy used for defining class intervals, it is reasonable to test the sensitivity of the observed patterns to the class break setting. To do such a testing, the user can move the class breaks interactively by means of sliders, which results in immediate updating of all displays where these classes are represented.

Data values can be discerned more precisely when applying two-tone pseudo-coloring [30] (see middle bands in Fig. 2). This technique (a.k.a. Horizon Graphs) requires sufficient height of the bands to achieve higher precision [15]. As we have found empirically, the two-tone coloring is visible when the height is at least seven pixels,

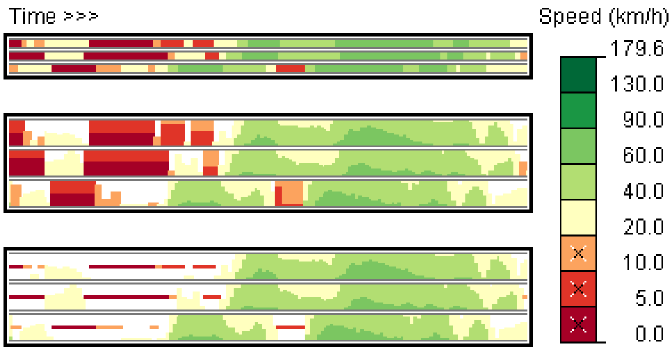

Fig. 2. Alternatives for color-coding attribute values along trajectory bands. Top: plain color-coding requires less space; middle: two-tone pseudo-coloring [30] increases precision; bottom: color filtering reduces visual load.

whereas just two or three pixels are enough for plain class-based coloring (see top bands in Fig. 2). This may have implications when large numbers of trajectories need to be visualized.

To facilitate focusing on value ranges of interest, which may be particularly useful for behavior search and behavior comparison, we allow the user to decrease the visual prominence of selected value intervals (see bottom bands in Fig. 2). This *color filtering* is activated by clicking on the corresponding rectangles in the color legend. The operation affects the bands in the trajectory wall and the time graph.

Grouping and selecting trajectories Grouping is useful for dividing a large set of trajectories into manageable portions, which can be analyzed one by one, or for focusing on interesting subsets of trajectories (with respect to the analysis goals) and disregarding uninteresting ones.

For analyzing trajectory attributes in respect to space $S \to A$, we start with identifying groups of trajectories that have similar geometries. The analyst can do this by means of spatial queries (e.g., trajectories passing a series of user-selected regions), or by means of clustering trajectories by similar origins, destinations, or route similarity [28]. When analyzing the temporal behavior $T \to A$, it makes sense to construct groups based on temporal queries, e.g., selecting evening or weekend trajectories. The results of the spatial and/or temporal grouping can be further refined by attribute queries (e.g., selecting trajectories with median speed higher than 70 km/h).

Stacking trajectories In order to enable analysts to carry out tasks at the synoptic level, an appropriate stacking of trajectory bands is needed. As mentioned earlier, chronological ordering of the trajectory bands brings a part of temporal information into the trajectory wall display. The ordering can be done according to the absolute times of the starts or ends of the trajectories (i.e., using the linear time model) or according to their positions within one of the temporal cycles, such as daily, weekly, or seasonal (i.e., using the cyclic time model).

The temporal ordering of trajectories is important for supporting synoptic $S \times T \to A$ tasks. With a temporally ordered stack of trajectories, vertical neighborhood of band segments corresponds to *temporal* neighborhood of the trajectory points. Similarly, horizontal neighborhood of band segments corresponds to *spatial* neighborhood of the trajectory points.

Due to the associative property of color, neighboring band segments with the same or close colors (representing similar attribute values) are perceptually united into larger spots. Hence, relatively homogeneously colored spots (perceived by human vision as unities) correspond to spatio-temporal regions of constant behavior.

Furthermore, like gradual changes of the color along the horizontal dimension signify a spatial trend, gradual changes along the vertical dimension signify a temporal trend, and changes in a diagonal direction correspond to a spatio-temporal trend. Hence, owing to the temporal ordering of the trajectory bands, the user can perceive local behaviors $S \to A$ and $T \to A$ and overall behavior $S \times T \to A$.

Additionally, it can be useful to stack trajectory bands according to other criteria. For example, ordering by the average speed supports comparison of faster and slower trajectories and detecting places of major speed differences between them, which may signify re-occurring traffic problems. We allow the user to arrange trajectories based on any attribute or sequence of attributes referring to the whole trajectories, while the temporal ordering is used as default. The generated trajectory sequences are then fetched to the visualization components described next.

3.3 Design of the Visualization Components

To facilitate the decomposition of the analysis into local $S \to A$ and $T \to A$ subtasks, we need to define complementary views that focus on each subtask's specific character. One view focuses on the spatial aspect $S \to A$ and another one on the temporal aspect $T \to A$. Moreover, each view must be equipped with facilities to establish a connection to the dimension it is not focusing on.

Because the concept of trajectory bands and their stacking is simple yet flexible by design, it can be easily adapted to the aforementioned requirements. We propose two instantiations: the *trajectory wall* with focus on space (see next section) and the *time graph* with focus on time (see Section 3.3.2).

3.3.1 Visualizing Spatial Attribute Behavior

In order to support $S \to A$ tasks, it is necessary to show trajectory attribute values in their spatial context. As we consider 2D trajectories, it appears as if a 2D solution would be fully sufficient. However, this is not true. A 2D solution would quickly suffer from severe overplotting because we deal with trajectories with very similar geometry. It would be difficult to separate individual trajectories and discern attribute values along trajectory paths. A 2D solution would also fall short in terms of maintaining an order of trajectories, which is required for detecting behavior at the synoptic level. Utilizing the third dimension for a 3D stacking of trajectory bands will help us resolve these concerns.

On the other hand, stacking trajectories along the third dimension means detaching them from their 2D reference space. This can make it more difficult for the analyst to understand the trajectory paths through space. Therefore, we need to integrate mechanisms that retain the basic 2D character of trajectories.

According to this thinking, we designed the trajectory wall as a hybrid 2D/3D approach. The spatial context is visualized by a 2D map that resides in a virtual 3D viewing space. The map is constructed in a straight-forward way by tiling the bounding box of the trajectories with appropriately scaled bitmaps from the OpenStreetMap project [26] (or any other tile server).

The virtual 3D viewing space serves as the spatial reference continuum into which the visualization of trajectories and attribute values needs to be embedded. For this purpose, we have to construct trajectory paths whose individual segments can be colored using the mechanisms described in Section 3.2.

Constructing trajectory paths Given a trajectory $\mathbf{d}$ one can connect its individual points $\langle d_1, \ldots, d_{l_\mathbf{d}} \rangle$ to form a path through space. Then each path segment can be color-coded according to the associated attribute value. There is a subtle detail that needs to be be taken care of: A trajectory $\mathbf{d}$ has $l_\mathbf{d}$ points, but there are only $l_\mathbf{d} - 1$ path segments to be colored. Unfortunately, we cannot simply append an artificial segment to the path, because it would inappropriately alter the spatial *characteristics* of $\mathbf{d}$. Neither can we rely on color interpolation along the path, because we are using segmented color scales.

Our solution is to insert split points midway between any two consecutive original trajectory points. Instead of connecting the original points directly, we create segments between the split points and the original points. The color of a segment is chosen so as to correspond to the attribute value of the original trajectory point incident to the segment. Fig. 3 illustrates the mapping for 2D paths. Note that our solution requires rendering $2l_\mathbf{d}$ segments, whereas simply appending an artificial line segment results in paths of length $l_\mathbf{d}$. So, for trajectories with very many points one might need to trade off correctness of the mapping against performance of the rendering.

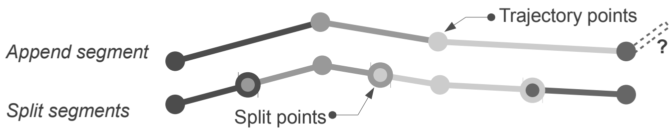

Fig. 3. Mapping trajectory points to form a colored path.

Visualizing trajectories and attribute values The described trajectory paths to are used to construct color-coded 3D trajectory bands as illustrated in Fig. 4. The bands are stacked along the z-axis perpendicular to the map. This 3D approach provides each trajectory with an exclusive layer on the z-axis. Going into 3D also enables us to indicate the directions of trajectories by means of arrows embedded into the bands.

Although our solution allows for ordering by any attribute, ordering by time is the most appropriate for the trajectory wall, because it brings a part of the temporal information (relative order) to the display. In this way the vertical dimension also represents time, but relative time rather than absolute time.

To better preserve the trajectories relation to the 2D map, they are additionally visualized as color-coded 2D paths. The 3D bands and 2D paths are used in a smoothly blended fashion. When the display is rotated to a bird's eye view, the bands fade out, whereas the paths fade in. When approaching a horizontal perspective, paths fade back out and the bands reappear. The angles at which the fading occurs can be adjusted, including the possibility to allow for an overlap where paths and bands are visible at the same time.

To further facilitate understanding the trajectory bands in connection to the map, we add a highlighting plane for the focused trajectory and project the focused trajectory point onto the map. Optionally, the highlighting plane can show a locally confined duplicate of the map, which is useful when the base map is outside of the current view.

Our hybrid 2D/3D design allows analysts to switch seamlessly between a 2D overview of all trajectory paths and the detailed investigation of attribute behavior in the 3D bands. Fig. 4 illustrates that the 2D paths are useful to assess the spatial characteristics of trajectories and the overall spatial distribution of attribute values, but as already mentioned, overplotting hinders detailed analysis of individual attribute values along trajectories. The 3D bands make attribute values of individual trajectories and of groups of trajectories easier to explore thus facilitating elementary and synoptic tasks.

Dealing with the implications of 3D We carefully analyzed the implications of our 3D environment. In particular, we need to address the problems of 3D navigation and occlusion [31, 19, 11].

Our goal is to make zoom, pan, and rotation functions in 3D simple and convenient. One way to achieve this is to consider the fact that the analyst is usually focused on something in particular when carrying out these operations. By adapting the 3D navigation to this focus point, we can reduce the complexity of the interaction. The zoom follows the point under the mouse cursor (e.g., zoom toward a specific segment of a trajectory), and the pan grabs exactly that point allowing the analyst to drag it closer. Rotation in 3D is realized as orbiting around the focus, where a virtual compass is provided to maintain user orientation. A specific requirement of our design is to enable the navigation along the stacking order of the trajectories. Therefore, we give analysts the opportunity to use the so-called *elevator*, which corresponds to a smooth navigation along the z-axis. User feedback obtained in a small study (see Section 5) indicates that the *focused* zoom, pan, and orbit and the *elevator* are practical in our scenario.

Occlusion can be addressed by two means. One option is to make the wall transparent allowing the user to look through it. Apparently, this option should be used only on demand due to the adverse effects of unintended color blending. An alternative is to use the *color filtering* (see Section 3.2) to narrow the trajectory bands in places where irrelevant data is shown. The analyst could for example focus on extreme values and narrow the bands for mean values. The filtering has two benefits: occlusion is reduced where bands are narrow and relevant data stand out where bands are of regular width.

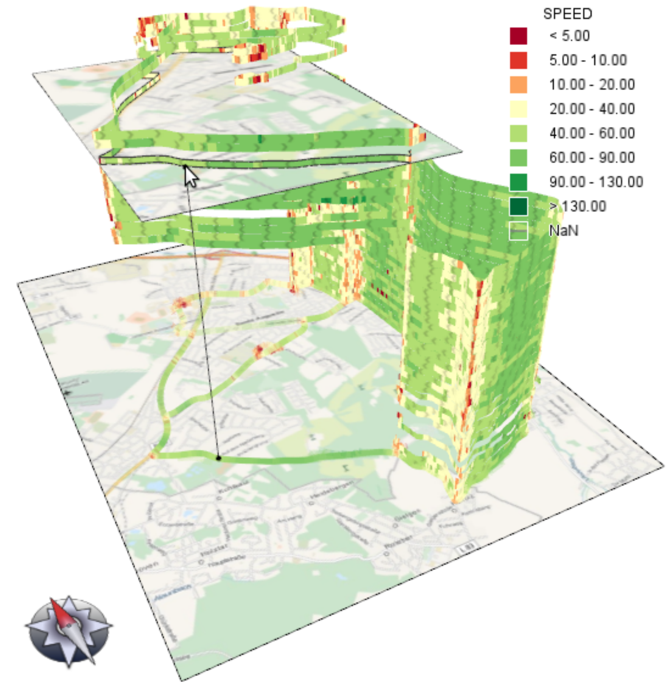

Fig. 4. Visualization of trajectories as colored 3D bands and 2D paths.

To further reduce possible interference of the map display and the trajectory visualization, the user can temporarily switch off the map or dim it to retain the spatial context.

The ensemble of visual and interactive components described so far facilitates the exploration of the spatial behavior of attributes $S \rightarrow A$. In order to better support $S \times T \rightarrow A$ tasks, a more direct link to time has to be established, in addition to the temporal ordering of trajectories.

Maintaining the connection to time Integrating time in full detail is hardly possible, because the trajectory wall is already visually rich with two dimensions showing the spatial frame of reference and the third dimension being utilized for the stacking. In order to limit the time-related information to a displayable amount, we developed the *time lens* (see Fig. 5), which shows temporally aggregated information for an interactively defined spatial query area. The time lens is a circular display (similar to the trip view in [22]) that consists of two basic components: (1) the lens interior for showing spatial aspects and (2) the lens ring for visualizing temporal aspects.

The interior of the lens shows those trajectory points that match a circular spatial query area. The spatial query is interactively specified directly within the trajectory wall display by means of a *query circle* (see Appendix A for details). Moving the query circle allows the user to determine which trajectory points are displayed in the time lens, and

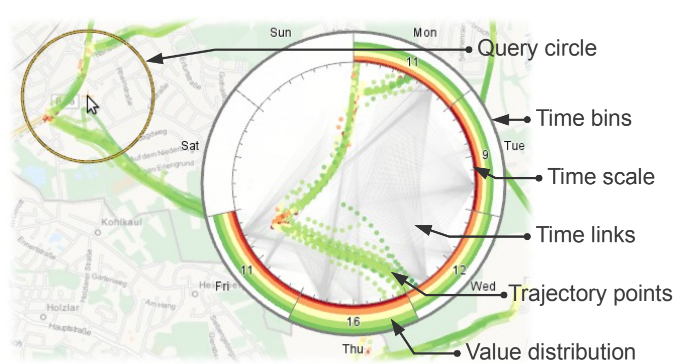

Fig. 5. The time lens visualizes temporally aggregated information.

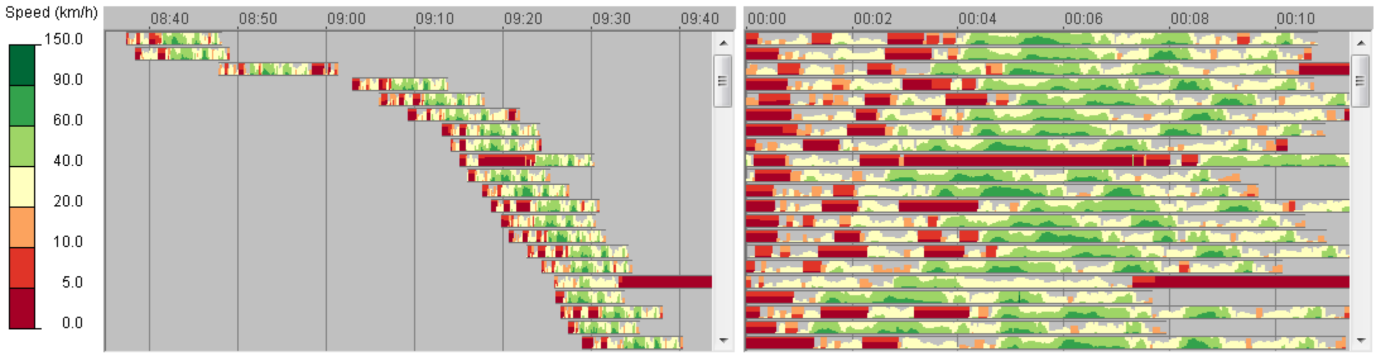

Fig. 6. The time graph shows the dynamics of attribute values within trajectories by two-tone pseudo-coloring. The alignment of the trajectories has a significant impact on what can be seen in the display (left: alignment by time of the day, right: alignment by start time).

resizing the query circle controls how many of them. Optionally, the user can extend the 2D query circle to a 3D query cylinder to further refine the query to specific trajectories from the stack of trajectories. Trajectory points that match the query are represented as dots whose color correspond to the points' attribute values. The dots are embedded into the time lens according to their spatial layout (as shown in Fig. 5).

The ring of the time lens is segmented into *time bins* based on the data's time model (see Aigner et al. [1]). Cyclic time is modeled as a set of recurring time primitives as for instance the 4 quarters of the year, 12 months of the year, 7 days of the week, or 12/24 hours of the day. If only linear time is semantically meaningful for the analyzed the data (e.g., eye-movement data), the time bins correspond to a suitable partition of the linear time domain.

The fill levels of the time bins visualize temporally aggregated information about the trajectories that intersect with the query. We provide three alternative aggregates: (1) *count* calculates how many trajectories intersect with the query area, (2) *total duration* accumulates the time spent by all trajectories in the query area, and (3) *average duration* averages the time spent by individual trajectories in the query area. Additionally, the time bins visualize the distribution of attribute values per time primitive. The time lens in Fig. 5 shows clearly that no trajectories pass on weekends and that the distributions of values are similar for all workdays.

In addition to displaying aggregated information, we can establish a direct connection to time on demand. This is done by means of so-called *time links*, which connect each trajectory point to the time lens' inner *time scale*. The inner time scale is chosen so as to represent a sensible subdivision of the time bins (e.g., hours if bins are days).

When the query area is sufficiently small (i.e., only few trajectory points are shown), the time links are useful to directly connect space and time. Even with larger numbers of time links it is possible to reveal temporal patterns. For example, the time links in Fig. 5 accumulate mostly at specific points at the time scale. These accumulations indicate that trajectories pass the query area only during specific hours of the day. In order to make such pattern discernible, the overplotting in the lens interior can be resolved interactively by alpha-blending the time links and rotating the outer ring of the lens.

The tight integration of the time lens into the trajectory wall facilitates $S \times T \to A$ tasks. Fig. 1 on the first page illustrates the time lens for the count of trajectories and the temporal resolution of months applied to trajectories of mobile sensors that measured radiation along the Tokio-Fukushima highway. In the particular example from Fig. 1 we can see that the proportion of the medium radiation values (yellowish color in the July and August bins) significantly decreased in September where lower radiation values (greenish colors in the September bin) became more frequent. Given the query area highlighted in the center of the figure, we can conclude that the situation improved in this part of the road. Further discoveries that can be made in the radiation data set will be described in Section 4.

Because the time lens depends on restricting the displayed temporal information via dynamic query mechanisms and aggregation, an additional display is needed that focuses entirely on the time aspect.

3.3.2 Focusing on the Temporal Behavior

To explore the temporal dimension in full detail ($T \to A$ tasks), we propose the complementary time graph display as illustrated in Fig. 6. Following our principal visualization design, this display shows individual trajectories as stacked horizontal bands. Designed in this way, the time graph provides a synoptic view in respect to time, as overall temporal behavior can be characterized and be searched for. By sorting the trajectories in the vertical dimension according to different criteria, analysts can conveniently compare the temporal behaviors in individual trajectories and in groups of trajectories.

The number of trajectory bands that can be simultaneously seen in the time graph is limited by the available screen height. Larger sets of trajectories can be explored by means of scrolling or by grouping trajectories as discussed in Section 3.2. To enable analysis of long time intervals, the display allows temporal zooming and panning, which can be done either fully interactively or through automated animation. To facilitate comparisons between trajectories that are far apart in time, the display supports two kinds of time transformation [5]: (1) in relation to the individual life times of the trajectories (start and/or end times) and (2) in relation to temporal cycles: daily, weekly, monthly, seasonal, or annual. The latter kind of transformation also supports the exploration of how the trajectories and attribute values are distributed with respect to the chosen time cycle, i.e., synoptic $T \to A$ tasks where T stands for a time cycle.

Fig. 6 shows the impact of time transformation by aligning the start times of the trajectories. This transformation allows us to see that all trajectories have similar patterns of speed dynamics over time: very low - low - very low values in the beginning, followed by rather high speed later, and ending with rather low speed. The display also supports the *color filtering* introduced in Section 3.2, which enables the user to focus the behavior analysis on particular value ranges (see bottom bands in Fig. 2).

To facilitate $S \times T \to A$ tasks, the time graph is dynamically linked to the map in the trajectory wall. This means that highlighting a trajectory segment in the time graph will highlight the same segment, and hence its spatial position, in the trajectory wall. The linking is bi-directional and enables elementary support in respect to S.

Note that a direct integration of spatial aspects into the time graph (similar to the lens tool of the trajectory wall) is hardly possible for the following reasons. First, space has no natural ordering which could be reflected by ordering of the trajectory bands. The bands may be ordered by the average or minimal distance to a selected point or object in space, but this is only a very limited part of the spatial context. Second, adequate representation of positions in the geographical space requires providing a recognizable cartographic background for reference, and this needs sufficient space. Hence, there is no good way to aggregate the space into a small display element directly integrated in the time graph display. Nonetheless, the coordination mechanisms between the spatial and temporal displays are fully sufficient for establishing connections between space and time.

3.4 Approach Summary

With the trajectory wall and the time graph, we have described two complementary visualizations that focus on $S \rightarrow A$ and $T \rightarrow A$ tasks, respectively. In order to support the analyst in making spatio-temporal findings with regard to $S \times T \rightarrow A$ at the elementary and synoptic level, time and space must be linked appropriately.

Therefore, both visualizations are integrated into an infrastructure that provides additional user controls and bi-directional coordination between spatial and temporal displays. Our infrastructure enables analysts to select trajectories (by clusters or by spatial, temporal, and/or attributive queries) and to order them according to space, time, and attributes, and the visualizations react to these operations dynamically. The class intervals and colors are coordinated as well to keep them consistent throughout all displays.

To further facilitate understanding, we provide direct access to attribute values and additional textual information by mouse over. An interactive legend highlights the class of the currently focused trajectory point, which makes it easier to associate colors with class intervals. By clicking the legend the analyst can filter out classes that are less relevant to the task at hand.

So far we have not yet discussed the aspect of multi-attribute analysis. To deal with multiple attributes, two approaches are possible. One approach is to visualize and explore each attribute separately. Our infrastructure allows for multiple instances of the visual displays, each with a distinct spatio-temporal attribute. This way, a few attributes can be investigated simultaneously, for example to compare them.

The other approach to explore the spatio-temporal behavior of multi-attribute value combinations is to cluster these combinations by similarity and represent the cluster membership of the trajectory points again by color-coding. Our infrastructure provides a variety of clustering methods for this purpose, and includes tools to establish the correspondence between the clusters and the attribute values (e.g., with color-coded parallel coordinates plots, frequency histograms, maps, or space-time cubes).

Overall, our solution provides a comprehensive set of tools to facilitate the exploration and analysis of attribute data of several hundred trajectories. The usefulness of our approach will be demonstrated by several examples in the next section.

4 Examples

In this section we demonstrate how the stacking based visualization approach can be used to gain insight into trajectory attribute data related to radiation surveillance, traffic analysis, and maritime navigation.

4.1 Data Set 1: Radiation measurements in Japan

The Fukushima Daiichi nuclear disaster is a series of equipment failures, nuclear meltdowns, and releases of radioactive materials at the Fukushima-I Nuclear Power Plant, following the earthquake and tsunami on 11 March 2011. A community of volunteers created a sensor network for collecting and sharing radiation measurements to empower people with data about their environment (see `blog.safecast.org/maps/`).

While the situation in major cities and around the station is carefully controlled by the authorities, it is also important to understand how radiation is developing on the neighboring roads. Data for the roads are collected by mobile sensors installed in the cars of the volunteers. The result is trajectories with radiation values attached to the position records. A publicly available data set consists of 1,014 trajectories including 1,936,261 measurements of so-called counts per minute (CPM).

The available data allow, in particular, the characterization of the radiation behavior along the major highway connecting Tokyo and Fukushima. After selecting trajectories along the highway using a spatial query, the CPM values have been shown in the trajectory wall (see Fig. 1) using the class intervals and color scale suggested by experts. The bands are chronologically ordered from bottom to top. The time lens is organized by months, from April 2011 till January 2012. The view has been rotated for maximum visibility of the trajectory wall.

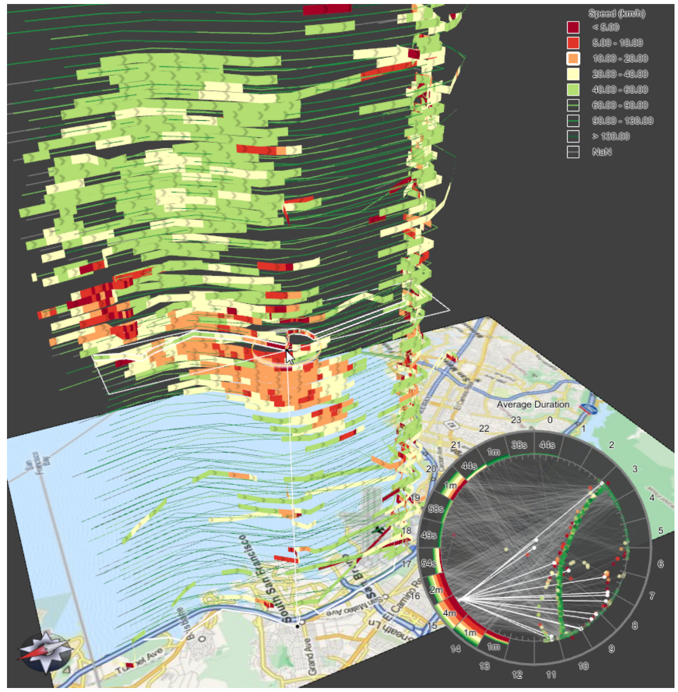

Fig. 7. The development of a traffic jam in San Francisco.

The following behaviors can be observed. There is a spatial trend of the values increasing as the distance to the station decreases ($S \rightarrow A$), which is observed at all times. The values in different places at medium distances from the station (from 25 to 75km) tend to decrease over time ($T \rightarrow A$). Closer to the station this temporal trend is less prominent ($T \rightarrow A$). In the places that are farther from the station the values are constantly low ($T \rightarrow A$). Hence, the overall spatio-temporal behavior ($S \times T \rightarrow A$) is that the radiation increases with approaching the station and decreases over time at medium distances from the station while being constantly low at farther distances and constantly high closely to the station.

4.2 Data Set 2: Traffic jams in San Francisco

This example demonstrates behavior search. The goal is to detect traffic jams on a highway connecting San Francisco downtown with the international airport and locate them in space and time. We use a publicly available data set [27] consisting of tracks of 535 taxi cabs during 4 weeks from 2008-05-17 till 2008-06-10 with 10,564,877 position records in total.

Using the controls provided by our infrastructure, the analyst has filtered the trajectories by visited regions (entrance to the highway and airport area) thus extracting 14,646 trajectories. The speed along these trajectories has been displayed in time graph and trajectory wall displays with class breaks at 5, 10, 20, 40, 60, 90, and 130km/h.

Next, the analyst searches for a particular behavior of interest ($S \times T \rightarrow A$) corresponding to a traffic jam: the speed decreasing to very low values in some part of the highway in multiple temporally close trajectories but not over the whole time. To facilitate the detection of this behavior, the analyst filters out the high speeds (more than 60km/h). Using temporal focusing, the analyst sequentially checks weekly portions of the data. Low speeds are observed in the area close to the airport but they occur all the time; hence, this is not the behavior of interest. The analyst also detects temporally limited "spots" of low speeds in other parts of the road, which signify the traffic jam behavior. Such spots occur once or twice per working day. The most prominent traffic jam happened around 16:00 on Friday, 2008-06-06. Fig. 7 shows 92 trajectories that passed the highway from 2PM till 5PM. The traffic jam began between South San Francisco and San Bruno. Later the situation has improved in the southern part, but the traffic jam has extended northward towards Brisbane.

The time lens shows that the cars in the selected query area (see circle around the mouse pointer in the center of the figure) used on average 5 minutes to cross the area of about 2km diameter. In a similar way, the other occurrences of the traffic jam behavior can be detected, located in space and time, and characterized in more detail.

Further investigation supported by navigation in the trajectory wall reveals how some taxi drivers tried to bypass traffic jams by taking alternative routes. Most of these attempts had no success. However, one of the drivers (highlighted under the mouse pointer) successfully used an alternative road in South San Francisco.

4.3 Data Set 3: Vessel traffic in the harbor of Brest

This example is meant to demonstrate behavior comparison. The data set with vessel trajectories in the harbor of Brest (France) has been collected and kindly provided by Dr. C. Ray, Naval Academy Research Institute. There are 4,137 trajectories (see Fig. 8) consisting of 782,404 position records for the period from 2009-02-11 till 2009-12-20. The analyst is interested in the spatio-temporal behavior of the movement tortuosity. The tortuosity values are computed from the position data using a sliding window of 1 minute. High tortuosity means frequent change of the vessel heading. Such situations are unpleasant for the passengers and may indicate dangerous situations.

By observing the trajectory wall for all trajectories, the analyst notices that the tortuosity is usually low on the lanes between the ports and high values mostly occur near the ports in small segments of trajectories ($S \to A$). However, there are outliers, i.e., trajectories with long segments of high tortuosity. One such trajectory is highlighted on the map (in black in Fig. 8 right). The zigzagged character of the movement is well visible. Possibly, the vessel had some technical problems.

The analyst then focuses separately on each port to investigate the tortuosity in its vicinity and, more specifically, to compare the tortuosity behavior in the subsets of incoming and outgoing trajectories. We show the analysis by example of the port on the Ile Longue peninsula (southwest). By filtering the trajectories using a spatial directional query, the analyst selects two subsets: 1,433 incoming and 1,413 outgoing trajectories. These subsets are visualized in two different instances of the trajectory wall display in Fig. 9.

Since high tortuosity values are of primary interest, the analyst decreases the visual prominence of the segments with low values by means of color filtering in the legend. The displays clearly show how the spatial behaviors of the tortuosity ($S \to A$) differ for the incoming and outgoing vessels. For the incoming vessels (see Fig. 9 left), high values usually occur closely to the destination point. For the outgoing vessels (see Fig. 9 right), high values occur at about 1km distance from the port. The segmented time lenses show us that both patterns are stable in time. However, at some time periods (6AM-8AM, 2PM-4PM) the traffic is more intensive and, respectively, the high tortuosity values are more frequent, especially in the afternoon. We can also see that the connecting lines accumulate at specific minutes at the time scale, which indicates that vessels follow a defined time table.

The examples demonstrate that our visualization design is useful for gaining insight into spatio-temporal behaviors of various kinds of attributes associated with trajectory positions. The interaction capabilities support the analyst in exploring the data with respect to different subsets of space, time, and attributes.

Unfortunately, in the available data sets we could not find interesting behaviors of combinations of multiple attributes. However, this does not cancel the principal possibility of doing multi-attribute analysis using multiple views or clustering.

5 User Feedback

In order to evaluate the usability of our solution, we conducted a small study. Our main intention was to investigate how easily and conveniently users can explore the hybrid 2D/3D trajectory wall given the implication of 3D as discussed in Section 3.3.1. Because the other parts of our solution are based on accepted designs we did not integrate them in the study as well.

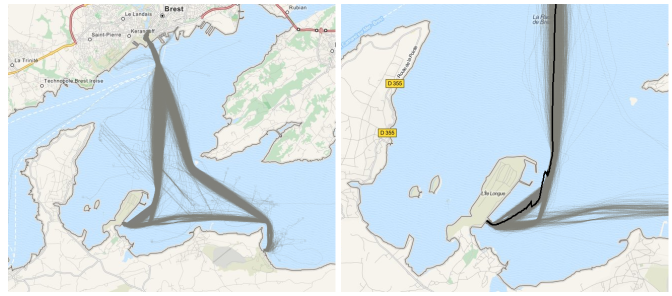

Fig. 8. Traffic in the Brest harbor (left) and in its south-west part (right).

For the study, we recruited 15 participants (2 female, ages 32 and 35; 13 male, ages 27–47) from the computer science department. 5 participants considered themselves experienced in visualization, the others had little or no exposure to this field. All participants were confident with mouse and keyboard interaction, 11 participants were familiar with 3D software (mostly from 3D games). None of the participants had used our techniques before.

Each session of the study started with an explanation of the trajectory wall and a demonstration of our focused zoom, pan, and orbit interaction as well as the elevator interaction, which were also summarized on a reference handout. Then the participants were asked to apply the interaction techniques to freely navigate around a trajectory wall showing "speed" of 250 clustered GPS-tracks of daily commuting. During the study, one experimenter encouraged the participants to "think-aloud" about what they were doing, why they were doing it, and how they would like to do it. The experimenter took notes of the participants feedback and provided assistance when it was needed. The participants were explicitly asked to include any negative comments they might have. At the end of each session, the participants had to answer additional Likert-type questions regarding the ease of use, helpfulness, smoothness, and learnability of the interaction. Individual sessions took between 15 and 20 minutes.

The feedback of the participants was mostly positive. 13 out of the 15 participants agreed that our focused zoom, pan, and orbit interactions made it easy to explore the trajectory wall. The idea of using a focus point for the interaction was immediately clear to the participants. Several participants highlighted the particular importance of the elevator navigation along the stacked trajectories. Although we had many participants who were used to classic 3D fly-through navigation, none of them had difficulties using our solution.

13 participants agreed that the switch between 3D trajectory bands and 2D paths on the map is easy to understand. All acknowledged the usefulness of the highlighting plane with the projection of the focused trajectory point onto the map. When being presented with the option of showing a map duplicate (as shown in Fig. 4), some participants saw this as a useful approach, others were concerned about the occlusion of the wall caused by the additional map.

All participants answered that the interaction was easy to learn; some participant spontaneously said that the interaction "is intuitive and works very much as expected". The implementation was positively rated by all participants as being smooth and fluid.

The participants also made constructive suggestions for improvements. 4 participants commented that the orbit was too sensitive to mouse movement, among them were the two participants who rated the interaction as not being easy. This problem can be corrected by providing user-adjustable interaction speeds. One participant mentioned that the 3D stacking elevator would be even more useful if it had a design similar to scroll bars. This would make navigation across larger distances easier. As a solution, we could enhance the elevator with an in-situ scrolling widget.

Four participants noted the absence of the possibility to temporarily lock the focus of the highlighting. A particularly interesting suggestion was made by one participant who felt it difficult to use the mouse to follow a trajectory precisely. His idea was to lock the trajectory highlighted in the wall, and to project all further mouse movement to

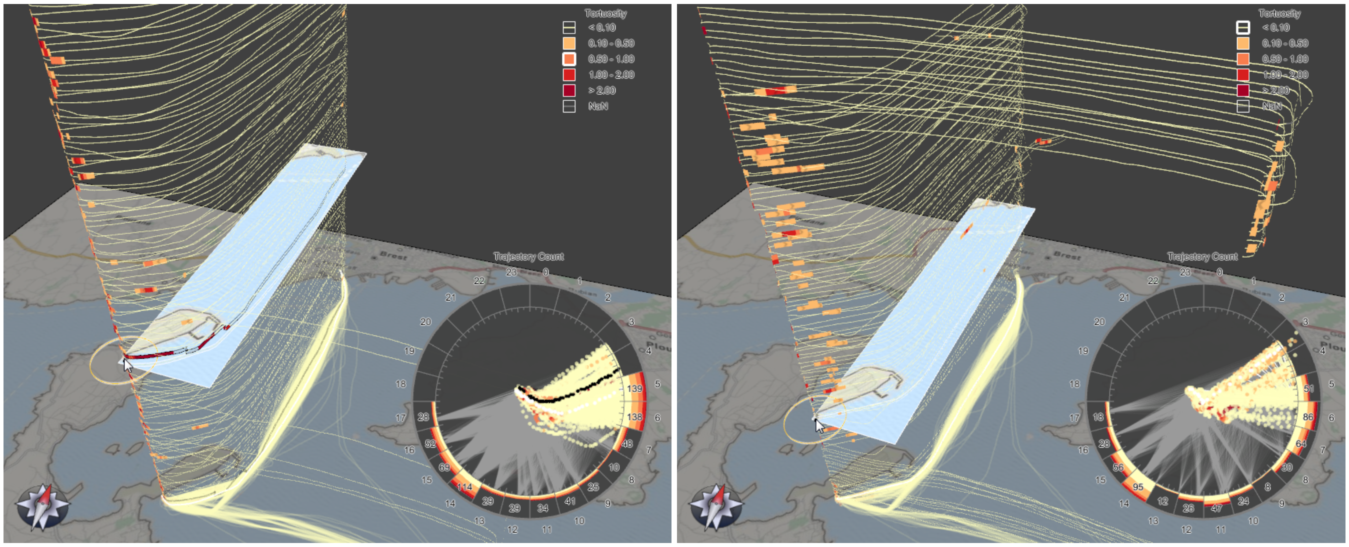

Fig. 9. Comparison of the tortuosity of incoming (left) and outgoing (right) vessels at the Ile Longue peninsula in the Brest harbor.

this locked trajectory. This way he could traverse a path without accidentally switching to another trajectory.

Overall we can conclude from the user feedback that the 2D/3D approach can be operated quite well using the provided interaction techniques. Several participants made impromptu comments about the visualization as well, including “I can easily compare the trajectories in the wall.” or “This looks like stop-and-go traffic, maybe there is a traffic light or a construction site.”. We take these comments as an additional indication that our solution is useful when analyzing trajectory attribute data, as already demonstrated in the previous section.

6 Conclusion and Future Work

We presented a novel visualization approach that facilitates gaining insight into trajectory attribute data. By integrating spatial and temporal displays, we support exploratory spatio-temporal analysis. Our visualization design is based on color-coded trajectory bands, by which we address elementary tasks, and on stacking the bands, by which we address synoptic tasks. The usefulness of our solution has been demonstrated by several examples and usability has been tested in a small experiment. We can conclude that the novel approach is indeed useful and usable.

Yet there is potential for improvement and future research. Our current solution works well with hard- and soft-constrained trajectories with similar geometry. As soon as the tracked movements become less and less constrained or even chaotic (e.g., for particle movements at the cellular level), clustering methods and so our visualization approach will produce worse results. More research is needed to find ways to cope with such data.

An interesting aspect in terms of the visual representation is to investigate further the combination of time and space. So far we use spatially separated views for full-detail time and space. We plan to integrate both views into a single display and use temporal separation instead (i.e., show one after the other). To this end, we could use dynamic transitions to deform bands smoothly between a spatial layout and a temporal one.

Additional interaction mechanism can be considered to better handle larger data sets. We imagine tools that allow analysts to interactively collapse and expand groups of trajectories (user-specified or computed), similar to collapsing and expanding nodes in a regular tree view. This idea requires enhancing the data model from a linear stack to an ordered hierarchy of groups, and enhancing the design of bands, because a single band must then be capable of showing the paths of multiple grouped trajectories.

Furthermore, the exploration process deserves more research. So far our solution leaves the decision which parts of the data to analyze with which visualization entirely to the analyst. To ease the decision making it is worth investigating guiding principles based on a more detailed study of analysis tasks and characteristics of the trajectory data. In combination with the previously mentioned ideas, we could then compute and present “grand tours” through space and time.

Finally, we encourage geo-science researchers and usability experts to use and evaluate our approach to identify and quantify its strengths and weak spots. An interactive prototype is readily available [34].

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A Some Details on the Dynamic Spatial Query

The dynamic query area is defined by two mandatory parameters related to the spatial domain S and two optional parameters related to the stacking order. The mandatory parameters *position* and *radius* define a query circle $S' \subset S$. The optional parameters *z-index* and *height* define a query cylinder to select only specific trajectories from the stack.

Testing a trajectory $\mathbf{d}$ against S' is based computing line-circle-intersections for the $2l_{\mathbf{d}}$ path segments of the trajectory. Fig. 10 illustrates the three different cases that need to be handled. For the case *outside*, nothing needs to be done. For the case *inside*, the corresponding trajectory segment is passed to the temporal aggregation. The *intersect* case requires cutting off the part of the path segment that is outside, where the precise intersection point (incl. coordinates, time, and attribute values) is computed by interpolation. Then the situation is a regular *inside* case. Optionally, the number of required line-circle-intersection calculations can be reduced by first checking if the index of $\mathbf{d}$ in the stacking order falls in a range $z\text{-}index \pm height/2$, as defined by the query cylinder.

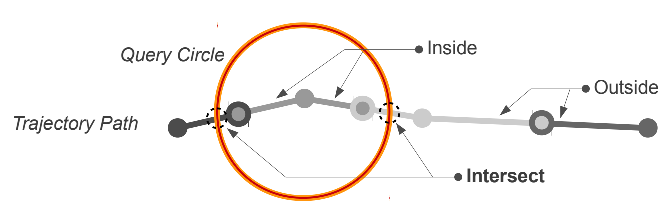

Fig. 10. Cases of path-segment-circle intersections.

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