IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 31, 2019, accepted September 18, 2019, date of publication September 23, 2019, date of current version October 16, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2942844

Variable-Based Spatiotemporal Trajectory Data Visualization Illustrated

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This material is based on work supported by the Cultural Experts and Four Batches project under Grant No. 20185660160. This work was performed at and supported by the School of Journalism and Communication, Tsinghua University and the College of Geoscience and Surveying Engineering, China University of Mining and Technology-Beijing.

ABSTRACT As a frontier research topic in the field of scientific visualization, trajectory data visualization extracts valuable patterns and knowledge from trajectory data for decision support via spatiotemporal trajectory visualization techniques. We propose the concept of multivariate trajectory data and interpret two categories of attributes that are based on geographical space and abstract space. Properly analyzing multivariate trajectory data depends on many factors such as visualization task and data sparsity. Therefore, we generalize rich interactions to explore the evolution of trajectory events and transform the issue into a more intelligibly perceptual task, which derives our discussion regarding advantages and limitations of the analytical methods. This review endeavors to provide a quick and thorough cognition and comprehension with regard to fundamental features and numerous outcomes in visual analytics for trajectory data, seeks to promote comparisons and criticisms about the descriptive framework for multivariate spatiotemporal trajectory data visualization, and aims to encourage the exploration of emerging methods and techniques.

INDEX TERMS Visualization, trajectory data, spatiotemporal data, attribute, multivariate trajectory.

I. INTRODUCTION

In the context of big data, the analysis of trajectory data, which can involve both dimensional and attribute with large amounts and high variability, is complicated. After years of research, the latest advances in trajectory data visualization techniques have created rich visual representations for different variables in spatiotemporal data, which has substantial value for comprehending dynamically evolutionary movement behaviors of objects and predicting their future mobile trends. However, the depiction of variable visualization is more diverse than dimensional visualization; understanding relevant analysis studies is therefore more challenging, which hinders the design potential for exploring multivariate spatiotemporal data visualizations. Thus, comprehensively sorting and analyzing the basic features and numerous outputs of these studies is worthwhile.

The associate editor coordinating the review of this manuscript and approving it for publication was Junchi Yan.

Our previous study has elaborated visualization methods and techniques of dimensional information based on data types [1]. As a supplement of the series, this paper concentrates on visual analytics of variables based on data environment. The objectives are therefore 1) to formulate an explicit conceptual framework, 2) to understand how these visual analytics are conceptually related, and 3) to organize the visualization forms of these variables, which can serve as the foundation of normative and evaluative work. In other words, our analysis is descriptively meaningful for better comprehending the advantages and disadvantages of different visualizations in terms of tasks and data and conceptualizing research issues in empirical research.

II. CONCEPTUAL FRAMEWORK

Trajectory data typically consist of a vast amount of high-dimensional or spatiotemporal vector data that consists of two parts—geolocations and attributes—where geospatial data represent the locations of spatial elements and attribute data describe their features. The difference in the correspondence

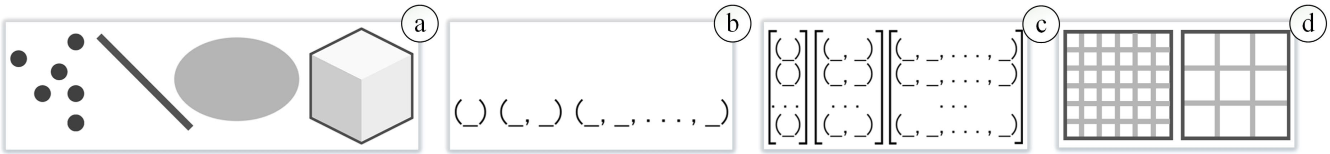

FIGURE 1. **Conceptual comparison among multidimensional, multivariate, multivalue and multiscale. (a) Multidimensional: 0D, 1D, 2D and 3D; (b) multivariate: Scalar, 2-tuple and n-tuple; (c) multivalue: Scalar, 2-tuple and n-tuple; (d) multiscale: High resolution and low resolution.**

between the two parts determines the data structures and storage methods of the vector data. Compared with raster data models, these vector models have complex characteristics. In the field of visualization, concepts and terms, such as multidimensional, multivariate, multivalue, multimodal, multichannel, are usually misemployed. ''Multidimensional'' indicates the dimensionality of independent variables in a physical space and focuses on the expression of spatial and temporal concepts. ''Multivariate'' is used to express the number of variables and attributes and represents the quantity of information and attributes involved in the data. ''Multivalue'' can also represent the information expressed by data but provides a different definition from ''multivariate'': it emphasizes the number of values other than attributes or variables. ''Multisource'', ''multimodal'' and ''multichannel'' emphasize the differences among data acquisition manners and their corresponding data structures and magnitudes. ''Multipass'' indicates that being subject to data quality, the data acquisition is typically not a one-time result but requires resampling erroneous data. ''Multiscale'' refers to the difference in the visualization results when observing spatial entities in a hierarchy of scales. ''Multicharacteristic'' indicates that trajectory data conform to the ''3V'' characteristics of big data (i.e., volume, velocity and variety) due to its rich data sources and diverse data structures. Fig. 1 illustrates the concepts of and distinctions among multidimensional, multivariate, multivalue and multiscale.

For example, if a set of trajectory data includes three-dimensional geospatial data and four variables of speed, acceleration, tire temperature and tire pressure, the data are referred to as three-dimensional four-variable trajectory data. If another temporal dimension is involved, the data are referred to as four-dimensional four-variable trajectory data. If the source data are acquired by multiple methods, including satellite monitoring, ground monitoring and numerical simulation, the data are referred to as multimodal or multichannel four-dimensional four-variable trajectory data. This paper considers 3D/4D trajectory data that contain at least one variable as the major research target, which we will refer to as trajectory data. Due to limitations of acquisition and processing methods, the major issues and challenges of its visualization are addressing multivariate, type-compositing, internally complex and intertwined data characteristics, and devising an effective visual encoding.

III. VISUAL REPRESENTATION

In the past few decades, many research achievements of trajectory data visual analytics can be divided into visualizations based on geographical space or abstract space according to their visual backgrounds. The former arranges data by geolocation using geographical space (e.g., maps), while the latter encodes the data into abstract space (e.g., parallel coordinates and high-dimensional projection). Due to different characteristics of the two types of visualizations, their application scenarios also differ. The geospatial-based visual designs emphasize the utilization of absolute geographic locations and are tightly coupled in geographical space. With geospatial as the exploring environment, users can quickly locate the spatial locations of trajectory data, and temporal and attribute feature distributions are intuitively displayed. However, due to these constraints in geospatial relations, the nonspatial correlated visualizations of temporal and attribute features in a geospatial space are also constrained. For example, visualizing time-sequential trajectory attributes among a large quantity of locations on a map can cause visual clutter problems, which increases the difficulty of devising a visualization approach. Conversely, without spatial constraints, these trajectory data visualizations focus on other feature analyses that combine multiple features in a loosely coupled manner, which enables a better flexibility in visualizing temporal features and attribute features in an abstract space. For example, when visualizing spatial features of trajectory data using spatial visual query languages in an abstract space, the relative spatial relations implied in spatial attributes can be described. However, if visualizing absolute geolocations is required, additional geospatial windows can be employed as assistance. Therefore, compared with geospatial-based visualizations, these designs have less difficulty and stronger expandability but poorer integration. Fig. 2 illustrates representations of various features based on geographical space and abstract space.

Trajectory visualization presents fundamental dimensional information and additional variable information of spatiotemporal objects. However, these two types of information are typically combined together rather than exist separately. Therefore, visualizations that illustrate variables are inevitably related to dimensions, and direct visualization and indirect visualization for attribute information of trajectory data are both commonly used. In this case, the core of spatial and temporal expression is to provide users with a visual environment related to the variable information.

A. TRAJECTORY-DATA VISUALIZATION BASED ON GEOGRAPHICAL SPACE

Temporality is the basic characteristic of a narrative, while events take place in a certain space and attributes are

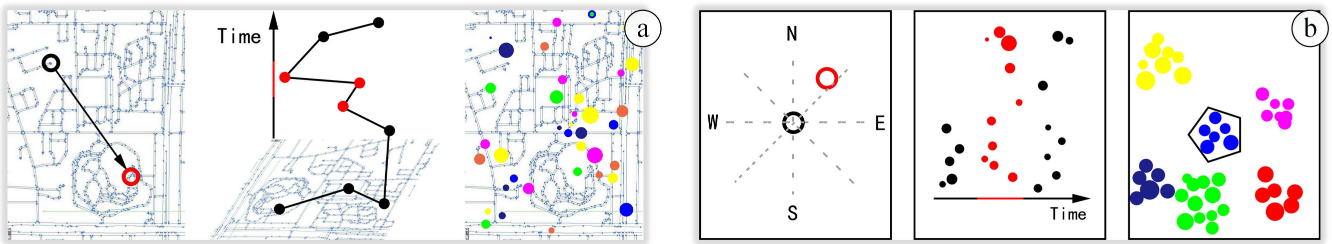

FIGURE 2. **Different design models for various features of trajectory data: Mappings of spatial features (left), temporal features (middle) and attribute features (right) in (a) geographical space and (b) abstract space.**

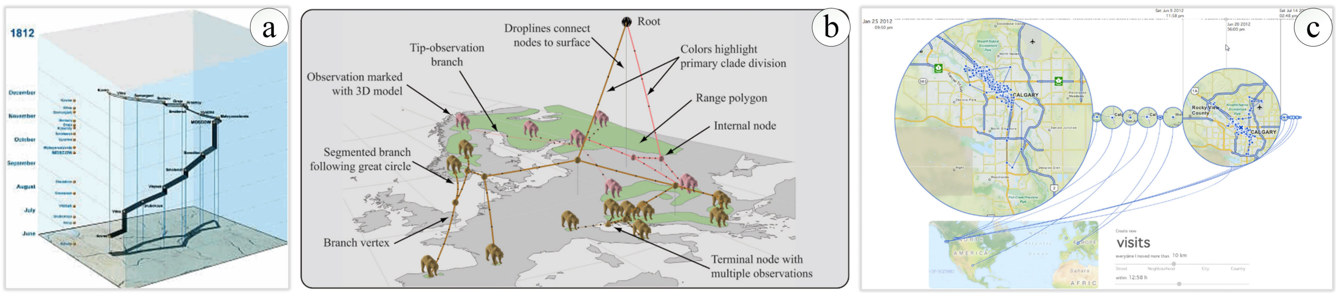

FIGURE 3. **Displaying spatiotemporal information of trajectory data based on geospatial visualization [2]–[4].**

correlated with both time and space. As a classic tool for displaying spatiotemporal data, space-time cube (STC) visually displays time, space and attributes in a three-dimensional form to observe motions, halts, encounters and separations of individual trajectories. Fig. 3a provides a visualization example of the Napoleon's Russian campaign using a space-time cube [2]. When depicting the Ursus arctos geophylogeny, Kidd [3] established a STC-resemble model to describe biological diversity and evolutionary process of each branch (see Fig. 3b). Additionally, most variable-based visual analytics systems combine geospatial visualizations and temporal visualizations, starting with an overview of geospatial data at a particular time, where users can extract information of interest via a linked view. However, this exploration should provide many snapshots of geospatial data and require switching from a spatial view to a temporal view, and vice versa. Thudt *et al.* [4] proposed a concept of map-timeline, which regards a space-time path as the narrative thread that is linked to other types of event elements to enhance attribute data (see Fig. 3c); such problem is therefore avoided.

1) SPATIAL VISUALIZATION

The conditions of geospatial-based visualizations of trajectory spatial features, such as location, area size and spatial relations, can be directly specified in a map. The coordinate system is generally used to describe the spatial position. The shape features are described by the size and spatial dimension of an object (e.g., using azimuth or directional relations to describe the relative orientation between two entities); polygons are shape descriptions of the objects, where points, lines and planes represent spatial dimensions; and topological relations describe relationships with other spatial objects such as contains, meet, cover, overlap and disjoint [5]. Spatial visualization can be divided into point-, line- and region-based visualization.

Point-based visualizations are the most direct type of visualizations for presenting and analyzing geolocations. These displays place trajectory samples into a spatial context as individual discrete points, each of which indicates a target or event, and encode related variables with visual channels of points. For example, in the traffic domain, Kristian *et al.* [6] designed a Trains of Data project that denotes each train as a mobile point running on a 2D map (see Fig. 4a). This type of visualization is particularly promising in the distribution of pick-up and drop-off events in trajectories through transport hubs. Fig. 4b shows the location of the Pudong International Airport [7], where orange dots and blue dots denote pick-up points and drop-off points, respectively. Subsequently, more scholars have researched the dynamic visualizations of locational information. Fig. 4c shows the participant-location animation based on the wireless network record of the venue created by the OpenDataCity [8]. This animated approach has strengths with regard to displaying data and verifying analysis results but is typically inadequate for comparative analysis.

As positioning techniques advance, discrete sample points can be converted to a continuous form. Line-based visualizations serve to present specified paths, including vehicle trajectories in the road network (Fig. 5a [9]), vessel trajectories (Fig. 5b [10]), marine-life trajectories (Fig. 5c [11]), and human trajectories. These visualization methods can globally or locally encode related variables with visual channels, which facilitate the depiction of spatial patterns of these

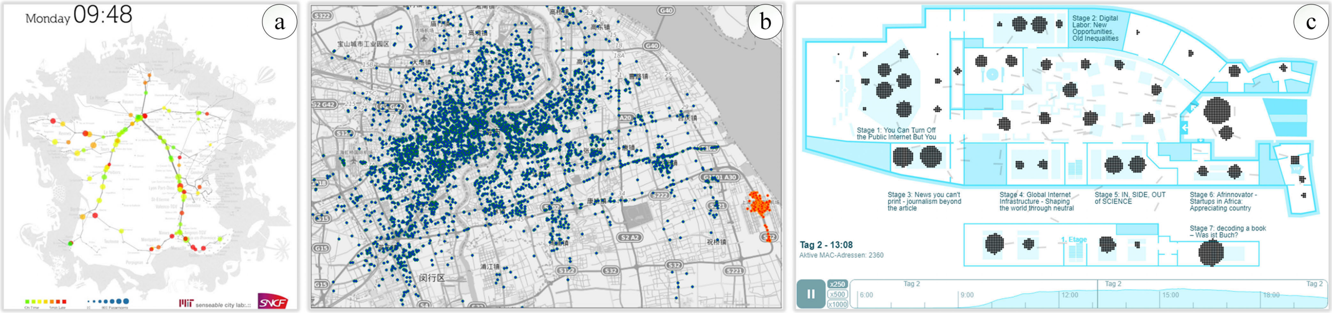

FIGURE 4. Geospatial-based point visualizations presenting spatial information in trajectory data [6]–[8].

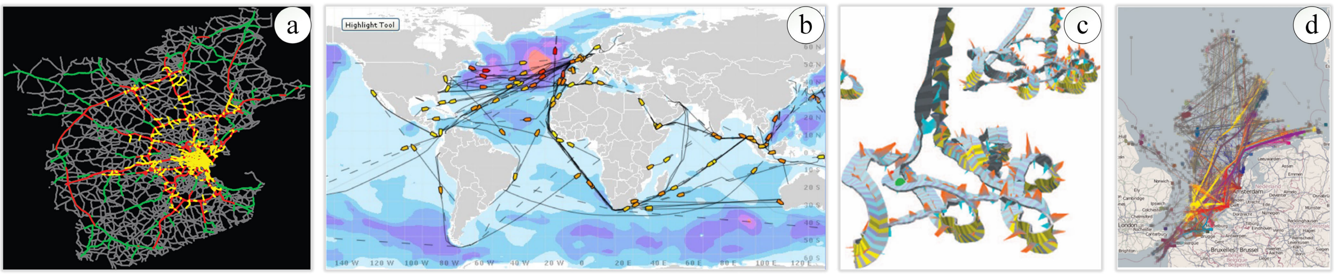

FIGURE 5. Geospatial-based line visualizations that present spatial information in trajectory data [9]–[11], [13].

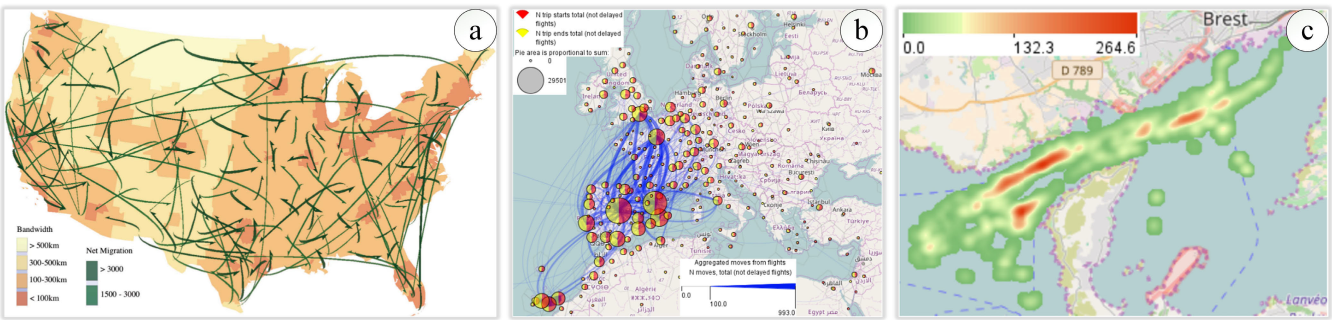

FIGURE 6. Geospatial-based region visualizations that present spatial information in trajectory data [14], [15].

trajectories. Clustering algorithms function well in loading large amounts of trajectory data; they can facilitate statistics and display macro information while preventing data loss and hence provide an applicable auxiliary for line-based visualization of trajectory data. Rinzivillo *et al.* [12] introduced a progressive-clustering method for visualizing the geometry of trajectory paths. In the vessel trajectory visualization in Fig. 5d, numerous vessel trajectories are clustered into and represented as various colored lines [13].

Region-based visualization is typically employed to encode related variables with aggregated visual channels according to predetermined spatial partitioning. Flow maps are a classic approach to visualizing interregional flows. For example, Guo and Zhu [14] proposed a novel flow-map method to demonstrate smoothed flows of U.S. migration (see Fig. 6a). Numerous other visualizations also exist in addition to flow maps. In the field of aviation, for example, ''spatial pattern'' can refer to the locations of regulatory events or affected flights. Fig. 6b shows a flight map that represents the spatial distribution of unregulated flights and interregional aggregated flows [15]. More robust visualizations are enabled with the auxiliary of other means. In the maritime field, detecting anomalous near-location events supports the prediction of traffic conditions. A density map of the extracted events is shown in Fig. 6c, which reveals spatial-density patterns of extracted regional trajectories [15].

Point-based visualizations exhibit advantages that enable users to clearly observe individual objects and events in the trajectory data and explore the variable information of objects of interest in target areas; however, these visualizations have poor efficiency in continuous-data display. As the number of objects or events grows, severe visual cluttering can result

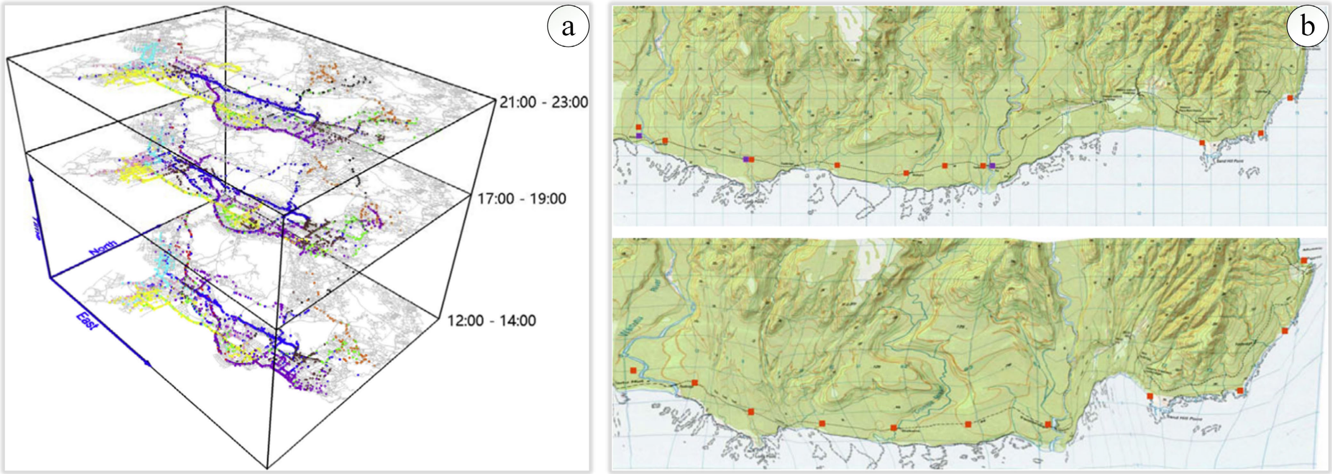

FIGURE 7. Geospatial-based visualizations that present temporal information in trajectory data [16], [17].

in a predicament of obscure visualization. Line-based visualizations perform excellently in addressing trajectory-analysis tasks, enable intuitive displays of trajectory-flow distribution, and lend clarity to the attribute expression, especially when visualizing trajectory origin-destination (OD) patterns is required. However, as the trajectory count increases, the cluttering problem becomes severe. Although edge bundling can mitigate clutters, it conceals the real link directions between two positions. Density maps can also be an effective solution compared with edge bundling, which can be used to display massive trajectories without distorting them. However, this advantage is exhibited in macro trajectory-data analysis but does not preserve any information about specific trajectories; thus, a comparison between two trajectories is impossible. Instead, area-based visualizations can reduce the complexity of the visualization results. Region-based visualizations play a proper role in discovering macro patterns for individual regions. However, these visualizations are not sufficient for analyzing micro patterns, such as speed patterns regarding individual vehicles. Therefore, this technique generally combines other techniques or merges various scales of information to support a comprehensive analysis with different levels of detail.

2) TEMPORAL VISUALIZATION

2D maps have always been the primary approach for trajectory visualizations, which are typically divided into four types of representations: 1) single 2D map, 2) multiple 2D maps and their linked views, 3) map animation, and 4) 2D display of abstract spatial information. A series of excellent temporal representations integrated with 2D spatial information exists, such as a static 2D map that serves to display trajectories with different timestamps, a 2D map that simultaneously displays limited amounts of tracking data for visualizing temporal data, and a separated timeline view for temporal information that is linked to a 2D floor plan with embedded trace representation. The expression of this kind of information can also be extended to a 3D form. Unlike geospatial information, time is one-dimensional and linear. Showing temporal information in a geographical space is not an easy task, which, however, does not burden the information representation of time-varying attributes. The space-time cube that we previously discussed enables visualizations of trajectory temporal data in a 2.5D or 3D spatiotemporal medium. Road segments in the trajectories may also involve variables of different points in time. Fig. 7a shows ten trajectories of OD (origin-destination) pairs during three different periods in Shenzhen, China, where different colors on particular road segments over a particular time period indicate that trajectories with different OD pairs have passed through this segment [16]. The visualization of temporal features is closely related to the encoding of time in geographical space. Temporal perspective, which is proposed by Abbott [17], transforms the spatial reference frame based on a geographical range into a temporal reference frame measured by time. In Fig. 7b, compared to the spatial-perspective view (top), the temporal-perspective view (below) depicts spatial accessibility and variable rendering in an explicit manner.

3) ATTRIBUTE VISUALIZATION

Attribute visualization reflects the changing patterns over time with respect to nonspatial information of research objects, where specific attribute features are typically encoded by visual elements. For example, Fig. 8a shows the glyph design by Scheepens *et al.* [18] that denotes information about vessel types and respective quantities. In addition to explicit attributes, such as visual encodings and visual mappings, implicit attributes also exist, such as the trajectory shape as a continuous geometric attribute feature. Guo *et al.* [19] designed TripVista for these attribute characteristics, which filters intersection-traffic trajectories to derive shape-resembled trajectories (see Fig. 8b).

In geographical space, attribute features are broad in scope, where different types of spatial entities correspond certain attribute fields for description. For example, the TWatcher

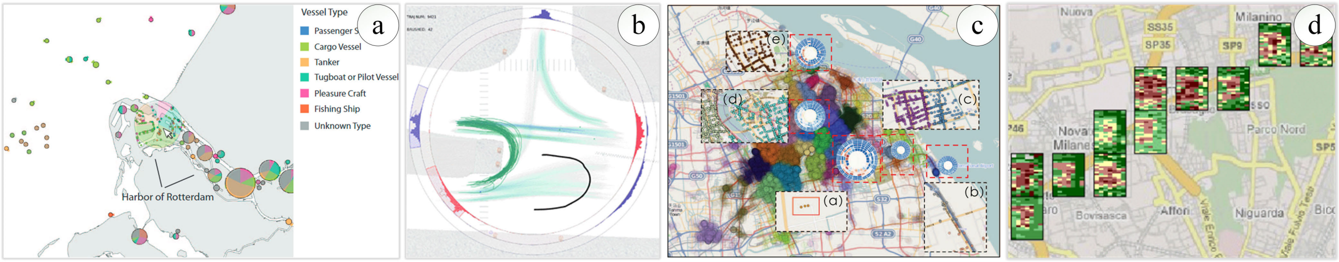

FIGURE 8. Geospatial-based visualizations that present attribute information in trajectory data [18]–[21].

system, which was developed by Pu *et al.* [20], maps the vehicle ID, average speed and on/off-taxi ID of taxis through spiral-shaped visual fingerprints to explore urban hotspots (see Fig. 8c). In terms of visualizing attribute-value variations, visualizations for specific requirements have different results. Andrienko and Andrienko [21] proposed a mosaic diagram to visualize a set of vehicle-collective movements, of which various attributes were referred to as ''traffic situation''. The meaning of mosaics differs in different contexts; in Fig. 8d, for example, their colors denote speed. However, traditional visualization methods often fail to provide a comprehensive display if the data exhibit complex attributes; rather, the application of diversified visualization methods facilitates the discovery of potential correlations and patterns in data.

The similarity of the above-mentioned studies concentrates on the attribute characteristics involved in the trajectories. How to integrate multiple attributes into one view to reveal the connection between these attributes and how to address the visual-cluttering problem caused by massive trajectory data are challenging tasks in trajectory visualization. The related techniques of geospatial-based trajectory-attribute visualization are applicable to low-dimensional datasets, and their visualization results are typically colorful and intuitive, exhibiting excellent performance with special dimensional attribute. However, a disadvantage of these techniques is insufficient adaptability. For example, if data attributes are rather dense, the visual channel-based method is vulnerable to occlusion problems. A poor response can cause visual cluttering or even mislead users with erroneous data observations and analysis results. Data fusion and hybrid rendering in trajectory-data visualization based on abstract space can exhibit excellent expression effects at this point.

B. TRAJECTORY-DATA VISUALIZATION BASED ON ABSTRACT SPACE

The previously mentioned trajectory visualization methods can preserve the integrity of the original spatial structure, while adding extra time and attributes to these visualizations can cause cluttering. When trajectory data are visualized in an abstract space, the expression of the spatial features is weakened to a certain extent without constraints from absolute geographical locations, while the temporal features and attribute features are more freely expressed.

Characterizing spatiotemporal information and attribute information in abstract space requires encoding positional information in geographical space into a time-dependent, abstract visualization skeleton. During this procedure, the relationship between dimensions and variables that cannot be easily displayed on a given geospatial map, especially for numerous entities, becomes more explicit in an abstract space by mapping the trajectory from absolute coordinates to relative coordinates. Fig. 9a shows a flight route over France and its representation in an abstract space, which facilitates mining the eight relationships among relevant transformed representations, namely, spatial concentration, co-incidence, concurrence, trends, fluctuation, convergence, meet, and divergence [22]. To an abstract extent, correlating the spatial dependence, interaction, causality or symbiosis between two different geospatial entities is enabled by combining other interactive modes. The abstract-space system interface by Chen *et al.* [23] shown in Fig. 9b visualizes geo-tagged social-media data and the movement distribution of its spatiotemporal information and variable information with multilinked views. In addition, numerous spatial-flow visualizations based on abstract-space views have been investigated to avoid flows that are displayed as intersecting lines, such as ordered matrices [24] and exploratory visualizations [25]. A persuasive example is the OD visualization designed by Zeng *et al.* [26] (see Fig. 9c). Although it cannot preserve more spatial context, the visual-cluttering problem is avoided to some extent. However, spatial distortion complicates the perception. The spatial pattern of the total flows is divided into multiple position-specific patterns; thus, an overview of spatial-flow patterns cannot be provided.

1) SPATIAL VISUALIZATION

Traditionally, trajectories can be plotted in geographical space as straight or curved lines from the origin point to the destination point. These trajectories can also be spatially transformed via topological or geometric algorithms and then re-rendered in other spaces. For example, Fig. 10a shows the simulated people-evacuation trajectories after an explosion in an office building by applying line-based visualization in geographical space (left figure) and proximity-based visualization in abstract space (right figure) [22]. As the amount of trajectory data grows, visualization often becomes troublesome due to over-plotting and

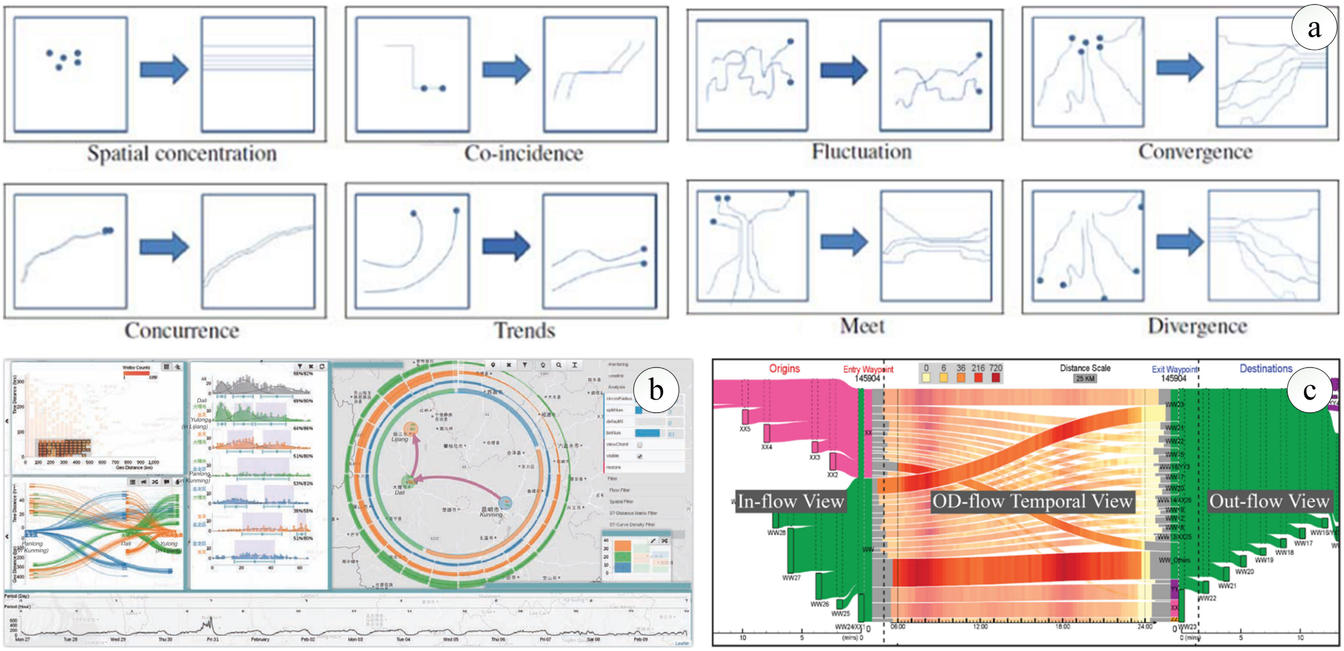

FIGURE 9. Visualizations based on abstract space that present spatiotemporal information in trajectory data [22], [23], [26].

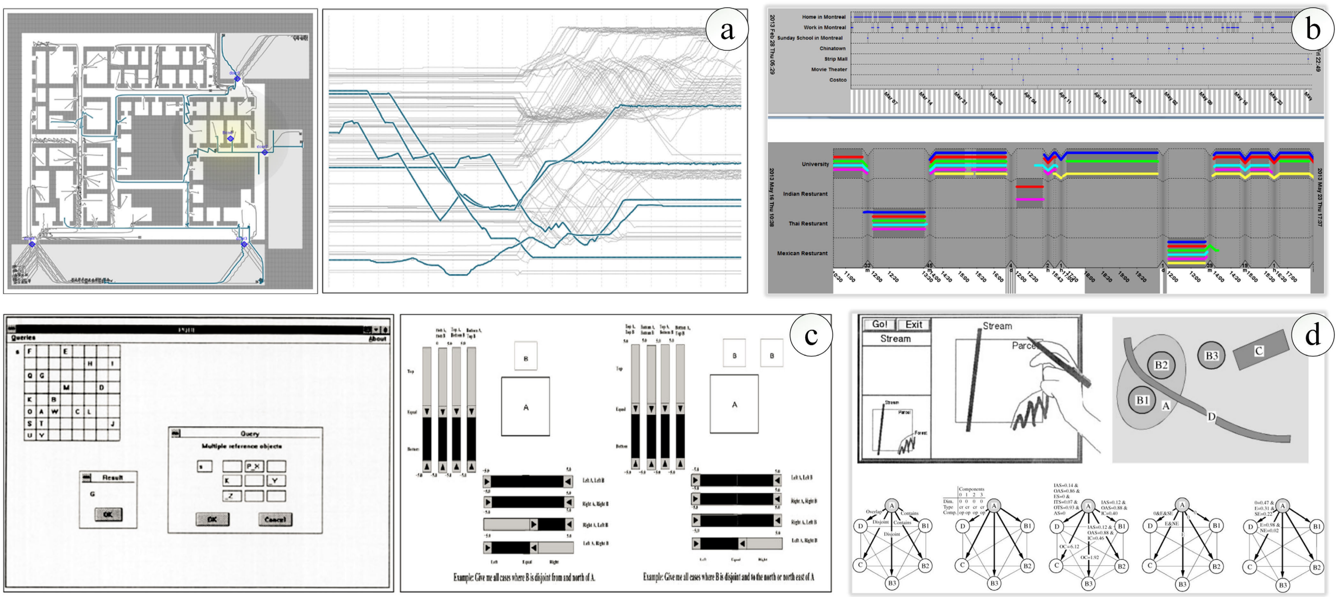

FIGURE 10. Visualizations based on abstract space that present spatiotemporal information in trajectory data [22], [27]–[29].

cluttering in the 2D-map display, especially when extracting beneficial and higher-level information from the original movement data. Gupta *et al.* [27] proposed MovementSlicer, a location access tool, for this issue to indicate individual behaviors or the meetings between them (see Fig. 10b). Furthermore, visualizations for spatial features are primarily achieved via visual spatial query language in abstract space. The spatial visual query language visualizes the spatial relations among spatial elements and defines the locational and topological relations among primitives, which includes defining intertarget positional relations by gridding query languages and quantitatively configuring spatial relations by scroll bars (see Fig. 10c [28]). In addition to this approach, which establishes interprimitive spatial relations by controls, some other studies support hand-drawing input, a more natural interaction. Egenhofer [29] converted these hand-drawn inputs (such as lines and surfaces) into the spatial relations among the objects; as shown in Fig. 10d. Users can input

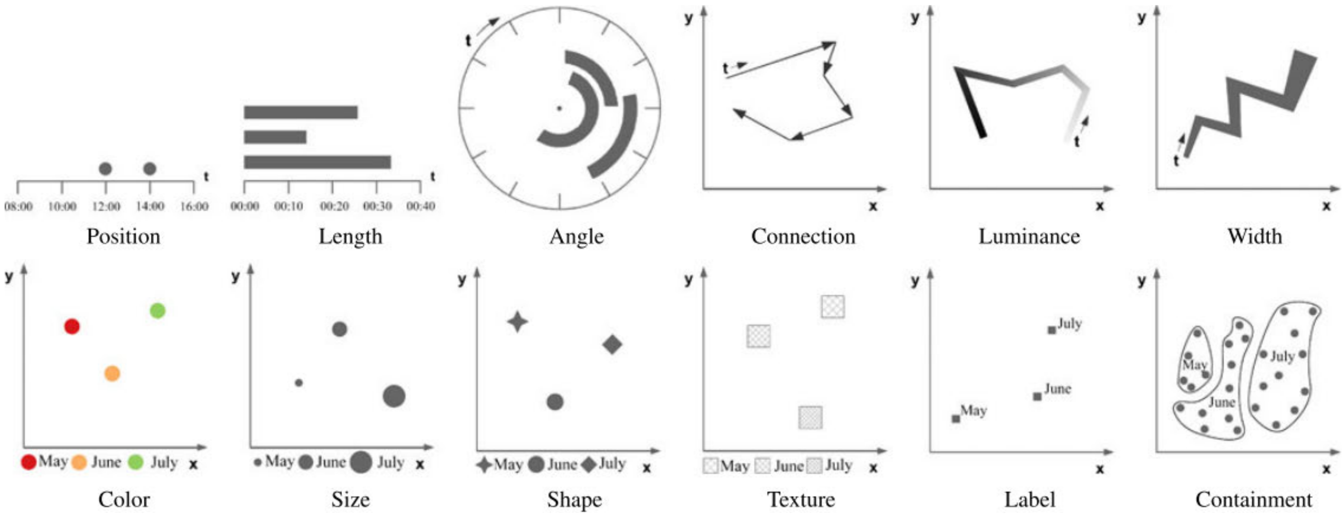

FIGURE 11. **Mappings from temporal information into visual variables [30].**

their visual queries by hand drawing to visualize spatial locations.

2) TEMPORAL VISUALIZATION

Several trajectory visualization methods are available for mapping time into visual variables [30]; some of these application examples are shown in Fig. 11.

Specifically, we focus on several types of representative temporal visualizations:

1) Linear time. Linear time considers time as a linear field from the starting point in time to the ending point in time, which indicates how the variables change and denotes their time-varying peaks and valleys (see Fig. 12a [31]). Linear-time representations exhibit fine intelligibility, but they are not a smart choice for displaying multiple variables because of the cluttering problem. In addition, linear-time representations cannot be displayed without sufficient space and thus fail to provide a strong overview.
2) Axis-based time. Axis-based temporal visualization can accurately present absolute times in abstract space, where colors and connections are two prevalent methods for relatively interpreting temporal data. However, the two methods are both constrained by limited scalability and can only function when processing low amounts of time-series data. To mitigate the spatial-information deficiency, the temporal display is associated with the spatial display by interactive techniques (see Fig. 12b [13]). However, once the quantity of time-series data excessively increases, clutter occurs and encompasses the features. Visualization technique based on time-axis variants was proposed to counter this problem (see Fig. 12c [13]).
3) Radial time. Many recursive processes, including iterations of seasons, weeks, and days, exist in our natural world. Radial times are geared to comprehend periodic behaviors and outliers. This type of time encoding efficiently reveals potential patterns but suffers poor spatial utilization (see Fig. 12d [23]).
4) Other time. Currently, many trajectory visualization systems or tools have extended visualization approaches that effectively resolve time solutions in abstract space to illustrate attached attributes. For example, timetables play an important role in providing information about routes and travel plans, which address the problem that the practical issues involving temporal information is usually ambiguous and cannot be fully interpreted to forms that support automatic processing (Fig. 12e [32]). A time mosaic display conveys contextual information about time periods via a specific arrangement of dominant elements (Fig. 12f 33]). The time-distance transformation technique [34] enables an overview of individual trajectory periods with different granularities (Fig. 12g [35]). Isotime flow maps are typically employed for efficiently comparing temporal information (Fig. 12h [36]).

3) ATTRIBUTE VISUALIZATION

Attribute features are typically time-varying and generally involve time-related visualization issues. When processing trajectory data from different sources, different scales, or different types, data fusion should be performed to prevent potential misunderstanding caused by incomplete information display and facilitate an observation with regard to the changing process of certain data and attributes in a context of other data and attributes and their correlation. For example, the security monitoring system designed by Willems et al. [37] displays the correlation between a pair of attributes in a trajectory contingency table (middle part of Fig. 13a). When the fusion of multiple datasets derives various types of multivariate data, a hybrid-rendering method is generally employed considering these data

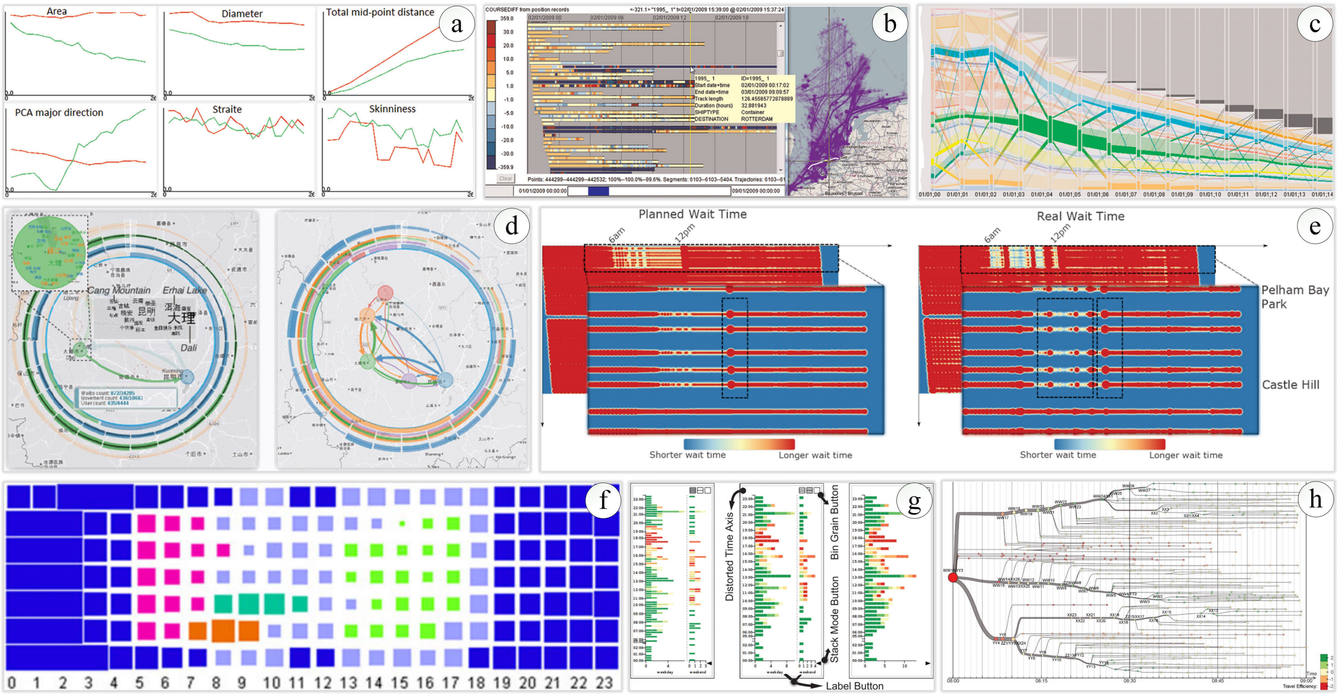

FIGURE 12. **Examples of temporal visualization [13], [23], [31]–[33], [35], [36].**

characteristics. Ryoo *et al.* 's visual analytics [38], which is based on pixel grid and horizon graph, comprehensively displays the time-varying changes of individual-athlete performance and team features (see Fig. 13b). One of the application purposes of rationally visualizing attribute features is to implement predictive analysis. To plan and determine flight routes, Hurter *et al.* [39] extended the visualization interface of FromDaDy to facilitate the operators and analysts accurately predict the weather impact on the trajectories (see Fig. 13c).

Trajectory data in the context of big data are likely to be high-dimensional and require high-dimensional visualization techniques. For example, parallel coordinates [40] is a general high-dimensional data-visualization method that shows the trajectory data distribution of different attributes and correlations among various attributes. For example, Guo *et al.* [19] applied parallel coordinates to plot multiple attributes of each trajectory when studying intersection traffic trajectories (see Fig. 13d). High-dimensional data can also be projected into a low-dimensional abstract space using a dimensionality-reduction approach. For example, Wang *et al.* [41] performed high-dimensional projection according to the similarities among graphs, extracting jam propagations of corresponding taxis and visualizing them on the projected graphs based on attribute features (see Fig. 13e).

However, visualizing trajectory data based on abstract space has certain limitations: these visualizations are not applicable to trajectory set issues that require detailed analysis and modeling. Although spatial abstraction serves as a tool to protect locational-data privacy [42], it can affect the accuracy of data-analysis algorithms. Even if the circumstance setting enables abstraction, the spatial scale cannot increase unlimitedly without distorting or destroying the curve shape that indicates spatiotemporal information and the relationships between the trajectory flows and attributes. Typically, increasing the spatial scale can intensify the noise amount within the geometric primitives of abstract objects, whose upper limit regarding size and style may depend on the quantity and diversity of existing physical connections.

IV. VISUAL ANALYTICS

In this section, we concentrate on how to visualize individual variable-based trajectories or an overall trajectory set from different aspects using different methods. These tasks seem very popular in trajectory visualization, which reflects the core interests and requirements of scientists in this domain. However, note that these tasks are not complete and are not orthogonal to each other; some tasks may depend on other tasks to some extent.

A. MICRO AND MACRO OVERVIEW: ESTABLISHING A CONCISE VISUAL SUMMARY OF DATA ENTIRETY AND CONVEYING OVERALL UNCERTAINTY

In most cases, moving-object-trajectory data can be analyzed on different spatial scales: from a detailed local-scale view of all individual movements to an overall wide-range view of a trajectory set. The interests of analysts focus on how the origins and destinations are arranged in space and how these routes vary over time. The analysis may emphasize trajectory events in specific space (e.g., traffic jams or

FIGURE 13. Visualizations based on abstract space that present attribute information in trajectory data [19], [37]–[39], [41].

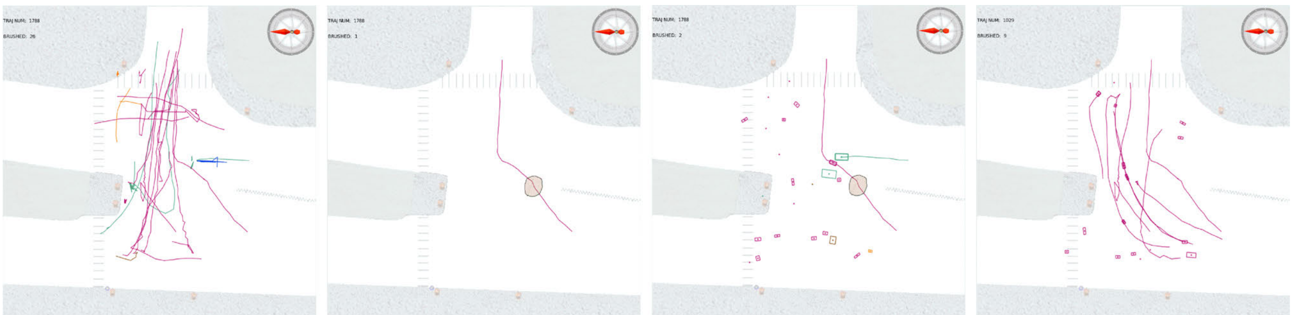

FIGURE 14. Example of a micro overview of trajectory data [19].

accidents) or interactions among trajectories and the contexts. The overview seeks to present advanced visual abstractions of data; in terms of trajectory data, the task typically shows the spatiotemporal conditions of either microscopic individual trajectories or a macroscopic trajectory set.

To illustrate some of these techniques, we magnify the example of individual movements from a micro viewpoint that consists of time-varying location records of moving points [43]. The advantage of concentrating on individual trajectory data is that its fundamental nature enables the construction of more complex trajectory events via combined manners. The TripVista [19] in Fig. 14 indicates the individual movements of vehicles and pedestrians at a road intersection with colored polylines that represent the types or speeds of individual moving-object movements; risk events are discovered and extracted from the trajectories.

To support the overall-view exploration of the spatiotemporal trajectory dataset, aggregating information from various trajectories is required in multiple views. The trajectory sampling points can be divided into continuous aggregation and discrete aggregation according to the sampling methods and scales.

In terms of continuous aggregation, for example, density maps and heatmaps for aggregated mass mobility flows serves as a general visualization method for high-hierarchy global overview: smoothly mixing flow points with high density or heat values based on a dedicated kernel function and creating and rendering a visual flow map that highlights the distribution of density and heat patterns. Continuous aggregation is not limited to 3D space. Zou *et al.* [44] combined the fourth dimension—4D time density into a 3D geographical space instead of a 2D space. Fig. 15a shows their visual application of presenting 4D temporal-density trajectories with a real flight dataset. Furthermore, the concept of density map and heatmap can be extended to a composite of time-varying movement behaviors in multiple trajectories, with different parameter settings to effectively highlight abnormal movements. Itoh *et al.* [45] employed a 2D heatmap to obtain an overview of the temporal variations of flows and 3D animated ribbons. The heatmap view in Fig. 15b visualizes the day of the Great Earthquake in Japan to discover traffic-volume anomalies in specific routes in crowded traffic hours and trajectory segments.

The discrete aggregation produces location-based and link-based space-time sequences. To macroscopically comprehend the behaviors of the overall trajectory set in space and time, a two-way clustering approach is preferred for observation and analysis, which involves time series that function in

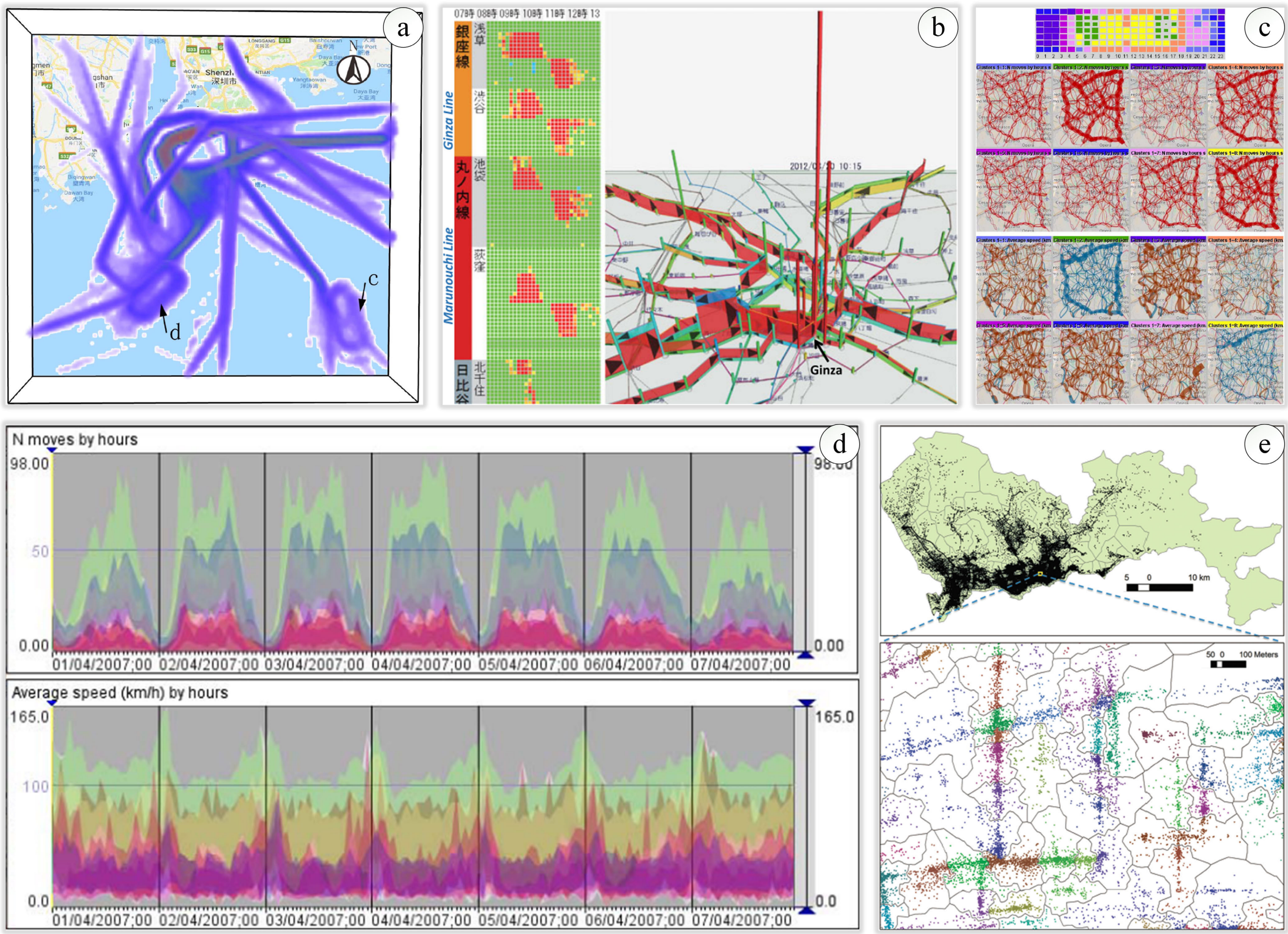

FIGURE 15. Examples of macro overviews of trajectory data [44]–[47].

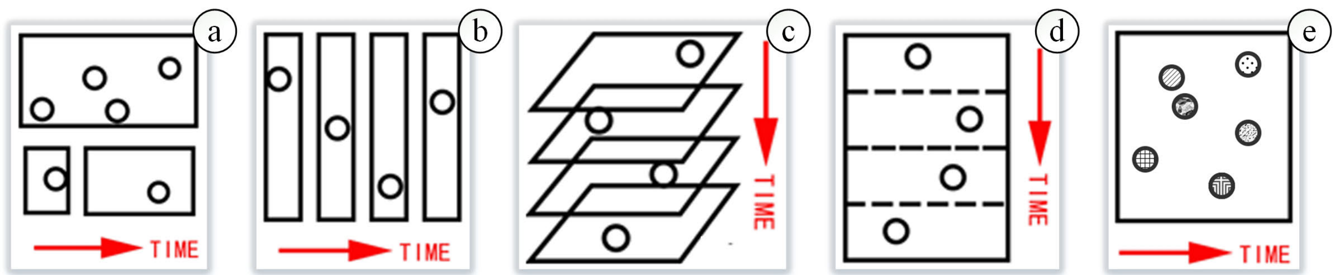

FIGURE 16. Visualization solutions of visual comparison: (a) multiple coordinated views, (b) juxtaposing, (c) superimposing, (d) cutting and (e) explicit encoding.

local time series and spatial contexts. For example, Fig. 15c shows the clustering of flows between two spatial compartments according to the similarities among flows and speeds in a local time series, which is an application regarding the local time series [46]. Fig. 15d clusters the hourly intervals in a week according to the spatial-context similarities among the flow magnitudes and average speeds, which enables the simplification and abstraction of space and time. However, the data typically exhibit high variability among trajectories. Guo *et al.* [47] modified the single-linkage clustering method to enforce the spatial continuity of clustering: first, the quantities of GPS points are spatially clustered to detect potential meaningful positions, and then, the traffic flows are extracted and plotted. This approach can extract information from complicated links among massive locations with spatial continuity ensured. They applied this method to a large set of

TABLE 1. Comparison of strengths and weaknesses of visual analytics.

	Strength	Weakness
Multiple Coordinated Views	Combination of 2D views; Extensive solution space; Connected by links or brushes.	Multiple focus; More display space occupied; No space-time involved.
Juxtaposing	High visual literacy expected; No occlusions; Sequential parallel visualization; Legibility.	Multiple focus; More display space occupied; Spatial shift.
Superimposing	Spatiotemporal integration and aggregation; Less display space occupied; Occlusions exist.	Extra mapping required for time; Visual cluttering; Plain visual effect.
Cutting	Arbitrarily add visual variables; Dynamic analytics visualization; Selectively fill the display; More details displayed.	Multiple and combined implementations; Memory dependency.
Explicit Encoding	Specified dimensional attributes; Rich configuration scheme; Intuitively and visually.	Limited applicable dimensions Over-plotting Implicit deviation

taxi trajectories in the working days of a week in Shenzhen, China, as shown in Fig. 15e.

B. COMPARISON: VISUALLY RECOGNIZING MULTIVARIATE CASES OF TRAJECTORY SETS VIA MULTIPLE COORDINATED VIEWS, JUXTAPOSING, SUPERIMPOSING, CUTTING AND EXPLICIT ENCODING

As a generally applied visual analytics method, visual comparison enables us to recognize the similarities/dissimilarities and correlations/decorrelations among different data instances. How can we enable an intuitive representation of trajectory events in a visualization system to enhance and magnify our reasoning? Many solutions for visualizing multivariate trajectory data have been analyzed. We list these standard techniques in common perspectives and visualize the spatiotemporal information and attribute information of trajectory data in a combined manner. Fig. 16 shows combined-view models that visualize spatial, temporal and attribute dimensions. These techniques require different affordances to frame internal representations and a hybrid method to construct trajectory events in spatiotemporal contexts. Table 1 summarizes the strengths and limitations of these visual analytics and illustrates a specific overview for each approach.

1) MULTIPLE COORDINATED VIEWS

There are two major challenges in trajectory data visual analytics: 1) The solution space is determined to be extensive, and 2) an intuitive visual-comparing analysis is required. The multiple coordinated views can adequately counter these problems by combining a standard map with the temporal view, which sometimes involves multivariate views, to simultaneously display spatiotemporal information and attribute information of trajectory data [48]. For example, the SmartAdP designed by Liu *et al.* [49] unifies three views by explicit visual links and user interactions and enables multihierarchical and multivariate comparison and analysis (see Fig. 17a). In terms of multiple coordinated views, users may create several separate internal representations with links that can be densely woven. The multi-linked views designed by Shi *et al.* [50] intensively shows the correlations and differences of people flows from spatial, temporal and multivariate perspectives (see Fig. 17b). Multiple coordinated views adequately integrate trajectory data, separately arrange the layout of geographic location, temporal expression and variable mapping in a trajectory event and coordinate these views with the interaction of links to enable a synergetic visualization of a multivariate trajectory dataset. For example, Konzack [51] composited the visualization view, density map and calendar view into an interactive visualization with multiple coordinated views to analyze seagull-migration patterns and show the stopovers (see Fig. 17c). Moreover, the effect of high-density local chaos on trajectory events cannot be exhaustively displayed in a single view, which often requires integrating maps of temporal overview and spatial context to predict the hidden mechanism in the context of space-time. Liang *et al.* [52] provided multiple coordinated views for meaningful attributes of flight trajectories to enhance the comprehension of trajectory behaviors. The global view in Fig. 17d displays all trajectories, while other views show more detail about the selected trajectory.

2) JUXTAPOSING

In trajectory visualizations, juxtaposing typically refers to placing different visualization productions of multiple trajectories regarding temporal, spatial and attribute information side by side for comparison, and many types of juxtaposing methods exist. We classify the juxtaposition based on temporal information into temporal-layer juxtaposition, which divides trajectory data into multiple parallel temporal layers.

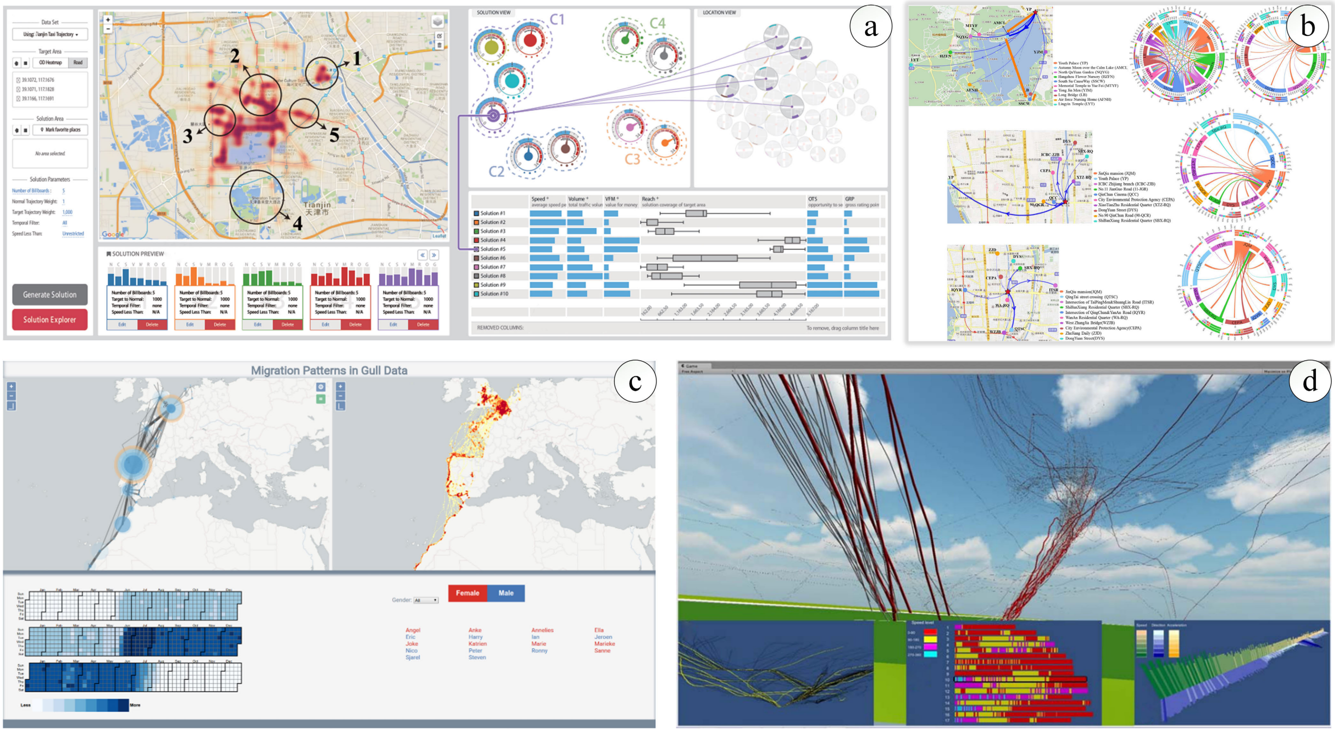

FIGURE 17. Examples of multiple coordinated views visualizing trajectory data [49]–[52].

These layers primarily read data by temporal dimension, which requires users to read and compare multiple sequential views, cognize visual changes or understand how trajectory events evolve over time. Likewise, the same categorization method may be introduced to spatial-layer juxtaposition and attribute-layer juxtaposition. For example, the Alavai tool [53] shown in Fig. 18a compares three simulated oil-spill trajectories in different sites for the prediction of drift trajectories on ocean surface. The utilized spatial juxtaposition is capable of visualizing complicated information in a simple and intuitive manner. But generally speaking, juxtaposing methods are closely related; the detail level of their cooperative visualization can smoothly interpret and explore the correlations and anomalistic patterns among various factors. Fig. 18b shows the trip exploration of selecting points of pick-ups (blue) and drop-offs (orange), which recognizes the travel-count variations and abnormality in hurricane mode of the analyzed taxi trips in 2011 and 2012 [54]. All juxtaposing methods rely on the short-term memory of users; observers can identify differences between parallel views by frequently switching visual attentions. Therefore, this approach effectively solves the cluttering problem in traditional visualizations caused by massive-data overlays with a low interaction cost. The MobilityGraphs [55] uncovers the occluded movement patterns in flow maps based on a graphical approach. Fig. 18c shows the transformation from traditional visualization mode to a juxtaposing visualization of simplified overviews. However, the juxtaposing scaling operation can shorten the time slices and space slices: the larger is the number of the displayed slices, the smaller is the space occupied by each slice and the lower is the resolution. Therefore, the operating time of juxtaposition expects the best trade-off between the spatial resolution and the temporal resolution. As Zeng *et al.* [36] states, the spatial views, isochrone map views and isotime flow map views in their PTS (public transportation system) mobility model can occupy larger display space, which may pose more difficulties on mobility-correlation analysis (Fig. 18d).

3) SUPERPOSING

Superposing primarily refers to combining temporal, spatial or attribute information into an integrated representation in the same context while comparing them in a view using transparency. Bennett et al. defined the concept of ''visual momentum'' as the extent to which an interface supports users' conversions between two different perspectives or information-seeking activities [56]. The seamless transitions between these two conversions form continuous links between two different views or perspectives by explicit variations, and PolyCube is one of the systems that support these operations. Fig. 19a illustrates two of these conversions that seamlessly transition from a space-time cube representation to a slice-juxtaposing perspective to a slice-superimposing perspective [57]. The analysis issue of trajectory visualization often involves multiple indicators and the analysis indicators for each attribute differs; thus, we cannot conclude by a view based on one attribute. Multilayered-data superimposition is a flexible visual layout, where user-obtained visual

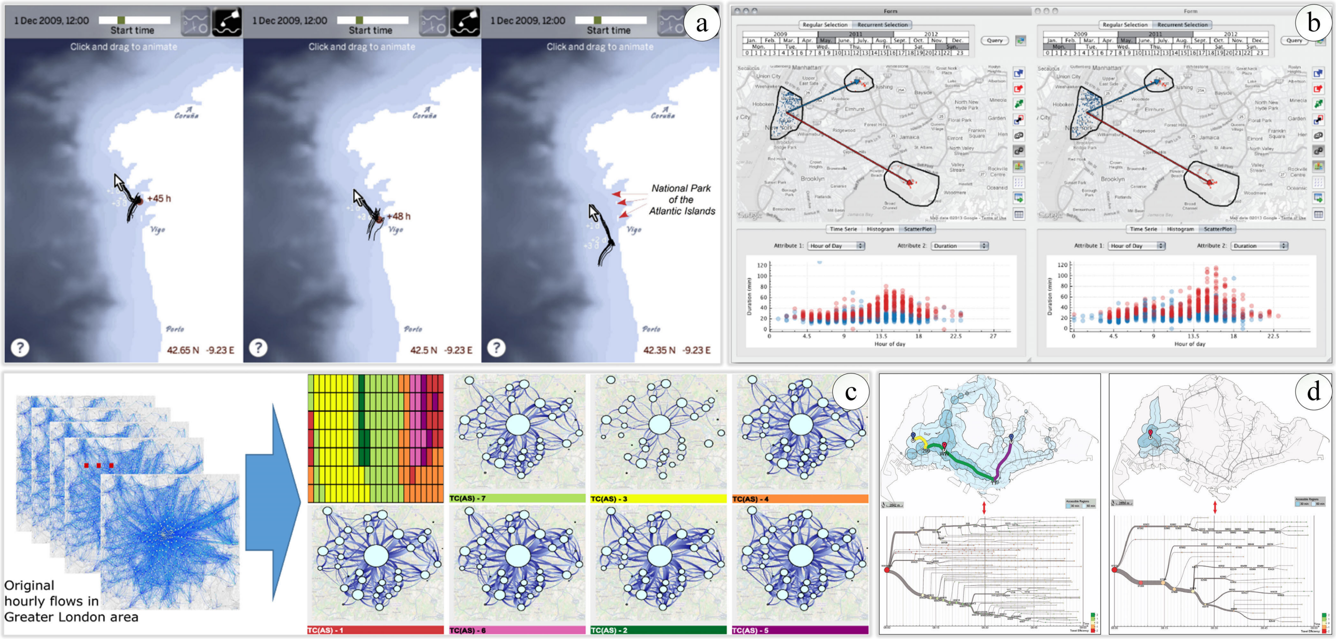

FIGURE 18. Juxtaposing examples of visualizing trajectory data [36], [53]–[55].

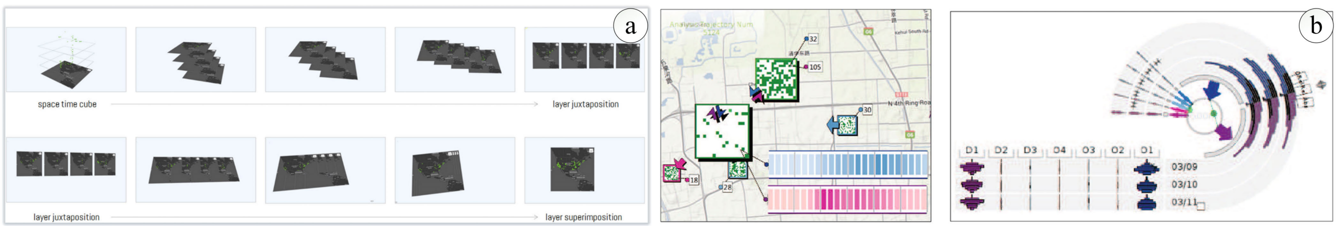

FIGURE 19. Superimposing examples of visualizing trajectory data [57], [58].

information is multivariate instead of univariate. For example, Lu *et al.* [58] thoroughly explored passenger-travel patterns via an adapted OD-wheel. The exchange flows in Fig. 19b can exhibit an entirely different distribution in the linear views, where the superimposing results are indicated by dark bars.

4) CUTTING

Cutting typically includes temporal-cutting operations and spatial-cutting operations, which extract temporally and spatially based information of interest from trajectory data, respectively. Although a single temporal cutting can provide a clean, complete and detailed snapshot with a specific timestamp, the goal of temporal visualization in practical cases is to display information throughout time. The space-time cube in Fig. 20a displays the temporal cross-sections that correspond to different instants, which reflects the event states at different moments [59]. This temporal cutting usually does not work independently: it is either performed multiple times or in combination with other operations or interactions. We studied an interesting experiment to illustrate a extraction-related dynamic visualization using mining-truck trajectory data of a mining area in Inner Mongolia, China, where we displayed the attributes of interest by performing temporal cuttings and spatial cuttings several times. Fig. 20b shows our attribute extraction of TR207-truck trajectory segments with tire pressure less than 93 psi (pounds per square inch). Furthermore, spatial cutting can also function in visualizing temporal data, which is primarily reflected in the static visualization in space-time cubes. Fig. 20c is a visualization view created by Marey [60] that displays major rail connections between two French cities, which can also be described as a spatial-cutting operation along the rail tracks [61]. Besides, spatial cutting can be separately performed to reduce the trajectory-exploration range, which is more beneficial for local trajectory analysis. When exploring the behaviors of taxis along a route, for example, Lu *et al.* [35] introduced TrajRank with uneven segmentations, which narrow the travel-behavior analysis to smaller sections. Fig. 20d visualizes several road sections with varying lengths.

5) EXPLICIT ENCODING

Explicit encoding refers to quantifying inter-object differences to be compared and visualizing these quantified values using specific metrics. Typically, a highlighting method for

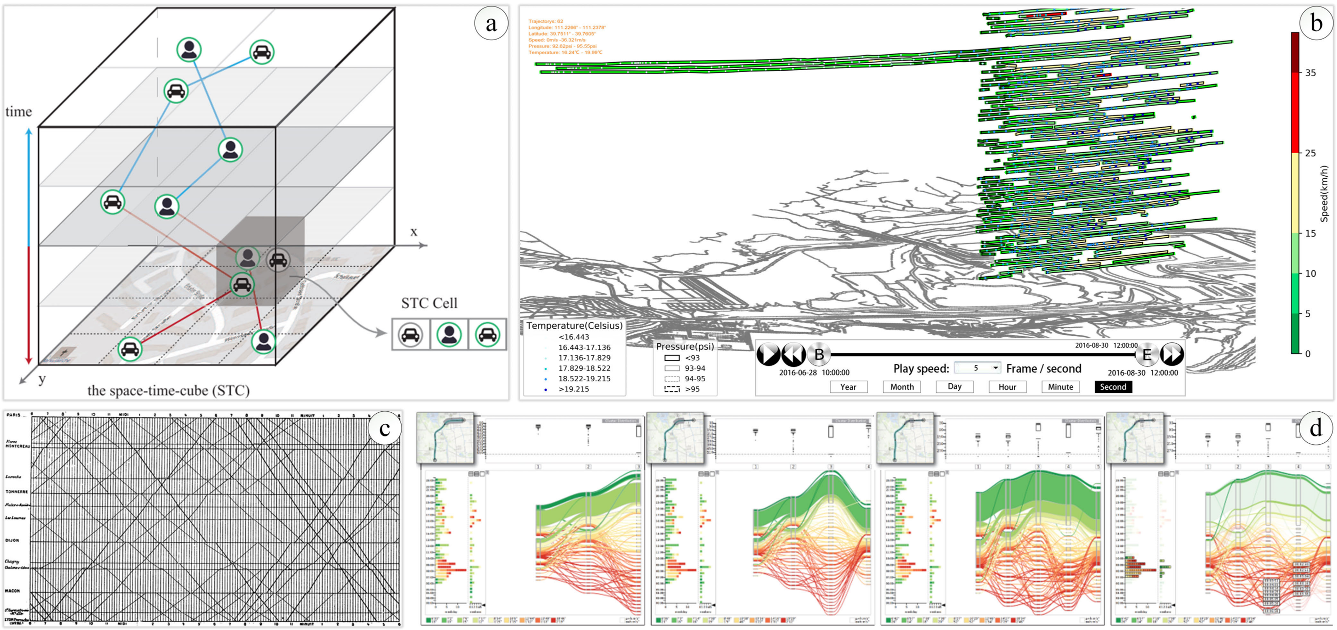

FIGURE 20. **Cutting examples of visualizing trajectory data [35], [59], [60].**

subject information is provided in animation or loaded maps to attract users' attention. Visual variables in maps are the basis for constructing various map symbols and conveying different visual perceptions, which serves well as a widely employed encoding that corresponds to different attributes in trajectory dataset. These methods exhibit invariant characteristics in the aspects of scale, translation and rotation, and intuitively depict the basic features of objects. In Kim *et al.*'s illustration in Fig. 21a, current (left) and future (middle) data distribution are shown for evaluating mobility patterns, which is, however, not so intuitive as the explicitly encoded diverging and converging flows (right) [62]. Reasonably adjusting the weights and priorities of the combinations is essential for facilitating visual differentiation and optimizing a visual-encoding scheme, which contributes to enhance interactivity with users and multiple variables of displayed data and exhibits the most intuitive visibility. For example, SemanticTraj, which was proposed by Al-Dohuki et al. [63], enables efficient visual encodings for large-volume and near real-time spatial and nonspatial data (multisource data) in urban transportation networks, where the intermittent red points indicate slow-traffic areas (see Fig. 21b). The explicit encoding can also express multivariate information using glyphs with multiple identifiable features, each feature of which can be used to represent one variable of the multivariate information. Fig. 21c compares several visual-highlighting methods that are applied to spatiotemporal trajectory data and interactively supports analytical reasoning based on context-aware graphs [64]. This technique generally creates a visualization of a complete image, in which the types, sizes and colors of the dots and lines indicate relationships among data. For example, Duffy *et al.* [65] proposed a glyph-based visualization to summarize and analysis sperm mobility by conveying over 20 parametric measurements with spatiotemporal contexts (Fig. 21d).

C. TEMPORAL-TREND ANALYSIS: REVEALING HOW SPATIAL AND ATTRIBUTE OBJECTS OF TRAJECTORY SET EVOLVE OVER TIME

Temporal expression presents a granular-level hierarchy: if trajectory data involve a time series, they can capture the time-varying features of spatial data. This variation includes two possibilities: the spatial features and attribute features of geographic objects can independently change over time or simultaneously vary over time. Fig. 22a explores the time-varying traffic patterns in different areas of Beijing by locating and analyzing congested roads [41]. According to previous research, temporal trends can be captured by three major methods: the topic evolution of trajectory events, time-series graphs and their changes, and path-based visualization. The event evolution is often used to recognize knowledge from trajectory data. Fig. 22b explores the topical-route evolution of massive taxi trajectories in Shenzhen, China over time by visualizing probability-based topical information [66]. Time-series visualization analyzes data features of time series from both perspectives of time and data, which depict not only the varying patterns of trajectory data over time but also the temporal patterns of trajectory-data distribution. Several commonly employed visualization methods exist for time-series data: 1) Linear graphs that can be simply implemented. When displaying time-series data, one of the axes is fixed as the time axis to represent the continuous relationship of time, while the other axis indicates the corresponding data values. 2) Stacked graphs that present data-accumulation

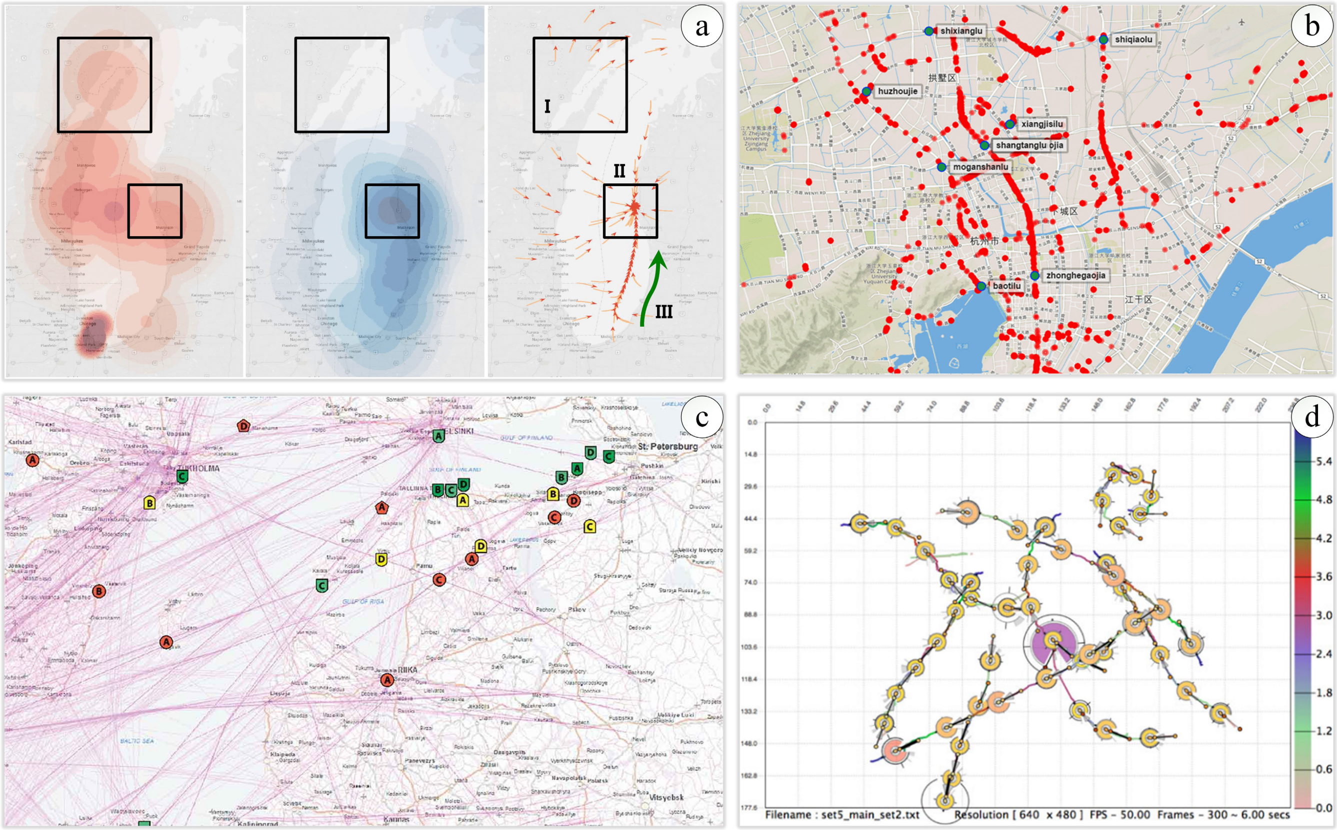

FIGURE 21. Explicit-encoding examples of visualizing trajectory data [62]–[5].

variations from different categories in various periods. The strength of these graphs is their intuitive display of the overall sequence variations. However, this approach lacks the ability to compare different types of data and performs poorly in processing data with negative values. 3) Animations that enable better user perception in time-dimensional data variation. In dynamic varying situations, this approach may result in worse user memory of the overall situation and thus harm the data comparison. In this regard, the animation method is not recommended for general time-series data visualization. 4) Horizon graphs proposed by Saito *et al.* [67]. These graphs can compensate for the visualization methods that are unable to represent cases with negative values, while differentiating positive-negative variations using color-channel properties. 5) Timelines that express narrative trajectory data. This tool indicates the described temporal ranges with a horizontal time axis by displaying data near the corresponding time scale. However, when handling a long time span and denser data points, the overall layout can become cluttered and suffer a poor visual effect. The space-time exploration mechanism applied in TaxiVis [54] concentrates on studying how the taxi-demand patterns change over time, of which the exploration results consist of multiple views of each time interval that are displayed on the timeline and an overall data view that integrates the results of time intervals (see Fig. 22c). Path-based visualization is an abstract timeline for describing the variations of the event target as it moves from one region to another. Fig. 22d shows the flow patterns of taxi trips for different periods and various zones, where regularity plots can witness some irregular patterns, which is reflected in the severe traffic jams during Hurricane Irene and Sandy in August 2011 and October 2012 [54].

D. CORRELATION ANALYSIS: EXPOSING ATTRIBUTE-INFORMATION CORRELATIONS OF TRAJECTORY SETS

The objective of correlation analysis in trajectory visualization is to visually analyze two or more attribute elements in the selected data, which qualifies the correlative degree between each of two variables. Some connection or probability exists between the elements of correlation, and the yielded visualization results tend to be relative. For example, when analyzing time-related data, to demonstrate the overall correlation among multiple variables (i.e., integral over time), Grottel *et al.* [68] visualized the correlations between robot-hand coordinates and joint angles of robot arms based on a robot-arm trajectory set (see Fig. 23a). This type of analysis is especially applied in transportation studies, and interdependence that fits basic traffic maps often exists at different levels of spatial abstraction. As shown in Fig. 23b, Andrienko *et al.* [69] displayed the interdependent relations between average speed and relative traffic intensity on

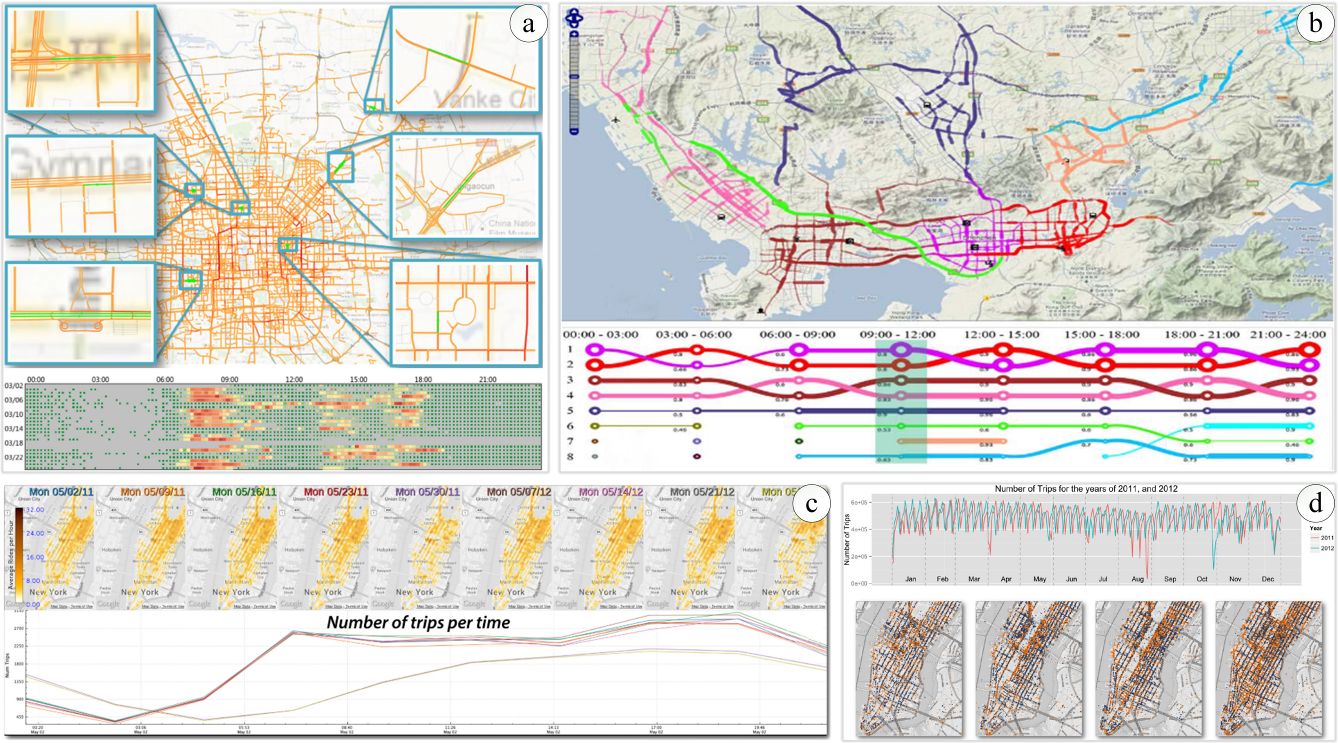

FIGURE 22. Examples of temporal-trend analysis [41], [54], [66].

different spatial scales in a spatially abstracted traffic network of Milan. The opposite dependency can also be modeled to indicate how the maximum vehicle count through a link during a period depends on the average speed, which demonstrates a dependency series from three selected clusters by a polynomial regression model with a higher polynomial order. Similarly, the authors employed the regression model to represent the dependence between traffic intensity and average speed (see Fig. 23c [69]).

E. INFORMATION EXTRACTION: EXTRACTING GEOMETRIC OR TOPOLOGICAL FEATURES FROM THE UNCERTAIN FIELDS OF TRAJECTORY DATA

In the trajectory big data era, the established models are becoming increasingly complicated. Information extraction for user-interested variables effectively alleviate the difficulties that most users encounter in comprehending the domain knowledge reflected in the entire visual analytics process. Data selection and content query comprise the critical tasks of visualization. Ding *et al.* [70] applied VIPTRA to a real taxi-trajectory dataset of Hangzhou, China, and their result in Fig. 24a displays map, trajectory points, trajectory information and query results (area query and moment query). The query interface of this visualization macroscopically and microscopically explain user requirements in different spatiotemporal extents. Fig. 24b explores behavioral needs regarding drivers' route choices in a certain area according to the attribute selection and ranking [71]. Points or segments extracted from a trajectory are often used to represent basic events regarding specific moving-object states. These events themselves may not be meaningful, but they can comprise or indicate an important and complex event. Trajectories can involve many events, of which negative events such as accidents, congestion, and dangerous actions, may require special attention and analysis. For example, a spatiotemporal cluster of speed-reduced vehicles may indicate traffic jams. To identify the locations and spatiotemporal extent of these complex events, not only detecting trajectory events of interest but also extracting them may be required to detect clusters of spatiotemporal density and track their further evolutions. For example, Buchmüller *et al.* [72] proposed a visual analytics method to explore and investigate air-traffic behaviors. Information extraction is often fulfilled with interactive-filtering techniques, and numerous interactive techniques for extracting events of interest from movement data and methods for analyzing temporal patterns and trends of events occurring in space currently exist. For example, sports analysts expect to effortlessly depict motion patterns based on individual-, formation- or team-related trajectories to identify tactical motions and unannotated scenes in a game. In Fig. 24c, the upper graphs explore soccer trajectories by systematically visualizing all team-turns over an entire match, which enables analysts to iteratively select and survey clusters of interest; the lower graphs enable further segmentation of player trajectories based on speed, acceleration and straightness [73]. However, extracting trajectory-event circumstances from multisource data can be more challenging. During the information extraction of trajectory data, data

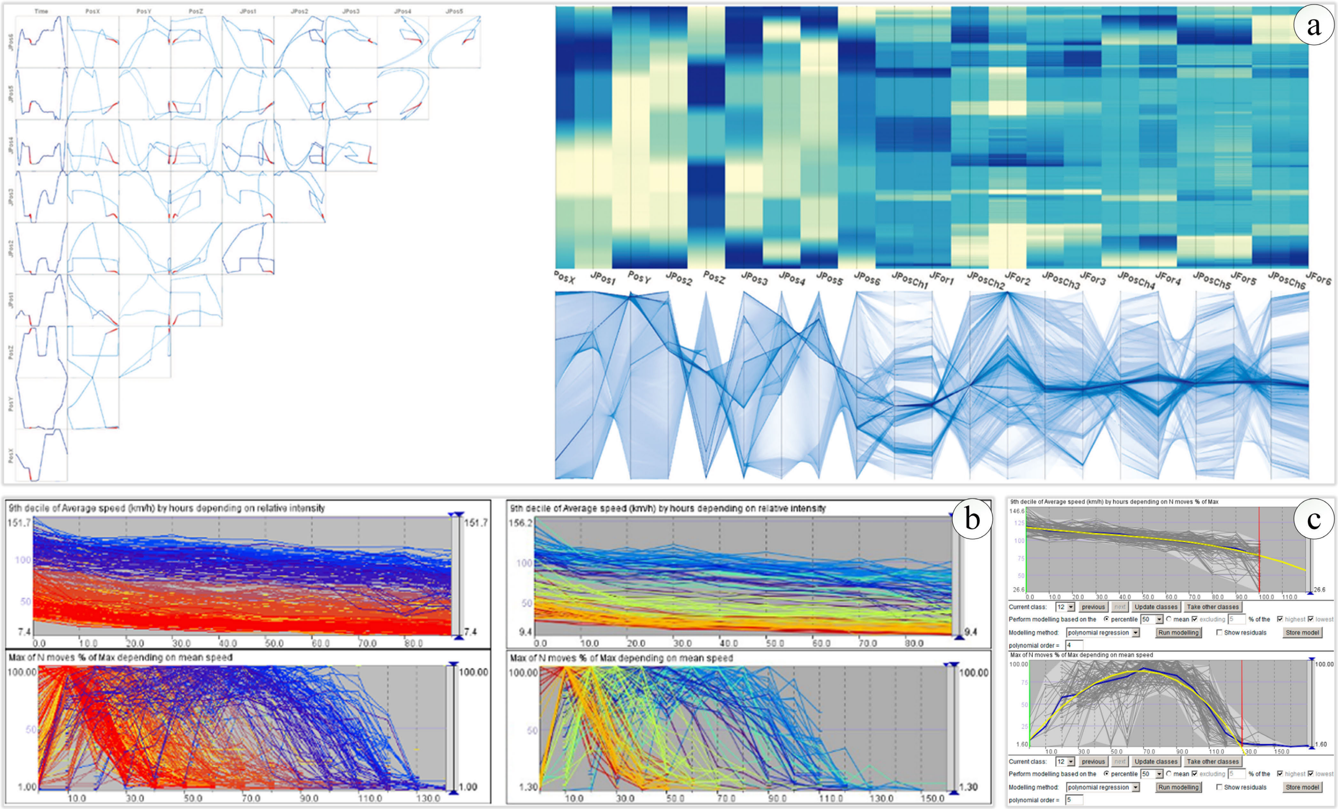

FIGURE 23. Examples of correlation analysis [68], [69].

filtering can select in terms of trajectory positions or time intervals, which helps users select an area from the central geographic circle of global view for analysis. All trajectories through this area are chosen and attributes of time and speed are highlighted in another view. Fig. 24d illustrates a seven-step information-extraction process for retrieving a missing iPhone, where taxi trajectories are tracked by selecting, filtering and aggregating multiple data sources [59].

F. DIMENSIONAL ANALYSIS

The task of dimensional analysis is to establish links among multivariate data. We have mentioned multidimensional expressions in section 2, and visualization techniques and methods for low-dimensional and high-dimensional trajectory data often possess different features. When focusing on trajectory data of high dimensions, although we are capable of visualizing trajectory data with higher dimensionality, their visualizations may become involved to understand. Therefore, we fail to derive a reasonable arrangement of data space. Sometimes transforming geographic space into abstract space is required to mitigate visual cluttering. If a dataset grows further, the human eyes can hardly capture meaningful information. Dimensionality should be reduced to two or three to visualize these data in 2D or 3D space. Data dimensionality reduction simplifies the scale of high-dimensional data and significantly reduces the complexity of clustering algorithms. Thus, an abstract and imperceptible high-dimensional data structure is partially exposed in low-dimensional space. However, the dimensionality-reduction process tends to lose data information, resulting in low-dimensional space that cannot accurately reflect data interrelations of the original high-dimensional space. The higher is the dimensionality, the more severe is the information loss caused by dimensionality reduction. Therefore, a visualization design that fits the trajectory data dimensions is especially critical.

1) LOW-DIMENSIONAL TRAJECTORY DATA VISUALIZATION

In trajectory data visualization, we consider that trajectory data below four dimensions is low-dimensional trajectory data. The space in which we live is three-dimensional, and humans can directly comprehend space of or below three dimensions, but a directly cognitive map is hard to design if the data dimensionality exceeds three. Visualizing low-dimensional trajectory data is relatively easier.

One-dimensional data can be visualized by basic charts, such as pie charts and bar charts, which is covered in temporal-information visualizations in section 3.1.1.

Two-dimensional data visualization comprises visualizations for geographic location, narrative trajectories and other two-dimensional data. For example, as an extensively applied visual widget, temporal heatmap serves to overview how a

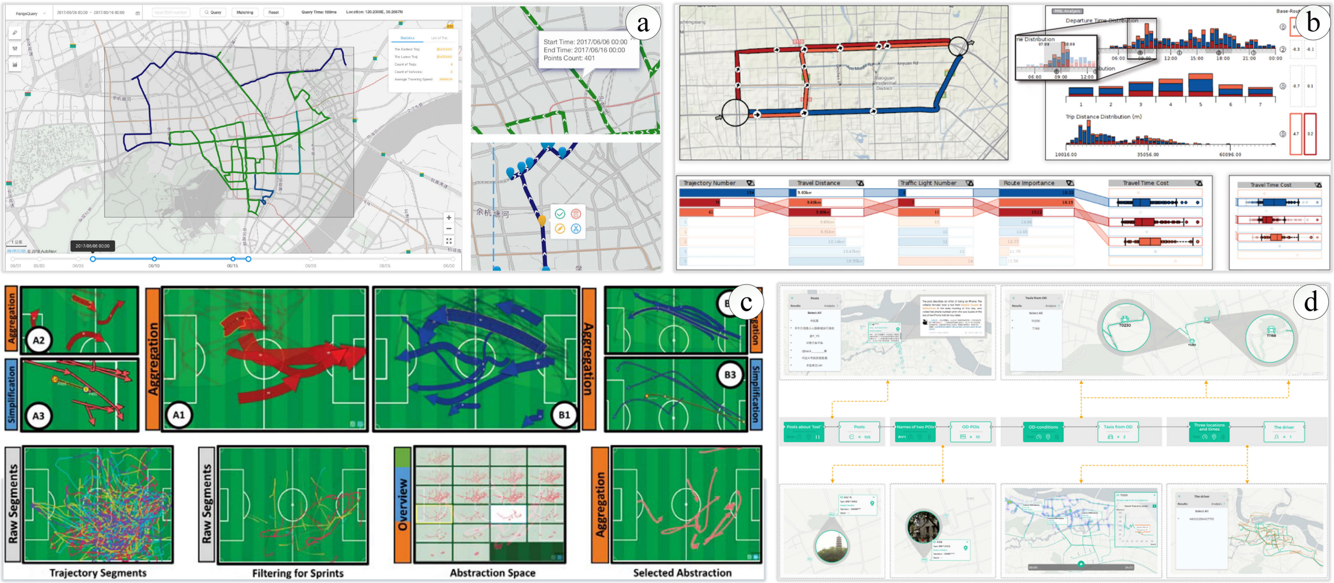

FIGURE 24. Examples of information extractions [59], [70], [71], [73].

particular variable evolves over certain periods (see Fig. 25a [50], [51]). In Fig. 25b, the two-dimensional scatter plot can map two-dimensional values of two dimensions to two axes and indicate other attribute values by different visual elements of the glyphs [74]. However, their elements are stretched in two dimensions, where the mining of more dimensional correlations and links is slightly weak. Elmqvist *et al.* [75] extended this work to three-dimensional space and developed mappable dimensions by a rolling ScatterDice (see Fig. 25c).

The space-time cube is a classic representation of three-dimensional spatiotemporal paths, which consist of two-dimensional geographical space and temporal dimension; the availability of this technique has been discussed in numerous studies. McArdle *et al.* [76] introduces a novel geographical environment that combines STC with Google Earth to explore movement data and analyze the spatiotemporal characteristics of trajectories. Fig. 25d shows 2D and 3D visualization that displays paths of two pedestrians in a city to explain how 3D visualization contributes to recognizing invisible spatiotemporal patterns in two dimensions.

2) HIGH-DIMENSIONAL TRAJECTORY DATA VISUALIZATION

Although low-dimensional data visualization is more intuitive, some data can be linearly inseparable in low-dimensional space. These data can be mapped to high-dimensional space and conduct classification by constructing hyperplanes. During the process of collecting actual trajectory data, massive datasets beyond three dimensions exist, which poses a serious challenge to the pattern recognition and principle discovery in trajectory data. Abundant information involved in high-dimensional data can create new possibilities for solutions. The earliest studies include two solutions: 1) Modifying the third-dimensional stacking of a space-time cube by visual channels. However, the extensibility of visual encoding is limited. 2) Analyzing and visualizing these data through methods of kernel heat or kernel density and plotting heatmaps or density maps by aggregating dynamic point datasets. However, these solutions do not regard movements as a dynamic process of temporal and spatial functions; aggregating and visualizing movement data only in maps fails to meet the requirements of spatial analytics and loss meaningful information. Therefore, visualization of high-dimensional trajectory data requires more practical techniques.

Thanks to the evolvement of machine learning, traditional low-dimensional data visualization methods become applicable by reducing the dimensionality of high-dimensional data to two or three. For example, Fig. 26a shows the process of stem-cell differentiation, where PHATE approach [77] embeds progression structures in high-dimensional data into lower dimensions to visualize trajectories and branches and extract biological meanings. However, the accompanied problem of dimensionality reduction is evident: its intention is to filter redundant and useless information from original dimensions, but this process may inevitably lose meaningful information. To alleviate this problem, the scatterplot matrix effectively displays the pairwise dimensional relationship. Fig. 26b shows all attribute-pair scatter plots within a matrix-layout view [78]. However, excessive dimensions of trajectory data can cause visual burdens. For example, the 12-dimensional scatterplot matrix in Fig. 26b comprises 144 subplots. The number of displayed views should be slashed without reducing dimensionality. The best case is to visualize high-dimensional trajectory data in a single graph, whose representative methods include parallel coordinates [40], RadViz [79], star coordinates [80], and UnTangle Map [81]. For example, when processing

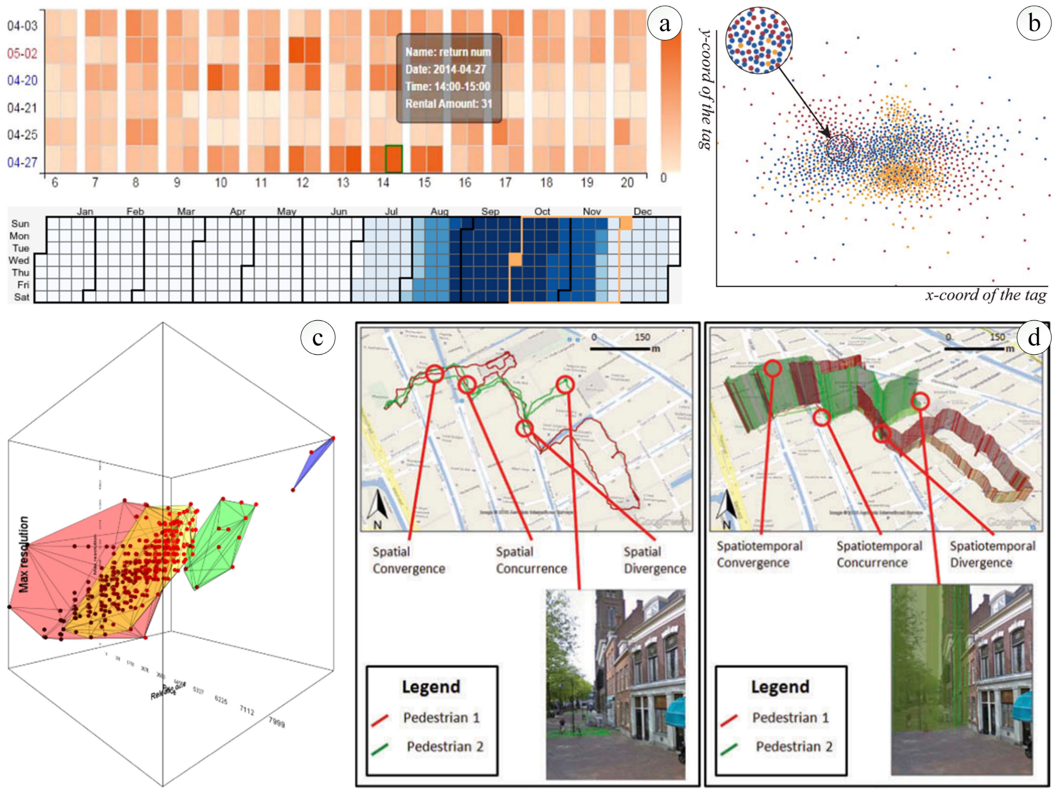

FIGURE 25. Examples of low-dimensional data visualization [50], [51], [74]–[76].

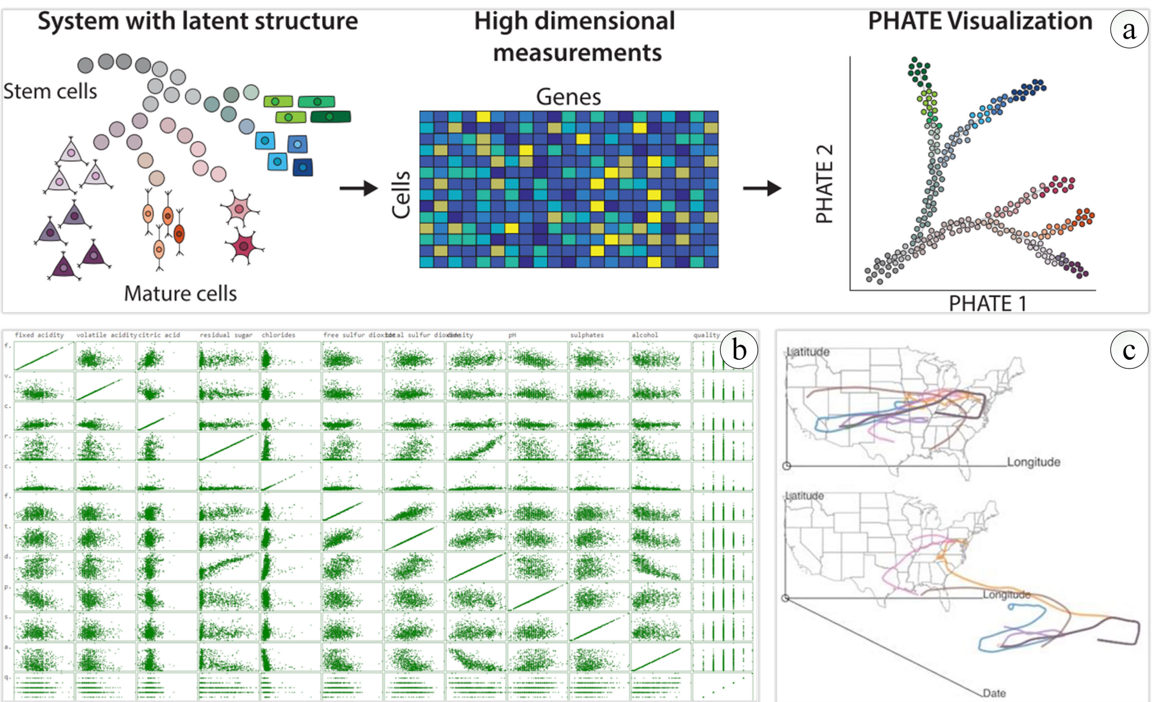

FIGURE 26. Examples of high-dimensional data visualization [77], [78], [82].

high-dimensional datasets, Murray and Forbes [82] explored multiple inter-attribute relations with extended star coordinates (see Fig. 26c).

G. INTERACTIONS

Proper interactivity is a primary aspect that affects users' knowledge acquisition from maps. The interactivity of space-time narrative is substantially reflected in the aspects of visualization-interface design, simple and reasonable map layout, and real-time interactive query. The limitations of human and display devices may result in the inability to display all data information at once, especially when the trajectory-data scale grows and complexity increases. Interactions facilitate addressing different requirements from different users and analysts, such as selecting and filtering information to browse data overview or explore data subsets in detail, customizing display background colors, reflecting user intents, and enhancing recognition of multivariate trajectory data. Based on the characteristics of target objects, we divide typical interaction techniques that promote trajectory-data visual explorations into the following categories.

1) VIEW MANIPULATION

Due to the limitation of the display screen, when visualizing a large set of trajectory data, some trajectory displays may surpass the screen range and, therefore, are invisible in the view. Interactive features, such as overview, zooming, panning, rotating, filtering, navigation, highlighting, details-on-demand, visibility and rendering sequence configuration of different information layers, and opacity configuration, enable observation and analysis of trajectory scenes from various perspectives, which supports users' exploration and research tasks in local and global space-time. As a basic application, various manipulations are adopted to select objects of interest, including trajectories, trajectory segments, moving objects and trajectory events, to address the issue of trajectory data complexity.

2) DATA MANIPULATION

The manipulation of data representation refers to selecting attribute information to represent the values in a trajectory dataset. Keim and Kriege [83] classified multivariate-data visualization methods into pixel-oriented, geometric, glyph-based, hierarchical, graph-based and blending techniques, which dramatically enriched the flexibility of interactive visual manipulation; their combinations can reach the optimal projection distance metric and thus can facilitate efficient and excellent data mining. Previous studies employ visual encoding as the original benchmark for manipulating data. For example, as shown in Fig. 27a, the well-known 1812 Napoleon Crusade map by French engineer Joseph Minard is a successful example of a map that depicts historical battles by expertly utilizing multiple static visual variables such as colors, line widths.

3) SPATIAL EXCHANGE

A direct way to specify spatial-exchange conditions is to discover variable data that meet certain spatial relations by explicit and implicit visualization methods. Explicit visualization of spatial exchange refers to directly presenting inter-regional exchanges on a map to indicate exchanging patterns. Spatial exchanges can be denoted by directed line segments and expressed as spatial-based flow visualization due to its data structure with weighted vectors. Although these methods can clearly visualize exchanges between certain and other regions and their spatial distribution, inevitable defects in depicting exchanging information exist. The location-implied visualization only represents spatial-exchange patterns but fails to reveal their spatial distribution. This approach therefore loses spatial features but avoids cluttering in explicit flow visualization. The flow visualization of explicit spatial exchange can be converted into a novel OD map [25] based on spatial transformation, where the spatial region is divided into rectangles (see Fig. 27b). However, the global patterns are split into minor subpatterns, which places higher requirements on user comprehension.

4) TEMPORAL MECHANISM

Trajectories cannot be instantly created by moving objects; thus, time is always involved in multivariate trajectories as an indispensable element. Temporal interactions are usually combined with visualization of temporal changes. Fig. 27c provides a snapshot of refugee movements between East Africa and Western Europe, which tracks the dynamic changes of spatial exchange between any two regions via a sequential heatmap (middle) [84]. However, temporal information in static views may lose a user's focus. To alleviate this situation, potential approaches are assigning similar visual representations to temporal and thematic attributes with visual variables or using additional notations to depict trajectory information of moving objects. An auxiliary temporal mechanism is applied, of which diverse operations include standard graphic control [54] brushing and selecting a timeslider [19]. For example, the time lens developed by Tominski *et al.* [85] can present temporal aggregation information about interactively defined spatial query areas, which depend on the display of temporal information via a dynamic query mechanism and aggregation (see Fig. 27d).

5) MAP INTERACTION

The powerful GIS features of fast interactions that enable viewing variations of variables in a map have broken the original state of paper maps and statistics and serve as a major tool for studying geospatial data. Users not only notice the resulting quantitative differences, but most importantly, make decisions in a qualitatively varied manner. Many geovisualization techniques are directly related to mapping techniques, such as map projection, map annotation and map generalization. In terms of extending these techniques, for example, as a traditional cartographic tool, the Choropleth map has combined animation and interaction to present richer information, which enables more flexible correlation and exploration of multivariate trajectory data (see Fig. 27e [86]). Further, novel geovisualization techniques are emerging. For example, the hierarchical structure in Fig. 27f, which consists of a base map layer, a thematic raster layer and a symbol layer, supports more sophisticated trajectory tasks in map design [64]. Several types of visual contrasts among the layers are used to establish a detecting sequence.

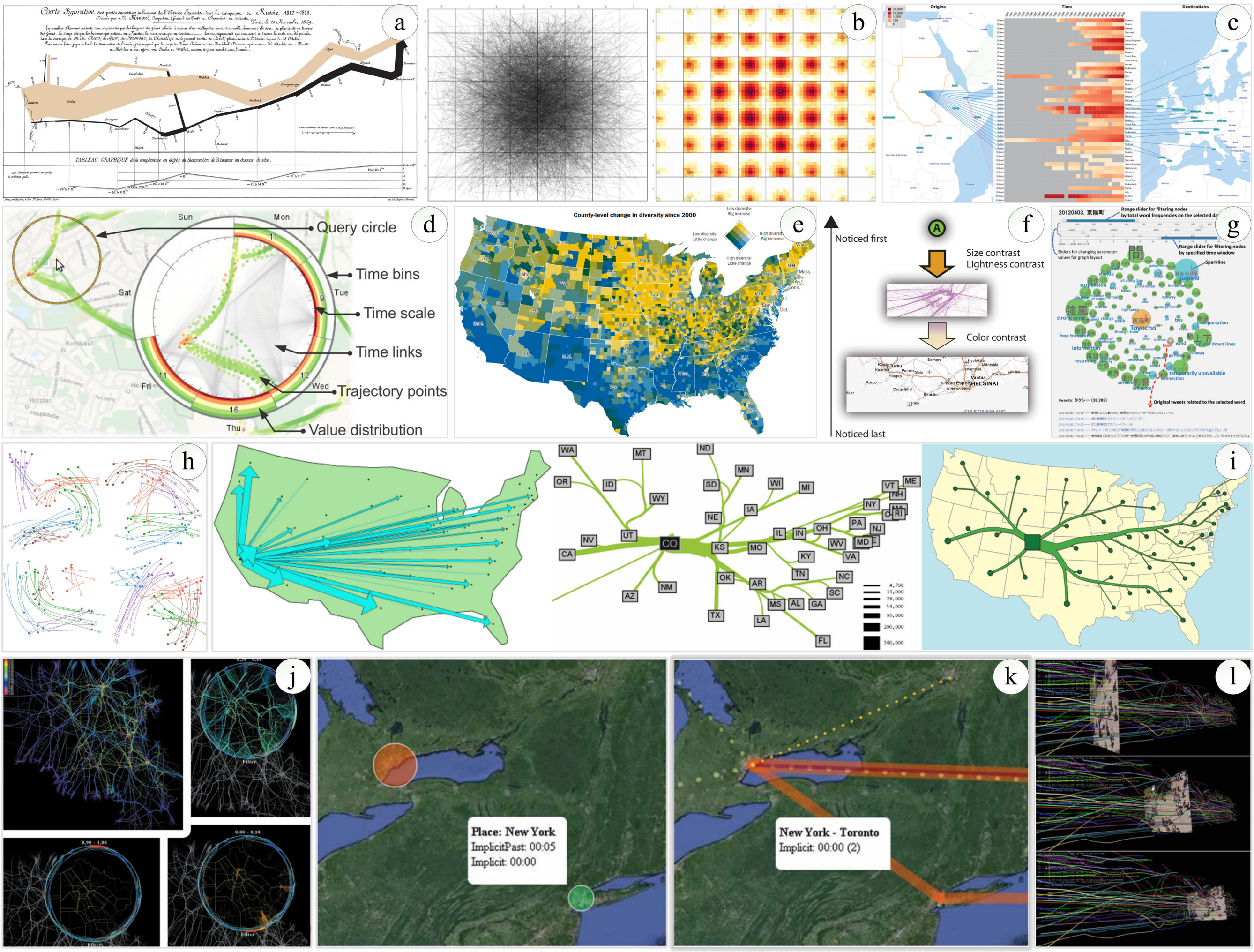

FIGURE 27. **Examples of high-dimensional data visualization [25], [39], [45], [64], [84]–[92].**

6) TEXTUAL INTERACTION

The intention of textual interaction is to effectively label, edit, and annotate trajectory variables. The visualization of static textual information includes feature-based textual visualization and topic-based visualization. In feature-based textual visualization, features indicate grammatical structures or nonoverlapping text chunks within a document. Word clouds, an emerging visual metaphor, indicate trajectory attribute information by their dominant keywords in documents. For example, Itoh *et al.* [45] proposed a TweetBubble view to visualize the overall trends of Twitter keywords (see Fig. 27g). Topic-based textual visualization provides an overview of static textual interactive context for trajectory data; its typical methods represent the dissimilarity between two documents with vector spacing after exchanging documents, which enables transformation from clustered documents into mathematical grouped vectors in hyperspace. Conversely, in dynamic textual information visualization, temporal attributes play a critical role in comprehending topic-evolution patterns in time-varying document collections and framing a correct storyline and solution, which illustrates the informative-evolution process in textual streams of trajectory data.

7) TRANSITION

Transitions serve as an alternative for visualizing variables and can be a central issue of visualization, of which the forms can be classified into static transitions and dynamic transitions. Static transitions, which are often employed for trajectory-event narrative interactions, comprise static transitions of user-oriented and interactive storytelling and static transitions of parallel narratives. When users interactively establish static transitions, the majority of the focus is interactive user-driven transitions instead of an automatic process. In terms of parallel narratives, the static transitions are displayed in parallel, in which case many transitions can simultaneously occur. For example, in the alternative to a trajectory map of the animated transition in Fig. 27h, animation is used to demonstrate time-varying evolutions [87]. These graphically animated trajectories can reduce clutter during animated transitions and tend to be smooth.

8) EDGE BUNDLING

Node-link diagrams have been the most commonly employed to represent graphs. Recently, however, researchers of variable visualization have recognized that various other applications exhibit their utility. A controversial issue of this utility is reducing clutter because thousands of edges can overwhelm the view and cover underlying patterns when the data amount becomes tremendous. Edge bundling serves as the most popular solution, and cost-based, geometry-based, and image-based edge-bundling methods can effectively work in cartography. For example, in the flow maps in Fig. 27i, Tobler [88], Doantam *et al.* [89] and Buchin *et al.* [90] applied tree-based edge bundling techniques to illustrate American migration data and achieved excellent bundling results. Despite considerable research attention on this approach, challenging issues regarding legibility, algorithmic complexity, and intuitive navigation may exist. Focus + context interactive techniques can benefit further cluttering reduction and present more complex spatial and data queries in trajectory visualization.

9) FOCUS + CONTEXT

As one of the most classic interactive models, focus + context technique enables both an overview of global contextual information and detailed focus views on components of interest by zooming in on areas of interest and zooming out on other areas. Among these methods, fisheye view is a focus + context interaction model based on polar coordinates. In terms of implementation techniques, focus + context adopts a spatiotemporally seamless data-presentation method, which differs from spatial segmentation in overview + detail (displays global and local information with individual views) and temporal division in zooming (sequentially presents overall and detailed information for different users), to effectively reduce users' burdens in comprehending spatially topological relations and short-term memorizing. For example, Fig. 27j demonstrates an exploration of bundling aircraft trajectories using the focus + context technique [39]. As mentioned in the previous section (edge bundling), this approach also contributes to mitigating the spatial-cluttering problem in sophisticated trajectory visualization and establish geographically accurate trajectory contexts.

10) ANIMATION

Static visualizations are relatively accessible to visualize trajectory data and enable interactive observation as users require. Dynamic or animated visualization techniques also demonstrate their considerable strengths. In terms of enhancing visual scalability, animation can address issues of insufficient display space or highly cluttering of static visualization techniques. Animation serves as a natural technique for conveying dynamically varying data and promoting perceptions of even subtle changes or dynamic displays, whose most expected utilization seems to present real-time variation and spatiotemporal reposition of variables.

Time-series maps and map animations are commonly used interactive dynamic visualization. A time-series map discretizes the time series and reflects its dynamic changes by displaying different time states of the same spatial domain, which is essentially an approach of simulating dynamic progress in a static manner. In a time-series map, the direct correspondence between two cells in different visualizations of the same data table enables smooth animation between them. However, time-series snapshots often present minor-scale and same-region changes. For geographically large-scale comparisons, interpretation difficulties are caused by limitations in resolution and precision. Time-series maps can only discretely show event states that correspond to certain moments and cannot reflect the progressive changes between two adjacent instants. Due to the limited number of frames, presenting the continuously varying long-term event sequence is difficult. Therefore, if the time series is rather brief, the maps can be juxtaposed; otherwise, map animation is recommended.

Map animation concentrates on three aspects: symbolic dynamic visual variables, animation establishment and statically displayed progression.

Visual variables of static maps are principally applicable to dynamic maps but require appropriate supplements, such as duration (the time required for each frame), rate of change (the ratios of graphically changed magnitudes to corresponding duration), order (the sequence of multiple scenes) and frequency (the frame count played per time). For example, Caquard and Fiset [91] employed glyph-flicker durations to effectively depict the temporal information of switching between and staying in different scenes (see Fig. 27k). This proper and flexible utilization of dynamic visual variables can convey more information via the map and dramatically strengthen the map legibility.

Map animation serves as a proper dynamic space-time visualization method that rapidly updates the content to demonstrate a series of maps in a single view. This approach generally simulates the event processes in a manner of dynamic deduction, which addresses the dynamic variations of space scale and spatial scenes and enables more efficient observation and exploration of event trends. These trends are typically patterns and relations that are ambiguous when observing a single map. Generally, each frame in a simple animated view corresponds to a spatiotemporal state at a certain moment. As shown in Fig. 27l, Poiesi and Cavallaro [92] utilized overlaid video frames to visualize the time-varying 2D trajectories, which enable frames to be navigated backward and forward while exploring 3D space. However, this implementation neither includes temporally contextual contents nor describes object distribution on the timeline or semantic relationships, such as temporal sequence and distance.

Animation is a natural way to illustrate variable-data evolution; however, animated progression displays pose certain requirements on users' mental maps. Therefore, the approach of the statically encoding temporal dimension has motivated research by scholars. Additionally, animation requires users' focused attention to capture the trajectory evolution, whose solution should reduce cognitive loads during observation. In this regard, timelines and small multiples tend to be popular choices.

H. DATA IMPACT

The evaluation and prediction of the visualized object movements often need to consider numerous uncertain factors and draw support from trend extrapolation, scene fitting and other methods by analyzing either individual trajectory evolution or overall trajectory set evolution by tracking information of each point or the overall information. The uncertainty related to trajectory visualization exists in visual representation. Although this uncertainty has a positive effect on protecting user privacy, its impact in trajectory data analysis can involve complex and diverse origin factors and cannot be disregarded. Consider traffic-flow visualization as a macroscopic example. The imbalance of trip distribution and peak travel volumes may cause cluttering in traffic flows, and individual driver behaviors have different behavioral patterns, whose direct consequence is short-term blocked intersections or congested roads. If uncertain factors such as terrible weathers, traffic controls, or sudden accidents are encountered, behavioral conflicts will inevitably occur and produce aggravated uncertainty and nonlinear characteristics of short-term traffic flows. At the data level, uncertainty is also reflected in erroneous data, missing data and fuzzy data, which are characterized by complexity, stochasticity, and periodicity. At the expressive level, the adopted parameters, models and techniques in the visualization process can cause differences in visualization results, which is considered as uncertainty in visual analytics. The limitations of visualization carriers (e.g., limited screen resolution) and user perception of visual-variable encoding are also prone to the uncertainty of user cognition.

The immense trajectory data resources have enabled a quantification process in various domains. Based on the spatial and temporal references that exist in movement data, the links to relevant contextual data are established. The visual analytics method generated in the context of this major environment involves a joint analysis with respect to movement-involved variable data and spatiotemporal contextual data, which is inevitably susceptible to external factors. For example, weather conditions (especially wind direction and wind speed) can affect the direction of takeoff and landing and ground speed. Reasonably establishing relationships with these factors can help explain anomalies and refer to contextual data. Conversely, trajectory data can exhibit promising application prospects. For example, logistic companies optimize a freight logistics system based on transportation data [93]. Police officers analyze the trajectory characteristics of criminal suspects to track them [94]. Meteorological centers establish a similarity analysis model that compares the current typhoon trajectory and historical typhoon trajectories to predict typhoon moving paths [95].

Although trajectory visualization analysis offers convenience in the context of big data, certain limitations of these visualization techniques remain to be conquered. In addition to issues related to normal trajectory events, illegal or abnormal trajectory information and its acquisition can trigger potential or further risks. Additionally, trajectory visualization does not concentrate on displaying one accurate image and cannot replace critical thinking; rather, it presents various representation effects as trajectory data applications. Therefore, excessive reliance on visualization when analyzing trajectories may also derive a biased result, hence a deviated final judgment.

V. CONCLUSION

We introduced the concept of multivariate trajectory data, covered the contemporary evolvement and representative applications of visualization techniques, and demonstrate that some variable visualization can be resolved into fundamental operations of specific tasks. These operations typically function synergistically rather than independently, and their combinations selected are even diverse; perception is therefore supported based on different levels of static or dynamic processing. However, no direct mapping between these operations and their best-supported tasks has yet been reached. While discussing the pros and cons of a variable-visualization operations, we primarily focus on the relative effectiveness with respect to data types and features, as the reference for trade-off, and explicitly descriptive analysis can help better discriminate the subtly different effects of design features and better control clutters. Although this review is imperfect to cover all aspects of all possible operations, it is meaningful to help visualization designers to pursue novel solutions, extend existing solutions and think outside the box.

ACKNOWLEDGMENT

The authors would like to thank Yang Shen, Professor with Tsinghua University, for comments that greatly improved the manuscript.

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