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Empirical Tracking and Analysis of the Dynamics in Activity Scheduling and Schedule Execution

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Empirical Tracking and Analysis of the Dynamics in Activity Scheduling and Schedule Execution

A Dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Geography

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ABSTRACT

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One of the major foci in transport research is the identification of the temporal-spatial decision making structure embedded in activity scheduling and its linkage to actual activity/travel execution. The latter part of the research in question has not been explored explicitly in real life situations due to the lack of effective data collection means. This research presented a real-time activity scheduling, activity/travel survey system that incorporates the extraction of activity scheduling and activity implementation information within one unified data collection framework, under the assumption that in reality activity scheduling and execution are an integral and dynamic process that continuously evolves over multiple time horizons. During a pilot study of 20 subjects, the system demonstrated its ability in successfully capturing the survey participants' activity scheduling process and relevant activity execution into an organized dataset in the real-life, mobile environment. With the uniqueness of these empirical data in their full coverage of travel modes, site-to-site travel trace and concurrent tracing of activity scheduling and execution, they were used for explicitly exploring traveler's routing choices, scheduling pattern and modeling the linkages (congruence and deviation relations) between the actual activity implementation and activity schedules with respect to the participants' social-demographic characteristics and recorded schedule/activity/travel attributes. Using a binary logistic modeling approach, the research revealed that people's routing behavior varies with gender, travel distance, different travel modes and activity categories. By exploratory statistics and missing value analysis, the research showed that activity scheduling behavior does not apply to activity categories in an equivalent way. Finally, the activity participation choice and start time decision making as revealed in the collected dataset were coalesced into a two-stage decision paradigm and modeled via nested logistic modeling and a multinomial logistic modeling approach. The influencing factors on the linkage between activity scheduling and execution were revealed. The multinomial modeling results showed the quantitative measures of the effects of factor changes on activity start time choices.

Keywords: activity scheduling and execution, real-time survey system, map matching and nested-logit-model

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Chapter 1 Problem Statement

Although a large portion of the activities that people perform daily is unplanned ahead of time, activity scheduling is inevitable when people try to make deliberate choices to accommodate competing activity needs or tasks. The action of scheduling could occur stochastically over time in an unpredictable way and serves as an effective means for average people to explore a path through the spatial-temporal constraints enforced by human and physical environment.

Researchers from various disciplines (e.g. psychology, geography, transportation) are interested in the different aspects of the activity scheduling problems. One of the major foci is to identify the temporal-spatial decision making structure embedded in activity scheduling and its linkage to actual activity execution. Theoretical advances and technological improvements during the past decades (e.g. cognitive model of planning and computational process models) have made the former portion of this pursuit clearer and easier as considerable modeling and simulation efforts were put in. But the latter part of the question is yet to be explored explicitly in a real life situation with a more powerful data collection means. The goal of this dissertation is to examine the execution status of activity schedules of a small group of sampled respondents with respect to a wide range of temporal-spatial constraints and socio-demographic characteristics by means of empirical data collection. Data are collected with a unique survey system that extracts the activity scheduling and execution information within one unified data collection framework in real time. These "revealed" data would be used for explicitly defining the relationship of the execution status of people's activity schedules with respect to the factors mentioned above through quantitative analysis and model construction.

1.1 Introduction

Activity scheduling is a complex process that involves information acquisition, information storage and organization, evaluation, action and learning via feedback (Einhorn & Hogarth, 1981). It is also a continuous process of spatial and temporal choice over time. The process of spatial choice involves determining the location for a future activity among the spatially distributed opportunities. Temporal choice involves the decision of starting time, the durations of activities (including the travel derived if the activity needs to be conducted at a non-local location) and ensures different activities don't overlap temporally in the course of their execution. Activity execution represents the process that converts the planned schedule into the sequence of implemented activities under various temporal-spatial constraints. However, activity execution is not solely the direct consequence of following activity schedules, no matter whether it is explicitly or implicitly formed. The concurrent feedback from activity execution experience provides the behavior agents the stimuli to develop better scheduling strategies for the next round via the processing of one's complex human cognitive system.

As revealed by Lee (1999, 2001), two distinct but complementary approaches can be identified from the literature for analyzing and predicting the dynamic process regarding the decision-making of daily activities. One is rooted in econometric studies, which center on the idea that people make their choices with the aim of utility maximization. The other approach can be traced back to Psychology, Geography and artificial intelligence literature, in which researchers attempt to delve into people's inner cognitive representation of the environment and model the decision-making mechanism with the production system that consists of a set of disjunctive condition-action rules. The first approach assumes that people evaluate the different characteristics that are associated with the choice environment based on personal experiences and preferences. The probability for people to choose one activity alternative over another is proportional to their valuations of the "utilities" of these alternatives (Stopher & Meyburg, 1975). The second approach – computational process modeling (CPM), views the individual choices regarding destination, departing time, travel mode, etc. as being interdependent with each other. CPM fully describes the whole individual choice process of information retrieval, analysis, and decision making according to sets of decision rules. It has the potential to simulate and forecast people's activity choices in real-life situations if more reliable data could be obtained via an enhanced data collection design. However, static CPM lacks the ability to model the fact that activity decision-making is composed of asynchronous choices regarding multiple facets of the activities under planning. Selection of activity site, duration, frequency, start time, and travel mode (if travel is derived to reach the remote activity site) may not occur concurrently at a single time point along the time axis. The effects of the feedbacks from activity execution to future scheduling action are yet to be incorporated into CPM to make them more approximate to the realistic dynamic decision making process (Goodwin et al., 1990, Garling et al., 1994).

These past efforts have been successful in explaining or simulating the process of how activity decisions are formulated, but are limited in not being able to analyze the interrelated activity scheduling and associated activity execution within one unified framework. Specifically, the existing models had put their emphasis on the activity schedule formulation but ignored the concurrent activity implementation process. A typical example would be the research focus that tried to quantify the sensitivity threshold of various types of scheduled activities with respect to the changes in human and physical environments. The challenge was approached from multiple perspectives - theoretical explanation, simulation of activity schedule formation, or study of scheduling strategies variation via controlled experiments, based on the assumptions that the scheduling process is composed of a sequence of stages from environmental information retrieval, information processing to scheduling decision output. Conclusions derived from these methods, however, are not able to explain the real-life phenomenon that sometimes people choose not to follow the schedule. This situation is exacerbated in the case that a rule-based model such as CPM is sometimes based on the stated preference data for rule extraction under an experimental setting. The rules derived from the single case data usually cannot be generalized to other situations (Ettema et al., 1996). Conceivably, the elongation of previous activity duration will consequently affect the execution of other scheduled activities following it. Hence the sole understanding of the activity scheduling process does not naturally lead to the understanding of the implementation of the scheduling choices (Gärling, 1998).

1.2 Research Objectives, Questions and Hypotheses

The objectives of this research are two-fold:

1. Develop the systematic data collection and analyzing techniques for tracking and recording the concurrent process of realistic activity scheduling and execution.
2. Identify the critical variables that affect the various relations between individual activity schedules and their actual execution based on the "revealed" in-field data. Model the relationship and quantify the effects of the factor changes on people's activity temporal-spatial choices with respect to their schedules.

To address the research objectives, a real-time system was developed and utilized in a pilot study to capture the activity scheduling/execution process as it is driven by time and events, based on the assumption that respondents take the initiative to report the consciously-aware activity decision making independently.

The following research questions are expected to be answered via various quantitative analyses on the revealed behavioral data:

1. What are the potential constraints faced by people in realistic activity scheduling and execution under one unified analysis framework?
2. Are all activities explicitly planned ahead of their execution? Does the action of scheduling specifically relate to the type of activity to be performed? What is the frequency of the scheduling action and relevant scheduling horizons?
3. How can we describe the sensitivity of the execution status of people's activity schedules with a series of factors—socio-demographic characteristics, spatial-temporal constraints, etc.?
4. Are the interactive real-time data collection means effective and efficient in capturing data regarding the dynamic process of activity scheduling and execution?
5. What are the issues involved in the design and implementation of such kind of device and the measures necessary to improve data accuracy and system reliability?

The research is expected to clarify the puzzles associated with the following hypotheses:

1. The congruence and deviation relations between individual activity schedules and their actual execution can be described in a series of factors -- socio-demographic characteristics, spatial-temporal constraints, etc. in several different modeling structures.

2. Various types of activities are differentiated from each other according to the degrees of flexibilities associated with them. Not every type of activity is planned ahead of time. Habitual activities are conducted without the elaborate planning process theoretically associated with them.

3. A mobile real-time system provides a powerful tool to capture the asynchronous activity decision-making and execution process with the least time and location constraints.

1.3 Theoretical Framework

Travel is generated from the competing needs to participate in activities. These needs can be further classified into three categories: maintenance needs (work or business related), subsistence needs (shopping etc.) and leisure needs (recreation etc.). Typical activity-based travel behavior studies are oriented towards examining people travel activities within the context of time and money allocation among the various activity needs. The interwoven travel/activities behavior and people's decisions with respect to them cannot be meaningfully interpreted in isolation from the general framework of activity time use and Hagerstrand's (1970) time-space geography. The various constraints enforced by the environment (as identified by Hagerstrand (1970) - capability constraints, coupling constraints and authority constraints) potentially limit people's ability to trade off time for achieving a bigger activity and action scope. This entails complex decision making with regard to what activity to pursue, when, where, and what people are involved when people are trying to fulfill various activity needs (Gärling, 1989). Many years of discrete-choice (travel) activity analysis have shown that the interdependent decisions regarding the various alternative activity attributes and derived trips might include complex choices of many aspects -- activity location, travel mode (if a trip is involved), starting time etc. (Ben-Akiva & Lerman, 1985). These choices, however, only represent the resulting activity-travel patterns derived from the individual's decision-making process. The computational process that generated these outputs in people's minds is the more complicated part to delve into. Classified as cognitive activity, scheduling is conducted implicitly and the schedule details can not be revealed unless structurally organized questions are asked to elicit them bit by bit. Two existing propositions – the successive refinement model and the opportunistic model –reflected different views and understanding about the scheduling process (Hayes-Roth & Hayes-Roth, 1979). Although Hayes-Roth and Hayes-Roth favor the latter model as they proposed them and tested it with the "think aloud" protocol, the elements (top-down versus multi-directional processing, complete versus incremental planning, hierarchical versus heterarchical plan structures) used to differentiate the two views are yet to be further examined in more empirical studies.

As they have suggested in their article, people with different personalities may choose to deal with the scheduling problem with the strategies that best suit the scenario. For example, the continuous 24 hours on weekdays is divided by fixed working schedules into several segments. The home-work-home (travel) activity pattern can serve as the skeleton of people's activity schedule for them to refine it in steps. However, the formulation of the activity schedule on weekends could be far more complex than what we can understand with the current research methodology (Damm & Lerman, 1981). Systematic techniques need to be developed for shifting the data collection emphasis onto the continuous tracking of the activity schedules and sequences in space and time and the interaction of them with the time-space constraints on individual behavior. Although the long-tradition activity-based approach outperforms the trip-based studies in many aspects, the conventional recall and recording methods for data collection have become the major constraint that hinders the retrieval of more accurate data and the use of a more comprehensive data collection design. As activity scheduling could continuously evolve over time even while the activity is being undertaken, it is reasonable to conceive a near-real-time data collection system to capture the activity scheduling process that is driven by time and events. If such a system can be activated by multi-modal input, its use would facilitate and encourage the reporting of en-route activity (destination) change, the previously under-reported short trips, the multi-stop trips and the associated activities with them. Hence not only providing the maximum information about the not-well-understood activity-related decision making process, but further improving the analysis of the trip-chaining phenomenon and complex travel patterns. Such a system will be fully described in section 3.

1.4 Organization of the Dissertation

The rest of the dissertation will be organized as follows: Section 2 reviews the past literature on the theory of activity scheduling, and modeling of the activity scheduling process. Section 3 discusses the proposed quantitative analysis on the data that are to be collected with a real-time data collection system and the models to be constructed for testing the research hypotheses presented in Section 1.2. Section 4 illustrates the implementation of the real-time activity schedule and execution data collection system and explains the activity scheduling and execution data survey that supports the research. The empirical data analysis results and modeling results are presented in section 5. Finally, Section 6 concluded the research with a summary of the research contributions and important findings. The further analysis and model constructions to fully realize the full potential of the revealed activity/scheduling data are proposed at the end.

Chapter 2 Review of the Theories and the Modeling of Activity Scheduling and Engagement

The various travel patterns exposed and revealed in the numerous travel surveys and travel activity analysis works are essentially the outcome of following and implementing activity schedules. Contemporary travel behavior researchers have recognized the importance of establishing the underpinning of travel pattern generation within the context of activity scheduling and engagement. For systematically researching the topic, they explicitly differentiate two basic concepts that are easy to confuse: the generation of an activity program and activity scheduling. Bhat and Koppelmen (1993) explained the former as an activity agenda that is motivated and driven by individual and household needs, while activity scheduling represents the decision making process that sequences the agenda and assigns the programmed activities to each feasible slot along the temporal and spatial path. As Recker et al. (1986a) pointed out, the scheduling process produces the feasible “activity pattern choices from individual activity program” (p307) and the actual activity participation depends on the scheduling determination among the potential choices.

Activity scheduling is a complex cognitive process that is not directly observable. The attempts to explain the underlying mechanism of activity scheduling can be traced back to the late 1970's and early 1980's Psychology literature. These early-stage researches focused more on examining the nature of the activity scheduling phenomenon than its relation to the choice of which activity to conduct and the travels derived. Einhorn and Hogarth (1981) pointed out that the human behavior to a large extent is sub-optimal. Due to people's limitation in obtaining an exact and complete cognition of the structure of the environment, intuition or heuristic rules play an important role in the so-called decision-making process such as activity scheduling. In other words, people act with "bounded rationality" when dealing with tasks like activity scheduling (Kwan, 1994). A good example is Hirtle and Garling's (1992) examination of people's use of heuristic rules for organizing the destinations within one multi-stop trip. The spatial decision-making process of their focus is subsidiary to activity scheduling when the planned activity is to be performed at an other-than-current location.

Noticing the inherent uncertainty and sub-optimality in people's decision-making, Hayes-Roth and Hayes-Roth (1979) attempted to explain it with an opportunistic model of activity planning. They consider the initial motivation for various activities as individual desires to perform and the matched operational condition-action rule as "cognitive specialists". "Blackboard" is used to refer to the current status of the mind regarding activity decision-making. Each "specialist" writes his decisions on the "blackboard" and the others formulate their further actions to be incorporated into the activity schedule according to "what was written on the blackboard".

Conceptually the "blackboard" consists of five planes with each for different aspects of the task for activity planning. For example, "knowledge-base" is people's cognitive representation of the world context. Its content can be dynamically adjusted according to the feedback from the execution of activity schedules on the "blackboard". On the other hand, the "meta-plan" guides what strategy the individual would use for approaching the planning problem. Conceivably, the composition of "meta-plan" varies with people's life experience and expertise in dealing with the scheduling problem.

Lundberg (1988) does not explicitly address the activity scheduling process but emphasizes the task-related decision-making of a human being when facing the perceived constraints through their information acquisition mechanism. He stressed the effects of environmental cue input on individual's travel behavior within a constrained environment. The cues serving as stimuli to human perception exist in the environment abundantly. People's attention to these cues need to be selective to reduce the information space (Einhorn et al., 1979). The time-varying attractiveness of various types of activities is represented with fuzzy functions. Top-down and bottom-up impulse effects additively determine if an activity should be performed at the time being, i.e. if the computed arousal value exceeds the predetermined system threshold, the corresponding activity is selected and the next task is continuously considered. Due to the use of fuzzy concepts and linguistic variables, the model possesses a distinctive feature: the arousal level threshold seems to mimic people's sensitivity to the temporal variation of different activities pretty well. The low arousal level threshold setting could make the model exhibit more of the opportunistic nature in human activity scheduling as suggested by Hayes-Roth and Hayes-Roth (1979).

Damm and Lerman (1981) concentrated their research on the activity scheduling of urban work on weekdays based on the utility maximization assumption. They attribute work as the type of activity that is associated with the least flexibility. Thus the other types of activities are considered as the next level concerns, to be filled in the five blocks of time period defined around the work schedule. The causal factors that affect activity decision-making are classified into two sets: One set involved the long-term choices of the household as a whole (residential place, household structure etc) and the needs that are generated for maintaining the household's operation; the other set of factors are related to spatial and temporal constraints that define the activity scope boundary imposed by the environment. Under the conceptual framework, the activity-scheduling problem is reduced to a two-fold choice regarding how to utilize the discretionary time in the five blocks of time period: either performs the planned activity at the home or work location or participates in the activity at a location other than home or work.

Damn and Lerman's (1981) work is insightful but subject to criticism that the description of the activity decision-making is structural and static. As indicated by

Smith et al. (1982), structural "black boxes" ignore the complex underlying behavioral reasoning process behind the phenomenal activity pattern. The preference and lifestyle inconsistency among people in a population could compromise the predicting ability of simultaneous structural models for people's reactions to the potential policy or transportation infrastructure changes. Based on real-life experience, it is easy to draw such a conclusion that people are not capable of behaving in a statistically rational way in many cases. Therefore a fixed structural description of the linkage between the arbitrarily chosen input and output variables is not flexible enough to cover the various facets of the human decision making process. On the other hand, Smith et al. (1982) claimed that the computational process model (CPM) is more powerful in comparison since it integrates people's representation of the world (the declarative knowledge in their knowledge structure --KS) and disjunctive inference rules (the procedural knowledge in KS) for responding to the changes in the world into one modeling framework. A large portion of these disjunction inference rules (equivalent to the "cognitive specialists" in Hayes-Roth and Hayes-Roth's (1979) opportunistic activity planning) is heuristic in nature, which better characterizes the non-optimality and uncertainty exemplified in the human decision-making process. In their point of view, CPM has a particular meaning in the field of Geography in that the "episodic" routing knowledge can be partially captured with the condition-action inference rules, as it is inseparable with the spatial learning process, which involves logical inference and deduction regarding spatial features. As a part of their next-step work, Smith et al. (1984)

tested and explored the derivation of the inference rules for a computational process model of the searching behavior in a housing market. Although the test setting is experimental in nature, their work indicates that it is practical to generalize the inference rules for building a production system model from the observed data regarding people's decision-making process if a "representational language" (e.g. disjunctive normal form (DNF)) can be found to fully describe the data and the rules can be formed based on the language. Garling et al. (1994) in their review of the up-to-date developments of CPM models further showed their support for strengthening the research efforts toward the direction to complement the traditional structure-based discrete-choice modeling approach.

Since the concept and application of the production system was first introduced into the activity scheduling study, researchers have realized the advantage of using it to model activity scheduling behavior. Thus many theoretical and operational computational process models (CPMs) have been proposed and implemented as computer programs. Several reviews (e.g. Arentze and Timmermans, 2000, Garling et al. 1994, Timmermans 2001) have partially or completely covered the currently available computational-process models. These models include TOUR (Kuipers, 1978), NAVIGATOR (Gopal and Smith, 1990), SCHEDULER (Garling et al, 1989, 1998), STARCHILD (Recker et al., 1986a, 1986b), SMASH (Ettema et al. 1996), GISICAS (Kwan, 1994), PCATS (Kitamura et al., 1996, Kitamura & Fujii, 1998), AMOS (Kitamura et al., 1993, Kitamura & Fujii, 1998), ALBOTROSS (Arentze &

Timmermans, 2000) and CHASE (Doherty and Axhausen, 2001). Each of the CPM models addresses a different aspect of activity scheduling and activity-travel behavior with its distinct approach. They replicate the complex human decision-making process and hence are the effective tools to test theoretical assumptions and policy effects before a transport policy is enacted (Garling et al. 1994). Some of them have been technically used to serve as the theoretical touchstone to the more in-depth exploration in the analysis of activity scheduling, generation and execution. In the following paragraphs, a brief tour of these models is given. Their key features and contributions to activity-travel research will be discussed in a condensed form. Note that not all the models are in a pure production-system form. Some of these models are in essence hybrid in terms of incorporating other approaches into them (such as utility maximization (STARCHILD and SMASH) and time-space prism (PCATS)) for improving the model performance. There is no unanimous agreement on the correct classifications of these models in the research community yet. An exemplifying conflict would be the categorization of STARCHILD as utility-maximizing model in Timmermans's (2001) review of models of activity scheduling behavior.

Kuipers (1978) considered the scheduling problem in a limited domain of route choice and route planning. He suggested a CPM model named TOUR, which consists of three parts: the cognitive map that represents the incomplete knowledge about the surrounding environment, the "you are here" pointer to record people's current positioning state and the set of inference rules that combine the use the map and current state knowledge for deciding the next step of action. The consequence of applying an inference rule to the current state would be the change of current positioning state in the environment and the filling-in of gaps in the knowledge structure. As a loop, an inference rule was searched repetitively and applied to the current state until people reach the destination. NAVIGATOR (Gopal and Smith, 1990) extends and goes beyond the TOUR model with its full devotion to the navigation purpose. Thus its information acquisition and storage focus more on perceptual information obtained along a linear features during people's movement. "Decision point nodes" and "action links" forms the knowledge network presentation. To facilitate the examination of complex scenarios that could occur in real navigation experience, NAVIGATOR uses groups of parameters to control the simulation of the whole spatial learning and retrieving process. The CPM in NAVIGATOR incorporates a two-level scale of searching strategy (global and local) for reaching the navigation goals. Which strategy to use depends on the completeness and accuracy of the cognitive map the system acquired during the learning process. These two models do not explicitly deal with the linkage between travel/navigation and activity choice in the constrained spatial-temporal space. But they indeed lead us into the insight that the knowledge storage and structure (cognitive map) in people's minds function as the important reference in the en-route spatial decision-making process. Considering that activity scheduling could involve the mental simulation of a sequence of activities for testing schedule feasibility and resolving potential conflict, these ambiguous and fuzzy beliefs of people partially contribute to their satisfaction of sub-optimal activity-travel plans and the performance that is associated with the execution of these plans.

Gärling et al. (1989, 1998) refined the representation of the knowledge structure in human's mind into several interrelated components (in addition to the cognitive map, short term calendar and long term calendar are added) in their model - SCHEDULER. The long-term calendar is assumed to be the container of activity-related information. If a specific higher-priority activity is activated for fulfilling household or individual needs, information retrieved from the long-term calendar will be incorporated into an activity schedule and the resulting schedule will be saved in the short-term calendar part. SCHEDULER is the first pure computational-process model that simulates the activity scheduling behavior based on heuristic search rules. Other researchers have used it as their work base. Golledge et al. (1994) tested the model in the scenario of telecommuting effects on people's travel pattern. Kwan (1994) expanded the SCHEDULER model in the context of ATIS (Advanced Traveler Information System) and explored their potential connection to GIS as the interface for spatial feature management and analysis. The model she proposed -- GISICAS (GIS-Interfaced CPM for Activity Scheduling) –expanded the functions of ATIS to include the activity scheduling and execution process within one integral modeling framework and provides a set of systematic en-route strategies to support the real-time control of the schedule execution. The CPM in GISICAS plays an important role in helping people make activity-travel decisions in response to the rapidly changing environment. Partially as navigational guidance, GISICAS takes the advantage of the real-time and pre-input spatial information from ATIS and uses CPM for searching among the set of feasible spatial opportunities that are supplied by the attached GIS. The searching strategies adopted are in nature heuristic (as what has been revealed in the past studies of human decision-making process), but more refined with the locational spatial binding effects taken into consideration.

STARCHILD (Recker et al. 1986a, 1986b) and SMASH (Ettema et al. 1996) are the two mixed-type CPM models that integrate the utility-maximization modeling approach together with the rule-based production system for simulating the process of activity-travel scheduling. The added-in utility measurement quantifies the degrees of satisfaction brought to the schedule makers by various activity plans. The emphasis of SMASH is solely on the formation of the pre-activity schedule. Its scope of modeling doesn't include the schedule execution process and the possible schedule change en-route. The same applies to STARCHILD. In SMASH, the formulation of a satisfactory schedule goes through a recursive stepwise adaptation procedure. The temporary schedule derived at each step is evaluated based on the associated utility measures. According to the evaluation result, the model determines if another activity can be inserted into the schedule or a satisfactory schedule has been found thus the whole simulation can be terminated. In comparison, STARCHILD adopts a comprehensive modular design to construct a "model system" with each module addressing the different stages in the suggested activity scheduling process (activity program generation, the identification of feasible activity-travel patterns, utility evaluation of these patterns, and choice among the patterns). Essentially STARCHILD uses a combinatorial algorithm with ordering and coupling constraints for pruning the solution space to generate all the feasible activity-travel patterns. The set of feasible travel patterns are further refined and reduced to a set of "non-inferior" activity pattern choices. Finally the "logit" choice is made among the "non-inferior" patterns to select the best one based on the utility associated with each of them. Many ideas put forward in the construction of STARCHILD are theoretically inspiring. But the assumption that the decision-makers are able to perceive/compare the possible distinctive activity-travel patterns and thus select the best opportunity among them is unrealistic. Obviously the human mind lacks the capability of dealing with complicated comparisons between large volumes of competitive daily activity-travel plans. In addition, the complex composition of STARCHILD and its exhaustive exploration of all the possible activity-travel patterns make it computational demanding and constrain it from becoming fully operational.

PCATS (Kitamura et al., 1996, Kitamura & Fujii, 1998) considers people's daily activity-travel behavior pattern within Hagerstrand's conceptual framework of time geography. The temporal-spatial "prism" determined by the various constraints is used to limit the potential choice sets in destination, travel mode and activity duration determination. The whole computational process assumes that people's decision-making regarding activity and travel is sequential in nature (choose activity type → choose destination→ choose travel mode →choose activity duration). Each step of choice conditionally depends on the decision previously made and is simulated by a discrete choice model by itself. As PCATS explicitly incorporates constraints enforced by the environment into the model construction, it is most useful in studying the effects of these constraints on people's activity-travel behavior.

AMOS's (Kitamura et al., 1993, Kitamura & Fujii, 1998) structure follows the streamline of human decision-making process that consists of stages such as information acquisition, generation of alternatives, organizing the alternatives, evaluation and final determination. Each of the modules in AMOS (i.e. baseline activity-travel pattern analyzer, response option generator, activity-travel pattern modifier, evaluation routine and acceptance routine) corresponds to each of the stages in a certain way. In addition, AMOS combined the use of a rule base and utility maximization within one model. The rule base is used for testing the validity of the shuffled activity patterns derived from the activity-travel pattern modifier, while utility measures constitute the basis of the judgment of which a modified activity-travel pattern would be finally chosen. AMOS has been successfully used for testing people's potential activity-travel behavior change in response to various transportation demand management (TDM) measures.

ALBATROSS (Arentze & Timmermans, 2000) is another purely rule-based activity-travel scheduling model. The method of utility comparison for determining the best activity-travel alternative is totally expelled from its model construction. Arentze and Timmermans (2000) view that the decision rules used in the human decision-making process vary with each individual's adaptation experience with respect to the rapidly changing environment. Therefore, they suggested using induction methods to capture from data the potential dynamic decision tree used by people in making choices regarding activity or travel. As a distinct feature, ALBATROSS also considered the interaction effects of two person's scheduling process within a household context (household heads- husband and wife). Due to the potentially large condition space in production systems and the preference difference across individuals, the decision rule set is difficult to be captured or simulated with a small sample drawn from the population. Thus ALBATROSS is not targeted at deriving the general set of decision rules to cover general activity-travel decision-making but only to search for the rule set that best fits the current observed data.

CHASE (Doherty and Axhausen, 2001) assumes that the week period is the appropriate time scale that captures the ever evolving activity scheduling process. Routine activities are first identified from the household and individual activity program to form the optimal "skeleton" schedule. Discretionary activities are incrementally filled in to "flesh" out the vacant time slots opportunistically. CHASE simulates the interaction among individual's activity agendas by simultaneous construction of each one's schedule. Impulsive or unexpected emergencies are built into the model via random events. In addition, scheduling and rescheduling in CHASE are assumed to be interleaved with the execution of the schedules. This makes it approximate the real-life activity scheduling behavior much better than other models.

These computational process models discussed above are based on some intuitive assumptions and concepts from research experience or expert's opinions. Their representativeness of decision-making principles is questionable when compared to real-life situations due to their embedded machinery production mechanism. For example, although the interleaving three-way interaction among activity generation, scheduling and action have been theoretically recognized, the implementation of many CPM models still treat people' activity scheduling and activity program generation as two isolated processes that are sequential in time. This implies that people's activity needs are treated like being completely formed prior to the start of the whole day. However, in reality the formulation of the activity program is as dynamic as the scheduling process while environmental stimuli continuously spur people's reaction. The feedback from the implementation status of the previous scheduled activity potentially affects the scheduling for the next activity and its subsequent execution. Besides, in CPM models the linkage between the simulated activity schedule and the consequent activity-travel pattern are only examined on the basis of simple comparison. To what extent the simulated schedule can predict the actual activity implementation is not fully understood yet. The real-life situation of activity execution could be easily under the influence of various psychological or environmental factors. One of the key interests that have been long neglected would be to identify the set of factors that affects the congruence or deviation of the activity-travel with respect to the original schedule. It can be expected that some of these factors could affect both the revealed activity-travel pattern and the activity planning process. This research intends to explore the interacting relations between activity scheduling and the consequent activity execution within one integral framework. The distinctive quantitative analysis technique and modeling approaches will be further elaborated in Section 3.

Chapter 3 Quantitative Data Analysis and Model Construction

3.1 Assessment of the Activity Scheduling and Execution Data Survey

Data for this research comes from the real-time activity scheduling/execution survey to be explained in detail in section 4. The survey centers on data collection with computerized real-time mobile devices. The entire data collection procedure will be assessed from three aspects. First, analyze the average time that people may spend on the scheduling task each day and the variation of data entry time length over the one-week survey period to check the data input efficiency. In general, the key to get sufficiently accurate in-field/in-situation data for research need is to minimize the intrusion effects of the observer or observing equipment on the phenomenon or subjects being observed. Second, plot the activity and trip frequency variation across the one-week period to check if significant report fatigue effects are involved in the data survey. This particular kind of non-response makes the sample lose its representativeness of the population from which it is drawn (Brog and Merburg, 1980, 1982; Clark et al. 1981; Golob and Meurs, 1986). Last, but not least, comments on the survey program are collected from the survey respondents after the survey is completed. The feedbacks are summarized in tabulated form to provide the user's perspective on assessing whether the survey design is sufficient to meet the data requirements of this research.

3.2 Quantitative Analysis on the Activity Scheduling/Execution Data and Travel Traces

Activities can be classified into obligatory ones and discretionary ones based on a rough criteria of the degree of flexibility associated with them. The activities that fall in the former class are fixed in schedule and in location, such as work (with no telecommuting involved) or study activities (that requires class attendance). The latter category can be referred to those activities that are more flexible in time arrangements, e.g. shopping, recreational activities, etc. Most of the obligatory activities are routinely performed and strongly committed over a certain long time period. Their schedules have been optimized as a habitual pattern in the long run (Doherty and Axhausen, 2001). It is worth noticing that no explicit pre-planning with regard to activity site, duration, start time etc. is associated with routine activities. A similar case also occurs for activity needs that arise from impulsive desires. For those activities that are indeed planned ahead of time, the pre-planning time scale could vary to a great extent, ranging from a few hours to a few days before their actual execution.

Compared to data from the past travel/activity surveys, the data collected in this research is unique not only in its integral records of the dynamic process of concurrent activity scheduling/pursuits, but also its coverage of the full spectrum of travel modes and complete site-to-site travel traces. Based on the survey data, several statistics will be analyzed and presented visually for enhancing our understanding of activity scheduling behavior, travel route choice, activity/travel time allocation and identifying the critical relationships between activity schedules and their actual activity execution. These quantitative analysis techniques applied include: 1) Off-road travel analysis; 2) travel route choices between time/distance optimized routes; 3)Activity duration and travel duration pattern analysis; 4) Scheduling/Rescheduling frequency analysis of different activity types; 5) Analysis of the variation of activity scheduling horizon against social-demographic characteristics of the survey sample and activity/travel attributes; 6) Missing value analysis to determine the relationships of scheduling horizons with respect to the schedule completeness.

3.3 Logit Modeling of Congruence Relationships between Activity Scheduling and Execution

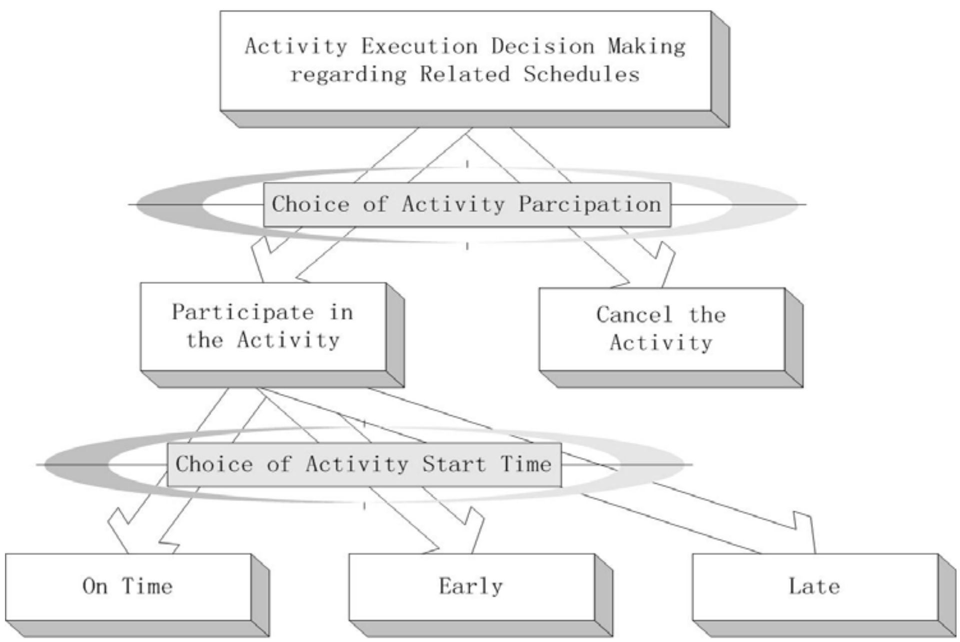
Several approaches for building the activity scheduling/execution model are available with the empirical observation of how activity scheduling and execution are actually made in real-life situation. The options at this research stage may include nested logit models, artificial neural networks (ANN), and learning trees etc. These different forms of model construction will facilitate the testing of those hypotheses mentioned before from different perspectives, in terms of how spatial–temporal constraints, household characteristics and other constraints (such as substitution) affect the scheduling, rescheduling of people's daily activities and their actual implementation. In this dissertation, the modeling attempts only focus on the discrete choice modeling methods – nested logit modeling and multinomial logit modeling.

Discrete choice modeling techniques have been the focus of activity-travel researchers since 1960's. They have been widely used for the analysis and prediction of transportation demands as part of the disaggregate travel demand modeling efforts. The so-called nested logit models to be discussed here were derived from the traditional multinomial logit models, which deal with the choice among multiple discrete alternatives under the IIA (independence of irrelevant alternatives) assumption. The nested logit model extended the application of multinomial logit model to the multi-dimensional choice situation based on the assumption that a subgroup of alternatives "shares unobserved utility components" (Ben-Akiva & Lerman, 1985). In this research, estimation of a nested logit model is used to study the potential deviation of the respondents' schedule execution from their stated intention – the schedule, with the assumption that schedule execution is an integrated decision-making process that conforms to a model in a decision tree form. In a strict sense, however, the phenomenon under study is not exactly a choice-among-the-alternatives situation. But the form of the nested logit model helps in modeling the relationship between activity scheduling and the associated activity execution into two stages. At the first stage, the respondent determines if the scheduled activity is executed as specified in the schedule or not. If it is not executed as specified in the schedule, it means that the activity has been deleted from the daily schedule. In the second stage, several model forms could be conceived. One is to model the temporal execution status about the activity starting time (on time, ahead of time, late can be viewed as the choice set). The other is to model the activity duration (longer, shorter, and the same as planned can be viewed as the choice set). Last but not least, the spatial attribute of activity execution status can be modeled as locational choice. Depending on if the actual execution location is the same as in the schedule or not, we may model this level of decision-making as the destination substitution/choice. The following diagram (Figure 1) provides a visual depiction of the possible two-level nested-logit models. The three forms of logit modeling could also be combined into one four-level nested-logit model if we assume that the choice of activity start time conditionally depends on the choice of activity location and that the choice of activity duration conditionally depends on the choice of activity start time, i.e. with activity location choice at the second level, activity start-time choice at the third level and activity duration choice at the fourth level. Of course, the resulting computational cost will be higher than the two-level cases. In general, diagnostic analysis is necessary to test which prior model structure is most suitable for the problem in consideration (Sobel, 1980). The sequential estimation method (Ben-

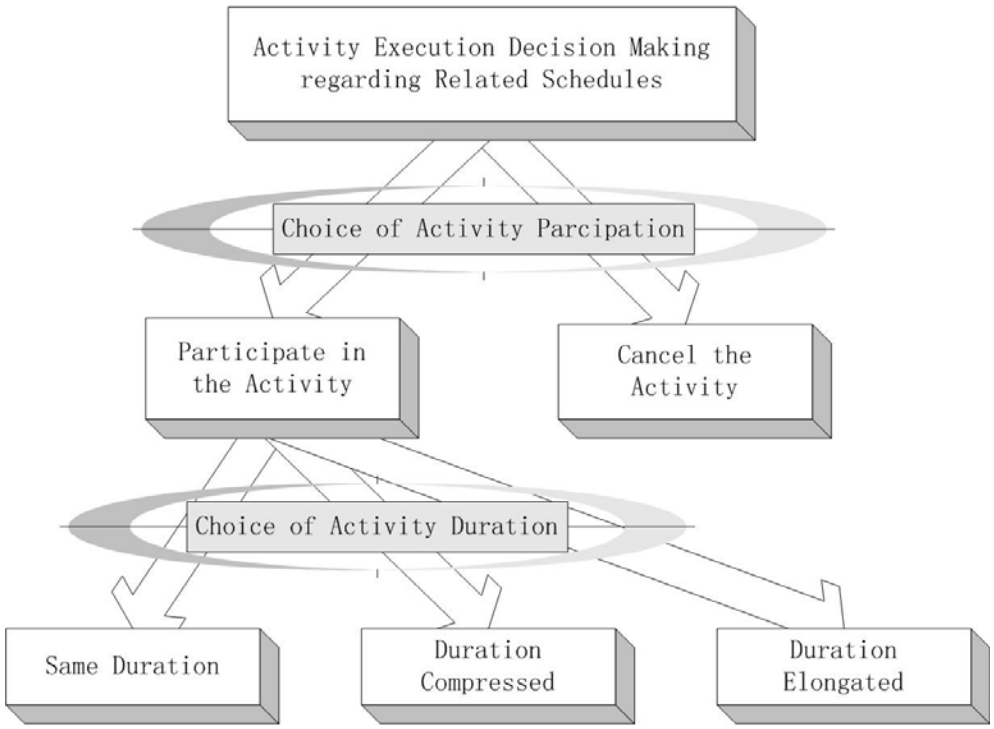
Akiva & Lerman, 1985) is most often used for estimation of the nested-logit-model parameters.

Figure 1 Illustration of the possible two-level nested-logit modeling of activity scheduling and execution (A, B, C)

Model A

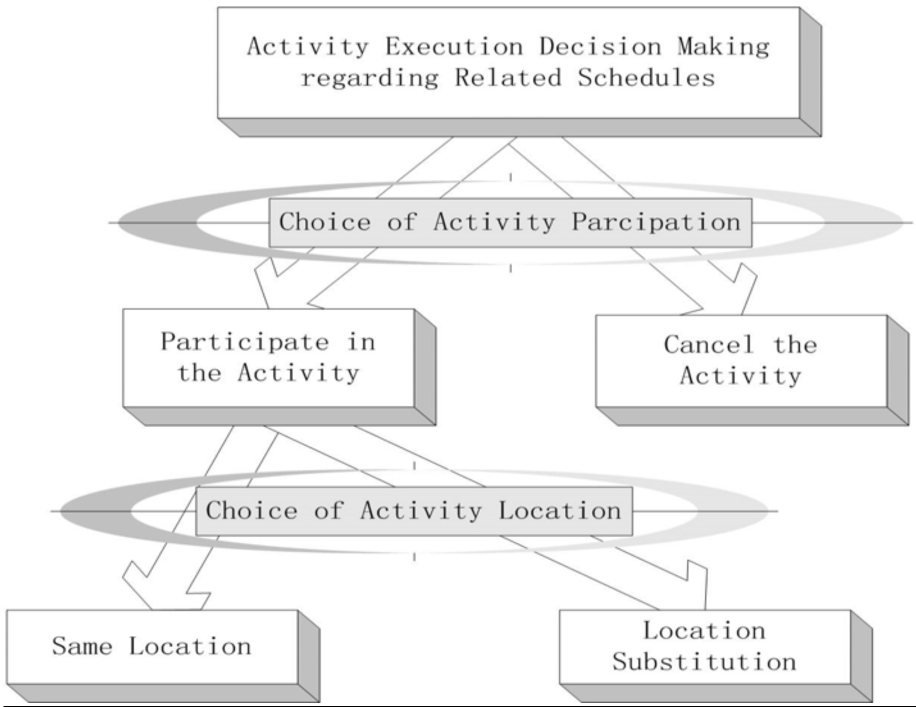


Model B



Activity Execution Decision Making regarding Related Schedules
Choice of Activity Parcipation
Participate in the Activity
Cancel the Activity
Choice of Activity Duration
Same Duration
Duration Compressed
Duration Elongated

Model C



Suppose that the survey respondent faces the activity participation and start time choice indexed as i = 1, 2 (upper level) and j = 1, 2, 3 (lower lever). Under the NLM, the probability that one alternative occurs or is chosen can be expressed as:

Prob (choice j, branch i) = $P_{j|i} * P_i$,

where i refers to the activity participation decision and j refers to the activity start time choice.

$P_{j|i}$ – the lower level choice in the nested logit model is a multinomial logit choice in essence and can be expressed as:

$$P_{j|i} = \exp(V_{j|i}) / \Sigma^{j=3}_{j=1} \exp(V_{j|i}) = \exp(\beta X_{j|i}) / \Sigma^{j=3}_{j=1} \exp(\beta X_{j|i})$$

Where

$P_{j|i}$ is the probability of alternative j to be chosen on the condition that the alternative I on the upper level has been chosen.

$V_{j|i}$ is the deterministic portion of the utility associated with choice j in the choice subgroup i.

β is a vector of model parameters,

$X_{j|i}$ is the vector of explanatory variables related to activity start time choice.

Pi – the upper level choice probability, which can be expressed as

$$P_i = \exp(\gamma Z_i + \tau I_i) / \Sigma^{i=2}_{i=1} \exp(\gamma Z_i + \tau I_i)$$

Where γ is the vector of model parameters

Z is the vector of explanatory variables related to activity participation decision-making.

I_i is defined as the inclusive value for the i_{th} branch, which measures the correlation among the random error terms due to unobserved attributes of activity participation decisions.

To build the nested-logit model, it is necessary to define a series of attributes for computing the "utility" of each alternative. The utility function will be expressed as the weighted linear addition of these attributes. Here we only consider the first two-level model structure illustrated in Figure 1. We may define three vectors of attributes of activity participation choice (A_{ap}), activity start time choice (A_{as}) and combinations of activity participation and start time choice (A_{aps}). The set of attributes in A_{aps} jointly affect both the activity participation and start time determination. Table 1 lists the independent attributes (variables) to be used in the model construction.

Table 1 Definition of independent variables for the two-level activity scheduling/execution model

Variable name	Variable representation	Definition	Variable type
Age	AGE	Age of the respondent	A_{aps}
Gender	GENDER	Sex of the respondent male, female. (1,0)	A_{aps}
Driver's license	DRIVERLI	Indicates if the person has a driver's license. (1,0)	A_{aps}
Income Level	INCOME	Income level	A_{aps}
Activity types	ATYPE	The type of activity	A_{aps}
Total work/school time duration	WORKTOTA	The duration of work/school time during the day.	A_{aps}
Precipitation	PRECIPIT	The precipitation condition	A_{aps}
Sky condition	SKYCONDI	The sky condition (sunny, cloudy etc.)	A_{aps}
Wind condition	WIND	The wind condition (no wind, breezy, etc.)	A_{aps}
Temperature	TEMPERAT	Temperature (cold, cool, etc)	A_{aps}
Traffic condition perception	TRAFFICA	Perception to the conditions of traffic at the time of activity/travel execution.	A_{aps}
Schedule Horizon	HORIZON	How far ahead the activity is scheduled.	A_{aps}

Start time missing	STARTMIS	If start time element missing in the schedule	A_{aps}
End time missing	ENDMIS	If end time element missing in the schedule	A_{aps}
Location missing	LOCMIS	If location element missing in the schedule	A_{aps}
Date missing	DATEMIS	If activity date element missing in the schedule	A_{aps}
IsWeekend	WEEKEND	If the activity date is at a weekend	A_{aps}
Participant withdraw	WITHDRAW	If a participant withdrew from the activity	A_{ap}
Activity Priority	PRIORITY	Activity Priority (scaled from 1 to 5, 1 as the highest)	A_{ap}
Real-time traffic conditions	TRAFFICR	Traffic conditions at the time of activity execution	A_{as}
Day of the week	WEEKDAY	Indicate the scheduled day in the week (1-7) for the planned activity	A_{as}
Travel duration	TRAVELDU	Travel duration	A_{as}
Activity duration	ACTIVI5	Activity duration	A_{as}
Length of Shortest time path (in Kilometers)	SHORTE1	Length of shortest time path (in Kilometers)	A_{as}
Length of Shortest time path (in Minutes)	SHORTE2	Length of shortest time path (in Minutes)	A_{as}
Length of Shortest distance path (in Kilometers)	SHORTE3	Length of shortest distance path (in Kilometers)	A_{as}
Length of shortest distance path (in minutes)	SHORTE4	Length of shortest distance path (in minutes)	A_{as}
Travel distance	BELIEFTR	The distance traveled to reach the activity location	A_{as}
The ratio of "off-road" travel	OFFRATIO	The proportion of the travel that can't be matched onto a base map (e.g. travel in parking lot, bike path, sidewalk, etc.)	A_{as}

Number of Intersections	INTERSEC	The number of intersections encountered during travel	A_{as}
Is Travel during Peak Time	TRAPEAK	If the travel is during the peak time (6-9am or 5-7pm)	A_{as}
Travel mode	TRAVELMODE	The travel model used to reach the activity location	A_{as}

Chapter 4 Activity Scheduling and Execution Data Collection

The scientific community is still seeking an effective means to observe the process of decision-making actually undergoing in the minds for truly understanding its inner working gears. Hayes-Roth and Hayes-Roth's (1979) tracing of the scheduling process by verbal protocol is a first attempt. Ericsson and Simon formally proposed the method during the early 1980's (Ericsson & Simon 1980, 1984). The method elicits the details of the cognitive process embedded in the decision-making task by asking the interviewee or survey respondents to speak aloud their ongoing mind activities. The action of "think aloud" occurs concurrently with the decision-making task being performed. As the information collected by the "Think Aloud" method originates from the "real-time" cognitive process that stores it in the short-term memory (STM), data derived are not subject to the possible distortion effects of any intermediate encoding or interpreting process. The only possible "negative" effect is that the duration of the whole decision-making process may be elongated a little due to the need to verbalize the originally silent cognitive process (Ericsson & Simon, 1980). However, the methodology requires extensive personnel supervision and recording efforts. In addition, the cost to analyze the data derived from it is high (Smith et al., 1982, 1984). This means the method could be useful in an in-lab experimental setting, but might not be a good choice for large-scale data collection efforts. In order to fully examine the activity scheduling behavior and its execution status in real-life activity implementation, an in-field data collection method is required, which enables the continuous activity scheduling and execution observation over a relatively long survey period. However, this does not preclude the incorporation of the previous “think aloud” approach in the data collection practice. The rapid development in speech recognition and text-to-speech make it possible to integrate the “think aloud” protocol onto in-field devices to fully develop its application potential.

The research presented and implemented a real time activity scheduling/execution data collection system augmented with a multi-modal input interface, which, with a client-server system design, will enable a researcher to monitor the travel data collection process in real time through time and space by wireless networking and respond to the possible data errors in a timely way. As data are collected in near real-time by its features for in-field use (with a Pocket PC and GPS) and the direct link of the survey unit to the central data server (with wireless network connection), the system has the capability of capturing the interleaving activity agenda generation and activity scheduling process and recording the associated activity-travel pattern under the guidance of refined activity schedules. In addition, the system enables the researchers to monitor behavior that happens infrequently and differentiates the random variations in people’s travel activities from the genuine trend change. By augmenting the existing interface of the data collection devices with speech input-output functions, it is expected that the system will be useful for simulating the role of interviewers who in the past home interview surveys help the respondent to "think aloud" the subconscious activity scheduling information varying with any space-temporal context. The solid database provided by the system will be used to support the intended modeling research elaborated in section 3 regarding activity scheduling and the associated activity execution status.

4.1. Past Data Collection Efforts

Among past efforts, one comprehensive approach for fulfilling an activity scheduling survey is the CHASE survey program by Doherty and Miller (2000), which was probably the first successful attempt to provide real-life scheduling data for researchers who work on general activity scheduling and execution. This activity scheduling survey assumes that people formulate next-week activity agendas during the weekends immediately before the week begins. Daily activity scheduling actions are recorded by revolving the agenda needs via Internet-connected home computers. This electronic survey procedure became the basis of Lee's work on REACT! (Lee et al., 2001, Lee and McNally, 2000). Survey results using either procedure are encouraging in terms of their success in capturing the dynamic activity scheduling processes over a relatively long survey period (one week), but both lack the ability to trace the actual activity-travel execution due to the mobility constraints of the computing device they use.

Many current computer-assisted travel/activity surveys have incorporated the use of a minicomputer, GPS, and Geographic Information Systems (GIS) for enhancing the data collection device's mobility and facilitating the activity-travel data capturing through automatic features. One of the pioneer applications is the semi-automatic data collection device used in the Lexington Travel Survey (Battelle Transportation Division, 1997). In that survey, an on-board mini-computer coupled with a connecting GPS module made possible the collection of physical travel paths and travel times with considerable accuracy. Other efforts (Guensler and Wolf, 1999, Draijer *et al*. 2000, Stopher and Wilmot, 2000) substituted the mini-computer with more portable devices such as PDAs. These approaches allow the survey respondents to "actively" interact with the computing device and trigger its data input/recording functions. Activity attributes data such as trip purposes, activity types, etc., besides the spatial-temporal path trace, are input in real-time via a pre-formatted interface.

As one manifestation of technology advances in survey methodology, the GPS-assisted device extended the spatial data collection ability of travel/activity survey to accurately-measured two-dimensional space. It helped alleviate the reporting burden of spatial-temporal attributes on the part of the survey respondents. Hence the survey data quality was subject to less potential fatigue effects than the traditional paper-and-pencil approach. In addition to facilitating the efficient capturing of spatial information, interactive geo-coding and other intelligent analysis functions provided by GIS may be applied to the raw data for inferring the derived geo-spatial information (e.g., the computer-based intelligent travel survey system by Resource Systems Group, Inc. (1999)). The disadvantages of the purely "active" data extracting approach were comprehensively discussed by Stopher, Bullock, and Greaves (2001). The main concerns are the intrusive effects of the device on respondents' travel/activity time usage. Real-time data input tasks typically interfere with daily travel/activity routines. In extreme cases, carrying the cumbersome device may even force the respondents to alter their travel/activity patterns (Draijer et al. 2000). These negative impacts on the data quality can not be neglected by the survey administrators.

To avoid the intrusive effects of the semi-automatic survey devices and to overcome other defects associated with it, some attempts have been made to segregate the recording of spatial-temporal travel trajectory from the activity/travel attribute data collection (Steer Davies Gleave and GeoStats, 2003, Stopher, Bullock and Horst, 2002, Stopher and Collins, 2005). The recording function GPS devices in these pilot studies/surveys were designed to be motion-sensitive to facilitate the "passive" collection of travel geography data. If further information on the relevant activity/travel attributes is required, they can be retrieved in a recall session afterward, either via a computer-assisted-telephone-interview (CATI) or on-line recall survey with animated trip maps as prompters. Currently, the "passive" data collection practice is mostly limited to automobile use, because the GPS loggers require a reliable external power supply. The wearable counterparts with rechargeable battery support and full coverage of the spectrum of travel modes are under further development by Stopher and his colleagues (Stopher, Greaves and FitGerald, 2005). The pilot study by Stopher *et al*. (2001) indicates no significant memory slip problem for up to 14 days after the travel geography data is recorded. However, periodic compilation of scenario information for assisting activity/travel attribute recall can be a complicated procedure in terms of identifying the missing short trips or temporary stops (Stopher, P., Bullock and Jiang, 2003).

The GPS device alone or its combination with other computing devices shows great potential for improving data accuracy, expanding data coverage, and lessening survey burdens. The integrated activity scheduling and execution survey required by this research can also benefit from the technologies that have been widely explored in these past travel survey applications. However, it should be noted that the innovative approaches that incorporate new technology for travel survey automation and data quality improvement are not cost-free. Furthermore, the utilization of advanced technology in travel/activity surveys restrains the acceptability of the practice within population subgroups other than computer-literate youngsters. The effects of the self selection of samples may cause under-representation of non-computer-users in the sample, especially when the active approach is taken for collecting activity/travel attributes in real-time. A variety of measures are commonly used to encourage survey participations from all population subgroups: for example, monetary incentives to decrease the non-response rate, simplified user interfaces and passive data recording to reduce the “intrusiveness” of the device. On the other hand, some preventive measures have been taken to prevent survey participants from walking off with the expensive survey devices after the survey finished. When commercial devices are used in the survey, it is usually necessary to customize them to hide all non-survey related functions, since single-function devices typically attract little interest from the participants beyond the survey period (Stopher, Greaves and FitGerald, 2005).

In spite of the issues that need to be fully explored and resolved, GPS and other computing devices remain powerful tools for tracking multi-day travel/activity data over long periods. The data collection methodology presented in this research means to bring the technology improvements together in order to extract activity scheduling, travel and activity implementation data within a unified data collection framework in an active manner. The feasibility of the system was tested later via a pilot study with a small subject sample.

4.2. Conceptual Framework and Survey Methodology

4.2.1. Dynamic Scheduling Tracing

In order to facilitate the data collection needs regarding activity/trip scheduling, special attention must be paid to the underlying mechanism of how respondents make planning decisions prior to the actual execution of activities/travels. Until recently, little has been known regarding the strategies that people use for sequencing and committing activities. According to Gärling, Gillholm and Gärling (1998), a person's intention to execute an activity at a future time may be unrealistic due to his/her ignorance about potential conflicts in other concurrent planning. The intention could be easily deferred or given up under time pressure in some cases (Gärling et al. 1999). Therefore, a sound activity/scheduling survey system should be able to elicit and record from various forms and stages of activity scheduling processes. According to the research by Doherty and others (Doherty and Miller, 2000; Doherty et al., 2001), the use of a tabular task scheduler potentially reinforces the survey respondents' awareness of the need to plan their activities with the various constraints being taken into consideration—otherwise, their activity plan construction and subsequent behavior may be inadvertently affected.

The survey system suggested in this research avoids using a uniform tabular visual interface for collecting people's decisions about trip planning. The embedded scheduling collecting module does not intend to function as a memory jogger or a scheduling tool to help the respondents track daily tasks. Instead, the respondents are allowed to "talk" or type into a data logger whenever an activity planning decision is being made. Data are collected in a way similar to a "think aloud" method (Ericson and Simon, 1984). The types of decision-making include "add/delete or schedule adjusting" operations as in the Ettema and Timmermans' (1994) simulation program or in CHASE (Doherty and Miller, 2000). This approach also corresponds to the common experience that activity scheduling does not occur at a fixed point along the time axis but, rather, continuously evolves.

Besides focusing on the activity scheduling action, the data collection system also keeps track of the execution consequence of the planned activity schedule in order to measure the degree of consistency between the activity planning and its actual implementation. Two types of plan-execution inconsistency can be differentiated, as indicated by Gärling et al. (1998). One such case is the "false alarm," which means the survey respondent made a plan for the activity but did not pursue it. The other case is "miss," which indicates that the survey respondent did not show an intention to perform the activity before or enlist it in the activity plan, even though the activity was actually performed. In our activity scheduling (execution) survey, the system deals with a "false alarm" by marking the execution status of the planned activity as "delete from activity plan"; and, in the case of a "miss," the system will remind the survey respondent that the activity is unplanned in nature. It will also ask the respondent if the planning decision has been forgotten and not been put into the system. If not, the “miss” activity will be recorded as an impulsive action.

4.2.2. Multi-modal User-Device Interaction: Human-machine “Talk” protocol

Speech capabilities are integrated into the survey program to facilitate the interaction between survey respondents and the computing device. The data collection process is enhanced from two perspectives: voice prompts and speech input. With the help of both, the mobile data collection terminal technically serves the role of survey interviewer, monitoring and recording the process of data collection via human-machine dialogues. A well-designed “Talk” protocol is built into the survey program and helps to elicit a maximum amount of information from the survey respondents. Talking to a machine rather than an interviewer is assumed to contribute to reducing the survey respondent’s privacy concerns.

The formulation of the “talk” protocol is based on interrelated dialogues. The vocabulary used in dialogue is limited to the survey screen display (i.e., voice messages pre-configured in the survey program). Words with minimal acoustic similarity have been selected to aid differentiation by the speech recognition engine. A “talk” dialogue can be initiated either by the machine or by the survey respondent.

The machine typically starts a “form scope” dialogue by reading the explanatory note displayed on the top of a survey form. The action is accomplished by feeding the screen-displayed text to synthesized speech on the computing device. The survey respondent triggers the “action scope” dialogue by requesting actions from the data collection device, e.g., vocalizing the button label or other form of expected input for the current screen. If the user’s voice is picked up by the microphone on the Pocket PC and processed and recognized as conforming to a pre-defined grammar, a corresponding action will be triggered and followed with certain audio/visual feedback. If the user conducts an inaccurate action or misses some part of the required input, pre-formulated auditory cues are supplied to alert the user about the error. The auditory warning is meant to supplement the traditional way of capturing users’ attentions by popping up a message box.

4.2.3. Speech-enabled Multi-modal Interface

Past research has shown that humans have the ability to handle/process simultaneous streams of input through the auditory channel and to focus on one of them selectively (Sawhney and Schmandt, 1998). Ideally, by obviating the need for hand use and eye focus when undergoing tasks, speech input and auditory output are more suited to survey needs for feeding information into data-recording equipment in a timely/convenient way. In a mobile, real-time data collection scenario that exists in a travel/activity survey, safety concerns demands that the user’s senses are not preoccupied and are cognizant of surrounding people and events. In addition, the speech-enabled interface may also help to boost survey respondent's awareness of the undergoing survey process. One of the disadvantages that associate with a self-administered travel/activity survey is that data quality and coverage partially relies on a user's enthusiasm in supplying data, which hopefully, would reflect the reality in sufficient details. However, an elongated survey period sometimes increase survey respondents' feeling of stress and reduces their vigilance to record travel/activity occurrences as accurately as possible.

On the other hand, although speech input and audio output approximates a human's natural means of interaction, speech/audio interaction is in essence sequential in time. It lacks the browsing and pre-fetching support offered by image/text-based display (Sawhney and Schmandt, 1998). Their usage within environment with significant ambient noise may also be questionable. Users are easily discouraged in using the device for data input after several times of speech input failure or misinterpretation. Multiplexing the strength of visual and touch screen means with speech input and audio output potentially avoids the shortcomings of each individual approach. Actions on survey forms can be triggered either by voice command or by a stylus click. A speech input context switches according to mode changes caused by other actions. Therefore, a user can choose the data input manner that works best in a given situation. Another approach that helps solve the problem is to exploit the idea of "push to talk." As pointed out by Starner (2002, p.

92): “speakers think out their sentences and articulate more clearly if they have to press a button before they speak to the computer.” The Pocket PC’s side button can be programmed to be a switch that controls the acceptance of speech input.

4.2.4. Survey Navigation and Monitoring by Voice

Navigation through the survey form is supplemented by synthesized voice output. A user can read the explanation printed on the electronic survey form. Simultaneously, “what to do” information is read to the user through auditory output. Feedback is provided to confirm the correctness of input when important information about scheduling or activity is being collected. Crucial information input is repeated in the feedback, thus confirming to the survey respondent that the information has been communicated correctly. In other cases, auditory cues (e.g., a chirping sound) are used to indicate operation success (e.g., goes to the next form or a voice command is recognized as valid).

The speech-enabled interface may also help to boost a survey respondent’s awareness of the survey process. One of the disadvantages associated with a self-administered travel/activity survey is that data quality and coverage partially relies on a survey respondent’s enthusiasm in supplying data, which, ideally, would reflect the reality in sufficient detail. The data collection terminals are programmed to monitor any unusual data input pattern that potentially affects the quality of collected data. For example, when it finds out that the user has spent more time on the activity than originally scheduled, the device reminds the survey respondent with “Please don’t forget to indicate when the current activity ends.” Or, when it reveals that the user has not scheduled an activity for a long time, it will remind the user by saying “Please input activity schedule when you have a plan for an activity.” These active reminders are trivial but play significant roles in keeping the human-machine interaction as smooth and tight as human-human interaction, and they also provide some guarantee that the “forgot-to-input” mishap is reduced to a minimum.

4.2.5. Sample Scenario of Speech/Audio Interaction

The following shows a demonstration of how the activity data collection system is used during an input session for the Schedule-an-Activity Form. Note that if the device has been idle for some time, the system detects that and turns off speech input and synthesis to save power. This is called sleep mode.

Now, suppose the device is in sleep mode --

Survey respondent says: “wake up!”

Device says: “ready for listening.”

Survey respondent says: “1” or “Activity type” or “Type of Activity”

Device shows the Select-Activity-Type Form (Figure 11) and reads the survey instructions.

Survey respondent says the activity type name: e.g. meal.

Device asks: “you have selected activity type name – meal. Is this correct?”

Survey respondent confirms: “yes”. The Select-Activity-Type Form is closed. The Schedule-activity form (Figure 10) shows up again.

Survey respondent says: “4” or “Activity location” or “location of activity” The surrounding environment is noisy and the device can’t recognize the command. Survey respondent gets the stylus or uses fingertip to click on the 4th button to select location for the activity.

Device shows the Select-Activity-Location Form (Figure12) and reads the survey instruction.

Survey respondent has come to a quiet place and wants to try the voice input function again. He/she says: “home”.

Device asks: “You have selected activity location – home. Is this correct?”

Survey respondent confirms: “yes”. The Select-Activity-Location form is closed. The Schedule-Activity form (Figure 10) shows up again.

Survey respondent has come to a very noisy environment. To avoid confusing the device, he/she says: “go to sleep.” Now the survey respondent wants to use the stylus solely to finish inputting the form.

Device responds: “stop listening.”

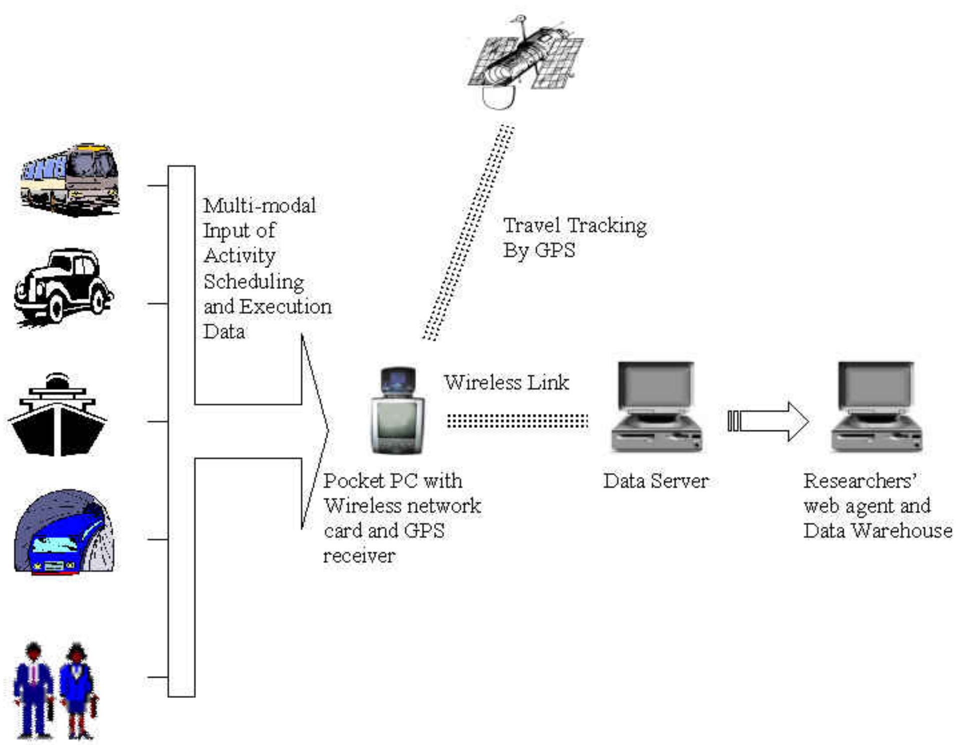
4.3 System Design and Survey Organization

4.3.1. Data Collection Infrastructure

The survey system used in the activity scheduling/execution survey adopts a single-server, multiple-client architecture design (Figure 2). The central database server, located at a fixed location, continuously accepts data uploading requests from the mobile data logger carried by the survey respondents. Received data is preprocessed and stored on the central data server. The mobile data logger equipment consists of four modules—a GPS receiver/antenna, a mobile networking card, a Pocket PC (with an additional 128 M SD memory card), and a dual expansion pack. Compared to a Palm/PDA, the Pocket PC performs better due to its high-contrast colorful screen for survey question highlighting, built-in power reservation feature, faster processing speed for accommodating computing extensive application such as speech recognition, and having more storage to cache the activity-travel data when the system goes out of wireless service coverage. The dual-slot expansion pack of the Pocket PC accommodates the wireless PC card and GPS receiver card and provides additional battery power to the PC cards. The data logger costs about $1500 (based on early 2003 pricing). It weighs about 1 pound and is easy to carry around for real-time data input. Speech recognition/output and touch/visual display are multiplexed to provide the survey respondents a multi-modal interface on the

Pocket PC. Either approach serves as an alternative to others in cases where one is inadequate for handling the current data input situation. Furthermore, its voice input capability potentially extends the system's sample coverage to computer illiterate and physically challenged people. Its ability to upload data via a wireless connection also eliminates the locational restriction of the traditional computerized data collection methods.

Figure 2 System Composition



For the pre-analysis of the received data, the central data server was used to check the consistency and logical coherence of collected data. This approach is similar to the post-interview phase conducted for a typical travel survey. The difference is that, instead of the reviewer holding the responsibility of detecting data inconsistency and incompleteness, the onerous checking task is delegated to a pre-processing center in the data collection system, for example, the SYLVIA system in ALBATROSS (Arentze et al., 1999; Arentze and Timmermans, 2000). A multi-level set of logical rules can be organized into modules to diagnose the fixable errors and inconsistencies in the collected data. The demands of travel/activity data validation and correction can be reduced dramatically when only irresolvable record inconsistencies are returned to the respondents for further clarification.

The data transmission infrastructure of the survey system is set up as follows (Figure 3). A SQL SERVER 2000 is installed on the central data server to offer an enterprise-level central database support. For our survey, the pre-formulated travel/activity data schemas are organized into two categories of database: "ActivitySurvey" and "ActivityData." "ActivitySurvey," with only one instance configured for survey management purposes, contains the demographic information of all survey respondents (Appendix A shows the complete database schema). The demographic information collected and stored in a local SQL SERVER CE database on the PocketPC is sent to the "ActivitySurvey" database located on the central data server via the remoteSQL methods (RDA). "ActivityData" includes multiple instances. The number of instances varies with how many survey respondents are surveyed at one time (depending on the server processing power and network bandwidth). Each of the instances stores the activity scheduling and implementation data received specifically for each survey respondent. The tables included in the "ActivityData" database (Figure 4), as specified in its schema, are published as "articles" on the SQL Server 2000 on the server machine. The SQL Server CE installed on the mobile data logger keeps a local snapshot of the "ActivityData" instance and subscribes to the published "articles" in order to maintain data consistency between them. The locally stored copy of activity/scheduling data facilitates fast information retrieval when activity or schedule scenario information is required to formulate some questionnaire forms. Any update on the local copy by survey participants' data input action can be propagated to the server side later. The data server may also update the published "articles" independently. The final results are merged into the same replication on both sides via bi-directional data synchronization called Merge Replication. Besides activity and scheduling data, the "ActivityData" database instance also includes trip data collected via GPS receivers in the form of ASCII files. Periodically, the trip log files are remotely sent back to the central server via FTP to free up the limited storage space. If any of the data transfer functions fail due to temporary network connection problems, the trip data will be cached for later resubmission until all the data submitting operations succeed.

Figure 3 Database Infrastructure (Adapted from SQL Server CE online Book)

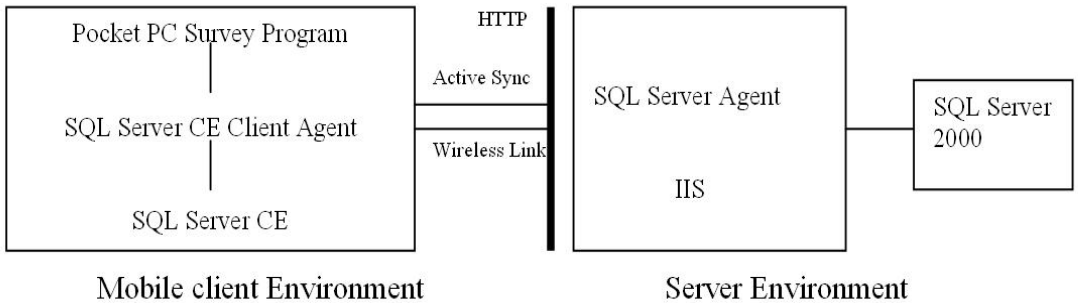
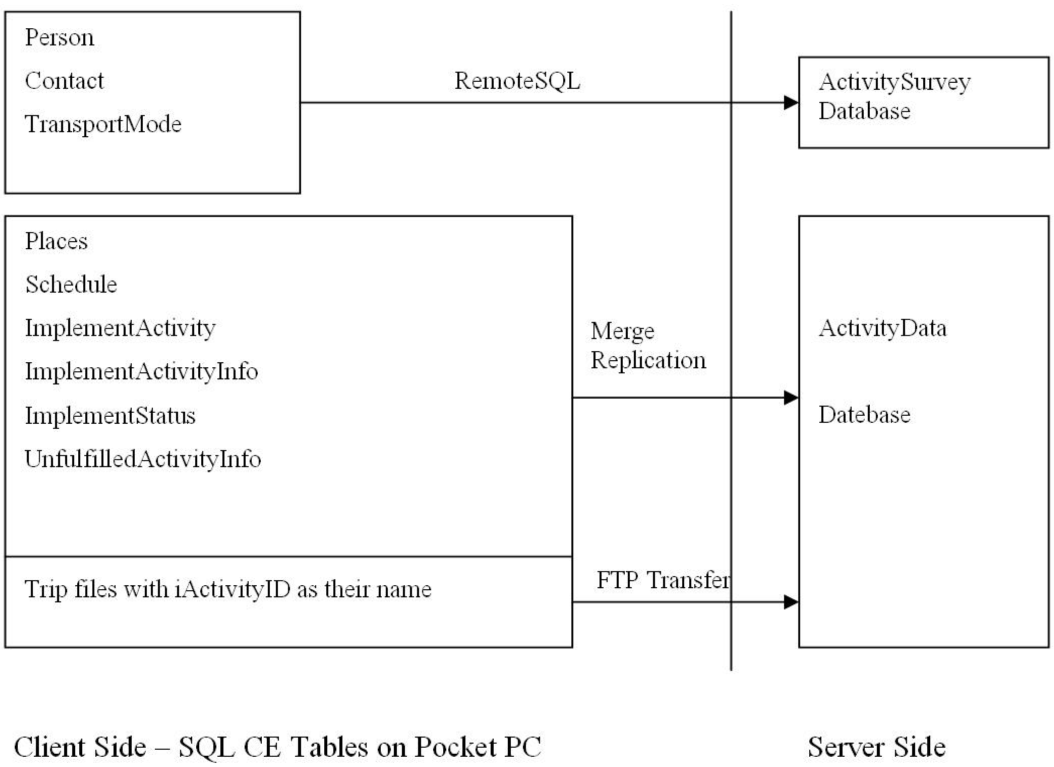


Figure 4 Illustrations of Data Organization and Transmission



4.3.2. Survey Program Organization and Questionnaire Forms

The survey program on the mobile data logger (Pocket PC) was programmed from scratch in Embedded Visual Basic and Embedded Visual C++, with a GIS mapping component – ARCPAD fully integrated. All of the development and testing work took the author 9 months to complete, excluding the equipment selection and evaluation time. The survey procedure flow was organized into a sequence of forms (the complete survey flow chart and organization diagrams are hosted at http://www.geog.ucsb.edu/~zhou/MyWeb/systemdesign.htm). The start-up form of the survey presents the survey respondents with four module components ("Personal Info and Week Schedule," "Schedule Activities or Refine the Schedules," "Trace Activity Implementation," and "Answer Questions related to Unfulfilled activities in schedules") of the activity scheduling and implementation survey (Figure 5). Each of the components is symbolized and linked to a corresponding button, which leads the survey respondent through the process of accomplishing a specific survey task after being triggered by a click action. When the survey respondents launch the survey program for the first time, only the first module "Personal Info and Week Schedule" is enabled for user's access. The gray colors of the buttons linked to the other modules are dimmed to indicate the current inactivity. These modules will only be accessible after the questionnaires in the up-front interview module have been finished. In this way, some personal information and activity/travel-related spatial information pre-collected in this module can be reused in the later real-time tracing of activity scheduling and implementation to reduce the data input burden on the user's part.

As the Pocket PC cannot automatically release the resources that a survey form occupied once it's created, it is essential in the survey program design to minimize the number of forms used for fulfilling all the survey tasks. To achieve the goal, some common survey questions have been extracted and arranged in a form to share among several parts of the survey program. In addition, to reduce the communication cost between mobile terminal and central data server, the survey program is designed to function as a fat client. That means, except that the central data server handles data storage and management, all the data entry, consistency checking, voice recognition tasks are to be performed on the mobile terminals. Even the maps to be displayed in the GIS module of the survey map are also installed on the memory storage of Pocket PC.

4.3.2.1. Personal Info and Week Schedule Module

The Personal Info and Week Schedule module serves the role of the up-front interview in traditional activity/travel surveys. As opposed to CHASE and REACT!, the survey unit is targeted at individuals rather than households. In the module, personal demographic data and activity/travel-related spatial information (frequently pursued activity types and frequently visited activity locations etc.) are collected before the beginning of the survey for management convenience.

Home address information is inquired in the pane of the form in a standard text input format. In addition a button link is supplied to the survey respondent for him/her to indicate the home location on a map presented via the built-in GIS (ARCPAD). ARCPAD will convert the stylus coordinates as the user pins down the Geographical longitude/latitude of home and channel the result back to data collection server. This additional Identify-Home-Address-On-Map requirement serves two functions in the survey: On one hand, it demands the user to double-confirm the home location to avoid the situation that a wrong address has been input and goes unnoticed into the backend central database, hence giving a hard time to the researchers who try to geocode the location when the activity space information needs to be compiled from the data. On the other hand, in many cases the survey respondents may rely on the built-in GIS map component to indicate their activity location when the address information of that location never caught their attention or temporarily slipped out of their memory. Home location on a map serves a good reference point for them to quickly indicate their planned activity location/travel destination in the real-time data collection scenario.

Similar to REACT!, the module asks the respondents about the frequently performed activities and the associated attributes. It is beneficial to have the information for establishing the baseline activity pattern of the survey respondents. And potentially later help us to differentiate the difference between scheduled activities and unscheduled ones. In this form, the survey respondent selects the types of those activities that they frequently conduct (at least once per month) from a predefined activity type list. Various activity category demarcation methods have been used in the past activity-travel surveys and relevant experiments. As remarked by Kuppam and Pendyala (2001), several researchers' work (Ma & Goulias 1997; Lu & Pas 1999; and Golob 1998) on activity participation distribution showed that "activity participation in general can be classified into six broader groups: work and work-related, in-home maintenance, out-of-home maintenance, in-home recreation, out-of-home recreation and sleep." This typology of activity participation, however, is a little too coarse for the survey respondents to describe their activity and travel pattern in details. To fully capture the spectrum of activities performed by a respondent during a particular survey day, activity types defined for this study follows the typology used in the CHASE survey by Doherty and Miller (2000, pp 80), which hierarchically organized the multitude of possible activities under generic types then further elaborate each activity type at the second level. The types of activities in the survey are organized into seven categories (Eat/sleep/personal hygiene, household obligation, recreation/entertainment, social, shopping, services/errands, work/school), following CHASE and REACT! except that the "Only for children" category is left out as the preliminary research is expected to be conducted on campus first. Considering the odds that the predefined list/categorization is not sufficient to encompass the wide range of all possible activity types, a supplementary "Add Activity Type" form follows immediately to allow the survey respondents to define their own activity type with the names they deem as appropriate.

Survey respondents are also required to compile a list of frequently visited (at least once per month) locations from the potential activity location set -- the online yellow page of the local study area (Digital City – Santa Barbara. http://www.digitalcity.com/santabarbara). The location set covers various possible activity locations and travel destinations (banks, bar, bookstore, car-repair, Chinese restaurant, church, college, convenience store, department store, gas station, grocery store, hair salon, Mexican restaurant, movie theater, park, pizza, post office, school K-12 and shopping centers). If the survey respondent can not find the frequently visited location from any of the locations listed, an alternative option based on mobile GIS techniques (ARCPAD) is provided for the user to pinpoint the location's position on an electronic map and input the location name. The manually captured location position is later recorded as geographic longitude and latitude and transferred together with location name back to the central data repository. As the function set offered by ARCPAD is way too powerful to fit in the real-time data collection needs, the built-in GIS component has been customized from the standard ARCPAD program with the special configuration, applet and visual basic script files. Note that as a major difference from the traditional desktop GIS brands, ARCPAD is not good at displaying text notation alongside with the corresponding icon symbols on the map display. Inappropriate algorithm design by ESRI partially contributes to the problem, which always fails to avoid the overlay of text labels between two nearby icon symbols when the map is displayed at small scales. Not to mention that the limited screen size of Pocket PC exacerbates the situation. To partially solve the problem, a customized identification tool has been offered on the second toolbar for the user's convenience to quickly narrow down onto a road or location's name. A better approach would be arranging the list of location/road names below the map and highlighting the linkage between the symbols and names with colors when the user clicks on any of them. However, this leads to even smaller map display area for users to navigate and complicated programming issues involving building the customized list display into ARCPAD.

At the end of the module navigation, a preliminary activity schedule for the upcoming survey period is solicited for identifying those "peg" activities with less flexibility and a relatively high repetition rate (Figure 6). All the preliminarily scheduled activities will be listed on the weekday tab panes with the arrangement sequence based on their input order. The information to collect with respect to a scheduled activity includes activity type, day of the week for the activity, planned timeslot for the activity, planned activity location, and the number of people that co-participate in the activity. The survey respondent may leave some details of schedule as unspecified at the time if the plan has not been well developed. The activity schedule can always be refined later in the "Schedule Activities or Refine Schedules" module in real time whenever some further thinking about it comes up.

Figure 5 Start-up Form of Activity Scheduling and Implementation Survey

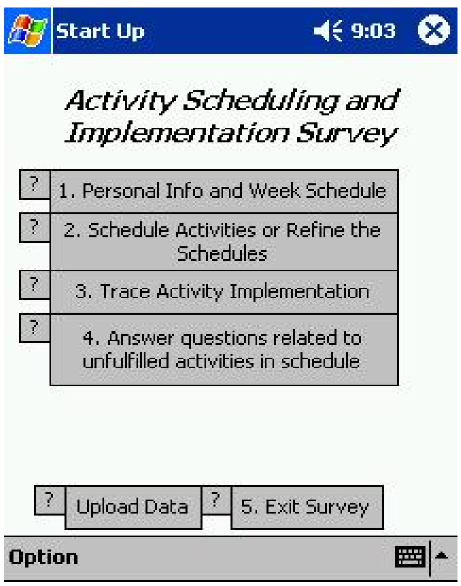
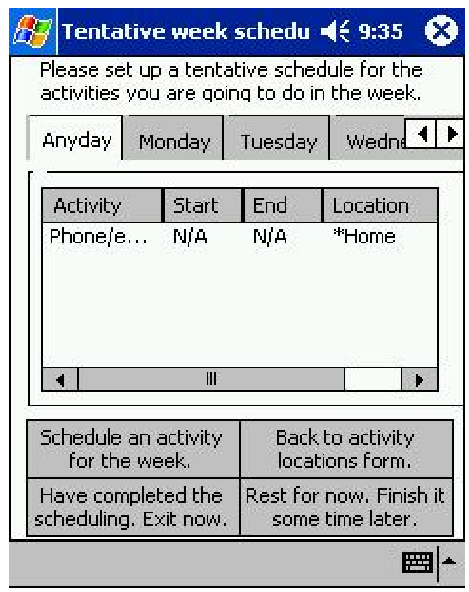


Figure 6 Set up the Preliminary Week Schedule



4.3.2.2. Schedule Activities or Refine Schedules Module

Activity scheduling behavior typically occurs in a stochastic way. Even activities pursued out of habit might be subject to an abrupt disturbance from unpredictable external factors. Arbitrarily choosing a fixed time or place to collect scheduling data (e.g., at the end of day/at home) seems sufficient for researchers to capture a static picture of scheduling behavior based on "what could be remembered up to now."

However, the quality of collected data can vary dramatically across the data capture periods (the time interval between adjacent data capturing actions), leaving the dynamics of scheduling changes unknown.

Integrating scheduling data capturing with mobile devices offers a different survey option that requires less time and labor costs and has almost no location constraints. The survey respondent has the freedom to record the activity scheduling decisions whenever the decision-making comes to mind. After the necessary information has been added, the accomplished schedules are subsequently listed on the weekday tab pane with a brief description. The simple list of activity name, location, and planned activity start/end time allows for quick identification when further refinement is required at a later time. A click on the row brings up the "schedule an activity" form (Figure 7) which is pre-filled with the previous activity plan, but it enables the user to modify/refine the specific schedule-related information. To avoid potential bias (a typical schedule tool could help its user optimize the daily time use), none of the schedules are ordered by time or name but are listed in their original decision-making sequence.

Figure 7 Schedule an Activity

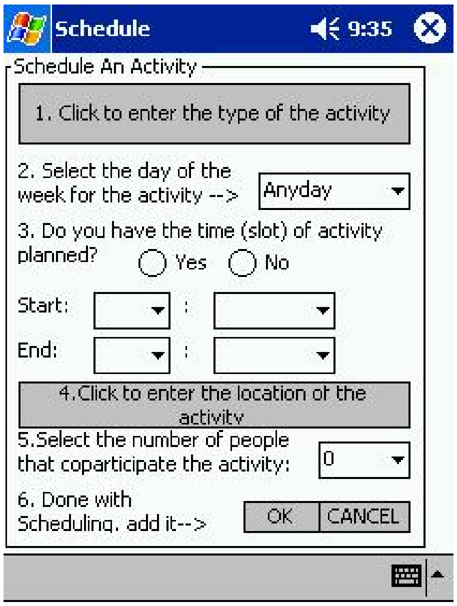
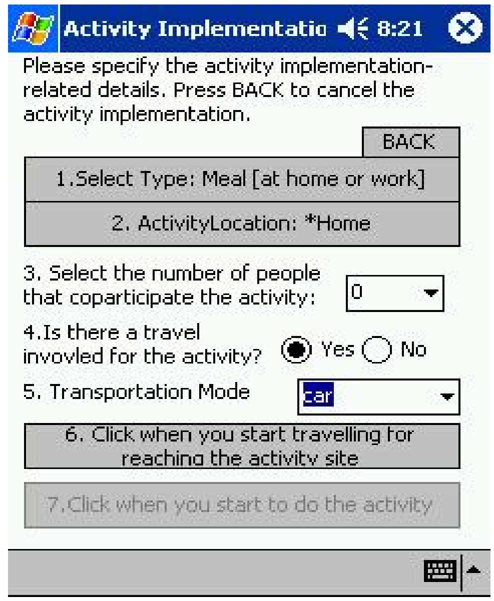


Figure 8 Trace Activity Implementation at Real Time



4.3.2.3. Trace Activity Implementation Module

The "tracing activity" implementation module is triggered at the time of activity execution to record activity-implementation details in real time. The whole tracing procedure is sequenced into two episodes:

(1) Activity to be implemented will be traced as shown in Figure 8. A click on button 6 then launches ARCPAD and activates its GPS tracking functions to start capturing the user's position data in travel. If travel finishes before the device is able to obtain a valid fix on the signal, or the surrounding buildings/trees along the travel

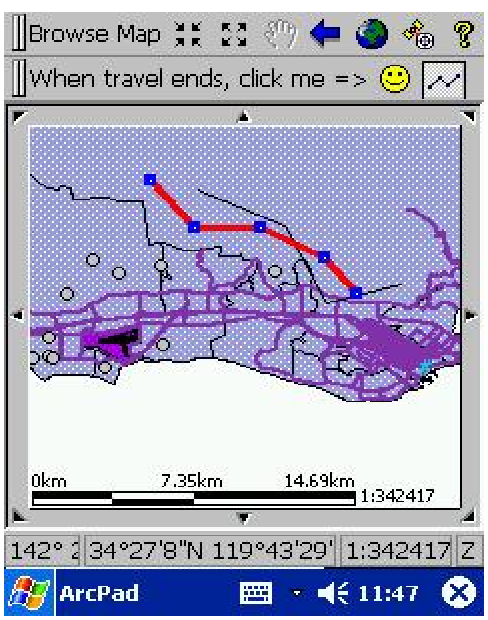
route significantly deteriorate the GPS signal quality, the number of invalid tracing records would be checked against a preset threshold. An additional “Draw Route” function offers the survey respondent a second chance to redraw the traveled route (Figure 9). The missing route will be constructed as a sequence of waypoints created by the user’s double-tapping on the Pocket PC screen. After the travel information has been collected, the survey respondent clicks on the “Start Activity” button to start a timer to track the time duration of the activity. Before the tracing of the activity starts, additional questions regarding the activity are asked about the factors potentially affecting the conformity relation between the schedule and the actual activity implementation. Then the survey respondent is directed back to the start-up form with the activity duration time displayed. This form branching design does not prevent the survey respondent from feeding the real-time scheduling decision information into the survey program while activity pursuit is undertaken.

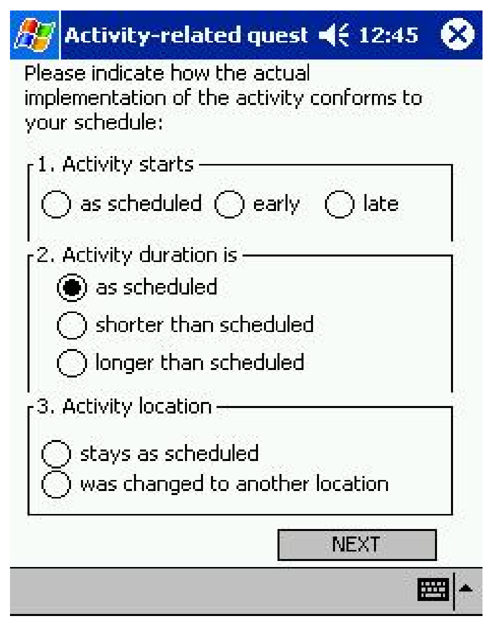
(2) After the activity tracking and the associated travel tracing are accomplished, the two categories of activities - scheduled and unscheduled - are differentiated by user selection. For “linked” schedules, questions are used to qualify the relationship between the actual implementation of the activity and the schedule (Figure 10). Two of the questions focus on the temporal relations between activity and schedule, i.e. if the activity starts early/late/on time or if the activity duration is as-scheduled/elongated/shortened when compared to the schedule. The last of the questions emphasizes the spatial linkage between them, i.e., whether or not the actual

activity location choice differs from the schedule. These relationships are not easy to demarcate by simply checking on the data alone, but have to be obtained from the survey respondents' perspective. In the end, additional questions are also posted to trace factors potentially affecting the conformity between the schedule and actual activity implementation, ranging from weather condition, traffic condition … to activity priority.

Figure 9 Draw the Travel Route with "Draw Route Tool" when Most of Sampled GPS Points are Invalid

Figure 10 How the Activity Implementation Conforms to the Schedule





4.3.2.4. Answer Questions Related to Unfulfilled Activity Module

For unfulfilled schedules, a series of questions are asked for later research model construction. As these activities have only been conceived in the mind rather than actually implemented, it would be inappropriate to allocate a fixed time in each survey day for collecting answers to these questions from the survey respondents. To avoid the possible disruption of activity/travel tracing due to information collection regarding missed activity plans, module 4 functions as a flexible, independent survey unit that allows the survey respondents to take their own initiative in deciding when to answer questions related to unfulfilled activities.

4.3.3. Mobile Usages of the Data Logger

For the practical use of the survey system by the respondents, the data collection terminal is equipped with a small camera bag with an external GPS antenna attached on the shoulder strap to suit various travel/transport modes. When the survey respondent is traveling by walking or bicycling, the device is carried in the bag and the coupled GPS receiver is connected to the external antenna to enhance the accuracy of collected position data. If a vehicle is involved in the travel, a multimedia PDA mount is used to hold the data collection terminal at a fixed and steady position close to the windshield for better access to the satellite signals. The mount can be easily transferred between vehicles that the survey respondent may have access to. In addition, the PDA cradle that holds the Pocket PC is DC powered and embedded with a build-in speaker, which ensures that the audio prompts from the survey program will not be compromised by ambient traffic noise. To reduce the risk of power drainage, another regular power supplement is also provided separately to the survey respondent for charging the device at home during the night or in an office during daytime.

4.4. Pilot Data Survey and System Evaluation

4.4.1. Pilot Data Collection Practice

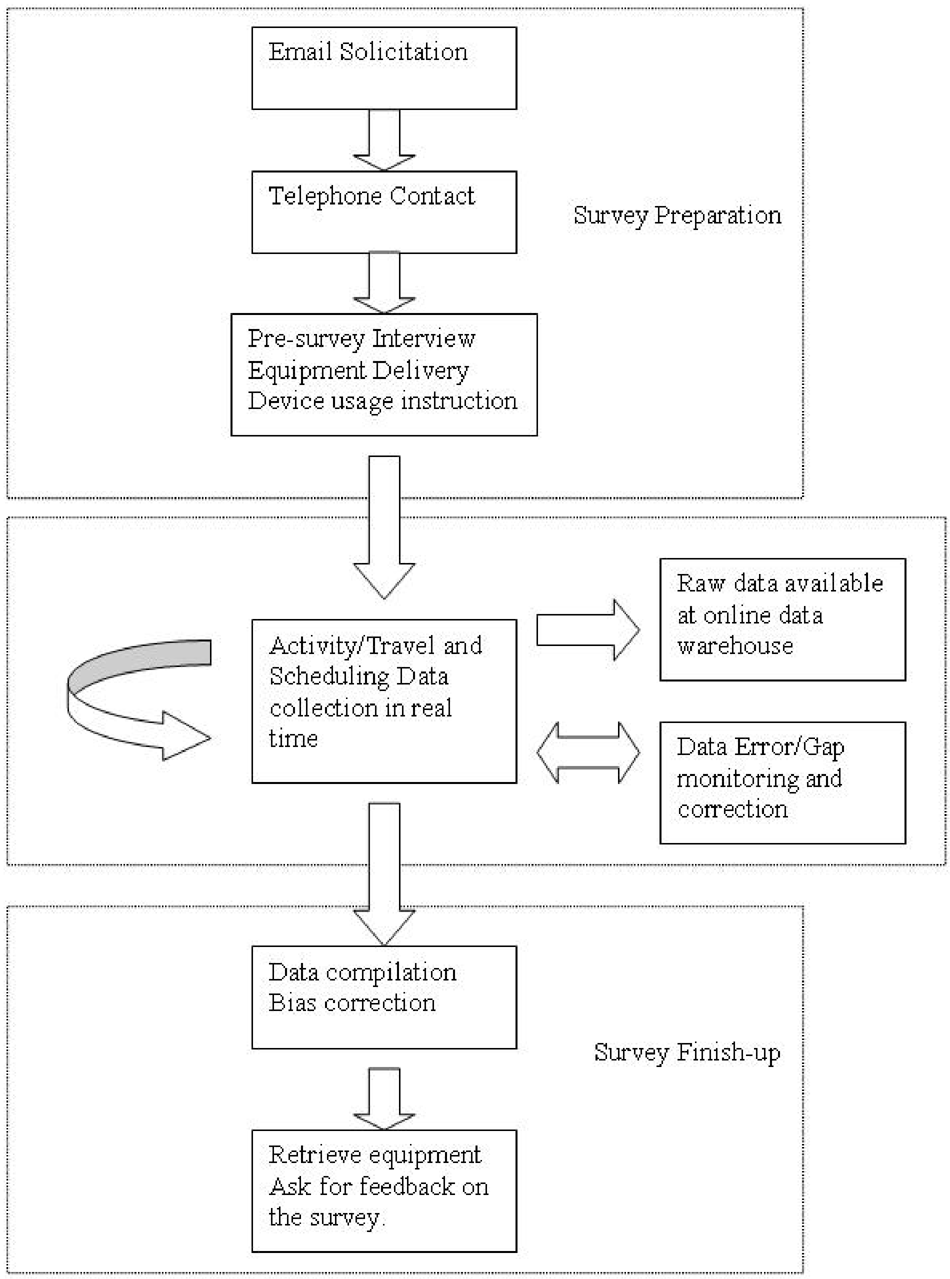
A pilot data collection with the implemented system was conducted at The University of California, Santa Barbara from January to July 2004. Due to a conflict with the speech recognition engine currently used and the SQL SERVER CE (the mini database for storing data on the Pocket PC), speech input function on the survey interface was disabled in the pilot survey. Prior to the beginning of the pilot data collection, the author of this dissertation personally carried the device and performed the daily data collection tasks for a two-week period. Some design weakness and logical errors that showed up during this phase were corrected before the final pilot version was released. Limited by time and funding resources for this research, the survey participants are not selected on a systematic or clustering sampling approach.

A total of 20 volunteers (13 males, 7 females) were recruited locally for the survey for one week per person. Only one device was available for this survey (Figure 11 and 12 shows the snapshots of the front and back of the device). The participants of the survey were organized into sequential one-week time frames to meet with the survey supervisor and to retrieve/return the equipment. The start day of the survey week was selected to fit the availability of the survey participants, which was expected to help randomize negative effects of start-time selection. One or two weeks before the time when the respondent was scheduled to participate, an email/phone call was made to confirm his/her availability. Once a positive answer was received, the survey guide and consent forms were subsequently sent either by email or in paper form to help the participants get familiar with the survey contents and procedure. An appointment was also made at the time for a brief survey tutorial session and equipment delivery, before the data collection process started. Figure 13 roughly describes the three phases of the entire data collection process.

Figure 11 Front of the Device

Figure 12 Back of the Device

Figure 13 Survey Procedure



4.4.1.1. Phase I: Background Information Collection

During the first phase, the basic information of the respondents was collected at the time when the equipment was delivered. A one-to-one tutorial was given to the survey respondents to facilitate the preliminary device usage and first time data input. This tutorial took 50 –70 minutes on average. Almost 2/3 of the time was used guiding the participant through finishing survey module one (personal information and week schedule). The span of information recorded during the tutorial session includes: residential location, work/school location, socio-demographic characteristics of the survey participant (age, sex, marital status, education level, income level, driver-license status, the set of routine locations for different types of activities (such as shopping), tentative activity schedule for each day in a week (repetitive activity routines such as work/study)), the number of cars and other motor vehicles, car/motor vehicles ownership, etc. Note that those fixed activities refer to the class of mandatory activities (work, study, meals or others) for each survey respondent. In terms of trip generation, the linkage of the mandatory activities and their derived travels is easy to identify and their frequencies are more stable in people's travel patterns (Hoorn, 1979). With the mandatory activities serving as the skeleton for the activity schedules of the survey respondents, our study assumes that the other non-mandatory (flexible) activities and their derived trips are organized around the skeleton constraints.

4.4.1.2. Phase II: Concurrent Data Collection

For the second phase, the survey respondents were asked to carry the device independently for one week continuously to record their daily activity scheduling decision-making and out-of-home activity pursuits (with derived travels included). The questions on the scheduled activities cover a plethora of attributes (scheduled start/finish time, tentative origin and destination if the activity involves traveling (selected from pre-input location choice set or input as a new location choice by the survey respondent), travel mode, number of co-participants, etc.). Some of these attributes may not have been fully conceived by the respondents during the activity-planning phase. They are allowed to be left unanswered.

The detailed real-time tracing of activity execution is as follows: When an activity is executed locally (at home or work place) in real-time, the system will record its start and end time and activity type. Whenever an activity that involves other-than-current location is executed, a GPS module automatically recorded the origin and destination of the associated trip in addition to the timestamp information. At the beginning of each trip, some particular information regarding the trip is collected. These include the name of the destination from the pre-input of a location set, travel mode, activity type, etc. In general it will be inconvenient for survey respondents to define the origin/destination locations by zip code, detailed street address or name of featured landmarks. An online GIS map was used to pin down these locations easily with the Pocket PC stylus. The tracing of trips start from the first step of the respondents out of their home and end only when the traveler has reached the final destination, with all access, egress and in-vehicle times recorded in detail. At the end of each survey day, the collected data was uploaded to the central data server to allow the survey supervisor to check for errors in the uploaded data. A phone call may be made to the survey respondent to identify the source of errors and offer the corresponding solution. Similarly, the survey respondents could use a dedicated phone number and email address to contact the survey supervisor for any emerging technical problems on the survey device and program.

4.4.1.3. Phase III: Survey Completion

After the survey was accomplished, the equipment was retrieved from the survey participants and a questionnaire is sent in order to obtain feedback from the survey participant with respect to the design and effectiveness of the survey program.

4.4.2. Summary of Pilot Data

4.4.2.1. Demographics of Survey Sample

This survey covers various demographic aspects of the survey respondents including age, education and income level, driver's license ownership, commonly-used travel modes, etc. The ages of the survey respondents fall within the range of 20-35, with the average being 28.75. As university students constitute the main survey body, most of the respondents possess a college or higher degree. Among the rest, one completed the two-year associate degree and the other finished K-12 study. 16 of 18 survey respondents earn a monthly income of $1000-$1999, with the exception of 2 earning more than $2000 per month and 2 refusing to answer the income level question. The survey also inquired about commonly used travel modes by the survey respondents. Seven travel mode options (including undisclosed travel mode, carpool, vanpool, walk, car, bus, and bicycle) were presented to them for selection. On average, each survey respondent commonly uses 4 types of travel modes - at most 6 and at least 2. A simple bivariate correlation was conducted on driver license ownership and the count of commonly used travel modes to test if possessing a driver license significantly affects the travelers' travel mode options. The result (Table 2) indicates that the ownership of a driver's license does not necessarily preclude the survey respondents from choosing other travel modes for a journey. Similar conclusion (Table 3) can also be drawn on the relationship between the vehicle accessibility and the count of commonly used travel modes (see the relevant correlation analysis). These analyses imply that the size of travel modes choice sets is independent of personal vehicle/license ownership.

Table 2 Correlations of Driver's license ownership and Travel Mode Counts

			Driver License	Mode counts
Kendall's tau_b	Driver License	Correlation Coefficient	1.000	.139
		Sig. (2-tailed)	.	.508
		N	20	20
	Mode counts	Correlation Coefficient	.139	1.000
		Sig. (2-tailed)	.508	.
		N	20	20
Spearman's rho	Driver License	Correlation Coefficient	1.000	.152
		Sig. (2-tailed)	.	.523
		N	20	20
	mode counts	Correlation Coefficient	.152	1.000
		Sig. (2-tailed)	.523	.
		N	20	20

Table 3 Correlations of Vehicle Accessibility and Travel Mode Counts

			Vehicle Access	Mode counts
Kendall's tau_b	Vehicle Access	Correlation Coefficient	1.000	-.019
		Sig. (2-tailed)	.	.927
		N	20	20
	Mode counts	Correlation Coefficient	-.019	1.000
		Sig. (2-tailed)	.927	.
		N	20	20
Spearman's rho	Vehicle Access	Correlation Coefficient	1.000	-.023
		Sig. (2-tailed)	.	.923
		N	20	20
	Mode counts	Correlation Coefficient	-.023	1.000
		Sig. (2-tailed)	.923	.
		N	20	20

4.4.2.2. Activity Locations

Activity locations were specified either from a categorized list of locations or pinpointed from the mapping component customized from ARCPAD. There are over 900 locations (in 20 categories) predefined in the survey program. On average, each survey respondent indicated 20.3 visited or frequently-visited locations over the survey period. Among them, 10.5 locations were selected from the location dropdown list and 9.8 locations were entered via the mapping interface. Overall, 406 activity locations were recorded: 210 (51.7%) selected from the location dropdown list and 196 (48.3%) pinpointed from the map interface. According to the survey feedback, the map component was generally more favored by survey respondents for activity location input for its convenience and ease of use. Although pinpointing activity location on the map would only be able to approximate the actual site, as long as the activity site had been visited at least once during the survey period, the input error could easily be corrected using the last GPS record for a trip ending with the activity site as a trip destination. This indicates that the map component can serve as an efficient tool in helping construct the survey respondents' activity space in a GPS-driven activity/travel survey. The exact activity site entered via map interface could also have been identified if it was the trip origin. However, the second option was dropped, due to concerns that the beginning phase of trip recording suffers from data inaccuracy due to multi-path signal reflection and the lengthy time requirement to gain a signal fix (typically it took 2 or 3 minutes to get stable signals).

4.4.2.3. Activities and Travel Records

The real-time scheduling and activity survey covers the activities that occurred in the daily out-of-home travel loop that starts and ends at "home," including any out-of-home activity and the first in-home activity after any out-of-home travel. Out-of-home activities further include the on-site activities and off-site activities (that require travel to reach the activity location). Each survey respondent starts their survey period on random weekdays or weekends, which helps eliminate the potential fatigue effects.

To summarize the survey activities and travel records, a series of diagrams have been generated for exploring the activities/travel frequency pattern by either activity class or travel mode. Figure 14 and 15 show that the average number of total activities start relatively high at the beginning the survey week; after a little dip on Wednesday, the average count levels to around 4 over the rest of the week, except the dramatic drop on Sunday. This pattern persists with the on-site activities included or excluded. In comparison, the pattern of the average number of social activities is quite simple--it remains low over the weekdays but rises over weekends. Surprisingly, the average number of recreation/entertainment shows a flattened pattern across the one-week survey period, with no trace of increasing activity level observed over the weekends. Figure 16 shows that the average number of on-site activities remains high over the weekdays but decreases dramatically over the weekends. Activity type break-down implies that the pattern seems to be dominated by the variation of work/school activities and Eat/Personal Hygiene activities over the survey week. In Figure 17, travel mode break-down reveals that car travel is the dominating travel mode for most journeys, seconded by walking. Note that the increased car uses on Saturday confirmed Lee's similar finding (p91, 2001) in his PH.D dissertation. As for activity coupling distribution among different activity classes, Figure 18 indicates that Work/School activities are subject to the least coupling constraints (about 82% completed alone). They are seconded by the Services and Errand Activities (about 67% completed alone). On the other hand, Social Activities usually are completed in groups of more than two people (about 75%). The percentage of coupling for the other types of activities is a little less favored compared to the “Alone” situation.

Figure 14 Plot of Activities per Person per Day (with on-site activities included)

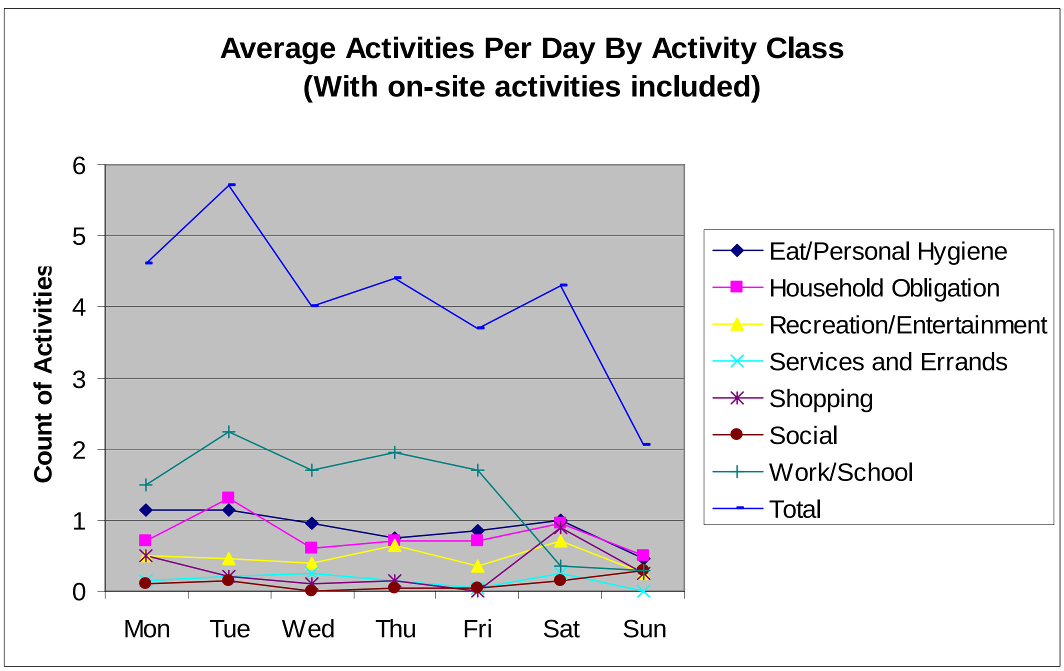


Figure 15 Plot of Activities per Person per Day (with on-site activities excluded)

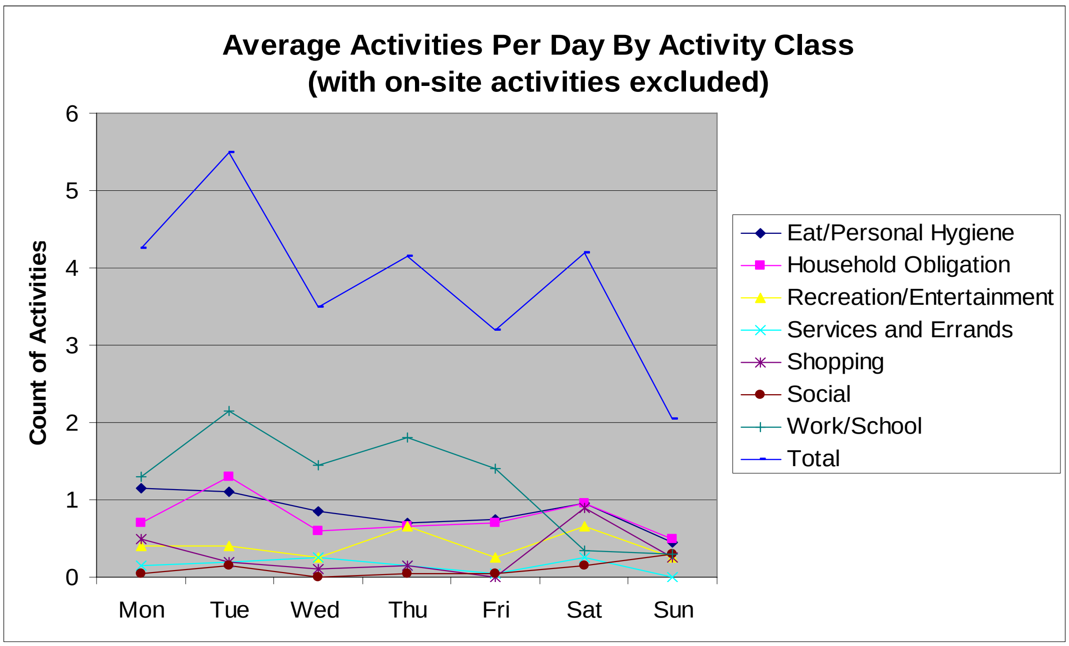


Figure 16 Plot of On-Site Activities per Person per Day

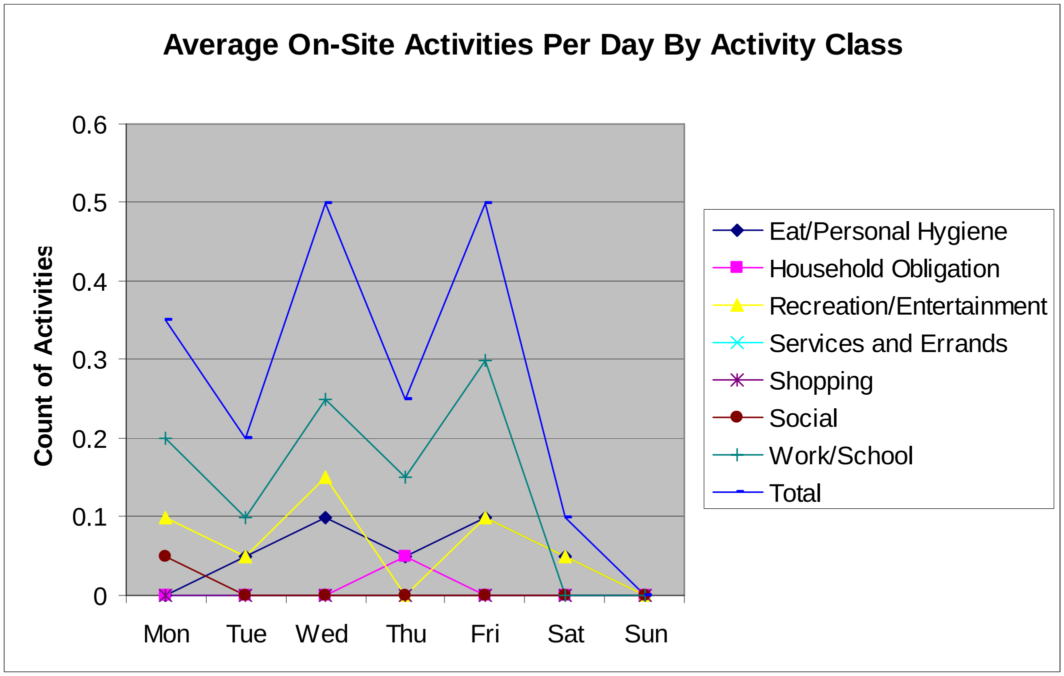


Figure 17 Plot of Average Trips per Person by Travel Mode

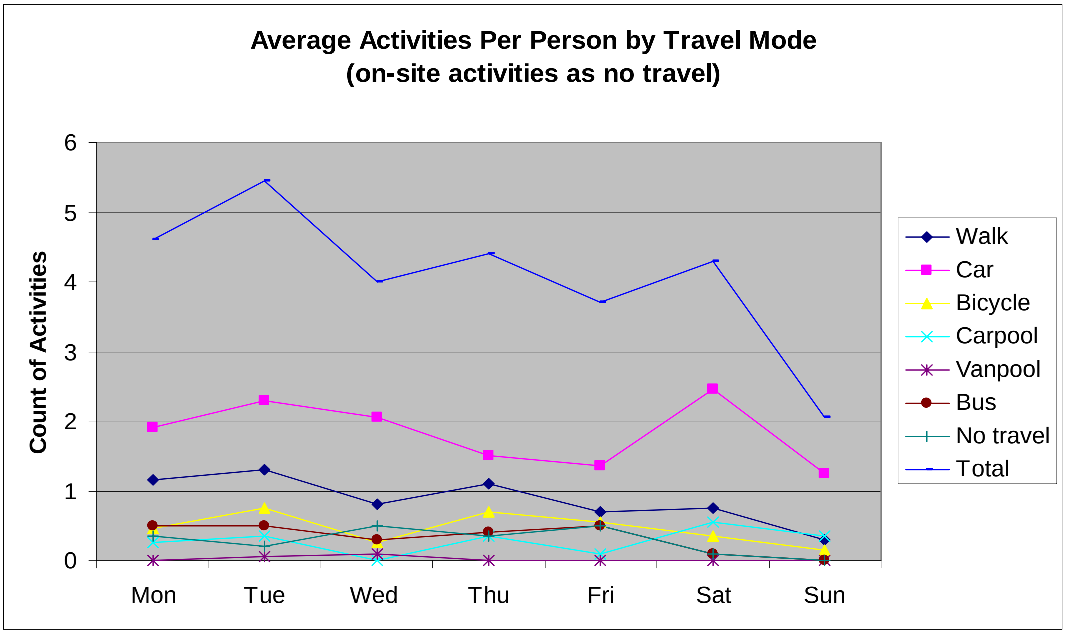
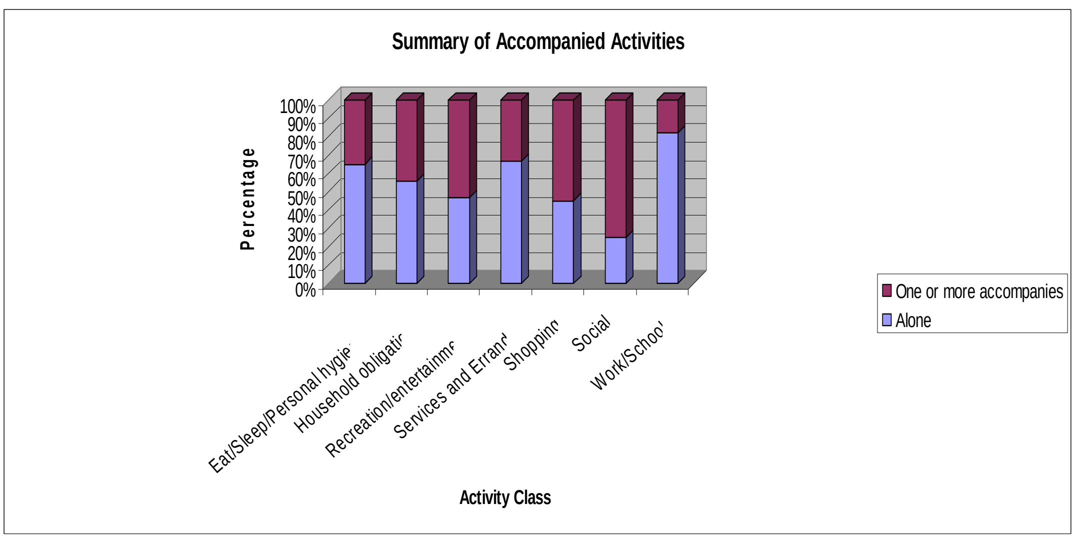


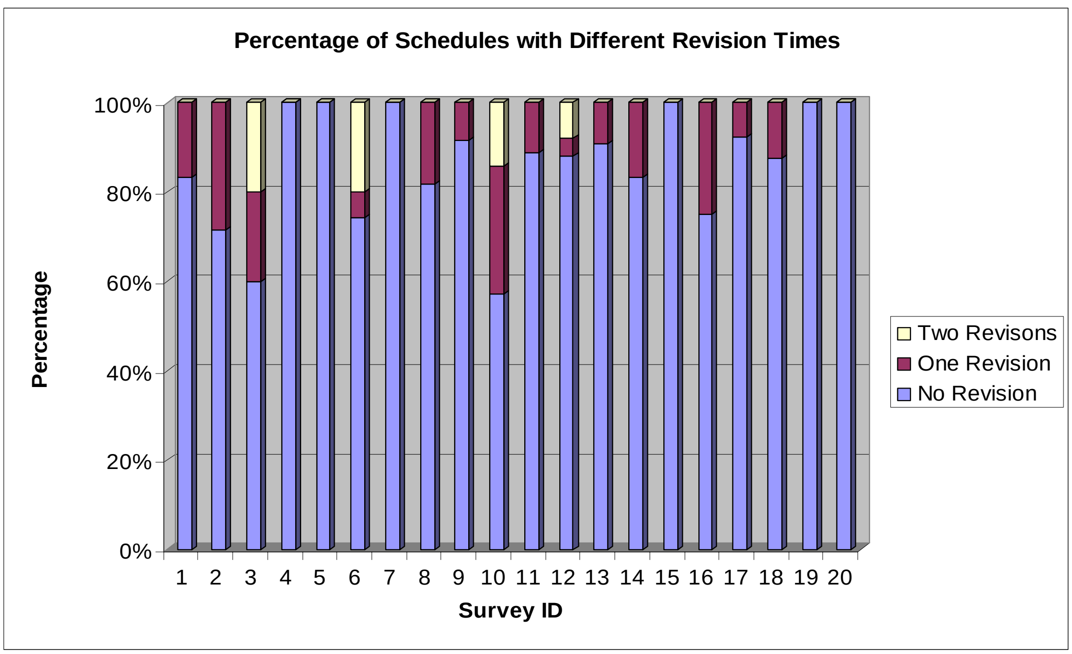
Figure 18 Summary of Accompanied Activities



4.4.2.4 Scheduling Records

The survey recorded a total of 582 activities over a one-week period among 20 survey participants. In addition, a total of 236 scheduling steps were made for formulating activity schedules over the survey week. Among the schedule records collected, 211 schedules were set up in one session. 25 (10.6%) schedules received revisions more than once. Figure 19 shows the percentages of schedules with different revision times per survey respondent.

Figure 19 Percentage of Schedules with Different Revision Times

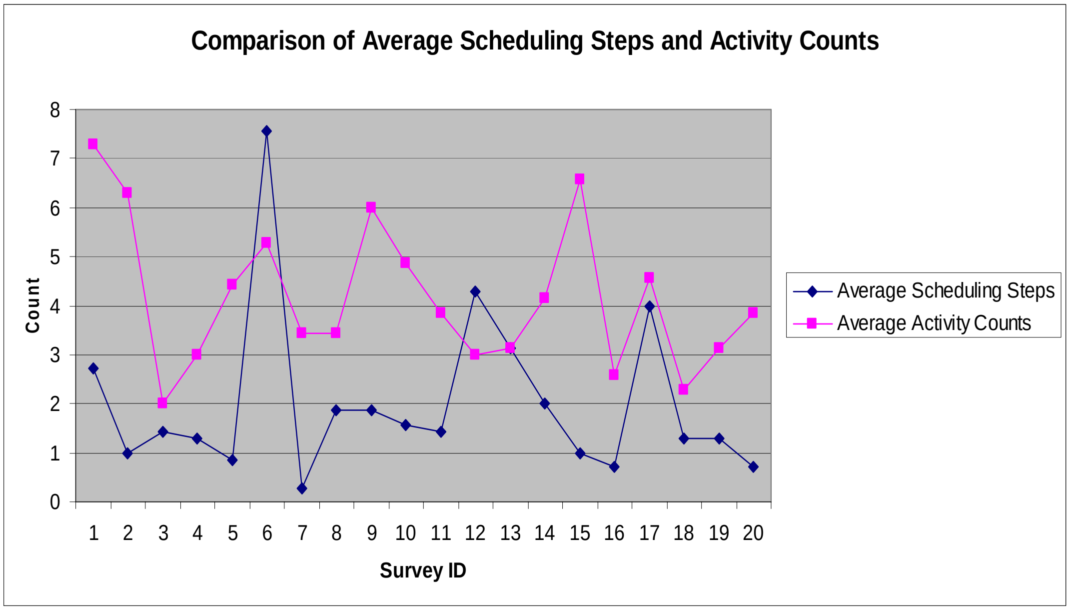


Average scheduling steps per day varies dramatically among the survey participants. A comparison of average scheduling steps and activity counts (Figure 20) did not reveal any strong correlation between activity intensity and the scheduling steps. The visual impression was confirmed by the correlation analysis result (Table 4). This suggests that a busy day does not necessarily lead to deliberate activity planning, and most of the motives behind the daily activities could simply be spur-of-the-moment. However, since the highest average daily activity count recorded in this survey is only 7.28, the proposition needs to be further investigated on survey respondents who pursue much tighter activity programs.

Table 4 Correlation between Average Activity Counts and Scheduling Steps

			ACTIVITY COUNT	SCHEDULE
Kendall's tau_b	ACTIVITY COUNT	Correlation Coefficient	1.000	.125
		Sig. (2-tailed)	.	.453
		N	20	20
	SCHEDULE	Correlation Coefficient	.125	1.000
		Sig. (2-tailed)	.453	.
		N	20	20
Spearman's rho	ACTIVITY COUNT	Correlation Coefficient	1.000	.166
		Sig. (2-tailed)	.	.485
		N	20	20
	SCHEDULE	Correlation Coefficient	.166	1.000
		Sig. (2-tailed)	.485	.
		N	20	20

Figure 20 Comparison of Average Scheduling Steps and Activity Counts



If the schedule records are classified by activity classes and plotted against their absolute quantities (Figure 21), Work and School activities turn out to be the most actively scheduled, and they are seconded by Recreation and Entertainment activities. The most rarely scheduled activity class is that of Services and Errands activities. Among the 20 survey participants, only 7 total schedules of the Service and Errands type were recorded during the one-week period. However, in terms of relative scheduling intensity (measured as the ratio of schedule count against the total activity count), Recreation and Entertainment activities turned out to be the most actively scheduled. Social activities are scheduled in roughly equal intensity to Recreation and Entertainment activities. Household Obligation activities are least planned before execution (Figure 22).

Figure 21 Comparison of Average Scheduling Steps and Activity Counts

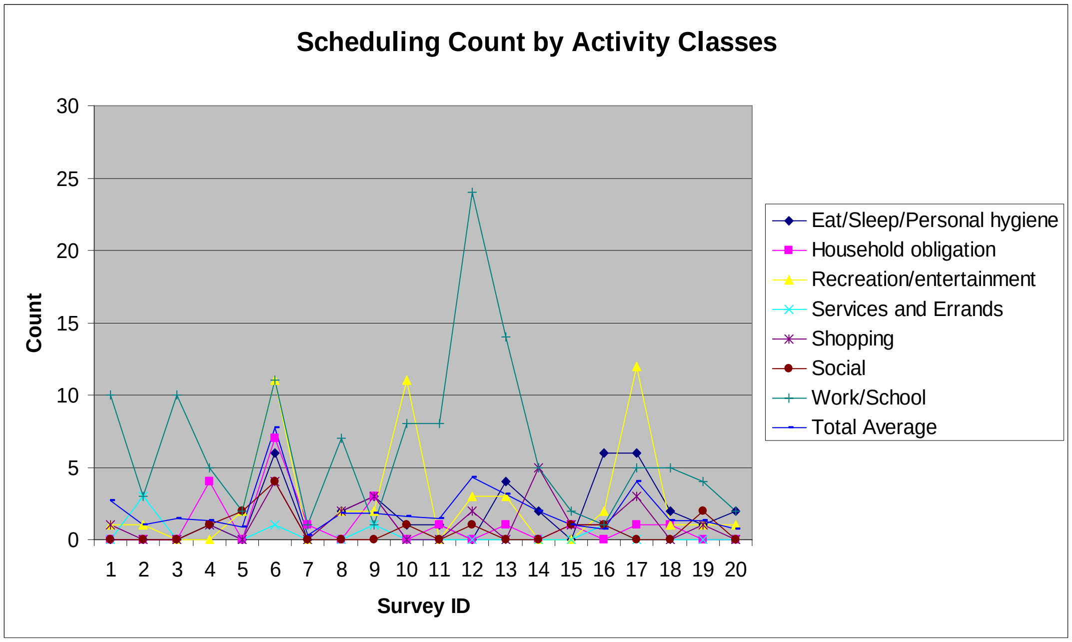


Figure 22 Summary of Activity Schedules by Activity Classes

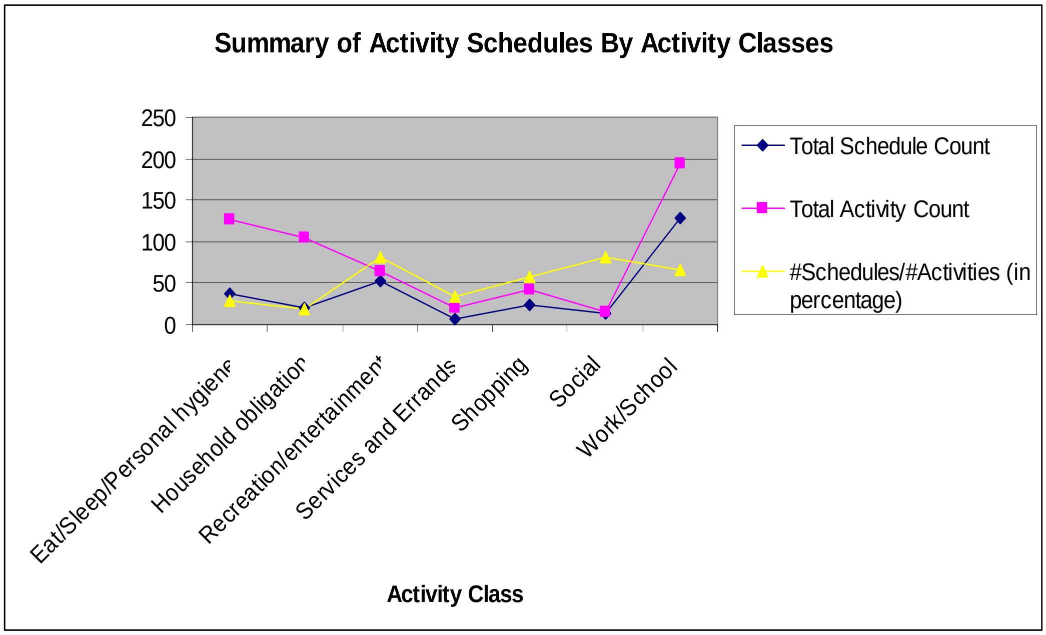
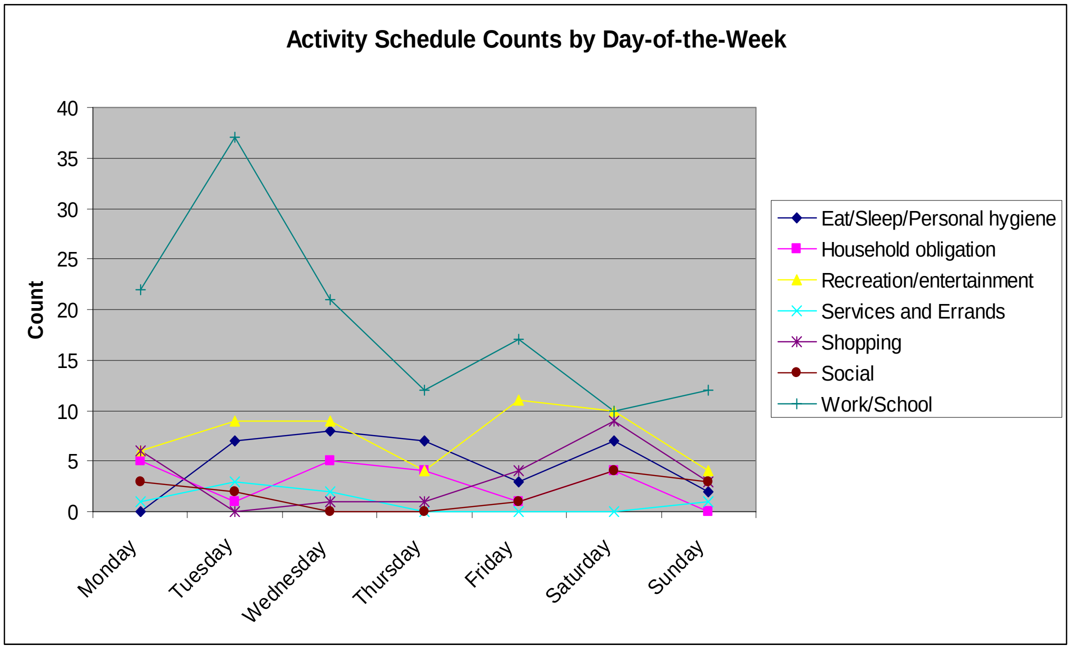


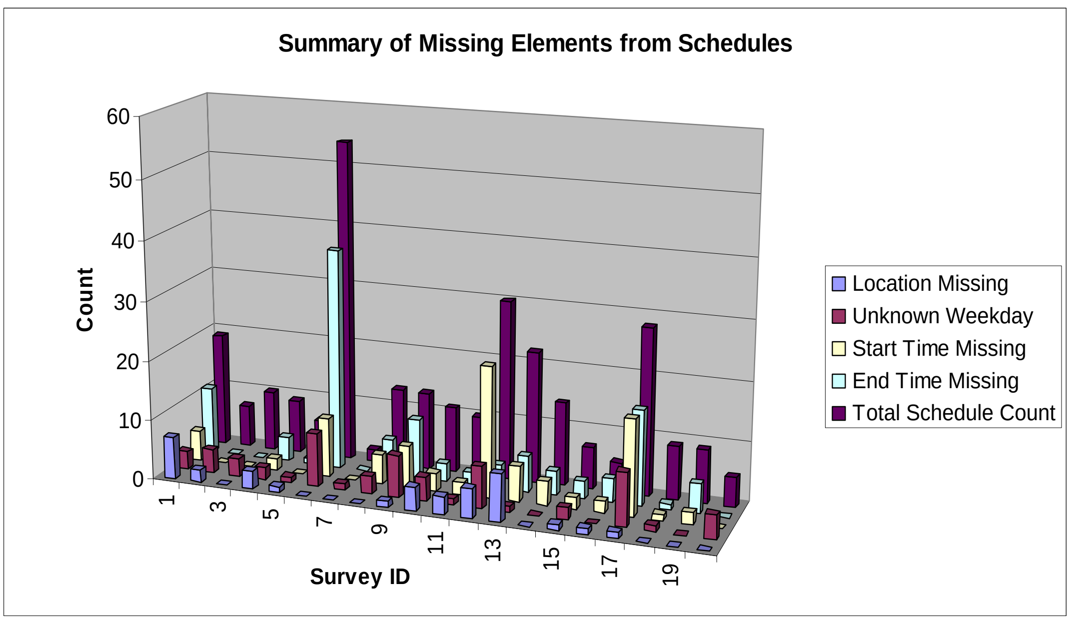
Figure 23 presents further indications of the variation of schedule counts along the temporal horizon. As illustrated by the diagram, Work/School activities are actively scheduled at the beginning of the survey week, especially on Tuesday. Their schedule count gradually drops over the rest of the week in a zigzag manner. Recreation/Entertainment activity schedule counts are almost evenly distributed across the week, except for a minor rise on early weekends (Friday and Saturday). Shopping activity schedule count is high on Monday, Friday, and weekends, but it remains low for the other weekdays, which implies that people may stock up on food and other supplies at the end of a week or early in the week.

Figure 23 Activity Schedule Count by Day-of-the-Week



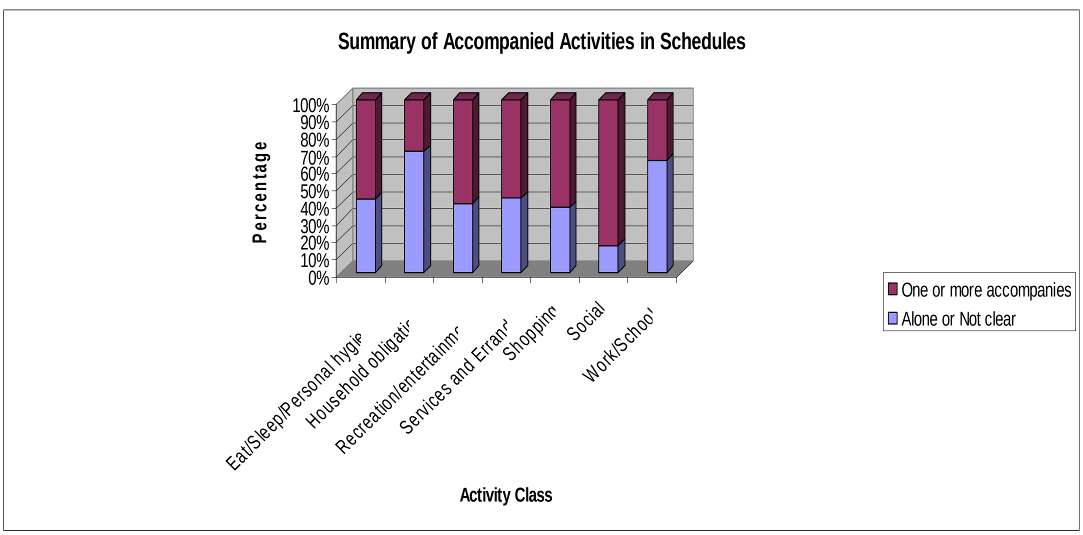
Besides the scheduling regularity, it is worthwhile to further examine the schedule attributes which are likely to limit the schedule formulation (including spatial, temporal, or other socio-demographical factors). Typically, schedules were not planned out with all spatial-temporal details covered. In this survey, these missing elements in activity schedules (“Activity Location,” “Weekday,” “Start Time,” and “End Time”) were marked as blank or “unclear.” In most cases, “Activity Location” regarding the schedule had been determined while the schedule was made (198 out of 236 schedules). “End Time,” on the contrary, was usually unknown or unclear at the time of scheduling (71 out of 236 schedules). Figure 24 summarizes the missing element distributions among the survey participants. As the figure suggests, in terms of projected daily temporal-spatial path before the actual activity pursuits, spatial constraints along the path seem to be more rigid than their temporal counterparts.

Figure 24 Summary of Missing Elements from Activity Schedules



In the previous section, we examined the activity coupling status from the traced activity records. Figure 25 shows a summary of the number of co-participants for the activity as planned in the schedule (with situation “not clear” un-separated from “alone”). As the figure reveals, Household Obligation and Work/school activities are subject to the least coupling constraints (about 65-75% completed alone), while about 75% Social activities are expected to be completed in a group. Except for Household Obligation activities, the extent of activity coupling planned in schedules was consistently higher than what was observed in activity implementations (compared to Figure 18). The finding suggests that people tend to spend more effort on synchronizing their temporal-spatial sub-paths for activities that potentially involve other co-participants. However, the reason why the Household Obligation activities distinguish themselves from the other activity types remains an open question.

Figure 25 Summary of Accompanied Activities in Schedules



4.4.2.5. Data Entry Time and Steps

Due to the survey's real-time nature, data entries occur across the entire survey weekday period rather than being constrained to certain time slots. In addition, the usage of mobile devices removed the location restriction for the data entry. During the survey, data entry time (how much time a survey respondent spent on finishing a survey form) and steps (the number of forms traversed during a survey period) are recorded per survey form for analyzing the survey program's usage pattern. The average data entry steps and entry time by survey modules are illustrated in Table 5. As mentioned in previous sessions of this dissertation, Module 1 is used in pre-survey interviews for collecting the social-demographical information and preliminary week schedule of survey respondents; Module 2 offers daily activity scheduling and schedule revision functionalities; Module 3 tracks the real-time activity implementation and schedule relations; Module 4 collects information with respect to the unfulfilled schedules after the survey period ends. For those survey forms which are cross-used in two modules, the data entry steps performed on these forms are marked with a dual module identifier (e.g. module12). As seen in Table 5, the average Module1 entries time (including cross-module entries such as Module12 entries or Module13 entries) are much longer then other module entries. This is due to the fact that the respondents typically spent extra time listening to the instructions while entering the data in the pre-survey interview (module 1) session. During the normal survey session, the total activity implementation and scheduling tracking steps (module 3) for the survey week are on average 247.35 steps (35.34 steps per day), which indicates that the entry task may not constitute a major interference to a person's daily activity pursuits. Unfulfilled schedule entries are on average 7.9 steps per week. They happened in the after-survey session and therefore barely contribute to any potential survey fatigue effects. Note that the average entry time for the tracking module is about 26.18 seconds per form. The similar entry time measurement for Module 3 and Module 4 (27.88 seconds) implies that time demand of the survey entry tasks is consistent over the survey period, i.e. growing familiarity with the survey program does not help shorten the time to enter data.

Table 5 Summary of Average Data Entry Steps and Time

	All Module Entries	Module1 Entries	Module3 Entries	Module4 Entries	Module12 Entries	Module13 Entries
Total	5798	89	4947	158	462	142
Average Entry Steps (per week)	289.9	4.45	247.35	7.9	23.1	7.1
Average Entry Time (seconds)	35.4	143.74	26.18	27.88	97.07	96.42

As can be seen in Figure 26, the total average data entry steps are dominated by the activity implementation and scheduling tracking data entries. Strong correlations have been found between respondents' activity counts and their Module 3 data entry steps (Table 6). This indicates that the variance of average data entry steps across survey respondents mainly lies in the difference of each individual's activity program, rather than arising from other factors such as data input or survey program usage pattern**.**

Table 6 Correlations between Average Activity Counts and Module 3 Data Entry Steps

			ACTIVITY COUNT	ENTRY STEPS
Kendall's tau_b	ACTIVITY COUNT	Correlation Coefficient	1.000	.581(**)
		Sig. (2-tailed)	.	.000
		N	20	20
	ENTRY STEPS	Correlation Coefficient	.581(**)	1.000
		Sig. (2-tailed)	.000	.
		N	20	20
Spearman's rho	ACTIVITY COUNT	Correlation Coefficient	1.000	.741(**)
		Sig. (2-tailed)	.	.000
		N	20	20
	ENTRY STEPS	Correlation Coefficient	.741(**)	1.000
		Sig. (2-tailed)	.000	.
		N	20	20

** Correlation is significant at the 0.01 level (2-tailed).

Figure 26 Comparison of Average Data Entry Steps

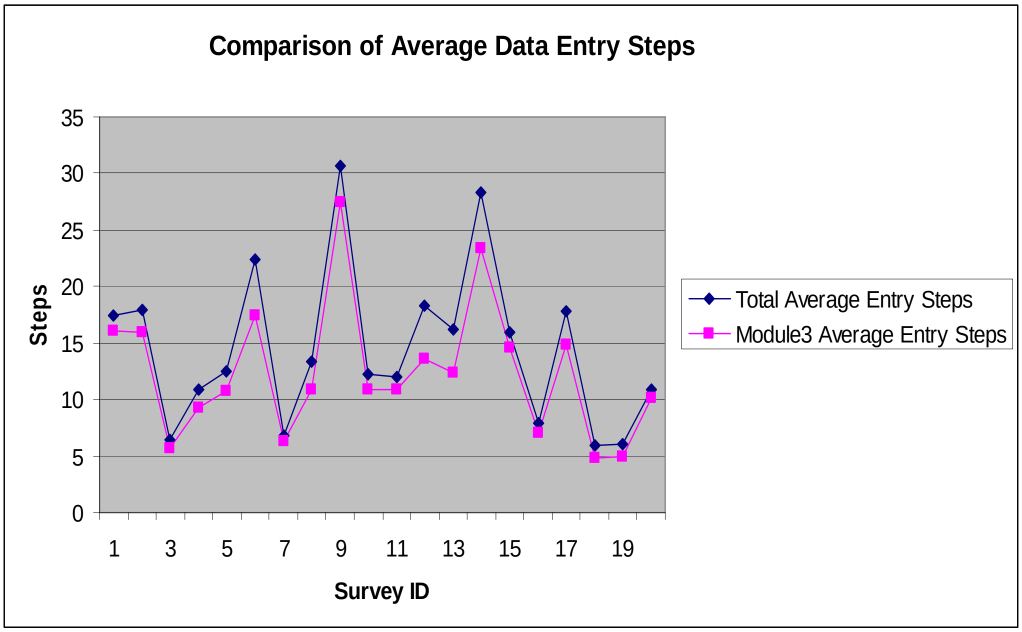
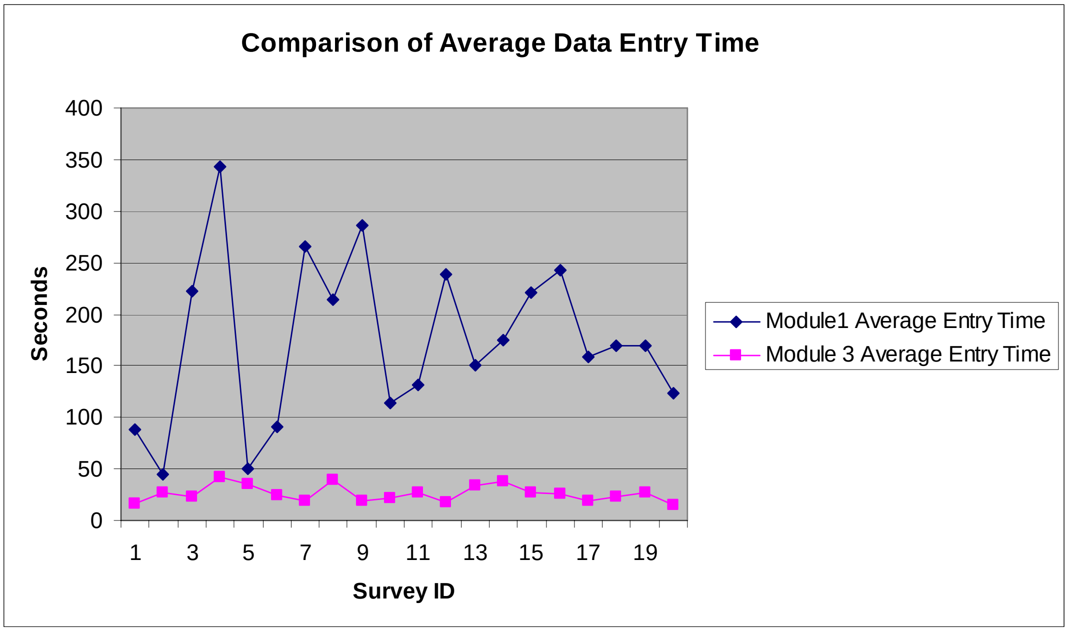


Figure 27 shows that the average data entry time for Module 1 is significantly longer than that of Module 3. The absorption ability of each individual to the survey program instructions defined its variance across survey participants. Data entry time for Module 3 is relatively flat though, with no significant difference observed among the survey participants.

Figure 27 Comparison of Average Data Entry Time



4.4.2.6. Missing Activity and Schedule Data

During the survey, the survey device recorded in total 502 activities and 211 schedules for 20 survey participants over the one-week survey period. 80 missing activities and 9 missing schedules were recovered via post-survey questionnaire and data analysis. The non-response rate for activities and scheduling tracking were 13.75% and 4.1% respectively. Survey data with insufficient details were mainly populated from the survey respondents' recall information. When possible, the temporal information about missing activities/travels such as start/end time, duration, etc. was derived from previous and afterward activity execution status. Figure 28 and

29 shows the detailed breakdown of the percentage of Recorded/Missing activity and scheduling count per survey respondent. Among the survey participants, the maximum activity data missing rate was 31.25% (or 5 out of 16); the maximum scheduling data missing rate was 50% (or 1 out of 2).

Missing records mainly result from the following scenarios:

1) Machine malfunction. Occasionally, the survey program froze while entering data or GPS collecting data. This is mostly due to the loose connection of the expansion pack. A device restart indeed fixed the problem, but caused loss of data.

2) GPS receivers were not positioned well for receiving satellite signals.

3) Simplified activity tracing. One short activity such as adding gas to the car along the way to a shopping mall could easily be ignored and recorded as part of the travel trace to the shopping location.

4) Inconvenience of carrying the survey device while participating in the activity. In certain circumstances, it is extremely inconvenient to carry a portable device in order to participate in an activity, especially when the activity itself may potentially damage the device (such as jogging).

4) Forgetting to carry the device while performing an activity. This commonly occurs when the need to pursue the activity is urgent.

Figure 28 Percentage of Recorded/Missing Activity Count

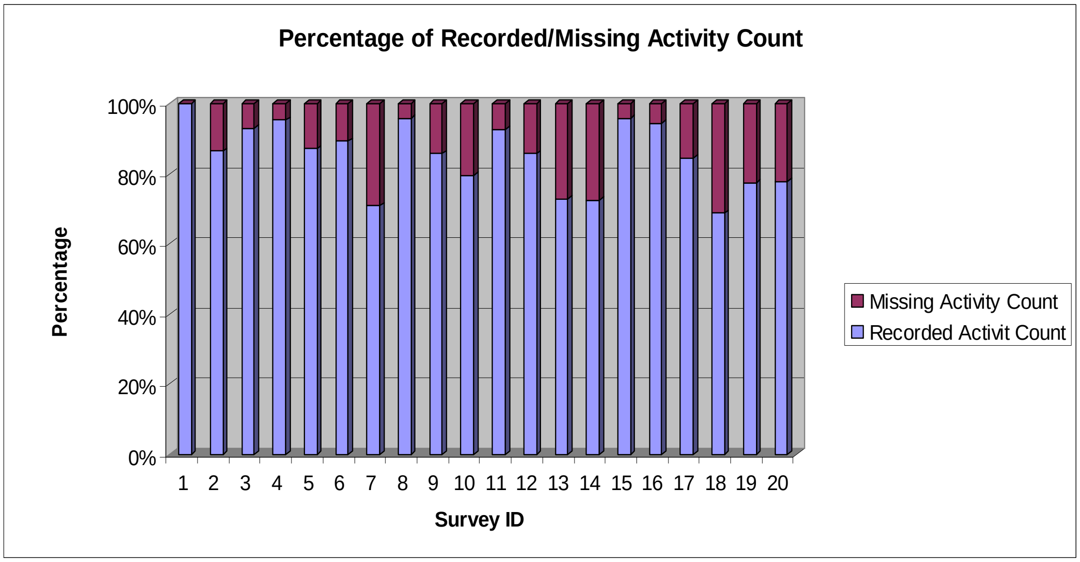
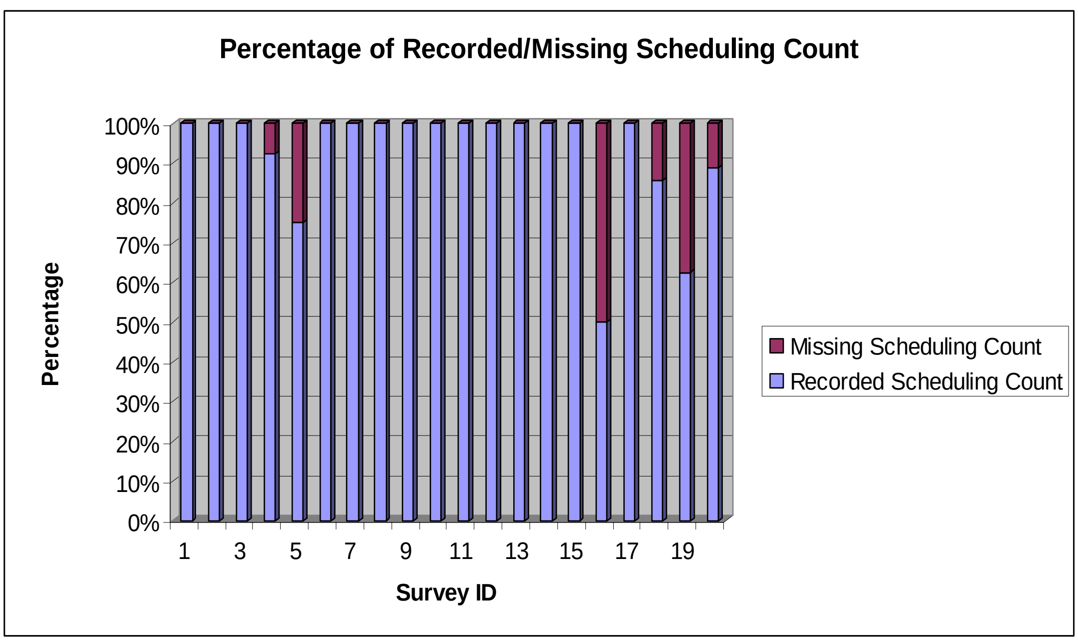


Figure 29 Percentage of Recorded/Missing Scheduling Count



4.4.3. User Evaluation of the Survey Program

After the survey participants finished the one-week survey, a questionnaire was sent to them for evaluating the survey and equipment design. Questions were asked for each survey module and data uploading utility in order to assess the survey program's usability and efficiency. All 20 participants sent in their responses, though with certain questions unanswered. Table 7.5 summarized the statistics of user evaluations on the survey. The tabulated results add to the comments from direct users of the survey device and reveal several interesting aspects about the survey:

1. Most survey participants consider the survey questions clearly and concisely organized (95% for Module 1, 85% for Module 2, 80% for Module 3 and 90% for Module 4). However, several participants did complain about the load of the survey task and the organization of the form flow. One confusing design about the survey program is that several traffic questions were repetitively asked before and after activity implementation. The intention is to collect data on how the travel experience affects people's perception of the traffic conditions. Unfortunately it potentially caused the illusion that a new activity trace started again.
2. It seems that about 30-35% (Module 1, question 4; Module 2, question 2) of survey participants were not aware that the survey is meant to not only record

activity schedules but also to track the schedule revision process – the evolving of a schedule from its embryo phase (with certain details not fully developed yet) to the complete activity plan. 30% of the participants do not quite follow the rationale that a linkage needs to be manually established between the input schedule and the following activity implementation.

3. About 45% survey participants (Module 3, question 2) feel difficulty on carrying the device in different travel modes. Some certain types of travels such as "jogging for exercise" make the participants extremely uncomfortable with carrying any unnecessary gear. Weather conditions in "walk" mode cause further concerns on the device's resistance to severe usage environment.

4. Most of the survey participants (90%) have no problem with data uploading at the end of the survey day. The others encountered various connection issues mainly due to the poor coverage of the subscribed wide area wireless network at their residential locations.

Table 7 User Evaluation of the Survey Program

	Questions	Yes	No	Unanswered
Module 1 (Personal Info and Week Schedule)	1. Are the survey questions clearly and concisely organized in this section?	19 (95%)	0	1 (5%)
	2. Has the location list provide you enough coverage to input the frequently	7 (35%)	13 (75%)	0

	visited locations			
	3. Does the activity list provide enough activity types from which you can select the activities you typically pursue?	14 (70%)	6 (30%)	0
	4. Are you aware of the fact when you know an activity you would like to do in the survey week, but you don't know some of the details on how to implement it, you should also need to input it in the schedule form?	13 (75%)	7 (35%)	0
Module 2 (Schedule Activities or Refine Schedules)	1. Are the survey questions clearly and concisely organized in this section?	17 (85%)	2 (10%)	1 (5%)
	2. Are you aware of that any of the change you made to a previously input schedule should also be input with survey program (Module 2) as a refined one?	14 (70%)	6 (30%)	0
Module 3 (Activity Implementation)	1. Are the survey questions clearly and concisely organized in this section?	16 (80%)	3 (15%)	1 (5%)
	2. Did you find any difficulty using the	9 (45%)	10 (50%)	1 (5%)

	device for tracking your travel to an activity site on various travel modes?			
	3. Do you think the rationale in the survey that after the activity tracking, if the activity is scheduled/planned before, a linkage to the schedule need be established is reasonable to follow?	11 (55%)	6 (30%)	2 (15%)
Module 4 (Answer Questions Related to Unfulfilled Activities in Schedule)	1. Did you check on and input information for the unfulfilled activities in your schedules at least once/day during the survey period?	7 (35%)	12 (60%)	1 (5%)
	2. Are the survey questions clearly and concisely organized in the section?	18 (90%)	2 (10%)	0
Upload Data	Data uploading via wireless connection is Difficult, fair or easy?	2 (10%) Difficult	9 (45%) Fair	9 (45%) Easy

4.5. Pilot Study Summary and Improvement

This section describes the results of the pilot real-time activity/scheduling study conducted at the University of California Santa Barbara. As a summary to the pilot study, the following will first discuss the survey achievements and challenges revealed during the survey process. Then possible enhancements to the survey will be explored from the perspective of survey procedure and program design. The final part will be dedicated to a description of expanding the current system by integrating it into an AI-enabled systematic survey design.

4.5.1. Achievements and Challenges

The survey demonstrated that the innovative approach of combining GPS, scheduling/activity oriented survey program and multi-modal data input onto a single-piece portable data collection terminal is viable and feasible. It went beyond other types of surveys by not only tracing scheduling/activity implementation in a close, real-time manner, but also by putting the whole data collection procedure in parallel with people's time use planning and activity execution. The design helped researchers significantly reduce the time interval between the occurrences of activity/scheduling events and the data extraction without introducing significant exterior interference. As one of the direct consequences, the streamlined procedure generated less missing data and made the “hole” in the data pool much easier to reveal and correct.

In terms of survey device design, the suggested and implemented scheduling/travel/activity data collection system relaxes the constraints on concurrency input of scheduling and activity tracing. Both of the survey respondents scheduling decision-making and activity/travel pursuits are recorded within one unified data collection framework in real time. The survey program is conceptualized in such a way that travel data is treated as an integral part of generated activity needed and collected with the relevant activity data in a single data collection session. Therefore, the chance of under-reporting for either travel or activity pursuits, which constitutes the major reason for incompleteness and inconsistency in diary-based travel/activity survey data, is reduced dramatically. Furthermore, insofar as travel data are collected prior to activity data, concerns for the validity of the survey data in terms of a travel event having to precede the relevant activity pursuit are obviated. There are very few cases where the survey respondent would use the travel itself as a way to satisfy his/her activity needs, e.g. jogging or walking for leisure. In an extreme situation, activity data itself would be used to describe the travel process. Therefore, the conceivable activity duration tracking following travel tracking is meaningless and the activity duration needs to be replaced by travel duration.

In spite of its strengths regarding data extraction and error endurance, the survey and the system used for this pilot study do face challenges in several regards:

1. For short out-of-home activity/trips, real-time data input tasks could be demanding and costly under the current survey framework. Under-reporting of short trips and activities remains an issue, although to a lesser extent. The rule of thumb is: whenever the cost of inputting data into the survey program by survey respondents outweighs the efforts of performing an activity and related travel, the data recording step for the relevant trip and activity pursuit may be ignored. The judgment to ignore a data input action is in nature arbitrary, potentially under the influence of various factors. Therefore, for a real-time data collection system, the cost (fatigue caused from data input) for inputting data in real-time to a certain extent determines the resolution of collected spatial-temporal and attribute data. However, it is certainly not the only determining factor. Survey respondents' decision-making and the tightness of their activity agenda at the moment might be the other contributing factors. In essence, their joint effects are unpredictable and difficult to explain. Hence, it is not surprising to see that the temporal-spatial resolution of the collected travel/activity data is not consistent across the entire survey period.
2. When monitoring in real time using a portable/wearable device, the scope of travel/activity tracing is broadened to encompass almost all possible types of

travel modes, except travel by air or train. Since the data collection scope was restricted to a local study area, the constraints of these two travel modes presumably did not affect the survey data quality. The portability of the device further expands the measurement of the travel route from parking lots to the true trip origin and destination (i.e., the actual activity locations). However, the density and quality of travel trace data suffers from the changing moving speeds of the survey respondent or the transport vehicles used. The recorded travel time and activity time may not be consistent when people occasionally decide to end their current travel traces prematurely rather than after he/she finally reaches the activity location. An even worse situation can occur when the current activity has been accomplished and the survey participant forgets to indicate the finish.

3. Fortunately, such worst-case errors are very noticeable by both the survey respondent and the supervisor and can be fixed quickly once a simple make-up questionnaire is exchanged between the parties. At this experimental stage, queries, problems, and answers regarding the survey are exchanged between the survey supervisor and the participants via email or phone. No real-time means such as pushing corrections and reminding notices from the server side are realistic yet. Pushing data to the mobile device demands a wireless connection that is always-on. Having the card activated all the time with the survey program occasionally pushes the memory usage on the Pocket PC to its limits, which increases the odds of machine malfunction during the real-

time tracing period. Hopefully, the problem can be solved in the near future with technology advances.

4. Last but not the least, the survey system's usage among seniors, children, or computer illiterate might be limited due to the system complexity and its real-time nature. Some people might find the data collection equipment/procedure overwhelming in terms of understanding and using it correctly. It also may not be a sound approach to collect data on an survey respondent who has a very tight daily schedule or needs to pursue an activity that is highly repeatable (e.g., moving furniture to a new home)--in such cases, the real-time survey device will usually be found to be intrusive and cumbersome to handle. The causes of such problems with the real-time survey derive mainly from two aspects: 1) the size, the integrity, and the limited power supply of the device; 2) problems of interacting with the device. The former can be easily addressed by using the up-to-date portable computing equipment (the current trend is toward multi-function computing devices that have a wireless card, GPS receiver, and replaceable battery support seamlessly integrated into one box). The latter is more or less a human-device interface issue, which has been discussed and partly addressed in the multi-modal input/output section in this dissertation. The efforts were incomplete, due to the failure to completely integrate the available voice recognition tools into the pocket device. As a result, the lack of input channels has made the process of adding locations on the GIS map component relatively demanding

in a real-time scenario, especially when the survey participant is facing a tight schedule and most of the activities pursued are time-critical. The situation is made worse by the fact that the burden could potentially change the survey participant's behavior pattern (e.g., reduce the number of out-of-home activities), due to unwillingness to carry the device and input data regularly.

4.5.2. Potential Improvements

As noted in the previous discussion, the biggest challenge to real-time activity/travel survey systems is probably the conflict between the time constraints implied by the survey participant's daily activity agenda and the time cost to input the data in real time. However, the challenge is never easy to fully address, insofar as today's computing devices are not sufficiently intelligent to function as a complete passive observer in terms of data recording. In general, the challenge (including others mentioned previously) has no near-term solutions in sight to date. A perfect solution to these problems demands much more research effort in efficient human-device interaction design and survey optimization. In the meantime, some minor improvements are worth considering as an interim means of reducing the time conflict between data capturing and activity pursuits:

1. Reduce the load of the survey task. To reduce the load on the participants' part, certain intelligent controls can be integrated to allow device carriers to selectively skip certain questions. In addition, secondary information regarding activity or schedules could be gleaned from other information channels or bypassed entirely. Generally speaking, survey data sources should not be limited to portable devices only—the central data server can also be coupled with a web robot to actively search for complementary data. One good example is the survey questions about the weather at the time when an activity was pursued. A weather web site could provide substitute data with similar qualities as long as the activity time slots are available.
2. Provide effective survey guidance. During the pilot study, only textual and oral instructions were offered to help the survey participants understand the survey procedure and survey input sequence. However, such consecutiveness of relation information could better be presented with pictures or picture sequences, as a referral base enabling the survey participants to remind themselves of how to proceed with the survey. A quick reference to screen snapshots and pictures of icons of the survey forms conceivably would be one means of communicating information that textual or oral descriptions cannot effectively deliver, especially when the survey subjects encompass multiple ethnic groups with varying levels of English literacy.
3. Enhance the multi-task mode of the survey program. Currently, the survey program only allows concurrent activity and scheduling tracking. However,

the limitation of the GIS/GPS components integrated into the survey program prevents activities from being scheduled while travel tracing is ongoing. In the case when travel occupies a significant portion of out-of-home time use, the lack of the multi-task capability provides no guarantee about the real-time recording of activity scheduling data.

4. Immediate feedback on data validity. In the after-survey questionnaires, some participants indicated their concerns about the validity of data they input via the survey program. Their shifted focus to data validity cost them more input time than is usually needed. Dynamic visual confirmation in icon forms beside the survey questions would provide one illustrative way to confirm the soundness of the data and to remind the user of any unanswered question. Also, the data (error) summary report could be compiled at the end of each survey day for the participants to determine if data validity had been compromised by their device usage pattern.

Furthermore, some steps could be taken to improve the survey data quality and coverage:

1. Modify the user interface to support concurrent activity tracing. People often interleave their activities and perform them simultaneously within a time slot. In such cases, the complex activity should be decomposed on the pre-defined list of activity types as a co-operating activity set.

2. Extend the tracing of schedule change to the activity execution phase. When the intervening opportunities emerge during travel, it often prompts trip, activity destination, or activity type change in the middle of travel. In a strict sense, the activity change/cancel operation should be classified as a type of spur-of-the-moment schedule change and be included in the survey data.
3. Allow indication of non-location specific activity, such as jogging, walking the dog, etc. The current survey design is in essence activity-oriented. Travel is considered to be the derivative of the activity to be performed. For non-location specific activity, the designated activity is performed along the travel. The activity tracking section should be skipped completely after travel tracing is accomplished since presumably the travel duration is equivalent to the activity duration.

4.5.3. Complete Framework- Intelligent Data Warehousing for Large-scale Real-time Survey

In spite of the weaknesses we previously discussed, the real-time computer-based survey system provides researchers with many benefits they have never had before. However, the benefits of an automated system are not merely restricted to reducing survey instrument and labor cost. Such a system also possesses incomparable advantages for large-scale survey data collection practices which demand consistent data quality control over a longitudinal survey period. Insofar as the survey tasks cannot be accomplished by the central data server alone, we envision the further development of an intelligent activity/travel data warehousing at the backend to complement the functions provided by the real-time activity/travel survey system. The data warehouse is designed to access the operational data collection center for management and data validation purposes. It helps analyze, plan and react to the quick change of survey conditions by organizing the collected data in a consistent format. The architecture of the data warehouse is composed of several interconnected layers: 1) the Process Management Layer; 2) the Information Access Layer; 3) the Information Directory Layer; and 4) the Application Messaging layer. The Process Management layer serves the role of extracting data from the operational data source (central data server) periodically, completing the dataset by extracting complementary information from external data sources, and converting them into common data models for efficient query and analysis. The Information Access Layer summarizes scheduling/activity data collected and their qualities, identifies survey errors, and reveals missing data to estimate non-response rates to the real-time system. The Information Directory Layer organizes the data into indexed directories to facilitate searching and queries. The Information directory service is dedicated to the survey administrators only. From the indexed travel/activity record, the administrator would have the capability of examining the survey progress and data quality from a central monitoring site, provided that a computer with Internet connection is available. The Application Messaging Layer compiles the revealed errors into GIS-enriched questionnaires and posts them on the survey website for participants' reaffirmation. According to the frequencies and criticality of the occurring errors, the layer also pushes the relevant warning messages to the portable devices.

Within the information access layer, a rule-based expert system can be overlaid upon the central database storage to overcome the potential bias effects of real-time system on survey participants' behavior, in terms of incorrect operation on survey devices or negligence of activity/travel reporting under agenda stress,. The set of rules would check the logical consistency of the dataset and any possible errors it contains. The possible errors include the unanticipated change of the system clock of the Pocket PC, potential missing activity reports, or an inconsistent answer to the survey questions (such as answering yes to the question "any survey participant withdrawal from the activity" but answering "0" to the question "The number of people co-participating in the activity").

To identify theses errors, a sample rule set may contain the following rules that represent the expert knowledge base in order to judge if an error is embedded in the data:

1. A sequence of out-of-home activities must be followed by an at-home activity.

2. No gap is allowed between adjacent travel and activity or between activities performed at the same location.
3. An off-current-site activity must be accompanied by travel records.
4. Travel/activities usually do not occur around certain time slots (say 1am – 6am).

The rule set would be modeled in “if … then …” form. The examination results would be posted regularly to the data warehousing web site as a scheduled task via ArcIMS and .NET/ASP. By keeping track of which rules have fired compliance, the chain of reasoning that led to the error conclusion would also be presented to the survey participants.

With the configuration of the intelligent data warehousing, the survey participant could be allowed to opt out of a data input task under a time-critical situation. Once the rule-set based expert system reveals the missing data or errors in an automatic manner, an online questionnaire form would be compiled with the accompanying scenario information. NET/ASP would be used to present the relevant text attributes from the central server database. The Geographical presentations of travels associated with the activity pursuits would be published by the ARCIMS service (a series of sample usages are presented in the figure from Figure 30 to Figure 34). Both, in tandem, prompt the survey participants to fill out the missing section or to make correctional changes. Survey respondents therefore get another chance to examine the data recorded by the survey system and help prevent data error from propagating to the analysis phase. The validation session of the survey website will be refreshed on a daily base by the data warehousing, typically at the end of a survey day. A survey participant could use any free time to examine his/her recorded daily travel/activity pursuits and to correct the incorrect records on his/her own initiative. Note that the correctional modification submitted to the data warehousing would not be applied to the collected data directly. Any suggested change by the survey participant would be stored alongside the data itself for further examination by the survey administrator. The ultimate configuration of the real-time activity/travel survey design with the intelligent data warehousing incorporated would be similar to the infrastructure illustrated in the following diagram (Figure 35).

Figure 30 Daily Activity Report

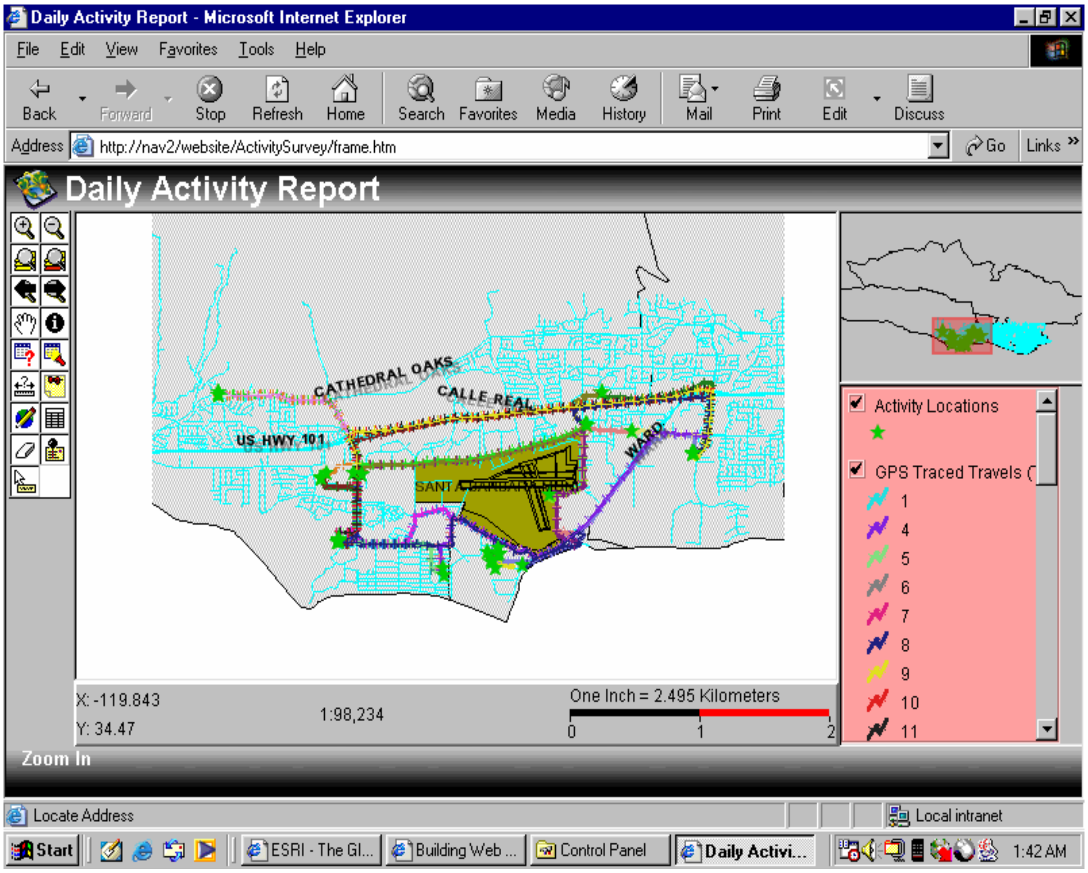


Figure 31 Use Search function to identify Trip 6. Trip 6 is highlighted with yellow color

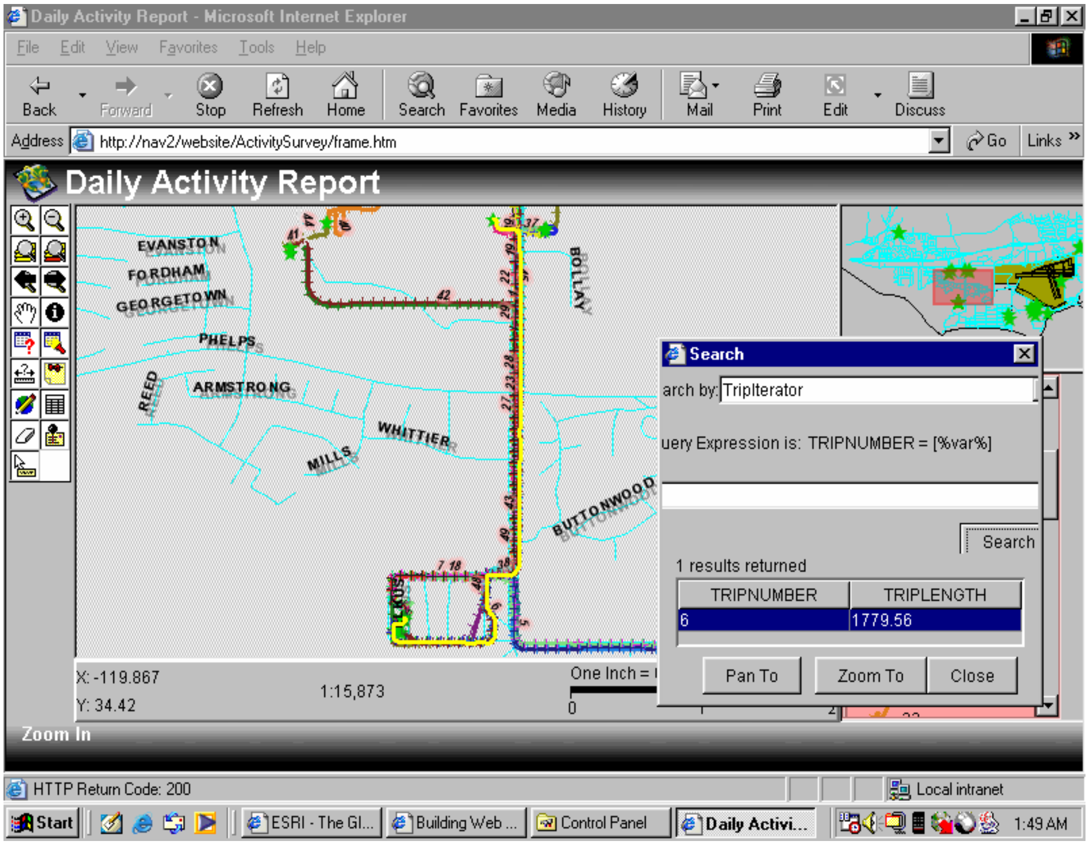


Figure 32 Edit Travel Records by Moving Selected Trip or Adding New Trip Features. Edit Notes are Sent Back to the Server

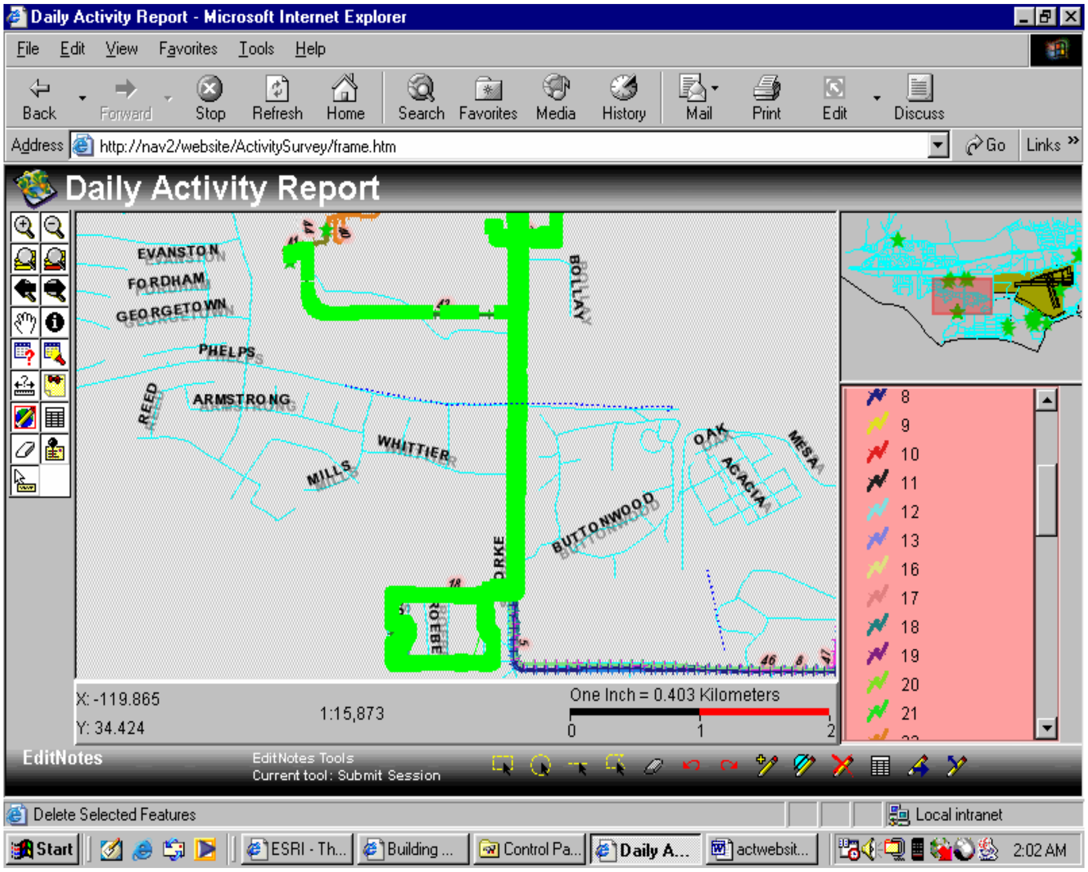


Figure 33 Use Map Note to Add a Freehand Drawing to the Map. The Map Note Then is Sent Back to the Server

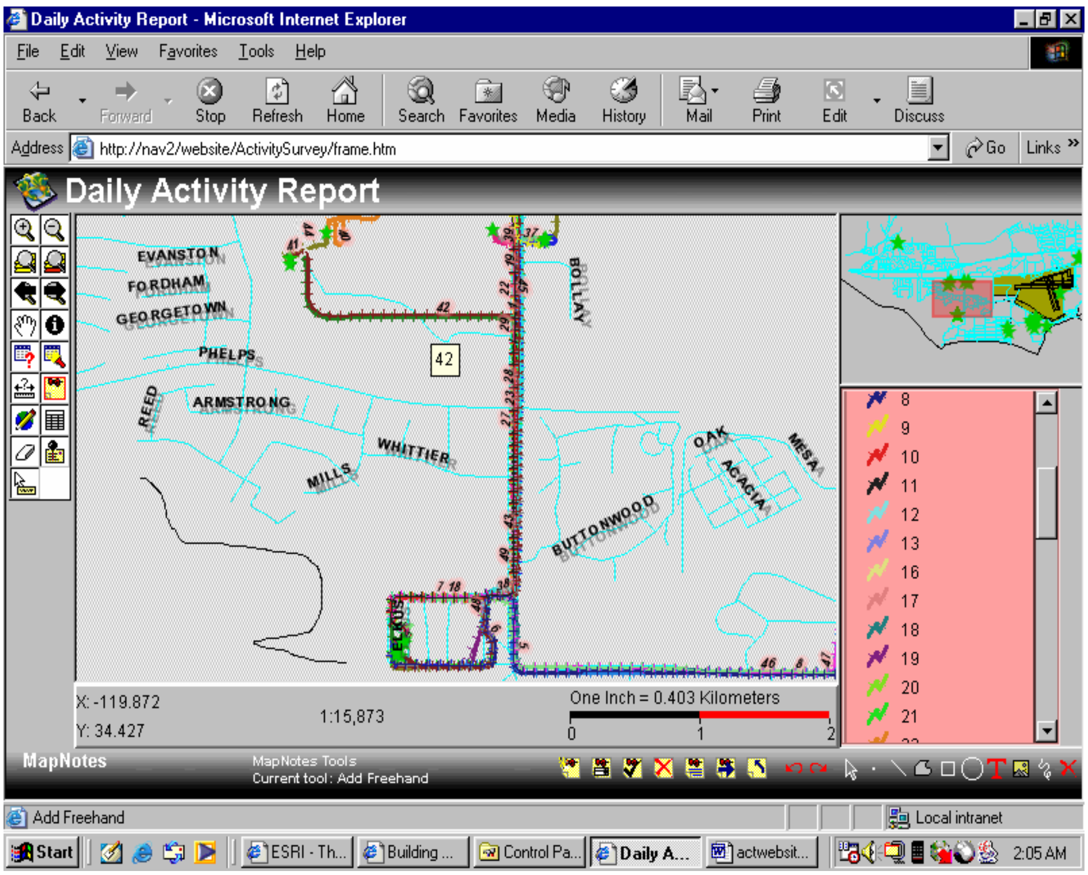


Figure 34 Use Geocoding Button Find Out Activity Location

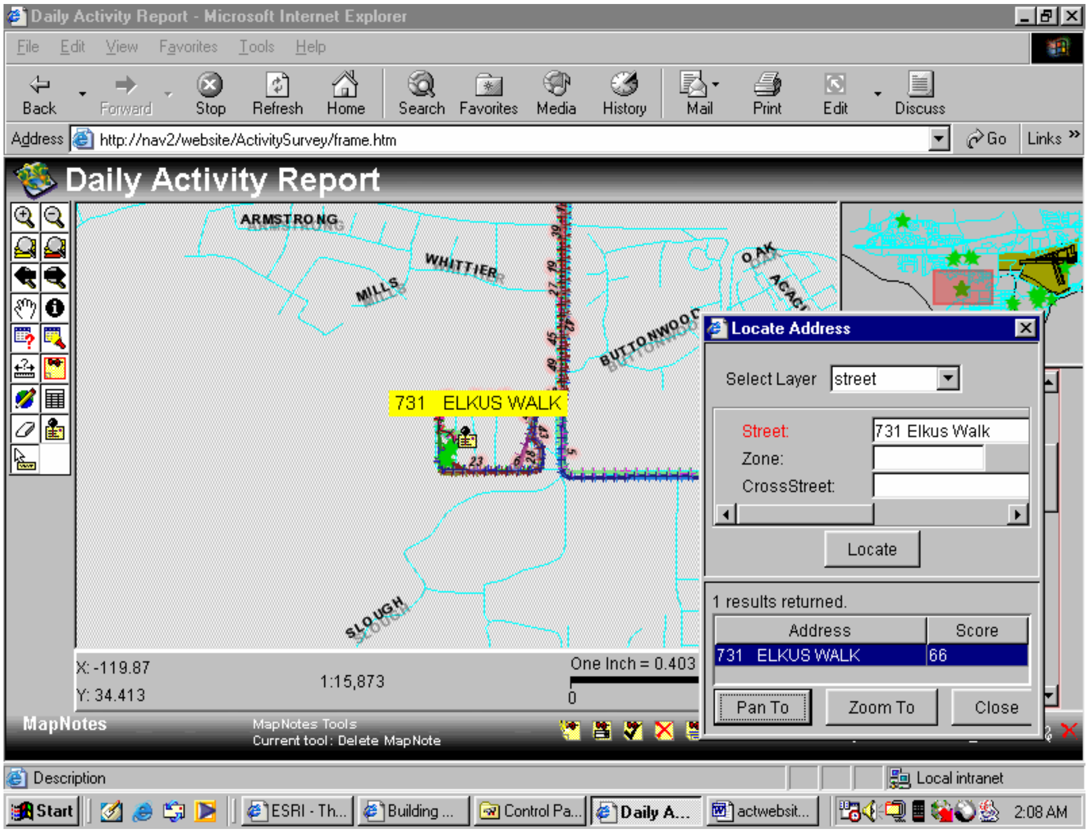
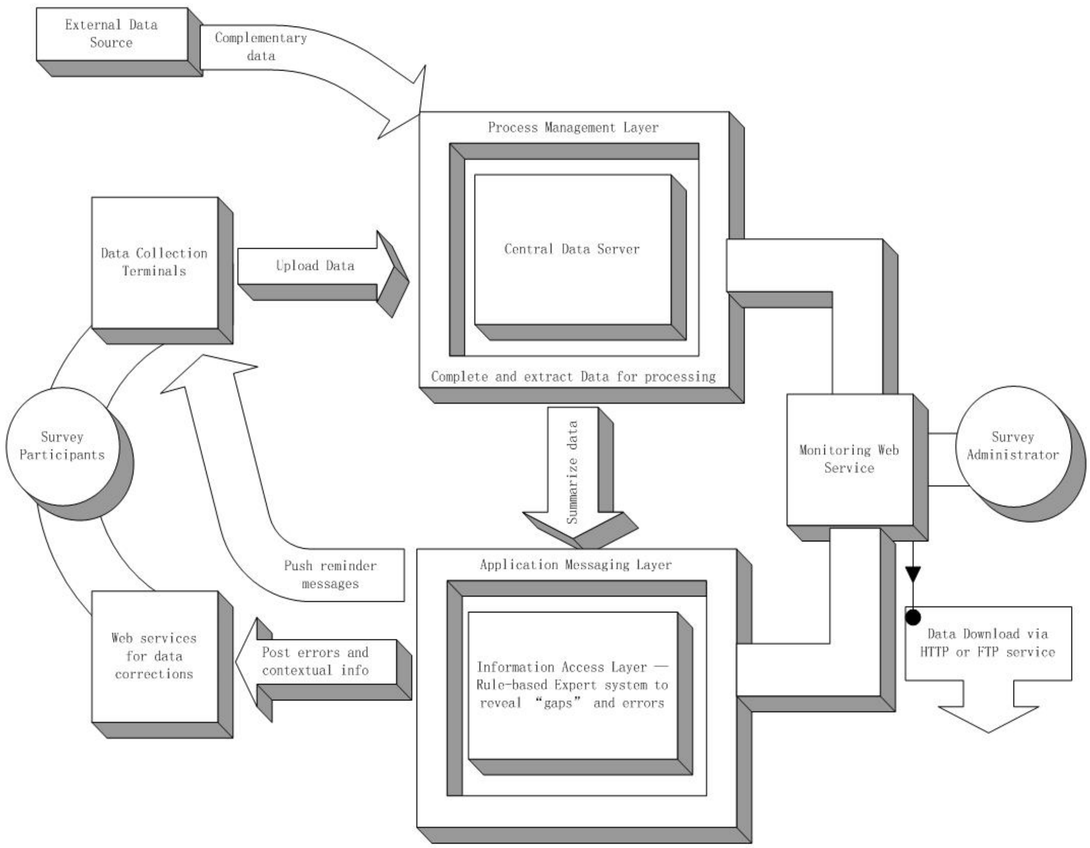


Figure 35 Survey Infrastructure with Intelligent Data Warehousing Incorporated



Chapter 5 Results Data Analysis and Model Fitting

5.1. Analysis of Travel Trace Data

5.1.1. Travel Data Compilation: A Three-step Map-Matching Procedure

To match the collected travel trace data to the existing base map, a three-step map-matching procedure has been developed to identify the traveled paths of each survey participant as represented by a sequence of street segments, which are extracted from the base map GIS shape file according to a set of pre-defined matching criteria. The difference between the actual travel route and the final match result is evaluated based on the concept of "edit distance" (ED) – the minimum number of insertions, deletions and substitutions needed to transform one route to another. The matching percentage is derived according to the following equation: 100 * (1- ED/n). Here n is the total number of arcs in the actual route. On average the map matching algorithm reaches a matching accuracy of 95.74%. The further break-down of matching results by travel mode is shown in Table 8. It can be seen that travels by bicycle are subject to the most map matching errors, which are mainly due to the lack of bike path information in the base map. The paper attached in appendix section B – “A Three-step General Map Matching Method in the GIS Environment: Travel/Transportation Study Perspective” further discussed the details of the map matching methodology and matching procedure.

Table 8 Map Matching Accuracy by Travel Modes

Travel Mode	Total Number of Trips	Average Matching Accuracy (in percentage)
Walk	104	94.75
Car	234	97.04
Bicycle	61	91.19
Carpool	34	97.17
Vanpool	3	100.00
Local bus	45	96.17
Total	481	95.75

5.1.2. Coverage of the Temporal-Spatial Travel Path - Off-road Travel

Off-road travel here is defined as travel on roads other than those dedicated for travel by motor vehicles. These types of “minor” roads (e.g. bike path, sidewalk, etc.) are typically not encoded in the generic GIS digital base map. In the map-matching process we previously referred to, the off-road segments of the travel records are identified according to the pre-defined fuzzy logic rules to derive a ratio of their aggregated segment length to the total travel distance. Table 9 lists the off-road travel ratios by different activity categories. On average, 28 percent of the total travel distances are not completed on the major road types designed for motorized travel. The percentage of off-road travel is the highest for the Work/School activity category, as many areas of the campus are not accessible to motor vehicles. In contrast, the Shopping travels on average only cover a small distance of "minor" roads, mostly thanks to the convenience brought by the thoughtfully designed parking facilities of the shopping malls. Note that the statistics here depend on the encoding resolution of the GIS base maps and the data we use encompass travels on various travel modes. Hence these results may not completely reflect the "off-road" travels in their true meaning. However, as many of the travel surveys are still targeting at tracing the travels by motor vehicles only, Table 9 provides us a rough estimation regarding the coverage of such surveys on the survey correspondents' daily temporal-spatial paths.

Table 9 Off-Road Travel Ratio by Activity Categories

Activity Category	Total Number of Travels	Average Off-Road Ratio
Eat/sleep/personal hygiene	108	0.25
Household obligation	91	0.16
Recreation/entertainment	52	0.27
Services and errands	18	0.23
Shopping	39	0.12
Social	12	0.34
Work/school	160	0.42
Total	481	0.28

5.1.3. Travel Route Choice: Shortest Distance Route or Shortest Time Route

Besides matching the travel trace to the base map, the shortest distance route and shortest time route are also generated with the help of ARCVIEW network module, which are further used as a comparison base to examine the routing behavior of the travelers recruited in this survey. Generally speaking, route choice is the joining consequence of activity needs, past travel experience, and current information about the activity to pursue and other conditions such as weather, traffic, safety etc. Travelers take routes that lead them to their destination based on their judgment on whether the route is the most efficient one. Occasionally, the traveler changes his/her routine route as a result of changing activity needs (e.g., “trip chaining”), or due to the varying information flow-in about the condition of the route. The factors that affect the traveler’s route choices may not weigh equivalently in helping them for route selection. Intuitively, the traveler’s primary objective should be to minimize the travel time or travel distance to reach the destination. Duffell and Kalombaris (1988), based on their study results, tend to attribute more importance to travel time minimization. Their research results showed that drivers are willing to travel a longer distance in order to trade for the reduced travel time provided “the distance is not doubled or the alternative is tortuous”. In the section, their point of view will be further tested against the empirical data collected in our survey.

Table 10 summarizes the edit distance between the actual travel route and the shortest distance/time route by travel mode. The results show that shortest path criterion (time or distance) can only approximate the rationale behind people's travel routing decision making process. Travelers recorded routes during this real-time survey deviate from their corresponding shortest paths in more than 13 arc revisions (Edit Distance) on average. Travelers on the labor-consuming travel modes such as walk or bicycle almost optimized their travel path by following the shortest time/distance path (with an ED of about 4.3 and 1.35 respectively). In the case, with the lack of road surface constraints on the travel route, the shortest time and distance path are almost identical. As for the other types of travel modes, travelers generally prefer to take routes that are closer to the shortest time path than to the shortest distance path. However the favoring degree varies with the flexibility associated with the vehicle's traveling scope and the travel participation status. Travel by local bus is typically subject to the strict bus route constraints, thus, they tend to deviate from the optimized route to a greatest extent. In contrast, travel by vanpool deviates from the optimized route significantly due to the potential conflicting activity objectives of the vast number of travel participants compared to the carpool case (which only has a small number of participants who usually shares a common activity destination).

Table 10 Difference of Actual Travel Route from Shortest Time/Distance Route by Travel Mode (measured in "Edit Distance")

Travel Mode	Total Number of Travels	Average Diff between Actual Route and Shortest Time Route	Average Diff between Actual Route and Shortest Path Route
Walk	110	4.32	4.36
Car	234	14.44	20.96
Bicycle	55	1.35	1.35
Carpool	34	10.71	21.38
Vanpool	3	37.00	45.33
Local Bus	45	48.40	64.73
Total	481	13.62	19.05

Table 11 indicates the difference between the actual travel route and the shortest distance/time route by activity categories in terms of edit distance (ED). The tabulated results show that Service and Errands activity category's travel routes closely resemble the optimized travel paths (with an ED of 5.22 with respect to the shortest distance path and 5.33 with respect to the shortest time path). As for other activity categories, the shortest time route seems to be favored more than the shortest distance route in types of activities with clear objectives and immediate demands such as Eat and Recreation/Entertainment activity type, while the activity categories with potential mixed activity needs (e.g. Household Obligation or Shopping) tend to be associated with relatively deviated travel routes from the optimized ones. Surprisingly, Work/School route comparison statistics likewise indicate non-optimal routing choice by the travelers. However, considering the facts that a significant portion of the survey respondents use local bus to reach their work/school locations, it is conceivable that their majority travel paths follow the restricted bus route instead of the optimal one.

Table 11 Difference of Actual Travel Route from Shortest Time/Distance Route by Activity Categories (measured in "Edit Distance")

Activity Category	Total Number of Travels	Average Diff between Actual Route and Shortest Time Route	Average Diff between Actual Route and Shortest Path Route
Eat/sleep/personal hygiene	108	8.84	18.84
Household obligation	91	19.63	25.86
Recreation/entertainment	53	7.57	14.70
Services and errands	18	5.33	5.22
Shopping	39	12.28	18.33
Social	12	12.17	5.08
Work/school	160	16.79	19.55
Total	481	13.62	19.05

In real life, the decision on which route to take to reach the destination depends on the various attributes associated with the route or the travelers' subjective perceptions to the route attributes. In the real-time survey as described in this dissertation, the objective attributes of the recorded travel trace has been collected with the help of the GPS PC card attached to a Pocket PC. The data provide us with detailed information on the factors that could prompt the traveler to choose a particular route rather than an alternative one. Here the Binary Logistic analysis is used to analyze the traveler's route choice preference between the shortest time path and the shortest distance path. The Edit Distance of actual travel route relative to the shortest distance path is subtracted from the Edit Distance of actual travel route relative to the shortest time path. The positive results are encoded as 1, indicating a routing choice close to shortest time path more than to the shortest distance path. Otherwise the derived results are encoded as 0. A series of objectively measured attributes of the actual route have been selected as the covariates in this analysis:

1. Route distance in miles.
2. Travel time in minutes.
3. Number of street links (extracted from the GIS base map).
4. Number of intersections encountered during the travel.
5. Off-road Ratio.
6. Gender of the traveler.
7. Travel Mode.

The binary logistic regression function is as follows:

$P = \exp(U)/(1+ \exp(U))$ here U is a linear combination of the covariates listed above plus a constant.

Both the forward Wald and back Wald methods have been used to fit the model and they generated identical fitting results. Table 12 and 13 show the part of the results from the forward stepwise Wald fitting process.

Table 12 Logistic Analysis Results with Forward Wald Method:

Classification Table (a)

Observed			Predicted		
			Route Choice Preference		Percentage Correct
			.00	1.00	
Step 1	Route Choice Preference	.00	11	5	68.8
		1.00	3	41	93.2
	Overall Percentage				86.7
Step 2	Route Choice Preference	.00	9	7	56.3
		1.00	3	41	93.2
	Overall Percentage				83.3

a The cut value is .500

Table 13 Binary Logistic Analysis Results with Forward Wald Method:

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1(a)	Travel Distance	.405	.102	15.804	1	.000	1.499
	Constant	-2.042	.797	6.559	1	.010	.130
Step 2(b)	Gender	1.790	.833	4.613	1	.032	5.990
	Travel Distance	.421	.118	12.832	1	.000	1.524
	Constant	-3.254	1.164	7.814	1	.005	.039

a: Variable(s) entered on step 1: Travel Distance.
b: Variable(s) entered on step 2: Gender.

At the end of step 2, the correctness of the regression analysis is up to 83.3%. The model underscores the significance of "Gender" and "Travel Distance" on the routing choice close to shortest time path more than the shortest distance path. The coefficients of both variables are positive (1.79 and 0.421 respectively), indicating that Male travelers tend to choose travel path that is relatively time-optimized compared to female travelers, while as the travel distance on a route increases, travelers will shift their routing aim toward time-optimization rather than distance optimization. In the backward Ward fitting process, variables other than Gender and Travel Distance are included in the analysis and assigned with a coefficient. However, none of these coefficients are statistically significant. Hence there is no need to comment on them further here.

5.2 Analysis of Schedule/Activity/Travel Patterns

5.2.1 Travel and Activity Duration Analysis for Out-of-home Activities

In this section, an analysis of the survey data on out-of-home travel and activity durations is performed to establish which activity in the daily travel/activity pattern generally requires the longest/shortest activity/travel duration to accomplish, as well as the potential relationship between activity durations and the corresponding travel time spans. Table 14 summarizes the difference in the survey participants' average out-of-home activity and travel durations by activity category and scheduling status break down. The tabulated results suggest that there is significant variance in the time requirements among the activities of different function classes. Unsurprisingly, Work/School activities are typically allocated the largest portion of survey participants' daily time budgets, followed by Social activities. In comparison, Household Obligation activities and Service and Errands activities demand the least time to complete. In terms of travel time, however, there is no significant difference observed across the different activity categories. All of the travel duration averages fall within the 30-minute time span. Longer activity durations do not necessarily imply longer travel times.

When considering the effects of activity planning on the activity duration and travel time spans, the table shows that the scheduled Eat/Sleep/Personal Hygiene activities (which is mainly dominated by the "eat outside" activity type, due to the fact that the survey mainly captures the out-of-home activities and the first in-home activities) required much longer activity durations than their unscheduled counterparts. In comparison, the average travel time needed to reach the activity locations for the scheduled "Eat" activities is shorter than for those of unscheduled ones. A similar observation also applies to the Social activity category.

Table 14 Activity/Travel Durations of Different Activity Function Classes

Activity Category	All Activities		Scheduled Activities		Non-Scheduled Activities	
	Average Activity Duration per Event	Average Travel Duration per Event	Average Activity Duration per Event	Average Travel Duration per Event	Average Activity Duration per Event	Average Travel Duration per Event
Eat/sleep/ personal hygiene	50.43	25.77	89.41	12.74	34.83	29.72
Household obligation	4.24	19.42	4.32	24.72	4.16	17.26
Recreation/ entertainment	90.03	14.39	93.93	15.93	85.59	12.85
Services and errands	6.76	15.30	5.28	12.32	7.11	16.00
Shopping	36.09	16.98	39.79	21.03	33.43	14.18
Social	134.34	15.44	263.59	12.85	91.26	16.24
Work/school	202.58	16.99	207.91	17.11	197.14	16.88
Total	124.89	18.97	145.30	17.53	108.56	19.82

A further tabulation of the activity durations of different function classes across the days of the survey week indicates that activity durations not only vary among activity categories, but are constantly changing over the days of the week even for a particular type of activity. Table 15 details the average time (in minutes) of the activity events per day of the week for each activity category. We can see that most of the rapid changes of activity durations occur between the demarcation of weekdays and weekends. For example, Recreation/Entertainment activity duration remains at a consistent level during weekdays but increases dramatically during weekends. In comparison, Social activities feature more than doubled activity durations on Weekends, with the highest average duration level peaking on Sunday. A similar activity duration level surge also occurs with Shopping activities, but to a less extent. On the other hand, for certain activity categories, exceptional activity duration distribution applies only to a certain day of the week. For example, for Eat activity, the unique day with the most significant increase of time expenditure is Friday, and, for Services and Errands activities, the average duration time drops to 0 minutes on Sunday, mainly due to the unavailability of services. Note that Work/School activities are generally constrained by routine classes, labs, research meetings, etc. during weekdays, and that Saturday is mostly devoted to household chores or other relaxation activities. These factors help explain why the survey participants tend to allocate a bigger chunk of time on Sunday to a single work/study activity event, making their Sunday's average activity duration longer than that of the other days of the week.

Table 15 Activity Durations of Different Activity Function Classes on Days of the Week

Activity Categories	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Eat/sleep/personal hygiene	24.22	61.70	24.85	40.52	80.06	52.29	47.28
Household obligation	1.29	5.07	12.37	4.84	3.87	1.78	0.27
Recreation/entertainment	84.86	71.76	69.39	86.23	58.25	128.09	130.28
Services and errands	4.94	13.88	8.88	1.19	0.07	4.71	0.00
Shopping	26.94	15.94	14.57	30.79	13.54	44.92	48.11
Social	61.73	62.34	0.00	37.42	0.00	136.16	199.02
Work/school	167.52	183.62	226.05	214.78	226.39	165.63	246.05

In terms of travel duration distribution of different function classes across the days of the survey week (Table 16), the only activity category whose travel duration stays at a stable level over the entire survey week is that of Work/School. The travel durations of Household Obligation activities remain consistent during the first six days of the week, but they drop nearly 34% on Sunday. A similar pattern can also be observed for the Shopping activities. Both of these two activity categories are somewhat significant in terms of maintaining the normal functions of households, and it is understandable that these "duty" activities take place within a smaller travel scope insofar as that prevents them from occupying a significant portion of relaxation time on Sunday. As for Services and Errands activities, their average travel duration drops to 0 minutes on Sunday as services are generally unavailable at that time. In comparison, the accumulated need to satisfy household service demands during the weekend results in increased travel on Saturday, which leads to longer observed travel durations at that time.

Table 16 Travel Durations of Different Activity Function Classes on Days of the Week

Activity Categories	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Eat/sleep/personal hygiene	14.88	19.40	12.09	12.93	10.41	93.18	12.48
Household obligation	21.90	17.11	22.04	20.14	20.30	20.43	13.46
Recreation/entertainment	9.52	8.00	9.18	20.01	16.25	16.70	20.89
Services and errands	9.80	10.28	7.50	9.63	18.82	33.09	0.00
Shopping	20.75	13.95	20.32	13.83	11.34	18.40	8.68
Social	1.15	34.43	0.00	8.82	33.82	8.89	12.52
Work/school	18.58	14.01	18.31	18.32	15.96	21.46	16.79

Note: The exceptionally longer average travel duration on Saturday for Eat activities is due to a long out-of-town trip.

Table 17 summarizes the variation of the activity/travel duration with the number of participants that are involved in the activity. Here, activities with more than one participant are defined as "coupled" activities. The table shows that more than half of the recorded activities (64.8%) are performed "alone." In general, the activity duration of "alone" activities are nearly 39% longer than that of the "coupled" activities. In comparison, the corresponding average travel duration is 21% shorter. This observation reflects the effects of the temporal constraints in joint activities on the activity participants' time allocation decision making – one's time arrangement is subject to his/her appointments with other persons. If we further tabulate the distribution of activity durations on the days of the week (Table 18), it can be seen that, except on Sunday, the activity durations of "alone" activities is consistently longer than those of coupled activities across the week. It seems that the reduced activity needs on Sunday allow the activity participants of joint activities more time resources for coordinating multi-agent activity pursuits, while, at the same time, the activity duration of "alone" activity drops correspondingly, mostly having been substituted by in-home activity pursuits or simply dedicated to resting purposes.

Table 17 Activity/Travel Durations of Activities with Different Participants (in minutes)

Participant Type	# of Activities	Average Activity Duration	Average Travel Duration
Alone	376	110.96	17.37
Coupled	204	79.97	21.91
Total	580	100.09	18.97

Note: 2 activity records do not contain the activity duration information. They are left out of this table.

Table 18 Activity Durations of Activities with Different Participants on Days of the Week

Participant Type	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Alone	86.84	124.62	124.79	121.38	130.46	90.70	65.97
Coupled	73.20	70.69	72.13	112.27	77.15	70.69	104.13

5.2.2. Schedule Horizon Analysis

Schedule time horizon can be defined as "the time between the activity planning and its execution," i.e., how far ahead an activity's temporal-spatial characteristics (and other attributes) are planned out in the behavior's activity agenda. If a schedule is planned further ahead, odds are that it may be subject to several changes before the planned activity is executed. Although the planned-ahead activities are less likely to be neglected, the scheduling action itself may have lost its efficiency. If the scheduler uses a short time frame, the schedule is more likely to be followed accurately in terms of the conformity of the executed activity to the plan. However, the scheduler may have less opportunity to leverage the resources for activity agenda optimization.

Regarding the scheduling recorded in this survey, the percentile analysis (Table 19) shows that, for out-of-home activities, nearly half of the corresponding activity schedules were planned within a one day period. But only 5 percent of the activities can be classified as being spur-of-the-moment (with a schedule horizon of 10-15 minutes). When the average schedule horizon data was further broken down by activity categories (Figure 36), Shopping activities and Services and Errands activities on average entail a relatively short schedule horizon (within one day); in comparison, Work and School activities and Household Obligation activities typically demand the most distant schedule horizon (on average, more than two days). Considering the characteristics of the two activity categories (Work and School activities are highly repetitive in nature and typically constitute the "back-bone" of people's daily travel/activity pattern; Household Obligation activities encompass highly coupled activity types such as pickup/drop off others), both seem to be ideal candidates for being planned out earlier than other events. In terms of the spread of schedule horizons (Figure 37), these two activity categories also show the most significant variation. The majority of schedule horizons of the Shopping activities, however, seem to cluster within only a one to two hour time span except for several outliers, which confirms the previous finding that they are largely spontaneous.

Table 19 Schedule Horizon Percentiles

		Percentiles						
		5	10	25	50	75	90	95
Weighted Average(Definition 1)	Schedule Horizon (in days)	.0077	.0223	.0993	.8006	3.3624	5.5250	6.6090

Figure 36 Average Schedule Horizon by Activity Categories

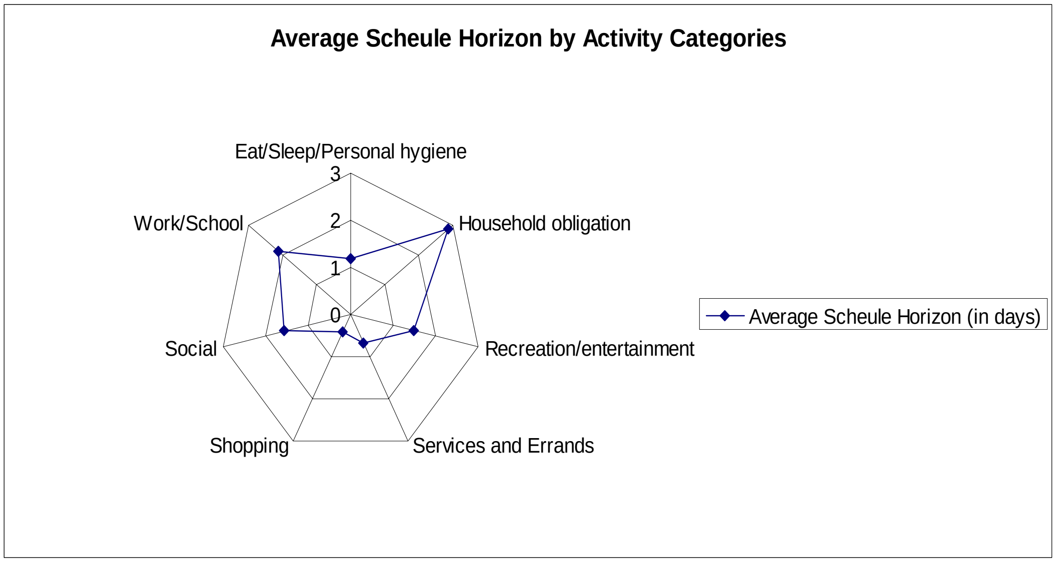
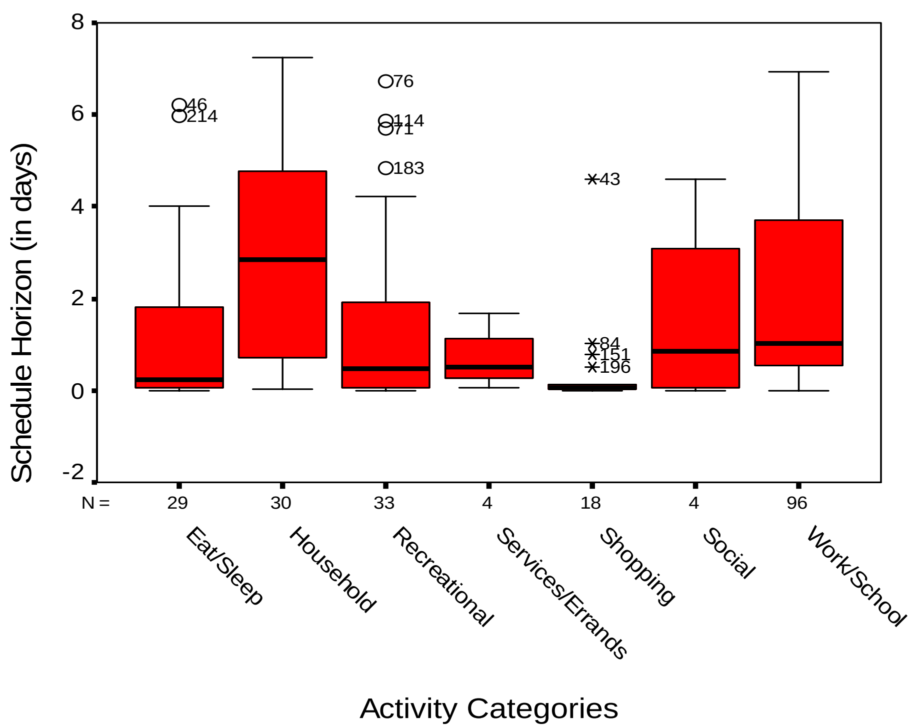


Figure 37 Box Plot on Schedule Horizons by Activity Categories



To analyze the relationship between the schedule horizon and activity coupling conditions, the data were separated according to whether or not a participant is accompanied during the activity. Descriptive statistics (Table 20) show the mean values and standard deviations of the schedule horizons for “alone” activities and “coupled” activities. The ANOVA analysis (N 211, F 0.036, Sig. 0.85) did not reveal any significant schedule horizon difference between them. However, as shown in Figure 38, if the activity-derived travel is subject to coupling constraints (i.e., carpool travel), the mean value and spread of the schedule horizon are more restricted. In addition, activities that require no travel possess a wider spread of schedule horizon than do those that require travel (Figure 39). This indicates that coupling constraints in travel relate to the flexibility of scheduling time to a greater extent than do those in activities.

Table 20 Comparison of Schedule Horizon for Activities with Different Participants

Participant Type	Mean of Schedule Horizon	N	Std. Deviation
Alone	1.8065	131	2.01693
Coupled	1.8626	80	2.22799
Total	1.8275	211	2.09331

ANOVA Table

			Sum of Squares	df	Mean Square	F	Sig.
Schedule Horizon * Activity Coupling	Between Groups	(Combined)	.158	1	.158	.036	.850
	Within Groups		933.195	209	4.402		
	Total		933.353	210			

Figure 38 Box Plot on Schedule Horizons by Travel Modes

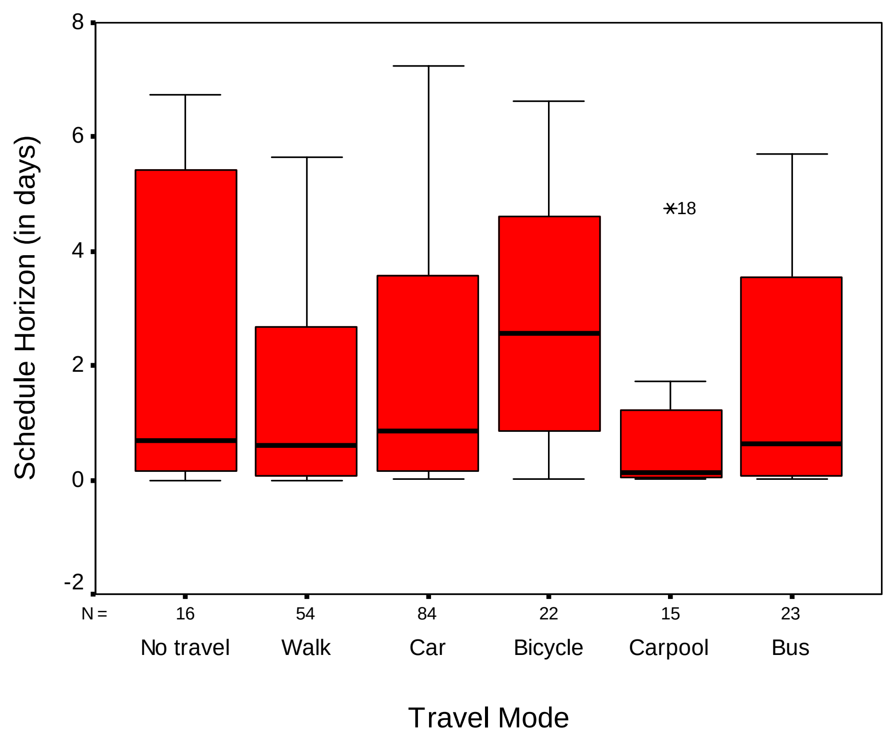
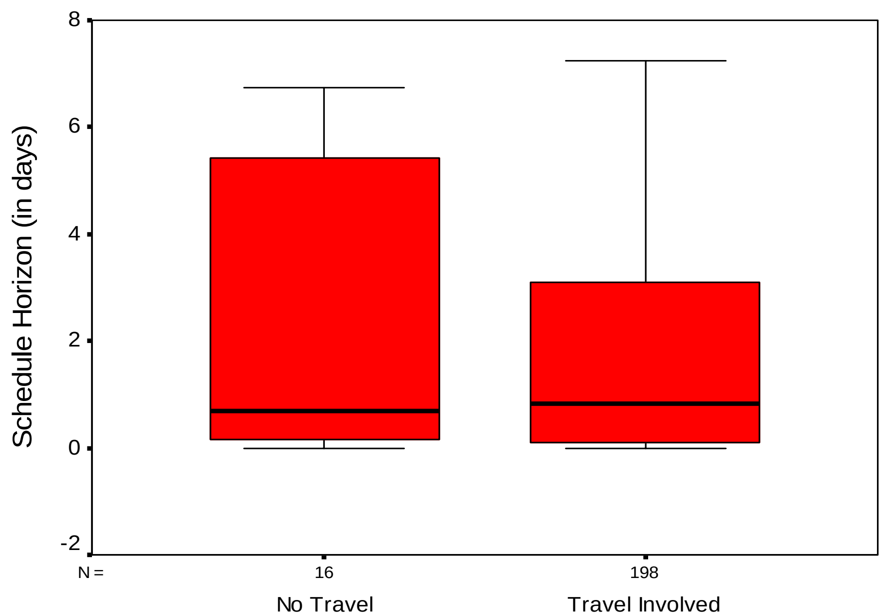


Figure 39 Box Plot on Schedule Horizons by Activity Travel Needs



As for the schedule horizon variation across genders, there is no significant difference (ANOVA, sig. 0.115, Table 21) found between female and male participants, although the mean schedule horizons of the females (2.1976) is a little longer than those of males (1.6899) (Figure 40). This may be due to the tendency of females to take more caution when it comes to making activity arrangements.

Table 21 ANOVA of Schedule Horizons by Gender

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10.901	1	10.901	2.505	.115
Within Groups	922.452	209	4.351		
Total	933.353	210			

Figure 40 Box Plot on Schedule Horizons by Gender

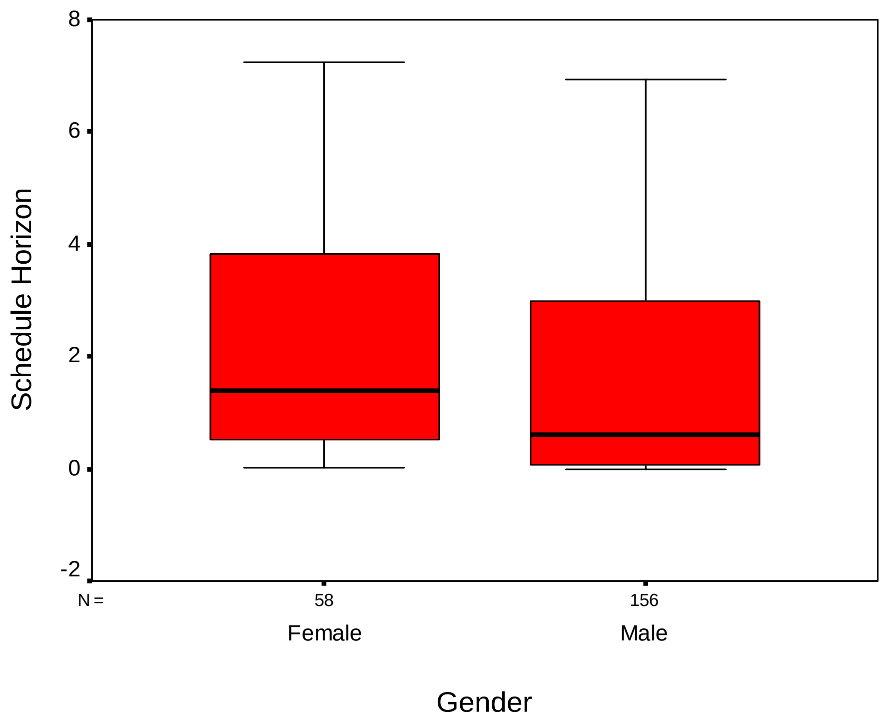


Figure 41 shows a scatter plot of schedule horizons juxtaposed with activity duration. The cases are labeled in different colors by Gender data. Similarly, Figure 42 shows a scatter plot of schedule horizons juxtaposed with travel duration. Both plots reveal that the pattern of schedule horizon relative to travel/activity duration does not vary significantly across gender. However, in both plots data points do cluster around the neighborhood of the (0, 0) corner. This phenomenon suggests that activities with short duration or with short derived travels are less likely to be planned out early. K-Means Cluster Analysis is further used to identify relatively homogeneous groups of cases according to the schedule horizon and activity duration characteristics. As indicated by Figure 43 all the cases are divided among four clusters, with the activity duration contributing more to the separation of groups than the schedule horizon. From the K-Means cluster center table (Table 22), it can be seen that, generally, activities with longer durations are associated with more distant schedule horizons. However, it seems that this association only applies when the activity duration is longer than 3 hours.

Figure 41 Scatter Plot of Schedule Horizon against Activity Duration (labeled by gender)

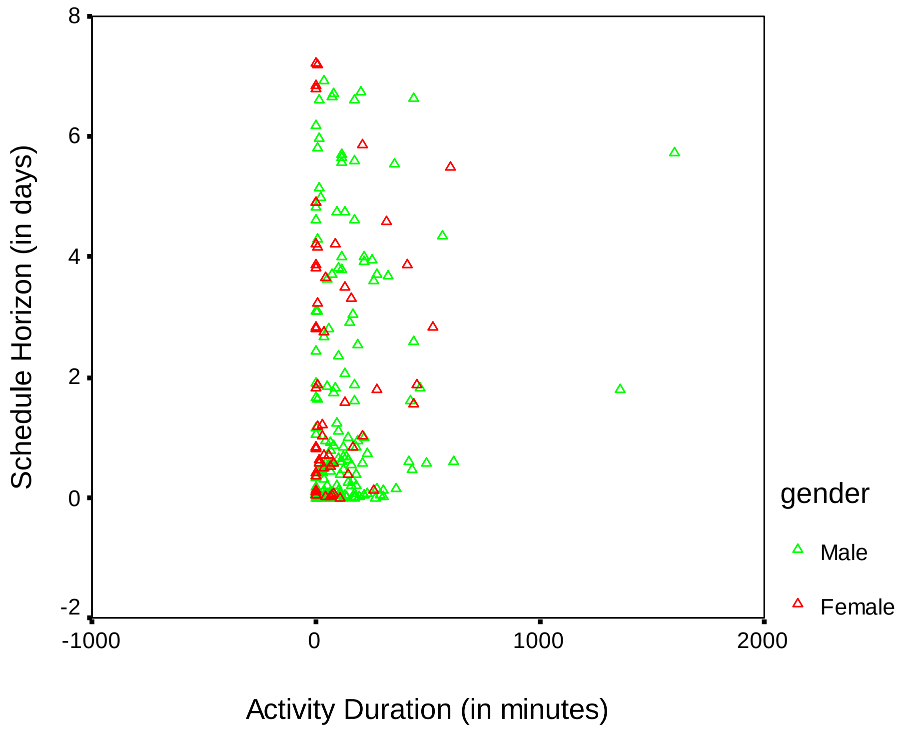


Figure 42 Scatter Plot of Schedule Horizons against Travel Duration (labeled by gender)

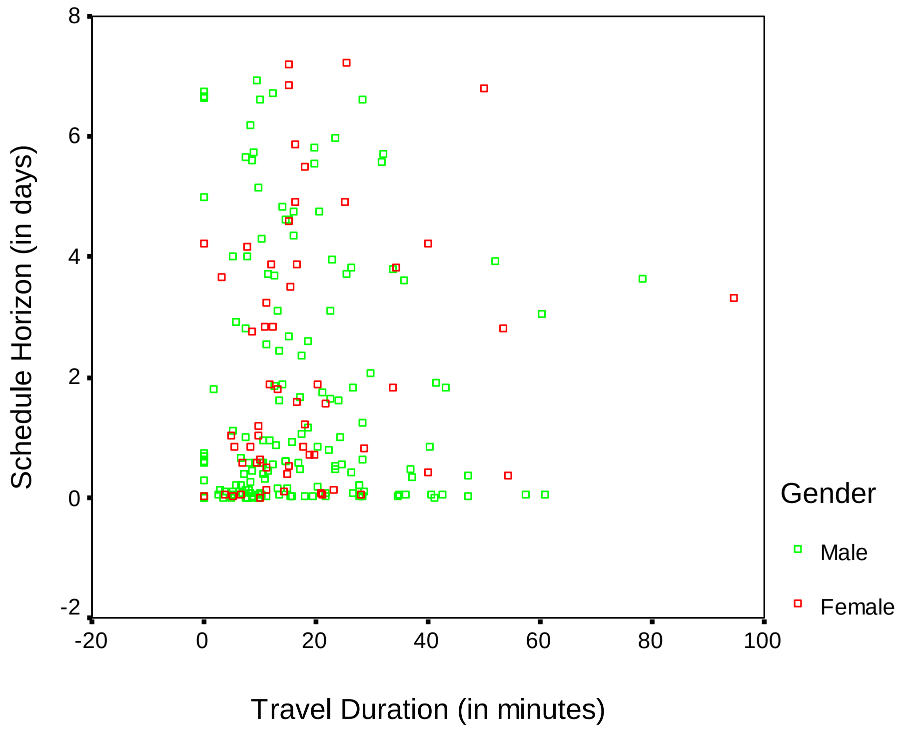
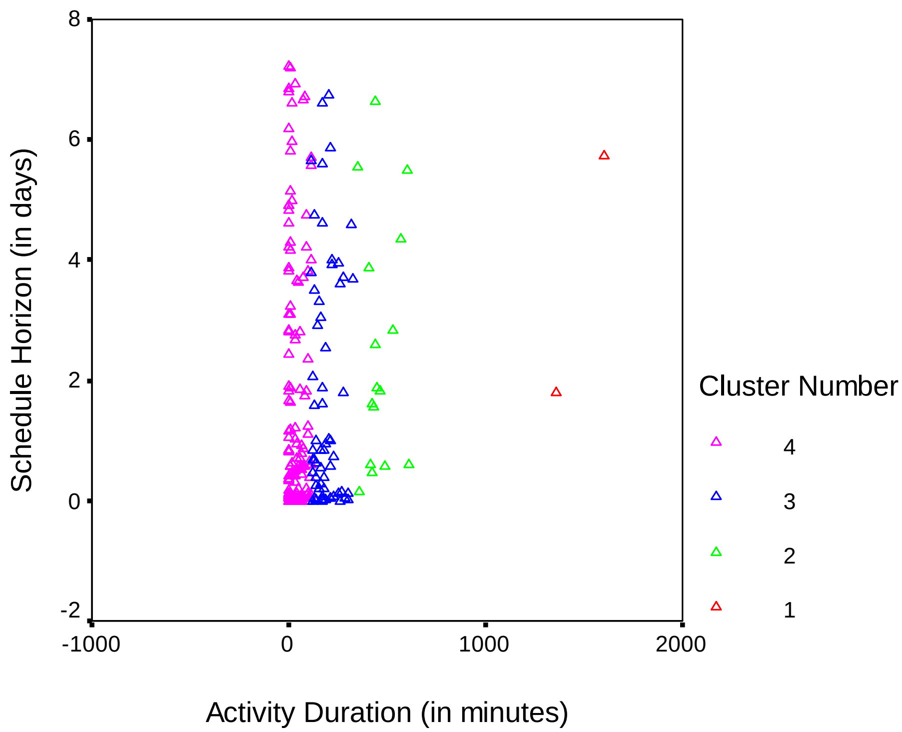


Table 22 K-Means Cluster Centers of Schedule Horizons with respect to Activity Durations

	Cluster			
	1	2	3	4
Activity Duration (in minutes)	1477.47	462.67	189	37.85
Schedule Horizon (in days)	3.77	2.54	1.79	1.73

Figure 43 K-Means Cluster Analysis Result on Schedule Horizons and Activity Durations



5.2.3. Missing Value Analysis on Activity Schedules

Missing value analysis is used to determine the relationship of schedule horizons with respect to the schedule completeness. Using the missing value pattern of schedule start time, end time, date, and location as grouping variables, two-sample *t* tests are conducted against schedule horizon data. The test helps determine if the schedule elements are missing completely at random (MCAR). If so, then other quantitative variables such as schedule horizon should have roughly the same distribution for cases separated into two groups based on value pattern (missing or present). From the following table (Table 23), we can see that the missing of schedule elements was not due to survey fatigue effects or pranks by survey participants. In addition, the t statistics help us compare the means of two groups of schedule horizon data. The table shows that the planned activity with start or end time undetermined tends to be associated with shorter schedule horizons. However, the schedule horizon is significantly longer when schedule location or date is missing than when they are present.

Table 23 T Tests with Groups Formed by the Missing Status of Schedule Elements

		Schedule Horizon (in days)
START TIME MISSING	t	4.3
	df	140.1
	# Present	156
	# Missing	58
	Mean(Present)	2.1424
	Mean(Missing)	.9806
END TIME MISSING	t	4.2
	df	209.5
	# Present	125
	# Missing	89
	Mean(Present)	2.3038
	Mean(Missing)	1.1584
DATE MISSING	t	-6.8
	df	143.7
	# Present	131
	# Missing	83
	Mean(Present)	1.0938
	Mean(Missing)	2.9855
LOCATION MISSING	t	-3.8
	df	38.0
	# Present	183
	# Missing	31
	Mean(Present)	1.5912
	Mean(Missing)	3.2220

For each quantitative variable, pairs of groups are formed by indicator variables (present, missing). Indicator variables with less than 5% missing are not displayed.

In the following tabulated display (Table 24), the missing patterns are further listed with the number of cases with the unique pattern and the corresponding mean values of the grouped schedule horizon data. The column labeled "Complete if" reports the number of complete cases if the variable(s) marked by *X* in that pattern are omitted. Thus, if End Time Missing is eliminated, the number of complete cases increases from 68 to 88; if only the Start Time Missing and End Time Missing are omitted, the number is 119; and, if the three variables (Date Missing, Start Time Missing, and End Time Missing) are removed, it becomes 181. The table further indicates that, in most of the activity schedules, the determination of activity locations is prioritized over other schedule elements (181 complete cases if the other three variables are removed). The schedule element with the next greatest importance would be the scheduled activity date (127 complete cases if the other three variables are removed). The tabulated missing pattern also confirmed the previous analysis result: i.e., an activity schedule with a short schedule horizon tends to have an undetermined start or end time (according to the pattern as shown by row 3 and 7). In comparison, schedules with a long schedule horizon are typically associated with the undetermined activity date (according to the pattern as shown by row 5 and 9).

Table 24 Tabulated Patterns of Missing Scheduling Elements

Row #	Number of Cases	Missing Patterns(a)				Complete if ...(b)	Horizon day(c)
		Location Missing	Date Missing	Start Time Missing	End Time Missing		
1	68					68	1.6513
2	20				X	88	.4171
3	32			X	X	119	.2348
4	30		X			98	2.7505
5	20	X	X			124	4.0085
6	6	X				74	2.1619
7	3	X		X	X	127	.1588
8	21		X	X	X	181	2.1066
9	11		X		X	129	3.2968

Patterns with less than 1% cases (2 or fewer) are not displayed.
a Variables are sorted on missing patterns.
b Number of complete cases if variables missing in that pattern (marked with X) are not used.
c Means at each unique pattern

For each schedule element, a missing indicator variable is also created to indicate whether its value in the schedule record is present or missing. In the following table (Table 25), the percentage of cases in which one schedule element has a missing value and the other element has a non-missing value (Percent Mismatch) is displayed for each pair. Each diagonal element in the table contains the percentage of missing values for a single schedule element. It can be seen that activity locations were planned out well in recorded schedules, while the activity end time tends to suffer the greatest degree of uncertainty. The off-diagonal mismatch statistics shows that activity start time and end time have the lowest mismatch percentage, which indicates that they tend to be missing in tandem.

Table 25 Percent Mismatch of Schedule Elements

	Location Missing	Date Missing	Start Time Missing	End Time Missing
Location Missing	14.49			
Date Missing	33.64	38.79		
Start Time Missing	37.85	45.33	27.10	
End Time Missing	51.40	49.53	15.42	41.59

The diagonal elements are the percentages missing, and the off-diagonal elements are the mismatch percentages of schedule elements.
A: Variables are sorted on missing patterns.
B: Schedule elements with less than 5% missing values are not displayed.

From another perspective, the missing pattern can also be examined in terms of frequency counts for each pair of schedule element variables. In the following table (Table 26), the number of non-missing cases for each schedule element is reported on the diagonal of the table; the sample size for complete pairs of schedule elements is indicated off the diagonal. Only 35 percent of the schedule cases (75 out of 211) have both activity date and end time predetermined together. Less than half of the schedule cases (95 out of 211) have both activity date and start time predetermined together. It seems that half of the time, the time data in activity schedules is incomplete, with at least one level of the time granularity information unplanned.

Table 26 Pairwise Frequencies of Schedule Elements

	Start Time	End Time	Schedule Date	Schedule Location
Start Time	156			
End Time	124	125		
Activity Date	95	75	131	
Activity Location	129	99	121	183

The following tables show the cross tabulations of categorical variables against the missing status of the schedule elements. A table is displayed for each of the categorical variables (gender -- Table 28, travel requirement of the activity – Table 27, and activity categories – Table 29). For each category, the table lists the frequency of non-missing values for the schedule elements in the first row of each pattern variable (for example, in Table 28, of the 156 schedule records that are present, 44 of them are made by female survey participants). The percentage each count of the corresponding sample size is given in the next row (156 is 73.9% of the total 211 schedule records, and 44 is 75.9% of the 58 female schedules). The percentage missing for individual categories can be compared across the different types of missing schedule elements. In the cross tabulation of patterns on activity travel requirement (Table 27), no significant difference in scheduling plans, no matter whether travel is required for the activity or not, is shown. In the cross tabulation of patterns with gender (Table 28), it can be seen that values of schedule date and location in male activity plans are missing to a lesser extent than those of female survey respondents. Combining the result with our previous finding that female's schedules are generally planned out earlier than male's schedules, we may further revise our conclusion regarding male and female' scheduling patterns, i.e., although females tend to lay out the events in their activity plan early, their plans are relatively incomplete in terms of location and time details. Lastly, the missing patterns of scheduling elements are cross-tabulated with activity categories. In Table 29, different activity categories present various degrees of scheduling flexibilities along the projected temporal-spatial paths. For the Work/School and Household Obligation activity types, it shows that the activity date is the least planned-out schedule element, while activity start time has usually been determined beforehand. For the Shopping activity type, both activity start and end time are often missing from activity schedules, which indicates that, within the pre-determined activity location and date framework, shopping activity is generally spontaneous. For Recreation/Entertainment and Eat/Sleep/Personal Hygiene activity categories, activity location turns out to be the element missing the least in the activity schedules. For Service/Errands activities, activity location and start time are planned with full details, in accordance with the authority constraints enforced by the activity locations which provide the needed services. For Social activities, the schedule elements are rarely missing except for the activity end time, which indicates that social activity plans are typically well defined ahead of time, except that the activity duration is left open ended.

Table 27 Analysis of Scheduling Missing Element by Travel Requirement of the Activity

			Total	Travel Needed	Travel Not Needed
Start Time Missing	Present	Count	156	53	103
		Percent	72.9	75.7	71.5
	Missing	% SysMis	27.1	24.3	28.5
End Time Missing	Present	Count	125	42	83
		Percent	58.4	60.0	57.6
	Missing	% SysMis	41.6	40.0	42.4
Date Missing	Present	Count	131	44	87
		Percent	61.2	62.9	60.4
	Missing	% 0	38.8	37.1	39.6
Location Missing	Present	Count	183	59	124
		Percent	85.5	84.3	86.1
	Missing	% SysMis	14.5	15.7	13.9

Indicator variables with less than 5% missing are not displayed.

Table 28 Analysis of Schedule Missing Elements by Gender

			Total	Female	Male
Start Time Missing	Present	Count	156	44	112
		Percent	72.9	75.9	71.8
	Missing	% SysMis	27.1	24.1	28.2
End Time Missing	Present	Count	125	32	93
		Percent	58.4	55.2	59.6
	Missing	% SysMis	41.6	44.8	40.4
Date Missing	Present	Count	131	29	102
		Percent	61.2	50.0	65.4
	Missing	% 0	38.8	50.0	34.6
Location Missing	Present	Count	183	45	138
		Percent	85.5	77.6	88.5
	Missing	% SysMis	14.5	22.4	11.5

Indicator variables with less than 5% missing are not displayed.

Table 29 Analysis of Schedule Missing Elements by Activity Categories

			Total	Work/School	Household obligation	Shopping	Recreation/ Entertainment	Errands and Services	Eat/Sleep/Personal Hygiene	Social
START TIME MISSING	Present	Count	156	84	24	5	18	4	17	4
		Percent	72.9	87.5	80.0	27.8	54.5	100.0	58.6	100.0
	Missing	% SysMis	27.1	12.5	20.0	72.2	45.5	.0	41.4	.0
END TIME MISSING	Present	Count	125	73	15	4	14	2	14	3
		Percent	58.4	76.0	50.0	22.2	42.4	50.0	48.3	75.0
	Missing	% SysMis	41.6	24.0	50.0	77.8	57.6	50.0	51.7	25.0
DATE MISSING	Present	Count	131	60	10	16	22	3	16	4
		Percent	61.2	62.5	33.3	88.9	66.7	75.0	55.2	100.0
	Missing	% 0	38.8	37.5	66.7	11.1	33.3	25.0	44.8	.0
LOCATION MISSING	Present	Count	183	80	21	15	31	4	28	4
		Percent	85.5	83.3	70.0	83.3	93.9	100.0	96.6	100.0
	Missing	% SysMis	14.5	16.7	30.0	16.7	6.1	.0	3.4	.0

Indicator variables with less than 5% missing are not displayed.

5.3. Logit Modeling Results of Activity Participation and Start Time Choices

In this research, with the availability of convenient software, SAS function – MDC -- is used to estimate the suggested two-level nested logit model A. The parameter coefficients β, γ, and τ are estimated using a maximum likelihood method. Due to the data requirement of the MDC procedure that a data case should exist for each possible choice alternative, the common set of explanatory variables -- A_{aps} -- is specified for the utility functions at each level of the decision tree. The "Activity type" variable is transformed into 7 dummy variables (value 0 and 1) to represent each of the activity categories. However, most of the variables in the set show nearly no effects on the utility functions of the model (with a p value of 1). After eliminating these redundant covariates, we only have two explanatory variables "Total work/school time duration" and "Schedule horizon" included in the final model construction. Table 30 shows the estimate results of the proposed nested logit model.

Table 30 NLM Estimation Result for Activity Schedule and Execution Nested-logit Model A

The MDC Procedure					
Nested Logit Parameter Estimates					
Parameter	DF	Standard Estimate	Error	Approx t Value	Pr> |t|
WORKTOTA_L1	1	0.003577	0.001507	2.37	0.0176
HORIZON_L1	1	0.001661	0.00791	0.21	0.8337
INC_L2G1C1	1	1.003	0.0791	12.68	<.0001
INC_L2G1C2	1	0.9975	0.0771	12.93	<.0001

The result offers some behaviorally plausible interpretations. Only the "Total work/school time duration" variable is statistically significant (5% level) in this model. Its coefficient affects the utility of the survey respondent for the chosen alternative, which either reduces or increases at the rate based on the value of the coefficient. The variable estimate depicts a positive sign indicating that the choices of activity participation and start time become irrelevant as the importance of the attribute decreases. The order of the coefficient (0.0036) corresponds to the order of the marginal effects of the choice probabilities.

Table 30 also shows the estimates for the inclusive value parameter -- INC_L2G1C1 and INC_L2G1C2. The inclusive value coefficient estimate of the nest comprising the activity start time choice is 1.003, while that for the nest comprised of activity participation decisions is 0.9975. Generally, for nested logit modeling, the value of this parameter should vary between 0 and 1. The extreme value 1 implies that the nested structure actually collapses to a multinomial logit model (MLM). To further explore the influence of the socioeconomic variables and various schedule/travel/activity attributes on activity schedule/execution choices in details, we continue to model the three discrete levels of activity start time choices under a MLM framework. Besides the attribute set $A_{aps,}$ Activity start time related characteristics -- A_{as} – are also incorporated into an independent covariate vector for building the model. The CATMOD procedure in SAS is used to fit the multinomial model. Those significantly irrelevant variables were eliminated from the input parameters list of the procedure via a couple rounds of model filtering process. By defining two generalized logit equations, the CATMOD procedure estimates the effects of the covariate vector on the log odds of two choice levels against the third one. Parameter estimations are simultaneously derived by maximum likelihood (ML). From the parameters of these two equations, it is possible to derive effects of unit changes in independent variables on the probability of each of the three outcomes. Table 31 shows the estimation results of the preliminary MLM model.

Table 31 Preliminary MLM Likelihood Estimation Results for Activity Start Time Choice

Maximum Likelihood Analysis of Variance			
Source	DF	Chi-Square	Pr > ChiSq
Intercept	2	6.17	0.0458
WORKTOTA	2	5.3	0.0707
TRAVELDU	2	9.33	0.0094
ACTIVI5	2	0.96	0.6201
BELIEFTR	2	6.73	0.0346
OFFRATIO	2	13.54	0.0011
INTERSEC	2	1.05	0.5912
HORIZON	2	3.1	0.2126
TRAPEAK	2	5.08	0.0788
WORKSCHO	2	12.65	0.0018
STARTMIS	2	4.59	0.1006
ENDMIS	2	9.42	0.0090
DATEMIS	2	3.63	0.1628
Likelihood Ratio	300	613.99	<0.0001

From the modeling results, it appears that “Travel duration”, “Travel distance”, “The ratio of Off-road travel”, “Work/School activity type” and “End time missing” are the significant factors that affect the activity start time choices at the significance level of 0.05. “Total work/school time duration” and “Is Travel during Peak Time” is suspected to be important in explaining the start time choices. Based on the preliminary result the model was refit using only the 7 covariates mentioned above. Now the covariates includes in the model are nearly all significant at the level 0.05 based on the Wald test (Table 32), except the “Is Travel during Peak Time” variable. This implies that these variables do have an effect on the activity start time choice.

Table 32 MLM Likelihood Estimation Results for Activity Start Time Choice with Reduced Covariate Set

Maximum Likelihood Analysis of Variance			
Source	DF	Chi-Square	Pr > ChiSq
Intercept	2	14.53	0.0007
WORKTOTA	2	7.79	0.0204
TRAVELDU	2	8.31	0.0157
BELIEFTR	2	8.49	0.0143
OFFRATIO	2	16.77	0.0002
TRAPEAK	2	5.7	0.0580
WORKSCHO	2	14.61	0.0007
ENDMIS	2	16.42	0.0003
Likelihood Ratio	312	627.06	<0.0001

Table 33 shows the intercepts and the parameter estimation for the two equations predicting the log odds of "activity starts on time versus other" and "activity start early versus other" respectively. From the parameters of these logistic equations, it is possible to derive the effects of unit changes in independent variables on the probability of each of the activity start time choices with some simple calculations. These effects are, by the nature of the logistic linking function, non-linear. The literal interpretations to those significant parameter estimates are listed below:

1. Given the same status of the other variables, for each 10 minutes increase of work/study duration, the odds of activity start on time decreases by 1- exp(-0.0002 *

10) = 0.02% and the odds of activity start early decrease by 1-exp(-0.00003 * 10) = 0.03%.

2. Given the same status of the other variables, for each 10 minutes increase of travel duration, the odds of activity start on time decrease by 1- exp(-0.00035 * 10) = 0.35% and the odds of activity start early decrease by 1-exp(-0.00118 * 10) = 1.17 %.

3. Given the same status of the other variables, for each 1 mile increase of travel distance, the odds of activity start on time decrease by 1- exp (0.12 * 1) = 12.7% and odds of activity start early decrease by 1- exp (0.2 * 1) = 22.1 %.

4. Given the same status of other variables, for each 0.05 percent increase of off-road travel ratio, the odds of activity start on time decrease by 1-exp (1.38 * 0.05) = 7.14%.

5. Given the same status of other variables, the odds of activity start on time for travelers who travel during non peak time is exp (0.2762) = 1.32 times greater than those who travel during peak time.

6. Given the same status of other variables, the odds of activity start on time for non-work/school activity pursuit is exp (- 1.544) = 0.21 times of that for work/school activity pursuit.

7. Given the same status of other variables, the odds of start activity on time for activities with end time fully planned is exp (-0.225) = 0.8 times of that for activities with end-time element missing in their schedules, while the odds of activity start early for activities with end time fully planned is exp (-1.53) = 0.22 times of that for activities with end time element missing in their schedules.

Table 33 MLM Parameter Estimation Results for Activity Start Time Choice with Reduced Covariate Set

Analysis of Maximum Likelihood Estimates						
Parameter		Function Number	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept		1	0.822500	0.294300	7.81	0.0052
		2	-1.704100	0.926300	3.38	0.0658
WORKTOTA		1	-0.000020	0.000006	7.31	0.0069
		2	-0.000030	0.000025	1.29	0.2569
TRAVELDU		1	-0.000350	0.000133	6.73	0.0095
		2	-0.001180	0.000746	2.49	0.1145
BELIEFTR		1	0.120200	0.044300	7.36	0.0067
		2	0.200000	0.091600	4.77	0.0290
OFFRATIO		1	1.384200	0.357400	15.00	0.0001
		2	0.023800	0.928100	0.00	0.9795
TRAPEAK	0	1	0.276200	0.122000	5.12	0.0236
	0	2	-0.040200	0.342200	0.01	0.9065
WORKSCHO	0	1	0.061900	0.118600	0.27	0.6020
	0	2	-1.544200	0.430500	12.87	0.0003
ENDMIS	0	1	-0.225100	0.124700	3.26	0.0709
	0	2	-1.530400	0.386700	15.66	<0.0001

Due to the limited data coverage, the logit model constructions tested here are not comprehensive enough to cover all the potential factors that affect the congruence relationship between activity schedules and their executions, e.g. the in-home versus out-of-home activity substitution. However, it does provide us a practical and convenient way to explore the deviation of activity participation/start time from the activity plans given the standard socioeconomic variables and various schedule/travel/activity attributes. With the help of the SAS statistical procedures, the nested logit model we tested offered us the particular insight that the daily work-study time duration significantly affects the activity participation and activity start time choice in the behavioral paradigm as represented by the postulated nest structure. This finding, although coarse in terms of its resolving power in predicting people's behavioral patterns with respects to their schedules, is consistent with our empirical expectation base on the real-life experience. The further multinomial logit analysis not only reveals the moving direction of the probability associated with a certain activity start time choice with respect to the variation in the activity/travel scenarios, but also allows us to defer the corresponding quantitative measures for such changes. These identified influencing factors from the model explicitly imply the effects of limited spatial and temporal flexibility to the activity schedule realization.

Chapter 6 Conclusion

6.1 Summary

This research conceptualized and implemented a real-time system tool that facilitates the study of the dynamic linkages between the activity scheduling and execution process at an individual level. The survey methodology opens the opportunity for researchers to gather information on the integral scheduling and activity execution process by means of empirical data collection and to model the relationship between them. This research contributes to the progress of the current computer-assisted travel/activity survey practices from two perspectives: on one hand, schedule/travel/activity data is collected in real time which is similar to the traditional paper-pencil-based approach, but overcomes its deficits such as limited storage capacity and linear survey format; on the other hand, with the multi-modal interface designed for the mobile computing device, especially with the enhanced voice capabilities, the silent machine is endowed with its own personality and limited intelligence. Ideally it would be treated more equally as an experienced "human" interviewer by the survey respondents in their role interpretation but without arousing the concerns of privacy invasion. Thanks to the reduced size and detachment of the computing device with a fixed location power supply (either an inwall socket or a car cigarette lighter), scheduling/travel/activity data collection with this system are broadened to encompass more travel modes and enlarged activity scopes. The small-scale pilot study by this research showed that the methodology was successful in achieving our goals without incurring significant survey fatigue effects. At the current development stage, it is not practical to expect the approach to be applied to a large sample base due to the advanced technology integrated in the survey device and its limited acceptance to specific population subgroups. Nevertheless, the unique approach did show clear potential in complementing the survey data from large-scale household travel/activity surveys, and, particularly, promoting our understanding of the role of dynamic activity scheduling processes in shaping the observed travel/activity pattern as derived from a traditional travel/activity survey.

As the second part of the research, the data provided by the system via the pilot survey were used for an in-depth analysis of the routing behavior, scheduling pattern of various activity categories and the inter-relationship between scheduling and correlated activity execution. With the advantage of full coverage of the spectrum of travel modes and site-to-site travel traces, the research revealed the varying routing behavior on gender, travel distance, different travel modes and activity categories. To summarize, Male travelers tend to choose a travel path that is relatively time-optimized compared to female travelers, while as the travel distance on a route increases, travelers will shift their routing aim toward time-optimization rather than distance optimization. For labor-consuming travel modes, shortest time and distance paths tend to coincide with each other, and the shortest-distance paths are favored a little more. As for the other types of travel modes, travelers generally prefer to take routes that approximate the shortest time. With regards to activity categories, the shortest time route seems to be favored more than the shortest distance route in types of activities with clear objectives and immediate demands such as Eat and Recreation/Entertainment activity type, while the activity categories with potential mixed activity needs tend to be associated with relatively deviated travel routes from the optimized ones.

The research also shows that scheduling behavior doesn't associate with each type of activity in an equivalent way. Among the seven activity category division used in this research, Recreation and Entertainment activities turned out to be the most actively scheduled, while Household Obligation activities are least planned before execution. Even with planned activities, scheduling horizons are significantly different. Shopping activities and Services and Errands activities on average entail a relatively short schedule horizon, while activities with longer durations are associated with more distant schedule horizons (when the activity duration is longer than a half day). In terms of projected temporal-spatial attributes in activity schedules, activity locations typically are planned out well, while the activity end time tends to suffer the greatest degree of uncertainty, although activity start time and end time tend to be missing in tandem. Scheduling horizon time scale, obviously, to a certain extent affects the details of the activity plans. Planned activities with start or end times undetermined are usually associated with shorter schedule horizons. In comparison, the schedule horizon is significantly longer when schedule location or date is missing than when they are present. For each type of activity, different scheduling elements tend to be emphasized in their activity plan. For Recreation/Entertainment and Eat/Sleep/Personal Hygiene activity categories, activity location turns out to be the element missing the least in the activity schedules. For Service/Errands activities, activity location and start time are planned with full details, in accordance with the authority constraints enforced by the activity locations which provide the needed services. As for Social activities, the schedule elements are rarely missing except for the activity end time, which indicates that social activity plans are typically well defined ahead of time, except that the activity duration is left open-ended.

Besides the commonly recognizable factors that influence the congruence relationship between activity scheduling and execution, the research revealed an additional factor -- the percentage of “Off-Road” travel, which may potentially affect activity participation decisions in a significant way. The percentage of “Off-road” travel to a certain extent represents the accessibility of the activity location to the activity pursuers as the uncertainty of an activity execution mostly lies in the travel portion covered by the slowest travel mode used to reach the site. As shown in the research, the percentage of off-road travel is the highest for the Work/School activity category, as many areas of the campus are not accessible to the motor vehicles. In contrast, Shopping on average only cover a small distance of “minor” roads, mostly thanks to the convenience brought by the purposely designed parking facilities of the shopping malls.

Using a nested logit modeling approach, the research was able to identify the single factor that dominates the activity participation and start time choice decision making. The choices of activity participation and start time become irrelevant as the importance of the “Total work/study duration” decreases. The further one-level multi-nomial logit modeling efforts identified five factors --“Travel duration”, “Travel distance”, “The ratio of Off-road travel”, “Work/School activity type” and “End time missing” that affect the activity start time choices at a significant level. These identified influencing factors from the model explicitly imply the effects of limited spatial and temporal flexibility to the activity schedule realization. The modeling results even offer us the quantitative measures for effects of the factor changes on activity start time choices. Similar models could be conducted on the activity location choices and duration choices.

6.2 Future Research

6.2.1. Improve the current data collection system

As shown by this research, the biggest challenge to real-time activity/travel survey systems, in comparison to the passive data collection practice, is the conflict between the time constraints implied by the survey participant's daily activity agenda and the time cost to input the data in real time. In the short term, several improvements are worth considering as an interim means for enhancing the usability, duration and reliability of the system:

1. Reduce the load of the survey task. To reduce the load on the participants' part, certain intelligent controls can be integrated to allow device carriers to selectively skip certain questions and provides the answers later. In addition, secondary information regarding activity or schedules could be gleaned from other information channels or bypassed entirely.
2. Provide effective survey guidance. The consecutiveness of relation information such as survey procedure and input sequence could better be presented with pictures or picture sequences, as a referral base enabling the survey participants to remind themselves of how to proceed with the survey.

3. Enhance the multi-task mode of the survey program. Currently, the survey program only allows concurrent activity and scheduling tracking. In the case when travel occupies a significant portion of out-of-home time use, the lack of the multi-task capability provides no guarantee about the real-time recording of activity scheduling data. The concurrent working mode should be further extended to travel tracking.

In the long term, we may further consider delegating the task of activity/travel attribute collection to a recall session. By combining the active scheduling data collection with passive activity/travel attribute retrieval in a balanced manner, the survey protocol holds out considerable promise in providing deep insights into the relations between the dynamic activity planning process and the resulting travel/activity pattern in an accurate, reliable way. It would also be interesting to compare instrument bias and survey burden brought by the system with traditional activity/travel data collection methods. Further improvement on duration and reliability of the system potentially endows the activity/travel researchers with a powerful tool to enlarge the data bases for the longitudinal trends of activity/travel pattern changes.

6.2.2. Further Modeling efforts

As mentioned in the previous section of this dissertation, two other options exist for building the activity scheduling -execution model with the empirical observation on how activity scheduling and execution actually evolve concurrently in real-life situations. These different forms of model construction could provide a different perspective in testing our research hypotheses mentioned, in terms of how spatial–temporal constraints, household characteristics and other constraints (such as substitution) affect the scheduling, rescheduling of people's daily activities and their actual implementation.

6.2.2.1. Artificial Neural Network (ANN) Modeling

The artificial neural network (ANN) provides us a method to learn and approximate the relationship between activity scheduling and activity execution status with a discrete-valued function in the form of a network of interconnected neurons. Derived from the analogy of human brain construction, ANN performs well in modeling the phenomena whose natural working mechanism is not fully understood (e.g. speech recognition). It is widely known that human behavior is sometimes "fuzzy" in the sense that people could make different choices under the same circumstance. This is the case for the inconsistency between the intended schedule and the observed real-life activity-travel pattern. ANN to a certain extent serves the purpose here in terms of its modeling capability for complicated phenomena.

The neurons that compose the ANN system can be one of two forms, Perceptron and Sigmoid (Mitchell, 1997). Perceptron units combine the inputs to them linearly and output a two-level result (0 and 1) according a threshold setting. They are mostly used for the modeling of linearly separable phenomenon. Sigmoid is similar to Perceptron with respect to the handling of the inputs but goes one step further to feed the linear combination through a logit function: $1/(1 + e^{-y})$ (in which y is the linear combination of the inputs). Therefore, the output of Sigmoid is continuous rather than discrete in comparison to that of Perceptron. With a wider output range, sigmoid is more powerful in interpreting complicated causal relationships.

In the potential ANN modeling of activity scheduling and execution status, Sigmoid will be the chosen neuron units that compose the ANN network. The whole network consists of three layers. The first layer accepts the 21 attribute inputs as listed in table 1. The input layer, one hidden layer and one output layer are connected in a feed-forward way. The links between different layers are complete (any neuron in one layer is connected to every neuron in the other layer). Five output units in the output layer represent each of the activity execution status – on time, early, late, deleted from schedule, and postponed. A back propagation algorithm can be used for estimation of the weights on the links in the network based on training data (Mitchell, 1997). For testing the validity of network weights and avoiding the overfitting problem, only two-third of the entire activity scheduling and execution status data set will be used for model estimation. The other one-third can be used for determining the best timing to terminate the back propagation algorithm.

6.2.2.2. Learning Tree Modeling

Decision tree modeling in essence is a learning method that infers the hierarchical decision structure from the training data by induction with no prior model-structure assumption made. The learned tree representation can be easily transformed into a set of disjunctive decision rules in the form of condition-action pair used in CPM models. Therefore this approach has been used in ALBATROSS (Arentze and Timmermans, 2000) to derive the sets of heuristic rules from empirical activity-travel data for intermediate stepwise decision-makings in the model.

The well-known decision tree learning algorithms that have been used widely are ID3, ASSISTANT, C4.5, CART and CHAID (Mitchell, 1997). C4.5, CART and CHAID (Kass, 1980) are the decision-tree learning algorithms tested in the ALBATROSS transportation simulation system (Arentze and Timmermans, 2000, Arentze, et al. 2000) for the derivation of heuristic decision rules. Each of the algorithms works its way from the construction of a root node of the decision tree to the leaf node where instances within the same category are captured. The nodes in the tree represent the attributes of the instances being examined for each level of classification decision. The training instances are allocated along the branches according to their associated attributes values. It is conceivable that the number of possible decision tree structures grows rapidly with the number of attributes to examine for the classification and the tree sizes could vary in magnitudes. Therefore, these decision-tree learning algorithms have the mechanism to bias the tree construction process in favor of smaller, shorter trees than bigger, higher ones with the assumption that simple theory that explains the data is better. In ID3, the order of the attributes to be examined is based on an entropy measure, which "characterizes the (im)purity of an arbitrary collection of examples" (Mitchell, 1997). The chosen attribute at each decision step is expected to reduce the information entropy contained in the current instance classification to a maximum extent. C4.5 (Quinlan, 1993) was developed based on ID3, but extends the ID3 algorithm in some aspects (e.g. missing attribute and continuous attribute value handling). Different from ID3 and C4.5, CHAID chooses the attribute that "maximizes the significance of a chi-squared statistic" at each instance-branching step (Kass, 1980, pp 119). In addition to select the best attribute that partitions the current subgroup at each step, CHAID includes a recursive split-merge sub-module to search for the best possible data segmentation for each attribute.

To use a decision tree for activity schedule and execution status modeling, the data need be grouped into vectors that consist of the attributes and the associated target classification value. The attributes would be the causal factors as previously identified in table 1, while the possible deviation of activity execution from activity schedule (on time, late, early, deleted from schedule and postponed) serves as the discrete classification value. Note that the value of some attributes in table 1 are in continuous range (e.g. travel distance) and thus need to be discretized into adjacent intervals when ID3 or CHAID algorithm are used (these algorithms can't handle the attribute with continuous value). The decision tree induction algorithm offers a hierarchical organization of different causal factors that indicates the variation of the significance levels associated with these factors in the human decision-making process. It can be interpreted as the decision dependence relationship or the priority difference among the activity-travel attributes in activity scheduling (execution) consideration. This information potentially can be used to provide the guidance for the nested-logit model construction. Similar to ANN modeling, the learned decision tree via training data needs to be validated against a test dataset for examining its generality. To avoid the overfitting problem, a post-pruning method is commonly used to examine and replace some sub-trees contained in the learned decision tree with a single leaf node for improving the decision tree predicting performance.

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Appendix A

The information collected in the activity scheduling/execution survey is organized in the following SQL database tables. First row in the table indicates the table's name. For the rows other than the first, the first column indicates the attribute name for each record in the database table; the second column indicates the data type of the attribute.

1) Nvarchar(n) --- variable length of string with the maximum length of n.

2) Bit – boolean variable with only two possible values (true or false).

3) Identity Integer – Auto incremented integer ID by database.

4) Datetime --- time data type that specifies date and time.

Contact	
personID	Reference to the personID field in person table.
Phone	Nvarchar(10)
Email	Nvarchar(30)

Person	
personID	Random number generated between 1-500000
First Name	Nvarchar (20)
Last Name	Nvarchar (20)
Gender	Bit
Age	Integer
Driver's License	Bit
Education	Integer
Income	Integer
Vehicle Access	Bit

TransportMode	
PersonID	Reference to the personID field in Person Table
Undisclosed	Bit
Walk	Bit
Carpool	Bit
Vanpool	Bit
Car	Bit
Bus	Bit
Bicycle	Bit

ActivityType	
ActivityID	Identity Integer
ActivityClass	Nvarchar(50)
ActivityName	Nvarchar(50)
Selected	Bit
UserDefined	Bit

Places	
placeID	Identity Integer
Place Name	nvarchar (60)
Latitude	Float
Longitude	Float
Street Address	nvarchar (60)
City	nvarchar(30)
Zip	Nvarchar(5)
State	Nvarchar(20)
UserDefined	bit
personID	Reference to personID field in table Person

Schedule	
sActivityID	Identity integer
ActivityID	Reference to activityID field in Activity type table
LocationID	Reference to the PlaceID in table places.
Day	datetime
Weekday	integer
Start Time	Datetime
End time	Datetime
Accompanies	Integer

Implement Activity	
iActivityID	Identity integer
sActivityID (could be null)	Reference to sActivityID field in table Schedule
ActivityID	Reference to the activityID field in table Activity Type
locationID	Reference to the PlaceID field in table places
Day	datetime
Weekday	integer
TravelMode	Integer
Accompanies	integer
TravelStartTime (could be null)	datetime
TravelDuration (could be 0)	integer
ActivityStartTime	Datetime
ActivityDuration	integer

ImplementActivityInfo	
iActivityID	Reference to iActivityID field in implementActivity Table
Precipitation	Integer
Skycondition	Integer
Wind	Integer
Temperature	Integer
TrafficAware	Integer
TrafficReal	Integer
ServiceStart	Datetime
Serviceend	Datetime
Withdrawal	Bit
Priority	Integer

UnfulfilledActivityInfo	
sActivityID	Integer reference to the sActivityID field in table Schedule
Precipitation	Integer
SkyCondition	Integer
Wind	Integer
Temperature	Integer
TrafficAware	Integer
ServiceStart	Datetime
ServiceEnd	Datetime
Withdrawal	Bit
Priority	Integer
Forget	Bit
LackofCondition	Bit

ImplementStatus	
Start	Integer
Duration	Integer
Location	Integer

iActivityID	
Longitude	Float
Latitude	Float
Fix	Integer

Note: the table could have multiples instances. The total number of the instances depends on how many trips are made during the survey.

Appendix B

A Three-step General Map Matching Method in the GIS Environment: Travel/Transportation Study Perspective

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Abstract

Despite its application in many fields, map matching in travel/transport geography study is unique in two aspects: 1) The correct road links traversed by the traveler need to be unambiguously identified; 2) All the identified links should form a meaningful travel route. This paper discusses the application of map matching methodologies in the context of deriving people's travel behavior from GPS-traced multi-modal trip data within the GIS environment. In recognition of the disadvantages associated with the existing map-matching algorithms, this research proposed and implemented in ARCGIS a heterogeneous map matching approach suitable for travel/activity research needs which is uniquely characterized by: 1) data preprocessing with point cluster reduction and density leverage; 2) offering the candidate solution within a pool of "the best"; 3) the balancing of matching results from multiple matching factors with rank aggregation; 4) Intelligently utilizing the basic network constraint attributes with "expert rules" to increase the matching accuracy; and 5) Dempster belief test to discern the noise and off-road travel. Our analysis has shown that the performance of the new algorithm is comparable with the others when the candidate pool size is small and network/GPS trace size is large. Further research needs to quantify the performance of this algorithm and others with respect to a complete set of survey travel routes recorded.

1. Introduction

Map matching is defined as the process of correlating two sets of geographical positional information (e.g., GPS records of object positioning versus road network, digital road networks from different vendors, etc.). Data types handled by map matching include point-to-line, line-to-line (Xiong, 2000) and polyline to polyline matching. Based on the temporal-response characteristics, map matching algorithms can also be roughly classified into online map-matching and off-line map-matching. Online map-matching methods snap the device-captured geo-spatial feature position to the base reference in real-time. Offline map-matching counterparts post-snap the point data/linear data after the whole set of data is collected (Yin and Ouri, 2004).

This paper discusses the map matching methods in the context of travel/transportation studies. Map matching is used as a means to transfer the road network attributes to the resulting travel route in order to derive certain travel behavior, and, hence, further analysis can be conducted based on the inferred information. Matching GPS recorded points to the correct position on the correct road link is secondary compared to obtaining the topologically correct travel route and the associated attributes/statistics. The paper is organized as follows: Section 2 briefly overviews the currently available map matching methods. Section 3 delves into the unique requirements for map matching algorithms in travel/transportation studies and describes an innovative three-step heterogeneous map matching methodology. Finally, section 4 presents conclusions and discusses future research on the proposed map-matching method and its application in travel/transportation studies.

2. Overview of Map Matching Methods

2.1 Applications and Conceptual Formulation

Map matching has widespread applications, including automatic vehicle navigation (Syed & Cannon, 2004), image processing, network data conflation (Xiong, 2002), and travel/activity surveys (Lexington Travel Survey, 1997). The common procedure for map matching is to establish the correspondence relationship between two sets of spatial features. Spatial information and attributes contained in the different spatial data sets are conflated into one of the spatial data sets via a matching operation, or are processed further to generate a new data set. The process of map matching helps researchers extract the characteristics of matched features from one data set and transfer/update the associated spatial/non-spatial information to/on the other data set. In this paper, we will focus on the research question of how to accurately match GPS-captured positional data onto linear data (road network).

2.2 Evolution of Map-matching Factors

A straightforward solution to the map-matching problem, as mentioned by White and his colleagues (2000), is to snap the GPS recorded location to the nearest road link node or road link. The simple solution, however, only generates perfect matching results in the ideal situation. Typically, due to the dual uncertainty and inaccuracy involved in both the point and network data, matching GPS recorded point data to road link nodes or to a road link itself is extremely prone to errors. The situation is exacerbated when only distance measures are used for guiding the matching process due to the potential map-matching zone overlay (Lakakis et al. 2004). Point to point matching (matching GPS points to road link nodes) could easily fall into the pitfall of matching to the wrong node on the wrong link if the correct and wrong links are close by in parallel and the correct link does not contain as many of pseudo-nodes as the wrong one. Point to curve matching, (matching GPS points to road link arcs), on the other hand, suffers from ambiguity issues when the GPS point is close to a road intersection (Bernstein and Kornhauser, 1996, 1998; White et al. 2000).

Notice that a distance measure would only constrain a spatial feature along one dimension. An additional measure - travel direction - naturally became the candidate to add on as the second dimension to quantify the relationship between GPS points and the matching road network. Unsurprisingly it ends up improving the matching accuracy dramatically (White et al. 2000). However, travel direction derived simply from GPS points could be very unreliable, especially when the carrier of the GPS receiver travels at a low speed or makes brief stops along the travel routes. In either case, GPS signal drifts exert unpredictable effects on the GPS-derived travel directions. This has forced many researchers to rely on gyroscope or digital compass as the second data source. These devices generally can provide accurate heading and heading change information at various travel speeds (Quddus et al., 2003; Syed and Cannon, 2004).

As more research efforts are devoted to searching better map-matching methods, other measurements have been incorporated to provide better selection criteria for deciding the best match from the neighboring candidate link set. The decision space for matched road link selection, hence, was expanded to a multi-dimensional level. For example, besides proximity and heading difference, Quddus et al. (2003) have used two additional measures for road link selection -- “GPS position relative to the road link” and “intersection relation between the GPS trace and the road links”; Syed and Cannon (2004) have used the “average distance traveled on current link” and “large distance traveled on current road link”. In addition, if the base road network contains detailed road attributes (speed limits, one way lanes, etc.) that potentially restrict a certain routing behavior, they can be utilized to further filter unqualified road links (Najjar and Bonnifait, 2003; Taylor et al. 2001).

Intuitively, taking more factors into consideration helps avoid matching errors that easily result from measurements from a single perspective. Nevertheless, different select criteria could also result in conflicting matching conclusions and therefore cause more confusion. To overcome the difficulty, two approaches have been taken to fuse the multi-dimensional selection criteria and reduce them to facilitate the deterministic matching decision. The one that is commonly used is to simply combine the selection factor with a weighting scheme. The weighting factors are typically derived empirically from data testing (Quddus et al. 2003) or from adaptive-fuzzy-network-based training (Kim and Kim, 2001). The second approach is complicated enough to use Bayesian Belief Theory and Dempster-Shafter's rule for deriving the unique non-ambiguous selection.

1. Improvements with Topological Information

With meticulous calibration of selection criteria, map-matching algorithms are sufficient to identify a series of the matched road segments from the pool of candidate links. However, this does not necessarily imply the matching result would be meaningful in terms of truthfully reflecting a traced travel route. A matching result could show up simply as a group of disconnected "paths".

Notice that both point-to-point and point-to-curve matching approaches do not reflect the fact that GPS records indeed represent the travel routes of the carriers but that only constitute a small sample of the route. Bernstein and Kornhauser (1996) and White et al. (2000) have suggested connecting the GPS points in sequence to form piece-wise linear curves, which are further matched against road network. The method is called curve-to-curve matching. The matched curve, consisting of road links that are selected from the base road network, should have the smallest L2 norm distance to the GPS trace or be viewed as the approximate variation of GPS trace after a small amount of translation and rotation. Techniques have been borrowed from the pattern recognition field that utilizes similar measures to evaluate the shape proximity between two geometrical figures. One of the good examples is the Joshi (2001)'s application of a rotational variation metric to measure the shape similarity between vehicle trajectory and the possible travel paths.

On the other hand, there are many other researchers who chose to further improve point-to-point matching or point-to-curve matching. As suggested by Bernstein and Kornhauser (1996, 1998), tested by White et al. (2000), and included in other researchers' work (Quddus et al., 2003; Syed and Cannon, 2004), road network topology information has been incorporated into the matching algorithm to maintain the topological integrity of map matching results and prevent the error of matching points to the wrong road link. The underpinning rational is simple: if, at time t, a road link is selected without ambiguity; at time t+1, the selected road link would most probably remain as the ideal matching candidate; or the end of the current road link has been reached, and, hence, a road link that is connected to it becomes the next candidate. Therefore, the topology relations (especially, connectivity) among road links restrain the search for the next matching candidate.

Unreachable road links from the current match in one GPS epoch thus would be easily eliminated from the candidate link set with confidence. However, the effectiveness of the approach depends greatly on the extent to which we can trust the previous match. A tiny bad match could consequentially lead to a matching blunder as the GPS epoch progresses, as commonly seen in the pure geometry- based matching algorithms (Quddus et al., 2003). It is not an easy task to clearly dichotomize the confidence/trust domain with a deterministic threshold setting.

As a solution to the problem, Pyo et al. (2001) and, later, Marchal et al. (2004) increased the number of testing epochs for determining the best "continuing" road link from the currently matched one. Their algorithms keep multiple possible "continuing" road links and the corresponding accumulated "fitness" values in a hypothesis space over a period of GPS epochs. The fitness measurements that grew smaller than a threshold over time will get pruned. Finally, a road link hypothesis is confirmed as the map matching result either if its fitness score is the highest or the ratio of its score to the next highest one exceeds a certain threshold. Note that there is no single definition for such fitness measures. Marchal et al. (2004) used the aggregated proximity measure between the GPS points and road links, while Pyo et al. (2001) used the recursive conditional probability formulation that was comprised of multiple measurements -- projected position, link direction, link connectivity, road facility, etc. Both approaches seem to perform adequately in empirical tests.

2. Statistical-Estimate-Based Map Matching

Distinctive from geometry and topology-based map-matching methods, current trends in map matching development have begun to incorporate more probabilistic and fuzzy elements. These constituents are more tolerant of the uncertainty, partial truth, and approximation involved in map matching processes. Taylor and Blewitt (2000) took a unique but innovative approach by simulating the working mechanism of differential GPS. Their algorithm, called road reduction filtering, defines a pool of virtual GPS "Ref" positions by projecting the "Raw" GPS point to the nearby road links. These "Ref" positions are used as virtual differential corrections for the next "Raw" GPS points and, in turn, to generate another pool of "Ref" positions. Conceivably, the correct matching position on the road link must be among the "Ref" positions. Based on the fact that bearing and distance measures between successive "Raw" GPS points and those between successive "Ref" positions are highly correlated, any false series of "Ref" positions can be filtered out. In essence, the road reduction filter is still mostly geometry/shape based. But, among the few first attempts, statistical rationale (i.e., correlation measurement) for the first time was introduced into the efforts of searching for a better map matching solution. In the mean time, Lakakis (2000) attempted the approach using linear regression analysis to fit GPS points to the road centerlines. Parameter significance tests serve to verify the linear relationship between GPS latitude and longitude coordinates. The fitted lines work as predictors for map matching GPS points to the base road network. This method, however, puts higher demands on GPS data accuracy. For stand-alone GPS data, there is a great possibility that map matching zones for two one-way parallel roads overlay each other. Walter and Fritsch (1999) viewed the map matching problem as equivalent to transmitting information through a communication channel. The ultimate aim of the map matching procedure, therefore, becomes minimizing the amount of information loss during the transmission or maximizing the mutual information shared between data sets. The method does not require any tuning parameters except a statistical investigation on the evaluation of the conditional probability involved in the mutual information formulation.

3. Data Enhancement Efforts

Apart from continuously refining the map matching procedures and techniques, other efforts have been made to improve map matching accuracy from the perspective of data preparation and compilation, either by increasing the accuracy of the localization estimates or by matching the these estimates against high-accuracy digital map. For an application that involves a larger and more stable carrying platform, data input for map matching typically incorporates simple GPS recorded point data with other data sources, such as from a digital elevation model, digital compass, gyroscope, velocity sensors or Antilock Brake System (ABS), etc. For other applications that allow post-processing in travel or transport-related studies, usually only the GPS point data serves as the input data source. While GPS recorded points comprise the single data source, a Kalman filter typically is executed to estimate the bias associated with a previous map-matching epoch. Then the estimation can be used to compensate the next GPS positioning input. In the situation where a GPS receiver is complemented and integrated with other data sources, a centralized Kalman filter (Extended Kalman Filter- EKF) has been used to incorporate the measurements from all data sources and generate a single stream of complex position estimates (Bétaille and Bonnifait, 2000). To further eliminate the errors and biases generated from the sensors, these EKF methods usually also build the geometrical shape of the platform into the data fusion model. The seminal localization approach has the ability to collect solid measurements even when the GPS signals are cut off by the obstruction of surrounding environment. The multi-data source combination method is superior in that it handles both of the disadvantages associated with the individual Dead Reckoning (DR) or GPS localization methods by allowing them to complement each other within an integrative measurement framework (Bonnifait et al., 2001).

Compared to the rapid advances of positioning technology, improving map accuracy is more of a long-term, energy-consuming task. Digital maps usually either contain errors or do not possess enough resolution power for some of the map matching applications. Although the current commercial digital maps already have sufficient coverage over the road networks in most metropolitan areas and even most parts of rural regions, mapping accuracy typically varies dramatically, and the map details have not been able to extend to the details of lanes and cover particular types of roads such as bike paths or sidewalks. The map resolution problem could be partially resolved by one of two ways. For simplified two-lane road representation (generalized as single road centerlines), Marchal et al. (2004) have replaced them with two oriented links derived by adding small shifts perpendicular to the link centerline. Therefore, the distance between GPS record and the road segment can be enhanced as the distance from the point to the augmented road links. The method reverses the map generalization process to generate more road link details. But it does require that the network attribute table contain the “number of lanes” details. Rogers (2000) attempted to address the problem by using the repetitive differential GPS (DGPS) measurements from a probe vehicle to augment commercial digital maps down to the drive lane levels. His approach is partially successful, but still suffers higher errors around road intersection and in cases where GPS signals are subject to multi-path effects.

3. A Heterogeneous Map Matching Approach for Travel/Transport Studies

Different from its application in other fields, the map matching in travel/transportation studies aims at: 1) identifying the correct road links traversed by the traveler; and 2) ensuring that the identified links form a meaningful travel route. Its main focus is to correctly transfer the road network attributes data to the GPS recorded travel route, hence further identifying how the spatial features (road, locations visited, function area traversed, etc.) interacted with the traveler during the behavioral process. Ideally, map-matching methodology should be able to help answer queries beyond the direct matching result, i.e., road type distribution along the travel route or delays encountered. Generally speaking, it is impossible to answer these queries if the travelers are off-road, or if the travel roads are not shown on the map. Thus, map matching in travel/transportation studies not only calls for accurate road network maps, but also takes into account the fact that the travel is not necessarily restrained to roads that facilitate a vehicle's travel and that the travel might include pedestrian walks and bicycle journeys.

In this research, three recent map-matching algorithms were empirically evaluated for travel route derivation from GPS point data and their performance is tested against the GPS data that were collected in a travel survey. The three map-matching algorithms are: weight-based map matching by Yin and Wolfson (2004), fuzzy-logic based map matching by Syed and Cannon(2004) and General map matching by Quddus et al (2003). They were implemented in the ARCVIEW network analysis module and the evaluation is conducted from multiple perspectives – data needs, selection factors, matching accuracy, and time complexity.

The empirical testing revealed several facts about these map matching algorithms and has inspired us on how to adapt them or how to design our own in order to solve the matching problem in travel/transportation studies.

1) Online map matching algorithms typically ignore or can not use the global information contained in the data. Occasionally a GPS position can be matched to a branching or disconnecting road link (Figure 1). Problems arose when the recorded GPS points are sparse due to fast travel speed by the carrier - a short road link could be ignored and unmatched (Figure 2).

2) In traditional GIS digital maps, nodes are not always digitized at street intersections and their density varies across the map. The position of a node plays an important role in the node-to-curve based map matching algorithms. If insufficient attention is paid to maintain the consistent topology of matching results, one minor mismatch could lead to a blunder (broken links or gaps).

3) Offline algorithm could use global optimization techniques such as the shortest path algorithm to generate a topologically correct route. However, the assumption that no road links have ever been repetitively visited deprives its ability to differentiate the travel loops.

4) Both types of algorithms could utilize the fact that travelers constrain their travel within the attributed road network. Thus, the particular regulations about the road links (speed limits, one-way streets, etc.) could be used to help enhance map-matching accuracy.

With these rationales in mind, we determined to take a heterogeneous approach for map-matching travel/transportation data. The targeted data input source for the algorithm is limited to GPS records. The algorithm consists of three phases: data preprocessing, multiple hypothesis map matching with rank aggregation and Dempster belief test.

4.1 Data Preprocessing—Cluster Reduction and Density Leverage

The new algorithm adds a data preprocessing step prior to the real map matching work. It consists of two steps: cluster reduction and density leverage.

Cluster reduction is meant to reduce the systematic noise in the data. Usually it is not easy to qualify the moving/still state solely based GPS receiver's input, especially when a tracking device is used to collect travel data across the full spectrum of travel modes. Even when the carrier keeps still at a fixed location, a GPS device would record a cluster of positions indicating random deviations around the true position point, which phantoms the slow moving speed of the carrier and random travel directions. Due to their unpredictability and falsifying characteristics, the GPS point clusters could be extremely misleading to map-matching procedures and are the greatest cause of overshoots and mismatch. With the spatial clustering modeling technique, the GPS collected travel data are filtered first to substitute the point clusters with their centroids. To model and identify these clusters, we selected the DBSCAN (Ester et al., 1996) clustering algorithm for cluster searching since it allows lack of information on the number and shape of the clusters in the input data.

Density leverage is meant to dynamically adjust the data sampling frequency against the model resolution of the base street map. The matching street layer consists of various lengths of street links. Similarly, the sampling interval of the GPS receiver varies with the carrier's moving speed and direction. Whenever the sampling interval is greater than the length of a traversed street link, there might be the chance that the street link is omitted from the matching algorithm, resulting in gaps in the match result. After the cluster reduction handling, the GPS trace data is streamlined in units of two. Every two GPS points are processed to generate a combined buffer area around them. If the sample distance between the two points is greater than half of the minimum-length street link that falls in the buffer, additional false data points are interpolated and inserted into the trace sequence.

4.2 Multiple-Hypothesis Matching Algorithm with Rank Aggregation

Borrowing the concept from the genetic algorithm, the map matching method we propose and implement keeps a pool of the best solutions. The solution pool is updated sequentially with the ordinal encountering of street intersections along the travel route. The GPS recorded travel trace is treated as a translated and rotated version of the match route. During the search for the best candidates, both accumulated 2-norm distance (A2ND) and rotational variation metric (RVM) (Joshi, 2001) is used to evaluate the matching result and guide the search directions around street connections. Norms constitute a quantitative measure of the geometric displacement between the GPS trace and the actual travel route. RVM, which accumulates the degree of variance between the orientations of two geometric shapes, measures the geometric distortion between them.

The algorithm starts with creating a pool of (N) seed candidates by buffering around the first valid GPS record. Any street segment that falls within the buffer is selected as one of the potential matches of the travel route start. Continuing with the next temporally adjacent GPS trace point, the norm distance between the GPS points and its projection on the current match link is computed and accumulated into A2ND as the match score of the current match candidate. In the mean time, a direction discrepancy between the current travel direction as indicated by the GPS records and the current match link is computed and accumulated to RVM metric. A2ND and RVM both serve to guide the match search in the street network space. However, we did not try to multiplex them to produce a single matching index, as a fixed or dynamic weighting schema are difficult to specify and unlikely to suit every possible individual tracing case. The partial match results are ranked in A2ND and RVM separately. Only the top N results of both are kept for the next round of match growth.

As the partial match results growth encounters a street intersection, a ground rule is set up to decide the right timing of when to select the next link to further the matching process. Two cases exist to judge when the traveler began to leave the current link and transit to the next one: 1) The projection of current GPS point falls on or out of the end point of the current link, which typically occurs when the travel direction change is less than or equal to 90 degrees; 2) The projection of the current GPS point comes near to the end point of the current link, but the point's position is getting away from the current link, which typically occurs when the travel direction change exceeds 90 degrees. For the second case, we set up two threshold values to switch on the turning signal -20 meters for coming near to the end point of a link and 30 meters for leaving the current link. When determining the next link, all the topologically connected links to the intersection node are considered as the potential next links, including the incurrent link to cover the U-turn situation. However, prohibited maneuver and turn restrictions information has been used to pre-eliminate certain search branches efficiently.

After the matching process is completed, a pool of top N match results is derived with different rankings of A2ND and RVM measures. With the rank aggregation method, we may combine the ranking of the two to obtain an aggregated ordering.

Ideally, Kemeny ordering minimizes the sum of the "bubble sort" distances and thus generates the best compromise ranking. However, it is a NP-hard problem (Dwork et al., 2001). Here, we implemented two of the other heuristic/sub-optimal ranking aggregation methods to composite the ultimate matching results (Table 1): 1) the simple Borda's method to generate a combined ranking for the pool of match results: Each candidate in the pool is assigned a score of the number of candidate ranked blow it. Its total score across the different ranking list is finally sorted in a descending order; and 2) a good approximation to Kemeny optimized rank aggregation – footrule optimal aggregation, which finds the median permutation of the rank lists to be combined.

4.3 Dempster Belief Test for Travel Off-Road/Noise Discernment

As discussed in the previous sections, uncertainties typically exist in both the trace data and the base matching street map. Given the dataset and the matching base, match results are considered as always producible without setting any restraint on the acceptable belief and plausibility level. However, considering the possible travel by walk mode, a matching algorithm could easily map a pedestrian travel onto a highway link nearby. Or under other scenarios, the GPS device could be "blacked out" by the surrounding tall buildings. In either case, the assumption that a candidate match link is identifiable from the base street map becomes void.

This research takes the advantage of Dempter-Shafter theory (Shafer, 1976) to fuse heterogeneous information in order to discern the off-road travel and GPS black-out situations. For each of the matching select criterion (proximity and direction), a frame of discernment {yes, no, perhaps} and its belief assignment functions as similar to Najjar and Bonnifait's (2002) was built to test if a matching link is a "good match". Each discernment type of a select criterion is associated with two quantities: belief and plausibility. The GPS trace point match to a link is considered invalid if the no belief value is greater than the plausibility values of the other two assumptions, the no belief value is 1, or the conflict parameter has a value of 1. A consecutive trace of more than 10 invalid GPS point-to-link match invalidates the corresponding segment of match results, which is then splinted out and replaced with the original GPS travel trace.

4.4 Match Results

Map matching is performed against the Dynamap/transportation data of Santa Barbara from GDT, Inc. It contains complete address information and routing features, including speed limit, cost, turn restrictions, one-way street information, etc. The travel data comes from a travel survey conducted locally. A test run of the algorithm against a single GPS trace generates the following results: Figure 3 and figure 4 show data processing effects of cluster reduction and density leverage, respectively. Figure 5 show the best match result from the match candidate pool as indicated by both the Borda and Footrule ranking aggregation methods. The second best match result as indicated from Borda method indicates an additional matching link at the end of travel route, while the second best match result as indicated by Footrule method indicates an alternative matching link at the end of travel route. They show up with the minimal difference from the best except the divergence at the end of the identified travel route. Table 2 shows the part of Dempster belief test result for the test route. The final part of the travel is discerned as the part of off-road travel and replaced with the original GPS data. In all, the algorithm generated a perfect match for the GPS trace input, without branch or gap in between, and segmented out the off-road travel portion with high accuracy (Figure 6).

Considering the performance of the algorithm, suppose the number of the road links in the road network is N, the number of the road link extremities is V, the number of collected GPS points is M, and the size of candidate Pool is K. The time complexity for the DBSCAN algorithm would be $O(M * \log(M))$ with R-tree implementation. Density leverage involves a spatial buffering operation, and, hence, is the most costly. Its time complexity is up to $O(M * \log(N))$. The map matching step involves $O(M * K)$ for candidate searching, and $O(K * \log(k))$ for pool updating at each step. Its total complexity is $O(M * K^2 * \log(K))$. The dempster belief test at the end incurs an additional $O(M)$ time cost. When K is small and N/M is large, the time complexity of the algorithm is comparable to most of the algorithms we discussed in section 3.

5. Conclusion

In this paper, we briefly overviewed the currently available map matching methods. Several recent online/offline map matching algorithms were implemented in GIS to provide a case study to evaluate from multiple perspectives. In recognition of the disadvantages associated with the methods examined, this research proposed and implemented an innovative map matching approach suitable for travel/activity research needs which is uniquely characterized by: 1) data preprocessing with point cluster reduction and density leverage, 2) offering the candidate solution within a pool of "the best," 3) balancing of matching results from multiple matching factors with rank aggregation, 4) intelligently utilizing the basic network constraint attributes with "expert rules" to increase the matching accuracy, and 5) Dempster belief test to discern the noise and off-road travel. Our analysis has shown that the performance of the new algorithm is comparable with the others when the candidate pool size is small and network/GPS trace size is large. Further research needs to quantify the performance of this algorithm and others with respect to a complete set of survey travel routes recorded. A matching index needs to be developed to evaluate the matching accuracy among the algorithms quantitatively.

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List of Illustrations:

Figure 1 Overshoot scenario

Figure 2 Gap scenario

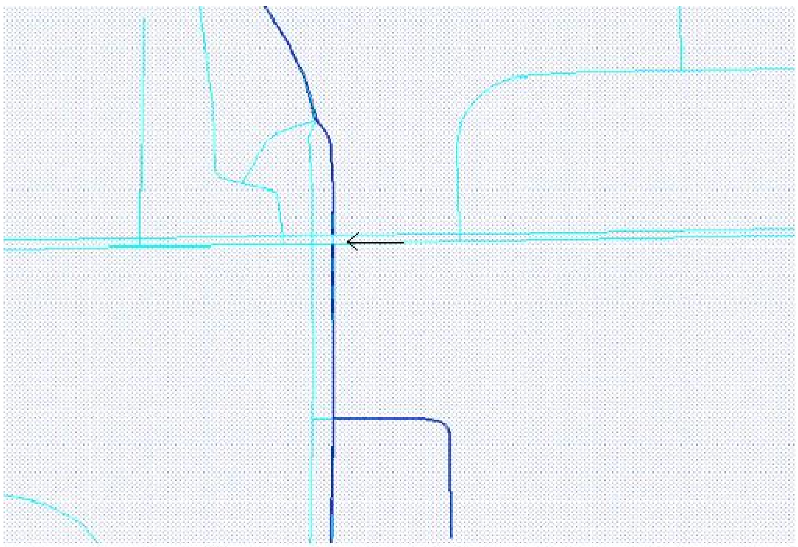

Figure 3 A cluster of GPS points recorded around street intersection is recovered via DBSCAN algorithm and replaced with its centroid

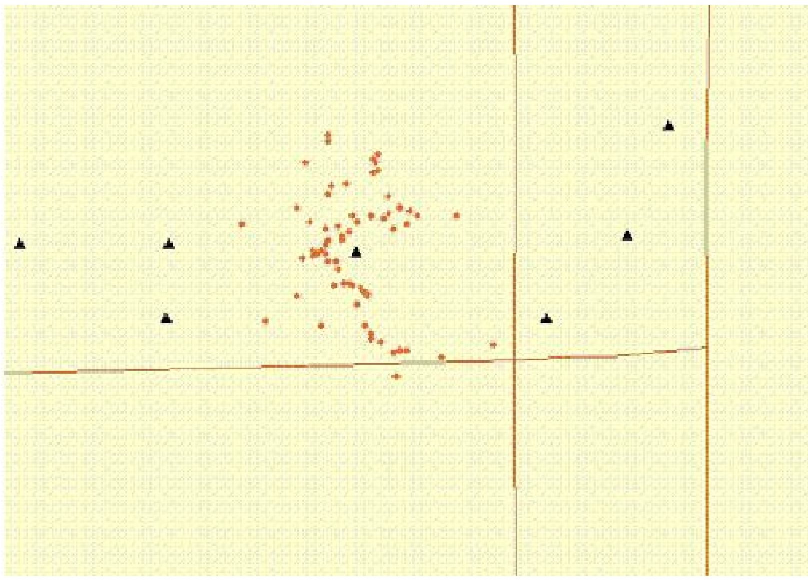

Figure 4 Original GPS trace (as indicated by the triangle symbols) didn't sample the short street intersection. Augmented traces by density leverage added three false GPS data points to cover it.

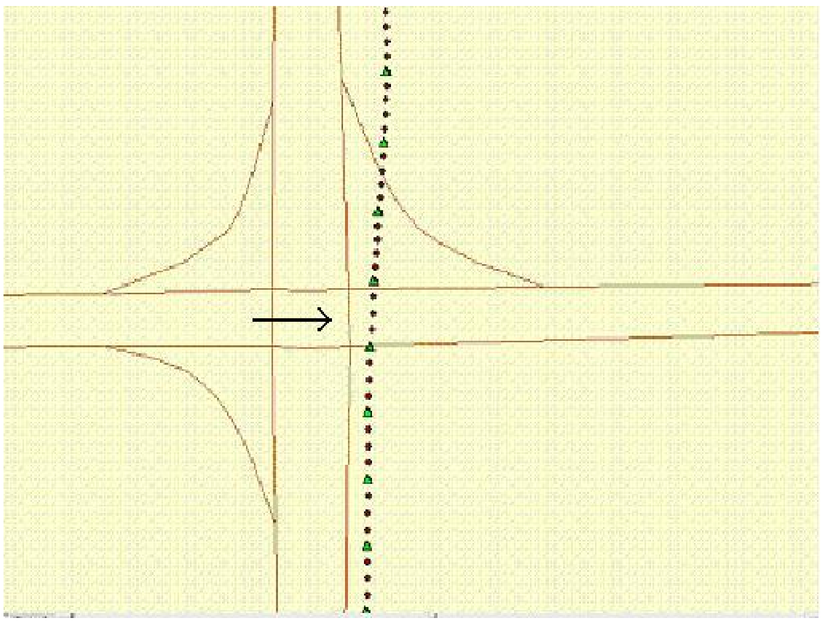

Figure 5 The best match result from both Borda and Footrule ranking aggregation.

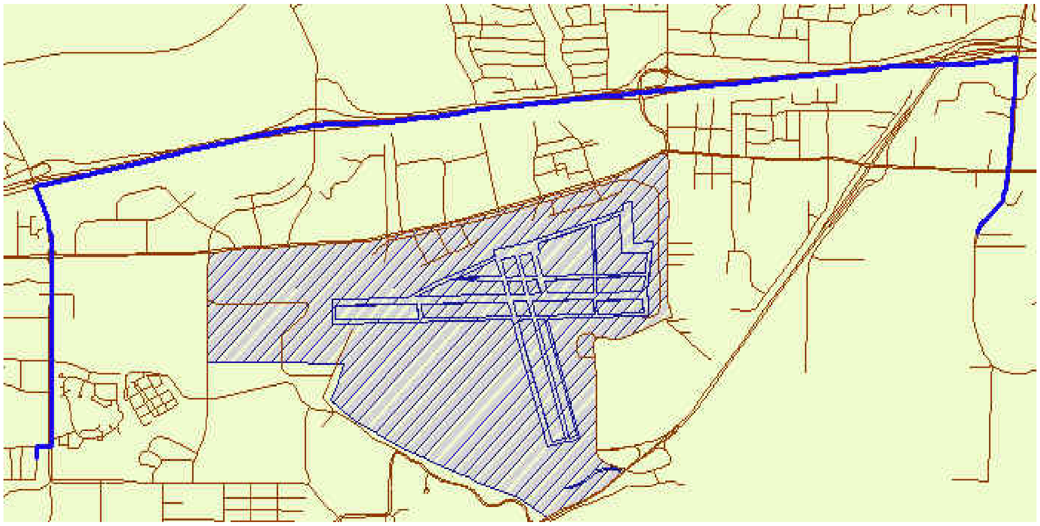

Figure 6 Map matching result after Dempter belief test with multi-criterion fusion.

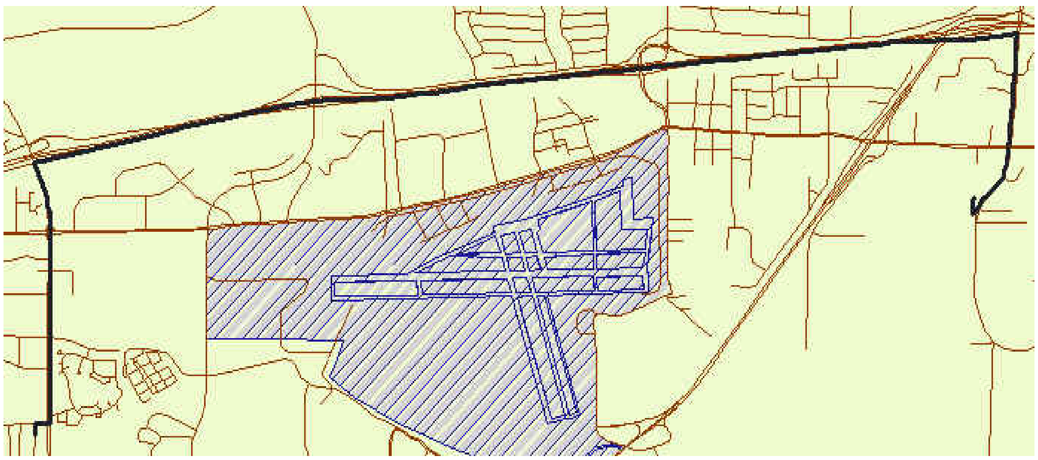

Table 1. Match Result Summary (including L2norm and RVM measures, rankings, ranking results from Borda and Footrule ranking methods, map matching trip distance and final trip distance after Dempster belief test.

L2Norm	RVM	L2NormRank	RvmRank	BordaRank	FootRuleRank	TripDistance	BeliefTripDistance
0.181785	565.459956	1	9	5	2	5.481127	-1
0.181879	570.568439	2	10	8	7	5.618900	-1
0.191356	476.092263	3	3	1	1	5.427727	5.480326
0.191451	481.221254	4	5	4	4	5.565500	-1
0.198498	479.225220	5	4	3	3	5.448950	-1
0.198593	484.334925	6	6	7	6	5.586724	-1
0.209626	441.107106	7	1	2	8	5.429427	-1
0.209627	499.215457	8	7	9	5	5.435327	-1
0.209720	446.224142	9	2	6	10	5.567200	-1
0.209721	504.321745	10	8	10	9	5.573100	-1

Table 2 Portion of the Dempster fusion result for the test travel route (PI = Plausibility)

Attributes of fusionresult

PointID	YesBelief	NoBelief	PerhapsBelief	YesPl	NoPl	PerhapsPl	FusionConflict
1	1	0	0	1	0	0	0.731278
2	0	0	0	0	0	0	1
3	0	0	0	0	0	0	1
4	0	0	0	0	0	0	1
5	0.057267	0	0.942733	0.057267	0	0.942733	0.562581
6	0	0	1	0	0	1	0.737395
7	0.823912	0	0.176088	0.823912	0	0.176088	0.481990
8	0.157464	0	0.842536	0.157464	0	0.842536	0.619850
9	1	0	0	1	0	0	0.960352
10	0.903953	0	0.096047	0.903953	0	0.096047	0.705019
11	0.336617	0	0.663383	0.336617	0	0.663383	0.736978
12	1	0	0	1	0	0	0.140969
13	0.919172	0	0.080828	0.919172	0	0.080828	0.353459
14	0.828980	0	0.171020	0.828980	0	0.171020	0.444416
15	0.900334	0	0.099666	0.900334	0	0.099666	0.611730
16	0.517693	0	0.482307	0.517693	0	0.482307	0.511791
17	0.991111	0	0.008889	0.991111	0	0.008889	0.339207
18	0	0	0	0	0	0	1
19	0.983086	0	0.016914	0.983086	0	0.016914	0.249287
20	0.887415	0	0.112585	0.887415	0	0.112585	0.387752