An Interactive Visualization System for Spatio-temporal Situation Awareness with Multi-data Fusion - IEEE VAST Challenge 2021 MC2 Award for Outstanding Comprehensive MC2 Submission

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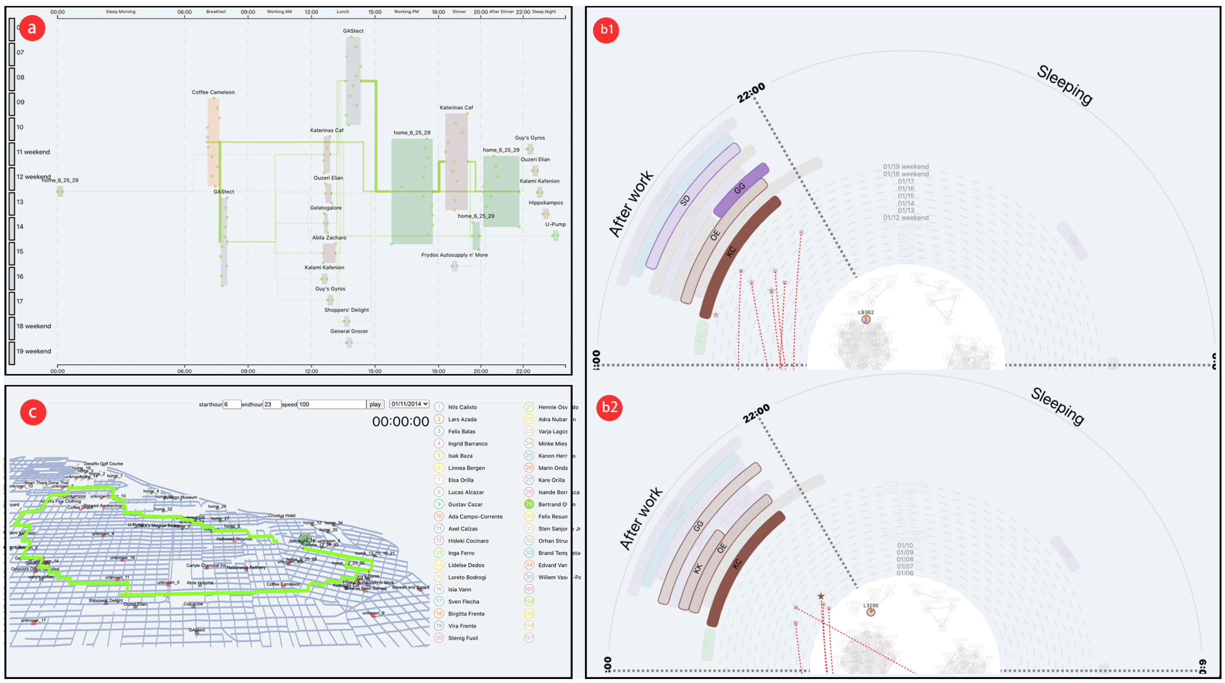

Figure 1: Analysis process for detecting lost loyalty card. (a) The dwell events shown in the trajectory of Bertrand Ovan's car during the 14 days. (b1) Bertrand Ovan's consumption behavior after January 11. (b2) Bertrand Ovan's consumption behavior before January 11. (c) Bertrand Ovan's trajectory in January 11.

Abstract

This paper designs a visual analytics system with spatial-temporal situational awareness based on various data sets. It combines three views, that is, consumption view, temporal behavior view, and spatial-temporal map to effectively identify the consumption and behavior patterns of employees and assist in the detection of suspicious activities and suspicious groups.

1 Introduction

Understanding crime patterns is a challenging problem due to the interplay between the spatial and temporal dynamics of suspicious activities, the great variability of behavioral patterns of individuals, and the large data volume involved in such analysis [2]. Visual analytic effectively combines automated data analysis techniques and interactive visualizations, helping analysts derive insights from complex data and discover patterns and trends for timely and thorough assessments [1]. Therefore, it supports means of analytical reasoning facilitated by interactive visual interfaces, allowing human participation to explore hidden information from data.

This paper designs a novel visualization system for spatial-temporal situation awareness specifically to address the VAST Challenge 2021 Mini-Challenge 2 based on the various data provided including car trajectory data, transaction data and employee information data. Our system presents 3 different views, including consumption view, temporal behaviour view and spatial-temporal map view, to analyse the consumption and action patterns of the individuals involved in the case from different perspectives. Based on the exploration and analysis, we summarize the suspicious information of trajectory and transaction data as proof of our speculation on crimes.

2 Visualization System Design

2.1 The Consumption View

We identify the specific identity of the consumer according to the uniqueness of the loyalty card ID in the consumption data. Since there is mapping relationship between loyalty card and credit card, we merge the two, encode the dimensions of time, location and consumption attributes separately, and design a radial consumption

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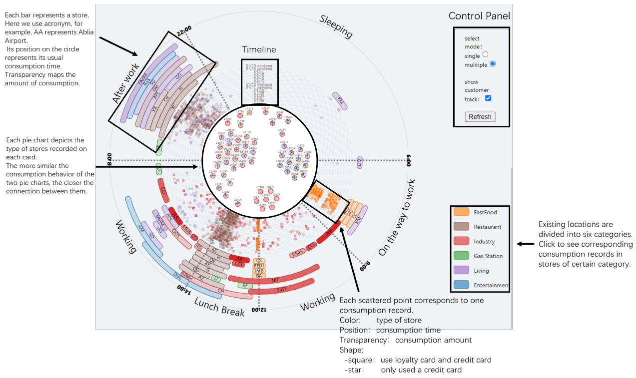

Figure 2: The Consumption View for Describing Consumption Behavior

graph to analyse the daily individual consumption patterns.

In Fig. 2, the radial consumption graph is constructed by three components including the innermost pie chart for credit card information, the middle radial scatter plot for specific consumption behaviours and the outermost multi-layer donut chart of specific consumption hours for each location.

While applying the view, users can first explore the innermost part of the pies that are clustered if they share similar consumption records. To classify the behaviours of the individuals, we divide the time of day into five time intervals. By clicking the pies, the detailed consumption records related to the card shown in the middle scatter plot will be highlighted, indicating their consumption time, their categories and their payment methods. In addition, another exploration mode that starts with consumption locations is also available. Users can click consumption locations to find the consumption records and cards related to them.

Through this view, users can acquire the daily individual consumption patterns and discover abnormal consumption behaviors and consumption locations.

2.2 The Temporal Behavior View

We define a dwell event as follows: the car stays within a small area for a period of not less than 5 minutes. Based on this definition, we calculate the dwell events that occur in each track based on trajectory data. A dwell event contains information such as coordinates, place, start time, duration, car ID and car owner.

In Fig. 1.(a), We created a coordinate system with the X-axis representing time and the Y-axis representing the number of dwelling events. We draw a rectangle for each place where a dwell event occurred, the more dwell events occurred at that place, the higher the rectangle, and the duration of these dwell events determines the width of the rectangle. Each dwell event is drawn as a circle inside the corresponding rectangle, and the x-axis coordinate of the circle is the start time of the event. With this view, we can determine where employees live based on the place and frequency of their dwell events during off-hours.

This view fully illustrates the spatial activity behavior of employees by extracting dwell events from the trajectory data. It is mainly used for the following purposes. (a) Analyze the daily activity patterns of employees. (b) Discover suspicious activities. For example, gathering activities at suspicious times. (c) Explore the relationship between employees. (d) Discover suspicious places that are not marked on the map.

2.3 The Spatial-Temporal Map

The above two views show consumption data and trajectory data respectively, and they lack the correlation analysis of the two parts of data. Meanwhile, we omitted some data, that is, we transformed the trajectory data and extracted corresponding dwell information. This makes it difficult for us to explore the process of suspicious activities and obtain clear evidence when we find abnormal activities. Moreover, the data not shown may contain abnormal behavior patterns. Therefore, we designed a 3D map to display the trajectory data and consumption data, shown in Fig 1.(c).To reduces occlusion of overlapped trajectory bands, we applies trajectory wall [3] which consists of stacked 3D trajectory bands for individuals. The view shows information such as dwell place, trajectories, and consumption data. It simulates the movement of a car, and plots consumption records on the corresponding consumption location. We also provide some interaction methods, for example, you can select time, place, and car. In addition, we normalize the data.

This view is mainly used for the following purposes. (a) Enhance the display of the trajectory data, such as distance, rate, etc. (b) Discover conflicts and deviations between trajectory data and consumption data. (c) Analyze and interpret suspicious events. (d) Provide a location-based analysis process.

3 Case

In the following section we will introduce the use of the system and our analysis method through the case of the lost loyalty card.

First we click on the circle with Bertrand Ovan's car ID on the right side of Fig. 1.(c) and choose data on January 11, the view shows that he drove the car around the city. Temporal Behavior View in Fig. 1.(a) shows his dwell events during 14 days. Bertrand Ovan went to Guy's Gyros, Ouzeri Elian, Kalami Kafenion, Hippokampos, and U-Pump continuously after 23:00 on January 11 and stayed for a short time, as if looking for something.. Second, by matching the track data with the consumption data, we conclude that the owner of both loyalty card L3295 and L9362 is Bertrand Ovan. Then we click on the pie chart representing L3295 in the consumption view, Fig. 1.(b1) shows that L3295 was only used before January 11, while clicking on the pie chart representing L9362, Fig. 1.(b2) shows that L9362 was only used after January 11. There is no spending record for both cards on January 11.

Therefore, we deduce that Bertrand Ovan lost his original loyalty card L3295 on January 11, and he went to look for it overnight but failed to find it. So he replaced it with a new card L9362 on January 12.

4 Conclusion

This paper designed a visual analysis system to address the VAST Challenge 2021 Mini-Challenge 2. It combined multiple data sets and has the ability of perceiving spatial-temporal situation, explore the behavior mode of employees and detect abnormal events. In future work, further improvements will be made to the Spatial-Temporal Map to better describe the trajectory data. For example, we need to deal with visual clutter and find a more suitable method for visualizing overlapping trajectories.

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