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Deriving Personal Trip Data from GPS Data: A Literature Review on the Existing Methodologies

Lei Gong[a,*], Takayuki Morikawa[b], Toshiyuki Yamamoto[c], Hitomi Sato[b]

[a] Department of Civil Engineering, Nagoya University, Furo-cho, Chikusa-ku, Nagoya, Japan 464-8603, Japan
[b] Graduate School of Environmental Studies & Green Mobility Collaborative Research Center, Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan
[c] EcoTopia Science Institute, Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan

Abstract

GPS technology was used in person trip (PT) survey since mid-1990, and this technology achieved its popularity because of the improvement of accuracy and portability of GPS device. Although GPS data could provide precise spatiotemporal information of vehicular or personal movements, the transportation mode (in the case of personal movements with wearable GPS devices) and trip purpose are unable to be obtained from the GPS directly. In addition, the GPS data error identification and the trip segment from the continuous GPS data are quite fundamental to transportation mode identification and trip purpose inference. In this paper, we summarized the methodologies and input variables utilized to segment trip, infer trip purpose as well as identify transportation mode in the existing researches. Compared to probability method and criteria-based method, Machine Learning are often applied in detecting transportation mode. On the other hand, rules-based methods are more popular than probabilistic method and machine learning as the tool for inferring the trip purpose. Finally, researches attempting to utilize the data from accelerometer which are popularly integrated in smartphones demonstrates the potential of more accurate personal trip data derivation from smartphones can be achieved with much less burden on the respondents in the future.

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Keywords: GPS; personal trip data; trip identification; transportation mode detection; trip purpose inference; literature review.

* Corresponding author. Tel.: +81-(0)52-789-3730; Fax: +81-(0)52-789-5728.
E-mail address: Leigongchi@gmail.com.

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1. Background

Household trip data are crucially infrastructural data for traffic demand analysis in transportation system planning. The methods used for personal trip data collection experienced the stages of original paper-and-pencil interview (PAPI), computer-assisted telephone interview (CATI), and computer-assisted-self-interview (CASI) (Wolf et al., 2001). Although the computer assisted surveys tried to help the respondents to understand the questions and recall the trips they had during the day (Hato et al., 2005), this involvement of computer technology still could not solve the inherent disadvantage of active methods for deriving PT data. These disadvantages include underreported trips, inaccuracies in times, surrogate reporting and sometimes confusion of appropriate trip purpose (McGowen and McNally, 2007).

Because GPS data is capable of providing accurate data including location, time, speed, heading and the measures of data quality (Stopher et al., 2008b), in the middle of 1990s, researchers started to investigate the possibility of obtaining the trip data from the GPS data and test the accuracy of the GPS data (Zitto et al., 1996; Wagner, 1997; Murakami et al., 1999; Sermons and Koppleman, 1998). At first, the GPS devices were installed in the vehicle and electrified by the battery in the vehicle. So it is applicable only to observe the movement behavior of persons when driving vehicles. This problem got solved in the early 2000s when the size and weight of GPS devices getting smaller and lighter with a detached battery (Stopher et al., 2008a). The smaller and lighter GPS devices, namely wearable GPS data logger (2nd generation, 3rd generation), appeared in the pilot study or personal trip survey in the UK (GeoLogger was used in 2002), and Australia (NEVE StepLogger was used in 2003; Starnav was used in 2005) (Stopher et al., 2008a). These wearable GPS devices still have the demerits such as respondents forgetting to take the devices, GPS signal unavailability in the building, underground, in the tunnel and "urban canyons" areas.

Since GPS function is attached to smart phone, some researches also started to use GPS data obtained from smart phones to derive personal trip data. These researches either combined a web-based diary system or Geographic Information System (GIS) to get the additional or confirmed information of transportation modes and trip purpose passively or actively (Hato et al., 2006; Itsubo et al., 2006; Byon et al., 2007; Reddy et al., 2008; Zheng et al., 2008; Gonzalez et al., 2010; Zhang et al., 2011; Lee et al., 2013; Pereira et al., 2013). Furthermore, the assisted GPS system, named AGPS, are getting widely contained in the smartphones, e.g. iPhone. This technology can receive satisfied GPS signal inside buildings, vehicles, as well as "urban canyons" in cities where tall buildings and other edifices block GPS signals. This system has improved and owned higher receiver sensitivity (Moiseeva and Timmermans, 2010). It means that GPS data with higher accuracy can be obtained with smart mobile phones. If the technologies of automatically deriving personal trip data can also be achieved with higher accurate results, GPS data collection through smart phone may become the main method of personal trip data collection in the future at lower cost and with minimum burden on respondents.

The elements of GPS data may vary depending on the types of GPS devices. They generally include: valid code marking, date, time, latitude, longitude, altitude, NSAT (the number of satellites that a GPS device used to calculate its position), HDOP (horizontal dilution of precision, measuring how the satellites are arranged in the sky at the time of the record), speed, and heading (Wolf et al., 2001; Stopher et al., 2005, 2008a; Gong et al., 2012). Although the path, time, speed, and acceleration could be obtained precisely from the GPS raw data (assuming the GPS data with high accuracy), start and end of trip, transportation mode, and trip purpose could not be derived from the GPS raw data directly without further data processing or other assisted information.

In this paper, we summarized the methodologies applied in the existing researches concerning personal trip data derivation from the GPS data. It is essential for the further development of methodologies and application on accurately deriving PT data from GPS data. From the summarized results, it can be concluded that Machine Learning is often utilized in detecting transportation mode while rules-based methods are popular for inferring the trip purpose. The rest of the paper includes the contents as follows: methodologies used in trip identification, transportation mode detection and trip purpose inference respectively. Finally, the future research directions in personal trip data derivation technology are discussed.

2. Data Error Recognition

Although the GPS data can avoid manual mistake of PT data, e.g. inaccurate time and under-reporting trips, some systematic errors may exist in the GPS raw data. As a result, the GPS raw data need to be examined to ensure the accurate data source for data processing in the next steps. Table 1 shows the features of GPS data used for error recognition in the major existing researches. Detailed interpretation of methods for data error recognition in each research is in the paragraphs below Table 1.

Table 1. Summary of data error recognition in exsiting researches

Year	Authors	GPS Devices	Records' Features Used for Error Recognition
2005 2008a	Stopher et al.	Wearable GPS devices including GeoLogger, StepLogger and Starnav	NSAT, HDOP value, speed,
2006	Tsui & Shalaby	Wearable GPS devices	NSAT, HDOP value, speed, heading, path
2009	Bohte et al.	---	Duration, speed, number of trackpoint per trip

Stopher et al. (2005, 2008a) utilized 2 rules to remove the invalid data. The first rule is data with less than 4 satellites (for 3-D use) or HDOP of 5 or more were removed. The second one is the record with a speed over 250 km/h were removed.

Tsui and Shalaby (2006) used Data Filtering Module to identify the systematic errors. In this module, the authors utilized 4 successive filters to ensure the records correct. The first and second filter use the factors of NSAT and HDOP respectively. The records with NSAT fewer than 3 (for 2-D use) and HDOP higher than 5 are not considered in the next step. The third filter treats records with 0 directional heading and 0 speed as errors when GPS data trace is plotted on a map. The last filter is to remove multipath error in "urban canyons" areas, causing GPS signal to jump around the area and form a data cloud instead of clear traces.

Bohte et al. (2009) set up the following rules to delete unreliable records of GPS raw data. The first one is that trackpoints whose distance with previous one was less than 10 m if these trackpoints collected in the same building. The second one is to remove the trackpoints with a speed higher than 200 km/h. The next rule deletes the trackpoints with a speed less than 5 km/h and a time gap with previous trackpoint of at least 1 minute. The final one is to delete the trips with less than 4 trackpoints.

3. Trip Identification

Most of the existing researches identified trip ends by identifying activities which are connected by trips. Most of the researches use a certain dwell time with or without other conditions to detect activities. Table 2 shows a summary of the features used for activities detection in the existing researches under two situations: GPS signal available situation and GPS signal lost situation.

Under the situation of GPS signal is available, different threshold of dwell time is set, such as 120s (Wolf et al., 2001; Tsui and Shalaby, 2006; Stopher et al., 2002, 2005, 2008ab; Schuessler and Axhausen 2009), 180s (Bohte & Matt, 2009), 200s (Gong et al., 2012) or even 300s (Axhausen et al. 2004). Actually, this threshold varies mainly depending on the characteristics of local activities. In addition, some researches simultaneously include the "0" speed or approximate to "0" as another necessary condition (Wolf et al., 2001; Tsui and Shalaby, 2006; Stopher et al., 2002, 2005, 2008ab; Schuessler and Axhausen, 2009). Furthermore, the change in latitude or longitude, the change of heading, and the density of track points of GPS data were also treated as necessary conditions in some researches (Stopher et al., 2002, 2005, 2008ab; Schuessler and Axhausen, 2009). Besides the features mentioned above, visual checking on map (Stopher et al., 2002, 2005, 2008ab) and the required boundary in which trackpoints satisfied dwell time threshold (Gong et al., 2012) are also included as the detecting rules in some researches.

For the situation when there is no available GPS signal, the dwell time between two successive trackpoints were utilized as a judging criterion to detect potential trip in some researches (Tsui and Shalaby, 2006; Schuessler and Axhausen, 2009).

Table 2. Summary of trip end identification methods in existing researches

Year	Authors	Signal Available						Signal loss
		S (m/s)	D (sec)	L / L(°)	H	PD	Other	D (sec)
2001	Wolf et al.	0	≥120	---	---	---	---	---
2004	Axhausen et al.	---	≥300	---	---	---	---	---
2006	Tsui & Shalaby	0	≥120	---	---	---	---	≥120
2002 2005 2008ab	Stopher et al.	0	≥120	≤0.00005	UC or 0	---	VC	---
2009	Bohte & Maat	---	≥180	---	---	---	---	---
2009	Schuessler & Axhausen	≤ 0.01	≥120	---	---	≥15	---	≥900
2012	Gong et al.	---	≥200	---	---	---	In 50m	---

Abbr: **S**: Speed. **D**: Duration. **L/L**: Change in Latitude or Longitude. **H**: Heading. **PD**: Point Density. **VC**: Visual Check on Map. **UC**: Unchanged. Note: Requirement in each cell in the same line should be satisfied simultaneously in the situation of GPS signal is available (except for Schuessler & Axhausen 2009 where the judging criteria is when either S & D or PD get satisfied).

4. Transportation Mode Detection

Fig. 1. demonstrates the main methodologies with the input variables for transportation mode detection applied in the existing researches. Methodologies from three categories are mainly utilized with the help of the GPS data and other assisted data.

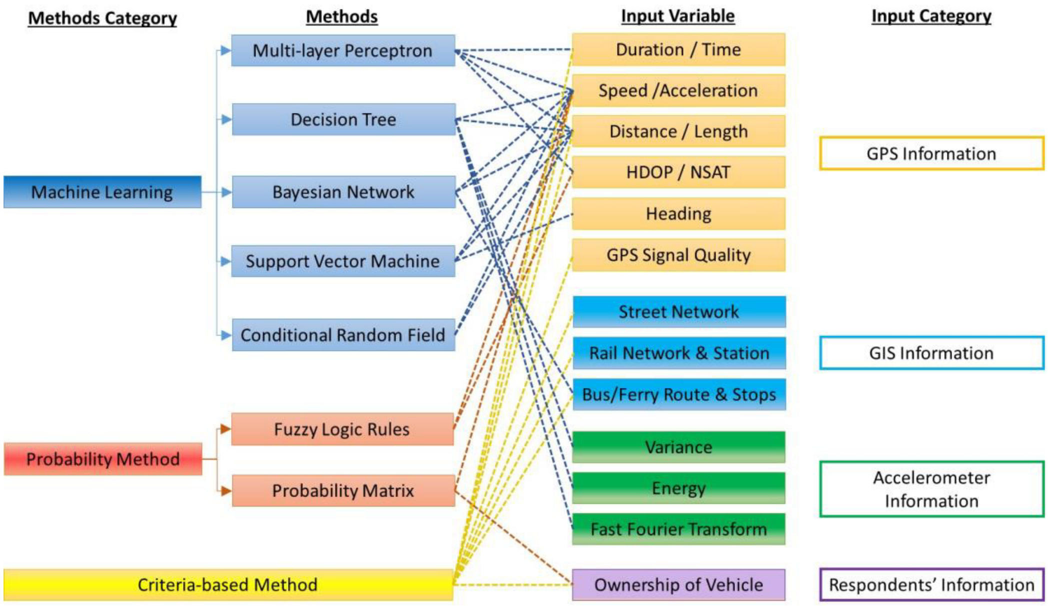

Fig. 1. Categorized methodologies for mode detection in existing researches and inputs variables

Many researches focus on the machine learning technology (a branch of Artificial Intelligence), concerning the construction and study of systems which can learn from training data set and use the learned knowledge to automatically deal with other data set which share the same characteristics as the former. A lot of methods in this category, including Multi-Layer Perceptron Neural Network (Byon et al., 2007; Gonzalez et al., 2010), Decision Tree (Pattterson et al., 2003; Zheng et al., 2008; Reddy et al., 2008), Bayesian Network (Zheng et al., 2008;

Moiseeva and Timmermans, 2010), Support Vector Machine (Zheng et al., 2008; Zhang et al., 2011; Pereira et al., 2013), and Conditional Random Field (Zheng et al., 2008), has been applied in detecting transportation mode. Most of the input variables come from the GPS data itself. In addition, some researchers compared several types of machine learning methods (Pattterson et al., 2003; Zheng et al., 2008) and got the most accurate method based on their data set and local personal trip characteristics.

Another category for transportation mode detection belongs to the Probability method. Fuzzy logic rules (Tsui and Shalaby, 2006; Schuessler et al., 2009) and probability matrix (Stopher et al., 2008a) are utilized to predict the probability of each mode based on the features of GPS data and respondent information. The mode with the largest probability will be decided as the estimated mode.

Furthermore, the criteria-based methodwhich judges the features of each segment of trip according to a series of rules, is also utilized in some researches (Stopher et al., 2005, 2008b; Bohte et al., 2008; Chen et al., 2010; Gong et al., 2012). The input variables needed in these methodologies come from 3 categories, the information of GPS, GIS, and respondents respectively. Detailed description of input variables utilized in each method and the corresponding accuracy rate are listed in Table 3.

Table 3. Summary of methods of transportation mode detection utilized in existing researches

Year	Authors	Steps/ Methods	Input variables	Accuracy
2003	Patterson et al.	Bayesian Model with Expectation Maximization	Velocity, standard deviation of the velocity in the previous 60sec. bus routes & stops	84%
2005 2008b	Stopher et al.	Criteria-based Method	85^{th} speed, 85^{th} acceleration, maximum speed, maximum acceleration, ownership of bicycle, GIS file (including rail line, ferry route, bus route & stops, intersection), GPS signal quality	95%
2006	Tsui & Shalaby	Fuzzy Logic Model	Average speed, 95^{th} speed, positive median acceleration, GPS data validity ratio in segment	91%
2007	Byon et al.	Multi-layer Perceptron neural network	Speed, acceleration, average HDOP, average NSAT	80%
2008	Reddy et al.	Decision tree with a first-order Hidden Markov Model	variance, energy, and sum of FFT(Fast Fourier Transform) coefficients between 1~5 Hz from accelerometer; speed from GPS	98.8%
2008a	Stopher et al.	Two steps; probability matrix used in first step	Ownership of bicycle, average speed, maximum speed, most frequent speed, distance of trip, street & public transport network in GIS	95%
2008	Zheng et al.	Decision Tree (DT), Support Vector Machine (SVM), Bayesian Net (BN), Conditional Random Field (DRF)	Length, mean velocity, expectation of velocity, covariance of velocity, top three velocities & accelerations of the segment of trips	74% (DT) 59% (SVM) 70% (BN) 47% (DRF)
2009	Bohte & Matt	Criteria-based Method	Average speed, maximum speed, public transport network in GIS	70%
2009	Schuessler et al.	Fuzzy Logic Approach	median of the speed distribution, 95^{th} speed, 95^{th} acceleration	NA
2010	Gonzalez et al.[1]	Multi-Layer Perceptron Neural Network	<u>For all points case:</u> average & maximum speed, estimated horizontal accuracy uncertainty, Percent Cell-ID Fixes, standard deviation of distances between stop locations and average dwell time <u>For critical points case:</u> average & maximum acceleration, average & maximum speed, ratio of the number of critical points over the total distance/time of the trip, total distance, and average distance between critical points	88.6% (all points) 91.2% (critical points only)
2010	Chen et al.	Criteria-based Method	Travel time, speed, network of public transport and bus route & stops in GIS, GPS signal quality	79.1%
2010	Moiseeva & Timmermans	Bayesian belief network	distance to the railway track, average and maximum acceleration, average speed, maximum deviation from the average speed and accumulated distance for the threshold period of the time (3min in this research)	NA
2011	Zhang et al.	Two-stage approach; Support Vector Machine used in 2nd stage	Mean speed, maximum speed, mean heading changes,	93%
2012	Gong et al.	Criteria-based Method	Average speed, 85th speed, duration, distance to the rail/subway stations and bus stops, 85th speed, 95th acceleration	82.6%
2013	Pereira et al.	support-vector machine	data of GPS and accelerometer	NA

Note: 1. two sets of data base, namely all GPS points and critical GPS points, were used in the research. The input variable varies depending on the data set.

5. Trip Purpose Inference

Fig. 2 illustrates the information of categorized methodologies utilized in the existing researches. These methods can be grouped into 3 categories.

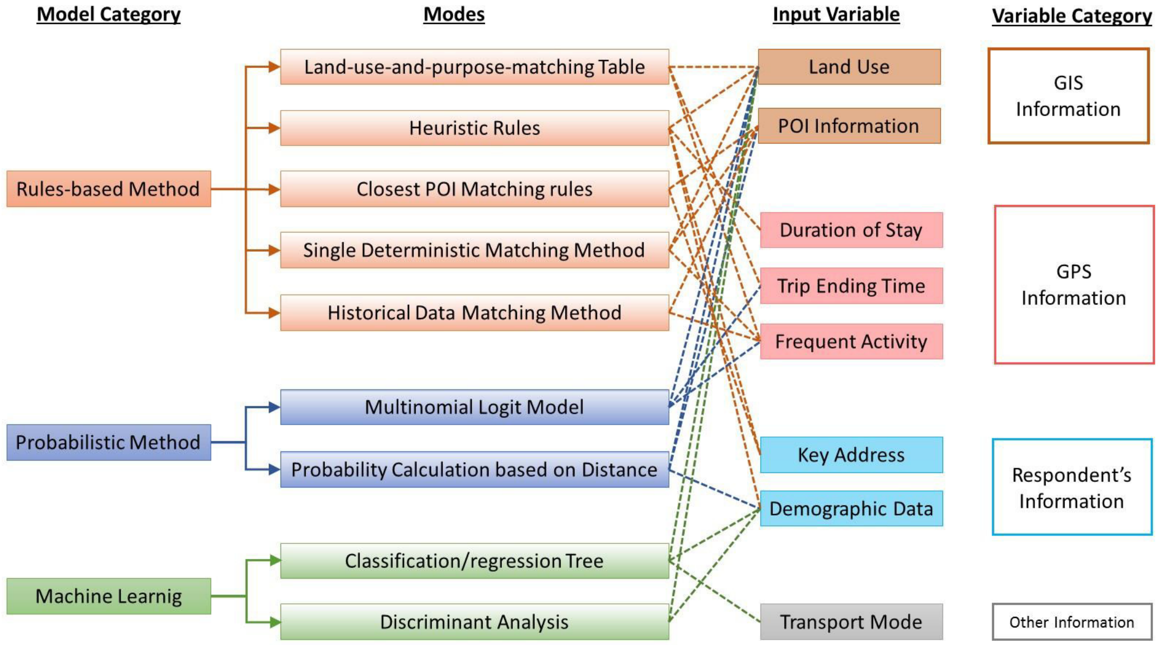

Fig. 2. Categorized methodologies for trip purpose inference in existing researches and inputs variables.
Note: POI (Point of Interest) is the specific trip attraction points, such as restaurants, banks, petrol stations, business locations, mode interchange area etc. Demographic Data include socio-demographic data and socioeconomic data of the respondents.

The most popular method for trip purpose inference utilized in existing researches is the rules-based method (Wolf et al., 2001; Stopher et al., 2005, 2008ab; Bohte and Matt, 2009; Chen et al., 2010; Pereira et al., 2013). Methods in this category match the selected information from GPS, GIS and respondents with a series of pre-defined heuristic rules to infer the trip purpose.

The second category is probabilistic method (Axhausen et al., 2004; Chen et al., 2010). The probability of each purpose is calculated based on the different values of information from GPS, GIS and respondents' information. The estimated trip purpose is decided by the calculated probability.

The third category is the machine learning (McGowen and McNally, 2007; Deng and Ji, 2010). Assisted with the information from GIS, respondents and transportation mode, different kinds of trip purpose can be separated by the experience from the learning data set.

Detailed description of input variables in each method and the corresponding accuracy can be found in Table 4

6. New Trend Discussion

Whatever methodology is utilized in detecting transportation mode or trip purpose, the obviously distinct characteristics of each transportation mode or trip purpose in local area is essential to distinguish them. Moreover, more kinds of contextual information involved, higher accuracy can be achieved by checking from mutual perspectives with more complicated process. Fast development and popularity of smart phone incorporating different kinds of sensors (e.g. GPS, accelerometer etc.) provides the possibility of obtaining the contextual information mentioned above. Some researchers have already made some trials in this field. Reddy et al. (2008) utilized a decision tree followed by a first-order Hidden Markov Model to separate transportation modes into still, walking, running, cycling and motor vehicle based on the data of variance, energy, sum of FFT coefficients from accelerometer and speed from GPS collected by Nokia N95. Besides, Nham et al. (2008) applied learning algorithms to acceleration data, FFT coefficients, mean a variance of the signal obtained from accelerometer in iPhone to separate transportation mode into walking, biking, running, trains and buses. Lee et al. (2013) utilized Global-local Co-training to divide transportation mode into stationary, walk, vehicle, run and subway based on the data of tri-axial acceleration, magnetic field, orientation obtained by accelerometer sensor, magnetometer sensor in Android-based smartphones. These pilot studies show high possibility to use smart phone as a data collection tool for personal trip survey if we could combine the GPS data, GIS data, and accelerometer data as well as data from other integrated sensors in the smart phones successfully.

Table 4. Summary of methods of trip purpose inference in the existing researches

Year	Authors	Methods	Input variables besides coordinates	Accuracy
2001	Wolf et al.	Land-use-and-purpose-matching table	Land use, trip ending time, duration of stay	93%
2004	Axhausen et al.	Probability Calculation based on Distance	Socio-demographic data, land use, distance to POI/ land use polygon	NA
2005 2008ab	Stopher et al.	Heuristic rules	Land use, duration, occupation and address of home/ school/ workplace/ frequently used grocery store of the respondents	NA
2007	McGowen & McNally	Category model (discriminant analysis and classification/regression trees model)	Land use, demographic data	73% and 74%
2009	Bohte & Matt	Closest POI matching rules	Home/work address, locations of POI	43%
2010	Chen et al.	Low-density area: Single deterministic matching method	Business listings, frequently visited locations, land use	NA
		High-density area: Multinomial Logit model	Trip ending time, activity frequency, land use	
2010	Deng & Ji	Decision tree methods	Trip ending time, speed, mode, trip distance, trip duration, occupation, income, family structure, age, land use	87.6%
2013	Pereira et al.	Historical data matching rules	Previous validation, points of interest, mode interchange	NA

Note: **Previous validation** is the historical travelling data of the respondents.

7. Conclusion

This paper carefully summarized and categorized the methodologies utilized for GPS data error recognition, trip identification, transportation mode detection and trip purpose inference based on GPS data in the existing researches. Also, the input variables in each method and corresponding accuracy are summarized in the tables for further convenient comparison. Finally, it is demonstrated that the new technology, especially the smart phones with sensors of GPS, accelerometer etc., will be a significant collection tool for personal trip survey data due to their popularity, high accuracy, comprehensive sensors integration and minimum burden on the respondents.

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