
Manuscript submitted to TRB 2006
Words: 5721 - Tables: 1 - Figures: 6 - Total: 7471

**Analysis of Commute Atlanta Instrumented Vehicle
GPS Data: Destination Choice Behavior and Activity
spaces**

Stefan Schönfelder
Hainan Li
Randall Guensler
Jennifer Ogle
Kay W. Axhausen

Arbeitsberichte Verkehrs- und Raumplanung

303
August 2005

 *Institut für Verkehrsplanung und Transportsysteme*
Institute for Transport Planning and Systems

ETH

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Analysis of Commute Atlanta Instrumented Vehicle GPS Data: Destination Choice Behavior and Activity Spaces

Stefan Schönfelder
Kay W. Axhausen
IVT
ETH
8093 Zürich
Switzerland

Hainan Li
Randall Guensler
Georgia Tech
Atlanta, Georgia
United States

Jennifer Ogle
Civil Engineering Department
Clemson University
Clemson, South Carolina
United States

Telephone: +41 44 633 3092
Telefax: +41 44 633 1057
schoenfelder@ivt.baug.ethz.ch
axhausen@ivt.baug.ethz.ch

Telephone: 404-894-0405
Telefax: 404-894-2276
hainan.li@ce.gatech.edu
rguensler@ce.gatech.edu

Telephone: 864-656-0883
Telefax: 864-656-2670
ogle@clemson.edu

August 2005

Abstract

The Commute Atlanta Instrumented Vehicle GPS Data is currently the longest running data source available for the comprehensive analysis of individual trip and activity demand. Among other exciting research opportunities for mobility analysis, the longitudinal data have opened the field for testing hypotheses developed to describe human spatial behavior over time.

This paper provides an overview of how the unique GPS data can be used in travel behavior analysis. At the same time, the paper provides analytical results of destination choice and activity spaces assessed for a one-year travel period.

The investigation focuses on the enumeration of trips and unique locations visited over time which is employed as a straightforward way to reveal spatio-temporal patterns of travel behavior. It offers new insights into the nature of stability, innovation, and variety seeking in locational choice.

Keywords

Commute Atlanta; vehicle activity; GPS; data processing; destination choice; activity space

Preferred citation style

Schönfelder, S., H. Li, R. Guensler, J. Ogle and K.W. Axhausen (2005) Analysis of Commute Atlanta Vehicle Instrumented GPS data: Destination Choice Behavior and Activity Spaces, *Arbeitsberichte Verkehrs- und Raumplanung*, **303**, IVT, ETH, Zürich.

1 Longitudinal data, GPS and the question of locational choice

The understanding of the variability of individual choices over time is a major precondition for integrated transport planning approaches (Jones, Koppelman and Orfeuil, 1990). Fortunately, over the last few years, considerable progress has been made in the analysis of stability and variability of individual travel behavior. European multi-week travel diary studies such as *Mobidrive* (Axhausen, Zimmermann, Schönfelder, Rindsfuser and Haupt, 2002) facilitated relevant research into *intra-personal* mobility which would become important in activity-based modeling (Pas and Koppelman, 1986). Meanwhile, the number of studies using such data is expanding, ranging from descriptive analysis of rhythms and routines (Schönfelder and Axhausen, 2001), to the development of activity space measures (Schönfelder and Axhausen, 2003a, b), to new advanced model developments in travel duration and time use (Bhat, Srinivasan and Axhausen, 2005).

Such successful experiences with the travel diary data have increased researchers' interest in accessing long-term travel databases which capture even great seasonal variability in vehicle/driver-specific travel demand. One means for collecting longitudinal data, which has been available since the late 1990s, is the use of in-vehicle or on-body Global Positioning System (GPS) devices in combination with GIS. GPS systems are especially promising for use in the field of route choice analysis (Li, 2004), but also in the context of travel behavior analysis (see Wolf, Guensler and Bachman, 2001) to which this paper adds.

Mixed data collection approaches have been successful in the enhancement of ordinary travel diary studies, making use of GPS/GIS technology for exact time and destination recording and capture of trip underreporting (Wolf, Oliveira and Thompson, 2003; Ogle, Ko, Li and Guensler, 2005). Such studies typically involve driver-computer interaction, and at the very least driver-survey interaction. In passive vehicle monitoring position data are collected by GPS/GIS systems without any information input by the drivers (Lee-Gosselin, 2002). In many cases the motivation for such passive data collection efforts have arisen from other concerns (such as traffic safety), often requiring extensive data post-processing to link onroad data to other parameters of concern (see also Wolf, Schönfelder, Samaga, Oliveira and Axhausen, 2004 and Ogle, 2005 for relevant examples).

The Commute Atlanta GPS data set serves as the base for this paper on destination choice. Commute Atlanta is an ongoing research effort that involves the passive monitoring of approximately 450 vehicles in the Atlanta metropolitan area (Ogle, Guensler and Elango, forthcoming). Second-by-second speed and position data are collected for every instrumented-vehicle trip and data processing activities are automated. When the study is complete, vehicle data will have been collected from each vehicle for two to three full years.

“Where are we heading?” – A focus on location choice

There has been a long tradition in human geography to develop approaches to represent and model location and destination choice as well as the usage of urban space. Most of the efforts such as the *Action Space* (e.g. Horton and Reynolds, 1971) or *Space-Time Prisms* (Lenntorp, 1976) are only conceptual, and where suitable data or surrogate information was available some models were selectively tested. Interestingly, there has more recently been an interest of geographers and transport researchers in re-implementing such geographic concepts using new GIS data (Newsome, Walcott and Smith, 1998 or Kwan, 1999). However, those concepts often only describe the individual *potentials* of travel based upon spatial knowledge, mobility resources, the objective supply of opportunities, etc., rather than revealed behavior.

Daily revealed structures of human spatial behavior are described as *activity spaces*. Activity spaces represent the space which contains the places that individuals are regularly in contact with over a given period of time. Empirical work on revealed locational choice over time is still rare. The collection of long-term household and person mobility data along with the possibility to easily geo-reference trip destination addresses has only now opened the field for testing hypotheses developed to describe human spatial behavior. Several recent studies use multi-day data to address several issues in activity travel behavior and space that could not have been empirically assessed in the past (Schönfelder and Axhausen, 2003a, 2003b; Kitamura, Yamamoto, Susilo and Axhausen, 2005). Such detailed analyses of longitudinal data allow planners and modelers to better understand the behavioral mechanisms behind the dispersion and concentration of activities. Furthermore, the identification of revealed individual activity spaces will increase transport planning’s ability to more realistically define choice set for destination choice.

This paper provides an overview of how the Commute Atlanta GPS data can be used in travel behavior analysis. At the same time, the paper provides analytical results of locational choice assessed for a one-year travel period.

The paper is organized as follows: The next section briefly describes the Commute Atlanta Program. Chapter 3 focuses on the post data-processing and the extracted data set itself which is used for the analyses. The next section examines the revealed structures of observed locational choice and activity spaces. In conclusion, the paper will suggest directions for further research, in particular the potential for the prediction of activity space structures as well as for the redefinition of individual choice sets in destination choice models.

2 Commute Atlanta research objectives

The Commute Atlanta program is funded by the Federal Highway Administration (FHWA) Office of Value Pricing Programs and the Georgia Department of Transportation (GDOT). The main objective of the multi-year Commute Atlanta program is to assess the effects of converting automotive fuel tax, registration fee, and insurance costs into variable driving costs. The project includes the parallel collection of instrumented vehicle data, household socio-demographic surveys, annual two-day travel diaries, and employer commute options surveys.

The research program spans three phases and includes multiple data collection efforts. The first phase included one continuous year of data collection with no treatments to define baseline travel patterns. Due to seasonal variations in travel, researchers desired a full one-year baseline to develop appropriate relationships between pricing treatments and changes in travel behavior in future years. The second research phase began in July 2005 and is designed to evaluate the effects of fixed cent/mile pricing. The third phase of research begins in 2006 and includes a real-time congestion pricing increment of 20 cents/mile when the vehicle is operated on the freeway under congested conditions (in-vehicle data terminals display real-time price). Households begin with larger incentive accounts, which are drawn down at a faster rate. The third phase is designed to examine the impact of such financial incentives on travel time choice.

To establish baseline travel patterns, the research team installed 487 GT Trip Data Collectors in the vehicles of 268 participating households to collect second-by-second vehicle activity data (vehicle speed, acceleration, position, and engine operating parameters). Monitoring began for most almost all vehicles in September-December 2003. The data used in preparing the analyses reported in this paper were collected from January-December 2004.

The random stratified sampling framework for household and vehicle recruitment was designed to accommodate hypothesis testing within the incentive-based research goals. Random sampling across the region was desired, given the differences in lifestyles, access to freeways and transit, and land use characteristics. Consumer response to pricing was foreseen to be dependent upon household income as well as ability to respond to pricing incentives, with household structure and vehicle availability being the variables likely to affect the potential for car and ride sharing (see Ogle, Guensler and Elango, forthcoming, for specific recruitment criteria and opt-in, opt-out analyses).

Due to equipment defect rates which run approximately 3-5%/year (random memory card, GPS, antenna, or other failures), not every vehicle could be monitored on every day in 2004. The sale and purchase of vehicles and household turnover also lead to unmonitored travel. However, the research design and equipment reporting routines allow researchers to determine on which vehicle-days travel is not electronically monitored. The origin and destination location (latitude/longitude) of each trip was recorded and used to examine travel patterns, distances, and ranges of operation for each vehicle. Because each vehicle is tied to a specific household, each trip can be linked to its demographic characteristics. Plus, home and work locations are known for each participant. Because approximately 80% of these vehicles are not shared, the majority of the trips can be linked directly to the age and gender of the driver.

3 Initial data availability as well description of processing and reduction

The Commute Atlanta data lacks a range of information ordinary travel survey data sets usually provide. Because only vehicle activity is monitored, there is a systematic omission of other travel modes such as walking, bicycling, and transit use¹. Positive driver identification for shared vehicles is also not provided by the system,² which appears to increase significantly weekend travel (Guensler, Ogle and Li, 2005). However, the most important element that is not directly collected for each trip is trip purposes. While approximately 60-70% of travel is fairly routine and trip purpose can be identified based upon physical location (home, work, school, day care, and basic shopping), significant additional data processing and imputation is required (geo-referencing of routine locations based upon travel diary data). However, given that the objective of this study is to demonstrate how the data can be used and the ad-hoc analysis of location choice structures over time, the data have been not processed to code known trip purposes as has been done in other studies (Schönfelder and Samaga, 2003 and Wolf, Schönfelder, Samaga, Oliveira and Axhausen, 2004). This coding work is ongoing and will be a component of the evaluation of travel change in the Commute Atlanta study. To match minimal needs for a straightforward investigation, the post-processing included initial filtering of the raw data as well as the identification of trip end positions.

Initial filtering and cleaning

The data used in the analyses reported in this paper were pre-processed to remove vehicle activity that does not contribute to travel demand. Vehicle engines are often started and then stopped and then restarted before a real trip begins (perhaps to go back into the residence for a forgotten item). Vehicles are moved in and out of driveways, and are often idled for extended periods. While such information is useful in vehicle emissions analysis, these activities do not constitute vehicle trips. Criteria established in previous studies (Wolf, 2000; Pearson,

¹ Note, however, that the two-day travel diary studies conducted for the participants showed a very low rate of alternative mode use. In spring 2004, only 19 of more than 3,500 reported travel diary trips were conducted on transit and only six were conducted on bicycle. Hence transit and bicycle use is not likely to significantly impact the results of the analyses reported in this paper (see also Ogle, Ko, Li and Guensler, 2005).

² Recent research indicates that positive driver identification may be possible through the analysis of engine operating parameters (throttle position, engine speed, manifold pressure, etc.) which vary from person to person.

2001; Wolf *et al.*, 2001) were applied here. To remain consistent with previous studies, trips with engine operating durations of less than 120 seconds or activity durations of less than 3 minutes were screened from the travel data.³ In addition, trips for which GPS data were not available (or where a previous trip's destination did not match the next trip's origin location) due to satellite data drops were eliminated. The filtering of the database applying a threshold approach does not systematically prevent that all erroneous trips are detected and erased. Especially if dealing with large data sets such as the Commute Atlanta data, it rather guarantees a minimum of quality.

Identification of trip end position

The Commute Atlanta study establishes trip starts and ends through engine operation. Trip recording begins at engine on and stops at engine off. Chained trips that do not include turning the engine off (approximately 15% of all trips made during the travel diary comparison period) must be identified through post-processing in a GIS system (see Wolf, Oliveira and Thompson, 2003; Ogle, Ko, Li and Guensler, 2005) and are not included in this analysis. For repeated trips to the same location, the final resting position of the vehicle can vary significantly. Parking location depends upon parking availability. To identify and categorize unique destinations, a straightforward statistical clustering approach was applied. All stop positions within a radius of 200 meters were grouped to one unique location using the highly efficient *nearest centroid sorting* cluster method (Anderberg, 1973).

The resulting data base

The resulting data base for analysis contains trips of 445 cars owned by 273 households with 655 household members (including non-drivers, children etc.) The number of monitored days per vehicle and mobile days ranges 6 to 367 and 4 to 361 respectively. The average share of

³ More recent analysis of the Commute Atlanta data indicates that these criteria are probably a bit too stringent. Drop-off trips to video stores, stops at automatic teller machines, and passenger drop-offs are often of much shorter activity duration. The research team is currently analyzing short duration trips to enhance screening criteria and methods.

usage is about 75%, i.e. the vehicles were used on 75% of the monitoring days in average. Up to more than 3.600 trips per car were observed.

The imputed trip data widely correspond with available cross-sectional travel – but not in total congruity. This is not illogical considering the unique longitudinal structure of the Commute Atlanta data, the limitations given by the sample size as well as structure and the rough post-processing of the data base. The average number of car trips per day (4.1) is about 20% larger than the NHTS average (3.4), with the mean daily trip duration (74.4 min/day) and distance (49 km/day) smaller than the national mean (88.7 and 52.8 respectively). Consequentially, considerably shorter drives were monitored compared to the national travel diary survey. Similar results were found in earlier comparisons of GPS traces with ordinary cross-sectional travel diary data (Wolf *et al.*, 2004).

4 Indicators of observed destination choice behaviour: Enumeration and listing of places visited

The enumeration of trips and especially of the unique locations visited over time is employed here as a straightforward way to reveal stability, innovation, and variety seeking in locational choice. The exercise is rarely performed (see Marble and Bowlby, 1968; Schönfelder and Axhausen, 2004). The approach acts as an indicator for which has been described above as human *activity space*.

One main methodological issue in the enumeration procedure is the concept of *unique locations* – especially when analyzing GPS traces. A unique location is usually defined as the product of geocode and trip purpose (see also Schönfelder and Axhausen, 2004). Here, unique locations were estimated by clustering stop end positions, but activity purpose information is not yet available. The number of unique locations under the classical definition (location and trip purpose) will be somewhat higher for the Commute Atlanta data than is reported here.

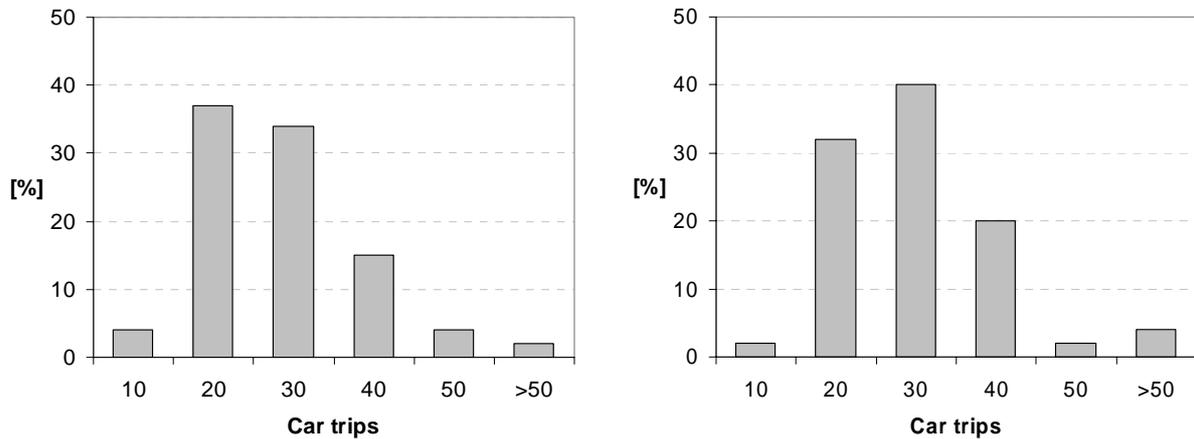
Distribution of trips and unique locations over time

The earlier analysis of long-duration data sets such as *Mobidrive* underpinned the hypothesis that the amount of travel, number of unique locations, and their spatial distribution are all directly related. To provide an impression of how much travel one can expect if people are observed over prolonged time periods, the observed trip rates are reported below.

Figure 1 shows the average weekly trip rates – covering mobile as well as immobile days. The numbers mainly follow a normal distribution with a slight right skew. The average is about 23 trips per week which corresponds with earlier analysis results from the comparable Copenhagen AKTA study (Schönfelder and Axhausen, 2004).

Figure 1 Mean number of observed trips per week and vehicle: Commute Atlanta and Copenhagen AKTA GPS for comparison

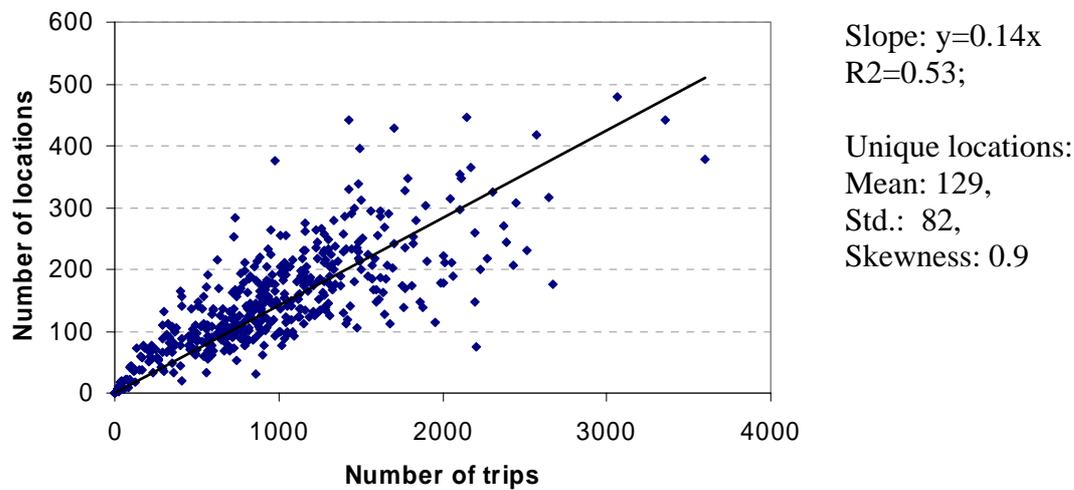
Commute Atlanta (n= 445 cars) - Mean: 22.9; Standard deviation: 10.2
 Copenhagen (n= 50 cars) - Mean: 25.6; Standard deviation: 10.4



The relationship of trips to unique locations was previously unknowable, as cross-sectional surveys cannot provide a credible estimate of this parameter. The available long-term travel data now permit an insight into this aspect of spatial choice behavior. If the number of unique locations grows consistently with the number of trips, then variety seeking, for its own sake, becomes an explanation of these choices.

Figure 2 represents the ratio which is about six trips to one unique location over time. Interestingly, ratios were found similar (about 1:5 to 1:6) in other longitudinal data sets analyzed (ibid.).

Figure 2 Relationship of number of trips and number of unique locations



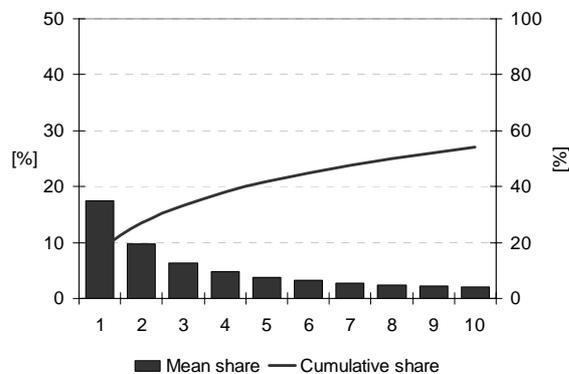
Share of trips to most important destinations

The definition of activity space as an area which contains the locations with which a person has regular contact expresses, per se, the day-to-day stability in destination choice. Although we can show that numerous places are visited, each place is not visited with the same frequency. There seems to be a small number of dominant locations within the observation period. From the perspective of survey design and transport planning, the number of locations necessary to describe a substantial part of a person's travel behavior is of interest.

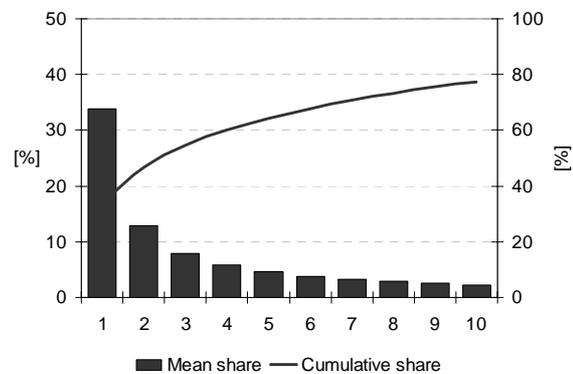
Figure 3 shows the average shares of non-home-based trips which are directed to the 10 most important unique locations identified. The cumulative share of these first ten locations is about 60% in the GPS observation. For travel diary studies, this figure can be even higher (see *Mobidrive*). Given the fact that in total about 25-40% of all trips are home-directed, over longer periods daily life is notably concentrated at few places.

Figure 3 Mean shares of trips to the ten most frequented locations (excluding home)

Commute Atlanta



For comparison: Mobidrive

**Spatial clusters**

Clustering activities around few major pegs of daily life – such as home – is common in travel behavior. To minimize travel times and distances and due to the proximity of opportunities, people tend to group their activity demand in clusters. Almost all drivers in Commute Atlanta behave this way. Given a rather rough definition of a cluster, i.e. a common catchment radius of 1000m crow-fly distance, a minimum of 10% of all trips directed to the cluster, and at least three unique locations associated with the cluster (over all trips and the whole period of observation), 85% of the drivers have at least one distinct centre of daily life. Compared to earlier investigations, the number of clusters in the GPS study is larger for the longer monitoring period, however it never exceeds five even after one year.

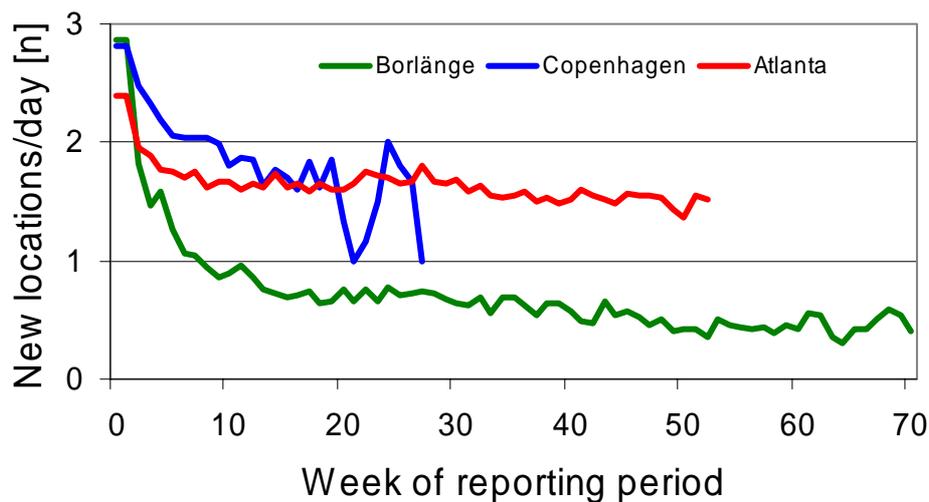
New locations over time

As shown so far, travel and activity behavior is dominated by a routine daily life structure. Travelers seem to “re-use” destinations due to an aspiration to simplify decision making (Diez and Stern, 1995) but simply also because the individual needs as well as the spatial supply is stable over prolonged periods. However, do people really have a restricted number of places they know and visit? Which is the “innovation rate”, i.e. the rate of places which is added to the set of already known places?

Longitudinal studies allow researchers to estimate an approximation of such innovation rate by enumerating the “new” or better so far unobserved places over the course of the monitor-

ing period. Figure 4 shows the average number of additional locations per day by observation week that had not yet been visited previously during the survey periods. There seems to be a limitless number of places people can come to know, because even after many weeks there are still places people travel to for the first time. Comparing the results to other similar GPS tracing experiments available (Borlänge and Copenhagen), there are similarities in the figure visible for the urban areas Atlanta and Copenhagen⁴ and a big difference compared to the small town of Borlänge (50.000 inhabitants; Sweden) which does not offer a comparable variety of destination and activity opportunities. In the long run, the GPS observations shows an average of about one to two previously not observed locations added per day which is about one trip higher than in longitudinal travel diary studies (Schönfelder and Axhausen, 2004).

Figure 4 Comparison of GPS studies: “New”, i.e. unobserved locations / monitoring day



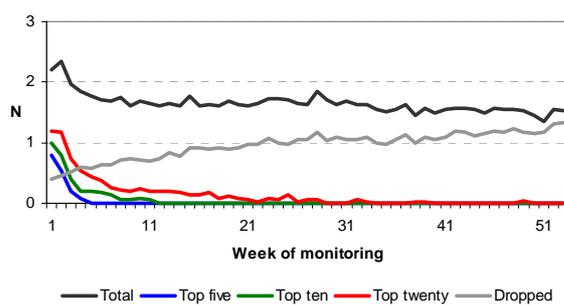
Clearly, this result provokes the question if these “new” locations are added to the personal standard destination repertoire. This cannot be answered explicitly as the drivers have not been asked to provide such information, but a further analysis offers some explanation: Figure 5 shows the total number of locations not previously observed, the locations which are added

⁴ The Atlanta and Copenhagen data include travel outside of the metropolitan areas whereas the Borlänge data is limited to a fairly small monitoring area covering a radius of about 20 km around the town centre.

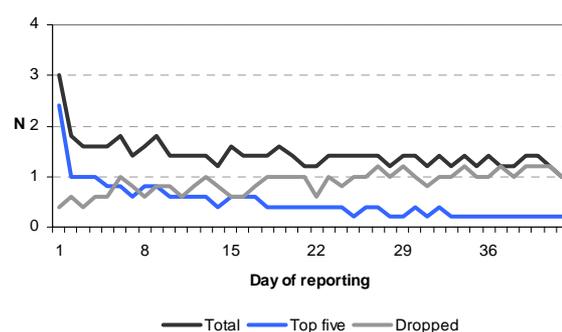
to a pre-defined standard locations repertoire, and those which are visited only once in the long run (“dropped places”). The standard sets represent the 5, 10 and 20 most visited places over the whole period of monitoring. Unsurprisingly, the average share of dropped places increases steadily as with ongoing time fewer new places get the chance to become a regularly visited destination. However, the standard destination repertoires obviously become entirely visible after a few weeks, which is interesting in terms of future survey design procedures. In other words, it takes about five to ten weeks of monitoring (see also *Mobidrive* for comparison) to gain a relative certainty about individual destination choice preferences. Given the complexity of daily life, this is a fairly small number.

Figure 5 Number of “new”, unobserved locations per monitoring day by week respectively by day of reporting (*Mobidrive*)

Commute Atlanta



Mobidrive



Development of activity space sizes

Apart from an estimation of the average number of new places over the course of the study period and the question of the consolidation of destination choice, the data allows to represent the development of activity space sizes over time. As a straightforward indicator of such development, we choose the (crow-line) distance of the unique locations visited from home. The hypothesis behind this analysis is twofold: First, “new” locations tend to be chosen further away from home as for example variety seeking aspirations in spatial choice values closer locations less than those further away from one’s centre of life. Second, even though this trend might be observed, the temporal development of day-to-day activity space size is rather stable

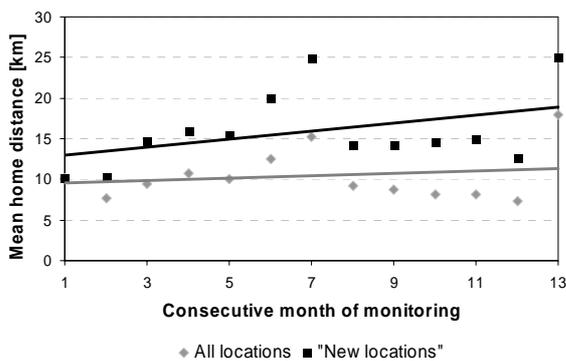
given the set of time, space, speed and social coordination restrictions one has to face (Hägerstrand).

Figure 6 (left) shows that on the aggregate level this hypothesis can be confirmed. The home distance of “so far undiscovered” places is substantially higher than for all unique locations visited. The average home distance (whole sample) of new locations is even increasing over the monitoring period (see linear trend line with a slope of 0.49). The average home distance of all places remains more or less the same, though, with no visible increase in the spatial distribution of places.

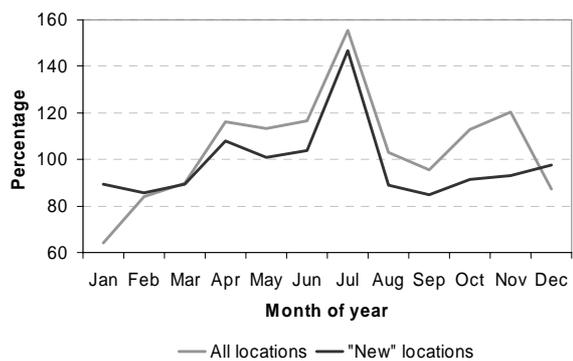
A side product of the analysis is an indication of how seasonality affects destination choice (Figure 6 right). If the monthly deviation of home distance from the yearly mean is calculated, we find that the spring and summer months yield a significantly more disperse choice of locations than the other months – again an indication of variety seeking in spatial behavior. This is true for the so far undiscovered as well as the total of places visited.

Figure 6 Development of activity space size: Average distances of locations from home

Mean distance from home by month of monitoring



Percentage of mean distance from home by month of year (sample average)



Destination choice and personal characteristics

The analysis will finally link some of the measurements to the socio-economic and life-style variables describing the respondents. As mentioned above, the GPS study was accompanied

by a comprehensive debriefing of the drivers and further household members which allows to describe the respondents in great socioeconomic detail (Ogle *et al.*, forthcoming). Only part of the available rich information is used here.

Table 1 summarizes the socioeconomic differences for three selected measures of destination choice structures. These are the ratio of number of unique locations to number of trips, the concentration of trips in the five most visited destinations, and the amount of activity clusters as described above. In general, there are only few differences salient. Differences in the means can be found for the percentage of trips directed to the five most visited locations, and here especially for gender, household size, working status and household income. The ratio of trips to locations varies little – however, there is an indication that low-income household drivers tend to visit few(er) locations with regard to their amount of trips. Clustering activities may be seen as an equally generalized behavioral pattern with little disparity between travelers. Again household income and to some extent the working status “homemaker” show some differences with higher rates than the general mean of 1.7.

An analysis of variance (SAS “General Linear Model” framework) confirms the impression of a modest socioeconomic influence. The model for the dependent variable ratio of locations to trips yields few clarity with significant main effects ($p < 0.05$) only for multi car household members (more than 1 vehicle per person in average) and the elderly. Even weaker explanation gives a model for the number of activity clusters with only the co-variable low income household members significant. This indicates the independence of socioeconomic factors for these two behavioral patterns. More significant main effects and the best explanation of variance ($R^2 = 0.1$) could be found for the concentration of trips into few important locations measure. Effects – corresponding to the descriptives given below – are visible for men, low income group drivers, members of households located far from Atlanta city center and especially for fulltime workers. This shows that the spatial concentration of trips may be greatly described as a function of occupation status and especially fulltime working connected with strong behavioral routines.

Table 1 Activity space indicator by socioeconomic characteristics: Differences in means (weighted by number of mobile days)*

	Ratio of number of locations to number of trips	Share of trips in 5 most visited locations [%]	N activity clusters
Gender			
Female (236)	0.16	39	1.7
Male (191)	0.16	42	1.6
Household size			
Single household (50)	0.15	45	1.5
Two persons (178)	0.17	39	1.6
Three and more persons (208)	0.15	41	1.7
Age			
17 to 24 years (36)	0.15	45	1.9
25 to 44 years (155)	0.16	41	1.6
45 to 59 years (155)	0.16	40	1.7
60 years and older (93)	0.16	40	1.6
Working status			
Full time (243)	0.16	43	1.6
Part time (43)	0.15	37	1.7
Retired (68)	0.16	39	1.8
Homemaker (39)	0.14	33	2.0
Unemployed (21)	0.15	41	1.7
Other(25)	0.16	44	1.9
Household income			
Low (<20,000\$) (11)	0.13	48	2.3
Medium (20,000\$-99,999\$) (281)	0.15	42	1.6
High (>=100,000\$) (147)	0.16	39	1.7
More than one car per HH member			
No (374)	0.15	41	1.7
Yes (65)	0.18	38	1.7
Person shares car with others			
No (362)	0.16	41	1.7
Yes (67)	0.15	41	1.6
HH location > 20 km from city center			
No (99)	0.15	43	1.7
Yes (340)	0.16	40	1.6

Cont.

High net residential density⁵
(≥ 6 residential units per acre)

No (433)	0.16	41	1.7
Yes (10)	0.14	44	1.7

* Excluding vehicles with less than 20 mobile days monitored and missings

⁵ Net residential density was calculated as part of the SMARTRAQ study (Bachman, 2002) and reflects the average number of residences per residential acre within a one kilometer grid cell. Unfortunately, the low spatial resolution tends to dilute the potential effects of higher density housing and may not reflect be a useful indicator of actual neighborhood density. These values will need to be refined for future studies.

5 Conclusions

The results of the initial data processing as well as analysis of the Commute Atlanta GPS traces have shown that the usage of the longitudinal data source for travel behavior analysis is promising and provides new insights into the structure, size and stability of human activity spaces. Clearly, the future post-processing procedure needs to focus on a better detection of structural inaccuracies, such as the systematic reconstruction of complete trips and the unambiguous identification of the actual driver. However, the bias within the data is moderate – even after applying a rough cleaning procedure, only.

The enumeration and mapping of the observed trips and locations reflects an empirical confirmation of conceptual approaches in transport geography and provides moreover a better insight into the structures of spatial choice. The major finding is clearly the ambiguity between strong habits and variety seeking in human spatial behavior. On the one hand, the concentration of trips into few predominant destinations is large; on the other hand, the innovation or discovery rate of “new” places remains stable even after one year of monitoring. Furthermore, while the activity space size in total remains mainly the same due the general limitations of given time budgets and speeds, new places regularly are searched beyond the boundaries of one’s daily “home range”. In summary, the empirical analysis has sharpened our understanding of what human activity spaces are: a manifestation of our daily lives (Jakle, Brunn and Roseman, 1976) – where places are permanently re-used, discovered, taken stock and put aside.

One interesting issue in further research will be the potential for predicting spatial choice and activity spaces. Will we be able to make reliable assumptions about the socioeconomic impact on the personal activity space? And is there a chance to “reconstruct” human activity spaces based on the observed equilibrium of the perceived choice set, individual innovation rates and one’s aspiration for variety seeking in general? What we could show so far is that the amount of travel directly affects the number of unique locations. Even if the latter number not necessarily leads to a greater dispersion of visited places and therefore to a larger activity space, the same determinants which control the amount of mobility will have an impact on the perception, knowledge and acquisition of urban space as well as on the personal innovation rate in spatial choice. Furthermore, if the structure of the activity space is a function of the places known and again, the observed extent and the consolidation of an individual innovation rate, activity spaces might be predicted to a certain extent.

Finally, the results inhabit the potential to influence current practice in transport modeling. The investigation will deepen the discussion on the size and structure of the individual choice set in destination choice. For simplicity, modeling widely assumes that all spatial alternatives are known to the traveler which allows create an arbitrarily composed choice set for estimation. The analysis of longitudinal data sets such as Commute Atlanta has shown that this practice eventually leads to biased parameter estimates, as the alternatives of which the traveler is aware are limited, clustered and unevenly known. Observed spatial behavior is a trade-off, which cannot be replicated by a random sample of alternatives. The challenge of defining appropriate – more likely condensed – choice sets needs to be addressed in future work.

6 Literature

Anderberg, M.R. (1973) *Cluster Analysis for Applications*, Academic Press, New York.

Axhausen, K. W., A. Zimmermann, S. Schönfelder, G. Rindsfuser and T. Haupt (2002) Observing the rhythms of daily life: A six-week travel diary, *Transportation*, **29** (2) 95-124.

Bachman, W. (2002) Net Residential Density White Paper: With regards to the SMARTRAQ Sampling Plan.

Bhat, C.R., S. Srinivasan and K.W. Axhausen (2005) An analysis of multiple interactivity durations using a unifying multivariate hazard model, *Transportation Research*, **39B** (9) 797-824.

Diez, T. and P. C. Stern (1995) Towards a theory of choice: Socially embedded preference construction, *Journal of socio-Economics*, **24**, 261-279.

Guensler, R., J. Ogle and H. Li (2005) Variability in 2004 Commute Atlanta Instrumented Vehicle Travel Activity, Manuscript submitted to TRB annual meeting 2006.

Horton, F. and D.R. Reynolds (1971) Effects of Urban Spatial Structure on Individual Behavior, *Economic Geography*, **47**, 36-48.

Jakle, J.A., S. Brunn and C. Roseman (1976) *Human Spatial Behavior – A Social Geography*, Duxbury Press, North Scituate.

Jones, P.M., F. Koppelman and J.O. Orfeuil (1990) Activity analysis: State-of-the-art and future directions, in P.M. Jones (Ed.) *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, 34-55, Gower, Aldershot.

Kitamura, R., T. Yamamoto, Y.O. Susilo and K.W. Axhausen (2004) On the day-to-day variability of prism vertex location, paper presented at the 83th Annual Meeting of the Transportation Research Board, Washington, D.C. January 2004.

Kwan, M.P. (1999) Gender, the Home-Work Link, and Space-Time Patterns of Non-Employment Activities, *Economic Geography*, **75**(4) 370-394.

Lee-Gosselin, M. (2002) Some reflections on GPS-supported travel survey methods in an increasingly ICT-rich environment, Presentation at Workshop on ICT, Innovation and the Transport System, Arlington, January 2002.

- Lenntorp, B. (1976) Paths in space-time environment: a time geographic study of possibilities of individuals, *Lund Studies in Geography, Ser. B. Human Geography*, **44**, Department of Geography, The Royal University, Lund.
- Li, H. (2004) Investigating Morning Commute Route Choice Behavior Using Global Positioning Systems and Multi-day Travel Data, Ph.D. Dissertation, Georgia Institute of Technology, Atlanta.
- Marble, D. F. and S.R. Bowlby (1968) Shopping alternatives and recurrent travel patterns, in F. Horton (ed.) *Geographic Studies of Urban Transportation and Network Analysis*, 42-75, Department of Geography, Northwestern University, Illinois.
- Newsome, T.H., W. Walcott and P.D. Smith (1998) Urban activity spaces: Illustrations and application of a conceptual model for integrating the time and space dimensions, *Transportation*, **25**(4) 357-377.
- Ogle, J. (2005) Quantifying Driver Speeding Behavior: Estimating Crash Risk with Vehicle Instrumentation, Ph.D. Dissertation, Georgia Institute of Technology, Atlanta.
- Ogle, J., J. Ko, H. Li and R. Guensler (2005) Analysis of Under-reporting and Other Errors in Commute Atlanta Travel Diaries Using Instrumented Vehicle Data, Manuscript submitted to TRB annual meeting 2006.
- Ogle, J., R. Guensler and V. Elango (forthcoming) Commute Atlanta Value Pricing Program: Recruitment Methods and Travel Diary Response Rates, *Transportation Research Record*.
- Pas, E.I. and F.S. Koppelman (1986) An examination of the determinants of day-to-day variability in individuals' urban travel behavior, *Transportation*, **13** (2) 183-200.
- Pearson, D. (2001) Global Positioning System (GPS) and travel surveys: Results from the 1997 Austin Household Survey, Paper presented at the Eighth Conference on the Application of Transportation Planning Methods, Corpus Christi, Texas, April 2001.
- Schönfelder, S. and K. W. Axhausen (2001) Analysing the rhythms of travel using survival analysis, in C. Kaspar, C. Laesser and T. Bieger (Hrsg.) *Jahrbuch 2000/2001 Schweizerische Verkehrswirtschaft*, 137-162, Universität St. Gallen, St. Gallen.
- Schönfelder, S. and K.W. Axhausen (2003a) On the variability of human activity spaces, in M. Koll-Schretzenmayr, M. Keiner and G. Nussbaumer (eds.) *The Real and Virtual Worlds of Spatial Planning*, 237-262, Springer, Heidelberg.
- Schönfelder S. and K.W. Axhausen (2003b) Activity spaces: Measures of social exclusion? *Transportation Policy*, **10** (4) 273-286.
- Schönfelder, S. and K.W. Axhausen (2004) Structure and innovation of human activity spaces, *Arbeitsberichte Verkehrs- und Raumplanung*, **258**, IVT, ETH Zürich, Zürich.

- Schönfelder, S. and U. Samaga (2003) Where do you want to go today? - More observations on daily mobility, paper presented the 3rd Swiss Transport Research Conference, *Arbeitsberichte Verkehrs- und Raumplanung*, **179**, Ascona, March 2003.
- Wolf, J. (2000) Using GPS data loggers to replace travel diaries in the collection of travel data, Dissertation, Georgia Institute of Technology, School of Civil and Environmental Engineering, Atlanta, Georgia.
- Wolf, J., M. Oliveira, M. Thompson (2003) Impact of Underreporting on Mileage and Travel Time Estimates: Results from Global Positioning System-Enhanced Household Travel Survey, *Transportation Research Record*, **1854**, 189-198.
- Wolf, J., R. Guensler and W. Bachman (2001) Elimination of the travel diary: An experiment to derive trip purpose from GPS travel data, paper presented at the 80th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2001.
- Wolf, J., S. Schönfelder, U. Samaga, M. Oliveira and K.W. Axhausen (2004) 80 weeks of GPS-traces: Approaches to enriching the trip information, *Transportation Research Record*, **1870**, 46-54.

Acknowledgements

The Commute Atlanta Spring 2004 Travel Diary is a research component of the Commute Atlanta Program funded by the Federal Highway Administration (FHWA) and Georgia Department of Transportation. The authors wish to thank these agencies for their continued support and guidance throughout this project. Finally, a huge thank you to the diligent graduate assistants that make this project happen.

