Research on visual analysis technology and application of urban road data

Ziyi Shao¹, Lin Zhang¹,²,³ and Hao Wu¹

¹Architectural Engineering Institute, North China University of Science and Technology, Tangshan, Hebei, 063000, Chain
²Hebei earthquake engineering research center, Tangshan, Hebei, 063000, Chain
³Sino-US center for urban transportation research, Tangshan, Hebei, 063000, Chain

Abstract. Many cities use the current wealth of multi-source data to create intelligent transportation systems, which visually process road data so that traffic consumers and traffic managers can better understand urban traffic conditions. Due to the heterogeneity, complexity and mass of these data, it is not easy to conduct effective analysis on them, and it is often necessary to integrate human perception in the analysis process, so as to cause extensive application of visualization. In this paper, we first briefly introduce the pre-processing of urban trajectory data, then systematically analyze the visualization of two data types of road traffic flow and traffic events, and finally briefly summarize the research trend of traffic visualization in recent years and put forward corresponding challenges. The results show that the early research focused on the visualization of road flow, including the main arrow diagram, Mosaic diagram, track wall, etc. With the deepening of visual analysis, the analysis of traffic flow increases to the analysis of traffic events. In recent years, there has been a new trend of mining and utilizing the attributes or semantics of traffic trajectories or traffic events. The research on traffic data visualization has been greatly expanded in breadth and depth.

1. Introduction

Faced with the trend of globalization and informatization, the traditional transportation technology and means can not meet the requirements of economic and social development. Solving the traffic problem in every city has become an urgent problem. Intelligent Transport System (ITS) is an advanced integrated traffic management System. The development of intelligent transportation is closely related to the development of Internet. As an important branch of intelligent transportation research field, traffic trajectory visualization develops rapidly and is widely used in intelligent transportation research field.

The visual analysis of traffic data has great potential because they can visually present tracks and provide rich interactions that allow users to explore the data. Historical data is also useful to analysts because humans need clues, such as visual clues or visual displays of past information. By analyzing a large amount of data through intelligent interactive means, it can provide convenience for diagnosing urban traffic problems and mining crowd travel patterns.

This paper comprehensively analyzes the research progress of visualization in the field of transportation in recent years. Firstly, the pretreatment technology of traffic data is briefly analyzed. Then the traffic flow and traffic event data types of road traffic are analyzed systematically. Finally, summarize the latest research trend of traffic visualization in recent years.
2. Traffic Data Preprocessing

Vehicle data collected by the Global Positioning System (GPS) is the most important and common data in the intelligent traffic management System[1]. A lot of research work is to record the coordinate information of vehicles by onboard GPS, and upload it to the server for storage and analysis to obtain the historical driving track of vehicles. In addition to the GPS, traffic data collection also includes China's BeiDou Navigation Satellite System, Russia's GLONASS and Europe's Galileo Satellite Navigation System. The traffic acquisition equipment includes laser detector and ground sensor. This paper focuses on the analysis of GPS trajectory data visualization technology, because the GPS data processing is relatively complex, so only a brief introduction to the data preprocessing.

The characteristics of data pre-processing are mainly reflected in the following aspects[2]:

- ITS has a large amount of data, and traditional manual processing methods are not suitable for processing massive data.
- The probability of errors and failures of traffic detection equipment increases greatly under long working conditions.
- Different real-time traffic data processing methods should be adopted according to the data requirements of different systems and users.

2.1. Data cleaning

There will be signal loss during the driving of vehicles, which will lead to the interruption of GPS data. Based on these cases, the data relationship is judged and handled in the correct way.

Data cleaning is to fill the missing data values, with noise (random error or deviation in a measurement variable) data smoothing (commonly used methods are: box, clustering and regression, etc.), the inconsistent data are correct, recognition or remove outliers of data (including: grammar class, abnormal semantic categories, covering such exceptions). Data cleaning is often associated with data integration. When data integration is carried out from multiple data sources, errors in data are eliminated through data cleaning technology to obtain high-quality data. Based on high-quality data analysis, it is possible to obtain reliable analysis results.

2.2. Data integration

In the process of processing GPS data, there will be some phenomena such as failure of fusion and data redundancy, so we need to integrate the data.

Data integration is the process of integrating data from multiple data sources into a consistent storage device to provide a unified view of the data. Metadata integration of the different data sources, and then to identify the entity (to match different data sources of the same entity in the real world), the final test and solve the conflict between the data values (attribute values of different or diverse: the difference of data management system, the differences between the communication protocol, the differences between the data model, data type differences, the differences between the values, the differences between the semantic). For example, for the redundancy in data set caused by different attribute or dimension naming, given two attributes, the correlation of data can be tested by the following formula[4]:

\[ r_{AB} = \frac{\sum(A - \bar{A})(B - \bar{B})}{(n - 1)\sigma_A\sigma_B} \]
Where $n$ is the number of tuples, $\bar{A} = \sum A/n$, $\sigma_A = \sqrt{\frac{\sum (A-\bar{A})^2}{n-1}}$.

2.3. Data transformation
Data transformation is to normalize the data to achieve a form suitable for mining, which is more convenient for effective extraction of data information. Common data transformation is: simple function transformation, normalization, discrete continuous attributes, attribute construction, wavelet transform.

2.4. Data protocol
The data is compressed to produce a new smaller data set while maintaining data integrity. Common protocol methods are: data cube aggregation, dimensional protocol, data compression, numerical protocol. After the protocol processing, the data set can be presented in the form of flat files by the three main dimensions of row (sample), column (feature) and feature value[3]. The data set after statute is more efficient in analysis and mining: it can reduce the impact of invalid and wrong data on modeling and improve the accuracy; it can reduce the time required for data mining; it can Reduce data storage costs.

3. Visual analysis of traffic data

3.1. Visual analysis of traffic flow
The early research work mainly focused on the visualization of traffic flow, with the purpose of intuitively displaying the spatio-temporal variation characteristics of traffic flow and assisting managers to understand and analyze urban traffic conditions.

Andrienko et al.[5] developed methods to support the understanding of motor behaviour and movement patterns, and proposed an analytical framework. It combines interactive visualization, database processing, and computing techniques for data conversion and analysis to analyze the interactions and synergies of different types of technologies. The system USES an OPTICS algorithm[6] to cluster selected points of interest and reconstructed transit trajectories to improve the OPTICS. The flow chart drawn on the map is an intuitive representation of the running track of vehicles, with arrows pointing to the direction of the track and width representing the flow size of the track (as shown in FIG. 1). By extracting trajectory feature points (starting point, ending point, turning point), drawing circles around points is extended to the region, and movements between pairs of circles are collected to form track fragments for visual expression (as shown in FIG. 2).

![Figure 1 Track traffic](image1.png)

![Figure 2 Feature point movement diagram](image2.png)

Literature [7] analyzes the structure and basic properties of traffic trajectory data and adopts different visualization methods. Considering the known methods, namely S×T aggregation (space × time) and S×S×T aggregation (starting point × end point × starting time × end time × end time), new methods are introduced: S×T×d aggregation (S×T× direction) and R×S×S×T×T aggregation (path ×S×S×T×T×T).
×T). Proving the possibility of moving data from two different perspectives, we put forward the trajectory oriented view and traffic-oriented view of vehicle movement data. The motion of a single entity is defined as a trajectory; The spatial position of all entities at time t is defined as traffic condition. Flow oriented, $S \times t$-aggregation expressed in Mosaic is proposed to divide time and space into regular rectangular grids. The horizontal coordinate of Mosaic represents days, the vertical coordinate represents hours, and the color represents velocity (as shown in FIG. 3). For trajectories, we propose to group trajectories according to starting point and ending point. The 2-dimensional Mosaic can only reflect a small area of the query plane, the temporal and spatial distribution of traffic flow of a section of road, and the lack of overall feature changes in time and space. Therefore, on the basis of time, space and attributes, Tominski et al[8] designed a visual solution based on the principle of superimposed track band. The property data of a single track is visualized as color-coded bands, and the bands are superimposed into a group of tracks. The mixed 2D/3D tracks are visualized by superimposing 3D color codes on the 2D map. The color-coded strips are built into the track wall from the bottom up according to time. As an auxiliary to the time analysis of track properties, a 2-dimensional time lens is established. The outer ring of the lens is the time distribution, and the interior is the space track points linked to the outside, which can clearly show the traffic conditions at a certain time and place (as shown in FIG. 4).

In fact, spatio-temporal information of 3d trajectory visualization method can be seen as early as in literature [9]. In the visualization scheme of literature [9], spatial-temporal aggregation of track data is emphatically analyzed, and different colored lines are used to represent the aggregation of different tracks above the map (as shown in FIG. 5). Similar to literature [8], Eccles et al[10] designed the visualization of moving track velocity, with the X-axis and Y-axis representing the spatial attribute and the z-axis representing the time attribute (as shown in FIG. 6). Similarly, reference [10] also USES color to express the speed of movement (red is fast movement, white is vice versa). The difference is that literature [10] USES notes with geography and time to describe important events to improve the visual analysis understanding.
Rinzivillo et al [12], investigated the possibility of visual exploration and analysis of a large number of motion tracks (i.e. time-stamp position sequences of some moving entities) based on the "progressive clustering" technique. Andris et al [15], took the GPS track movement data of taxis in Shenzhen as an example to conduct visualization research and analysis, and found their driving rules. Zhang et al [19], used the clustering method to excavate the motion track and found its driving rules. Based on the GPS mobile data history information of taxis, Microsoft has developed a t-drive system [13], which extracts driving directions and recommends the optimal path for users at specified time. A clustering method based on variance entropy is proposed to estimate the travel time distribution of two markers in different time gaps. Microsoft's t-drive has been able to recommend suitable routes for experienced taxi drivers to reach their destinations in a given time, which usually takes less time than a route based on distance. In the real world, however, taxi drivers may take different routes to reach the same destination. Liu et al [14], proposed a new visual system (as shown in FIG. 8) that USES taxi track data to analyze route diversity, displaying high-dimensional attributes and statistical information related to different paths, so as to help users analyze diversified patterns. Li et al. [17] visualized the historical track data of taxis and predicted the number of passengers in a certain area in a certain period of time. Qi guande et al. [18] used taxi GPS data as samples to calculate the probability distribution of passenger waiting time to predict the passenger waiting time at a certain time and place in the future.

Pu et al. [11] proposed an interactive visual analysis system, t-watcher, based on taxi track data, for monitoring and analyzing complex traffic conditions in big cities. Compared with literature [8], literature [11] pays more attention to the time-varying characteristics of traffic flow in different regions and roads, providing reliable information support. The system adopts fingerprint identification method, which converts the obtained data information into visual clues such as shape, color and size to improve the user's operation experience. The fingerprint view is a spiral and annular view (as shown in FIG. 7). The annular and axial directions respectively represent different time scales, and the values of attributes
(flow rate, vehicle speed, etc.) shown in the color depth recognition are high and low.

Lv et al. [20] conducted cluster analysis on the GPS track data of taxi passengers and divided their traffic districts. Chen et al. [16] visualized and analyzed the GPS track data of floating vehicles in zibo city, shandong province as the research sample, presented the changes of urban regional operation in the form of thermal map, and divided the functions of urban areas. Urban areas are color-coded for vehicle density. Based on the color classification established by Bergman et al. Road grade: green for main road, red for minor road and branch road. Baskaran et al. [21] applied visualization of GPS track data set of taxi and proposed a new time representation method: mapping time to time curve in color space. Three different visual schemes are designed: circle type, circle type and spiral type (as shown in FIG. 9). Haubler et al. [22] used travel-related data and individual point data as samples to conduct semi-automatic classification and propose an interactive visual analysis.

3.2. visual analysis of traffic events

The study of traffic trajectory data is not limited to effectively expressing its spatio-temporal characteristics. In recent years, researchers pay more and more attention to how to deeply dig traffic data through effective and intuitive visualization technology to discover hidden traffic events. Knowing when, where, and why traffic events occur is more valuable to traffic planners in making decisions. Traffic events are commonly understood as events that affect road capacity.

In a multi-car track in a city, traffic planners may first need to find out where traffic jams occur, and then investigate The Times and duration of traffic jams throughout the day. Andrienko et al. [24,25] proposed a visualization technology based on density clustering to identify road congestion points. In this technology, the trajectory of congestion is defined: m- event is the speed below a certain threshold. This visual interface displays the congestion in different directions in different colors on the map, and distributes the time dimension in the cube in the 3d visual interface (as shown in FIG. 10).

In addition to visualization of traffic congestion, Wang et al. [26] further studied the propagation state
of congestion on the road network. Based on GPS track data, the strategy of extracting and deducing traffic jam information is proposed. Match the processed tracks with the road network, calculate the speed of each section, and automatically monitor traffic jams. In Beijing, for example, when users select a traffic jam, the system will display the distribution characteristics of traffic speed over time in a pixel map.

![Figure 10 Spatio-temporal cube track information](image1)
![Figure 11 Dynamic categorization data view](image2)

The traffic events in this paper include not only traffic congestion, but also the state transition of vehicles in the process of moving. Von Landesberger et al. [23] proposed a new visualization analysis method for spatio-temporal classified data: dynamic classified data view (DCDV). This method supports global and local representative time step selection algorithm based on classification variation. It is mainly composed of space, time, and classification attributes. Users can select in space or classification view, effectively switching between states. Such as driving from home to work, arriving at the office, and returning home. DCDV interface view is composed of columns and inter-column strips. X axis represents time attribute, each cylinder represents different vehicle states, cylinder length represents the number of vehicles under different states, inter-column strips represent the number of vehicles under different states, and different colors represent related activities between different points (as shown in FIG. 11).

4. Latest research trends

4.1. semantic analysis
Chu et al. [27] visualized the hidden theme of taxi movement by using semantic transformation. The method converts the geographic coordinates (i.e., longitude and latitude) to the name of the road section, and then the trajectory of each taxi is converted to a "document", so as to carry out identification based on LDA (latent dirichlet allocation) modeling technology. Wang et al. [28] proposed a data-driven solution based on the visualization analysis system to evaluate the real traffic conditions based on the taxi track data. A visual interface is designed to support dynamic query and visual reasoning of traffic conditions in multiple coordination views, and a new road-based query model is proposed for analysts to perform interactive assessment tasks. Some mature visualization technologies are integrated into the system as coordination views, including traffic comparison view, velocity/distance view, traffic/velocity view, topology view and traffic density view, for users to deeply study various traffic phenomena.

4.2. context analysis
Road traffic accidents and vehicle faults are the main causes of vehicle congestion and delay, but the mechanism of traffic congestion is not fully understood. In order to help traffic controllers make effective decisions when emergencies occur, Anwar et al. [29] proposed traffic origins. The visual interface USES an expanded circle to mark the area where the traffic accident occurs. The central point is the location of the accident, the area within the circle is the state of the road around the accident, and the color is used to indicate the road condition (as shown in FIG. 14). The flow condition of the road section in the circle is the relevant context of the event.

In addition to the origin of traffic, the destination and buildings of pedestrian travel are also one of
our researches in the visualization of urban traffic trajectory. Human activities are not independent of their surroundings (that is, the places they visit). Most of the time, people travel with specific goals and often revisit their favorite places. The correlation between human trajectories and different nearby "points of interest (POI)" was studied by using the GPS movement trajectories of a large number of users distributed in different locations. Krueger et al. [31] proposed a way to enrich trajectory data using semantic POI information and showed how to obtain additional insights. This method is based on density clustering to extract destination from database and query effective information to enrich semantic background.

4.3. Interactive Means
In the traditional data visualization, especially the traffic trajectory data visualization, the map will be covered to a large extent. The combination of visualization and map effectively enables users to observe and analyze data information more clearly. Guo et al.[36], based on three different path conditions: starting and ending position, passing position and geometric shape, take the traffic track data of the intersection as an example, and select them from left to right. Krueger et al.[34], stratified the time axis, supporting different time measures such as year, month, day and hour respectively. Filtering the time range is done through graphical controls. Ferreira et al.[35], also had similar visual design. Sun et al.[33], extended seam carving algorithm to extend interested roads in the map to other areas with minimal distortion, and then embedded time display into the road to display time patterns without masking map information. Design decisions are validated by the user by encoding time direction and time display.

In addition to effectively combining visualization with maps, visualization can also be combined with data mining to make optimal decisions for users. Wang yongsheng et al.[32], designed and implemented VISDMiner by improving mic-pca algorithm based on principal component analysis with maximum information coefficient. The traditional data visualization only takes the data as the research object, but does not visually display the data mining algorithm itself. The interactive data mining visualization system combined with data mining and visualization will make it easier to observe and understand the hidden information of data in the mining process and make better solutions.

5. Conclusion
We're in the midst of a data explosion, and the implications of data are both opportunities and challenges. On the one hand, many achievements have been made in the research and analysis of traffic trajectory data: traffic status estimation, traffic behavior analysis, travel OD prediction, taxi operation level evaluation, etc. Semantic analysis and context analysis have different degrees of breakthroughs, providing a strong analytical processing capacity. Visual analysis technology combines human-computer interaction to effectively convey information to users in a graphical way and provide solutions, decision support and other functions. On the other hand, despite the boom in traffic visualization in recent years, we still have quite a few challenging problems to solve. Firstly, in the process of data collection, data uncertainty may be caused by sampling errors or privacy protection. How to improve the quality of data acquisition is our first challenge. Second, current visual analysis tools typically support only a single data type, and some programs require real-time data flow to support real-time decisions. How to effectively process data isomerization and real-time data will be our second major challenge. Third, most urban trajectory visualization should be designed and developed around users. User preference, task performance and algorithm efficiency should be considered comprehensively in this system. This is the third challenge we have to solve. With the increase of urban data volume and complexity, data analysis and data visualization will be applied to different fields for development in the foreseeable future. The combination of automatic analysis and visualization methods to achieve better information decision-making will be the focus of future research.

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