Exploring 3D Trajectory Visualization in a Virtual Environment

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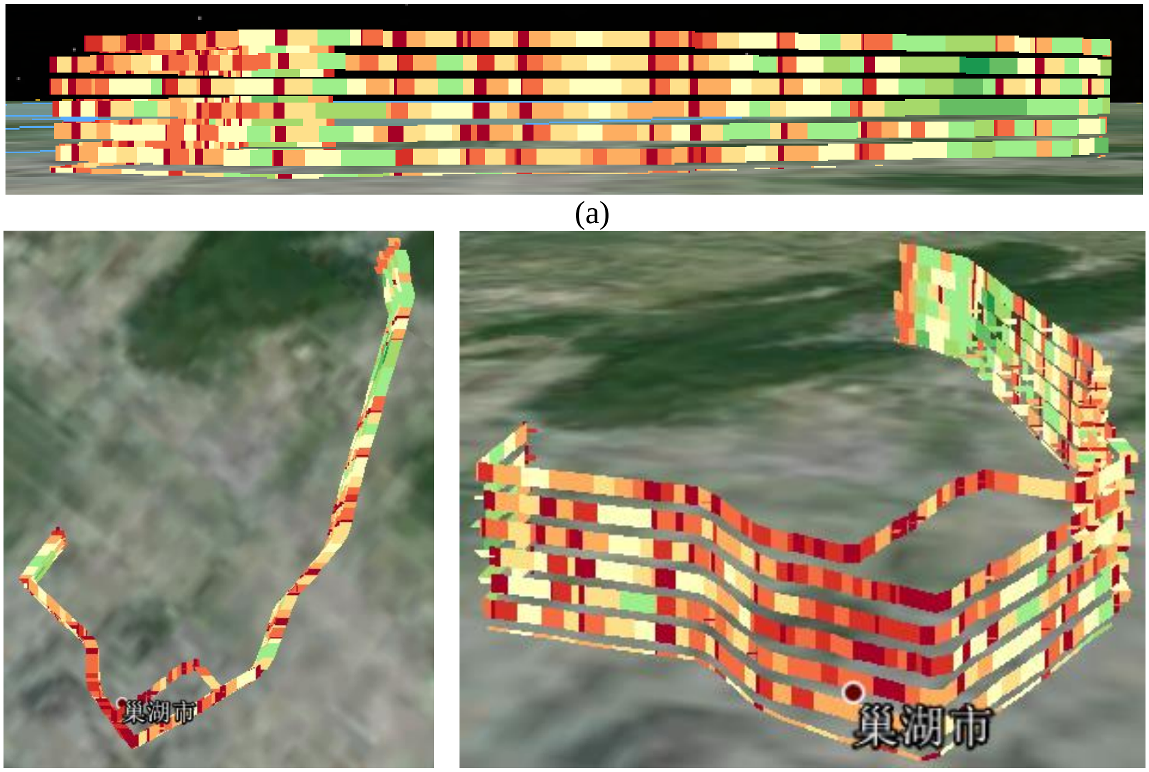
1. Introduction

As a common type of geographic data, trajectory data are represented in a three or higher dimensional space in nature. Information visualization technique comprehensively using multiple visual elements such as layout, colour, texture, shapes, etc. (zhang. 2007) has been considered an effective manner to find the spatiotemporal patterns of trajectory data. Especially, 3D visualization is useful to explore the spatial, temporal and multi-dimensional aspects in geographic data and to gain insight into the spatiotemporal dynamics of attributes. However, the usefulness of 3D visualization in practice is limited to several inherent drawbacks, such as clutter, overlapping and slow interactive operations. To address the above issues, we developed a new visualization technique on trajectory data. Distinct from existing approaches, our solution considers both the visual layout and human cognition in the visualization and thus increases the effectiveness of identifying and understanding the patterns from the visualization. More specifically, given the input data and application requirements, our approach supplements the visualization with multiple viewpoints which are optimized to observe different facets of trajectory visualizations, such as detail, overview and temporal variations. All of the generated viewpoints form a viewpoint sequence that allows the user to quickly and smoothly switch between different viewpoints and observe the visualization in an effective manner. In order evaluate the usability and effectiveness, we conducted a user study and the result is promising. Furthermore, we tested our technique in the immersive virtual reality, i.e.,Oculus Rift. The user study justified that our visualization technique is suitable in a virtual environment.

2. Our Approach

Among all of the information visualization techniques used to analyse the trajectory data, trajectory wall (Tominski et al. 2012) has been proved to be one of the most effective methods. By reading the colour distribution on the wall, the user can easily understand the attribute distribution in relation to the space and time. However, the diverse shapes on the trajectory wall make it challenging to easily find a viewpoint suitable for observing all the details of the entire wall (see Fig. 1). Consequently, it is time consuming for users to manually adjust the viewpoints to find a better perspective to observe the entire wall.



(b) (c)

Fig. 1. A trajectory wall observed from three viewpoints. (a) Side view. (b) Top view. (c) Oblique view.

In order to minimize user operations, our approach first divides the trajectory wall into multiple sections, each close to a straight line, and then establishes an orthographic viewpoint (see Fig. 2) for each section as the optimal *Detail Viewpoint*. This design is based on the assumption that the orthographic viewpoint is the most unbiased point for observing the projections of 3D visualization in a given plane. All of the established orthographic viewpoints form a sequence that can be played to explore the trajectory wall while maintaining the best viewing angle.

Assume $v = \{v_1, v_2, \dots v_{N-1}\}$ is the spatial location set of the route of a trajectory wall *W*, which divide *W* into multiple sections *w* (see Fig. 2). Given an angle threshold α and a distance threshold β, then a segmentation point s_i is added between w_i *and* w_{i+1}, if $angle(w_i, w_{i+1}) > \alpha$ *or* $length(w_i) > \beta$, in which *angle* function indicates the turning angle between w_i and w_{i+1}, and *length* function represents the length of w_i. This means that if the direction of two adjacent sections w_i and w_{i+1} changes a lot or the length of w_i too long to be carefully viewed in one viewpoint, a breakpoint will be added. Fig. 2 shows an example of trajectory being divided into 7 sections, in which s_1, s_2 , s_3 and s_6 are added for a direction reason, while s_4 and $s_5$is added for a distance reason. Seven viewpoints are added to different sections correspondingly.

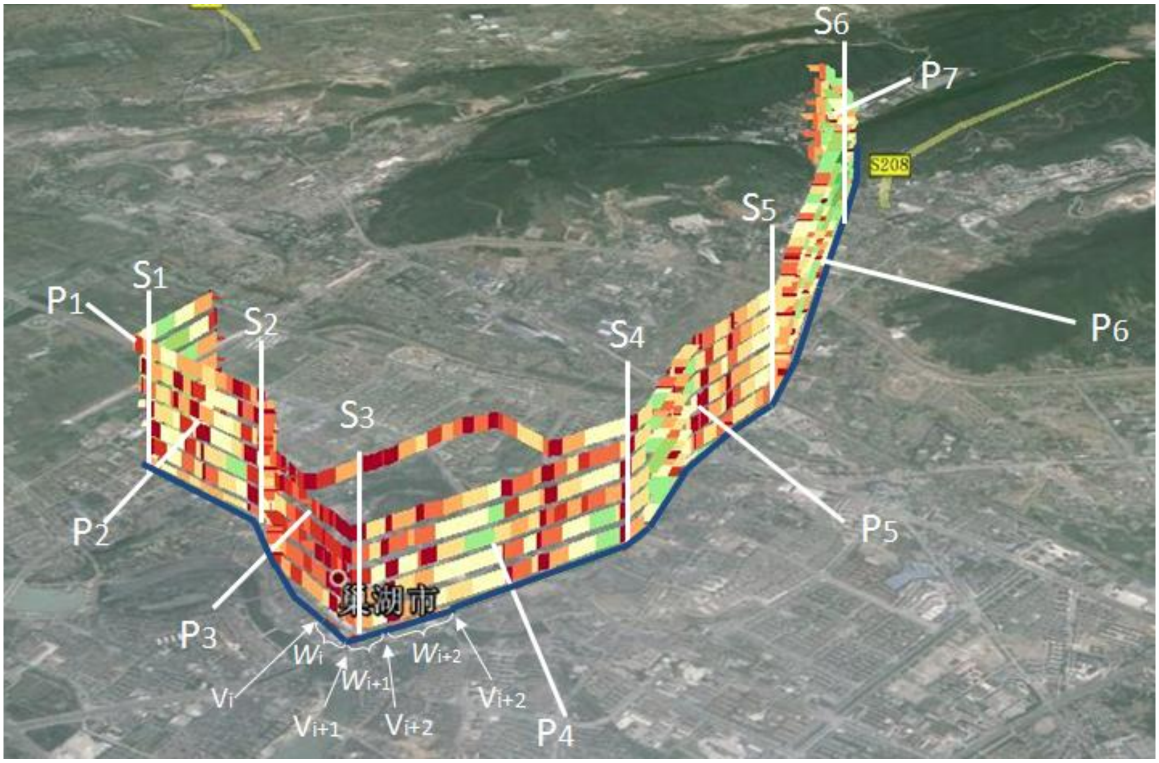


Fig. 2. Illustration of the viewpoint generation algorithm. Blue line indicates the route of the trajectory wall that consists of a spatial location set v.

It is important to provide an overview in the visual analysis of trajectory data. However, it is impossible to demonstrate the entire trajectory wall due to the overlapping problem. According to the characteristics of trajectory data, we design a viewpoint generation algorithm for determining an optimal viewpoint that can expose the largest amount of information to the viewer. To keep the viewpoint directly facing the direction that can give the most information, we find the longest intersection of the trajectory wall. Based on the definition of the spatial location set *v*, the longest intersection can be described as follows:

$$l = \left\{ \max\left(\mathrm{distance}\left(v_i v_j\right)\right) \middle| i, j \in (0, N) \right\} \tag{3}$$

Fig. 3 shows the longest intersection of a trajectory wall. We obtain the longest intersection by iteratively comparing the distances between every two vertices. It can be easily inferred that one can see the longest possible wall when facing the longest intersection.

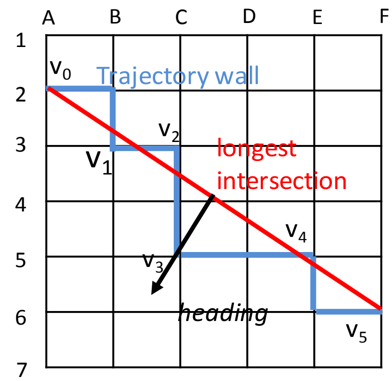


Fig. 3. Illustration of *longest intersections*.

3. Case Study

We use the public transportation data to evaluate the effectiveness of our approach. The dataset contains about 10 million bus GPS records of Chaohu (a small city in China's Anhui province). Our approach is implemented in two platforms. We first represent visualizations and the viewpoints in the form of KML (Keyhole Mark-up Language) and then import them into the Google Earth (a 3D GIS platform), as shown in Fig. 4. By playing the viewpoint sequence and utilizing the components of Google Earth, users can efficiently capture the attribute variation patterns of the trajectories.

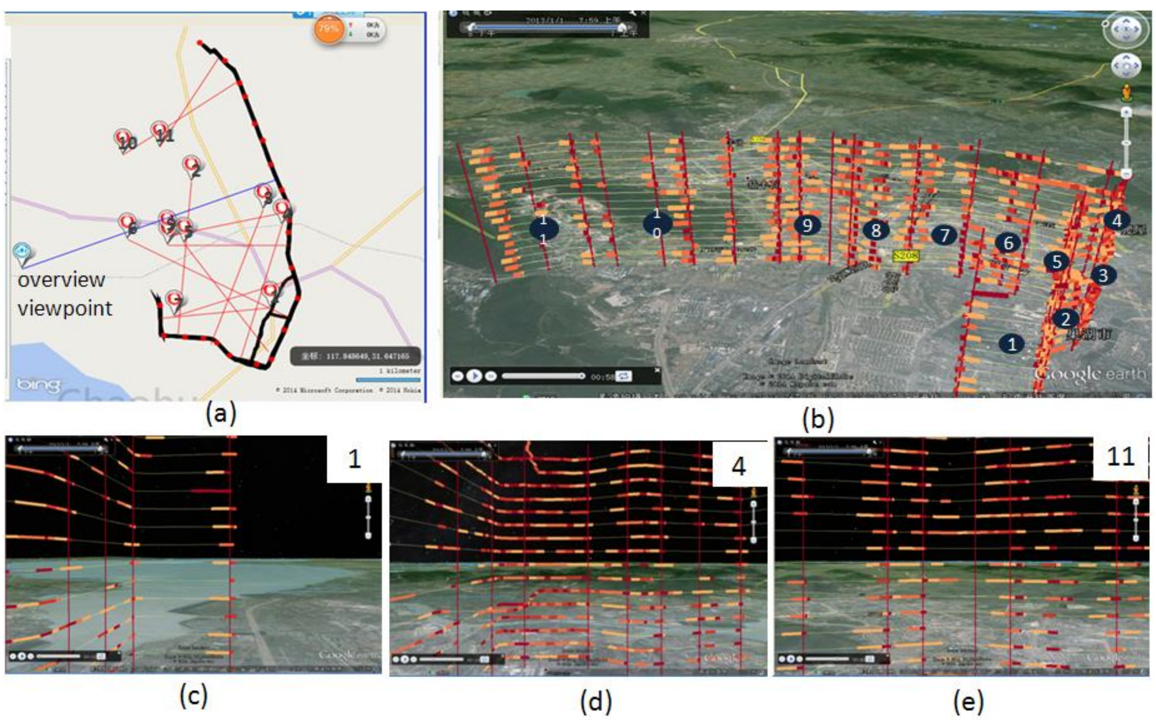


Fig. 4. Exploring a trajectory wall using our approach in Google Earth. (a) The generated viewpoints. The blue mark represents the *overview viewpoint*, while the red marks indicate the *detail viewpoints*. The viewing direction is drawn as a directed straight line.

(b) Observing the trajectory wall from the *overview viewpoint*, marked with 11 *detail viewpoints*. (c-e) Three *detail viewpoints.* The viewpoint number is written on the upper right corner.

As shown in Fig. 5, we also utilized Oculus Rift to render the generated visualization in a virtual reality environment. We created a specialized renderer for trajectory dataset using Oculus SDK with a steady frame rate of 60HZ. Using a keyboard as the movement controller, the user can orderly traverse each viewpoint in the 3D space, and observe the trajectory wall through natural gestures instead of using mouse and keyboard shortcuts.

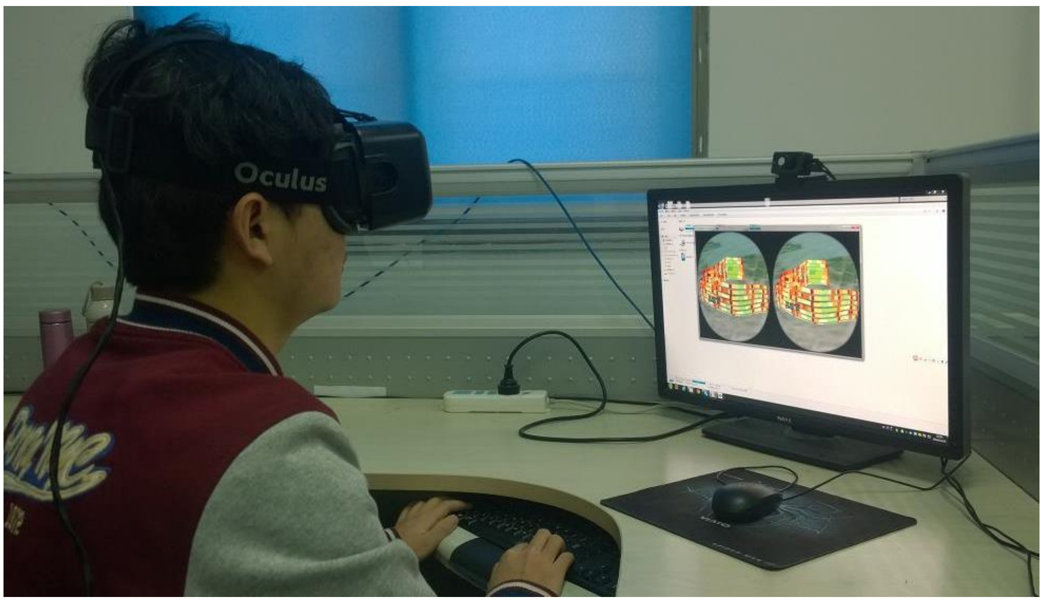


Fig. 5. Implementing our approach in Oculus Rift.

4. Experiment

We compared our approach with the original trajectory wall technique (Tominski et al. 2012) by testing 10 predefined tasks and analysing the completion time and *correctness* of each task in a virtual reality environment. For the study, we recruited 16 subjects from the School of Software Engineering, Tianjin University. Two of the subjects were female, while others were male. All the subjects were graduate students (aged 23-30), of whom 10 had experiences in visualization, and 4 had analyzed the public transportation data. None of the subjects had used our approach, and 13 of them had used Google Earth. The experiment implemented a between-group design. A total of 16 subjects were randomly divided into two groups, each group using either our approach or the original trajectory wall.

Generally, the exploration manner similar to the physical world received positive feedbacks. From the experiment result (see Table 1), we find the performance of our approach is significantly better than the original trajectory wall without viewpoints for the element of *time* $(t(9) = -2.569, p < 0.05)$, but not for the *correctness* $(t(9) = -1.406, p > 0.1)$. In our approach, the subjects can quickly find the targets by viewing the *overview viewpoint*, and switch to the targets by dragging the progress bar to the viewpoint sequence. On the contrary, the subjects had to manually control the viewpoint, when using the original trajectory wall. Sometimes, although the subjects had already found the target area, they had to manually adjust the viewpoint to that area to determine if the findings were correct. The no significant difference in *correctness* is mainly because the dataset used in our experiment was carefully selected, and the characteristics were easily recognizable.

Table1. Experimental Result

Task	Group A Our Approach		Group B Original Trajectory Wall	
	Time (s)	Correctness	Time (s)	Correctness
Task 1	38.875	100%	51.375	100%
Task 2	35.75	100%	83.625	100%
Task 3	18	87.5%	26.25	87.5%
Task 4	19.625	87.5%	32.75	87.5%
Task 5	18.25	100%	20	75%
Task 6	16.125	100%	19	100%
Task 7	16.625	87.5%	22.5	87.5%
Task 8	16. 5	100%	22	87.5%
Task 9	16.5	100%	24.125	100%
Task 10	18	100%	22.25	100%

5. Conclusion

This paper has presented a viewpoint based approach for exploring trajectory data. Three types of viewpoints specialized in different tasks and the corresponding algorithms have been developed. Our approach provides a general framework for exploring spatiotemporal data. Without losing generality, our approach has been evaluated on the public transportation data. The evaluation results justified that our approach is effective and useful in real-world scenarios. In the future, we plan to improve the approach in two aspects. First, we will investigate the theoretical aspect of the viewpoint generation using information entropy theory. Second, we will attempt to enrich the visual design of the 3D visualization.

6. References

Tominski. C, Schumann. H, Andrienko. G, and Andrienko. N, 2012, Stacking-based visualization of trajectory attribute data. IEEE Trans. Vis. Comput. Graph. 18(12): 2565-2574.

Zhang. K. 2007, From abstract painting to information visualization. IEEE Computer Graphics and Applications, 27(3), 12-16.