Visualization of Life Patterns through Deformation of Maps Based on Users' Movement Data

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Abstract. This paper proposes a system for visualizing individual and collective movement within dense geographical contexts, such as cities and urban neighborhoods. Specifically, we describe a method for creating "spatiotemporal maps" deformed according to personal movement and stasis. We implement and apply a prototype of our system to demonstrate its effectiveness in revealing patterns of spatiotemporal behavior, and in composing maps that more closely correspond to the node-oriented "mental maps" traditionally used by individuals in the act of navigation.

1 Introduction

In this paper, we propose a system that models users' localized movement patterns to generate "spatiotemporal maps" of their pedestrian and vehicular movement within a city or urban neighborhood. These spatiotemporal maps are deformed according to the amount of time spent at locations and en route. The project aims to reveal awareness and dialogues not easily discerned from traditional geographic maps.

At present, most of the maps we use are formed by topographical projections of "geographical distance". Though these maps provide a baseline of valuable information, we must recognize that, when large numbers of people move between similar points on a map, travel time will depend more on local traffic conditions than on physical distance, and that, for the most part, our current topographical maps fail to reveal this dependency.

If you are asked for directions by travelers, you will tend to assemble a schematic map from your current position to the destination inawareness your head, and attempt to explain direction and orientation with respect to relevant nodes, such as the buildings and intersections en route. Generally, we regard these schematics as cognitive maps, assembled from various geographical or spatial memories and generally inaccurate in comparison to the topographical map. Nevertheless, they support consistently successful navigation to desired destinations. This is because a cognitive map, though geographically inaccurate, contains the minimum information required by human navigators, and as such, can be regarded as more streamlined and easier to use than the corresponding, geographically accurate, map.

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We can assume that cognitive maps depend greatly on an individual's life patterns and his/her perception of time. As a result, we expect to be able to visualize the spatial structure and nodes of a city based on the cognitive maps of individuals living in that city.

2 Related Work

Ashbrook et al. demonstrated a system that automatically clusters GPS data, taken over an extended period, into meaningful locations at multiple scales [1]. In our approach, we consider that we can use the portion to extract landmarks for map deformation.

Agrawala et al. described algorithmic implementations of these generalization techniques within LineDrive, a real-time system for automatically designing and rendering route maps [2]. In this paper, we regard route maps as similar to our spatiotemporal maps, except that spatiotemporal maps are based on time, by way of movement data.

Patterson et al. demonstrated that by adding more external knowledge about bus routes and bus stops, accuracy is improved [3]. We want to determine whether there are new awareness by generating the spatiotemporal maps from human behavior.

Schoning et al. presented a study that discusses the suitability of various public maps to this task and evaluated whether geographically referenced photos can be used for navigation on GPS-enabled devices [4]. In the future we would like to create a system that generates spatiotemporal maps based on the built-in GPS of smartphones and similar mobile devices. For example, if a mobile user takes pictures for inclusion in PhotoMap, these pictures could be deformed into spatiotemporal maps based on the user's movement leading up to the photograph.

Shen et al. created a visual analysis tool called "MoviVis" that presents spatial and social information as a heterogeneous network [5]. The distance between any two points of the resulting maps is similar to the distance represented between landmarks of our spatiotemporal maps. Also, if the actual distance is far, it is close as distance sense.

3 Spatiotemporal Maps Generation System

3.1 System Configuration

Our spatiotemporal maps generation system visualizes users' movement patterns based on their GPS movement data, which must be captured using a GPS logger (using the model of user action proposed by Ashbrook et al. [1]). Based on this data, we create a time scale and spatial scale focused around the region and time span of activity. We then use threshold processing to determine the dwelling time of users, based on whether a mesh separated according to spatial location exceeds a certain time scale. The result is a set of points called nodes, joined by lines called links. The locations of these nodes are adjusted to reflect travel times along links and, finally, a general map is deformed to fit the adjusted nodes. The result is what we call a spatiotemporal map.

3.2 Features of the Spatiotemporal Maps

Our spatiotemporal maps are based on time-tracked movement data, and deformed by time-based depending on the life time of the individual.

Fig. 1. Example of a spatiotemporal map

Fig. 1 is an example of an actual spatiotemporal map. Note the deformation of the general map to reflect movement (i.e. motion and stasis) data.

- Spatiotemporal maps for individual users
  Because our maps reflect movement data, their deformations will vary according to individual users—i.e. where they live and work, and their means of transportation.
- Spatiotemporal maps for multiple users
  When mapping multiple users, places common to several users will become nodes. Note that some of these nodes can only emerge in the visualization itself, as aggregations of movement in space and time.

4 Prototype System

When mapping multiple users, places common to several users will become nodes. Note that some of these nodes can only emerge in the visualization itself, as aggregations of movement in space and time.

4.1 Collection and Storage of Movement Data

The data we want to collect must include the latitude, longitude, and time coordinates for individual users. We use the GPS data as movement data.

Fig. 2. Movement data everyday we collect

As shown in Fig. 2, GPS data is collected everyday. We are collecting GPS data now. We use GPS data collected in this way, visualize location, season, time, and more, and compare them.

All GPS data was initially stored in CSV format; however, this led to inefficient programming. Therefore, we extracted only the required CSV data, stored it in a relational database, and queried it as needed. We use the SQLite database and management system.

In our SQLite database, we created three simple tables: User, File and Data. The User table manages all user data, the File table includes userid and filepath columns to associate users with file-based data, and the Data table includes fileid, Latitude, Longitude, and Date columns for specifying space-time coordinates.

4.2 Creating Sparial Scales and Time Scales and Generating Nodes

We created the spatial mesh and time mesh. The spatial mesh is the mesh has a scale of two dimensional in the spatial direction. The time mesh is the mesh has a scale of one dimensional in the time direction. We tuned the spatial mesh and time mesh. As a result, the spatial mesh was in the 10m 10m, and the time mesh was in the 1 minute. Fig. 3 shows the stay time of the user in the spatial mesh. If the stay time is over the 1minute, we generate a point called a node in the spatial mesh from Fig. 3. The size of the node depends on the stay time of the user. Further, we display a link that connects between nodes. Links are calculated the sequence of connection between the nodes. It connects to the starting point and the end point as a link along the time axis in the movement. Fig. 4 is view that nodes and links are generated based on a spatial mesh.

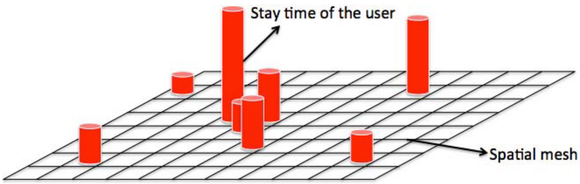

Fig. 3. Generation of nodes from a spatial mesh

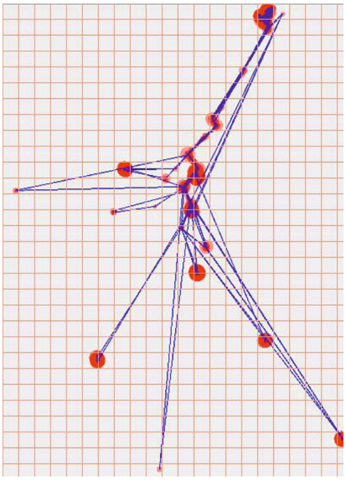

Fig. 4. Generation of nodes and links from a spatial mesh

4.3 Map Deformation

Next, nodes and links are repositioned, and a general map covering their geographical region is deformed accordingly.

– Restructuring of nodes and links
  The spatiotemporal maps are based on the amount of time spent at locations and en route. We consider that the links should to be based on the average of travel times. Therefore, we need to restructure the positions of nodes and links. We shift the position of the node that is mapping on the map in according to the travel time.

  We use a "a generalized solution of time-distance mapping" [6] as a reference. The problem of generating this time-distance map is how best to place a set of points given the time-distance between them on the plane. Shimizu et al. modeled this as a nonlinear least-square problem and proposed a generic solution on that basis. Their proposed solution is as follows.

$$\min \sum_{ij \in L} \left[(t_{ij} \sin \Theta'_{ij} - (x_j - x_i))^2 + (t_{ij} \cos \Theta'_{ij} - (y_j - y_i))^2 \right] \tag{1}$$

– Map deformation
  To maintain useful context, it is important to deform the geographical map without critical loss of geographical information. To accomplish this, we perform image deformation using the moving least squares method proposed by Schaefer et al. [7].

  We try the map deformation by separating and distorting a map in the virtual mesh. In this deformation, we reconfigure the mesh by using the information the nodes displaced (x, y) (x', y'). We use the moving least squares method to reconfigure of the mesh. The moving least squares method corresponds to find the solution to the following.

$$\sum_i w_i |l_v(p_i) - q_i|^2 \tag{2}$$

  We can distort the map to affine transform the image by depending on the mesh reconfigured.

  Fig. 5 shows an example deformation. The blue dots in the figure indicate control points, and the green dots indicate the adjusted location of those control points. Image deformation is accomplished by simply clicking a part of the image on the left and dragging to produce the image on the right.

4.4 Demonstration

To demonstrate the effectiveness of our prototype system, we used it to create several spatiotemporal maps. For this purpose, we found three users willing to have their GPS data collected and visualized for a one-month period.

Fig. 6 is a side-by-side comparison of the three users' spatiotemporal maps. Note that the maps differed significantly, even though the users lived and worked in the same city. All three users come and go different places. But it can be read from the Fig. 6 that left user has moved to the range of the left from the point A, middle user has moved to various locations around the point A, and right user has moved to the range of the right from the point A. This is because living space of person is different. This is a direct indication of the differences among the users' lifestyles—i.e. their dwelling places and transportation behaviors—resulting in different spatiotemporal deformations.

Fig. 7 is a comparison of spatiotemporal maps of the same user displaying different places. The left figure is the spatiotemporal map of user's hometown, the right figure is the spatiotemporal map of business trip destination. The user in the hometown walks around the neighborhood and goes quickly by a car to the long way as the airport. When the user moves by a car, the deformation of the spatiotemporal map is constant. But the user in the business trip destination moves by the train and walks to the destination from the station. When the user moves by the train, the deformation of the spatiotemporal map is also constant. When the user walks to the destination from the station, the spatiotemporal

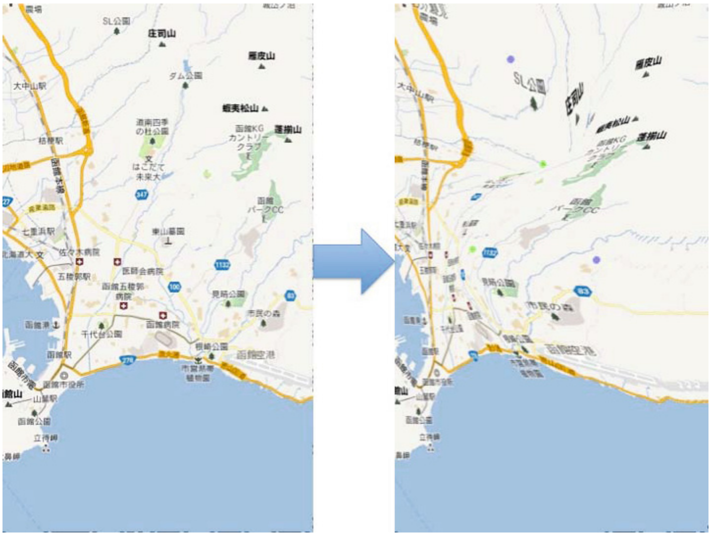

Fig. 5. Example of Map Deformation

Fig. 6. Comparison of three users' spatiotemporal maps

map is distorted as fish-eye lens at the center of the station. We surmise that the different deformations are due to use of different means of transportation. In addition, we can guess also transport used by the region is different.

Fig. 8 is a comparison of spatiotemporal maps with different hours. The left figure is the spatiotemporal map of the day, the right figure is the spatiotemporal map of the evening. The road is quiet during the day, but the road is crowded in the evening. Since users tended to favor the same routes of travel, we can assume that the change in deformation is due to variations in traffic conditions, which may be hourly, daily or seasonal.

Fig. 7. Comparison of spatiotemporal maps for an individual using different means of transportation

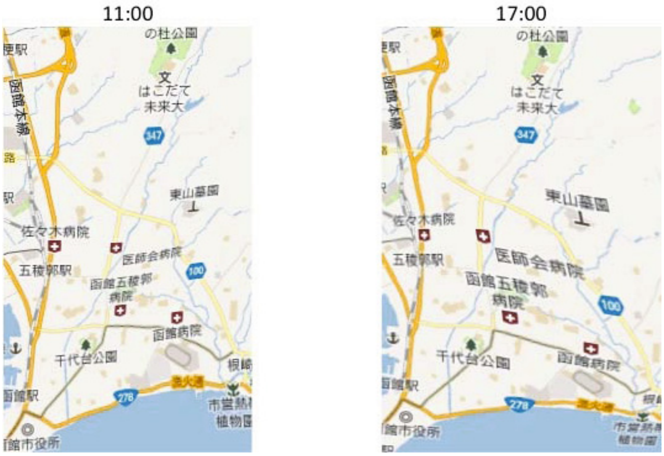

Fig. 8. Comparison of spatiotemporal maps with different hours

5 Conclusions and Future Work

In this paper, our purpose was to provide an insightful visualization of individual life patterns as they apply to movement in time and space. Specifically, we proposed a new kind of map deformation based on the movement and stasis of users within a city environment. By collecting data that reflects individual variations in destination, schedule, and transportation mode, and applying our prototype system to this data, we were able to generate a series of individual and multiple-user spatiotemporal maps. These maps made clear certain differences in individual and collective behavior over time, and helped to distinguish key features of the mental and transportation-related landscape.

In future work, we intend to focus on two important features.

- Automation of map deformation program
  Map deformation program that incorporates the method of Shimizu et al. did not work well. Therefore, we innovate the elements of the spring model in this program and distort to let a natural length of the spring be travel time. And another thing, we use Google Maps as images now and image deformation makes also characters distort. We want to devise such as divided into separate layers of map image and characters.
- Experiments on the "awareness due to show each other the maps"
  It is possible to be aware the part was not awaken by oneself by others by showing each other the generated spatiotemporal maps. For example, there are problems in the city and special local information. Otherwise, we can aware the differences between profile from showing each other. So, we should do an experiments on the "awareness due to show each other the spatiotemporal maps".

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