Optimal Viewpoint Finding for Space Time Cube to Explore Spatio-temporal Characteristics of Vehicle Trajectories on Crossroads

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ABSTRACT

Visualization combining space and time in a single display called "space time cube (STC)" is used for visualizing spatio-temporal movement data. An STC enables us to explore not only shapes and positions of vehicle trajectories but also their temporal distributions. However, it is difficult for users to manually find optimal viewpoints for understanding such characteristics of trajectories. In this paper, we propose an optimal viewpoints selection method for visualizing the spatio-temporal characteristics of vehicle trajectories on a large set of crossroads using an STC. For this purpose, we provide an algorithm based on viewpoint entropy weighted by angles of trajectories with a horizontal line as a measure of viewpoint quality on a projected 2D image. We then argue that our method can be adapted to crossroads with different trajectory shapes.

1 INTRODUCTION

Widespread vehicle recorder systems enable us to track, collect, and analyze the location of automobiles. Visualization helps us understand and analyze such spatio-temporal trajectory data [2]. Some systems add a third axis to represent time, and are sometimes called "space time cube (STC)". In an STC, movements with latitude, longitude, and time become trajectories in a 3D space.

Amini et al. conducted an experimental comparison of 2D and 3D visualizations of movement data to reveal their advantages and disadvantages [1]. Although they found that an STC has an advantage of exploring temporal information, users spend much time rotating the camera view in the STC. Camera angle reorganization is crucial for an STC to obtain optimal viewpoints for understanding targets.

There have been studies on viewpoint selection for general 3D meshes and volume rendering [8] [3] [6]. Lee et al. and Tao et al. studied viewpoint selection for flow visualization [5] [7]. Although they focused on streamline selection and viewpoint selection to identify salient flow regions, our study was focused on viewpoint selection to understand both the shapes of streamlines on a map and streamline distribution on the time axis.

We have been studying systems for exploring caution spots from vehicle recorder big data [4]. We have developed a system for ranking caution crossroads based on vehicle recorder data, road shape, and weather information. Visualization of the spatial structure and temporal distribution of vehicle trajectories is required for analyzing caution crossroads in detail. However, it is difficult for users to manually find optimal viewpoints that effectively display both the spatial and temporal characteristics of vehicle trajectories for observing them on a map. This is particularly impossible on a lot of crossroads. Therefore, a method for automatically selecting optimal viewpoints in an STC is necessary.

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This paper proposes a novel method for automatically selecting optimal viewpoints for visualizing the spatio-temporal characteristics of trajectories on multiple crossroads using an STC. For this purpose, we provide an algorithm based on viewpoint entropy weighted by angles with a horizontal line as a measure of viewpoint quality of rendered trajectories on a projected image. We then argue that our method can be adapted to crossroads with different trajectory shapes. To the best of our knowledge, there has been no research on viewpoint selection for visualization of trajectories using an STC.

2 VIEWPOINT ENTROPY BASED APPROACH

What is an optimal viewpoint in our required system? First, such a viewpoint should display as much as possible shapes and positions of trajectories on a map for understanding what types of driving operation, e.g., braking, occurs on caution crossroads. Second, it should show the distribution of trajectories on the time axis to understand when traffic volume is high.

To satisfy these requirements, it is first preferable that trajectories be widely distributed throughout the 2D screen. However, if the trajectories are widely spread on the screen, it is sometimes difficult to read the trajectory shapes. From our observation, it is difficult to understand the shapes and temporal distributions of trajectories whose projected angles on a 2D screen with a horizontal line are close to vertical. It is easy to understand them if there are many trajectories with loose angles with the horizontal line.

We divide screen space into tiles and compute weighted viewpoint entropy with the following formula:

$$E = \sum_{x=1...n} \frac{|s_x|}{S} log_2 \frac{|s_x|}{S} \cdot log_2 c\lambda_x \qquad (1)$$

Each trajectory consists of m segments[1] to show the trajectory around a crossroad. We count the number of segments $|s_x|$ for each tile x. The notation S means the total number of segments. We modify the formula for Shannons entropy $\sum_{x=1...n} \frac{|s_x|}{S} log_2 \frac{|s_x|}{S}$ by weight $log_2 c\lambda_x$, where c is a constant value. The notation $c\lambda_x$ is defined by the angles of projected segments with the horizontal line in each tile as $\lambda_x = \frac{\sum_{s \in S_x} f(\theta_s)}{L}$, where L is defined by $\sum_{x=1..n} \sum_{s \in S_x} f(\theta_s)$. From our observation, we assume that the amount of information is large when the angle is close to 30 degrees, so we define $f(\theta_s)$ as

$$f(\theta_s) = \begin{cases} -a * \theta_s + b & (\theta_s \leq \theta) \\ a * \theta_s - b & (otherwise) \end{cases}$$

where $0 \leq \theta_s \leq 90$[2].

To search for the optimal viewpoint, we sample 144 viewpoints from the upper hemisphere surrounding the target STC. We rank viewpoints by the corresponding entropies to select the optimal viewpoint. The viewpoint samples are generated by rotating a viewpoint by 15 degrees up, down, left and right around the center of the STC.

3 RESULTS OF VIEWPOINT RANKING

We have been studying systems for exploring caution spots from the big data recorded from multifunctional vehicle recorders that have

[1] $m = 20$ in this experiment.
[2] $c = 1$, $a = 1.0/60$, $b = 0.5$ and $\theta = 30$ in this experiment.

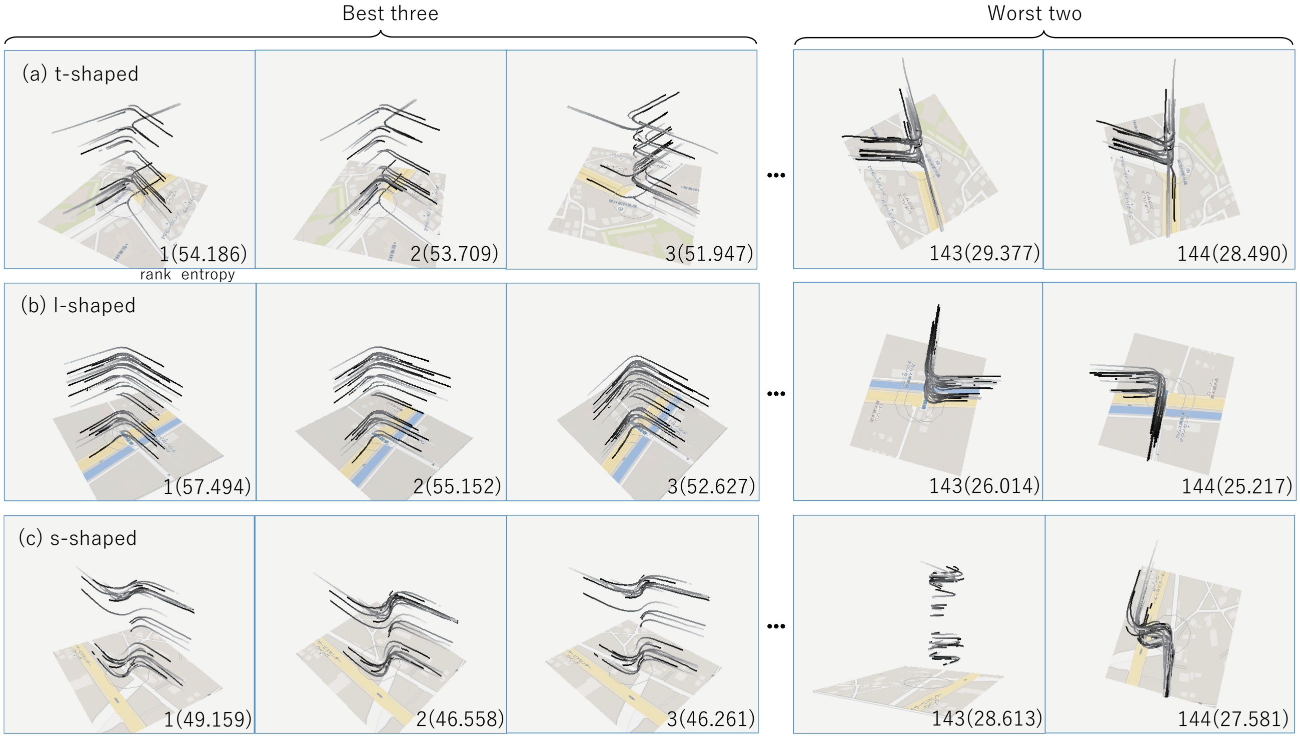

Figure 1: Ranking of viewpoints with proposed viewpoint entropy based method. Each row represents results for different types of crossroads having different characteristic trajectory shapes: (a) t-shaped, (b) l-shaped, and (c) s-shaped.

longitudinal accelerometers, lateral accelerometers, gyro compasses, and GPS [4]. A drive recorder automatically detects basic driving operations such as braking and handling. Several statuses are recorded such as speed, acceleration, and jerk during such an operation. We have developed a method for ranking caution crossroads based on vehicle recorder data[3], road shape, and weather information.

In this section, we discuss the sampling of certain caution crossroads and verify the results of viewpoint ranking calculated with the proposed method. Figure 1 shows the results of viewpoints ranking for three types of crossroads, t-shaped, l-shaped, and s-shaped. Each row shows the best three and worst two viewpoint rankings for each crossroad. Their rankings and weighted entropy values are at the bottom of the images. Each crossroad displays the top 30 caution operations with 20-second trajectories before and after operations occurred. The types of trajectory shapes are characterized more by such caution operations than road shape.

We confirmed that the best three viewpoints clearly display the 1) characteristics of trajectories shapes and 2) distribution of trajectories on the time axis compared to the worst two viewpoints.

4 Conclusion

We proposed a novel method of selecting optimal viewpoints for exploring trajectories in a space time cube. We provided an algorithm based on viewpoint entropy weighted by angles of trajectories with a horizontal line on a projected 2D image. We plan to verify our method through user evaluation and extend it to find an optimal viewpoint for multiple crossroads to compare them from the same angle. We also plan to construct overviewing catalogs of caution crossroads to discuss and analyze them with stakeholders of the vehicle recorder data for evaluating the usability of the method. The computation time for obtaining maximum viewpoint entropy (including drawing time of trajectories) is approximately under one second using a 2.20-GHz Intel Core i7 PC with 16-GB RAM; however, this should be improved.

[3]collected from over 2,700 drivers for about one month.

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References

[1] F. Amini, S. Rufiange, Z. Hossain, Q. Ventura, P. Irani, and M. J. McGuffin. The Impact of Interactivity on Comprehending 2D and 3D Visualizations of Movement Data. *IEEE Trans. Vis. Comput. Graph.*, 21(1):122–135, 2015.

[2] G. L. Andrienko, N. V. Andrienko, P. Bak, D. A. Keim, and S. Wrobel. *Visual Analytics of Movement*. Springer, 2013.

[3] U. Bordoloi and H. Shen. View Selection for Volume Rendering. In *VIS 2005*, pp. 487–494, 2005.

[4] M. Itoh, D. Yokoyama, M. Toyoda, and M. Kitsuregawa. Visual Interface for Exploring Caution Spots from Vehicle Recorder Big Data. In *Big Data 2015*, pp. 776–784, 2015.

[5] T. Lee, O. Mishchenko, H. Shen, and R. Crawfis. View Point Evaluation and Streamline Filtering for Flow Visualization. In *Proc. PacificVis 2011*, pp. 83–90, 2011.

[6] S. Takahashi, I. Fujishiro, Y. Takeshima, and T. Nishita. A Feature-Driven Approach to Locating Optimal Viewpoints for Volume Visualization. In *Proc. VIS 2005*, pp. 495–502, 2005.

[7] J. Tao, J. Ma, C. Wang, and C. Shene. A Unified Approach to Streamline Selection and Viewpoint Selection for 3D Flow Visualization. *IEEE Trans. Vis. Comput. Graph.*, 19(3):393–406, 2013.

[8] P. Vázquez, M. Feixas, M. Sbert, and W. Heidrich. Viewpoint Selection using Viewpoint Entropy. In *Proceedings of the Vision Modeling and Visualization Conference 2001 (VMV-01), Stuttgart, Germany, November 21-23, 2001*, pp. 273–280, 2001.