PERGAMON

Transportation Research Part C 8 (2000) 185–203

TRANSPORTATION
RESEARCH
PART C

www.elsevier.com/locate/trc

Interactive geovisualization of activity-travel patterns using three-dimensional geographical information systems: a methodological exploration with a large data set

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Abstract

A major difficulty in the analysis of disaggregate activity-travel behavior in the past arises from the many interacting dimensions involved (e.g. location, timing, duration and sequencing of trips and activities). Often, the researcher is forced to decompose activity-travel patterns into their component dimensions and focus only on one or two dimensions at a time, or to treat them as a multidimensional whole using multivariate methods to derive generalized activity-travel patterns. This paper describes several GIS-based three-dimensional (3D) geovisualization methods for dealing with the spatial and temporal dimensions of human activity-travel patterns at the same time while avoiding the interpretative complexity of multivariate pattern generalization or recognition methods. These methods are operationalized using interactive 3D GIS techniques and a travel diary data set collected in the Portland (Oregon) metropolitan region. The study demonstrates several advantages in using these methods. First, significance of the temporal dimension and its interaction with the spatial dimension in structuring the daily space-time trajectories of individuals can be clearly revealed. Second, they are effective tools for the exploratory analysis of activity diary data that can lead to more focused analysis in later stages of a study. They can also help the formulation of more realistic computational or behavioral travel models.

1. Introduction

As evident in early time-use and activity-travel studies (e.g. Chapin, 1974; Cullen et al., 1972; Szalai, 1972), a major difficulty in the analysis of human activity-travel patterns is that individual

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PII: S0968-090X(00)00017-6

movement in space-time is a complex trajectory with many interacting dimensions. These include the location, timing, duration, sequencing and type of activities and/or trips. This characteristic of activity-travel behavior has made the simultaneous analysis of its many dimensions difficult (Burnett and Hanson, 1982). Often, one has either to focus on a few component dimensions at a time (e.g. Bhat, 1997, 1998; Chapin, 1974; Golob and McNally, 1997; Goulias, 1999; Lu and Pas, 1999; Michelson, 1985; Pendyala, 1997), or to treat the pattern as a multidimensional whole and use multivariate methods to derive generalized activity-travel patterns from a large number of variables (e.g. Bhat and Singh, 2000; Golob, 1985; Hanson and Hanson, 1980, 1981; Janelle and Goodchild, 1988; Koppelman and Pas, 1985; Ma and Goulias, 1997a,b; Pas, 1982, 1983; Recker et al., 1983, 1987).

The development and application of these quantitative methods in transportation research have enhanced our understanding of activity-travel behavior. Through the use of multivariate group identification methods, such as clustering or pattern recognition algorithms, complex patterns in the original data set can be represented by some general characteristics and organized into relatively small number of homogenous classes. Further, once activity-travel patterns are represented, they can be related to a large number of attributes of the individuals or households which generate them and used as a response variable in models of activity-travel behavior (Koppelman and Pas, 1985). While these quantitative methods are useful for modeling purposes and for discovering the complex interrelations among variables, they also have their limitations.

First, few of these methods were designed to handle real geographical locations of human activities and trips in the context of a study area (Kwan, 1997). Often, the spatial dimension is represented by some measures derived from real geographical locations (e.g. distance or direction from a reference point such as home or workplace of an individual). Further, locational information of activities and trips was often aggregated with respect to a zonal division of the study area (e.g. traffic analysis zones). Using such zone-based data, measurement of location and/or distance involves using zone centroids where information about activity locations in geographic space and their spatial relations with other urban opportunities is lost (Kwan and Hong, 1998). As point-based activity-travel data geocoded to street addresses have gradually become available in recent years, new analytical methods that can handle the location of activities and trips in real geographic space are needed.

Second, since many analytical methods (e.g. log-linear models) are designed to deal with categorical data, organizing the original data in terms of discrete units of space and time has been a necessary step in most analyses of activity-travel patterns in the past. Discretization of temporal variables, such as the start time or duration of activities, involves dividing the relevant span of time into several units and assigning each activity or trip into the appropriate class (e.g. dividing a day into 8 or 12 temporal divisions into which activities or trips are grouped). Discretization of spatial variables, such as distance from home, involves dividing the relevant distance range into several "rings". Since both the spatial and temporal dimensions are continuous, results of any analysis that are based upon these discretized variables may be affected by the particular schema of spatial and/or temporal divisions used. The problem may be serious when dealing with the interaction between spatial and temporal variables since two discretized variables are involved. Visualization may have an important role to play in alleviating this difficulty since the spatio-temporal patterns of the original data can be explored before they are discretized for further analysis or modeling.

Third, as the amount and complexity of activity-travel data increase considerably in recent years (Cambridge Systematics, 1996a), effective methods for exploring these data are also urgently needed (McCormack, 1999). Without them, the researcher may need to model activity-travel patterns without a preliminary understanding of the behavioral characteristics or uniqueness of the individuals in the sample at hand. This can be costly in later stages of a study if the model's specifications fail to take into account of the behavioral anomalies involved. Since exploratory data analysis (EDA) can often lead to more focused and fruitful methods or models in later stages of a study, the recent development and use of scientific visualization for EDA suggest a possible direction for overcoming the problem (Dykes, 1996; Gahegan, 2000). Recent developments in the integration of scientific visualization and exploratory spatial data analysis (ESDA) also indicate the potential of geovisualization for the analysis of activity-travel patterns (Anselin, 1998, 1999; Wise et al., 1999).

This study explores the application of interactive geographical visualization (or geovisualization) in the analysis of georeferenced activity-travel data. It describes several GIS-based three-dimensional (3D) visualization methods for handling the spatial and temporal dimensions of activity-travel behavior that avoid the interpretative complexity of multivariate pattern generalization or recognition methods. These include space-time activity density surfaces, space-time aquariums and standardized space-time paths. These methods are operationalized using interactive 3D GIS techniques and an activity-travel diary data set collected in the Portland (Oregon) metropolitan area in 1994/95. While some of these methods were developed by the author for analyzing a smaller data set collected in Columbus, Ohio (Kwan, 1999a), new methods are developed and explored in this paper. These include the use of GIS-based surface modeling and virtual reality techniques. Further, as these visualization methods are computationally intensive, implementing them for handling a large data set would shed light on their feasibility, value and limitations for the analysis of activity patterns in space-time for transportation researchers.

2. The case for the interactive 3D geovisualization of activity-travel patterns

Visualization is the process of creating and viewing graphical images of data with the aim of increasing human understanding (Hearnshaw and Unwin, 1994). It is based on the premise that humans are able to reason and learn more effectively in a visual setting than when using textual and numerical data (Tufte, 1990, 1997). Visualization is particularly suitable for dealing with large and complex data sets because conventional inferential statistics and pattern recognition algorithms may fail when a large number of attributes are involved (Gahegan, 2000). In view of the large number of attributes that can be used to characterize activity-travel patterns, and given the capability of scientific visualization in handling a large number of attributes, visualization is a promising direction for exploring and analyzing large and complex activity-travel data. Geovisualization, on the other hand, is the use of concrete visual representations and human visual abilities to make spatial contexts and problems visible (MacEachren et al., 1999). Through involving the geographical dimension in the visualization process, it greatly facilitates the identification and interpretation of spatial patterns and relationships in complex data in the geographical context of a particular study area.

For the visualization of geographic data, conventional GIS has focused largely on the representation and analysis of geographic phenomena in two dimensions. Although 3D visualization programs with advanced 3D modeling and rendering capabilities have been available for many years, they have been developed and applied largely in areas outside the GIS domain (Sheppard, 1999). Only recently has GIS incorporated the ability to visualize geographic data in 3D (although specialized surface modeling programs have existed long before). This is so not only in the digital representation of physical landscape and terrain of land surfaces, but also in the 3D representation of geographic objects using various data structures. There are many methods for representing complex geographic objects in 3D (Li, 1994). One is to assign the Z value using attributes available in the two-dimensional (2D) database to produce a "3Dable" geographic database. For example, a 3D representation of a building can be created by extruding the 2D building outline along the Z-axis by the height of the building. This practice is often referred to as $2\frac{1}{2}$-D as there can be only one Z value for any single location (X, Y) on the 2D surface, thus limiting its ability to represent complex geographic objects in 3D. To represent geographic entities as true 3D objects, one has to use other methods. These include solid modeling used in computer-aided design (CAD) software, the voxel data structure that covers 3D space with 3D pixels (voxels), or object-oriented 3D data models (Lee and Kwan, 2000).

Although GIS-based 3D geovisualization has been applied in many areas of research in recent years, its use in the analysis of human activity patterns is rather limited to date. In many early studies, 2D maps and graphical methods were used to portray the patterns of human activity-travel behavior (e.g. Chapin, 1974; Tivers, 1985). Individual daily space-time paths were represented as lines connecting various destinations. Using such kind of 2D graphical methods, information about the timing, duration and sequence of activities and trips was lost. Even long after the adoption of the theoretical constructs of the time-geographic perspective by many researchers in the 1970s and 1980s, the 3D representation of space-time aquariums and space-time paths seldom went beyond the schematic representations used either to explain the logic of a particular behavioral model or to put forward a theoretical argument about human activity-travel behavior. They were not intended to portray the real experience of individuals in relation to the concrete geographical context in any empirical sense.

However, as more georeferenced activity-travel diary data become available, and as more GIS software has incorporated 3D capabilities, it is apparent that GIS-based 3D geovisualization is a fruitful approach for examining human activity-travel behavior in space-time. For instance, Forer (1998) and Huisman and Forer (1998) implemented space-time paths and prisms based on a 3D raster data structure for visualizing and computing space-time accessibility surfaces. Their methods are especially useful for aggregating individuals with similar socioeconomic characteristics and for identifying behavioral patterns. However, since the raster data structure is not suitable for representing the complex topology of a transportation network, the implementation of network-based computational algorithms is difficult when using their methods. On the other hand, Kwan (1999a, 2000a) implemented 3D visualization of space-time paths and aquariums using vector GIS methods and activity-travel diary data. These recent studies indicate that GIS-based geovisualization has considerable potential for advancing the research on human activity-travel behavior. Further, implementing 3D visualization of human activity-travel patterns can be an important first step in the development of GIS-based geocomputational procedures that are applicable in many areas of transportation research. For example, Kwan (1998, 1999b), Kwan and Hong (1998) and Miller (1991, 1999) developed different network-based algorithms for computing individual accessibility using vector GIS procedures.

The use of GIS-based 3D geovisualization in the analysis of human activity patterns has several advantages. First, it provides a dynamic and interactive environment that is much more flexible than the conventional mode of data analysis in transportation research. The researcher not only can directly manipulate the attributes of a scene and its features, but also can change the views, alter parameters, query data and see the results of any of these actions easily. Second, since GIS has the capability to integrate a large amount of geographic data in various formats and from different sources into a comprehensive geographic database, it is able to generate far more complex and realistic representations of the urban environment than conventional methods (Weber and Kwan, 2000). The concrete spatial context it provides can greatly facilitate exploratory spatial data analysis and the identification of spatial relations in the data. Results can also be exported easily to spatial analysis packages for performing formal spatial analysis (Anselin and Bao, 1997). Third, with many useful navigational capabilities such as fly-through, zooming, panning and dynamic rotation, as well as the multimedia capabilities to generate map animation series such as 3D "walk-throughs" and "fly-bys", the researcher can create a "virtual world" that represents the urban environment with very high level of realism (Batty et al., 1998). Lastly, unlike quantitative methods that tend to reduce the dimensionality of data in the process of analysis, 3D geovisualization may retain the complexity of the original data to the extent that human visual processing is still capable of handling.

3. Data

The data used in this research are from the Activity and Travel Survey conducted in the Portland (Oregon) metropolitan area in the spring and autumn of 1994 and the winter of 1995 (see Cambridge Systmatics (1996b) for details of the survey). The survey used a two-day activity diary to record all activities involving travel and all in-home activities with a duration of at least 30 min for all individuals in the sampled households. Of the 7090 households recruited for the survey, 4451 households with a total of 10,084 individuals returned completed and usable surveys. The data set logged a total of 128,188 activities and 71,808 trips.

Besides the information commonly obtained in travel diary survey, this data set comes with the geocodes (*xy* coordinates) of all activity locations, including the home and workplace of all individuals in the sample. This greatly facilitates its incorporation into a geographic database of the study area. Besides the activity diary data, geographic information about the Portland metropolitan region are also used in this study. This includes data on various aspects of the urban environment and transportation system. This contextual information allows the activity-travel data to be related to the geographical environment of the region during visualization.

The next two sections explore several methods for the 3D geovisualization of human activity-travel patterns in space-time. For the implementation of these methods, various segments of a subsample of the original respondents are used. The subsample consists of individuals who were identified as head of household or spouse or partner and are employed full-time or part-time. It provides information for 4,744 individuals who are working adults in households with at least one adult. All geoprocessing is performed using ARC/INFO and ArcView GIS, while the 3D interactive geovisualization is conducted using ArcView 3D Analyst.

4. Geovisualization of activity density patterns in space-time

The conceptual basis for the GIS-based 3D geovisualization methods discussed below is the time-geographic perspective formulated by Hägerstrand (1970) and his associates. In time-geographic conception, an individual's activities and trips in a day can be represented as a daily space-time path within a 'prism' defined by a set of constraints (Hägerstrand, 1970; Lenntorp, 1976; Parkes and Thrift, 1975). This time-geographic conception is valuable for understanding activity-travel behavior because it integrates the temporal and spatial dimensions of human activity patterns into a single analytical framework. Although time, in addition to space, is a significant element in structuring individual activity patterns, past approaches mainly focus on either their spatial or temporal dimension. The significance of the interaction between the spatial and temporal dimensions in structuring individual daily space-time trajectories are often ignored. Yet, using the concepts and methods of time-geography that focus on the 3D structure of space-time patterns of activities, not only this kind of interaction can be examined, but also many important behavioral characteristics of different population subgroups can be revealed. As a result, many transportation researchers have found the time-geographic perspective useful for understanding human activity-travel behavior (Kitamura et al., 1990; Kondo and Kitamura, 1987; Kostyniuk and Kitamura, 1984; Kwan, 2000b; Recker et al., 1983). This section focuses on interactive 3D geovisualization methods for representing activity intensity in space-time. Geovisualization of space-time paths will be discussed in the next section. Color versions of the figures are provided on Web site http://geog-www.sbs.ohio-state.edu/faculty/mkwan/gis-t/Links.htm.

A note on the quality of the figures is warranted at this point. Since the 3D patterns involved are highly complex and the figures are non-scalable raster images produced from screen captures, there are many limitations on producing clear illustrations using 2D graphics. The reader may find it hard to follow the discussion simply by looking at these figures since the text is based on observations enabled by the computer-aided interactive 3D visualization environment (which is not available to the reader). The difficulty the reader may have in "seeing" these 2D images clearly is the inevitable outcome of the need to present results of the color display of complex 3D patterns in the form of 2D graphics. The visual quality of the 2D figures in the paper, therefore, should not undermine the argument that interactive 3D geovisualization is useful. Further, as these figures cannot convey the same amount and quality of information enabled only by interactive 3D visualizations, it is best to treat them as illustrations of what one might see when performing the interactive 3D visualizations. Their purpose is to give the reader a feel for what the interactive visualization does. To fully appreciate the value of the methods discussed in the paper, one needs to go through the real computer-aided interactive geovisualization sessions instead of looking at their black-and-white 2D representations.

4.1. Simple activity patterns in space-time

A simple method for visualizing human activity patterns in 3D is to use the 2D activity-travel data provided in the original data set and convert them to a format displayable in three dimensions. An important element in this conversion process is to identify the variable in the original data file that will be used as the Z value, which represents the value of a particular activity in the vertical dimension (besides the geographical coordinates X and Y). For a meaningful representation of activity patterns in space-time, the Z variable in this study represents the time dimension of activities and trips. In this particular example, activity start time is used as the Z variable in the conversion process. Using this Z value, each activity is first located in 3D space as a point entity using its geographic location (X, Y) and activity start time (Z). To represent the duration of each activity, the activity points in 3D are extruded from their start times by a value equal to the duration of the activity.

Fig. 1 shows the result of using this method for the 14,783 out-of-home, non-employment activities performed by the 2157 European–American (white) women in the subsample. In the figure, activity duration is indicated by the length of the vertical line that represents the temporal span of an activity. Activity start time can be color-coded so that the temporal distribution of activities can be viewed during interactive visualization (these color codes are used in the color version of Fig. 1 posted on the Web). A helpful background for relating the activity patterns to various locations in the study area is created through adding several layers of geographic information into the 3D scene. These layers include the boundary of the Portland metropolitan region, freeways and major arterials. For better visual anchoring and locational referencing during visualization, a 3D representation of downtown Portland, which appears as a partially transparent 3D pillar derived from extruding its 2D boundary along the Z dimension, is also added into the scene.

Through interactive geovisualization, it is apparent that the highest concentrations of non-employment activities of the selected women are found largely in areas close to downtown Portland inside the "loop" and areas west of downtown along and south of Freeway 84. Important clusters of non-employment activities are also found in Beaverton in the west and Gresham in the east. Most of the non-employment activities are of very short duration (94% of them with duration under 5 min, and less than 1% have duration over 10 min). Further, most of the non-employment activities that were undertaken during lunch hour are found largely in the high density areas near downtown, while non-employment activities in the more suburban areas tend to take place in the morning, late afternoon or evening (perhaps associated with the commute trip). There is strong spatial association between the location of non-employment activities and the locations of workplace for the selected individuals.

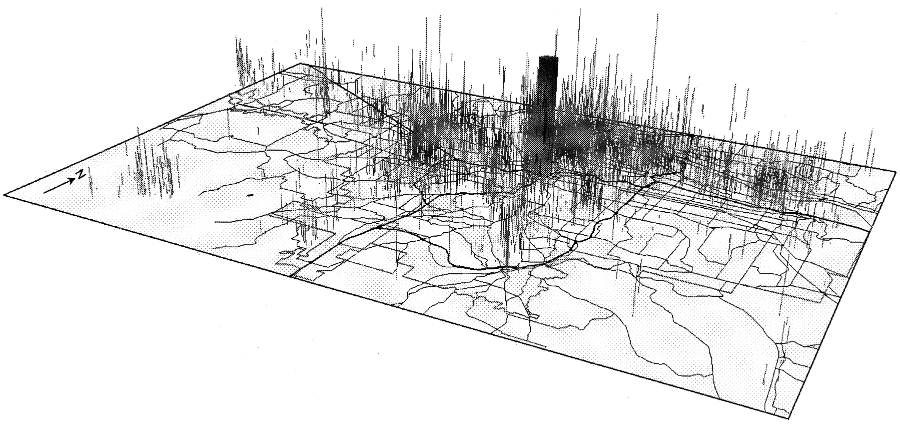

Fig. 1. Simple activity patterns in space-time.

4.2. Activity density patterns in geographic space

Comparison of the patterns of different activities for the same population subgroup or the patterns of the same activity between different population subgroups using this simple representation, however, is difficult. As the number of activities involved will increase considerably when more population subgroups are included and the patterns may be difficult to compare visually, other methods that facilitate inter-group or inter-activity comparisons are needed. This section explores the use of 3D activity density surfaces for representing and comparing the density patterns of different activities in real geographic space. The same group of respondents discussed above is also used here. The purpose is first to represent the spatial intensity of the locations of workplace, home and non-employment activities of these individuals, and then to examine the spatial relationships between these density patterns.

To generate a density surface from a point distribution of n activity locations, a non-parametric density estimation method called kernel estimation is used (Gatrell, 1994; Silverman, 1986). Following Bailey and Gatrell's (1995) formulation, if $\mathscr{R}$ represents the study area, x represents a general location in $\mathscr{R}$ and $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n$ are the locations of the n activities, then the intensity or density, $\lambda(\boldsymbol{x})$, at $\boldsymbol{x}$ is estimated by

$$\lambda_h(\boldsymbol{x}) = \frac{1}{\delta_h(x)} \sum_{i=1}^{n} \frac{w_i}{h^2} k\left(\frac{(\boldsymbol{x} - \boldsymbol{x}_i)}{h}\right), \quad \boldsymbol{x} \in \mathscr{R},$$

where $k(\cdot)$ is the kernel function, the parameter $h > 0$ is the bandwidth determining the amount of smoothing, w_i is a weighing factor, and $\delta_h(\boldsymbol{x})$ is an edge correction factor (Cressie, 1993). In this study, the quartic kernel function

$$k(\boldsymbol{x}) = \begin{cases} 3\pi^{-1}(1 - \boldsymbol{x}^{\mathrm{T}}\boldsymbol{x})^2 & \text{if } \boldsymbol{x}^{\mathrm{T}}\boldsymbol{x} \leqslant 1, \\ 0 & \text{otherwise} \end{cases}$$

described in Silverman (1986) is used for generating space-time activity density surfaces. The method is implemented through covering the study area by a 1110×723 grid structure (with 802, 530 cells) and using bandwidths appropriate for the point pattern at hand (2.0–3.6). The density surfaces, originally created in the grid data structure, are then converted to 3D format and added into a 3D scene (Fig. 2).

In Fig. 2, the density surface of non-employment activities is displayed transparently on top of the density surface of home locations of the selected individuals. To help identify the location of density peaks and troughs, three geographic data layers, namely freeways, major arterials and rivers, are draped over the density surface of home locations. The figure shows that the major peak of non-employment activities is centered at downtown Portland within the "loop", whereas the highest density of home locations is found at two peaks in the east and west of downtown Portland.

Fig. 3 provides a close-up view of another 3D scene in which the transparent workplace density surface is displayed on top of the home location density surface for the selected individuals. These two surfaces are vertically closer in this figure than those in Fig. 2 so that the peaks of the home location surface (bottom) pass through the transparent workplace density surface (top) from below, highlighting the spatial relationships between the peaks of the surfaces. Three distinctive

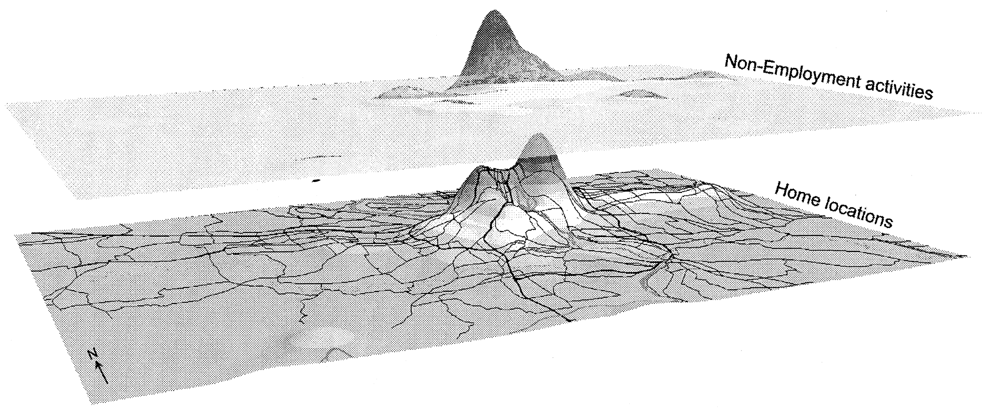

Fig. 2. Activity density patterns in geographic space, with the surface for non-employment activities over the surface of home locations.

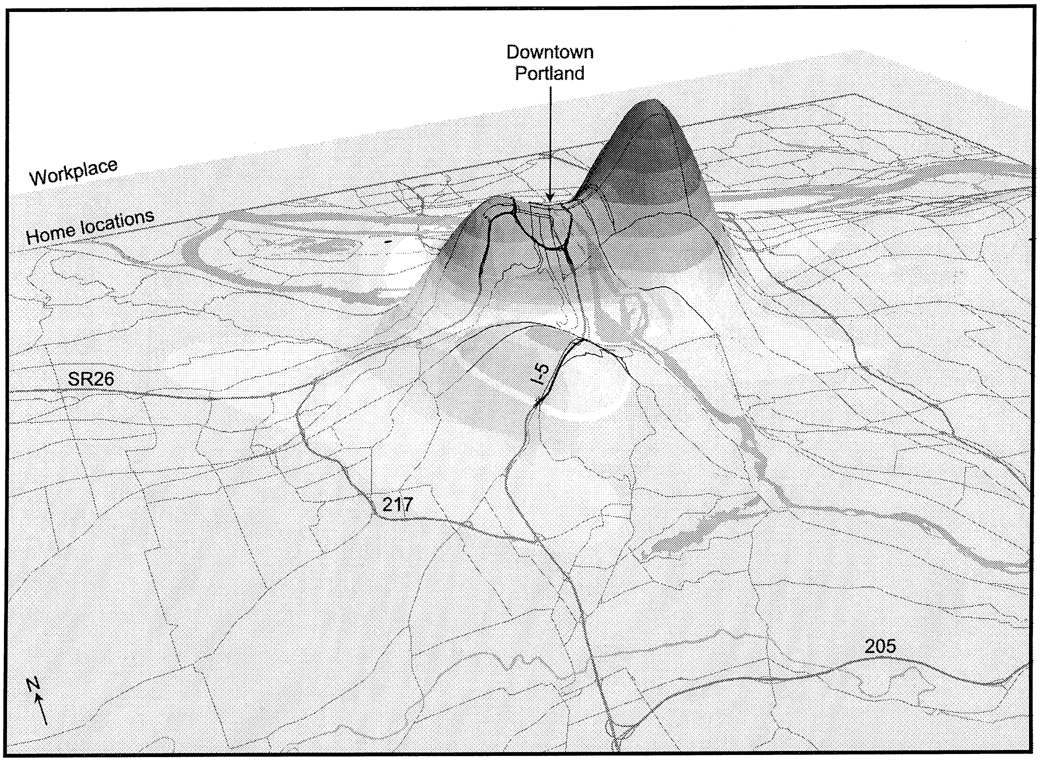

Fig. 3. A close-up view of activity density patterns in geographic space, with the surface for workplace over the surface of home locations.

peaks of home locations can be clearly seen. The most intensive one is in the east of downtown Portland while the other two are in the west of downtown and southwest of downtown along Freeway 5. Not as obvious in the figure is the peak of the workplace surface which is centered at downtown Portland inside the "loop" (it cannot be seen easily because the surface is interrupted from below at the "saddle" between the peaks of the home surface due to its transparency). Another area with high density of workplace is found in areas along Freeway 217 on the southwest between the junctions with State Route 26 in the north and Freeway 205 in the south. During the interactive 3D geovisualization of this scene, the proximity and spatial relationship between the peaks of the two surfaces are striking.

The major advantage of this method is its capability for examining the spatial relationships between different surfaces in their concrete geographical context. However, to explore the temporal dimension and its interaction with the spatial dimension, another visualization method is needed.

4.3. Space-time activity density surfaces

For representing the intensity of activities in space-time, kernel estimation is used again to generate 'space-time activity density surfaces' (Gatrell, 1994; Silverman, 1986). In this implementation, a space-time region $\mathscr{R}$ is established with a locational system similar to an $x - y$ geographic coordinate system. The time-axis of this coordinate system covers a 24-h day from 3 a.m. and the space-axis represents the distance of an activity from home. A fine grid structure of 960×960 space-time grids (with 921, 600 cells) is then created by dividing a day into 960 1.5-min time slices and distance from home into 960 40.2-m (132-foot) blocks. The quartic kernel function described above is also used here with a bandwidth of 0.6. This method is used to generate three space-time activity density surfaces for individuals in the subsample. One is for women employed part-time (Fig. 4); the second one is for men employed part-time (this figure, Fig. 4(b), is provided on the Web); and the third portrays the difference between these two density surfaces (Fig. 5).

The density surface for part-time employed women (Fig. 4) shows that there is a considerable amount of non-employment activities close to home (largely within 8 km) throughout the day from 7:30 a.m. to 10:00 p.m. There are two especially intensive peaks of non-employment activities. One is found at noon about 4 km from home, and the other happens around 2:45 p.m. about 2 km from home. There is only moderate amount of non-employment activities between 8 and 16 km from home, and during the evening hours between 6 and 9 p.m. The density surface for part-time employed men (see Fig. 4(b) on the Web) reveals that the density of non-employment activities throughout the space-time region is not as intensive as those found in the surface for women. These activities are largely performed between 9:00 a.m. and 8:30 p.m. within 6 km from home. There are two fairly distinctive peaks: (a) a very sharp peak at 8:00 p.m. about 3 km from home, and (b) a peak very close to home (within 1 km) about 3:00 p.m.

Fig. 5 shows the difference between these two density surfaces. It is obtained by using the map algebraic operator "minus" for the two surfaces, where the value in a cell in the 20 output grid is obtained by deducting the value of the corresponding cell in the surface for men from the value of the corresponding cell in the surface for women. Peaks in this "difference surface" indicate areas where the intensity of women's non-employment activities is much higher than that of men, and vice versa. The overall pattern suggests that the activity density for the part-time employed women is in general higher than that of the part-time employed men. Women performed more activities throughout the day from 6:00 a.m. to 9:00 p.m. from 4 to 8 km from home. There is a very sharp trough centered at 2:00 p.m. very close to home (within 1 km) indicating that men

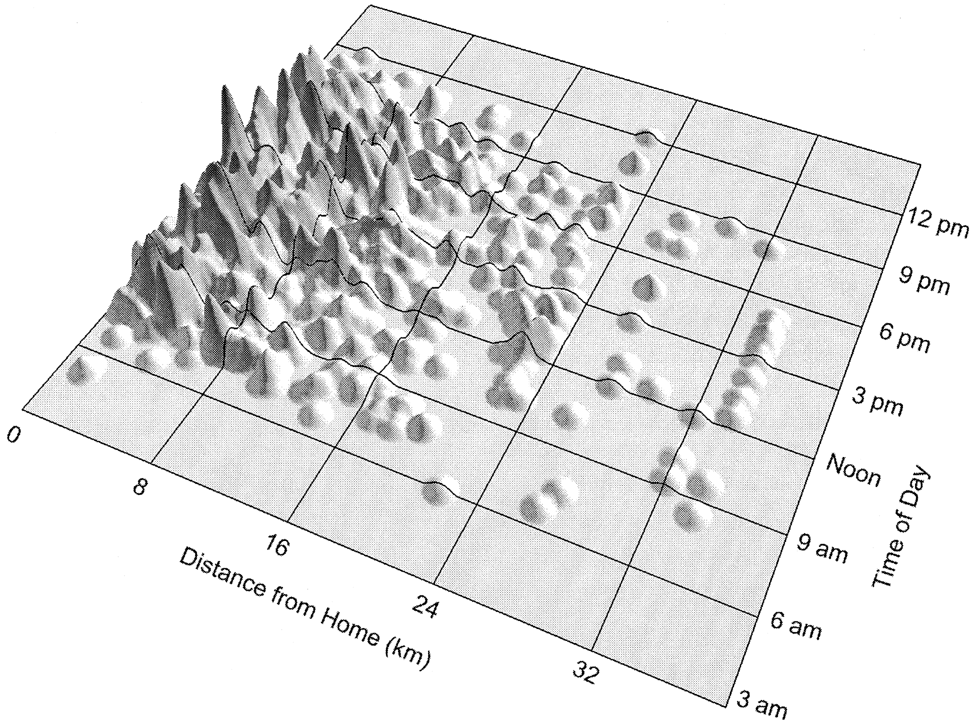

Fig. 4. Space-time activity density of non-employment activities for women employed part-time.

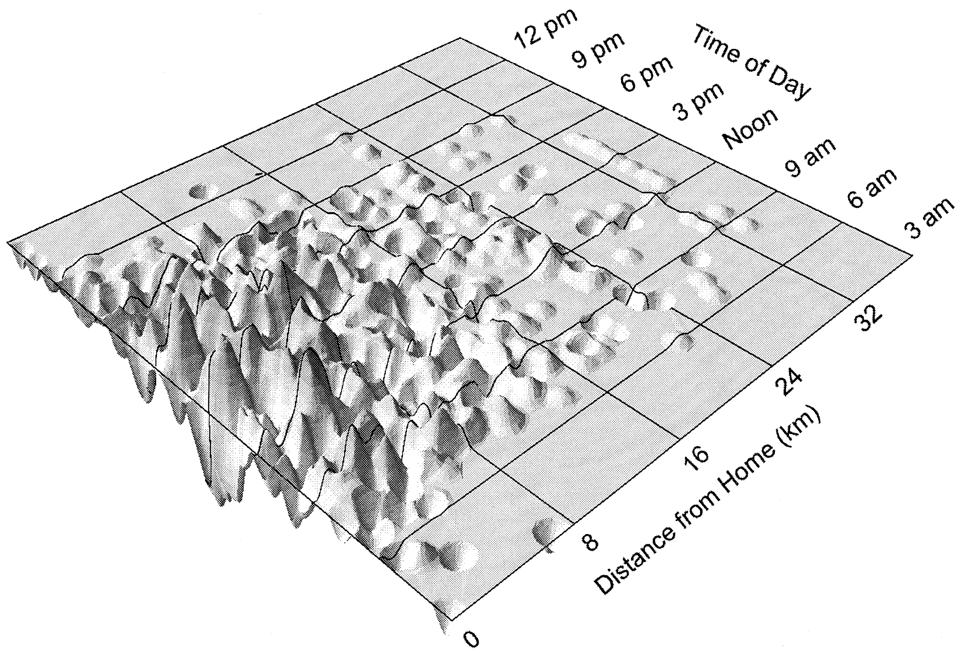

Fig. 5. Gender difference in the density of non-employment activities between women and men employed part-time.

performed many more non-employment activities than women in this space-time area. Another sharp trough is found in the evening hours between 7 p.m. to 8 p.m. about 3 km from home.

There are two major advantages in using these 3D space-time activity density surfaces. First, they reveal the intensity of activities in space and time simultaneously, thus facilitating the analysis of their interaction. Second, the grid-based method is amenable to many map-algebraic operations that can be used to adjust the computed raw density for highlighting the distinctiveness in the activity patterns of a particular population subgroup. It also makes the derivation of a "difference surface" for two population subgroups relatively easy, thus facilitating the examination of inter-group difference. The following section turns to explore the 3D geovisualization of space-time paths.

5. Geovisualization of individual space-time paths

5.1. The space-time aquarium

For the visualization of individual space-time paths, the earliest 3D method is the 'space-time aquarium' conceived by Hägerstrand (1970). In a schematic representation of the 'aquarium', the vertical axis is the time of day and the boundary of the horizontal plane represents the spatial scope of the study area. Individual space-time paths are portrayed as trajectories in this 3D aquarium. Although the schematic representation of the 'space-time aquarium' was developed long ago, it has never been implemented using real activity-travel diary data. The main difficulties include the need to convert the activity data into "3Dable" formats that can be used by existing visualization software, and the lack of comprehensive geographic data for representing complex geographic objects of the urban environment. The recent incorporation of 3D capabilities into GIS packages and the availability of contextual geographic data of many metropolitan regions have greatly reduced these two difficulties.

To implement 3D geovisualization of the space-time aquarium, four contextual geographic data layers are first converted from 2D map layers to 3D shape files and added to a 3D scene. These include the metropolitan boundary, freeways, major arterials, and rivers. For better close-up visualization and for improving the realism of the scene, outlines of commercial and industrial parcels in the study area are converted to 3D shapes and vertically extruded in the scene. Finally, the 3D space-time paths of individuals who are African Americans, Hispanics and Asian Americans from the subsample are generated and added to the 3D scene. These procedures finally created the scene shown in Fig. 6.

The overall pattern of the space-time paths for these three groups shown in Fig. 6 indicates heavy concentration of day-time activities in areas in and around downtown Portland. Using the interactive visualization capabilities of the 3D GIS, it can be seen that many individuals in these ethnic minority groups work in that area and a considerable amount of their non-employment activities are undertaken in areas within and east of downtown Portland. Space-time paths for individuals who undertook several non-employment activities in a sequence within a single day tend to be more fragmented than those who have long work hours during the day. Further, ethnic differences in the spatial distribution of workplace are observed using the interactive capabilities provided by the geovisualization environment. The space-time paths of Hispanics and Asian

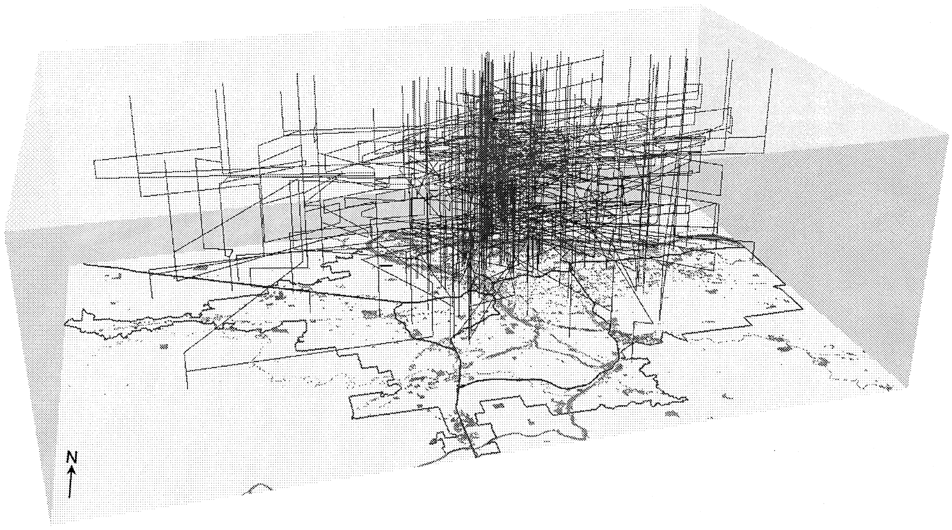

Fig. 6. Space-time aquarium with the space-time paths of African Americans, Hispanics and Asian American in the subsample.

Americans are more spatially scattered throughout the area, while those of the African Americans are spatially restricted, concentrating largely in the east side of the metropolitan region.

A close-up view from the southwest of this interactive geovisualization session is given in Fig. 7, which shows some of the details of downtown Portland in areas around the "loop" and along the Willamette River in the foreground. Portions of some space-time paths can also be seen in this scene. With the 3D parcels and other contextual layers in view, the figure gives the researcher a strong sense about the geographical context through a virtual reality-like view of the downtown area. This interactive virtual environment not only contextualizes the visualization in its actual geographical surrounding but also enables the analysis of local variations at fine spatial scales. For instance, in the color version of the figure provided on the Web, commercial buildings are color-coded orange–brown, while industrial buildings are in green. The use of color codes for distinguishing different types of buildings would give the analyst a sense of the potential interaction space and its context, which can then be compare to activities and paths of the individuals (where activities and stops can also be color coded by activity type). This approach will therefore have considerable potential for the development of person-specific, activity-based methods at fine spatial scales.

5.2. Standardized space-time paths

Although the 'aquarium' is a valuable representational device, interpretation of patterns becomes difficult as the number of paths increases with the number of individuals examined. Further, since the home-work axis for different individuals have different locations and are oriented in different directions, it may be difficult to detect patterns through visualization. One way to overcome these limitations is to plot space-time paths using a standardized or transformed

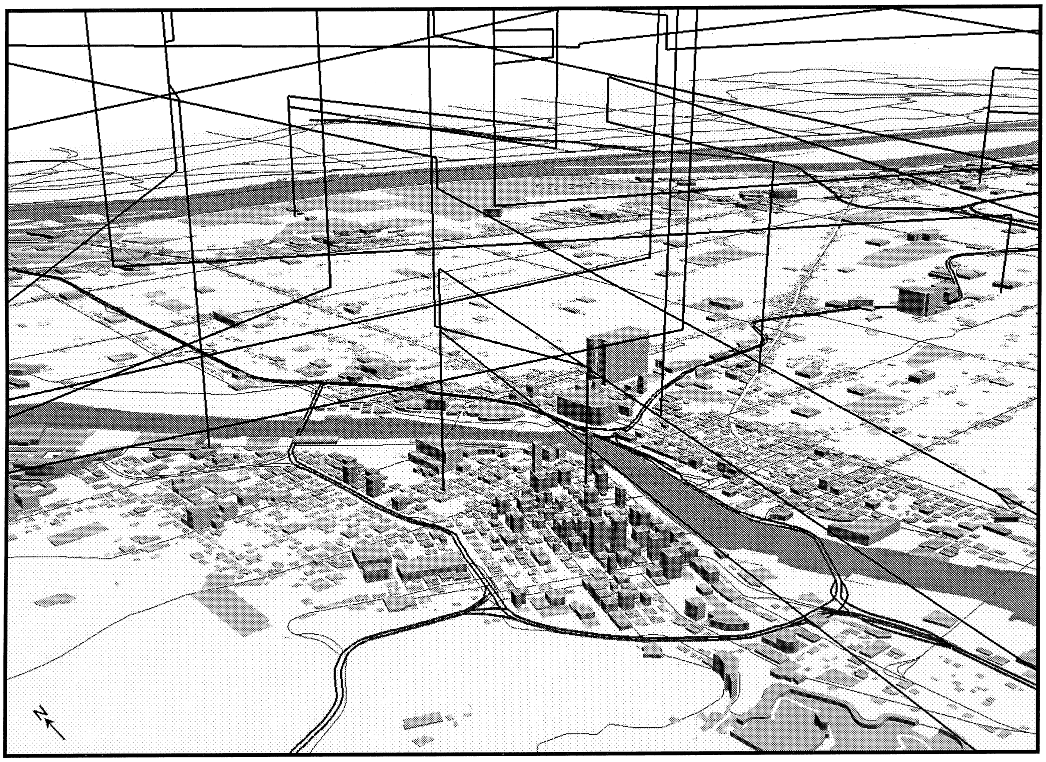

Fig. 7. A close-up view of downtown Portland from the 3D scene shown in this figure.

coordinate system. This can be done by shifting the locational coordinates of all activity sites for an individual so that the home location becomes the origin (0,0) and the home-work axis is rotated until it becomes the positive x-axis. Using these transformed or 'standardized' space-time paths, many distinctive features of the trajectories of a particular population subgroup may still be identifiable even when numerous space-time paths of many individuals are plotted. Fig. 8 shows the standardized space-time paths for the individuals of the three minority groups in the subsample. The vertical plane is the home-work plane where the home location is indicated by the origin (0,0). In the interactive visualization session, it can be seen that there are considerable amount of non-employment activities during the day, and that there are distinctive bundles of work activities at particular distances from home. Further, the spatial distribution of these non-employment activities reflects a bias toward the home-work axis, supporting similar observations in previous studies (e.g., Kitamura et al., 1990; Saxena and Mokhtarian, 1997).

In view of the complex space-time patterns the researcher has to deal with when using these methods, pattern extraction algorithms and other geocomputational procedures can be developed to complement the geovisualization methods discussed in this section (e.g. the GIS-based geocomputation of individual accessibility by Kwan, 1998; Miller, 1999). Thus, these 3D methods enabled by the 3D geovisualization environment can be the basis for developing and formulating quantitative methods for the characterization and extraction of patterns from the large number of space-time trajectories as valuable analytical tools.

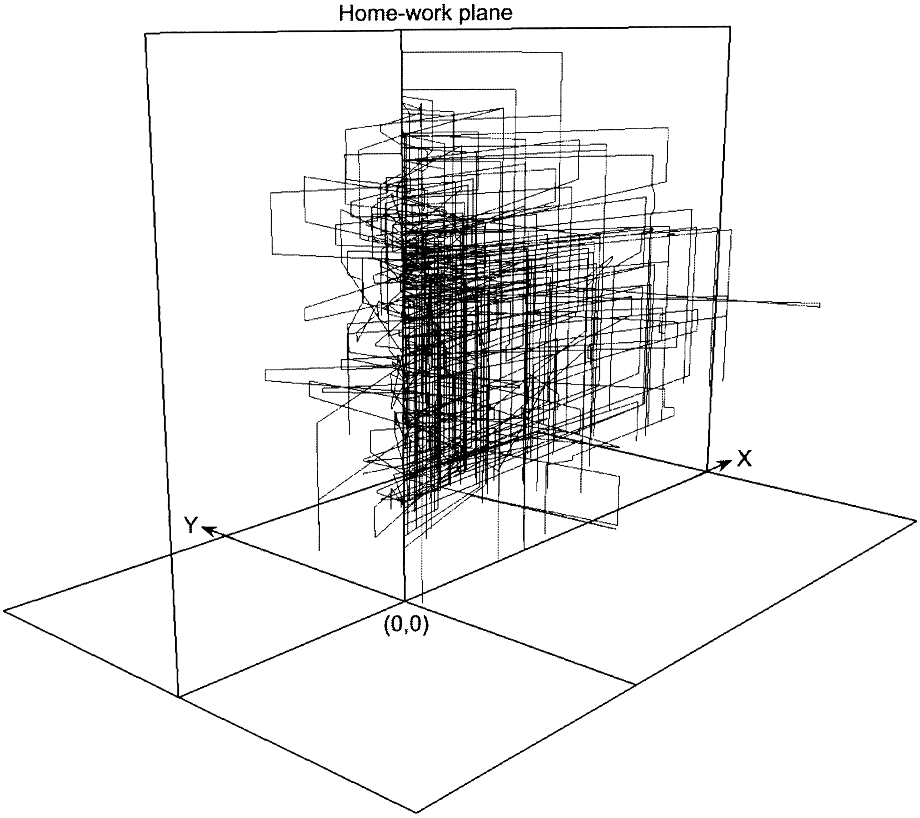

Fig. 8. Standardized space-time paths.

6. Conclusions

The dynamic and interactive GIS-based 3D geovisualization methods discussed in this paper are useful for the exploratory analysis of activity-travel patterns. They allow the researcher to interact, explore and manipulate the 3D scene. Not only the visual properties of objects can be altered to reflect their various attributes, the highly flexible viewing and navigational environment is also a great help to the researcher. As shown by the examples, these methods are capable of revealing many important characteristics of the space-time activity patterns of different population subgroups in relation to the concrete urban environment. They also facilitate the identification of complex spatial relations and the comparison of patterns generated by individuals of different gender/ethnic subgroups. Further, these interactive 3D geovisualization methods may provide the foundation for developing geocomputational algorithms or formulating operational measures of various aspects of activity-travel behavior. As individual-level, geo-referenced data become increasingly available (Kwan, 2000c), the development and implementation of these kind of geovisualization methods is a promising direction for transportation research in the future.

There are, however, several difficulties in the development and use of these 3D methods. First, there is the challenge of converting many types of data into "3Dable" formats for a particular geovisualization environment. Since every visualization software may have its unique data format requirements, and the activity and geographic data currently available are largely in 2D formats, the data preparation and conversion process can be time consuming and costly. For example, considerable data preparation and pre-processing are required for converting the Portland activity-travel data before they can be displayed as 3D space-time paths. Future research should investigate how the effort and time spent on data conversion could be reduced when data from various sources are used.

Second, the researcher may encounter barriers to the effective visualization of large and complex activity-travel data sets. Four such potential barriers identified by Gahegan (1999) are: (1) rendering speed: the ability of the hardware to deliver satisfactory performance for the interactive display and manipulation of large data sets; (2) visual combination effects: problems associated with the limitation in human ability to identify patterns and relations when many layers, themes or variables are simultaneously viewed; (3) large number of visual possibilities: the complexity associated with the vast range of possibilities that a visualization environment provides (i.e., the vast number of permutations and combinations of visual properties the researcher can assign to particular data attributes); and (4) the orientation of the user in a visualized scene or virtual world. Implementation of the interactive 3D methods in this study shows that a geovisualization environment which provides a geographical context for the researcher may considerably alleviate the fourth problem. However, the other three barriers may still remain a significant challenge to researchers who want to use this kind of methods. For instance, rendering the density surface in Fig. 4, which involves 227,041 triangles, can be taxing on the hardware. Further, identifying patterns from the space-time paths covering 129,188 activities undertaken by the survey respondents may push our visual ability beyond its limit. Future research should examine how human cognitive barriers involved in the interpretation of complex 3D patterns may be overcome.

Third, the use of individual-level activity-travel data geocoded to street addresses, given their reasonable degree of positional accuracy, may lead to considerable risk of privacy violation. As Armstrong and Ruggles (1999) demonstrated, although "raw" maps that comprised of abstract map symbols do not directly disclose confidential information, a determined data spy can use GIS technology and other knowledge to "hack" the maps and make an estimate of the actual address (and hence, a good guess of the identify of an individual) associated with each point symbol. This practice, called "inverse address-matching", has the potential for serious confidentiality or privacy violation. As "map hackers" may be able to accurately recover a large proportion of original addresses from dot maps, any use of such kind of individual-level geocoded data should be conducted with great concern in protecting the privacy of survey respondents and maintaining the confidentiality of information. As apparent in the 3D geovisualization examples in this paper (e.g., the details in Fig. 7), releasing a 3D scene created from several accurate data themes in virtual reality markup language (VRML) format may lead to significant risk of privacy violation because map hackers may be able to recover the identity of a particular survey respondent. This may further lead to the disclosure of other confidential information. As a result, researchers using the 3D geovisualization methods discussed in the paper should pay particular attention to this potential risk.

Acknowledgements

Support for this research from the College of Social and Behavioral Sciences, the Ohio State University, is gratefully acknowledged. The author would like to thank three anonymous reviewers for their comments on an earlier draft of this paper.

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