Analysis of Travel Route Data from a System Efficiency Perspective

Project No. UCNR15-4

New England University Transportation Center, Region 1, Year 04/05

March 23, 2005

Analysis of Travel Route Data from a System Efficiency Perspective
Final Research Report

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March 23, 2005
Final Report
New England University Transportation Center - Year 15 (04/05)

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Analysis of Travel Route Data from a System Efficiency Perspective		5. Report Date March, 2005 6. Performing Organization Code
7. Author(s) Lisa Aultman-Hall, University of Connecticut; Emily Parkany, Villanova University; Jianhe Du, University of Connecticut; Ryan Gallagher, Delaware Valley Regional Planning Commission		8. Performing Organization Report No.
9. Performing Organization Name and Address University of Connecticut, 261 Glenbrook Road, U – 2037, Storrs, CT 06269		10. Work Unit No. (TRAIS) 11. Contract or Grant No. DTRS99-G-0001
12. Sponsoring Agency Name and Address New England (Region One) UTC Massachusetts Institute of Technology 77 Massachusetts Avenue, Room E40-278 Cambridge, MA 02139		13. Type of Report and Period Covered Final Report for UTC Year 15 14. Sponsoring Agency Code UCNR 15-4

15. Supplementary Notes

Supported by a grant from the US Department of Transportation, University Transportation Centers Program

16. Abstract

Traveler route choice behavior is the cornerstone of numerous advanced traffic management technologies. Yet, few datasets of actual travel routes have been collected and analyzed. There are two specific objectives of the analysis work conducted in this NEUTC research project (the data collection was only partially funded by this project). The first was to advance the methodological aspects of using GPS to collect route data, including constructing the spatial model that automatically identifies trip ends in the large-scale continuous GPS data stream. This work makes use of 10-days of in-vehicle travel routes collected from 256 households using Global Positioning System (GPS) receivers from 2002 to 2003 in Lexington, Kentucky (population 250,000). Information for each vehicle, such as speed, latitude, longitude, and heading was recorded every second or every five seconds (depending on the power feature in the particular vehicle and the corresponding settings of GPS devices). A travel habits survey was also conducted with every driver in each household after the ten-day data collection cycle was completed. This dataset was used for the second project objective: to estimate routing efficiency and selection patterns by determining if route choice is influenced by attitudes, travel habits, roadway characteristics, congestion, or a combination of a few or all of these elements. Surveys were collected from 524 drivers in the 256 households.

This study has demonstrated the importance of validating GPS trip dividing methods against known trip start and end locations in order to defensibly measure the accuracy of algorithms. The relatively small range of parameters tested here resulted in a significant variation in accuracy and error results, indicating that trip division is highly sensitive to the parameters used. Some recent studies have found GPS dramatically increases the number of trips reported by travelers. However, it is possible that the method or combination of parameters used to divide the GPS data stream into individual trips significantly affected these trip rate estimates. Therefore, caution should be exercised in interpreting GPS travel data.

The analysis of the route choice data in the follow-up surveys indicates that a wide variety of data types influence route consistency: travel habit variables, attitudinal variables, route characteristic variables, and demographic variables. Demographic and route characteristic variables have less influence in the some route models suggesting that attitudinal data may be valuable for predicting specific routes.

17. Key Words GPS, GIS, Route choice, Driving behavior, Travel survey	18. Distribution Statement		
19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages 41	22. Price

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1. Introduction

Traveler route choice behavior is the cornerstone of numerous advanced traffic management technologies. Yet, few datasets of actual travel routes have been collected. This is understandable given that route data cannot be easily collected with traditional travel survey methods and the relative amount of information needed to capture a complete route is extensive. On the other hand, new technology such as GPS cannot be used directly in route choice study as widely assumed and extensive data processing is required to tabulate useful route choice data.

In the last decade, the advent of widespread Geographic Information System (GIS), the reduction in the cost of computer memory, and the increase in computing power have led to the potential to easily and more cost effectively manage this type of disaggregate route data. Furthermore, within the last decade, improvements in the Global Positioning System (GPS), which uses fixed-orbit satellites to determine location on the earth, and legislation allowing more accuracy have enabled the creation of relatively inexpensive systems for use in vehicle tracking. Therefore, use of GPS data to study route choice behavior will become a routine method for data collection if the spatial models to automatically process the GPS data can be constructed and made available for route choice study.

This research makes use of 10-days of in-vehicle travel data collected from 256 households using Global Positioning System (GPS) receivers and data from a travel habits survey (see Appendices A and B for survey instruments) conducted with every licensed driver in each household after the ten-day data collection cycle from March 2002 to July 2003 in Lexington, Kentucky (population 250,000). In the GPS data, information for each vehicle, such as speed, latitude, longitude, and heading was recorded every one second or every five seconds (depending on the power feature in the particular vehicle and the corresponding settings of GPS devices) to collect as much information as possible while avoiding data overflowing. The travel habits survey collected data from 524 drivers in the 267 households. Respondents of the survey identified the frequency of specific driving patterns, rated the importance of factors affecting route choice for both shopping and work trips, and identified specific routes that would be preferred or not preferred by the respondent during identified peak and off-peak time periods. These data collection efforts were only partially funded by this New England University Transportation Center project.

There are two specific objectives of the analysis work conducted in this NEUTC research project. The first was to advance the methodological aspects of using GPS to collect route data, which involves constructing the spatial model that automatically identifies trip ends in the large continuous GPS data stream. This objective contributes to the ability to utilize GPS devices in travel data collection and thereby better evaluate applications of advanced technologies, such as traveler information systems and incident management systems, which seek to improve system operations and routing efficiency. This work was primarily conducted by the University of Connecticut NEUTC project team members. The second objective was to investigate route choice patterns using the post-survey to determine if route choice is influenced by attitudes, travel habits, roadway characteristics, congestion, or a combination of a few or all of these elements. This objective was primarily accomplished by the Villanova University team members (formerly of the University of Massachusetts within the NEUTC). The body of this report has two chapters: the first summarizes the results of the efforts to identify trip ends in the GPS data stream and the second presents the evaluation of route choice consistency.

2. Identifying Trip Ends in Multiple-Day GPS Data Streams

2.1 Background

Trip rate, the number of trips made by a household or an individual in a period of time (usually an hour or a day), is an essential measure in travel behavior research and transportation demand modeling. It is widely used in planning for trip generation, emissions modeling, as well as other transportation related evaluations. Conventional survey methods, such as mail and phone surveys that collect travel information based on participant recall, are limited, especially in capturing short trips or trip chains. Short trips are frequently omitted by survey participants, especially when data collection lasts for multiple days and participants are required to record trips at the end of a day or at the end of the entire data collection period.

It is widely agreed that GPS offers significant advantages over traditional survey methods in collecting travel data. Murakami and Wagner (1999) concluded, based on a field experiment, that even though GPS was not perfect, its ability to capture multiple-day data and record routes and speed is better than retrospective surveys. Yalamanchiliv et al. (1999) determined that the GPS-based data furnished more than twice as many multi-stop chains as recall data. Wolf et al. (2001) compared the number of trips collected by GPS to those by traditional computer-assisted telephone interview (CATI) in a California study and concluded that GPS captured 29.2% more trips than the equivalent CATI method.

Passive GPS requires no intervention from participants and collects data automatically. This can serve the need to minimize both the participant burden and trip reporting fatigue while at the same time collecting as complete a dataset as possible. It is easier for participants, but requires post-processing because all trips are stored in a single continuous data stream. Although the data processing is challenging, the completeness of the data and the lower cost and burden of passive GPS merits its use and several researchers over the last several years have pursued the specific development and evaluation of methodologies to post-process the data. Accurate post-processing methods are necessary to enable more routine collection of large passive GPS travel datasets that are useful for trip rate information.

Ideally, the trip dividing methods should be calibrated using field-based data where actual true trip start and end points are known. Unfortunately, many travel data collection efforts that used GPS devices either did not include a corresponding manual log of trips or only part of the survey period had both manually logged travel data and GPS data collected. Furthermore, the completeness of manual trip logs in previous research was not always guaranteed. Therefore, the comparison of GPS derived trip data with actual trip ends was either impossible or the comparison was conducted with qualitatively and quantitatively limited manual logged data.

The focus of this part of the study was to use in-vehicle logs validated for completeness to quantitatively evaluate post-processing techniques for passive in-vehicle GPS data. Travel data were collected for 10 days using both GPS devices as well as in-vehicle booklets where participants recorded information about each of their trips. The multiple-day GPS dataset was divided into individual trips using three methods and the automatically identified trip start points were compared to the actual trip start points that participants recorded. While the full study consisted of 256 individual households, only the 12 datasets with well-record in-vehicle logs were used here because of the time-intensive process to manually check the in-vehicle logs against the GPS datasets for completeness as well as manually augmenting the in-vehicle booklets. The objective is to measure the relative performance of these three trip dividing methods and compare them to existing methods. In addition, the settings for parameters within these methods are evaluated. The data collection period was longer than many previous studies, making the size of the dataset an advantage.

2.2 Data Collection and Preparation

The data used for this analysis are a subset of a large GPS travel dataset collected in Lexington, KY between March 2002 and July 2003. Lexington (population 250,000 and 293 square miles) has a relatively self-contained 1350 mile road network comprising of 13,000 links. Within the city, there are divided highways (including a circle freeway), boulevards, and one-way streets. Overall, the city serves as an ideal medium-complex network for developing and calibrating the trip dividing methods. Furthermore, Lexington has a relatively accurate and complete GIS database of road centerlines which includes even minor private driveways.

Early in 2002, recruiting emails were sent out to invite people to participate in the study. Phone calls were made to confirm people's participation and collect demographic information. A maximum of 12 participants were recruited for each run of the survey every two weeks between March 2002 and July 2003. Each participant had a GeoStats GeoLoggerTM Version 2.x[1] installed in his/her vehicle for 10 days. A simple tabular check box format log book was designed and customized for each household with the first names of the household members printed in the driver and passenger sections of the booklet. During installation of the GPS device, the in-vehicle log book was distributed and the participant was instructed to record information indicating the driver, passengers, approximate start time, and trip purpose for each of his/her trips. We explained carefully with examples including diagrams that a trip occurred "Every time you leave a particular location or intermediate stop".

In total 276 vehicles were surveyed and 256 valid GPS datasets were recorded (many vehicles had multiple drivers). It was originally intended that trip ends identified by the

[1] The antenna used in the GeoLogger TM is the Garmin GPS 35.

automatic method would be calibrated with the corresponding trip log. However, a preview of the in-vehicle booklets indicated that not all participants recorded complete information for all trips. Some participants were prone to omit short trips as well as return trips presumably due to the burden of recording trips in a multiple-day data collection, a misunderstanding that a round trip to a given destination was only one trip or a misunderstanding about how to code trip chains. Given the extensive design effort and pre-testing of the travel log, these incomplete trip logs provide a further argument for the need for an automatic trip end identification procedure, especially for a long study period in which people can not or will not record complete logs.

Since incomplete travel logs were not suitable for developing and calibrating the algorithms described in this paper, manual selection of the best-recorded booklets was necessary. This manual selection included two steps. The preliminary step was to inspect the trips in in-vehicle booklets to locate 'preliminary' higher quality booklets and the secondary step with higher quality booklets was to examine the corresponding GPS record of the trips visually in a GIS environment. The preliminary selection of well-recorded booklets included filtering out booklets that had obvious omitted trips. For example, if the last trip in a day was to a commercial area or not to the home of the vehicle, or, if the number of passengers recorded for trips increased or decreased without the driver indicating a "drop off/pick up passenger" purpose for a trip, we questioned the completeness. In the advanced step, the student researcher imported the GPS data of the candidate households into ArcView, a GIS software, and visually examined trips on the computer screen to compare those trips with the trips recorded in the in-vehicle booklets. If the trips for a given vehicle based on the visualized GPS data matched trips recorded in the in-vehicle booklet, the booklet was deemed well-recorded and was selected for use.

Although it would be ideal to include as much data as possible from the 256 participant vehicles, the extensive manual check of the in-vehicle booklets, as well as the manual marking of additional trip ends found in the GPS data, limited the number of datasets that could be used. In total 12 well-recorded in-vehicle booklets and the corresponding GPS datasets were selected. The number of people in each household varied between 1 and 4 (average of 2.7). Five of the households have only one driver, while six have two drivers and one had 3 drivers. Each household has either one or two vehicles.

Using the GIS software for manual viewing of the GPS data as well as the in-vehicle log information, the actual trip start and end points for these 12 households were manually identified by the research assistant. The verification process consisted of three steps. The first step was to flag the start points in the GPS dataset by locating the records with a time stamp similar to the start times recorded by the participant in the in-vehicle booklet. The second step was to note obvious missing trips based on the trip purposes/destinations recorded in the log. For example, if two adjacent trips both had work as the trip purpose, at least one return trip must have occurred in between. The third step was to find trips omitted by the participants in the log but identifiable in the GPS data stream (with the aid of GIS software to visualize the GPS data). The following additional criteria were used to flag trips not recorded by participants in their booklets: i) Parallel parking tracks (Figure 1), ii) Links used twice, once in each direction within a short time period (Figure 2), iii) Approximately 180 degree heading changes (Figure 2), iv) GPS points off the road network (Figure 3), and v) An extraordinarily circuitous route between the start and end point of a trip recorded by the participant in the booklet (Figure 4). Note here that Figures 1-4 also illustrate some of the complex situations where an extended dwell time is not present and that the automated algorithms, such as those proposed in this paper, must be able to find trip ends. A total of 121 trips were manually identified in addition to the 764 trips recorded in the booklets. Therefore, a total of 885 trips were made by the 12 household vehicles in their respective 10 day study periods (5-6 weekdays and 3-4 weekend days). This suggests that even in this sample where trip reporting fatigue was not found, participants could not be relied upon to identify all trips in an in-vehicle log. This further motivates the need to develop trip dividing methods for passive GPS data collection. We acknowledge that the manual augmentation method is also not 100% foolproof, but we would assert that it is a solid benchmark against which the success of the automated methods can be measured. It is a better measure than use of the best reported in-vehicle booklets in our study.

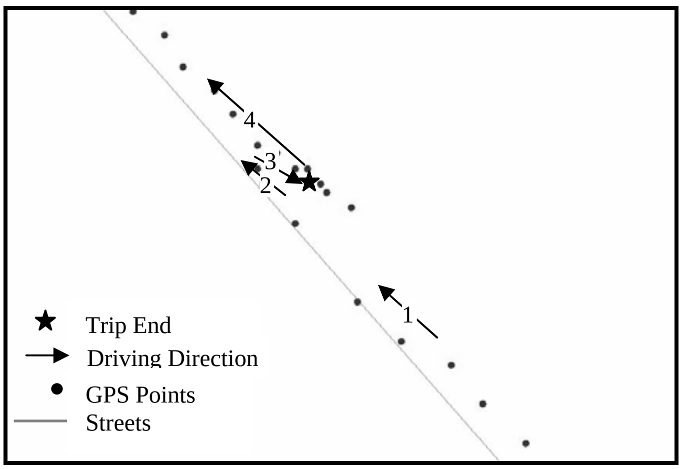

Figure 1 Parallel Parking Tracks

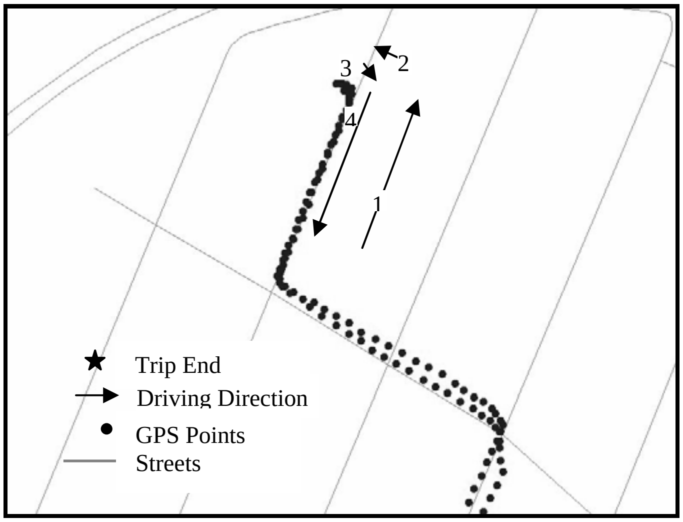

Figure 2 Repeated Use of Road Links

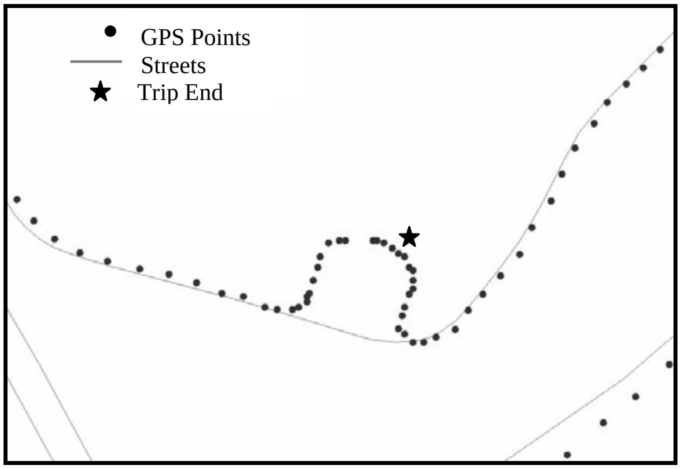

Figure 3 Points Off the Road Network

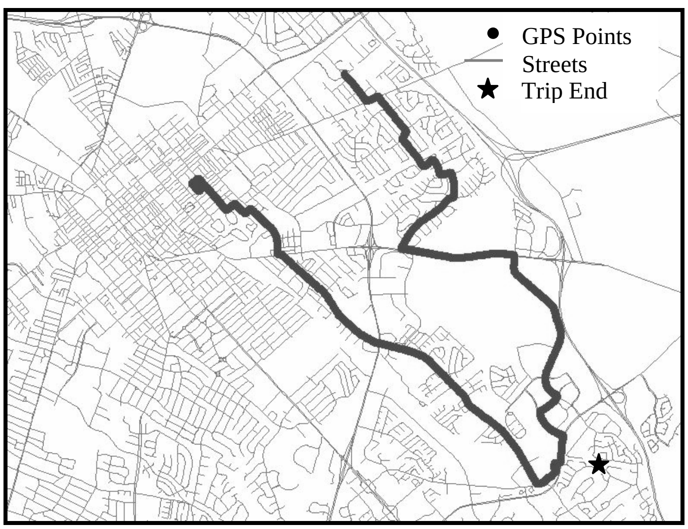

Figure 4 Circuitous Route

A unique feature in our study relative to some previous data collection efforts is the GPS device settings. As the data collection period was relatively long, to avoid an overflow of data beyond the 4 MB device memory, the GPS devices were set to record data only when the speed was above 1.15 miles per hour. Therefore, the zero speeds used by others to identify trips cannot be easily used to identify trips in this study. It is not uncommon that GPS settings affect the methods that can be used to post process data. And in most cases trade offs must be made.

2.3 Identifying Trip Ends

It is often straightforward to identify the features described above from direct visual interpretation of the data in a GIS map environment, especially if one is familiar with the particular region where the data were collected. However, locating a trip start or end point automatically in a tabular GPS data stream is more complicated. For example, the selection of threshold values that work in all cases is not straightforward. Since satellite signals are not always available, in urban canyons for example, a method for identification of trip ends during signal loss must be developed simultaneously with methods used during normal GPS data acquisition.

When there is a signal loss, this particular GPS device will flag the first valid point recorded after the signal loss. Therefore, it is straightforward to locate where gaps in data have occurred. Trip ends may or may not have occurred during a signal loss.

The check for trip ends (based on Stopher et al. (2003)) during a signal loss is the first step conducted before any of the methods discussed below. To determine if there is a trip end during the signal loss time, the time a vehicle should have taken to travel the distance during a signal loss is estimated based on the average speed before and after the signal loss. This estimated time is compared to the real time (the time length of the signal loss period). If the estimated time exceeds the real time by more than a threshold value, a trip end is assumed to have occurred.

The following methods were used to identify trip ends where no GPS signal loss occurred. The most frequent method to identify trip ends in previous research uses the dwell time. The selection of dwell time is very critical. It must be large enough not to misidentify stops for traffic control devices or congestion as trip ends. However, if too large, the dwell time criteria will miss some trips with short stops, such as dropping off or picking up passengers or trips through a "drive-thru" restaurant.

Therefore, in this study two dwell time parameters were used: a minimum dwell time and a maximum dwell time. The minimum dwell time is the threshold value below which no trip end is deemed physically possible. With the speed check on, results for minimum dwell time values of 20, 30, and 40 seconds are presented in this paper. The maximum dwell time is the time above which we can be reasonably certain a trip end or purpose occurred. The following 3 values for maximum dwell time were tested in this study: 60 seconds, 100 seconds and 140 seconds.

When a dwell time between the minimum and maximum is found in the GPS data stream, one of the following three features are often present if a trip end has occurred: repeated use of one road link in opposite directions, a heading change of approximately 180 degrees (Figure 2), or a series of the GPS points fell more than a pre-defined threshold distance away from road links (Figure 3). Tests were conducted and it was found that the check for a heading change always caught the repeatedly-used links in opposite directions. Therefore, only the heading change criterion was used. A different number of GPS points (20, 40 or 60 points) before and after the dwell time gap were used to check for a heading change. When a trip end with a time gap greater than the minimum and smaller than the maximum does not have a heading change, another pattern was often present if a trip end had occurred: a series of the GPS points fell more than a pre-defined threshold distance away from road links. Therefore, the distance of GPS points away from the network was used as another logic to check for trip ends. In this study, we evaluated 2 different levels of distance (15 or 30 meters) from the network as a criterion for trip end identification.

In summary, three different combinations of these three criteria were tested and compared: dwell time, heading change and distance away from the network. In addition, it was necessary to determine the optimal values for parameters used in these combinations. All of the methodologies were developed and programmed using AVENUE, an ESRI Corporation programming language designed to be used with the product ArcView 3.2.

2.4 Analysis of Results

The five parameters tested in this research are: 1) the minimum dwell time, 2) the maximum dwell time, 3) the threshold value for distance from the road network that qualifies points to be eliminated and dwell times recalculated, 4) the number of points before and after a flagged point that should be incorporated into the test of a heading change, and 5) the minimum number of points a trip end should be away from another trip end to be deemed a separate trip. In total, the number of levels for each of these variables would result in a total of 162 combinations to test. In order to reduce the number of scenarios tested, we established the optimal level for each parameter individually and then moved to the next parameter. In total 18 combinations were tested. The first 13 runs tested three different combinations of the criteria described above (combination of dwell time and distance off the network, combination of dwell time and heading change, and combination of all the criteria). According to the results from the first 13 runs, it can be seen that the combination with all the criteria (listed in the last column in Table 1) works best. Therefore, from run 14 to run 18, the goal is to find the best parameter levels for the combination 3.

Assessing the accuracy of the methods and parameter levels required consideration of two types of errors. Error type 1 occurs when a trip end is flagged but no trip end actually exists. This type of error occurs either when there was a GPS signal loss or during abnormal traffic stoppage or congestion. The second type of error is generated when the method fails to identify a trip end where one actually exists. This usually happens when there is trip chaining or trips with quick stops such as dropping off and picking up passengers. Given this methodology for dividing trips is part of a larger research project to study route choice behavior, the latter type of error is considered more serious than the former. However, others studying trip rate or trip production might argue the opposite.

The final results for the 12 households were averaged for each combination of parameter levels and the results are shown in Table 1. In addition to the 18 sets of results for the methodologies discussed in this paper, the results of identifying trips based only on dwell times of 45, 120, 140, or 180 seconds are also shown in Table 1. These dwell times are chosen based on those used in previous literatures. The results using only dwell time are provided to evaluate the improvement due to the use of both the minimum and maximum dwell time in addition to the heuristic methods involving heading change and distance from the road network. The number of trips (N_{real}) in the dataset based on the in-vehicle booklets and manually verification was 885 (on average 74 per household). The '% Difference' is defined by Equation [1]

$$\frac{N_{diff}}{N_{real}} \times 100\% \qquad \text{[Equation 1]}$$

Where N_{diff} = $N_{identified}$ - N_{real}. The '% Difference' measures the extent to which the estimated number of trips is different from the real number of trips. A positive value of N_{diff} means that the number of automatically identified trips is more than the number of real trips, while a negative value means the opposite. Table 1 lists the number of trips identified by each method with each combination of parameters. The distance from the network and heading change methods on their own (in most cases) underestimate the number of trips, while the combined method slightly overestimates total trips. Because error type one increases the count of trips and error type two decreases the count, the actual and estimated number of trips could be relatively close even given large errors. Therefore, two additional error measures were provided. The first, '% Error', is defined by Equation [2]:

$$\frac{N_{error}}{N_{real}} \times 100\% \qquad \text{[Equation 2]}$$

Where N_{error} is the number of trip ends identified by algorithm that were not actually there (type 1 error) and N_{real} is the number of trips actually made by the households (885). The second measure, '% Accuracy' is defined by Equation [3]:

$$\frac{N_{correct}}{N_{real}} \times 100\% \qquad \text{[Equation 3]}$$

Where $N_{correct}$ is the number of actual trip ends correctly identified by the methodology. Therefore, in examining the results in Table 1, one should consider that a perfect trip dividing approach would have a 0% difference and 0% error, with an accuracy of 100%.

Table 1 Trip Identification Results

	Parameters					Methods/Combinations											
						Distance from Network				Heading Change				Distance and Heading			
Run	Min. Dwell Time (s)	Max. Dwell Time (s)	Distance from Network (m)	# of Points in Heading check	# of Points for Duplicate Trip Check	Trips Identified	Difference (%)	Error (%)	Accuracy (%)	Trips Identified	Difference (%)	Error (%)	Accuracy (%)	Trips Identified	Difference (%)	Error (%)	Accuracy (%)
1	20	140	15	60	30	826	-7	4	89	1160	31	40	91	1219	38	41	96
2	20	140	15	20	30	826	-7	4	89	770	-13	8	79	950	7	12	95
3	20	140	15	40	30	826	-7	4	89	808	-9	13	79	1099	24	28	96
4	20	140	15	20	30	826	-7	4	89	770	-13	8	79	950	7	12	95
5	20	140	30	20	30	810	-8	3	88	770	-13	8	79	942	6	12	95
6	20	140	30	20	30	826	-7	4	89	770	-13	8	79	950	7	12	95
7	20	60	30	20	30	1167	32	38	94	776	-12	9	79	1237	40	44	96
8	20	100	30	20	30	915	3	11	92	771	-13	8	79	1013	14	20	95
9	20	140	30	20	30	826	-7	4	89	770	-13	8	79	950	7	12	95
10	20	140	30	20	60	802	-9	4	87	730	-18	5	77	892	1	9	92
11	20	140	30	20	30	826	-7	4	89	770	-13	8	79	950	7	12	95
12	30	140	30	20	30	826	-7	4	89	739	-16	8	76	921	4	11	94
13	40	140	30	20	30	810	-7	4	89	720	-19	5	76	893	2	9	94
14	40	140	30	20	40									881	0	9	91
15	40	140	30	20	50									870	-2	8	90
16	40	140	30	20	60									854	-4	7	89
17	40	120	30	20	60									891	0	9	91
18	40	140	15	20	30									904	2	9	93
19	Dwell Time = 45 seconds					1509	71	80	91								
20	Dwell Time = 120 seconds					909	3	13	90								
21	Dwell Time = 140 seconds					854	-4	9	88								
22	Dwell Time = 180 seconds					813	-8	7	85								

Overall, the results in Table 1 indicate, as one might expect, that the cost of identifying more actual trips correctly is the false identification of additional trip ends. In general, the distance from the network or heading change method alone performs poorly. Parameter combination 13, using both the heading and distance from network check, is considered the best and provides an accuracy rate of 94% with an error rate of 9%. Although the accuracy rate is not the highest (slightly lower than some runs), the error rate is more acceptable. This is an improvement over dwell time alone. Using a short dwell time (45 seconds) only provides a relatively high accuracy in identifying actual trips but an unacceptably high error rate. A dwell time of 120 seconds alone provides an accuracy rate of 90% but still an error rate of 13%. Dwell times of 140 or 180 seconds produce less acceptable results.

3. Attitudinal and Travel Habit Variables: Effect on Consistency of Route Choices

3.1 Objectives

Information concerning drivers' choices and the influences on those decisions can be used by many groups. Researchers, marketers, planners, drivers, politicians, engineers, and those involved with transportation technologies are all included in these groups. To better understand the value and use of traveler information systems, we have chosen to gather information on the consistency of current choices during peak and off-peak travel periods. Furthermore, we will investigate how common it is to stray from typically-used routes and whether consistency is linked to variable types such as attitudes, travel habits, route characteristics, and demographics.

The objective of this work is to determine using stated preference–style survey data if route choice, specifically the consistency of route choices, is influenced by attitudes, travel habits, roadway characteristics, congestion, or a combination of a few or all of these elements. Another goal is to determine the extent of those influences in comparison to other variables.

3.2 Background

Route choice modeling is necessary for many reasons, but most work has been motivated by the need to improve existing advanced traveler information systems. Abdel-Aty et al. (1995) used a mail-back survey to collect data for this purpose. The data were used in developing a binary logit route choice model that showed significance for travel time, information reliability, safety, and roadway characteristics. In a different paper, Abdel-Aty et al. (1994) bases a statistical analysis of commuters' route choice behavior and the influence of traffic information on a computer-aided telephone interview survey. Two models were estimated that show an important relationship between the use of traffic information and the propensity to change routes. Polydoropoulou et al. (1994) analyzes commuters' route choice behavior in the presence of traffic information. It was found that en-route diversion is primarily influenced by attitudinal factors and information acquisition; therefore, a reliable and frequently updated traffic information system will encourage utilization of traffic information and affect route diversion. Katsikopoulos et al. (2000) found that risk attitude in route choice is influenced by whether the route choice scenario is classified as belonging to the domain of gains or to the domain of losses.

Modeling of route choice is mainly carried out with the use of random utility modeling approaches, such as logit and probit models. This modeling work is often complicated by the correlation, overlap and lack of independence between independent route choices. Vaughn et al. (1993) developed a dynamic probabilistic model of subjects' advice compliance and Emmerink et al. (1996) analyzed the impact of both radio traffic information and variable message sign information on route choice behavior. The types of models described in these works analyze discrete choices, but they are limited in analyzing the variations or fuzziness in a subject's behavior. Research by Abdel-Aty et al. (2004) confirmed that route choice is a function of multiple factors, not just travel time or distance. This is confirmed by a multinomial logit route choice model that evaluates the effect of expressway ramp location on drivers' ramp selection. The data for this analysis were gathered from an origin-destination travel survey.

Attitudes play an important role in an individual's interpretation of the world around them. Attitudes, which are positive or negative evaluations or beliefs held about something, help guide behavior and the consistency in actions when using previous knowledge about different situations. Many researchers believe that there is no significant direct effect of attitudes on behavior. In one of his articles, Wicker (1969) reviewed 42 previous studies and suggests that there is no significant defining empirical evidence to link attitudes directly to behavior. The average correlation between attitudes and behavior was approximately 0.15 and it was concluded that attitudes and behavior may be slightly, but not closely, related.

Defining and measuring attitudes and behavior is not as simple as it might appear. Behavior eventually results through a continual combination of attitudes toward a situation. Many different types of behavior can lead to the same outcome, and we may actually be more interested in one or more of these types of behaviors due to attitudes than in the outcome itself. A single act is defined as a specific behavior performed by an individual coupled with a high degree of agreement among observers that the act took place. Behavioral criteria are comprised of four elements that in some way affect future attitudes toward the same behavior: the action, the target at which the action is directed, the context in which it occurs, and the time at which it is performed. To determine the influence of a type of behavior it is necessary to come to an understanding of these elements. Ultimately, when an appropriate measure of intention or attitude is identified it will provide the most accurate prediction of behavior. Theoretically, intentions determine behaviors, but it should not always be assumed that intention is an accurate predictor of behavior (Ajzen and Fishbein, 1980).

There are numerous transportation related attitudinal data applications. Thirteen different applications have been reviewed and summarized in Parkany et al. (2004). The paper lists the goal of the different applications, the attitudes or types of attitudes analyzed in the applications, the methodology and the data that were used for the analysis, along with the results of the various applications. It is clear from this work that attitude does have an impact on travel decisions such as route choice. Even if it is difficult to collect data and quantify this effect it is imperative that we continue to gather and test hypotheses in this area since route choice is critical to so many transportation modeling activities.

3.3 Data Collection

The primary data used for this study was collected from 524 drivers in the 256 households who participated in the GPS vehicle tracking experiment in Lexington, Kentucky. The mail-back travel habits follow-up survey is shown in Appendix B. In addition to these data, demographic data collected by phone (Appendix A) during recruiting for the in-vehicle GPS experiment are used. The phone survey collected demographic information of the participants such as age, gender, number of individuals per household, the number of drivers per household, the number of vehicles per household, and the number of workers per household. As a way of measuring a participant's familiarity with the road network, respondents were asked for the time spent at their current home and worksite; they were also asked for the total time that they had lived in Lexington.

The Travel Habits Survey (Appendix B) asked for specific travel habits given various situations. In one part of the survey participants were asked to trace the routes they would use between known origins and destinations in both directions in the peak and off-peak times. In another part of the survey responses were given as worded frequencies increasing as follows: Never, Seldom, Sometimes, Often, and Always. This wording had to be coded for statistical analysis purposes. Responses were coded on a Likert scale ranging from 1-5. In this section of the survey, participants were asked to rate from Never (1) to Always (5) an action that they would take if they were placed in a specific situation. This action would most likely be determined based on the previous behavior of the participant. In order to accurately answer a question of this nature, a respondent would need to recount actions that had been previously carried out in order to provide a rating. This section consisted of ten similarly worded stated action questions that were intended to capture the travel habits of the respondent. The final section of the survey asks for the respondent to rate the importance of several different factors when determining a travel route for work or for shopping trips. The factors to be rated are the same for either work or shopping trips, but the order varies depending on the color of the survey. Four survey colors were used to mix question orders. All of these factors are rated on a Likert scale ranging from Not Important (1) to Very Important (7).

3.4 Route Choices and Consistencies

Respondents were asked to trace their most likely and unlikely routes in peak and non-peak times between a known downtown/university location and the city airport (6.35 miles). The three most-utilized routes by the survey respondents are depicted in Figures 5-7. These routes were drawn by the respondent to indicate their preferred Friday afternoon (peak) route and their preferred Sunday afternoon (off-peak) route. Unfortunately, no other route was used by as many as five different respondents. The other routes are lumped together as "other" in the following tables of route choices.

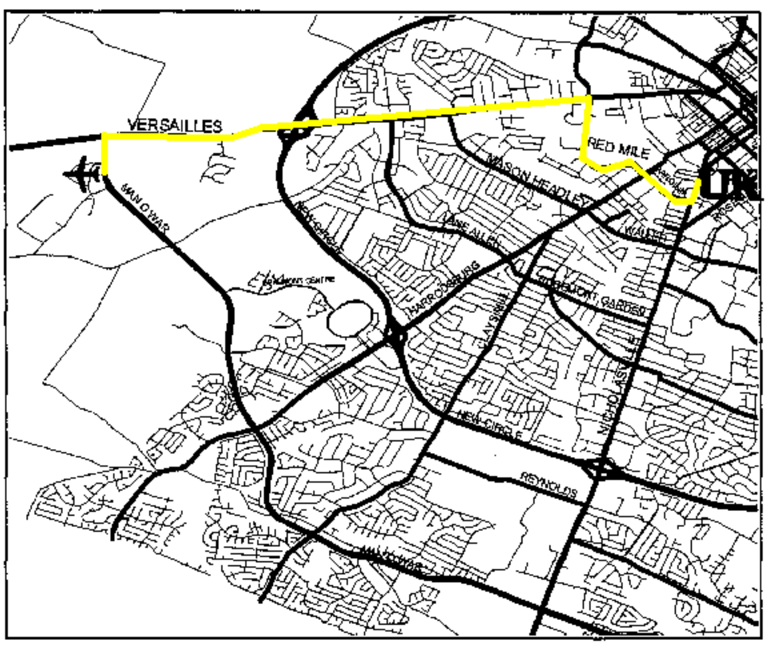

Figure 5 Most Traveled Route in the Roadway Network: Route 1

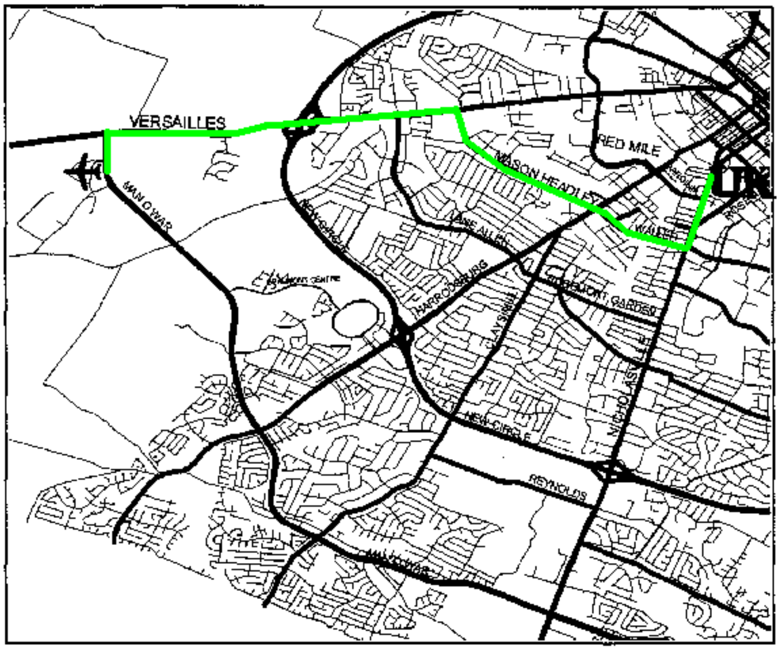

Figure 6 Second Most-Traveled Route in the Roadway Network: Route 2

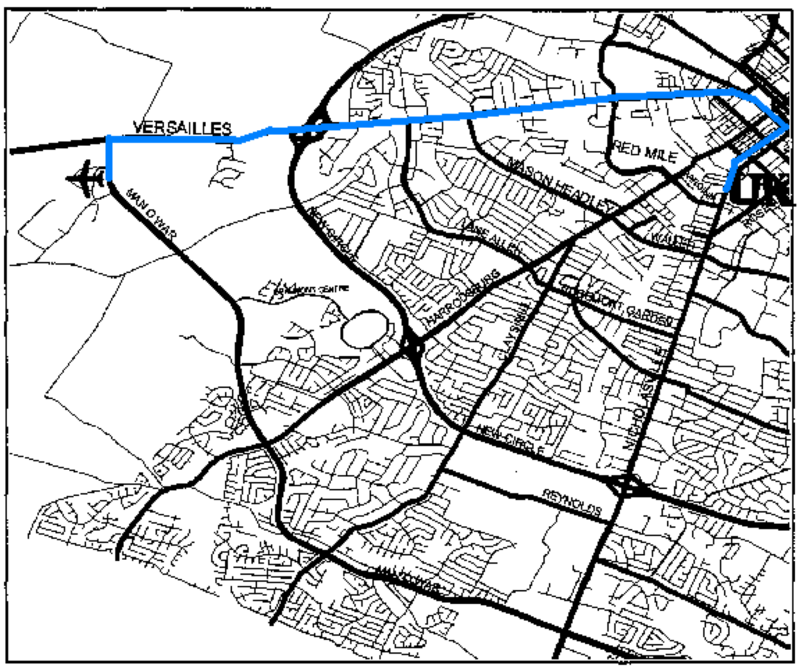

Figure 7 Third Most-Traveled Route in the roadway network: Route 3

In Table 2 we see a comparison of the route characteristics of the three major routes. This includes comparisons between the number of signals, turns, and the segments that are being used for travel on the various routes. These segments or links describe whether or not a particular part of a roadway was used. If a roadway was used, the number of links on that particular roadway was listed. There is a negative correlation between the number of signals per route and the popularity of the routes according to the respondents. The route with the lowest number of signals correlates to the most popular route and the route with the highest number of signals correlates to the least popular of the three routes considered. The number of turns taken over the three routes as well as the use of a freeway does not show any significant variation. The arterial, Versailles Rd, is by far the most popular roadway chosen. This is the only tabulation for the number of links on a particular roadway because the use of a roadway was input as a dummy variable in the models described below.

Table 1 Comparison of Route Characteristics of the Major Routes

Alternative Route	Number of Signals	Number of Right Turns	Number of Left Turns	Freeway Use	No. of segments on Versailles	No. of segments on Harrodsburg	No. of segments on Nichlasville	No. of segments on ManOWar	No. of segments on NewCircle
Route 1	14	2	1	0	4	0	1	1	0
Route 2	16	2	1	0	3	0	3	1	0
Route 3	19	2	0	0	7	0	3	1	0

In Table 3 we can observe specific trends for preferred and non-preferred peak and off-peak routes. For the combined preferred peak trips we see that Route 1 is clearly the dominant route. This is not true for the combined non-preferred trips or the off-peak preferred trips. In these cases, Route 1 and Route 2 have the same number of trips. We also see that the other route category contains the most trips. The “other” route category contradicts the idea that travel on the three designated routes is the dominant choice within the Lexington roadway network. Even though the combination of respondents for the three main routes for the preferred trips is much larger than the other routes category, the other routes category shows that respondents choose various routes between the same origin and the same destination. Much more interestingly, when respondents were asked about non-preferred, but realistic routes, they identified a variety of routes (only 25% identified one of the three main routes). This dispersal of travelers through a user equilibrium-like process may aid the overall efficiency of the roadway network system by reducing travel times, minimizing deterioration, and reducing costs for travelers. It is possible that this use of diverse routes edges closer to a system optimal approach.

Table 2 Preferred and Non-Preferred Peak and Off-Peak Routes

	From the University of Kentucky to the Kentucky International Airport			
	Friday (Peak) Preferred	Sunday (Off-Peak) Preferred	Friday (Peak) Not Preferred	Sunday (Off-Peak) Not Preferred
Route 1	65(35%)	54(29%)	17(9%)	21(12%)
Route 2	28(15%)	53(29%)	22(12%)	18(10%)
Route 3	22(12%)	18(10%)	6(3%)	6(3%)
Other	69(38%)	59(32%)	136(75%)	135(75%)
Totals	184	184	181	180
	From the Kentucky International Airport to the University of Kentucky			
	Friday (Peak) Preferred	Sunday (Off-Peak) Preferred	Friday (Peak) Not Preferred	Sunday (Off-Peak) Not Preferred
Route 1	53(34%)	49(31%)	18(12%)	20(13%)
Route 2	32(20%)	43(27%)	16(11%)	17(11%)
Route 3	15(10%)	15(10%)	6(4%)	5(3%)
Other	57(36%)	50(32%)	113(74%)	109(72%)
Totals	157	157	153	151

The percentages in Table 3 also indicate that there is little directional route choice effect in Lexington. Throughout the table, similar percentages of people use the three main routes or choose other routes to travel either towards the airport or away from the airport and to the University. Recall that question order was randomized.

Table 4 presents these route data in terms of consistency. Table 4 presents the consistency with which respondents picked their peak and off-peak routes and how their choices relate to the alternative routes that they indicate others might use. More than half of the sample (of about 340 individuals with “good” data) indicated the same preferred route on peak and off-peak. About a third of the sample filled out maps showing the same route for peak and off-peak non-preferred routes. Equally interesting are the more than 20% of the people (74/340) who selected one route as their preferred route and one route to recommend to others.

Table 3 Route Choice Consistencies

	Combined from the University of Kentucky to the Kentucky International Airport (KIA) and from KIA to the University of Kentucky				
	Same Choice SP & FP	Same Choice SN & FN	Same Choice SP & FN	Same Choice SN & FP	Same Choices SP & FP **&** SN&FN
Route 1	78	16	6	3	40[1]
Route 2	47	16	8	4	28[1]
Route 3	22	3	2	0	16[1]
Other	42	77	7	1	
Totals	**189**	**112**	**23**	**8**	**74**
	From the airport to the University of Kentucky			**From the University of Kentucky to the airport**	
	Same Choice SP & FP	Same Choice SN & FN		Same Choice SP & FP	Same Choice SN & FN
Route 1	37	10		41	6
Route 2	26	6		21	10
Route 3	8	2		14	1
Other					
Totals					

1. Either the preferred or the non-preferred trips are the indicated routes.

Table 4 Respondents That Select The Same Route for Peak and Off-Peak Conditions

With Single-Person Household Demographic Variable Worksite:

Log likelihood =	-94.8062
Number of obs =	246
Pseudo R2 =	0.4440

Without Worksite:

Log likelihood =	-113.38044
Number of obs =	252
Pseudo R2 =	0.3509

	With Worksite		Without Worksite	
sameroutespandfp	Coef.	z	Coef.	z
betterscenery	-0.491969	-1.75	-0.3465236	-1.35
avoidfreeways	-0.3830898	-1.78	-0.2446401	-1.3
differentroute	-0.4077822	-1.38	-0.5091608	-1.91
savoidsignal	0.3416013	1.95	0.1904355	1.25
saccesstostores	0.4071162	2.87	0.3121033	2.52
spasspreference	-0.3042981	-2.34	-0.1774728	-1.58
sinfobyradio	0.3855799	2.37	0.2347674	1.76
straveltime	-0.3745121	-2.34	-0.2904606	-2.1
savoidpolice	-0.5169512	-2.39	-0.3861731	-2.14
wavoidstop	0.4617585	2.71	0.2977394	1.99
wavoidsignal	-0.6776489	-3.3	-0.4072601	-2.39
wroadcondition	-0.2776461	-2.07	-0.2224428	-1.87
waccesstostores	-0.2894086	-2.03	-0.1591361	-1.29
wpasspreference	0.3715904	2.34	0.3936978	2.82
winfobyradio	-0.4103672	-2.71	-0.2925884	-2.31
wfamiliarity	0.2178531	1.91	0.1128483	1.17
wavoidpolice	0.4793421	2.3	0.3065814	1.69
spchangedirectionatinterchange	-1.283047	-2.15	-1.025784	-1.9
fpnumberofsignals	0.2304032	3.94	0.1763237	3.7
fpnumberofrightturns	0.5979166	1.74	0.4551863	1.49
fpchangedirectionatinterchange	1.264449	1.92	0.9610928	1.56
persons	-0.8348534	-2.26	-0.6950333	-2.12
drivers	0.5554299	1.58	0.3403966	1.1
workers	0.976487	2.61	0.785953	2.41
worksite	0.068506	3.22	-	-
employed	0.8846086	1.85	0.3042806	0.73
_cons	-2.63951	-1.41	-0.6956277	-0.43

Note: A positive coefficient indicates that respondents with high values of this variable are more likely to pick the same routes in peak and off-peak conditions.

3.5 Consistency Models

This section of the report describes a model for the consistency of the route choices and determination of which travel habit and attitudinal variables influence the peak and off-peak decisions.

Table 5 shows the binary logit model corresponding to the respondents that choose the same route for both peak and off-peak conditions. Again, as shown in Table 4, this is 60% of our sample—a surprisingly large number showing non-variance in their preferred travel choices. More independent variables significantly influence this dependent variable than any of our other dependent variable models in this research. The pseudo R-squared value is relatively large: 0.444 and 0.351. Two models with and without the demographic variable “worksite” are provided in an attempt to capture more observations. The length of time at one work site has a large influence on the model—the length of time living in Lexington or at one address do not influence the choice to use the same route in peak and off-peak conditions. The first few variables in this list are the significant travel habits variables that all have negative coefficients, indicating a greater likelihood to choose different routes for peak and off-peak conditions. These variables include better scenery, avoiding freeways, and desiring a different route for a change of pace. The next list of variables is the attitudinal variables—respondents reported which variables were important or not important for both shopping (off-peak) and work (peak) trips. The trip characteristic variables, including the number of signals and number of right turns on Friday preferred (peak trips) are listed next. The last variables are demographic which, with the exception of the number of people in the household, positively correlate to taking the same route in peak and off-peak conditions.

Fewer variables are exhibited in the model of the respondents that indicated the same non-preferred route for peak and off-peak conditions. One third of the respondents are included in this category. In this model, only one travel habit variable, desiring different routes, plays a role (negatively, as expected). Also, no demographic variables significantly explained choosing the same peak and off-peak non-preferred route. Two shopping attitudes (preference for wider travel lanes and preference for familiar roads) and one work attitude variable (travel time) play a negative role in choosing the same non-preferred routes. Four route characteristic variables (number of signals, number of right turns, changes of directions at interchanges on Friday/Sunday) are significant and they all have to do with the respondents preferred choices. A similar number of variables help explain the handful of respondents that suggest that their preferred off-peak route will be used by others during the Friday peak (in another model). Here, no travel habit or demographic variables play a role.

4. Conclusions and Summary of Contributions

It is essential that methods to generate more usable complete route data from GPS be developed. In this study, a combination of a maximum and minimum dwell time, a heading change and a check for distance between the GPS points and the road network were found to provide an improvement over dwell time alone in automatically identifying trip ends in a passive GPS data stream. On average, 94% of trips are correctly identified. This good performance makes it realistic to confidently batch-process GPS data obtained from passive GPS devices and use the data for trip rate or route choice research. In the test dataset used in this project, the methods proposed also identified over a third of the trip ends which occurred during GPS gaps or times when GPS points were not being recorded continuously.

The first part of this study has demonstrated the importance of validating GPS trip dividing methods against known trip start and end locations in order to defensibly measure the accuracy of algorithms. The relatively small ranges of parameters tested here resulted in a significant variation in accuracy and error results, indicating that trip division is highly sensitive to the parameters used. Some recent studies have found GPS dramatically increases the number of trips reported by travelers. However, it is possible that the method or combination of parameters used to divide the GPS data stream into individual trips significantly affected the trip rate estimate. Therefore, caution should be exercised in interpreting GPS travel data.

In the second part of this study, the analysis of route choice data in the follow-up survey, revealed that a surprising number of respondents pick the same route between the University of Kentucky and the Kentucky International Airport during peak and off-peak conditions. A smaller but significant number select the same non-preferred routes that others may use, but these choices varied between peak and off-peak trips. Quantitative models were used to examine the types of variables that influence route consistency. The results indicate that a wide variety of data types influence consistency: travel habit variables, attitudinal variables, route characteristic variables, and demographic variables. Demographic and route characteristic variables have less influence in the same-route model. This suggests that attitudinal data is valuable in determining route choices.

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Appendix A. Phone Survey

Household #:

Name of Person called:

Contact number:

Hello I'm Jianhe Du at the University of Connecticut. You recently replied to my email (or letter) regarding a travel habit survey I am conducting in Lexington as part of my PhD dissertation.

Is this an OK time to talk for a couple of minutes?

First, can I answer any questions regarding the survey process, the confidentiality of the data or the purpose of the study before you make a final decision on whether you can participate?

As you know the GPS receiver will be plugged into your car lighter and will require no effort from you. We also have an in-vehicle booklet in which you check the driver, passengers and type of destination for each trip. One of the items you will check off in the booklet is who the passengers are for each of your trips. To minimize your work in using the in-vehicle survey booklet, we will customize the forms specifically for your household and fill in the names of your household members beforehand.

So if you wish, you can tell me the first names of the people in your household.

If you are willing we are also collecting the age range for each person.

Is **{insert name}** employed full time or part time outside of the home? {**If the answer for this question is PT or NO, ask if student.**}

Is {**insert name**} a student?

Name	**Age (Please circle category)**	**Sex**	**Driver**	**Stud.**	**Employed Outside Home**
			Check for Yes		
	0-5 6-11 12-17 18-20 21-30 31-50 51-65 >65	M F			F P NO
	0-5 6-11 12-17 18-20 21-30 31-50 51-65 >65	M F			F P NO
	0-5 6-11 12-17 18-20 21-30 31-50 51-65 >65	M F			F P NO
	0-5 6-11 12-17 18-20 21-30 31-50 51-65 >65	M F			F P NO
	0-5 6-11 12-17 18-20 21-30 31-50 51-65 >65	M F			F P NO

How many vehicles does your household own? ____________

What type of vehicle will we be putting the GPS receiver in? ____________________

My last question is so we can compare the travel patterns of people who are more and less familiar with the road network in Lexington.

I would like to ask how long have you lived in Lexington? How long have you lived at your current address and how long have you worked at your current job site?

Lexington Years: Months:

Current Address Years: Months:

Job Site Years: Months:

We have hired a UK Geography PhD student to install the GPS receiver. Her name is Jean. Installation will take only 5-10 minutes and she can come to your home or work, whatever is most convenient for you. We have an installation ***(date)*** which will be for pickup ***(date)***. Would this time work for you?

Let me provide you with a Lexington number to contact us if you need to change your appointment time or if you have any questions while participating in the study: 361-0469

(Reconfirm appt date and time.) Thank you very much for your help in our research. Would you be willing to provide a second telephone number where we can reach you when we are trying to arrange pick up at the end of the 10 day period?

Hi this is Jianhe Du from the University of Connecticut. You replied to an email from me regarding a travel habit survey that is part of my Ph.D. dissertation. I am calling to answer any questions you might have about the survey process, the purpose of the data collection or the confidentiality of the data, so that you can make a final decision as to whether or not you can be a participant in our study. You can send an email to jianhedu@engr.uconn.edu and let me know if there is a better time or number to call you at. Otherwise we will try you again at another time. Thank you very much for your interest in our research.

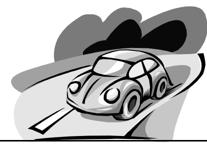
Appendix B. Follow Up Survey

Travel Habits Survey 2002

THANK YOU very much for your participation in our study. This is the last stage of the survey where we are using tables and maps to ask you what factors affect your route choices. This should take less than 5 minutes.

This form should be completed by the driver indicated above. You can return this questionnaire to the research assistant picking up your data logger or ask him for a pre-stamped envelope and mail it back to us. We assure confidentiality of all of responses. Please contact us if you have any questions.

Lisa Aultman-Hall, Associate Professor
University of Connecticut
Lexington # 859-361-0469



Jianhe Du
Ph.D. Candidate
jianhedu@engr.uconn.edu

Please note that for this questionnaire a **ROUTE** is the series of road segments that you travel from the starting point of your trip to the ending point of your trip.

1. Would you like to receive an executive summary of our findings in this study?

☐ YES – please provide email ___________________________________
☐ NO

2. Please check the box corresponding to your travel habits.

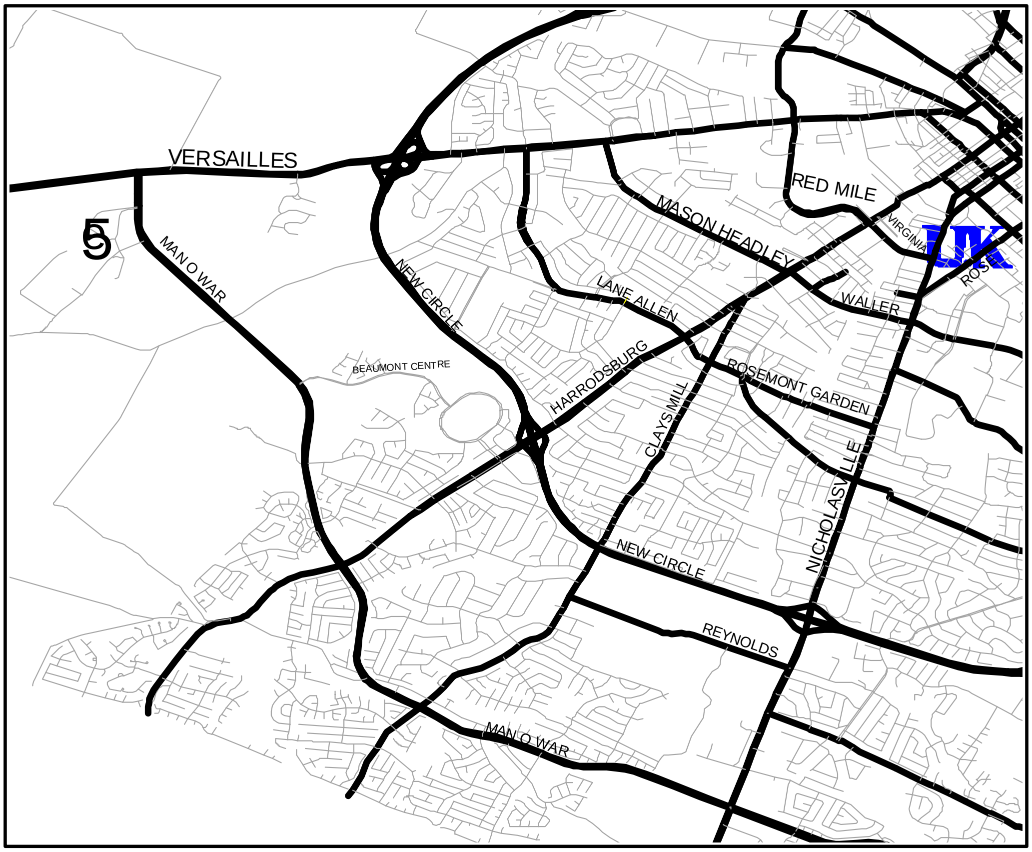
Items	Description				
1. At intersections with traffic signals, how often do you change your mind about turning based on the color of the light?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
2. How often do you select your whole route before your trip begins?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
3. During rush hour how often do you use neighborhood roads to avoid busy main roads?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
4. How often do you choose a route with better scenery even if it is longer than other routes?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
5. When traveling to a new Lexington destination that you have never been to before, how often do you consult a map?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
6. When traveling to any Lexington destination, how often do you consult a map?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
7. How often do you try to avoid freeways?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
8. How often do you choose to use a freeway when other non-freeway routes are physically shorter?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
9. When traffic becomes unexpectedly clogged, do you try to turn and take another route, even if it might be a longer route?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always
10. How often do you take a different route to a regular destination just for variety or change of pace?	☐ Never	☐ Seldom	☐ Sometimes	☐ Often	☐ Always

3. a) On the map to the right, trace your preferred route

at **4:00 PM** on a **FRIDAY** afternoon when the traffic is very heavy

FROM the University of Kentucky (at the UK symbol shown)

TO the airport.

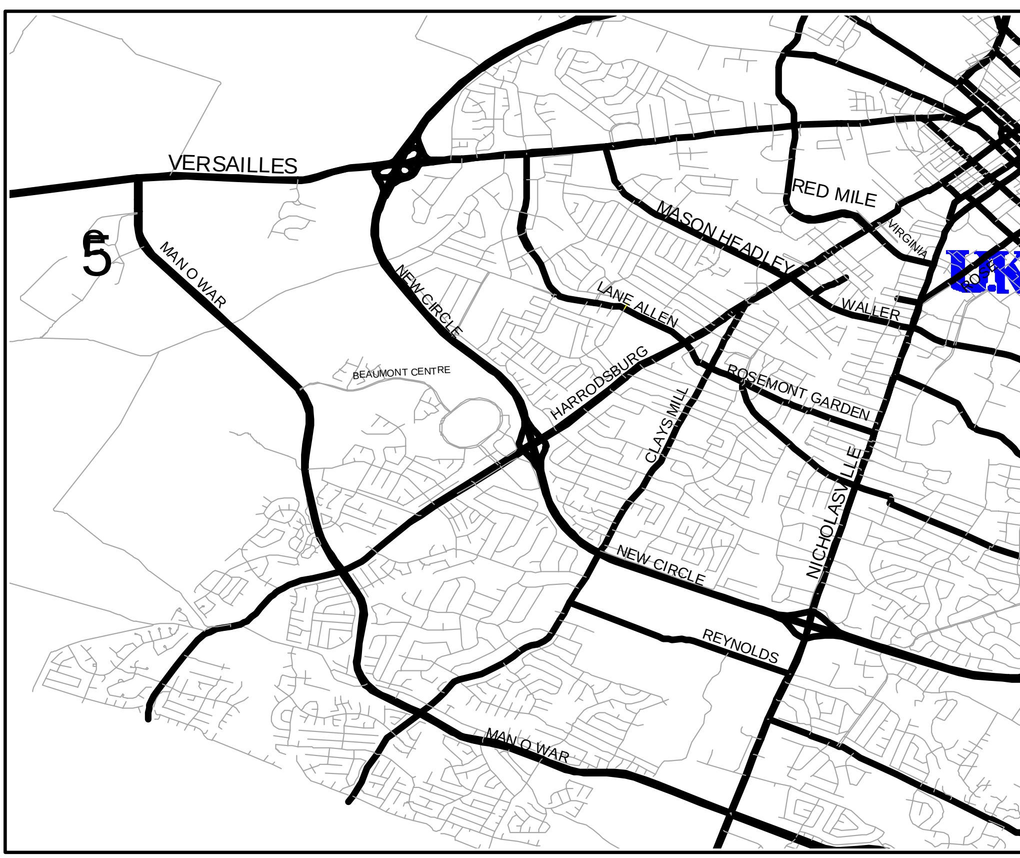


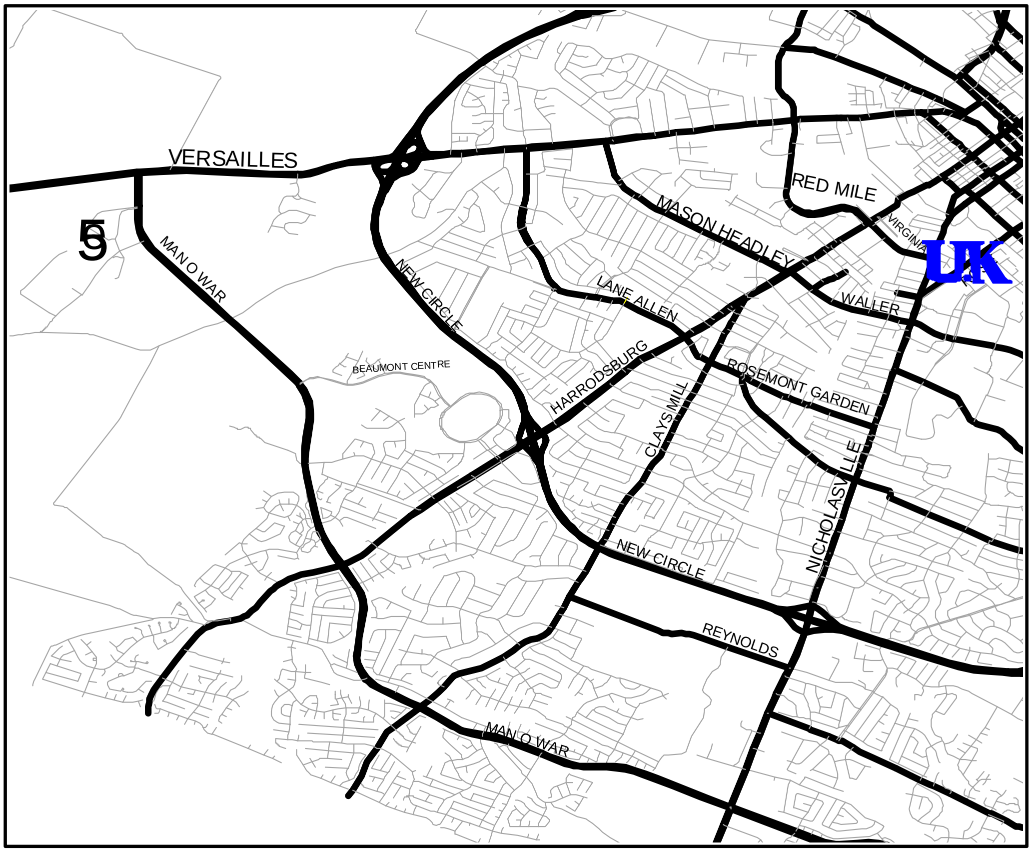
3. b) On the map to the right, trace your preferred route

on a **SUNDAY morning** when traffic is light

FROM the University of Kentucky (at the UK symbol shown)

TO the airport.



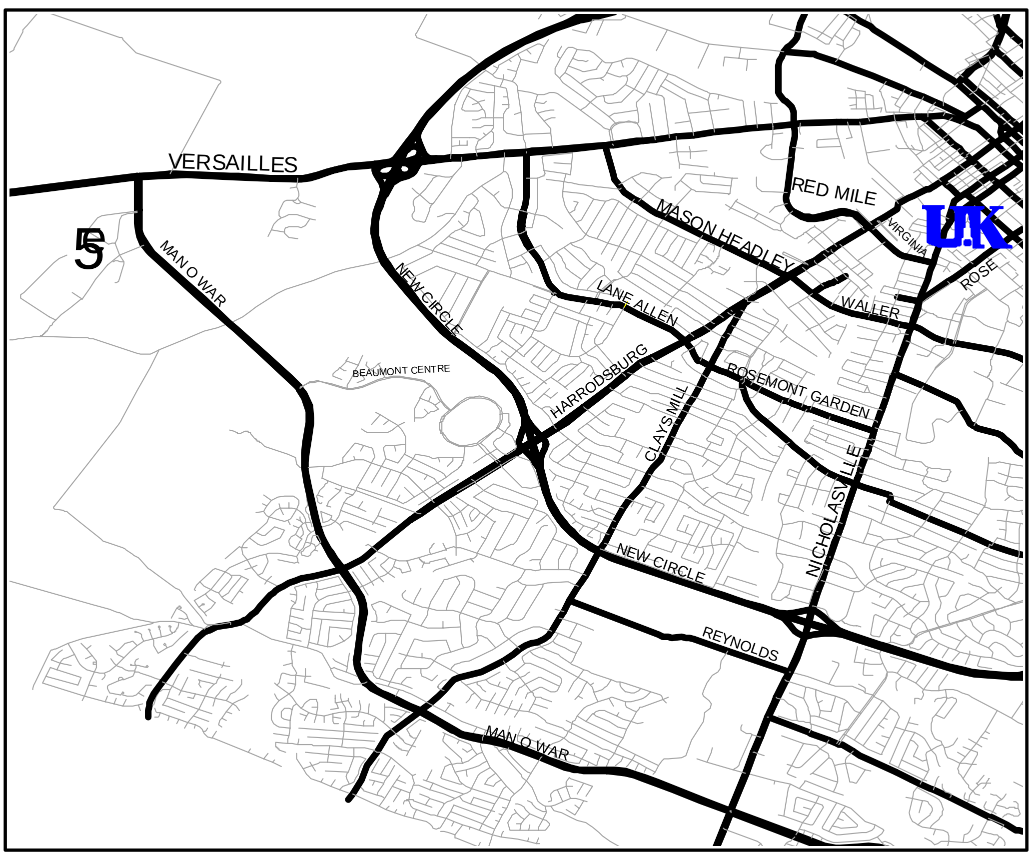


4. a) On the map to the left, trace a realistic route that you know others might use, but you would NOT

at **4:00 PM** on a **FRIDAY** afternoon when the traffic is very heavy

FROM the University of Kentucky (at the UK symbol shown)

TO the airport.



4. b) On the map to the left, trace a realistic route that you know others might use, but you would NOT

on a **SUNDAY morning** when traffic is light

FROM the University of Kentucky (at the UK symbol shown)

TO the airport.

SURVEY CONTINUES ON REVERSE PAGE

5. **In the following tables (one for work trips and one for shopping trips) please rate the importance of each factor when deciding on your travel route.**

Table A: Work Trips (If you do not work outside the home, complete only Table B)

Rate the importance of the following factors in affecting the route you choose to travel to WORK…	Not Important						Very Important
Avoiding stop signs	1	2	3	4	5	6	7
Avoiding traffic signals	1	2	3	4	5	6	7
Street lights at night	1	2	3	4	5	6	7
Wider travel lanes	1	2	3	4	5	6	7
Road condition (potholes, bumps, maintenance)	1	2	3	4	5	6	7
Avoiding streets with lots of stores and services	1	2	3	4	5	6	7
Having access to stores and services	1	2	3	4	5	6	7
Preference of the passengers with you	1	2	3	4	5	6	7
Road traffic information provided by radio	1	2	3	4	5	6	7
Safety	1	2	3	4	5	6	7
Avoiding lower speed limits	1	2	3	4	5	6	7
Travel time (route is faster)	1	2	3	4	5	6	7
Scenery	1	2	3	4	5	6	7
Avoiding traffic congestion	1	2	3	4	5	6	7
Familiarity (there may be better routes but you know with your route you won’t get lost)	1	2	3	4	5	6	7
Reliability (there may be faster routes but your route has a consistent travel time)	1	2	3	4	5	6	7
Avoiding routinely policed roads	1	2	3	4	5	6	7

Table B: Shopping Trips

Rate the importance of the following factors in affecting the route you choose to travel to SHOPPING (ex. Mall or Grocery Store)…	Not Important						Very Important
Avoiding stop signs	1	2	3	4	5	6	7
Avoiding traffic signals	1	2	3	4	5	6	7
Street lights at night	1	2	3	4	5	6	7
Wider travel lanes	1	2	3	4	5	6	7
Road condition (potholes, bumps, maintenance)	1	2	3	4	5	6	7
Avoiding streets with lots of stores and services	1	2	3	4	5	6	7
Having access to stores and services	1	2	3	4	5	6	7
Preference of the passengers with you	1	2	3	4	5	6	7
Road traffic information provided by radio	1	2	3	4	5	6	7
Safety	1	2	3	4	5	6	7
Avoiding lower speed limits	1	2	3	4	5	6	7
Travel time (route is faster)	1	2	3	4	5	6	7
Scenery	1	2	3	4	5	6	7
Avoiding traffic congestion	1	2	3	4	5	6	7
Familiarity (there may be better routes but you know with your route you won’t get lost)	1	2	3	4	5	6	7
Reliability (there may be faster routes but your route has a consistent travel time)	1	2	3	4	5	6	7
Avoiding routinely policed roads	1	2	3	4	5	6	7