A Visualization Strategy for Analyzing High Volumes of Space-time Activity Data

Thesis

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Abstract

In the four decades of work in time geography, research has shed light on a number of social science topics related to human activity. Access to critical resources or spaces, patterns of behavior, and migration are subject areas that have benefited greatly from the time geographic framework. Since the field’s inception in Sweden in the 1960s, some of the largest developments have been operationalizing the concepts of time geography in computerized systems, and an increase in the availability of human activity data. With activity data easier to acquire, it is likely that it will be collected in ever larger samples. Future research will need to handle these higher data volumes, or risk being overcome by large, complicated data sets. The analysis techniques useful for analyzing the space-time activity of an individual, or a small set of individuals, may not be efficient for analyzing data sets of thousands of individuals. This study begins with a literature review that covers the fundamentals of time geography, reviews important applications of the time geographic framework, and surveys the visualization and analysis methods utilized in the prior work. Next, a method is developed that combines successful elements of prior work with the space-time aquarium with a 3D points cloud-based visualization technique that may be suitable for large data volumes. Finally, a prototype analysis environment is created, and its capabilities in detecting behavioral patterns among a large volume of activity diary data is determined.
Dedication

Dedicated to my parents.
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Introduction

Forty years ago, the time geographic framework emerged as an alternative to large aggregate models of human behavior. The framework advocates using the individual human being as the analysis unit, and recognizes that regional-scale phenomena are emergent from the behavior of a diverse population of individuals. In the context of phenomena like the spread of disease, migration, traffic, tourism, and the consumption of goods and services, the existence of a linkage between the two scales is clear.

Time geography is so-named because in order to understand human behavior, it is necessary to know not only the spatial situation of individuals, but also their time constraints. These time constraints are influenced by the number, location, and timing of individuals’ mandatory activities, and the means they have to travel between them. While some correlation can be found between constraints and demographic attributes, there is enough diversity among people within a demographic group that it is still their individual concerns that dictate their behavior. Therefore, even in a relatively homogeneous areal unit, it would be inappropriate to generalize the behavior of the individuals that live there.

In the preceding decades, many studies have surveyed populations to collect data on
individual space-time behavior. Lately, advanced technology has enabled human space-time behavior surveys to be conducted more easily, which will likely lead to more datasets being collected, and a trend towards a greater number of individuals in each dataset. This sort of data has the potential to fulfill time geography’s mission to improve quality of life by better understanding how behavior influences, and is influenced by, regional phenomena.

This study will examine if current spatial analysis methods are suitable for understanding increasingly large human space-time behavior (HSTB) datasets. Previous research in time geography has utilized the two complementary approaches of geocomputation and geovisualization. Both have advanced greatly in recent years, but while geocomputation is likely mature enough to be used with high volumes of behavior data, geovisualization is in need of more work in order to support large data volumes. Additional work on geovisualization is worthwhile because of its importance during the beginning stages of analysis, when a researcher is becoming familiarized with the data. In this process of exploratory data analysis, geovisualization can help researchers avoid improper assumptions of the HSTB data and formulate the questions for further investigation.

This study begins by describing the previous work in the study of HTSB, and then develops a geovisualization method that leverages the strengths of previous approaches. The proposed geovisualization method is tested on a dataset of thousands of individuals on the city scale to identify patterns among groups of people. Increasing the ability to recognize patterns in a large dataset has potential benefit in a broad range of applications,
including site selection for commercial and public enterprises, emergency response, and understanding human space-time accessibility.
Chapter 1: A Review of Existing Capability for the Analysis of Human Space-Time Behavior

1.1 Time Geography

Time geography was initially developed in the 1960s at Lund University in Sweden. The central figure in the field is Torsten Hägerstrand, who first described the key features of time geography in his 1969 address to the Regional Science Association. He advocated a shift in focus in regional science from modeling regional systems as homogenous zones to methods that use individuals as the unit of analysis. Regional science was seen to be in a position to improve the quality of life of individuals, and quality of life is only meaningfully measured at the individual scale. Access to important resources like schools, health care, and recreational opportunities is one way in which an individual’s quality of life might be better understood. Previous work had been conducted on population in highly aggregated form, “without explicit statements about the assumed social organization and technology that exist at the micro-level” (Hägerstrand, 1970). Using large aggregations of people as the analysis unit leads to assumptions and broad generalizations on the variety of existing behavior, perhaps with serious consequences. If urban planners, for instance, were to continue to assume uniform zonal demographic distributions, they would run the risk of wasting public funds on projects that would not
meet development goals, or in a worse case, possibly alienate and disenfranchise elements of their population.

The main ideas of time geography are that regional data should be collected at the level of the individual human being, and for those individuals, time should be considered along with space to understand their behavior. The decisions that we make as individuals navigating our world are easily as influenced by our temporal location and the time that is available to us at that moment as they are by our spatial positions. The actions we actually take are manifestations of not only our needs and desires, but our time and space constraints. Hägerstrand identified three different kinds of constraints on human behavior: capability constraints, coupling constraints, and authority constraints. Capability constraints include the limitation placed on a person’s available time by personal maintenance activities like sleeping and eating, and set a maximum distance a person can travel from home, based on the idea that the person must return there to rest. There also exist coupling constraints, which describe scenarios where a person must be co-located with another person or object in order to carry out an activity. Authority constraints are the manifestations of legal and power relationships. For instance, a person may be denied entry to an area due to trespassing laws, or from occupying a seat at a sporting event that does not match the one assigned by a ticket (Hägerstrand, 1970; Pred, 1977).

In order to visualize the relationship between space and time and to provide an analytical framework, Hägerstrand (1970) envisaged time as an axis perpendicular to the two spatial
axes of a map, producing a three-dimensional space-time cube, or space-time aquarium. In truth, adding a dimension of time to real three-dimensional space would produce a four-dimensional space, but such a framework would be difficult to effectively visualize, and thus the height dimension is usually ignored.

A person, or any other living or non-living object, has a life path that traces its position in the space-time aquarium for as long as it exists. A life path begins at the coordinates representing the spatial position and temporal location of a person’s birth, and does not end until a person is deceased. As long as an individual can be said to exist, at no time can their life path occupy than one spatial location at once, or no location at all (Hägerstrand, 1970). The more generic term for such a path is the space-time path, and instead of representing an entire lifetime, it may reference only the time interval for which a researcher is interested in, or for which data was collected. Often, space-time paths are shown in the context of a single day.

When a person is staying in one place, their space-time path is vertically-oriented, parallel to the time axis. During the course of a normal weekday, an individual will likely have several vertical sections of their space-time path associated with common stationary activities like working, eating, and sleeping. When an individual is moving from one place to another, their space-time path is sloped, with a steeper slope indicating a slower rate of travel.
In any given day, an individual will have activities that are required of them, and are fixed in space and time. It is the time between these activities that provides individuals the opportunity to participate in discretionary activities. A volume of space-time exists between fixed activities, encompassing the varying spatial region that can be visited by an individual given the time remaining before their next fixed activity. This volume is called a space-time prism, after the shape of its upward cone-shaped walls beginning when one fixed activity is finished, and downward cone-shaped walls leading up to the point where their next fixed activity is located (Hägerstrand, 1970). The size of a prism is therefore a function of the locations of the fixed activities and the time available between them, and also of an individual’s access to transportation. A space-time prism for someone driving an automobile will be much larger than for a person traveling on foot.

All of the space-time locations in the prism have a non-zero probability of being inhabited by an individual’s space-time path, which leads to the prism defining the potential path space (PPS). The prism can also be represented as a 2D projection onto a map, which would show its maximum spatial extent, called the potential path area (PPA) (Lenntorp, 1976).

1.2 Implementing Time Geographic Concepts

The concepts of a space-time path and PPA allowed for the first computerized operationalization of time geography. Lenntorp (1976) implemented the concepts in a
simulation model named PESASP, the Programme Evaluating the Set of Alternative Sample Paths. Input data was derived from surveyed data of 202 individuals, and was used to calculate numerous alternative paths that fulfilled the daily activities for individuals in the survey. The data was a subset of the original sample of 2,041 persons that met several requirements, such as the space-time path including visits outside the home, flexible activities, and a requirement for the path to be “manageable operationally.” The last requirement eliminated relatively rare trips by boat, and also limited the travel range of individuals for the sake of computational and data preparation simplicity.

For each person, the model simulated all of the potential space-time paths a person could follow in a day, given a requirement to conduct certain activities and the amount of travel time available between them. In the study, a higher number of potential space-time paths is understood to represent a higher degree of space-time accessibility. General activity programs were derived from the 202 observed space-time paths, and were used as input data for the model. Activity programs contain information on the stations that an individual visited, or the type of station if the specific facility is flexible. The observed times of arrival at stations in the space-time paths are listed in the activity programs, with some converted into a range of ten or twenty minutes that an individual may arrive during. In the model, three different scenarios were considered. In the first scenario, the order of the activities prescribed in the activity program was completely flexible. In the second, the order of activities must equal to the order in the space-time path, which still allows for flexibility in which grocery store is selected to shop at. The final scenario is
similar to the second, but requires the simulation to select a grocery store at least as large as the one present in the original space-time path.

In all three scenarios, those individuals that traveled by car had the greatest number of modeled space-time paths, and thus the largest amount of space-time accessibility. On average, car drivers had three times the number of potential paths than those that used other methods of transportation, which included walking, public transportation, and combined walking and public transit. The flexible order scenario resulted in the largest number of potential paths due to its relaxed rules. The fixed order scenario contained roughly half as many potential paths, and the most restrictive scenario with a requirement on food store size halved the resulting number of paths again (Lenntorp, 1976).

The 1976 PESASP simulation remains one of the few successful attempts at operationalizing space-time concepts in a computer model. At the time, it represented a huge accomplishment born out of a lengthy process of creating digital versions of the activity data and the local transportation network. The model was programmed using thousands of punch cards, and took over five hours to run. Today’s agent-based population models have some features in common with the way PESASP handles activity schedules, and the most important differences between Lenntorp’s 1976 simulation and current models lie in areas of detail and complexity. For example, PESASP has a simplified transit network with uniformly-spaced public transit stops, and individuals move about the region at a fixed speed. In a more modern model like TRANSIMS, transit networks are reproduced with high fidelity to their actual layout, individuals move
about at varying speeds, and those speeds are influenced by the modeled congestion of traffic around them (TRANSIMS, 1999). Of course, this additional detail is possible because modern simulations run on computers several orders of magnitude more powerful than what was available in the 1970s.

1.3 GIS Implementations of Time Geography

The first geographic information systems (GIS) in the 1960s and 70s were constructed in a similar fashion to PESASP and other scientific models, in that they were created from the ground up to suit a particular agency’s needs, and were usually not available outside the owning agency. Commercial GIS systems began to become available in the early 1980s, making widely available for the first time the kind of complex analysis enabled by overlaying multiple spatial data sets.

Working with HSTB data within a GIS is an advantageous approach not only because it uses a system that natively understands geographic data, but also because it allows the joint analysis of accessibility data with other complementary data sets. It was not until the 1990s until time geographic concepts were integrated within a GIS, however.

The following are descriptions of previous work in two complementary fields of research in the GIS analysis of time geography: geocomputation, and geovisualization. The cited studies are not completely exhaustive of these broad and developing fields, but reflect
key developments that have enabled the current state of the art in understanding human space time behavior.

1.3.1 Geocomputation

Lenntorp’s 1976 study demonstrated the potential for advanced computational techniques to explore human space-time behavior. Around twenty years later, geocomputation emerged as an interdisciplinary field that utilizes the state-of-the-art in computer science and statistics in order to solve geographical problems. The techniques offered by these complimentary disciplines are helpful for handling the size and complexity found in HSTB data. Previous research has utilized geocomputation to calculate space-time accessibility measurements for individuals, creating a single index value for each person out of their complex behavior. These index values can be used to discover who is experiencing a high quality of life, and who may be excluded from doing so by situational and institutional constraints. The following section describes several formulations of these quantitative accessibility measures and the differences between those that use the time geographic framework versus other techniques based on spatial interaction.

1.3.1.1 Miller’s Algorithm

In 1991, Miller developed an algorithm for determining network-based PPAs within a GIS (Miller, 1991). The algorithm begins by identifying all of the network arcs that are
accessible from a starting location given a time budget. Once the set of arcs has been built, each arc is tested to determine if a person in the arc could reach the next fixed activity within the time budget. The algorithm does so by proceeding along the shortest path to the node of the next fixed activity, deducting the time used in travel from what remains of time budget. If the time budget is exhausted before the destination node is reached, the starting arc is removed from the set of arcs that make up the PPA.

The procedure required certain abilities of the GIS with respect to data handling and network calculations, which Miller determined were not present in the GIS systems available at the time. The then-current version of ARC/INFO had the basic network operations required, but limitations like requiring the processing of each potential path that makes up the PPA separately, and an inability to only calculate a path up to a time budget made the software impractical for calculating PPAs using the proposed algorithm.

1.3.1.2 Kwan’s Algorithm

Later in the decade, Kwan successfully implemented space-time accessibility measures in ARC/INFO GIS, and compared space-time accessibility measures against integral measures, such as those from gravity models and cumulative opportunity models (Kwan, 1998). Data on space-time constraints was derived from a mail survey conducted in Columbus, Ohio in 1995. From the respondents, eighty-seven people were selected from households in which both males and females had access to automobiles. With access to transportation held equal in the sample, the space-time measures are able to describe
differences between male and female accessibility based on their space-time constraints. In the survey, respondents were asked to rate the degree of spatial and temporal flexibility of their activities on a scale from one to five, with one being the most flexible. Activities were considered fixed if they were rated a value of four or five, and the time between fixed activities was used as the time budget to calculate PPAs (Kwan & Hong, 1998).

Kwan found that exhaustive definitions of PPAs using Miller’s (1991) method described above, or a method involving the precalculation of a distance matrix using the shortest path algorithm were too computationally intensive to be feasible (Kwan, 1998). Instead, Kwan and Hong’s (1998) method was used, which runs more quickly because it does not calculate shortest paths. The method involves dividing the time budget into two parts, one representing travel time from the origin location, and the other representing travel time to the next fixed location. The proportion of the total time budget assigned to each part is varied by a regular interval, and for each variation, an arc allocation is performed that determines the set of arcs that can be reached given their assigned times. These two sets of arcs are then intersected. The results from the intersection operation represent the street segments that can link the two sets of arcs. By performing this operation over varying time intervals, and creating the union of each intersection result, the true PPA is approximated without the need for the shortest path algorithm.

This procedure is performed for every pair of fixed activities, and for each person in the sample. The union of every approximated PPA for a person creates their daily PPA
Three ways of measuring space-time accessibility can be derived from the DPPA. One is the number of opportunities that the DPPA contains, the second is the weighted sum of the opportunities (in this case, the opportunities were weighted by the opportunity’s parcel area), and the third is the total length of the street segments in the DPPA (Kwan, 1998).

Kwan compared these ST measures to two integral measures of accessibility: gravity-based and cumulative-opportunity indices. Gravity-based measures are based on formulas that weigh opportunities by some measure of attraction, and reduce their weight by some measure of impedance. For example, if the opportunities are retail stores, a store’s gross sales could be used to measure its attractiveness, and the distance from a person would increase the impedance in the function. Kwan used exponential, Gaussian, and inverse power functions to calculate impedance, each having different characteristic rates of decline over distance from an origin. The inverse power function has the most rapid decline over distance, and the Gaussian function the most gradual decline.

Cumulative-opportunity indices, on the other hand, are based on the weighted sum of opportunities within a specified distance or travel time. Kwan used two kinds of impedance functions for the cumulative measures: the rectangular function and the negative linear function. The first assigns full weights to all opportunities regardless of the distance from the origin, as long as the location is found within the specified distance range. The second reduces the weights assigned to locations in inverse proportion to distance from the origin, until the specified distance is reached, where locations would have a weight of zero.
Kwan found that the integral measures correlated strongly with each other, but weakly with the space-time measures. Additionally, gravity indices, cumulative indices, space-time measures for men and space-time measures for women weighed strongly on separate factors in factor analysis. Both statistical tests suggest that the integral and space-time measures are measuring distinct properties.

Spatially, the gravity measures show the largest accessibility values near the intersections of major highways, and the cumulative measures show high accessibility in the downtown area, with steady decreases towards the edges of the study area. The space-time measures do not feature distinct spatial patterns, however. This is because individual situations and space-time constraints do not strongly correlate to home location, due to the fact that the space-time measures are based on a sequence of activities conducted at locations that include, but are not limited to the home. In this light, it is not surprising that no strong relationship was found between the spatial distribution of activities and the space-time accessibility surfaces, but this is a key difference between space-time accessibility measures and integral measures (Kwan, 1998).

The space-time measures are also able to exhibit gender differences. Spatially, the accessibility patterns of males, while mostly indistinct, more closely resemble the pattern seen in the gravity measures. The space-time accessibility values for females, however, seem to have no meaningful pattern. The space-time accessibility levels for males and females in the same household were found not to be strongly correlated, and in factor
analysis, male and female measures were found to load strongly on separate factors (Kwan, 1998).

However, individual differences based on gender or most other categories can not be discovered by the integral measures. The only personal attribute that could have affected the values of the integral measures is a person’s access to mode of transportation. Since all members of the sample had access to a car, male and female members of the same household would be considered to have the same level of accessibility by the integral measures. Another disadvantage of the integral measures relates to their accounting of accessibility to a single location (usually the home). In contrast, space-time measures acknowledge that activities are conducted in a sequence, from potentially many different points of departure in any given day. Integral measures also do not consider spatio-temporal constraints, which will render activity locations unreachable depending on a person’s position and time budget before their next fixed activity (Kwan, 1998).

1.3.1.3 Miller’s 1999 Algorithm

Miller’s (1999) algorithm expands on previous work by incorporating space-time accessibility benefits offered by locations. The method combines time geography with the frameworks of attraction-accessibility and transportation benefit. Miller’s earlier study (1991) found that the then-current GIS software was unsuitable for accessibility calculations, but eight years of advancement in the ARC/INFO GIS software and the
custom development of accessibility measurement software enable such calculations to be computationally tractable.

Miller (1999) rigorously defines space-time accessibility measures within Weibull’s axiomatic framework, which ensures consistency between the measures with other standard attraction-accessibility measures (Weibull, 1976). Using a generic utility function, Miller defines an additive, a transform-additive, and a maxitive accessibility measure. Each incorporates the properties of the space-time prism, and considers the maximum amount of time that can be spent at an opportunity location. With the additive and transform additive measures, it is possible for several relatively unattractive locations to yield an accessibility figure as high as a single attractive location, while the maxitive measure is affected only by the location that is most desirable (Miller, 1999; Weibull, 1980).

Miller (1999) utilizes a hypothetical street network and locations in example calculations for the accessibility measures. Shortest paths between each network node and activity locations are pre-calculated before accessibility queries are run. While this calculation could integrate the effects of congestion, the specific proposed version does not support congestion effects varying over time, although the method could likely be adapted to support it with little difficulty. Using the hypothetical network, Miller (1999) demonstrates that each kind of accessibility measure can be utilized in three different ways. First, the measures can apply to an individual. Given the locations of the origin and destination fixed locations, travel time assigned to the street network links, and a set
of possible flexible activities with varying locations and attractiveness, each of the three measures can give a single numerical result meaningful at the ratio scale.

The measures can also be used to interpolate accessibility values along network nodes. Miller (1999) gives the example of varying the potential location of a second fixed activity relative to the first. The algorithm can calculate the values on network links between existing nodes, and the sample calculation demonstrates decreasing accessibility on all three measures as distance increases.

Finally, the measures can be used as an attribute query. A researcher can query the software asking for areas on the network that meet a minimum threshold of accessibility, given the location of one fixed activity and the attractiveness of several other locations.

1.3.1.4 Weber and Kwan’s Algorithm

Weber and Kwan’s 2002 and 2003 research enhanced Kwan’s (1998) algorithm with a better representation of travel time on the street network, and incorporated the open hours of opportunity locations. Potential path areas were calculated with different speeds mapped to different street types, and incorporated an evening congested travel period. This research was based on an activity survey conducted in Portland, Oregon in 1994 and 1995.
The 2002 study examined the accessibility of 200 persons with access to an automobile using five different accessibility measures. The first three are: the total miles in the DPPA, the number of opportunities in the DPPA, the total area of opportunity parcels in the DPPA. The fourth is the parcel area, with regions of multistory buildings given a larger weight. The fifth is a variation of the previous weighted area measure, but considers opportunity locations to only be available from 9 AM to 6 PM (Weber & Kwan, 2002).

Confirming the results of Kwan’s previous (1998) study, the spatial distribution of computed accessibility values showed no distinct pattern, even given the weight that was applied to the Portland central business district (CBD) in the weighted area measure. The authors attribute this partially to the travel speeds varying by road type and to the varying activity times for individuals. Those individuals that attempt to conduct activities during the period that roads are congested will have their accessibility more negatively impacted. Congestion lowered accessibility city-wide, but had the greatest effect on those living thirty to thirty-five minutes from the CBD.

In addition to calculating the space-time measures, Weber and Kwan examined their relationship with the traditional ideas of a monocentric or polycentric city. With these concepts, individuals would be expected to have the highest accessibility close to a city center, with decreases in accessibility over distance. In the test of the monocentric paradigm, the first four accessibility measures were found to have average values until a peak of maximum accessibility for those living twenty to twenty-five minutes from the
CBD. This distribution suggests that the suburbs would have the highest accessibility. However, the fifth measure, which has opportunities closing at 6 PM, has a markedly different distribution over distance. The highest values are found around ten to fifteen minutes from the CBD, with steady decreases after that. The suburbanites that were favored by the other measures were more affected by the restriction of opportunity hours due to more of their activities being scheduled at night, and this suggests that measures that do not take into account the hours that opportunities are open are overestimating accessibility.

To test the polycentric city paradigm, Weber and Kwan also analyzed the relationship between the accessibility measures and distance from twelve distributed city centers identified by Metro, the Portland regional government (Metro, 1997). All measures were highest near the centers, and lowest at the farthest distance interval, with a local minimum and maximum in between. The fifth, time aware measure had by far the highest standardized value at the five minute travel time interval from urban centers, showing that those who live close to these centers conduct more of their activities during the open hours of the opportunities. The variability of the each standardized measures, excluding the high value at the short time interval for the time-aware measure, was relatively low (around twenty percent). The conclusion is that the relationship of distance with the time-sensitive and non-time-sensitive measures shows distinct geographies of accessibility. However, accessibility is not determined solely by distance from urban centers, as the monocentric and polycentric models of behavior advocate (Weber & Kwan, 2002).
In a follow-up study, Weber and Kwan sought to further understand the influence of place on accessibility (Weber & Kwan, 2003). Using a larger subset of the Portland survey data, 755 individuals, regression modeling and multilevel modeling were employed to determine the relationship of a neighborhood’s contextual attributes with accessibility. The 2003 study used the same five measures of accessibility as the 2002 study.

Attributes selected for the study were numerous, and the following is only a partial list. Demographic attributes included age, sex, race, household income, and children in household. Attributes representing the distance to the central business district or other urban centers were also included to once again test the monocentric and polycentric city paradigms. Finally, neighborhood contextual variables such as average housing values, age of homes, percent owner-occupied homes, housing density, detached (single-family) homes, and neighborhood income.

Each of these attributes was entered into stepwise regression models to predict each of the five accessibility measures. In the best-fitting models, the only significant contextual attribute is the proportion of detached homes. Increasing proportions of detached homes was found to have a strong positive effect on the number of opportunities and the time-sensitive weighted area measures. Only two demographic variables proved significant: the number of hours worked, and the household size. While household size only appeared in the measure of miles in the DPPA, the number of hours worked was present
in the final model for each of the five measures. This underscores how important the
temporal demands of work are to accessibility. Large constants in each of the models are
due to the individual spatial and temporal variations in activity scheduling that transcend
the comparatively minor influence of socioeconomics and neighborhood context.

The regression model determined that, on the city scale, individual variation is more
important than contextual variables. In order to determine if accessibility is affected by an
individual’s habitation in a particular neighborhood, or is still due to their individual
activity schedule, Weber and Kwan employed multilevel modeling (MLM). Multilevel
modeling has the advantage of considering both disaggregate individual data and data
summarized to zones, or in this case, neighborhood groups. The results of MLM showed
nearly identical coefficients to the regression models, and the neighborhood effects were
determined to be insignificant. This confirms the impression that accessibility is
overwhelmingly determined by individual differences, not the neighborhoods in which
individuals live, or by the distance of the home from urban centers. This conclusion
would be expected from the space-time accessibility model, which acknowledges that
activities are conducted throughout a city, and do not exclusively use the home as a point
of departure. The regression and MLM results of the study demonstrate that the
monocentric and polycentric models of the city are poor models for determining
accessibility when accessibility is conceptualized as the distance from these centers to a
single point of departure.
1.3.1.5 Kim and Kwan’s 2003 Algorithm

Kim and Kwan expanded on the accessibility algorithms used in previous studies by more realistically defining the conditions that an individual can participate in an activity. One of the most critical additions is the concept of weighting opportunities by the duration of time that an individual can actually spend there. To arrive at a possible duration (as opposed to a maximum duration), there are additional travel and participation characteristics that need to be incorporated. For one, individuals are unlikely to use their entire time budget for a flexible activity by traveling to the boundary of their potential path area, only to spend a trivial amount of time there. To incorporate this, a minimum activity participation time of ten minutes is implemented, as is a maximum travel distance.

As in Weber and Kwan (2002, 2003), opportunity open hours are considered in the accessibility calculations. However, in this study industrial parcels are considered to be open from 9 AM to 6 PM, while commercial parcels are considered open from 9 AM to 9 PM.

Another area of enhancement to the accessibility algorithm is in the handling of the digital street network. Previous studies have ignored the topology of the network, allowing turns to any link connected to a node. Kim and Kwan’s implementation preserves turning rules by respecting the directional flow of one-way streets and
disallowing turns where the topological relationship is unsuitable. For instance, a car should not be able to turn onto a street when the link is coded as an overpass.

While congestion was included in Weber and Kwan’s previous work, it was only included for the evening rush hour. In Kim and Kwan (2003), the morning rush from 7 AM to 9 AM is also considered a congested period for road links. Because even outside of congested times, individuals rarely complete trips in the minimum possible time, delays are implemented into the algorithm for both travel time (dynamic delays), and the time spent locating a parking space and walking to or from the activity location (static delays). Dynamic delays are reductions in average travel speed caused by street signals, the slower rate of travel while turning, and possible roadway accidents, and are represented by a 25% increase in the shortest path travel time. Static delays are represented by an additional five minutes at the beginning and end of each activity.

Unlike some of the previous studies, the proposed algorithm is not implemented on a population, but the algorithm is demonstrated with an example of a single person selected from the Portland activity survey used by Weber and Kwan. Several accessibility measurements are calculated, including the number of opportunities, the area and weighted area of the opportunity parcels, and the amount of time that can be spent at opportunities. In each case, the measure was also calculated taking into account the open hours for locations, resulting in a comparative decrease in the accessibility value. The measure recommended by the study is one that combines opportunity weighting by area with weighting by the possible activity participation time. The space-time accessibility
algorithms that utilize activity duration and facility open hours capture more facets of the individual decision-making process, and measures that do not take these elements into account are likely overestimating accessibility (Kim & Kwan, 2003).

1.3.2 Geovisualization of Time Geography

While numeric measures of accessibility are useful for distilling such a large amount of data, they can be difficult to interpret. Geovisualization can be used as an exploratory step to first gain an understanding of the source data, to place the geocomputational accessibility measures in context, or even to explain variations in accessibility on their own (Kwan & Lee, 2004).

Geovisualization draws broadly from disciplines complementary to cartography in order to explore, analyze, and present geospatial data (Kraak & MacEachren, 2005). The first cartographic representations of space-time activity data lacked the hallmark of geovisualization, interactivity, as computing power at the time was insufficient. The early depictions of space-time did lay the groundwork for the today’s state of the art, however.

Members of the Lund School utilized illustrated schematics depicting time parallel to one or two spatial axes to demonstrate the fundamental concepts of time geography (Hägerstrand, 1970; Lenntorp, 1976). Space-time paths, stations, prisms, and activity
spaces were either precisely sketched by hand, or rendered on computer systems that could take days to complete a graph (Cleveland & McGill, 1988).

While all of the schematics were rendered on a sheet of paper, and thus two-dimensional (2D) in the interactive sense, some depicted a three-dimensional (3D) space composed of time and two spatial axes using graphical perspective. These 3D spaces were the first depictions of the space-time aquarium (Hägerstrand, 1970). It would be some time before computer hardware and software was sufficiently advanced and affordable to enable interactive versions of the space-time aquarium. In the meantime, the traditional 2D map, charts, and tables were used to convey the results of time geographic studies. Some of the 2D techniques became sufficiently capable that they remain preferential to 3D methods, depending on the needs of the particular research study.

The following sections describe methods that have been successfully implemented to analyze human space time behavior data, and are divided into the broad categories of two- and three-dimensional approaches.

1.3.2.1 Two-dimensional visualization

Lenntorp’s landmark 1976 PESASP simulation combined 2D maps, charts, and tables to convey the model results. The book also uses meticulous 3D-style depictions of space-time paths and prisms, but these were used only to review the concepts of time geography
and demonstrate the relationship between prism and potential path area size. Categorical results were represented effectively in tables.

2D maps with dots representing activity stations were utilized to illustrate the difference between observed space-time paths and modeled possibilities. Interestingly, Lenntorp opted not to connect the dots as in a 2D projection of the space-time path, a technique used by Chapin (1974) to show connections between activity pairs. Lenntorp instead provides a verbal narrative for each figure explaining the connections between the plotted points. Both authors used charts to express data on time expenditure (Chapin, 1974; Lenntorp, 1976).

**Interactive Maps**

Nearly three decades later, human activity research can be conducted on personal computers, rather than mainframes. Current personal computers all feature at a minimum a color display and a pointing device, which were absent from the computing resources available to the founders of time geography. Dykes and Mountain (2003) leverage these resources and utilize more advanced 2D maps and interfaces to interpret space-time data.

Using a program called Location Trends Explorer (Mountain & Raper, 2001), Dykes and Mountain (2003) analyze a large point data set representing momentary GPS locations of an individual over time. Their data tracks an individual’s position over two years, with 80,000 individual data points. They argue that the 2D perspective with additional
synoptic views is better suited to extracting periodicities than the 3D perspective of the space-time aquarium because of the continuous and linear representation of time that the aquarium model suggests. The program facilities pattern recognition by linking, brushing, and focusing (Cleveland & McGill, 1988).

In Location Trends Explorer, there are two windows: one containing the 2D map of GPS points, and another with a bar chart that represents the intensity of data collection over time. These windows are linked, in that the selection of data in one display would select it in the other. Dykes and Mountain (2003) are particularly interested in finding discrete episodes of activity out of a large dataset. Episodes of activity could be determined by identifying a cohesive group of data points in the time plot, which would be separated from other clusters of data by break points, which are sudden changes in the time or location from one record to the next. An episode could be selected and made a subset of the whole, so that only the selected data records appear in both displays (the focus technique). Repeated episodes would indicate a pattern of periodicity. Brushing is also supported, where that a paintbrush-like cursor can be moved across one display, triggering a reaction in the linked display (such as highlighting).

Even with these exploratory techniques, it can be difficult to visually interpret a map with thousands of data points, as they tend to overlap and hide the data volume, or become so dense that they block underlying layers of ancillary data (Dykes & Mountain, 2003). An alternative method uses a density surface, a raster representation of the point data that stores the count of the data points in each raster cell. When a color ramp is applied to the
raster representation, areas of higher and lower relative values become clear, and the surface can optionally be smoothed to emphasize trends from one region to another.

In addition, Dykes and Mountain (2003) derive morphometric surface features (Bajaj, Pascucci, & Schikore, 1998) that summarize local conditions in a raster into meaningful features. Local maxima and minima can be identified from the raster density surface, along with ridges (linear maxima), channels (linear minima), and saddles (a linear minima crossing a linear maxima) (Dykes & Mountain, 2003). Thus a point map, density surface, and derived surface features allow a user to look at the spatial distribution of data at different levels of abstraction, and support time geographic analysis by being coupled to a time querying capability.

**Animated Maps**

Another interactive visualization method is the animated map. Although animated maps could be represented as a pre-recorded movie that simply plays back the temporal arrangement of the data, a more informative solution would animate the data live while taking input from the user. Andrienko, Andrienko, and Gatalsky (2005) describe three different methods of displaying an animated map containing moving individuals. The *snapshot in time* method is the simplest version, displaying the positions of people (in the context of this research, otherwise, any object) moment to moment as those positions change. A *movement history* method moves the individuals from moment to moment, but also displays all of the previous locations. This could be implemented as a path that
follows an individual up to the moment the user has stopped the animation. The drawback is that the display could quickly become visually crowded if this method is implemented for a large time span or number of individuals. The third method is a *time window*, which is similar to the movement history method, but only displays a range of data designated by the user (Andrienko et al., 2005). Objects would then move with the animation, but the track of previous locations connected to the objects would be of a shorter length, and the endpoints would continuously be updated as the animation progressed.

### 1.3.2.2 Three-dimensional visualization

In the years between the first time geographic studies to the present day, computer power has been increasing exponentially (Intel Corporation, 2008). This has enabled the creation of interactive three-dimensional displays – a huge contrast to the mainframe computers used in four decades ago, which ran without monitors and printed all of their output on paper. The advantage of the additional representational dimension is that more of the actual dimensionality of the data can be preserved, and different visual perspectives of the data become available.

*Activity Density*

In the case of density surfaces, the move to three dimensions can make the data easier to interpret. In Kwan (1999, 2000) and Kwan and Lee (2004), density surfaces are shown
with vertical relief, making the variation in the surface very clear with the topographic analogy.

One variety of density surface is similar to those described by Dykes and Mountain (2003). These density surfaces use the 2D map as the referential for the data values in the surface, and peaks would indicate that more time was spent in those locations than in others (Figure 1). These surfaces can be augmented with ancillary data like a street map in order to give the values of the surface meaningful spatial reference to the analyst (Dykes & Mountain, 2003; Kwan, 2000a; Kwan & Lee, 2004).

A key difference between Kwan and Dykes and Mountain’s method is that Kwan’s uses kernel estimation to generate the surface from the data points rather than just the count of the points in each raster cell’s borders (Gatrell, 1994). Kernel estimation creates a smooth surface representing the local intensity of the spatial data points, weighted by the time spent at each location. The amount of smoothing required depends on the distribution of data points, and can be changed by using a different bandwidth size in the calculation formula (Kwan, 2000a; Kwan & Lee, 2004).

Another kind of density surface collapses the two spatial dimensions into a single dimension representing distance from home (Kwan, 1999; Kwan, 2000a; Kwan & Lee, 2004). The second dimension is the time of day, and the third reflects the value of the kernel estimation function. With this setup, the density surfaces display the times and distances from home where most activities take place. In Kwan (1999), the location and
timing of activities for the Portland sample is demonstrated to be quite different for men and women employed full-time. Both groups show peaks of activity during commuting and lunch hours, but during the day, men are found to be conducting more nonemployment activities at a wide range of distances from the home, indicating a degree of flexibility during the daytime hours. In addition, the surfaces show women are conducting a large amount of nonemployment activities after working hours, suggesting an inflexibility caused by the time budget constraint. The patterns seen for full-time Columbus workers are nearly opposite of those observed among full-time workers in Portland (Kwan, 2000b), where women conduct non-employment activities with a more constant intensity throughout the daytime hours (Figure 2) compared to men.

Density surfaces created by the kernel estimation function are raster data files. Some software packages can display raster data as a surface where the raster values correspond to height (ESRI, 2007), or the raster could be converted to a triangular irregular network (TIN), a kind of polygon layer that can represent varying surface height. Whichever representation is ultimately used, an important benefit of the kernel function result being a raster file is that comparisons can be made relatively easily between population groups. To see the difference between two of the time-distance type density surfaces, for example, map algebra can be used to subtract the values of one surface from another. This elegant method was used by Kwan (2000) to show the difference in the distribution of nonemployment activities of men and women in a single display.
Each kind of density surface collapses time into a single value, so temporal information regarding when activities begin and end, whether the time spent at a location is contiguous or spread across multiple intervals, and the number of individuals that have visited that location is lost. An alternative visualization that delivers similar information without these drawbacks is one that displays the time spent at stations on an axis perpendicular to the spatial longitude and latitude axes. This is equivalent to the space-time aquarium visualization, but instead of full space-time paths being displayed, only the time spent at stationary locations is represented (Kwan, 2000a; Kwan, 2004). The result can be more clear due to less links being drawn on the screen, and would be suitable for use if the research questions do not involve travel between activities. However, this stationary time visualization is inappropriate to compare different population subsets, as it is likely that one data group would occlude the other unless they had very different spatio-temporal distributions. Comparing population subsets is much more feasible with density surfaces, as described previously.

*The Space-Time Aquarium, Vector Model*

The space-time aquarium was first implemented in an interactive environment by Kwan (1999). In the 3D space-time aquarium, it is possible to preserve information regarding the timing and duration of activity participation (Kwan & Lee, 2004). ArcView 3D Analyst was used to visualize the individual space-time paths of seventy-two European-Americans in Columbus, Ohio. Because the study was designed to explore gender
differences in accessibility, three subsets of the population sample were explored: women working full-time, part-time, and men working full-time.

The space-time aquarium visualization technique shows that women employed full time are constrained by long periods spent at the workplace, and are therefore unable to participate in many nonemployment activities. When women working part time are displayed, the aquarium shows their characteristic shorter working hours, along with a more fragmented distribution of nonemployment activities. Men working full time have a pattern similar to women working full time, but because men have on average less nonemployment activities, the nonemployment activities they participate in display a wider variability in duration, timing, and location (Kwan, 1999). The aquarium is particularly helpful here because it shows the duration spent at activity locations, whereas a simple point map would ignore the time commitments associated with activities, and show only their spatial distribution. The aquarium supports the rest of the study, which uses the density surfaces mentioned previously and quantitative techniques to determine that the space-time fixity constraint effects women more than men, possibly due to traditional gender roles of women related to household responsibilities (Kwan, 1999).

Kwan (2000b) also used the space-time aquarium to demonstrate different space-time activity patterns for racial groups in Portland, Oregon. Ethnic minorities were shown to be likely to work in downtown Portland, and conducted many of their non-work activities within the downtown area or in the region east of downtown (Figure 3). Of the minority ethnic groups in the visualization, African Americans are the most likely to conduct
activities on the east side of downtown, while the activities of Asian Americans and Hispanics were more spatially scattered.

The activity data for Kwan’s 1999 and 2000(b) studies were obtained from a travel diary survey, which at a minimum record the addresses of activity locations and the time intervals spent there. Activity surveys usually do not contain information regarding the route used to get from place to place, so when one activity location is connected to another in a space-time path, it is done so with a straight line. This visualization of the space-time path in either 2D or 3D would suggest an impossibly direct route from place to place, and a significant underestimate of distance traveled (Kwan, 1999).

However, it is becoming more common to use Global Positioning System (GPS) measurements to record human space-time behavior. Because a GPS device can record positions at regular intervals, an individual’s space-time path can be rendered with high accuracy and precision, and fully represent the routes used to travel between activities. The GPS recordings could then be augmented with descriptions of activities given by the participants after the fact (Stopher & Wilmot, 2000). It may be possible that by comparing the recorded coordinates to ancillary datasets that individual activities could be approximately determined, but it would certainly be preferable to have authoritative data gathered from the participants.

Kwan and Lee (2004) use the space-time aquarium to visualize the GPS-recorded space-time paths of individuals from Lexington, Kentucky over six days. While the aquarium is
often used for a single day’s length of data, it is possible for the time axis to represent any length of time. In their visualization of sixteen women without young children, it is easy to identify repeated trips along major roads, showing that the space-time aquarium can be used to identify periodic behavior (Kwan & Lee, 2004).

While the previously-mentioned studies have used the popular ArcView GIS software to render space-time data in the aquarium, it is also possible to use open web-based standards to create an interactive space-time aquarium (Rinner, 2004). Riner (2004) used the Virtual Reality Markup Language (Consortium, 2003) to display sample GPS data in an interactive environment. Some advantages of this approach are that the data could be visualized in the space-time aquarium without expensive commercial software, and that it could be shared online with collaborators. However, this sort of environment would need to be programmed from scratch, which would require a researcher to dedicate many hours in creating the environment that would not have to spent when using a commercial solution.

The Space-Time Aquarium, Raster Model

An alternative to representing individual paths as vectors in the space-time aquarium is a model that represents the paths as a series of solid volumes in discretized time and space. Forer (1998) presents such a model, which uses a 3D raster format to represent spatio-temporal positions. The model has one particular advantage, in that the inherent topology of time with space makes many kinds of spatio-temporal queries a simple geometric
operation, which should enable rapid processing for responses to user queries (Forer, 1998).

For a given study area, space would be divided into regular intervals (as in a grid), as would time. The intersections of these intervals create space-time volumes, called *taxels*. The term is derived from *voxel*, but where a voxel is a discrete representation of real 3D space, a taxel replaces the height dimension with time (Forer, 1998).

Space-time prisms can be calculated using network distances as in the previously described accessibility measures. In the 3D raster model, the prisms would be represented as a series of slices with the thickness equal to the temporal resolution. These prisms can then be intersected with other discretized features in the 3D raster format. By intersecting a person’s space-time prism with an activity location’s open hours, the time that a person can participate in the activity is revealed. The resulting space-time volume from intersection operations can also be used as a measure of accessibility (Forer, 1998).

Due to the raster data model, each individual must be stored in a separate data file. This is because the data values stored are binary, merely showing whether or not a taxel is occupied. Because of this, if the space-time paths of multiple individuals were to overlap in a single data file, it would be difficult to distinguishing them. For data layers without overlap, like a layer representing the spatial locations and temporal availability of activity opportunities, multiple entities can be stored in a single file. While Forer (1998) points
out that the data structure could accommodate non-binary values, which would make it more flexible, it would also increase data storage requirements significantly.

The data storage requirements for the raster model of the space-time aquarium can be expected to be larger than those for the vector format in most situations. One of the largest differences between how the storage requirements for a single entity can vary would be the representation of an activity station. If the activity is available all day, it would be stored as two points that make up a line in the vector format. In the raster format, however, there would be a data element stored for every division in the discretized time axis. In the case of highly-detailed GPS tracks, it is possible that the generalizing effect of the raster format could actually save storage space, however. Whether or not the detail lost by rasterizing a space-time path is problematic will depend on the research question, but Forer (1998) used a very fine resolution for the 3D raster, and such an implementation could alleviate concerns over loss of detail.

While queries can be conducted quickly and easily due to the binary format of 3D rasters, the model does require that these rasters be pre-computed. Creating a raster representation of extant vector data is simple for the aforementioned activity station example, and the conversion of the more sinuous space-time paths is still straightforward. However, the calculation of prisms is network-based, and thus is no faster than methods that are vector-based from start to finish. In fact, the prism calculation will likely take longer in the raster model because the prisms must be converted to raster format after their vector versions have been computed (Forer, 1998).
1.3.2.3 Other Visualization Techniques

Mountain (2005) revisits the space-time aquarium with a space-time point cloud representation, rather than the vector or raster models described earlier. The space-time point cloud is composed of the coordinates logged from a GPS device, again using time as the height attribute. The representation is particularly well-suited to a circular plotting of time, in which the time range of the aquarium is a single day, but data over the course of many days (ten months, in Mountain 2005) are plotted over the same interval. An individual’s habitual trips and stations then become clear because of the high density of the points in the cloud in those areas. Trips that are unusual stand out in contrast to what is otherwise mostly repeated behaviors (Mountain, 2005).

Another variation on the space-time aquarium idea is the standardized space-time paths proposed by Kwan (1999). Because the vector representations of space-time paths in the aquarium can become visually crowded when many individuals are displayed, additional ways of extracting meaning are helpful. Standardized space-time paths use the home location of all individuals in the data as the origin of the space-time coordinate system, and individuals’ space time paths are rotated until their work locations are located along the X axis. By aligning all work trips along the X axis, it is easier to compare work trip timing and distance among the visualized individuals (Figure 4). The advantage of interactive 3D visualization is that the viewpoint can be rotated, and if the user aligns the X axis perpendicular to the computer monitor’s screen, work trips are hidden, and
nonemployment activities are then emphasized. Because the space-time paths have only been translated and rotated, this technique keeps the spatial distribution and distance relationships of the activities relative to home and work undistorted (Kwan, 1999; Kwan, 2000b).

There are many options in both 2D and 3D visualization that are useful for statistical analysis, but may not be appropriate visualizing the dynamic properties of individual people. However, some of these methods may be useful for representing immobile features of the space, or in the analysis of related ancillary data. Pencil icons, for example, take the visual metaphor of the pencil placed upright in the space-time aquarium (Müller & Schumann, 2003; Tominski, Schulze-Wollgast, & Schumann, 2005). On each of the pencil’s sides, a different attribute can be displayed as it varies through time. Such a visualization applied to a business location could represent sales by product type over time, or it could be used to represent time-varying atmospheric emissions of a factory. An interactive method to rotate the pencils or change the viewpoint would be necessary to counter data occlusion.

Charts and graphs common in exploratory data analysis (EDA) can be useful when analyzing the relationships between activity data and ancillary datasets, like census demographics for areas that individuals are frequenting. Dykes and Mountain (2003) use geo-centered parallel coordinate plots that reflect the selected attributes of nearby districts. The parallel coordinate plots and a linked 2D map are updated as the time series of a space-time path is played back. Software packages such as GeoDa and GeoVista
Studio are comprehensive tools that can be used to show the relationship of attributes between a 2D map and common kinds of charts through linking and brushing (Center, 2007; Center, 2009).

1.4 Summary of Existing Analysis Capability

The work done in bringing time geographic concepts to computer models has enabled researchers to better understand a population's space-time behavior. With the collection of human space-time behavior data made much simpler due to affordable GPS devices and the ubiquity of the Internet, more and larger human activity datasets will be collected in the future than we have seen thus far. Methods that will aid in our understanding of large population space-time behavior will be made possible by the time geographic framework, and will be built upon the innovative techniques described in the previous section.

The preceding review has focused on two main approaches to analyzing human space-time behavior data. The geocomputational approaches discussed can distill information about individuals or groups into quantitative measures. These studies did so by computing measures of accessibility, some derived directly from the properties of space-time prisms, others from more complex metrics including concepts like utility. In terms of their effectiveness for analyzing the large populations of space-time activity data, the studies have proven their effectiveness at populations ranging from single individuals to over seven hundred individuals (Kim & Kwan, 2003). The studies have demonstrated
that today’s computer systems are capable of handling the detailed street networks that make realistic space-time prism calculations possible, and the algorithms referenced are computationally tractable. Therefore, in order to support very large populations, the basic philosophy of existing geocomputational approaches will not necessarily have to be changed.

This is not to suggest that the realism and situational appropriateness of algorithms can not be further enhanced, but in order to support the analysis of large populations, all a researcher must do is give the computer additional time to process the data as the size of population or accessible area increases. The algorithms discussed have no inherent characteristics that prevent them from being scalable to larger domains. Over the course of three decades of research in the review, geocomputational approaches have shifted from running on expensive minicomputers or mainframes to being run on consumer-grade microcomputers. The continuing increase in computing power will further reduce processing times, and increase the maximum computationally tractable populations.

The other key approach to understanding human space-time behavior is geovisualization. While a large population does not pose difficult obstacles to current geocomputational approaches, the effectiveness of a visualization technique can be highly sensitive to the number of individuals being analyzed. Methods that show human beings individually are the most sensitive to their number. Early 2D maps such as those by Chapin (1974) attempt to visualize hundreds of individuals, but due to the high spatial density and variation of the individuals, their representations obstruct each other, and only the
simplest of patterns can be identified. Animated maps can make 2D visualization of individuals suffer less from display crowding, but because a smaller range of time is displayed in each instant, the analyst must assemble relationships across time mentally, rather than seeing the entire variation at once (Andrienko et al., 2005; Ware, 2008).

A three-dimensional version of individual representation uses space-time paths the space-time aquarium, where time’s role as the third dimension makes the sequence of activities visible. The extra separation between entities in the 3D space-time aquarium (3D distance as opposed to 2D) helps differentiate them, and therefore can accommodate a larger number of individual space-time paths before it becomes to visually crowded. In addition, the interactive nature of 3D computer environments allows the analyst to change the view of the aquarium and to look at the individuals from different perspectives, allowing the analyst to avoid viewpoints that lead to more visual occlusion. However, in the case of figures printed in publications, readers are at the mercy of the authors to pick as viewpoint of the aquarium that effectively conveys the point being made, and it may be that no single image of the 3D environment can do that (Kwan & Lee, 2004). Despite the added dimension of distance and interactive capabilities, the number of individuals that can be effectively visualized with 3D space-time paths is still relatively small.

Some other geovisualization techniques are less sensitive to data volume. Space-time paths that sprawl all over the study area and obstruct the view of each other can be aligned so that each has the same origin location. Additionally, paths can be rotated so
that an activity of interest is in a set direction from the origin. In Kwan (2000), a data
volume in the lower hundreds of individuals is represented with their paths rotated so that
their work locations lie in the same direction. In this representation, it is easier to see
when people make work and non-work related trips, and while an increasing number of
individuals will still render the technique less comprehensible, the alignment of related
information along the home-work plane makes reduces noisy variation, and can
successfully visualize more individuals. The compromise made in this and some other
techniques is that actual spatial locations have been traded in for relative locations.

Density surfaces are perhaps the most scalable visualization technique in terms of the
number of individuals that can be effectively visualized. Kwan (2000) used a vertically-
extruded (2.5D) density surface to indicate the amount of time a population of over four
thousand people spent around the study area of Portland, Oregon. Dykes and Mountain
utilized a 2D representation of a density surface to show the time spent in a region by a
single person over two years. While the surface represented a single person’s data, it
effectively summarized over eighty thousand data points taken over the two years. There
is no inherent maximum to the number of data points that can be summarized in a density
surface, but the sacrifice made is that precise spatial locations are aggregated to regions,
and that if multiple individuals are visualized, the identity of each individual person is
lost in favor of aggregate counts.

An ideal representation technique for a large human space-time behavior study would
pick its best qualities from the list of approaches above. A method that worked in the
same fashion with small and large counts of individuals, with equal effectiveness, would surely be desirable. Equally desirable is a method that shows the actual spatial locations of individuals, rather than relative locations. Finally, a method that shows the entire range of time in a single representation would allow for easier visual processing than a method that shows snapshots or small ranges of time. The next chapter seeks to outline an analysis technique for large volumes of space-time activity data built around the strengths of existing methods.
2.1 Goals of this study

Future research using the time geographical perspective will continue to expand our understanding of human accessibility, supporting the causes of social equity and effective urban planning. Outside of accessibility, understanding the time-varying positions of a population will be critical for emergency management and location-based services (LBS). In the beginning of human space-time behavior (HSTB) studies, it was only practical to collect data on small numbers of people, and typically with only moderate spatial and temporal accuracy and precision. Due to technological advancements that have provided a dense, reliable telecommunications network, GPS, and affordable electronics that make it easier for volunteers to submit their activity data and for researchers to use in analyzing the data, it is reasonable to expect that future datasets have the potential to be much larger than in the past. The cost of recruiting individuals to provide their activity data will remain an obstacle, but even if this constrains the growth of datasets in the future, researchers have expressed interest in using agent-based models to study behavior, and these models produce enormous output datasets. In that case, a city-scale study would need to deal with possibly hundreds of thousands of individuals instead of the sample
sizes typical of current work that top out at around ten thousand individuals (e.g. (Kwan, 2000b).

This study seeks to identify computer-based methods that will be useful in understanding large human activity datasets. In the previous chapter, we have reviewed several approaches used in previous research to understand human space-time activities. In section 1.4, we noted that geocomputational approaches and consumer-grade computation hardware are sufficiently advanced such that quantitative studies of large datasets should currently be feasible. There does not seem to be any single geovisualization technique that is perfectly suited to the analysis of large HSTB datasets, however. This study seeks to create a geovisualization technique that is capable of handling large populations while not making serious compromises that could negatively impact results in order to display the data.

Like purely geocomputational approaches, visualization of human activities has been greatly aided by the advancement in computer technology in the last few decades. Lenntorp’s (1976) computer model’s output was in the form of thousands of pages of computer printer pages. Today’s computers have high-resolution color displays that refresh at least sixty times per second, and discrete graphics processors that can render millions of 3D polygons for every single refresh of the display. Geovisualization is still a relatively new field, and 3D geovisualization in particular is receiving a great deal of attention thanks to the enabling advancements in computer technology (Kwan, 2000b).
Each of the geovisualization approaches reviewed in the previous chapter has its own particular strengths, but not all are scalable to the kind of data volumes that we will be dealing with in the near future. This study suggests that there is potential for more effective visual analysis methods, and that the need exists for them. This chapter is dedicated to identifying what methods would be effective for the visual analysis of large datasets, and the next section lays out two basic guiding principles for method selection. Using those principles and considering the unique characteristics of high-volume HSTB data, section 2.3 systematically identifies techniques that should be effective. These selected methods will be tested in a prototype analysis environment discussed in chapter 3.

2.1.1 End Product

The prototype geovisualization environment constructed in this study is expected to be able to identify important characteristics of groups of people when analyzing HSTB. In this usage of HSTB, the reporting unit of the analysis is not the individual person. This study keeps the spirit of time geography by using data that is collected at the individual level, and the analyst is never forced to use particular classifications, groupings, or aggregations a priori. All generalizations from the individual data will be done by the analyst’s specifications, which marks a critical difference between studying human behavior via the time geographic framework versus models that either do not use individual data at all (using census or traffic analysis zones instead), or do not consider the time dimension of activities (see review in Weber and Kwan 2002).
This study posits that group behavior is most likely to be the interest area if the analyst is working with a large HSTB dataset. There are some exceptions to this assumption. For instance, if the goal is to use an individual’s space-time behavior in order to support location-based services on the person’s mobile device, then the reporting unit of the analysis will be the individual. If a large dataset of many thousands of individuals is at hand for a LBS application, it is most likely that each of these individuals will be considered on their own in an iterative process. However, if a large dataset of individuals is to be used in an accessibility study, the analyst will be interested in making abstract statements about how activities are distributed in space and time, and what potential relationships to ancillary datasets may exist (Andrienko & Andrienko, 2006; Kwan, 2000b). The reporting unit in this case will be groups of population, which may be determined by pre-analysis hypotheses, or emergent out of the familiarization with the data that interactive geovisualization provides. The prototype geovisualization environment will support exploratory analysis, which may produce interesting insights on its own, but is principally for forming better-informed questions for further analysis (Kwan, 2000b).

2.2 Guiding Principles in Method Selection

As mentioned in the previous section, there are certain ideals in geographical representation that are worth trying to uphold when developing new analysis techniques. Any technique that deals with complex datasets must make some compromises in order
to simplify and create understanding, but it is important not to make compromises that could lead the analyst to incorrect conclusions by misrepresenting the data.

In their treatise on data analysis and visualization, Exploratory Analysis of Spatial and Temporal Data, Natalia Andrienko and Gennady Andrienko identify ten principles for the selection of analysis methods. Depending on one’s experience in spatial analysis, many of the concepts will seem familiar or make intrinsic sense, a fact they attribute to influential previous publications, and to the fact that the concepts must be derived from objective truths (Andrienko and Andrienko, 2005, p480). All ten are useful in spatial analysis, but this study selects two in particular with special relevance to the issue of large HSTB datasets: “see the whole,” and “simplify and abstract.”

2.2.1 See the Whole

“See the whole” is perhaps the greatest challenge to meet with for an analysis method for large volumes of data. The concept means that in order to maximize the accuracy and efficiency of the research, the complete dataset should be on the display. Completeness can refer to the set of individual data elements (people, in this case), or the dimensions by which the elements can be referred to (Andrienko & Andrienko, 2006). In terms of accuracy, it can be intuited that if an incomplete dataset is analyzed, the analysis may not be an accurate characterization of the entire dataset (if it is intended to be). Therefore, it is desirable to avoid unnecessary generalizations before the data is displayed for visual analysis.
“Seeing the whole” is relevant to efficiency because it supports visual thinking, a
cognitive process where what is seen is translated into abstract concepts (Ware, 2008).
Interpreting Rudolf Arnheim (1967), Andrienko and Andrienko (2006) note that
“perception does not provide some ‘raw material’ for thinking but immediately forms
concepts, which are already quite general and abstract.” Thus, the act of seeing
something produces concepts just as other forms of data analysis, but can do so
immediately.

Ware (2008) describes a two-step process of visual analysis where first, a pattern is
identified in the data, and then other occurrences of the pattern are sought out elsewhere
in the data. From this repetitious process, minimizing the time between pattern searches
would be critical in keeping the visual analysis time-efficient. Recalling and recognizing
identified patterns would also be quicker if they were stored in the cognitively-cheaper
short-term memory instead of long-term memory.

Ware provides an example of how dramatic of a difference there can be between a
method that fully supports visual thinking versus more inefficient means. Ware’s
research group originally used an animated map approach to detecting patterns in whale
movement data over time. The process would require playing back a whale’s entire
movement path, utilizing long-term memory to store detected patterns. Then analysts
would need to replay the tracking information to thoroughly check for the detected
patterns throughout the time range. After switching to a method that effectively
displayed a whale’s entire range of movement data in a single representation, pattern
detection and comprehension was sped up dramatically. To find repeated patterns, it was
only necessary to move the eyes from one part of the screen to another, rather than play
back an entire log of movement data. The enhanced technique displaying the full
temporal range was estimated to be at least two orders of magnitude faster than the
animated map technique (Ware, 2008).

“Seeing the whole,” then, is certainly desirable. In order to visualize the data on a
computer display, the data’s referential dimensions must be mapped to the display
dimensions (Andrienko & Andrienko, 2006). This can be difficult for some datasets
where the data has higher dimensionality than the display, and would necessitate some
form of generalization that would compromise the completeness aspect of the “see the
whole” principle. The usual computer display is two dimensions, but a third can be
reasonably approximated using depth representation. In the case of human space-time
behavior, we are fortunate that the data has three referential dimensions (two spatial, one
temporal), matching the potential of the display to be used.

Besides the dimensionality mapping issue that we are able to avoid, Andrienko and
Andrienko (2006) identify another concern in the representation of data: the volume of
the data. If there is not enough space so that all of the data points are visible without
obstruction, then there are too many data points to be effectively visualized. This sort of
visual crowding or overplotting can be problematic in any individualized view of data
points, which include previously discussed geovisualization techniques like space-time
paths, point clouds, and icons. These visualizations can still be effective, but their effectiveness will be dictated by the number and arrangement of the data points. To handle high data volume, there is a need to simplify and abstract.

2.2.2 Simplify and Abstract

“Simplify and abstract” reflects a need to cut through the noise and find the patterns relevant to the research question (Andrienko & Andrienko, 2006). Space-time activity data is prone to being highly-detailed, and increasing dataset size means that visual displays can become overwhelmed with plotted data quickly. If the default view of the data is too complicated for visual understanding, it should be simplified somewhat so that cognition is possible. Ideally, simplification should be done without losing data from the display (and violating “see the whole”). This is possible in circumstances where data item positions can be rearranged into what can be perceived as coherent trends or groups. When studying HSTB, relocating the positions of space-time data elements (people) would risk ignoring or misrepresenting the spatial or temporal contexts of human activity. Andrienko and Andrienko (2006) demonstrate that applying color or symbol size ramps to a visualized data attribute similarly simplifies the view so that regions with similar or trending values can be visually identified, achieving a similar cognitive effect without removing or rearranging data on the display.

Even with an optimized attribute visualization scheme, HSTB data may be too complicated or dense to visually interpret. More dramatic methods of simplification will
result in some data loss, however. The two most effective solutions to the problem of
data volume are aggregation and filtering. Filtering (a selection by existing qualitative
groups or data ranges) reduces data volume, but assuming that the population of interest
is already displayed and is too large to handle, further filtering would violate the principle
of “seeing the whole.” Aggregation also removes data and renders the resulting
visualizations technically incomplete, but if the research question is compatible with the
new data resolution, its simplifying power mitigates this loss. Andrienko and Andrienko
(2006) suggest that if one or the other is to be done, aggregation is preferable, as it retains
the whole range of the data, as opposed to a strict subset created by filtering.

Classification also simplifies data by reducing a large range of data values into a set of
smaller ranges with precise definitions. While the resulting display may show clearer
patterns after classification, the visual representation implies homogeneity within classes,
and the loss of variation within the classes may hide important characteristics of the
activity pattern. Some sort of smoothing (e.g. a kernel function or low-pass filter) can
also reduce the high detail information into the sort of general trends the researcher is
interested in (Andrienko & Andrienko, 2006). Using any of these techniques will need to
be weighed against the potential cost of the data loss to the visual analysis.
Simplification should also be kept to a minimum because the goal of geovisualization is
to support visual thinking (Ware, 2008). It is the job of the human analyst to abstract
meaningful patterns from the data, so any simplification by the computer system should
be done to the minimum amount necessary such that the data can be understood by the
analyst (Gahegan, 2000). Performing too much data simplification before the visual
analysis begins will bias the results of the analysis, and if carried out in the extreme, would essentially be programming the computer to guess what the patterns are for the analyst.

2.3 Geovisualization Methods

This section discusses the geovisualization techniques reviewed in the previous chapter. For each technique, it will be determined whether or not they are compatible with the basic principles established in the previous section, and if they are otherwise suitable for the analysis of large HSTB datasets. Several methods that are truly useful for understanding human space-time behavior will be excluded from this study’s final product based on these criteria. These methods still have merit for smaller datasets on their own, and could still be useful for large datasets as follow-up steps in the analysis.

2.3.1 Interactive 2D Visualization

The approach pursued by Dykes and Mountain (2003) leverages multiple 2D representations of data that function as synoptic views. The ability to use multiple perspectives on the data is certainly useful, but the cognitive process is best facilitated by seeing as much of the data as possible in a single representation (Andrienko & Andrienko, 2006; Ware, 2008). This study finds no fault with the linking and brushing techniques used to relate the same data shown in different representations. However, there is a failure to “see the whole” in the need to use the techniques to focus on a
selection of data in order to identify any patterns. Without an effective means of
displaying the whole range of data, it is doubtful that any patterns existing among the
dataset as a whole or a large group of people will be noticeable, or that the detected
patterns among smaller groups will be put into the appropriate context.

Part of the difficulty in interpreting a large dataset in a method similar to that employed
by Dykes and Mountain (2003) is their use of a 2D map showing each data record as a
point on the map. Such a display is likely to be too difficult to comprehend for large data
sets. However, Dykes and Mountain also use another representation technique that is
capable of representing overall behavior of the complete dataset.

2.3.2 Density Surfaces

Converting the point locations of individuals over a time span into a density surface
reveals areas with higher and lower habitation rates (Dykes & Mountain, 2003). A
density surface is built from a raster data model, which can represent an unlimited
number of individuals in its discrete view of space without contending with overlapping
data ink, the elements of the display that represent the data (as distinct from ancillary
elements like scale bars and grid lines) (Tufte, 1983). While the generalization of spatial
coordinates used to achieve a clearer display may seem like it sacrifices “see the whole,”
the clearest omission from a density surface is the loss of the time dimension. Density
surfaces express sums of the amount of time that is spent in each spatial location, but do
not represent the actual intervals of time that the space is occupied. Three-dimensional
representations of density surfaces (Kwan, 1999; Kwan, 2000b; Kwan & Lee, 2004) provide more natural-looking results, but the third dimension is used to accent the variation in the raster values, rather than being assigned to the time dimension as in the space-time aquarium. Because the time variation is crucial to the understanding of HSTB, density surfaces are not appropriate for an overall view of high volumes of HSTB.

2.3.3 Animated Maps

Animated maps represent time varying data by indexing the time dimension over multiple images shown in succession. This method provides a natural metaphor to memory when representing events over time. However, its inability to show the entire range of data in a single representation results in a slower analytical process, as an analyst’s short-term working memory is not sufficient to remember detailed patterns seen every frame of an animation (Ware, 2008). Using the time window technique (Andrienko et al., 2005), it is possible to depict a small range of time in each frame of the animation, which is helpful for recognizing trends. Andrienko et al. demonstrated that the time window technique was effective for studying the migration of a small number of birds, but the trails shown by the moving icons would likely create significant overplotting in a display representing a smaller geographic region with many more individuals.
2.3.4 The Space-Time Aquarium

The greatest advantage of the space-time aquarium is that it can visualize HSTB in its complete spatial and temporal contexts in a single display. One of the best examples its use is the display of space-time paths. 3D space-time paths are perhaps the most accurate depiction of human space-time behavior, and are a significant improvement upon older 2D representations, where information on “the timing, duration and sequence of activities and trips was lost” (Kwan, 2000b, p188). However, a large number of space-time paths in the aquarium can be very difficult to understand visually. Thus, it is too difficult to “simplify and abstract” large populations with a vector representation of space-time paths in the aquarium.

A simpler alternative to visualizing space-time paths shows only the stationary portions of person itineraries, relieving some visual cluttering in the display by not showing the positions of individuals during travel episodes (Kwan, 2000b). Kwan was able to visualize over two thousand individuals using this method in a much more readable display than would have been possible with full space-time paths. The visualization without travel episodes could be seen as a violation of “see the whole” if those are relevant to the analysis. In the case of some activity surveys, there are no good data collected on the routes individuals take from one location to another, and showing the links between activities would simply utilize straight lines that do not depict actual travel behavior. While it may not seem like much of a loss to lose such data from a visual representation, there may be some cases where the analyst would be interested in
directional flows from one part of a city to another. In addition, more GPS data is being collected that will accurately log the travel episodes of individuals, and this data’s value will be harder to dismiss. In summary, Kwan’s (2000a) use of the method provided a display suitable for visual abstraction, but an ideal method for an overall view of large HSTB datasets would support “see the whole” without removing all travel episodes.

The standardized space-time paths used by Kwan (1999, 2000a) relocate the origin of each person’s space-time path to a common origin, and then rotates the paths so that each person’s work activities lie on a home-work axis. The result is a less noisy representation that is easier to comprehend. While excellent for exploring the distance and time relationships between home and a work (or any other selected activity), this representation does not “see the whole” because of the loss of the true spatial locations of individuals.

Chapter 1 also reviewed two uses of the space-time aquarium that do not utilize vector lines in the display. Mountain’s (2005) space-time point cloud visualizes the movements of a single person over ten months. Each day begins at the origin of the time dimension of the aquarium, allowing the detection of repeated activity patterns. It is unclear if this method’s visual effectiveness would scale to the large populations we are preparing for, but further exploration seems warranted as it meets “see the whole,” and was at least effective in working with a large dataset for a single individual.
The final use of the space-time aquarium is the raster-based model used by Forer (1998). This version of the aquarium used a discrete version of time and space, creating a raster-like representation of space, as opposed to the vector representation of space-time paths. Forer’s method and the issues revolving around the use of discretized space are discussed at length in the next section.

2.3.5 The Raster Model of the Space-Time Aquarium

Forer (1998) proposed a raster data model for the space-time aquarium that uses discrete space-time units called taxels. One advantage of the model is that it makes accessibility queries a simple matter of geometric intersection. However, this geocomputational ability does not factor into the model’s suitability to geovisualization.

For visual analysis, the raster model is advantageous for having less high-detail noise compared to the visualization of space-time paths. The effect is achieved by discretizing space and time into a number of space-time volumes (taxels), generalizing precise locations to the nearest taxel centroids. It would appear that the raster model violates “see the whole” in order to satisfy “simplify and abstract.” However, this form of generalization is far less dramatic than previous methods discussed. The spatial resolution of the raster cells used in Forer’s (1998) study was ten meters, which is within the error range of GPS units. Temporal aggregation into multiple divisions per hour may also be a trivial loss of resolution when solely trying to visually detect general patterns.

We suggest that small spatio-temporal aggregations provides the correct level of
granularity (Hornsby & Egenhofer, 2002) when considering behavior on the city scale over the time span of a day. The method is expected to be scalable to any size region by adjusting the spatial resolution of the derived raster data.

In the 1998 study, Forer described the need to keep the raster data for each person separate, since there would be no way to tell individuals apart if they were recorded in the same binary raster file that simply indicates whether someone is present in the taxel (or potential presence, in the case of prisms). In follow-up work, the method is employed to represent aggregated accessibility spaces for students in Auckland, New Zealand (Forer & Huisman, 2000). The approach summed up activity spaces for all individuals in the dataset to yield density surfaces of potential overall accessibility. While density surfaces are undesirable because of their loss of the distribution of activity over time, it would be possible preserve the time-varying information by displaying the 3D raster resulting from the sum of every individual’s rasterized space-time paths.

Doing so would mean aggregating individuals into taxels, and losing their individuality in the resulting display. This may be an alarming concept in the context of the time geographical framework, which came about in a response to the prevalence of aggregate models. This study argues that when performing visual analysis on a large spatial-temporal dataset, analysts will mostly be interested in behavior that is common among groups of people, meaning that the reporting unit of the analysis is not the individual. In the scope of the collective behavior of a population, it is of little consequence that HSTB
data is not displayed as a set of individuals, so long as the level of spatio-temporal aggregation is kept to a reasonable level.

The generalization achieved by discretization and aggregation is helpful because it achieves a reduction in redundant data ink (Tufte, 1983) by collecting nearby space-time paths and representing them as a single feature. The taxels used in the 3D raster are intended to be large enough to provide a simplification over the space-time path representation, but small enough as to not aggregate too much space and time and remove the variation that defines a pattern at a finer scale.

It is important to remember that after discretization and aggregation, the individual-level HSTB data is still available for use; it is merely not visually represented in its native format. The complete individual data may still be used to create a new raster representation using a different level of aggregation, to produce a complementary statistical visualization product, or to pursue geocomputational approaches to accompany the geovisualization if desired. This study’s implementation of the raster model will make frequent use of the individual-level data in order to create new representations (see section 2.4.2 and 2.4.3).

2.3.6 The Discretized Space-Time Cloud

The specific geovisualization method that this study will use is called the discretized space-time cloud. It is based mainly upon the space-time cloud representation used by
Mountain (2005) and the 3D raster data model advocated by Forer (1998) and Forer and Huisman (2000). Several other details play an enhancing role in the method, and are discussed in section 2.4.

The critical element that the discrete space-time approach brings to the space-time cloud is the ability to show a virtually unlimited number of individuals in any given taxel. Using the sum of the of individuals in each space-time volume, the activity data can be more easily perceived as being dense in particular regions and as a trend of density from region to region.

Absent from Forer’s approach was a space-time aquarium representation of multiple people. Retaining the temporal dimension of the behavior data will make the discrete approach compatible with “see the whole,” and by leveraging the scalability of the 3D raster data model, provide a geovisualization solution for understanding large HSTB data sets. We believe that the full potential of the discrete model of space-time to visualize large populations has not been realized, and its effectiveness in examining large populations with full space-time dimensionality will be assessed in this study.

A point cloud can be used to represent 3D raster data simply by rendering a symbol at the center point of each taxel, rather than a solid volume (as is usually done for voxels). The space-time cloud approach is used in this study because it is expedient to implement in the available software, but we believe that visualizing the 3D raster data as point symbols
or solid cubes are of equal utility, and the additional specific software techniques discussed in the next section are applicable to either representation.

2.4 Additional Geovisualization Techniques

The following are additional elements that will be implemented in the prototype HSTB exploration software. Some methods are elementary requirements for spatial analysis that must be included in order for the software to be effective, and others relate specifically to the discretized space-time cloud method.

2.4.1 Contextual Data

In order to relate the behavior patterns to their spatial context, contextual geographic data will be displayed in a base map in the aquarium, as in Kwan (2000a). Land use data may suggest areas that would be expected to relate to certain activity types, and highways and landmarks can make the orientation of the space-time cube and spatial relationships more clear.

2.4.2 Queries

The analyst will need a capability to focus on specific groups of individuals, which facilitates comparisons between groups and between a group and contextual data. Queries by population attributes (such as demographic characteristics), activity type, and
time range seem like the minimum query capability that should exist in an HSTB exploration environment. These sort of comparisons have been made using density surfaces and space-time paths (Kwan, 1999; Kwan, 2000b; Kwan & Lee, 2004), but were not utilized by the reviewed space-time cloud and raster space-time aquarium studies, which focused on either a single individual or the entire population (Forer, 1998; Forer & Huisman, 2000; Mountain, 2005).

2.4.3 Variable Spatio-Temporal Aggregation

Forer (1998) points out that more work is needed on determining the appropriate taxel size. Some strategies have emerged to leverage aggregation’s positive qualities without becoming a victim of spurious results. Andrienko and Andrienko (2006) recommend that analysts “play” with the levels of aggregation. Fotheringham (1989) recommends performing an analysis at multiple scales to understand the extent to which results are influenced by the analysis scale. This recommendation was made in the context of the modifiable areal unit problem, which is normally discussed in regards to spatial statistics (e.g. (Fotheringham, 1989; Openshaw, 1984; Tobler, 1989). There is a great deal of overlap in the perspective on aggregation among the geovisualization and statistical fields, the full breadth of which is not essential to cover here. In short, because geovisualization and statistics are both processes of abstraction, the problems posed by variable analysis units are similar, and propose similar solutions. The ability to experiment with different aggregation levels will help analysts make a more informed decision on the appropriate level of granularity.
2.4.4 Transparency

There may be an issue of data points closer to the view point (henceforth, “camera,” following 3D modeling convention) blocking the view of more distant points. One method that may help alleviate that problem is the use of alpha-channel transparency (Theus, 2005). With semi-transparent points in the cloud, collections of points that are close together and overlap in a view will be seen as more opaque, and this will naturally de-emphasize the appearance of more rare trips in the HSTB data which will appear more transparent. Kwan (2000a) and Kwan and Lee (2004) utilized transparency to show the spatial relationship of multiple density surfaces. Similarly, it may be possible to show the differences in space-time arrangements of different groups in the discretized space-time cloud by using transparency. For instance, the space-time distribution of men’s shopping activities could be shown at the same time as women’s, and if each group was assigned different colors, the degree to which they overlap would be illustrated by the semi-transparent points blending together.

2.4.5 Thresholding

The data points in the space-time cloud will have varying symbols according to the count of individuals in each taxel, but the density of data may make it difficult to discern features in the point cloud. The point cloud may also block other elements of the display, such as the base map showing related data. To counteract these possibilities, a
thresholding technique will be employed so that data points representing the least number of individuals can be hidden from the display. Data points representing the largest numbers of people are likely to be located near each other in space-time, and clusters will be more apparent when low-magnitude data are hidden. This is analogous to identifying peaks in a 3D density surface (Kwan, 1999; Kwan, 2000b; Kwan & Lee, 2004). The analyst will be able to select any threshold value as the minimum necessary for point display, and will be able to easily vary the threshold in one person increments in order to find the scale where patterns are most clear. This technique will also pick up where transparency left off for further reducing the noise caused by spatially and temporally isolated space-time paths.

2.4.6 Smoothing

Identifying cohesive spatial, temporal, or spatio-temporal clusters is the main task when interacting with the space-time point cloud. Depending on the actual distribution of the data and the orientation of the camera, structures in the data may not be easily apparent. In that case, the form of the space-time cloud can be smoothed into features that may be more amenable to visual detection. A 3D moving window filter will be run on the 3D raster data to create a smoothed version of the data. This would achieve an effect similar to the smooth density surfaces created by kernel density functions in Kwan (1999, 2000a) and Kwan and Lee (2004). The user will have the ability to switch between smoothed and unsmoothed versions of the data during geovisualization.
2.4.7 Application Linking

Linking and brushing has already been mentioned as an effective way to identify relationships between different views of the same dataset. This study advocates the creation of a single geovisualization method that is effective with large populations up to at least the city scale, without sacrificing dimensionality. This does not mean that in later stages of analysis that complementary techniques using other, more specific geovisualization and geocomputation techniques are discouraged. Quite the opposite – this study simply advocates having a better solution for gaining a general understanding of HSTB data, which is expected to be more time-efficient than the use of multiple views for exploratory analysis. A high quality exploratory method is also expected to help the analysts pose better questions for further study.

The prototype 3D geovisualization software will be developed from scratch using software with no prior knowledge of spatial data (the reasoning for this is explained in the next chapter). In order to support the conversion of individual HSTB data into 3D raster data that will be visualized, and to make the transition to later stages of analysis smoother, the 3D geovisualization software will be linked to a geographic information system. Analysts will select the HSTB data from industry-standard GIS software, and custom computer code within the GIS will send the data over to the 3D environment for visualization.
By using GIS in conjunction with the prototype 3D geovisualization environment, numerous basic GIS functions do not need to be duplicated in the 3D software. Experienced GIS users will be able to perform the basic tasks they expect in a system they are accustomed to. The GIS will manage the original individual-level HSTB dataset, which will allow the analysts to continue spatial analysis within the GIS or in separate statistical software, after gaining a general understanding of the data in the 3D environment. Such linking across programs is not without precedent, and is inspired by previous work done in coupling GIS with statistical software (e.g. Anselin & Bao, 1997).
Chapter 3: Implementation and Application of the Discretized Space-Time Cloud

3.1 Software Implementation

There are many possible ways to implement the discretized space-time cloud as described in the final sections of chapter 2. Programming a completely custom visualization environment and writing code targeted at OpenGL or DirectX visualization APIs has the potential to create the highest performance solution, and could be as flexible or specific as the programmer desired. However, building a quality visualization environment in such a way would be an enormous time commitment. The time spent on creating a software product following all computer science best practices may be hard to justify for social scientists that are unlikely to already have the required programming expertise.

Another option is to implement the cloud in existing 3D GIS software. Previous research has utilized ESRI’s ArcScene software (Yu & Shaw, 2007), or its precursor 3D Analyst in ArcView GIS 3.x (Kwan, 2004). This approach has the advantage of working within a system that natively understands geographic data and its associated complexities. Where the previous method involving programming a solution from scratch would require duplicating GIS functionality or a separate step of data pre-processing in a GIS, using a 3D GIS to begin with simplifies the process. However, using existing 3D GIS software
means using only the visualization capability that is included with the software. With the application programming interfaces (APIs) available in the ESRI products, it is possible to customize many elements of the experience, but the programmer is ultimately limited to the functionality the application developer has made available in the API.

3.1.1 Virtools

This study will utilize an approach with a complexity somewhere between the two approaches described above. A custom 3D visualization environment will be created in Dassault Systèmes’ Virtools 4.1 software. The Virtools development environment (known as Virtools Dev) provides a high degree of customization while including a large amount of basic functionality through pre-built Building Blocks (McCarthy & Callele, 2006). Using Building Blocks, functions for creating, placing, moving, and setting the properties of objects is made relatively simple. Building Blocks (BBs, henceforth) can be connected in a visual programming environment resembling a flow chart, lowering the barrier to program automation for those inexperienced in computer programming (Figure 5). In addition, Virtools allows more extensive customization through its own scripting language (a C-like language called VSL), an application programming interface that makes the functionality available to new programs, and visual effects through programmable graphics shaders. In this study, the interactive elements of the environment were implemented through the visual programming interface using BBs and VSL scripts, and the visualization of the point cloud was implemented by using programmable graphics shaders in the HLSL language (Microsoft Corporation, 2009).
The Virtools compositions can be played from within Dev, as standalone application, or in web browsers. This ability to deploy the visualization product on a web page has potential to change the way 3D visualization is discussed in the academic journals, as the actual 3D analysis environment could be run from a web page and used by the readers, rather than having to rely on 2D screen captures of 3D geovisualization techniques.

### 3.1.2 ArcMap

As mentioned above, a drawback of building a 3D visualization environment from scratch (or mostly from scratch, in this case) is the need to handle geographic data. Geographic data can come in many file formats, and spatial coordinates can be stored in a wide variety of coordinate systems and geographic projections. Modern GIS systems handle this variability seamlessly, and rather than re-inventing such functionality in the customized 3D environment, a 2D GIS will be linked to the Virtools composition to provide these functions. Besides its role in preparing the data for exploratory 3D geovisualization, the use of the 2D GIS program in the process will make the transition to later steps of the analysis easier, where more conventional spatial analyses methods can be employed.

For this study, ESRI’s ArcMap 9.2 will be the 2D GIS used. The ArcGIS suite of products is a de-facto industry-standard (NIIT Technologies, 2005), and many researchers are already familiar with the software and have access to it through existing
institutional licensing agreements. However, free and open source GIS is becoming sufficiently advanced that it provides a viable alternative (Pucher, 2003). It is an attractive prospect to distribute the 3D visualization product on a freely-accessible website, and link it to a free GIS system in order to facilitate truly open access. While this is possible in future work, the current study will utilize the author’s expertise in the ArcGIS platform in order to build a prototype more quickly. This will allow more time to be spent refining the core functionality of the experience.

The typical usage scenario will begin by preparing the data in ArcGIS. The data management capability within ArcGIS should be sufficient for selecting data in the appropriate region for analysis, editing the data to remove problematic records, and for reformatting the data if necessary. Section 3.2.1 describes some of the data preparation steps needed in this study.

3.1.3 VBA Program

After the relevant data is prepared using the built-in functionality of ArcGIS, a custom interface within ArcMap programmed with Visual Basic for Applications (VBA) is launched by the analyst. This program is used to query the HSTB data and convert it from known GIS formats to the 3D point cloud format. Algorithms were developed for the program to convert stationary and travel episodes into counts of individual presence in the 3D point cloud format. The program supports the customization and variation of the spatial and temporal resolution of the discretized space-time cloud by the user. This
is to support the user’s need to experiment with the scale effects that was identified in Chapter 2. The user inputs the resolution in terms of the cell count in each dimension of the point cloud, and the geographic distance corresponding to these Cartesian coordinates will depend on the extent of the input dataset.

The data conversion algorithms determine the spatial position of an individual for each time slice. If the individual is present within a spatial cell for at least half of the time interval, the population of the 3D cell delineated by the spatial boundaries and time interval is increased by one. The data being used for this study is based on an activity survey rather than GPS data that logs precise locations frequently. To represent travel episodes, a number of spatial locations are interpolated between known locations of fixed activities. The number of interpolated locations is equal to the number of time intervals between the two activities. The algorithms for stationary and travel episodes are repeated for each individual in the dataset and over every time interval, creating a 3D point dataset recording the aggregate population counts in each discrete volume.

The VBA program supports the creation of attribute queries in a similar fashion to the functionality built into ArcMap. The attribute queries can be used to select for individuals with certain demographic characteristics and/or for certain activity types. A more novel feature is the ability to query the dataset by a range of time. When a time range query is specified, only the portions of an individual’s space-time path that exist within the defined range are converted to the space-time cloud format. The program’s interface stores previous queries along with source datasets so that they can be exported
again as space-time clouds with different resolution settings if the analyst desires. The analyst also has an option to extend the space-time paths of individuals to the beginning and end of the day, under the assumption that their first and last activities take place at their home and are stationary. Because the spatio-temporal interpolation of travel episodes may not always be desirable for activity diary datasets, it is an option that can be turned off, so that only stationary activities are displayed.

VBA’s greatest advantages are its relative simplicity to program with, and that it is included within ArcGIS without additional cost. Because VBA is compiled to an intermediate language that is run by a virtual machine (Wikipedia, 2009), there may be performance gains in implementing the algorithms in a fully compiled language, such as C. Many other languages also support multithreading, which could allow for the partitioning of work across multiple CPU cores. In this study, the longest processing time encountered is when the start and end times of the input HSTB records are being converted to a common data format. The longest processing time encountered was around five minutes on a CPU running at 2.0 GHz. This is an acceptably small time demand, because this step must only be run once for the input dataset. When creating a query to subset the main input dataset by attributes or time ranges, the time format conversion process does not need to be run again.

The processing time for creating the discretized space-time cloud from the input tabular data is trivially small, at only a few seconds for tens of thousands of records. Some additional seconds are used to write the results as a tab-separated text file that is read into
Virtools. It is possible to tighten the link between the two programs by transferring the point cloud data over a network connection rather than writing and reading to the hard drive, which may reduce the time between specifying data to analyze in ArcMap and first seeing it in Virtools. Since the current implementation’s time requirements are manageable at a relatively high data volume, a more motivating factor for implementing a network data link in the future would be increased support across computers with different file directory structures, and across platforms (Virtools runs in Windows and Mac OS X).

3.1.4 Additional Features

Four other features mentioned in Chapter 2 are contextual data, transparency, thresholding, and smoothing. To provide contextual data in the 3D environment, a base map will be displayed in the X-Y plane. As part of the data export process in the VBA program, a base map is exported from ArcMap based on the extent of the HSTB data being worked with. Upon loading new point cloud data, the Virtools composition loads the map as a texture and applies it to the base map plane in Virtools. The map can be any rectangular size, and scaling factors are exported from ArcMap to ensure that the relative size of the 3D environment is scaled appropriately in two dimensions, and the point cloud is correctly registered to the base map. This study uses the 2005 edition of ESRI StreetMap data for base map layers representing major roads, water bodies, urban areas, and large park land.
Smoothing is accomplished through a 3D moving window filter applied to the 3D points cloud data while it is still held in memory by the VBA application. When in memory, the points cloud data takes the form of a 3D array, conceptually identical to a 3D raster. A Gaussian-style filter is implemented in the 3x3x3 moving window, where the filter’s 27 cells surrounding and including the center focal cell multiply the original values by factors that decrease with distance from the focal point, and divides by 27 in order to achieve a weighted average value (Figure 6). This has the effect of spreading out the areas that are marked as populated in the points cloud. This implementation of a filter does not produce meaningful output values for quantitative analysis, but achieves the desired visual effect. The output 3D points cloud data contains both the original population counts and the filtered values for each point, and the analyst can switch between these representations within the Virtools composition.

Transparency and thresholding are implemented on the Virtools side. Thresholding is accomplished through the use of keyboard keys that increase or decrease the minimum population threshold necessary for a data point to be displayed. How the data point is displayed is then determined by the custom HLSL shader files written for the point cloud. The shader allows each data point to be visualized based on its own data values, and to have different color, size, and transparency values than its neighbors. A great deal of experimentation was done to determine useful visualizations, and two versions were eventually settled upon. The first version displays all points as the same size, color, and as mostly transparent. The perceived opaqueness is determined by the number of points in the area, and the clustering of a large number of points will result in a darker, more
opaque region. However, there is no way to distinguish population magnitude in this visualization other than the use of the data thresholding. A second method is also selectable where point size and opaqueness is increased as their population magnitude exceeds the threshold value. In both methods, the default transparency values can be increased or decreased during visualization through scaling factors.

In both visualization styles, a single point cloud uses one color. The 3D environment has been designed to support up to two simultaneous point clouds, so that overlay comparisons can be conducted. The two point clouds will use the same selected visualization style, but different colors. Red is used for the first cloud, and blue is used for the second. The effect is that if the two clouds overlap, the region appears purple. The second style with varying point size makes it easier to distinguish co-located points between the two clouds.

The visualization environment also has some smaller features of note. In many space-time aquarium applications, it can be difficult to know precisely what time corresponds to a given height from the base map. One way to address this is to make the base map plane movable (Kraak, 2003), and intercept the cloud at different heights. In addition to this capability, a “selection ring” was added to the environment. The ring wraps around the data, and moving the ring up and down the time interval selects the point cloud points that it intersects with (Figure 7). The selected points are visualized using a more opaque dark grey color in order to easily differentiate them. The ring has a height corresponding to one hour in time, and riding atop the ring are text labels indicating the time coordinates
at the bottom of the ring. The ring also helps keep the analysis grounded with the
placement of another text label atop the ring indicating the north direction.

3.2 Data Preparation

This study will use the Household Activity and Travel Behavior Survey dataset collected
in Portland, Oregon in 1994 and 1995. With valid data available for 10,048 individuals,
it has been the subject of much research over the last decade, including the previously
reviewed work of Kwan (2000b, 2004), Kim and Kwan (2003), Weber and Kwan (2002,
2003), and many other studies (e.g. Buliung, 2001; Farber & Páez, 2009; Weber, 2003).
In order to rigorously test the proposed discrete space-time cloud technique, the largest
feasible proportion of the total sample size that will be used.

First, a suitable analysis extent must be selected. The data is centered on Portland,
Oregon, but extends into the rest of Multnomah, Clackamas, and Washington Counties,
as well as parts of Columbia and Yamhill County. Because this study is interested in
city-scale phenomena, a rectangular analysis region encompassing the urban areas of
Portland and some of the smaller surrounding communities was used. The area has
dimensions of approximately 61 miles east-west and 48 miles north-south, for an area of
around 2900 square miles (Figure 9). This extent captures around 90% of the activity
records in the whole dataset, but excludes activities separated by very long distances from
Portland. There is a 20% expansion on the selected data’s extent in order to provide
room between the point cloud and the edge of the map.
Each individual in the sample was surveyed for two consecutive days. To avoid double-counting individuals, it is necessary to select the records corresponding to a single day for each person. While it is possible to select either the first or second surveyed day for each person, it may be preferable to capture more variability by selecting the day with the longest record of activities for each individual. In section 3.3, the 3D visualization will be used to determine if there are systematic differences in these different possibilities for selecting a single day’s data.

Table 1 shows the data volume of the Portland HSTB data in its original version and in successive subsets during data preparation. The first selection of the activity records that fall within the declared analysis extent contains 90% of the whole sample, but the data can not be left in this state because it would create gaps in the activity diaries of individuals that have traveled outside the extent. To avoid misrepresenting the space-time behavior of individuals, any person that traveled outside the declared extent is removed from the data set.

In addition, some activities were missing data for their spatial location. Because this would also create gaps in some individuals’ activity diaries, those individuals with missing activity locations are removed from the analysis. In the case where the longer activity diary day is selected for each individual, if the longer day had instances of missing location data, the shorter day’s records were used for that person if that day’s records were complete.
After a single day’s records for each individual has been selected in the next section, the spatio-temporal patterns of different demographic groups, activity types, and combinations thereof will be investigated in the following section.

### 3.3 Preliminary Analysis for Data Selection

Because the population demographics of the three selections are very similar (given that the only characteristic differentiating these selections are whether or not a person traveled outside the analysis area on a given day, see Table 2), the differences that are being sought out are in spatio-temporal patterns. Therefore, the discretized space-time cloud is first used to help decide which day’s data to use in further analysis. Besides serving that function, this first use of the prototype method is informative for learning the sets of options in the environment that make analysis more productive.

When two point clouds representing any two of the three day selections were overlaid, it is immediately apparent that their spatial distributions are practically identical (Figure 10). However, this says little of the varying population densities, since the visualization methods in the shaders were not designed to represent the full range of population density values in the cloud. Rather, the option to vary point symbol size and transparency is adjusted to differentiate points with population density values near the threshold. By adjusting the population density threshold, the differences in the magnitude of spatio-temporal occupation can be explored, making thresholding one of the most useful
functions in the visualization environment. The threshold value can be increased rapidly in order to quickly cover the range from zero to hundreds of individuals per cell, creating an animation where layers of lower spatio-temporal occupation rates are stripped away from the most frequented spatio-temporal regions.

Through this process, it was determined that the differences in space-time population density between the three daily activity selections were small enough as to not constitute different patterns. This is a comforting find, in that it suggests the sample size is large enough that the behavior of the minority of individuals that may have vastly different activity schedules in two consecutive days do not influence the city-level pattern. Because the selection of a single day’s data is necessary, and no systematic differences were identified between the three options, further analysis will use the dataset that selects the day with the longer list of activities for each person. This dataset is believed to include the most variability, owing to its larger record count.

The point clouds can be created at any resolution, and for these initial steps, two different levels of spatial and temporal resolution were used. First, the datasets were converted to point cloud with a 100 by 100 spatial resolution of cells (Figure 11), and with a temporal resolution of 15 minutes (resulting in 96 time steps for a 24 hour period). A coarser version with a 50 by 50 spatial resolution was also created (Figure 12). The higher resolution dataset corresponded to 0.6 by 0.48 mile areas, and the coarser resolution had 1.2 by 0.96 mile cells. Generally speaking, the higher spatial resolution was found to be preferable, as more interesting spatial patterns could be identified with less spatial error.
resulting from aggregation. However, switching to the coarser resolution to look at a simpler version of the data was sometimes helpful to find areas of interest to explore in higher detail. A drawback of the coarser resolution is that gaps between the points become larger, and create a distracting pulsing sensation when moving the camera viewpoint.

With the temporal resolution set to 15 minutes, there was quite a bit of point symbol overlap within the same spatial unit, which made it difficult to accurately judge point density in an area. Switching to 30 minute time increments proved helpful at both spatial resolutions.

3.4 Patterns in the Dataset as a Whole

The first thing an analyst would want to do in the 3D environment is to get their bearings by moving the camera around and examining the layout of the plotted space-time cloud points in relation to the base map data. When data is first loaded into the space-time aquarium, it may initially be as visually crowded as some of the other methods noted in the review. In the case of this dataset, numerous individuals living in the surrounded unincorporated areas break up any visual patterns that may be detected in the urban areas. The thresholding tool allows these individuals to be hidden without disrupting larger clusters.
We do not want to remove all individuals outside the strict Portland urban area from view, however. There are several smaller communities surrounding Portland that are integral to the local economy and house individuals that make trips into Portland in their daily schedules. The sample contains only a small number of people in these communities, so in the process of increasing the data threshold to remove isolated individuals in the countryside, these communities are de-emphasized. The solution to this problem lies in the visualization of filtered data rather than the raw population counts. Because the people in the small cities are clustered, the moving window filter creates larger output values in those cities than for individuals that are located in isolation. Using a small threshold on the filtered data achieves visual clarity by once again removing the isolated individuals, but preserving the clustered individuals whose values are now more resistant to being hidden by the threshold (Figure 13).

In addition, the use of the equal size visualization style in Figure 13 makes the occupation of the smaller cities more clear than the alternative size-varying style. The size-varying style is the preferred method in most instances, as many other exploratory questions involve population magnitude.

Temporal patterns are also observable in this large dataset. Many of the smaller surrounding cities and areas within Portland, but outside downtown, exhibit higher occupation during the nights than the day, suggesting that in these regions, more people leave during the day to work elsewhere than come to the regions to work. Figure 14 demonstrates these patterns. Region C of the figure is the downtown core of Portland.
Regions B and E show areas where the population is lower in the midday than in the mornings or evenings. Finally, regions A and D are exceptions to the more common pattern by exhibiting higher occupation during midday. Note that while region D appears very low in the screen capture, its temporal range is actually from 9 AM to 2 PM. The points in region D are very close to the camera, and while they appear low on the screen, the gray points that have been selected by the time ring help place this region in its proper temporal context.

Figure 10 was captured at a threshold value of 18, which is moderate for this dataset. It is high enough to remove much of the peripheral areas of the point cloud from view. However, a similar pattern of lower population at midday was also discovered at a much higher threshold value of 55. In Figure 15, the filtered version of the dataset is displayed, which shows the Hillsdale neighborhood near downtown Portland exhibiting the lower midday occupation rates. With the filtered values, this visual pattern is much easier to identify. Once found, visualization was switched back to the true data counts, where the pattern still exists, but was previously overlooked. Finding the same type of pattern at widely varying population thresholds proves this method is flexible enough to be effective at a range of data volumes, accomplishing one of the goals of this study.
3.5 Home and Work

Other than looking at the entire dataset of over 6,000, we can use the query capability within the VBA program in ArcMap to ask more specific questions of the data. Because the temporal demands and spatial location of an individual’s work can influence the rest of their schedule and overall space-time accessibility, exploring the relationship of work and non-work activities is worthwhile. Note that when examining a selection of only certain kinds of activities, the option to extend individuals’ paths to the start and end of the day is turned off when creating the 3D points cloud, as is the display of travel episodes.

3.5.1 Full time and Part Time Employment

First, the non-work and outside-the-home activities of full time and part time workers were examined to see if the time commitment to a regular working schedule could effect the spatio-temporal distribution of the rest of an activity schedule. Comparing these two patterns visually proved difficult, however, because the full-time workers constituted four times as many people as the part time workers. This meant that the two point clouds had widely different population density values that respond to thresholding differently, and the higher number of individuals in the full time set naturally lends itself to more potential spatial variability. These two characteristics resulted in an employed persons cloud that dwarfed the part time cloud and made comparisons difficult (Figure 16).
Still, through experimentation with different visualization options and the use of the selection ring for identifying time ranges, some information was gleaned. There seemed to be a slight preference for early non-work activities among the part-time workers. The part time workers also seemed more likely to have longer activities, but it is difficult to be certain of that when using this visualization method because individuals are not being visualized, and being that activity length is a property belonging to individuals. There were enough instances of single columns of occupied space-time disappearing with a threshold value of one that it seemed likely that this was indeed happening at the individual level, though. While the visualization was not able to answer the question, raising the question is the purest kind of goal for exploratory visualization. Checking the already queried data in ArcMap and generating the statistics on activity length confirmed that part time employees do indeed have longer non-work-related out-of-home activities than full time workers do.

3.5.2 Work, Non-work, and Home activities

Another possible way to understand the influence of work on activity patterns is simply to select the work activities for display. In examining the work patterns, it is observed that many work activities start between 6 AM and 7 AM, and most end between 4 PM and 5 PM. However, in the downtown area of Portland, workers are more likely to work later into the night (Figure 17). While only a threshold of 4 is required to remove all work activities after 6 PM outside of the downtown area, at that level there are still workers displayed downtown until 9 PM.
Similar to work activities, non-work related out-of-the-home activities decrease in the evening, except in downtown, where they continue late into the night. In the opposite pattern, any kind of home-based activities becomes more common towards the end of the day.

Work and home activities have similar spatial distributions, with the exception of two regions near downtown. The Hillsdale area southeast of downtown has a very high residential population, but only a small working population that is quickly eliminated by a threshold value of only two. Likewise, just east of downtown contains the highest amount of home activities. But in both these cases, there are relatively few work activities. This can be demonstrated by overlaying the point clouds for work activities and home activities. However, if we are examining a simple presence/absence pattern, the whole dimensionality for the work activities may not be necessary in the display. An alternative way of visualization how the high density work areas do not overlap with the two highest residential density areas is to show home activities as a density surface instead of a cloud, while leaving the work activities expressed as the points cloud with their full time variation. This is a simple task, given that the base map in the Virtools composition is created by ArcMap, and refreshed whenever new cloud data is loaded. In Figure 18, the use of a density surface with the base map demonstrates that when appropriate, the use of ancillary 2D representations can add to the clarity of the display.
3.6 Gender and Ethnicity

Because gender and ethnicity has been found to influence accessibility in previous work (Kwan 1999, 2000a,b), these characteristics were examined to discover if different spatio-temporal patterns can be detected by the discretized space-time cloud method.

3.6.1 Gender Patterns

There is a high amount of temporal and spatial variation in the patterns of men and women, so much so that it is difficult to detect many common patterns among their non-work activities. There was the greatest degree of clustering near downtown, and both men and women tended to perform activities in greater isolation as distance increased from downtown. In order to attempt to discover fundamental patterns, the visualization was repeated at the coarser 50 by 50 spatial resolution (Figure 19). Under these conditions, the decreased clustering with increasing distance from downtown was confirmed, as well as the appearance of some temporal patterns. While the temporal patterns for males and females were similar, females were noticed to be more likely to conduct early morning activities, and men were found to conduct relatively fewer activities in the early afternoon. Detecting earlier activities for women partially confirms the temporal patterns Kwan (2000b) detected using space-time density surfaces.

Because of the large variety of activities that qualify as not being work-related, the shopping activity type was investigated on the possibility that it may be expressed in a
more coherent spatio-temporal pattern. Women were generally found to perform shopping activities in a wider range of time, from approximately 10:00 AM to 7:00 PM, while men were more likely to shop between 11:30 AM and 4:30 PM. Women also tended to create temporal patterns that were less interrupted, continuing in many locations for eight to nine hours. For both sexes, shopping activities were found to be conducted almost entirely within the areas marked as urban in the base map.

3.6.2 Ethnicity

Next, the work-related and the non-work out-of-home activities for the four largest ethnic groups in Portland were examined. In order to see those activities in relation to where members of each group live, their at-home activities were visualized as a density surface plotted on the base map.

Even though African-Americans, Asian-Americans, and Latin Americans were the second through fourth largest ethnic groups in Portland, they were distant minorities behind a 94% Caucasian-American majority (see table 2). Because Caucasian-Americans make up such a large portion of the sample, it is not surprising that their observed space-time patterns are very similar to those observed of the whole dataset (Figure 20). A large number of African-Americans live in or near downtown, particularly east of downtown in Gresham (Figure 21). There were few activities carried where African-Americans lived in Gresham, and none at all in the Newburg area on the southwest.
The time ranges of activities were also investigated, although the relatively small samples of the minority ethnicities may not have truly representative data. While Latin-Americans (Figure 22) and African-Americans outside of the downtown area were found to finish work activities by 5:00 PM, the work activities of Asian-Americans (Figure 23) outside of the downtown area carried on to around 8:00 PM. Individuals from all ethnic groups in the downtown area were more likely to work earlier or stay later for work. Non-work activities in downtown during the evening were popular for Caucasian-Americans and African-Americans, but less so for Asian-Americans, and non-work activities for Latin-Americans were no more common downtown than other locations.

There was also a noticeable alignment of work activities for Latin-Americans in an east-west direction, passing through downtown, and covering the full east-west range of Portland’s urban area. Asian-Americans tended to work near major roads in the west side of the city, even though they were more or less evenly spread in terms of home locations, and conducted non-work activities throughout the city. The lack of strong correlation between work and non-work activities for Asian-Americans and Latin-Americans does not seem consistent with the clustering of activities Kwan (2000b) found when utilizing standardized space-time paths, but the discretized cloud is not an authoritative representation of individual activity schedules, and it is possible that the non-work activities conducted away from work locations were being conducted by non-working individuals.
3.7 Discussion

The proposed discrete space-time cloud has proven to be a scalable geovisualization approach effective to very high data volumes. In this study, it was able to represent over six thousand individuals without losing any of the dimensionality in the activity data, supporting the concept of “see the whole” in doing so. The visualization environment also contained capability to “simplify and abstract,” allowing the large, highly variable data to be conceived in basic concepts. Good practice in geographic data handling and visualization design were followed by giving the analyst full control over the aggregation process, so the amount of spatio-temporal error introduced is predictable, and allows the modifiable areal unit problem to be controlled for through experimentation. Finally, the linked nature of the software solution allows the Virtools program to work on its strength in 3D interactive virtual environments, while ArcMap processes geographic data and remains available for generating ancillary data layers and running statistics at any moment.

The discrete space-time cloud was found to be effective at recognizing patterns at a range of data volumes, proving it is a method suitable for more than just niche analysis questions. However, it was less effective with very sparse datasets. The method is best-suited for population that clusters in time and space, and if the population is more evenly distributed, it does not create patterns that are any easier to understand. Decreasing the resolution of the cloud may simplify the data enough so that general trends can be understood, but it should be done carefully knowing that spurious patterns may emerge.
It may be that space-time paths in the aquarium are better-suited to sparse data, and that
the users of a visualization environment would need the ability to switch between these
representations.

Kwan (2000b) was able to use a space-time density surface to describe distance from
home as it varies through time, and standardized space-time paths to show the
relationship of all other activities to an individual’s home and work locations. These sort
of derived individual characteristics allow the individual scale to be tied to the aggregate
scale, and being able to do so is one of the great challenges of time geography. It may be
possible to achieve similar results by precalculating these derived individual
characteristics so that they are available to visualize as an attribute in the cloud.
However, it is likely that doing so would invite the use of bivariate visualization, where
perhaps color represents the derived characteristic (like distance from home), and the size
of the point represents the number of individuals in a location. Without further
exploration, it is difficult to say if such an approach would be simple enough to visually
understand. A complicating factor is that if the color attribute needs to be used to
represent the variation of data, multiple individuals in a cell would have their values
averaged for display, possibly washing out patterns that exist on a finer scale.

Time geography was conceived as a way to improve quality of life for individuals, and
this visualization method can help support that goal by exploring how different groups of
people’s life experiences vary. However, without a stronger link to the individual level
discussed above, the patterns that are perceived as possibly space-time accessibility
issues cannot be said to be certainly so. If the methods proposed above are not effective in bringing additional characteristics that reflect individual experiences into the visualization, then more work should be done on how the space-time cloud can be used along with alternative geovisualizations to understand the data at multiple scales.

There are other minor programming additions that may prove beneficial to the approach. The ability to mark locations or data in the 3D Virtools application and send it back to ArcMap would be helpful, even if it is only to select the matching data in the linked application. Another possible improvement would be sequence-aware selections. A query such as “show me the people that have at least three sequential activities after they get off work” is not compatible with the usual database selection methods, but this sort of complex query could be a powerful enhancement to exploratory analysis.
Conclusion

This study has shown that the proposed discretized space-time cloud method is effective for finding patterns emerging from the behavior of groups of people. The analysis was carried out on the city scale with data selections containing between two dozen and six thousand individuals. Because it is most informative when groups of individuals exhibit space-time clustering, the discretized space-time cloud tended to be more useful for higher data volumes.

The proposed method can serve its purpose as a tool to understand group behavior in the city, but it is not intended to replace other geovisualization methods. However, it is the only geovisualization method that can represent such large populations as general trends while preserving both their temporal and spatial dimensions. Geovisualization is useful throughout the analysis process, but methods such as the space-time cloud are particularly useful in introductory stages of the analysis. It is during this stage that researchers begin to form a basic understanding of the data and form hypotheses and questions for further examination. This method can aid in the process by revealing the important spatio-temporal locations to different groups of people.

Future work should examine ways to understand individual constraints while using the discretized space-time cloud as a visualization method. As mentioned previously, pre-
calculated measurements, such as those based on distance from home or work, could bring information reflecting individual characteristics to the visualization. This study has used actual surveyed data in the prototype visualization, but it is also possible to represent computed space-time prisms for the population. By doing so, the potential path space of different population groups could be explored, allowing more insight into potential constraints and accessibility.

While more work needs to be done to enable this method to represent individual constraints, the method already has utility in representing the dynamic collective behavior of a population. For example, the time-varying positions of a population would be critical information for emergency response in the event of a natural disaster or terrorist attack (Bhaduri, Bright, Coleman, & Urban, 2007; McPherson, Rush, Khalsa, Ivey, & Brown, 2006). Future work could leverage the ability of the discretized space-time cloud to temporally segment HSTB data and isolate the time range affected by a disaster for further analysis. Besides instantaneous disasters, the cloud could represent a population’s longer-term exposure to a chemical spill by overlaying the time-varying spatial extent and density of the toxic plume with population.

The population density patterns in a city can also be used to optimally place a commercial location that depends on a nearby mobile population to exist, such as restaurants, convenience stores, and gasoline stations. Public resources such as parks, community centers, and public transportation represent large civic investments, creating pressure for local politicians to locate and manage these resources optimally. The
utilization of these resources will depend on the targeted population’s flexible time and spatial location during the available hours of the facilities, and the method is capable of revealing those traits.

Space-time accessibility research in general is also served by the method. If exploratory analysis with the space-time cloud identifies clusters or systematic trends, they will need to be explained, as they may play a causal role in determining quantitative accessibility measures. The method’s ability for comparing different population groups can illustrate how a larger number space-time constraints affect a population’s distribution and activity participation rates.

The discretized space-time cloud leverages a 3D virtual environment and established GIS technology to fulfill a need for an exploratory geovisualization technique for large populations. Further research on HTSB data can benefit from its capability for data synthesis and simplification, and future work should examine the technique’s role among more established spatial analysis techniques.
Works Cited


Appendix A: Figures
Figure 1 – 3D density surfaces of home activities and non-employment activities in a sample of Portland, OR.
Figure 2 – Activity density surface of non-employment activities of part-time employed women in a sample of Portland, OR.
Figure 3 – Space-time paths of African Americans, Hispanics and Asian Americans in a sample of Portland, OR, shown in the space-time aquarium. Reprinted from Transportation Research C, vol. 8, Kwan, M.-P., “Interactive geovisualization of activity-travel patterns using three-dimensional geographical information systems: a methodological exploration with a large data set,” pages 185-203, Copyright 2000, with permission from Elsevier.
Figure 4 – Standardized space-time paths.
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Figure 23 - Asian-American work and non-work activity patterns over a density surface of home locations.
Appendix B: Tables
### Data Selection Name

<table>
<thead>
<tr>
<th>Activity Records</th>
<th>Person Count</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original</strong></td>
<td>129,188</td>
</tr>
<tr>
<td><strong>Portland Analysis Area</strong></td>
<td>117,365</td>
</tr>
</tbody>
</table>

*All following tables are based on the 61x48 mile analysis area*

<table>
<thead>
<tr>
<th></th>
<th>Activity Records</th>
<th>Person Count</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Day 1</strong></td>
<td>42,466</td>
<td>6,586</td>
</tr>
<tr>
<td><strong>Day 2</strong></td>
<td>42,277</td>
<td>6,626</td>
</tr>
<tr>
<td><strong>Longer Day</strong></td>
<td>46,385</td>
<td>6,412</td>
</tr>
</tbody>
</table>

*All following tables are based on the Longer Day dataset*

<table>
<thead>
<tr>
<th></th>
<th>Activity Records</th>
<th>Person Count</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>At Home</strong></td>
<td>29,612</td>
<td>6,392</td>
</tr>
<tr>
<td><strong>Non-work</strong></td>
<td>43,201</td>
<td>6,412</td>
</tr>
<tr>
<td><strong>Non-work, outside home</strong></td>
<td>13,156</td>
<td>5,113</td>
</tr>
<tr>
<td><strong>Work and work-related</strong></td>
<td>4,084</td>
<td>2,361</td>
</tr>
<tr>
<td><strong>Full-time employed persons: non-work, outside home</strong></td>
<td>4,688</td>
<td>2,027</td>
</tr>
<tr>
<td><strong>Part-time employed persons: non-work, outside home</strong></td>
<td>1,135</td>
<td>413</td>
</tr>
<tr>
<td><strong>Male: non-work, outside home</strong></td>
<td>2,724</td>
<td>1,216</td>
</tr>
<tr>
<td><strong>Female: non-work, outside home</strong></td>
<td>3,099</td>
<td>1,224</td>
</tr>
<tr>
<td><strong>Male: shopping</strong></td>
<td>1,287</td>
<td>930</td>
</tr>
<tr>
<td><strong>Female: shopping</strong></td>
<td>1,939</td>
<td>1,314</td>
</tr>
<tr>
<td><strong>Caucasian-American home only</strong></td>
<td>27,792</td>
<td>5,985</td>
</tr>
<tr>
<td><strong>Caucasian-American non-work, outside home</strong></td>
<td>12,341</td>
<td>4,795</td>
</tr>
<tr>
<td><strong>Caucasian-American work</strong></td>
<td>3,870</td>
<td>2,230</td>
</tr>
<tr>
<td><strong>African-American home only</strong></td>
<td>396</td>
<td>90</td>
</tr>
<tr>
<td><strong>African-American non-work, outside home</strong></td>
<td>221</td>
<td>72</td>
</tr>
<tr>
<td><strong>African-American work</strong></td>
<td>57</td>
<td>35</td>
</tr>
<tr>
<td><strong>Latin-American home only</strong></td>
<td>374</td>
<td>89</td>
</tr>
<tr>
<td><strong>Latin-American non-work, outside home</strong></td>
<td>160</td>
<td>60</td>
</tr>
<tr>
<td><strong>Latin-American work</strong></td>
<td>50</td>
<td>32</td>
</tr>
<tr>
<td><strong>Asian-American home only</strong></td>
<td>365</td>
<td>77</td>
</tr>
<tr>
<td><strong>Asian-American non-work, outside home</strong></td>
<td>142</td>
<td>62</td>
</tr>
<tr>
<td><strong>Asian-American work</strong></td>
<td>41</td>
<td>25</td>
</tr>
</tbody>
</table>

Table 1 – Data volume of each population subset used in the analysis.
Table 2 – Racial demographics of the three single day selections.

<table>
<thead>
<tr>
<th></th>
<th>Day 1</th>
<th>Day 2</th>
<th>Longer Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>White/Caucasian</td>
<td>6,165</td>
<td>6,209</td>
<td>6,004</td>
</tr>
<tr>
<td>Black/African American</td>
<td>89</td>
<td>89</td>
<td>89</td>
</tr>
<tr>
<td>Hispanic/Mexican American</td>
<td>86</td>
<td>89</td>
<td>89</td>
</tr>
<tr>
<td>Asian/Pacific Islander</td>
<td>81</td>
<td>74</td>
<td>76</td>
</tr>
<tr>
<td>Native American</td>
<td>44</td>
<td>43</td>
<td>41</td>
</tr>
<tr>
<td>Other</td>
<td>94</td>
<td>97</td>
<td>89</td>
</tr>
<tr>
<td>Don't Know/Refused Answer</td>
<td>27</td>
<td>25</td>
<td>24</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>6,586</strong></td>
<td><strong>6,626</strong></td>
<td><strong>6,412</strong></td>
</tr>
</tbody>
</table>