IOP Conference Series: Materials Science and Engineering

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To cite this article: Yujie Fang *et al* 2020 *IOP Conf. Ser.: Mater. Sci. Eng.* **782** 022013

IOP Conf. Series: Materials Science and Engineering **782** (2020) 022013 doi:10.1088/1757-899X/782/2/022013

A Survey of Time Series Data Visualization Research

Yujie Fang[a], Hui Xu[b], Jie Jiang[*]

College of Systems Engineering. National University of Defense Technology. Changsha, China

*Corresponding author e-mail: JieJiang@nudt.edu.cn, [a]17719498319@163.com, [b]xuhui17@nudt.edu.cn

Abstract. Time series data visualization integrates data analysis and mining, computer graphics, interaction design and other technologies and methods. This paper first analyzes the characteristics of time series data, including time and data attributes. Secondly, two kinds of visualization methods are summarized: one is the visualization method of time attribute, including spiral chart, calendar view, theme river view and dynamic view; the other is the visualization method of high dimensional time series data, which mainly summarizes four kinds of parallel coordinate methods. And the visual interaction design method is analyzed. Finally, the visualization of time series data is summarized and prospected.

1. Introduction

With the rapid development of society and the arrival of the era of big data, data analysis and mining capabilities are becoming more and more important. But for massive data, data mining may not have the desired effect. Compared with traditional data mining, the combination of visualization methods can help people understand data faster. In the massive data, a large part contains time attributes, which belong to time series data. Time is a very important attribute and dimension. Time series data [1] refers to a series of observations arranged in chronological order. Time series data visualization mainly studies the changes of data attributes and states over time and the moments when data states are abrupt. This facilitates the analysis and mining of data. At present, the time series data visualization methods are mainly divided into two categories: 1) static display, which combines multi-view and multi-view methods to show the evolution trend and law of data [2]. 2) Animation method [3], which records the state of the data on a time slice in each view, and then shows the state of the data as a function of time in chronological order. These two methods have their own advantages and disadvantages. The first method has the characteristics of being intuitive and effective, and the dynamic data is displayed in a static way to avoid the user's additional cognitive burden. The second method is more in line with people's long-term cognitive habits. However, users need to spend a lot of time recording changes between animations, increasing cognitive burden and reducing visualization. Therefore, most visualization schemes combine these two methods.

This paper analyzes the characteristics of time series data and summarizes two kinds of visualization methods. One is the visualization of time attributes, and the other is the visualization of high-dimensional time series data. Finally, the interaction design in time series data is summarized.

IOP Conf. Series: Materials Science and Engineering **782** (2020) 022013 doi:10.1088/1757-899X/782/2/022013

2. Characteristics of Time Series Data

Time series data refers to data with time attributes that change over time. Thus time series data has both time and data attributes. There are three main ways to characterize time attributes [4]:

- Linear time and cycle time

Linear time means that the time from the past to the future is linear. The cycle time refers to the cycle of the time domain, such as the change of seasons.

- Time points and time intervals

The time point corresponds to a discrete time point, and the time interval is a small linear time domain.

- Sequential time, branch time and multi-angle time.

Sequential time refers to events occurring in chronological order, and branch time refers to multiple time branches, such as different main lines in the novel. Multi-angle time can describe different points of view of a fact.

According to the framework of [5, 6], the data attributes can be divided into abstract and spatial features according to the reference standard; according to the number of variables, they can be divided into low-dimensional and high-dimensional features; and according to the data types, they can be divided into events and state features. Mastering the characteristics of the data is very helpful for us to visualize time series data.

3. Time Series Data Visualization

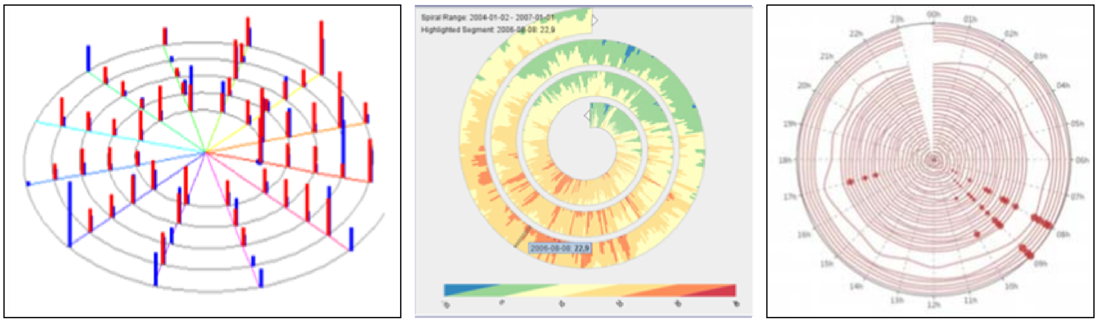
This section mainly summarizes two types of visualization methods: one is about the time attribute visualization method, and the other is about the high-dimensional timing data visualization.

3.1. Time Attribute Visualization Methods

Different types of time series data are expressed using different visualization methods. The standard display mode is that the x-axis represents time and the y-axis represents other variables, such as a line chart. This method can represent changes in data elements in the linear time domain, but it is difficult to express the periodicity of time. To this end, Carlis et al. [7] first proposed a spiral diagram method.

Spiral diagram: The spiral diagram is ideal for analysing periodic data. It is a spiral on the placement of the data loop, and a circle represents a cycle. For example, Fig. 1 (a) shows the population size of the data for two different chimpanzees (red and blue) travel. After that, the spiral diagram is constantly evolving and perfecting in terms of shape and interaction. As shown in Fig. 1(b), the literature [8] improves the traditional spiral graph from both visual expression and interaction, and displays the temperature sequence data with the new colouring method and the overview + detail interaction. The reference [9] changed the shape of the traditional spiral diagram and proposed a spiral fish-eye view (as shown in Fig. 1 (c)). It realizes the periodic display of timing data and the organic integration of user's attention.

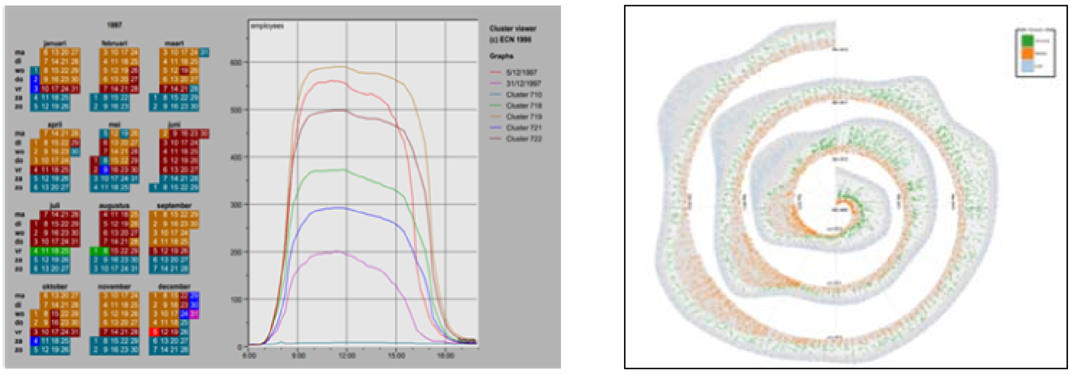
Calendar view: In reality, the time is divided according to the year, month, day, hour, etc. Also in the time series expression, the time attribute can be displayed according to the granularity, that is, the calendar time is visualized. Wijk et al. [10] propose a calendar view for clustering of everyday data values. Fig. 2(a) shows the number of employees on the job from 6:00 to 18:00 after 5 types of aggregation, and the comparison with the two types of average charts. Catarina et al. [11] improved the calendar view and proposed a radial calendar-based visualization model to analyze the consumption data of Portuguese retail companies. This model helps people identify periodic patterns and outliers. Reference [12] combined with the calendar view, visual analysis of air quality data reveals its relationship with quality of life and prevents harm to citizens' health.



(a) (b) (c)

Fig. 1. Three types of spiral views. In the figure, (a) is Classic Spiral, (b) is Enhanced Interactive Spiral, and (c) is Spiral Fisheye View.

ThemeRiver View: ThemeRiver [13] uses river flow to metaphorize the progress of time. The width, direction, and color of the river characterize different subject objects and attributes. Jiang et al. [14] combined the ThemeRiver and spiral view to propose a Spiral Theme Plot. The themes are stacked along a spiral curve, which represents the time axis. Each data point is drawn within the subject area and has various visual features. Fig. 2(b) shows that seasonal characteristics of flu, malaria and CAD during 3 years. Reference [15] proposes an intelligent transportation system, which aims to analyze the diversity of time-space urban mobility data and use the theme river map to visually analyze traffic flow data.



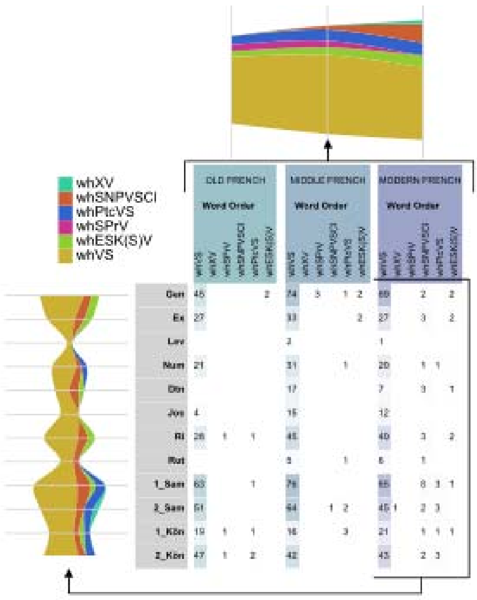
(a) (b)

Fig. 2. Calendar View and Spiral Theme Plot.

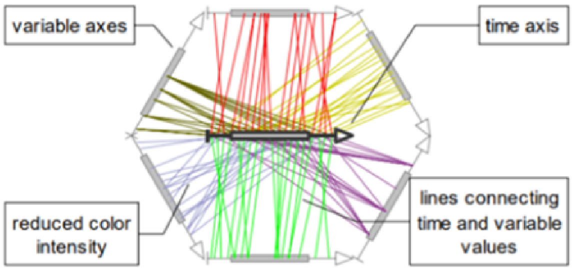
Dynamic visualization: Animated expression [3] refers to a visual chart that plays each time point frame by frame. This can continuously show the changing trend of the data. Hans et al. [3] proposed the Gapminder Trendalyzer. Trendalyzer uses the position information (x-axis and y-axis) of the bubble chart, the size of the shape to display the three dimensions of the data, and the animation of the fourth dimension (time). An example of Trendalyzer Tools is the trend of wealth and longevity in various countries from 1800 to 2018. Fig. 3 is one of the frames that visualizes the wealth and longevity of each country in 2018. References [16, 17] use 3D animation techniques. The former uses 3D animation technology to evaluate human motion in motion. The resulting animation clearly depicts the athlete's posture and the acceleration synchronized with the gait cycle. The latter is an analysis of molecular dynamics (MD) simulations to understand protein dynamics and functions. Although there are certain flaws in animation expressions, when we interpret dynamic events, we use animation expressions appropriately to achieve a thousand words.

Fig. 3. Gapminder Trendalyzer.

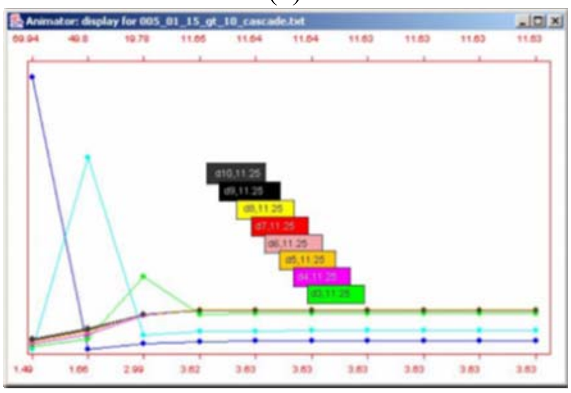
There are many other ways to visualize time attributes. For example, the worm map [18] is based on a scatter plot. Draw a scatter plot for each individual moment and then represent some clusters or specific points as a circle. The circles belonging to the same cluster or data item are then connected by an interpolation algorithm. In this way, a pipe will be formed, which is called a worm. The distribution of data over time can be obtained by observing the direction and shape of the pipeline. But for high-dimensional time series data, the visualization of these methods may not be good. Below we will discuss the visualization of high-dimensional time series data.



(a)



(b)



(c)

Fig. 4. TimeWheel, Animator and ParHistVist.

3.2. High-dimensional Time Series Data Visualization Methods

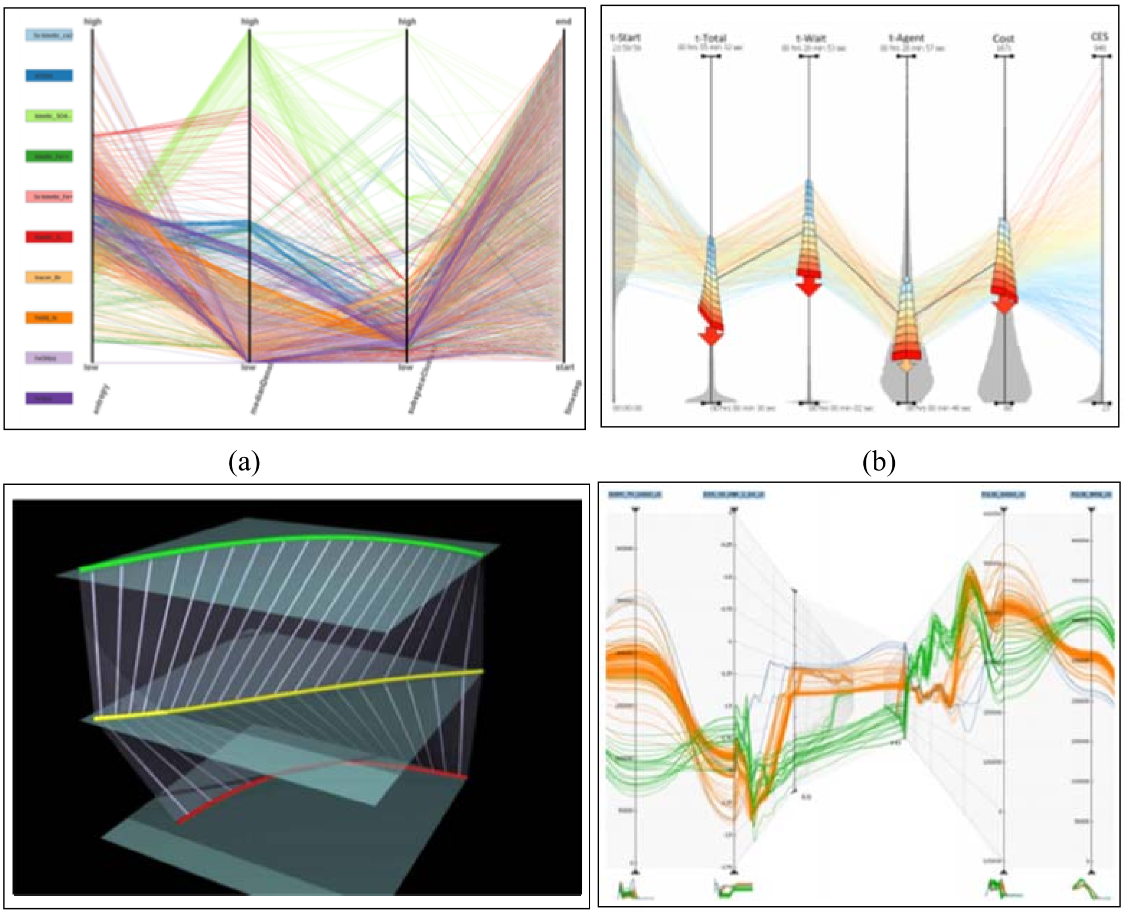
High-dimensional timing data visualization needs to show the process of changing data state over time and the process of each dimension changing with time. At present, common high-dimensional time series data visualization methods include a theme river view and a parallel coordinate chart with a time axis. ThemeRiver [13] is a variant of the stacked graph, which is stacked in the order of attributes to get ThemeRiver. ThemeRiver shows the process of changing each dimension over time, and linearly superimposes each dimension to show the overall state of the data over time, so it can visualize high-dimensional time series data. Kalouli et al. proposed a new visualization tool, ParHistVis [19], which analyzes the complex interactions between time, text and language for the same level of multi-language historical data. As shown in Fig. 4 (a). The following mainly introduces the visualization method of High-dimensional timing data based on parallel coordinate graph.

1) Represent time as a single axis in a parallel graph. A tool was developed in Reference [20] - TimeWheel. It places the time axis in the center of the display, and the other attribute axes are arranged around the time axis, instead of the parallel axis, as shown in Fig. 4(b). The disadvantage of this method is that rapid over-drawing causes visual redundancy.

2) Parallel coordinates only show high-dimensional data at a certain moment, and the current time is adjusted by animation or slider to show the data changes with time. Barlow et al. [21] proposed the animator tool, Fig. 4 (c) shows display area of the animator tool at time slice 60.

3) Integrate the timeline as a separate axis into parallel coordinates, which actually converts it into a partial time series plot. The biggest problem with this type of method is the clutter of the edges caused by the excessive number of polylines when the amount of data is large. Dasgupta et al. [22] proposed a quaternary parallel coordinate system, Meta Parallel Coordinates (MPC). The MPC calculated the three parameters (entropy, density, and subspace density) and the time axis of all the arguments to form a parallel coordinate system, as shown in Fig. 5(a). In recent years, Roberts et al. [23] proposed a smart brushing technology that enhances the interaction of parallel coordinate systems, which is more convenient for data analysis, as shown in Fig. 5(b).

4) Extend the parallel coordinates of the high-dimensional time series data set to three dimensions. Wegenkittl et al. [24] created a parallel coordinate system for each different time step and moved along the third spatial axis, as shown in Fig. 5(c). They create a set of height fields by connecting line segments of a single data item, and are transparently rendered by multiple height fields to reduce occlusion. Reference [25] improved the work of Wegenkittl et al., analogous to the z-axis, embedding time series between two adjacent axes of a parallel coordinate map as a three-dimensional time axis. It integrated the focus and context of the two views, as shown in Fig. 5(d). Recently, Okada et al. [26] introduced three-dimensional parallel coordinates and added 2D to 2D visualization functions to propose a visualization tool—PCTT. The central axis of the PCTT is the time axis, and the other color planes represent different dimensions. Thus, the cross section of the time axis is a radar chart, and the trend of data over time can be seen on each color plane.



(a) (b)

(c) (d)

Fig. 5. Four types of parallel coordinate views, where (a) is Meta Parallel Coordinates, (b) is Smart Brushing, (c) is Extended Parallel Coordinate View, and (d) is a parallel coordinate view with the time axis as the z axis.

To help you better understand the time series data visualization methods, the above methods are summarized in the following table.

The visualization of high-dimensional time series data is very helpful for mining massive data. But the charm of visualization is not only this, but more importantly, it makes people a part of the system. The visual interaction design of time series data is described below.

Table. 1. Summary of Time Series Data Visualization Methods

<table>
<tr><th>Two types of methods</th><th colspan="2">Visualization methods</th><th>Related references</th></tr>
<tr><td rowspan="5">Time Attribute Visualization Methods</td><td colspan="2">Spiral diagram</td><td>[7], [8], [9]</td></tr>
<tr><td colspan="2">Calendar view</td><td>[10], [11], [12]</td></tr>
<tr><td colspan="2">ThemeRiver View</td><td>[13], [14], [15]</td></tr>
<tr><td colspan="2">Dynamic visualization</td><td>[3], [16], [17]</td></tr>
<tr><td colspan="2">Others</td><td>[18]</td></tr>
<tr><td rowspan="5">High-dimensional Time Series Data Visualization Methods</td><td>ThemeRiver Mothods</td><td>ParHistVist</td><td>[19]</td></tr>
<tr><td rowspan="4">Parallel coordinate methods</td><td>TimeWheel</td><td>[20]</td></tr>
<tr><td>Animator</td><td>[21]</td></tr>
<tr><td>MPC and Smart Bushing</td><td>[22], [23]</td></tr>
<tr><td>3D parallel coordinate methods</td><td>[24], [25], [26]</td></tr>
</table>

4. Visual Interaction Design

In order to effectively combine people and systems, and to take advantage of visualization, interaction is an essential part. Data interaction visualization is designed to engage users and better understand and analyze data. Shneiderman's principle of visual interaction [27]: Overview first, zoom and filter, then details-on-demand. There are currently seven comprehensive visual interaction methods in general [28]: select, explore [29], reconfigure, encode, abstract/elaborate, filter, and connect. The specific meanings are as follows.

In order to solve the problem of data complexity, four visualization interaction modes are proposed: dynamic change view, multi-view association [30], view content reduction, focus + context [31]. Dynamically change the view, it can mainly transform the view through reorganization sorting, animation transition, colour coding, etc., to achieve the purpose of clear data contrast. Multi-view association [30] is to divide the display area into multiple views or layers, using different association methods (such as overview + detail, side-by-side multi-view, multi-style coordination association, etc.) to reduce data complexity. The reduction of the view content is to reduce the display content, only show the aspects of interest, and let the user actively filter information or aggregate information. Focus + Context [31] embeds the selected element, the focus, into the overview map in the same view, the context. It reduces the amount of data presented in the view through complex filtering and aggregation operations. This can alleviate the lost direction caused by standard navigation technology and provide contextual identification to support positioning. A new interactive visual analysis method was designed and developed in reference [17] for long time and crowded MD simulation. In this approach, dynamic three-dimensional focus + context visualization is combined with two-dimensional diagrams of time series data to guide detection and navigation of important patio-temporal events. Visual Interaction Methods

Table. 2 Visual Interaction Methods

Interactive methods	**meaning**
Select	Filter interested objects
Explore	Show different information
Reconfigure	Show different visualization configurations
Encode	Show different visual performance
Abstract/Elaborate	Show overview or more details
Filter	Show partial data based on criteria
Connect	Show relevant data

5. Conclusions and Outlook

This paper summarizes the research work of time series visualization from three aspects. First, the characteristics of time series data are analysed from time attributes and data attributes. Secondly, the visualization method of time attribute and the visualization method of high-dimensional time series data are analysed. Finally, summarize the seven methods of visual interaction and the four visual interaction modes.

With the advent of the era of big data, massive time series data is emerging, and time series data visualization faces enormous challenges. Traditional visualization methods encounter bottlenecks and need to be improved. How to effectively reduce the amount of data and more intuitive interactive expression is the current research difficulty. Integrating data analysis and mining techniques into visualizations and improving existing interactions may have better results.

Acknowledgments

Thanks for funding from the National Natural Science Foundation of China under Project 61873274.

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