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A GPS/GIS method for travel mode detection in New York City

Hongmian Gong [a,*], Cynthia Chen [b], Evan Bialostozky [a,1], Catherine T. Lawson [c]

[a] Department of Geography, Hunter College of the City University of New York, New York, NY 10065, United States
[b] Department of Civil and Environmental Engineering, University of Washington, Seattle, WA 98195, United States
[c] Geography & Planning, University at Albany, Albany, NY 12222, United States

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ABSTRACT

Handheld GPS provides a new technology to trace people's daily travels and has been increasingly used for household travel surveys in major cities worldwide. However, methodologies have not been developed to successfully manage the enormous amount of data generated by GPS, especially in a complex urban environment such as New York City where urban canyon effects are significant and transportation networks are complicated. We develop a GIS algorithm that automatically processes the data from GPS-based travel surveys and detects five travel modes (walk, car, bus, subway, and commuter rail) from a multimodal transportation network in New York City. The mode detection results from the GIS algorithm are checked against the travel diaries from two small handheld GPS surveys. The combined success rate is a promising 82.6% (78.9% for one survey and 86.0% for another). Challenges we encountered in the mode detection process, ways we developed to meet these challenges, as well as possible future improvement to the GPS/GIS method are discussed in the paper, in order to provide a much-needed methodology to process GPS-based travel data for other cities.

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1. Introduction

Regional planning organizations have relied on household travel diary surveys since the 1970s in order to acquire data to build transportation models (Stopher & Greaves, 2007). These traditional surveys are expensive and time consuming, requiring survey respondents to fill out many pages of travel diaries. Quite often, respondents miss short trips, report trips out of sequence, and round up the departure and arrival times (Stopher, FitzGerald, & Xu, 2007; Wolf, Oliveira, & Thompson, 2003). Travel surveys using Global Positioning System (GPS) devices have gradually become more prevalent worldwide since the first experiment in Lexington, Kentucky in 1996 (Stopher & Greaves, 2007). Especially in the past few years as the cost of these devices has fallen, GPS surveys appear more appealing to organizations seeking individual travel data. Studies have shown that surveys either enhanced by a GPS component or carried out entirely with GPS can avoid many of the problems associated with the traditional methods (Forrest & Pearson, 2005; Murakami, Taylor, Wolf, Slavin, & Winick, 2004).

While GPS can record accurate location, time, and speed information about people's travel, it cannot record all the variables for transportation modeling. Travel modes, for example, are not recorded in GPS, but could be derived from GPS data. With a few recent exceptions (Chung & Shalaby, 2005; Tsui & Shalaby, 2006), methodologies have not been developed to process the enormous amount of GPS data to derive more travel information. Our study takes advantage of the capabilities of Geographical Information Systems (GIS) to identify travel modes from GPS-based survey data in New York City (NYC).

The remainder of the paper is organized into five sections. First, we provide a background of how our study fits into the literature of using GPS and GIS for travel mode detection. This is followed by a section on the GPS and GIS data available for our study of NYC and a section on the methodology we used to develop a GIS algorithm for identifying five travel modes. The fourth section discusses the success rates of our mode detection and the challenges we encountered in NYC. We conclude the paper with a summary of the key findings and a discussion of future research on improving the GPS/GIS method for travel mode detection.

2. Background

2.1. GPS-based travel surveys

The use of GPS technology in travel surveys has many advantages over the traditional method. Because the logger is a passive data collector, the survey requires little time and effort from the respondent. GPS therefore reduces respondent burden and increases data accuracy (Murakami et al., 2004; Wolf, Hallmark, Oliveira, Guensler,

* Corresponding author. Tel.: +1 212 772 4658; fax: +1 212 772 5268.
E-mail address: gong@hunter.cuny.edu (H. Gong).
[1] Present address: MTA Bus Company, Metropolitan Transportation Authority, 2 Broadway, New York, NY 10004, United States.

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& Sarasua, 1999; Zhou & Golledge, 2007). GPS data show a traveler's exact route choice, data that is time-consuming and difficult to gather via paper methods (Duncan & Mummery, 2007). GPS data also show exact vehicle speeds on particular roads, information used to assess the level of service on the transportation network but that is usually only estimated (Murakami et al., 2004).

One of the greatest advantages of using GPS devices is the ability to significantly reduce sample sizes of travel surveys due to the increased accuracy of the collected data (Greaves, Fifer, Ellison, & Germanos, 2010; Stopher, Clifford, & Montes, 2008). Because of the very low level of respondent fatigue when using GPS, the length of these surveys can also be extended from the traditional single day to multiple-day data collection. This benefits travel demand modelers because the chance is quite low that the 1 day chosen for a single-day travel survey is typical for any given respondent. As the length of the survey increases, the average number of trips and VMT per respondent per day evens out and is considerably more accurate (Stopher, Kockelman, et al., 2008; Stopher, FitzGerald, Zhang, & Bretin, 2007).

Disadvantages of the use of GPS devices in travel surveys are few. In fact, respondent's privacy concerns have been minimal (Swann & Stopher, 2008; Wolf, Bonsall, Oliveira, Leary, & Lee, 2006). The main difficulty with relying heavily on GPS technology is the lack of accurate data that accompany signal loss or degradation during warm start/cold start or in "urban canyons" (Schuessler & Axhausen, 2009; Stopher, FitzGerald, & Zhang, 2008). Urban canyon effect is particularly noticeable in densely built central business districts (CBDs), where the greatest travel data accuracy is often needed (Stopher & Greaves, 2007).

2.2. Combining GPS and GIS for mode detection

Although much attention is still focusing on how to better implement GPS into travel surveys, there have been early and promising attempts to identify travel modes from GPS data. An early attempt by Chung and Shalaby (2005) used a GIS-based map-matching algorithm to identify transport links and a rule-based algorithm to identify four travel modes (walk, bicycle, bus, and car) from GPS data in Toronto. They correctly matched 78.5% of all traveled links with the road network and accurately determined the transportation mode used 91.7% of the time. They did not use real GPS-based travel survey data, but used GPS to reconstruct trips sampled from a prior Toronto travel survey. To avoid the common problems of GPS reception, they assumed no trip starting or ending in an urban canyon area and no warm or cold start of GPS receivers.

Another study in Toronto (Tsui & Shalaby, 2006) used fuzzy logic-based mode identification algorithms both with and without additional GIS-based analysis. While the overall rate for accurate mode detection remained the same (91%), using GIS improved the bus detection rate from 76% to 80% by taking advantage of the bus route information. In addition, matching GPS traces with public transportation routes in GIS made it possible to identify 88% of the streetcar travel and 100% of the subway travel, yielding a detection rate of 98% for off-road modes.

In Australia, Stopher, FitzGerald, et al. (2008) differentiated walk, bicycle, and vehicle modes through a probability matrix that was defined by bicycle ownership, various speed characteristics of the trip, and the distance of the trip. They further classified the vehicle trips into car, bus, and rail by using street and public transport layers in GIS. Modes were correctly identified 95% of the time, although no detection rate was reported for each individual mode. In addition to using GIS to match vehicle trips, minimum path in GIS network analysis was used to correct signal loss problems from cold starts, urban canyons, tunnels, and public transport vehicles such as buses and trains.

Bohte and Maat (2009) achieved a 70% success rate in a mode detection effort in the Netherlands, with 75% for car mode, 35% for rail, 72% for bicycle, and 68% for walk. Bus mode was not included. The assignment of a mode was almost exclusively based on average and maximum speeds of trips, although GIS data were used to separate rail from car mode. A web-based user interface was built for validation of the mode detection and entering of the bus mode by the survey respondents.

2.3. Improving on existing GPS/GIS methods

Our study continues and expands upon the work discussed above. It is the first study to introduce GPS/GIS techniques into travel data analysis in NYC, one of the most complex urban environments in the United States, if not the world. In addition, our study further develops the GPS/GIS method beyond what has been previously done. For instance, the study by Chung and Shalaby (2005) only allowed for one-purpose trips and a maximum of two possible modes per trip: under their assumptions, walk–car–walk was acceptable but walk–car–walk–bus–walk was not. Considering that those assumptions are hardly realistic in NYC, we design our algorithm to allow for an unlimited number of mode transfers within a trip.

As in most of the previous studies (Chung & Shalaby, 2005; Stopher, FitzGerald, et al., 2008; Tsui & Shalaby, 2006), we use GIS for matching GPS traces with transport links in mode detection. Furthermore, we build connectivity into our multimodal transportation network in GIS to recognize when mode transfers within a trip are feasible. This is especially important in NYC where it is common to have streets crossing spatially but not connecting (such as bridges and overpasses) or underground subway tracks, streets, and elevated train tracks available at different levels of the same transportation corridors.

In many handheld GPS travel surveys, GPS loggers do not record data when stationary, either because the GPS loggers were programmed to "sleep" (Stopher, FitzGerald, et al., 2008) or the survey respondents were instructed to turn off the loggers to save battery or memory space. In car-based GPS surveys, the GPS loggers are turned off when the respondents arrive at the destinations and turn off the car engines (Wolf, Schönfelder, Samaga, Oliveira, & Anhausen, 2004). Trip ends were often identified when the dwell time between two consecutive in-motion data points meets a set threshold, such as 120 s (Stopher, FitzGerald, et al., 2008), 180 s (Bohte & Maat, 2009), or 300 s (Wolf et al., 2004). When the GPS loggers start moving again, it takes a few seconds to a few minutes for the loggers to warm start, resulting in missing GPS points at the beginning of the trip (Schuessler & Axhausen, 2009). To reduce the problem of warm start, we keep the GPS loggers on all day long and modify the method for the trip end identification to deal with the cluster of data points collected when stationary. We add a radius in addition to the dwell time criterion. A trip end will be identified based on a survey respondent staying within a set radius for a set dwell time. This radius should be large enough to allow for changes in locations based on the error of the GPS loggers, but small enough not to include clusters of stationary points (other potential trip ends) elsewhere. Points that meet these criteria are grouped together and the centroid of these points is calculated as the trip end. Our more complex trip end identification method is made possible by the GIS.

3. Data and study area

3.1. GPS data

We conducted two small GPS-based travel surveys to test the accuracy of the algorithm developed. The first survey was conducted in the fall of 2008 in conjunction with the New York Metropolitan Transportation Council (NYMTC), the metropolitan planning organization for NYC and other NY counties in the New York Tri-State metro region. Thirty-five employees volunteered to carry a handheld GPS logger with them for all of their travel for 1 weekday. Each volunteer was also requested to complete a more traditional travel diary, either on paper or on the Internet, on the day after the survey. The second survey was conducted during the spring of 2009. Twenty-eight volunteers, primarily students, faculty, and staff at the City College of New York, carried a GPS logger with them for five consecutive weekdays. Each volunteer was also requested to complete a 1-day paper travel diary for one of the 5 weekdays on the next day. For this study, only the GPS data for the weekday with the diary were used. Aside from the differences described above for the two surveys, the same set of GPS loggers, same travel reporting logs for the 1-day diary, and similar instructions and procedures were used to generate compatible datasets for our analyses and comparisons.

We carefully reviewed the 1-day travel diaries from the surveys and checked them against the GPS traces in Google Earth. Volunteers were contacted when entries in the diaries were missing, not clear, or inconsistent. A total of 49 datasets (each with a 1-day diary and GPS data file) were eventually selected for this study, with 25 from the NYMTC survey and 24 from the City College survey. They are considered as the "truth sets" for testing the accuracy of the mode detection algorithm. Other datasets were excluded for various reasons such as incomplete diaries or GPS traces, erroneous diaries without the volunteers being available for verification, or all travel occurring outside of the NYC boundary.

The handheld GPS logger used for both surveys is i-Blue 747 (Fig. 1). It is about the size of a cell phone, much more portable than a car-based GPS logger. We tested the logger under many circumstances in NYC and found that it only fails to log when it is underground or in tunnels. Whenever aboveground, it records positions inside buildings, buses, elevated trains, bridges, ferries, and in urban canyons, although the positions recorded may not be always accurate. The logger was pre-set in both surveys to record variables such as date, time, latitude, longitude, speed, number of satellites used (NSAT), and horizontal dilution of precision (HDOP). NSAT is the number of satellites that a GPS logger used to calculate its position. The greater the NSAT value, the more accurate the calculation is likely to be. HDOP is an index to describe how well the positions of the satellites, used to calculation latitude and longitude, are arranged in the sky at the time of the recording. The greater the HDOP value, the less accurate the calculation is.

Fig. 1. i-Blue 747 GPS logger.

3.2. GIS data

People travel on transportation links to reach their destinations, whether walking or driving on the streets, or taking subway or commuter train on railroad tracks. In order to match GPS traces to these links for mode detection, various GIS layers were obtained from different local agencies:

(1) Street centerlines from the NYC Department of City Planning's Linear Integrated Ordered Network (LION) file.
(2) Bus routes and bus stops from NYC Transit (NYCT).
(3) Subway lines, subway stations, and subway station entrances from NYCT.
(4) Commuter rail lines and commuter rail stations from NYCT.
(5) Aboveground railroad lines from the NYC Department of Information Technology and Telecommunications (DOITT).

These GIS layers were cleaned and edited to build a multimodal transportation network in ArcGIS for mode detection. For example, connectivity was built into the network to distinguish regular crossing streets from those that crossed spatially but were not connected (bridges and overpasses). Incomplete subway station entrances were updated manually based on information garnered from such publicly-available Internet sources as Google Maps' Street View and DOITT's NYCityMap. Because GPS signals cannot be obtained underground, underground segments of subway or commuter rail lines were separated from aboveground segments and will not be used to match GPS traces. Street segments that do not overlap with bus routes were also noted and will not be used to identify bus mode.

3.3. NYC as the study area

With eight million people living in Manhattan, Brooklyn, Queens, Bronx, and Staten Island, NYC is the largest city in the United States. It has a population density over 10,000 per square kilometer (Demographia, 2010) and the most comprehensive transit system that carries an annual ridership of over 1.5 billion by subway and 0.7 billion by bus (MTA, 2009). Manhattan, in particular, is highly developed, with 220 high-rise buildings over 150 m in height (Emporis., 2010) and a population density of about 27,000 per square kilometer (Demographia, 2010). The complex urban environment in NYC makes it the ideal study area to test the feasibility of a GPS/GIS method for urban travel mode detection.

4. Methodology

An algorithm was written in the Visual Basic for Applications (VBA) programming language and runs through four major steps to detect travel modes (Fig. 2). The algorithm requires 9.3 or later version of ArcGIS as well as the Network Analyst extension.

4.1. Preparing GPS table

GPS data are downloaded from the loggers and formatted, for example, to have the correct local (daylight saving) time and the negative value for longitude. They are saved as point features in ArcGIS and clipped using a NYC boundary file to remove points

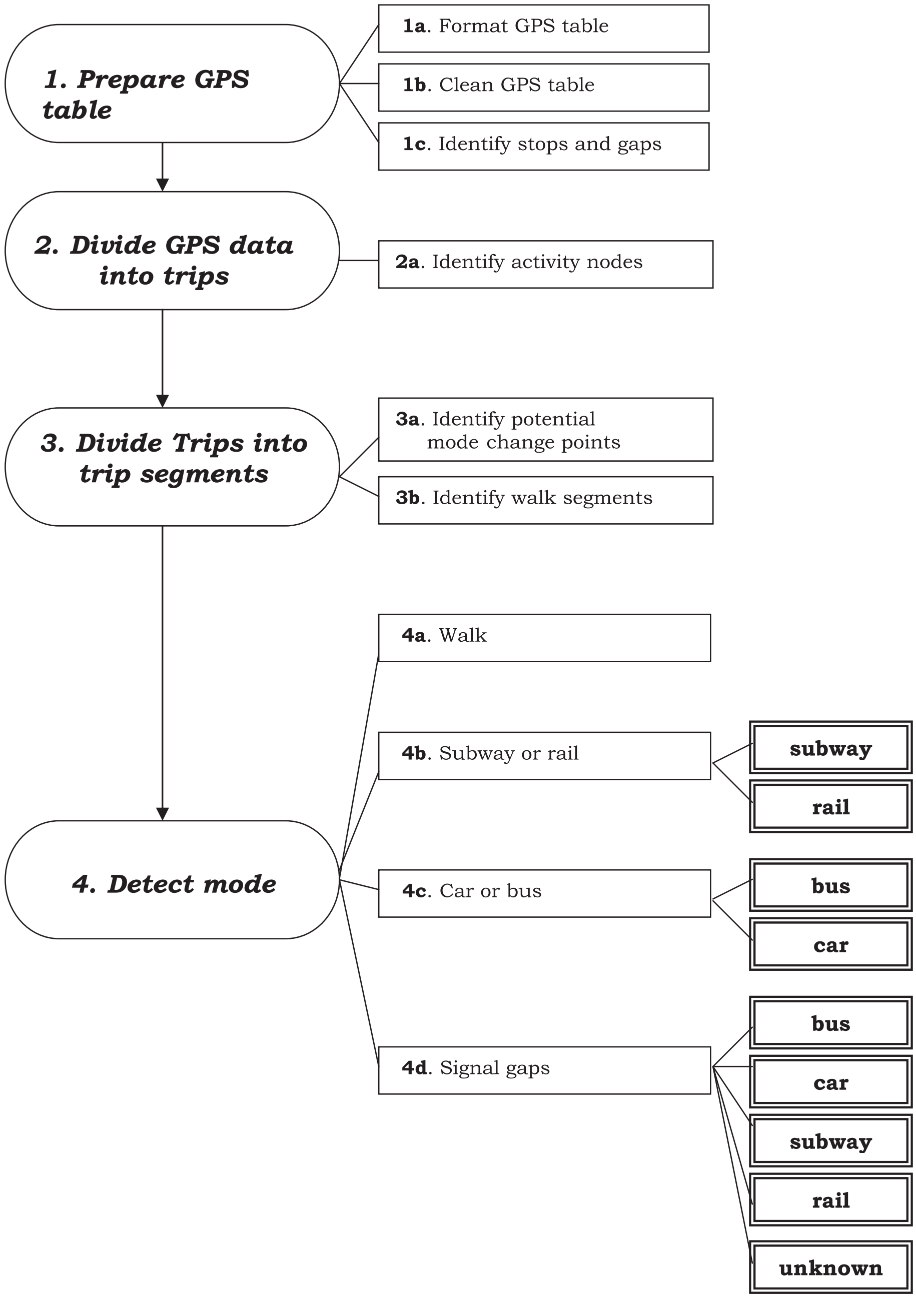

Fig. 2. Flow chart of the GIS algorithm.

outside of NYC. They are then cleaned using the parameters in 1b of Table 1 (same 1b in Fig. 2) to remove low-quality data points. Stops in the travel and gaps in the data are identified using the rules in 1c of Table 1.

4.2. Dividing GPS data into trips

A trip is all travel between two consecutive activity nodes. Any cluster of points is initially assumed to be the location of an activity node and therefore a trip end. Though this assumption likely identifies more trip ends than truly occurred (because transfer activities such as waiting at a bus stop can also appear as a cluster), it is preferable to have too many trip ends at this stage of the process and later refine the identification with further analyses than to miss trip ends from the start. An activity node cluster is marked if points are within 50 m of each other for more than 200 s. A trip end is the first stopped point of a cluster and a trip start is the point immediately following the last stopped point of a cluster.

4.3. Dividing trips into trip segments

A trip segment is a portion of travel on exactly one transportation mode. In order to divide a trip into trip segments, mode change points must be identified. They are the first and last points of a gap or of a walk segment that is longer than 60 s.

Five rules are developed to identify walk segments (3b of Table 1). The 2nd and the 4th rules allow for noise in the data due to signal distortion that might occasionally push the speed above the 10 km/h threshold for walking. The last rule is based on the study by Stopher, Clifford, Zhang, and FitzGerald (2007).

Table 1
Rules used in the mode detection process.

1. Prepare GPS table
1b. Remove points if NSAT < 4 or HDOP > 4.
1c. Stops if speed < 1.6 km/h; gaps if time interval > 120 s and distance > 250 m
2. Divide GPS data into trips
2a. Activity node if a cluster of points < 50 m of each other for > 200 s
3. Divide trips into trip segments
3a. First and last points of a gap or of a walk segment > 60 s
3b. Walk segment:
(1) First point if speed ⩾ 1.6 km/h and < 10 km/h
(2) Speed of each subsequent point ⩽ 15 km/h
(3) Duration > 60 s
(4) 85th percentile of speed of all points ⩽ 10 km/h
(5) Average speed of all points ⩽ 6 km/h
4. Detect mode
4a. Similarity index
4b. Subway or commuter rail:
(1) Distance from first point of trip segment to the nearest subway entrance < 100 m or to the nearest commuter rail station < 200 m; or distance from first point of trip segment to nearest subway or commuter rail link endpoint < 200 m
(2) Distance from last point of trip segment to nearest subway entrance < 100 m or to the nearest commuter rail station < 200 m; or distance from last point of trip segment to nearest subway link endpoint < 200 m
(3) Distance from each point of trip segment to nearest subway or commuter rail link < 60 m
(4) If possibly elevated train, then distance from each stopped point to nearest subway station < 184 m or to the nearest commuter rail station < 311 m
4c. Bus:
(1) Distance from first point of trip segment to nearest bus stop < 75 m
(2) Distance from last point of trip segment to nearest bus stop < 75 m
(3) 85th percentile of speed of all points ⩽ 88 km/h
(4) 95th percentile of acceleration of all points ⩽ 5.4 km/h/s
Car: any remaining trip segments

4.4. Detecting modes

4.4.1. Walk

All segments previously identified as walk are double-checked. Each consecutive pair of GPS points within a walk segment is matched to the most similar link of the street network. The methodology for these subroutines is derived from Chung's map-matching techniques (2003). At the heart of these techniques is the "Similarity Index," which calculates the similarity of a pair of GPS points to a link based on the distance between them and the similarity between the azimuth of the theoretical line connecting the two points and the azimuth of the link. The pair of points is then matched to the link with the highest index. In order to reduce processing time in our study, the only links for which the index is calculated are those, based on the multimodal transportation network in ArcGIS, that are connected to the link matched to the previous pair of points. Finally, for each walk segment, the map-matching subroutines output a list of all unique links used.

4.4.2. Subway or rail

While the underground subway and commuter rail are determined in the last step, four rules are developed for detecting an aboveground subway or commuter rail segment (4b in Table 1). The last rule applies only to subway or commuter rail tracks above streets. Though it is not a failsafe rule, the assumption is made that subways or commuter trains will only stop at stations. The algorithm therefore looks for stopped points. If they are within 184 m of a subway station or 311 m of a commuter rail station, then subway or commuter rail mode is identified. These particular thresholds were determined by the maximum length of trains in NYC. The longest subway trains are 184 m, and the longest commuter trains are 311 m (Anastasi, 2002; Bombardier, 2009; Metro North Commuter Council, 2006).

4.4.3. Car or bus

Prior to distinguishing car travel from bus travel, some walk segments need to be reexamined. When a bus (or a car) is stuck in traffic, the speed is slow, so this section of the bus (or car) trip segment may be singled out and falsely identified as a walk segment by the algorithm. This could create a potential problem in identifying bus mode for the sections before and after the false walk segment because these sections do not start and end near bus stops. To prevent these from happening, we add an extra step here to recheck the walk segments. If there are three consecutive segments within one trip that has the pattern of bus–walk–bus (or car–walk–car) and the middle walk segment is less than 5 min long, the algorithm combines these three segments into one. This combined segment will be classified into car or bus later on.

Four rules are developed to identify bus mode (4c in Table 1). In the third rule, 88 km/h is the maximum physically possible speed for a NYC express bus. In the fourth rule, 5.4 km/h/s comes from the maximum acceleration for a standard NYC bus. Any remaining trip segments after the bus mode are considered as car mode.

4.4.4. Signal gaps

If trip segments immediately before and after a gap segment have been identified as the same non-walk mode, then these three segments are combined into one and marked as having used this non-walk mode. For instance, a car–gap–car pattern is likely caused by driving through a tunnel. Gap segments that are not part of this type of pattern are analyzed for possible underground subway or commuter rail. The first two rules for identifying aboveground subway or commuter rail are used to identify underground subway or commuter rail. After these steps, the remaining gap segments are marked as unknown.

At the end of the flow chart in Fig. 2, the mode detection process is complete. Table 2 is an example of an output table.

5. Findings

5.1. Success rates

The 25 sets of GPS traces from the NYMTC survey and the 24 sets of GPS traces from the City College survey were run through the GIS algorithm. The resulting 49 trip segment output tables were then checked against travel diaries for accurate mode detection.

The average success rate in identifying the five modes for both surveys combined is 82.6% (Table 3). It is 78.9% for the NYMTC survey (Table 4); lower than the 86.0% for the City College survey (Table 5). Walk mode are detected with high accuracy for both surveys, with success rates all higher than 90% (Tables 4 and 5). Car mode has the second highest success rate for both surveys, while the commuter rail mode is consistently the lowest.

For NYC travel in particular, the high rates associated with the walk mode are particularly encouraging because more than half of all segments were walk segments (Table 3). Due to the relatively low vehicle ownership rate here and the almost ubiquitous need to walk to access transit, the 92.5% success rate for walk segments (Table 3) is an essential piece to an accurate mode detection algorithm for NYC.

In addition to the overall success in mode detection, the algorithm is quite accurate in identifying mode change points and trip segments. Of the 281 trip segments whose modes are correctly identified, 268 segments (greater than 95%) have durations within 5 min of those reported by the survey respondents. Of the 345 total trip segments reported in the diaries, 340 (greater than 98%) are identified. The algorithm correctly identified 100% of the trip segments for the City College survey. These results are much better than those from traditional travel surveys in which rounding up time and missing short trips by survey respondents are widely reported in the literature.

5.2. Challenges in NYC

Although our mode detection rates are better than those reported by Bohte and Maat (2009), they are generally lower than those in studies by Chung and Shalaby (2005), Tsui and Shalaby (2006), and Stopher, FitzGerald, et al. (2008). This is the result of the complex urban environment in NYC that poses many challenges to detect travel mode using the GPS/GIS method. Although they are discussed separately below, they in fact interact with each other to further complicate the mode detection process.

5.2.1. Urban canyon effect

The most serious challenge in NYC is the urban canyon effect. In urban canyons created by tall buildings, radio signals from satellites used in determining the location may bounce off the surrounding buildings, causing the GPS logger to derive inaccurate locations. Although urban canyon effect is known to affect GPS readings elsewhere, it is especially a problem in NYC. One reason is that urban canyons are more extensive in NYC, Lower and Midtown Manhattan in particular, than elsewhere. Another reason is that while advanced equipment could be installed in automobiles to eliminate urban canyon effect where car mode is predominant, it is too heavy and bulky to be a practical solution in NYC.

Urban canyon effect explains the lower success rates, across all five modes, for the NYMTC survey (Table 4) than those for the City College survey (Table 5). Volunteers in the NYMTC survey were primarily NYMTC employees and traveled to work at NYMTC's Lower Manhattan offices on their survey day. NYMTC's Lower Manhattan office is only one block away from the Wall Street historical financial center where urban canyon effect is the greatest in NYC according to our field testing. We had students carry GPS loggers and walk around some streets in the Wall Street area 30 times (Fig. 3). The average deviation between the streets on which students walked with the GPS loggers and the location points recorded by the GPS loggers was almost 52 m, higher than the 43 m in Midtown Manhattan and the 13 m in NYC as an average. In comparison, volunteers in the City College survey were primarily students or employees at City College, which while still located in Manhattan is in West Harlem with wider streets and substantially fewer tall buildings.

Because of the urban canyon effect, we have to modify some parameters and methods used in previous studies. For example, to identify underground gaps, the distance parameter used is increased from Chung's 150 m (2003) to 250 m to allow for greater urban canyon distortion in NYC. We modify the method for trip end identification and calculate the centroid of location points within 50 m of each other for more than 200 s as the trip end.

5.2.2. Warm start

When GPS loggers are brought aboveground from underground subway or commuter rail, it takes a very short period of time to start calculating the current location after being inactive underground. This very short period of time is called warm start time. According to our field test on subway 1 line in the Upper West Side of Manhattan and subway F line in Brooklyn, the average warm start time is 39 s and may go up to 106 s. In urban canyons in Lower and Midtown Manhattan, warm start may take a few minutes. During warm start, a survey respondent continues walking away from the subway entrance or commuter rail station. By the time the GPS logger starts recording the first good-quality location data after the underground gap and the warm start, it has been too far from the subway entrance or commuter rail station for the gap segment to be linked to these modes.

Warm start lowers the success rates for subway and commuter rail modes. When a subway or commuter rail gap segment is not correctly identified because of warm start, the GIS algorithm will try to fit the gap segment to the rules for car or bus mode. This may cause a subway or commuter rail segment falsely identified as car or bus mode. If the gap segment does not fit the rules for car or bus, it cannot be identified as one of the five modes and therefore marked as unknown. Warm start is solely responsible for the 11 subway trip segments being identified as unknown in Table 3.

Instead of using one point to represent a subway station as in previous studies, we use the locations of subway entrances in our mode detection. In NYC, there are usually two or more entrances to a subway station. Some entrances are a few blocks away from the station (Fig. 4). Using several entrances to replace one station location in our mode detection helps to reduce the problem caused by warm start. When entrance location is not available in GIS for commuter rail stations, we increase the maximum threshold distance from 100 m for subway entrances to 200 m for commuter rail stations to mitigate the effect of warm start.

5.2.3. Sophisticated transportation network

The sophisticated transportation network in NYC adds many difficulties to the mode detection. Horizontally, the dense street network entails close street segments and intersections, providing too many candidates to match GPS traces. Vertically, 44% of the subway tracks in NYC are aboveground, most of which are elevated directly above streets in the four boroughs outside of Manhattan. GPS traces logged from these elevated subway tracks appear spatially similar to those from street modes such as walk, car, and bus. Within Manhattan, almost all subway tracks are underground. Commuter rail tracks below 97th Street in Manhattan are all

Table 2
Example of a trip segment table after mode detection.

TripNo.	SegmentNo.	StartLat	StartLong	StartTime	EndLat	EndLong	EndTime	Mode
1	1	40.910397	−73.903166	12/1/2008 7:00:01 AM	40.714481	−74.005665	12/1/2008 8:12:11 AM	Bus
1	2	40.71446	−74.005695	12/1/2008 8:12:12 AM	40.709643	−74.010292	12/1/2008 8:33:46 AM	Walk
2	1	40.709657	−74.010568	12/1/2008 10:00:30 AM	40.707353	−74.004552	12/1/2008 10:35:03 AM	Walk
3	1	40.706927	−74.00537	12/1/2008 2:57:51 PM	40.706726	−74.00536	12/1/2008 3:24:11 PM	Walk
3	2	40.706725	−74.00536	12/1/2008 3:24:12 PM	40.706228	−74.005496	12/1/2008 3:26:01 PM	Car
3	3	40.70625	−74.005482	12/1/2008 3:26:02 PM	40.705804	−74.005318	12/1/2008 3:38:31 PM	Walk
4	1	40.706232	−74.004846	12/1/2008 4:44:19 PM	40.893906	−73.896421	12/1/2008 5:31:45 PM	Car
4	2	40.893897	−73.896458	12/1/2008 5:31:46 PM	40.891218	−73.894551	12/1/2008 5:39:23 PM	Walk

Table 3
Accuracy rates from both surveys combined.

	Identified by algorithm as						Total trip segments	Correct segments	Success rate (%)
	Walk	Subway	Rail	Car	Bus	Unknown			
Walk	182	0	0	11	4	0	197	182	92.4
Subway	0	40	0	3	3	15	61	40	65.6
Rail	0	1	5	8	0	0	14	5	35.7
Car	2	0	0	37	5	0	44	37	84.1
Bus	2	0	0	7	15	0	24	15	62.5
Total	186	41	5	66	27	15	340	281	82.6

Table 4
Accuracy rates from NYMTC survey.

	Identified by algorithm as						Total trip segments	Correct segments	Success rate (%)
	Walk	Subway	Rail	Car	Bus	Unknown			
Walk	101	0	0	7	2	0	110	101	91.8
Subway	0	20	0	2	1	11	34	20	58.8
Rail	0	1	2	5	0	0	8	2	25.0
Car	2	0	0	21	2	0	25	21	84.0
Bus	2	0	0	5	6	0	13	6	46.2
Total	105	21	2	40	11	11	190	150	78.9

Table 5
Accuracy rates from City College survey.

	Identified by algorithm as						Total trip segments	Correct segments	Success rate (%)
	Walk	Subway	Rail	Car	Bus	Unknown			
Walk	81	0	0	4	2	0	87	81	93.1
Subway	0	20	0	1	2	4	27	20	74.1
Rail	0	0	3	3	0	0	6	3	50.0
Car	0	0	0	16	3	0	19	16	84.2
Bus	0	0	0	2	9	0	11	9	81.8
Total	81	20	3	26	16	4	150	129	86.0

underground, even though 82% of the commuter rail tracks in NYC are aboveground. GPS loggers cannot receive satellite signals underground and therefore cannot provide information for mode detection on those trip segments.

Mode detection becomes more difficult in Manhattan when the extensive underground subway and commuter rail tracks are well connected to each other. The mode change between the subway and commuter rail modes happens underground and cannot be identified from the GPS data. This reduces by 50% the chances of detecting these subway and commuter rail segments because only one end of these segments can be linked to GPS traces for mode detection. It significantly lowers the success rates for both the subway and commuter rail modes, although more so for the commuter rail mode for two reasons. One is that it is much more common for commuters to make rail–subway connections while most subway riders in NYC have no need to transfer to commuter rail (unless they want to travel out of NYC). Another reason is that for commuters taking the PATH train from New Jersey to Lower Manhattan, the end of the commuter rail segment in New Jersey is outside of the study area and cannot be used to detect the commuter rail mode either. As a result, the success rate for detecting the commuter rail mode for the NYMTC volunteers in Lower Manhattan is only 25% (Table 4). The success rate of 50% (Table 5) for commuter rail for the City College volunteers in West Harlem is much better because they mostly took Metro North or Long Island Rail Road, a significant portion of which is aboveground in Bronx or Queens Borough before going underground in Manhattan. Still, the success rate for detecting the commuter rail mode is the lowest among all modes for both surveys, primarily because the subway–rail underground connections in Manhattan are undetectable from the GPS data.

Connectivity among networks of streets, subway lines, and commuter rail lines in our multimodal transportation network often provides the critical information to find the right link for

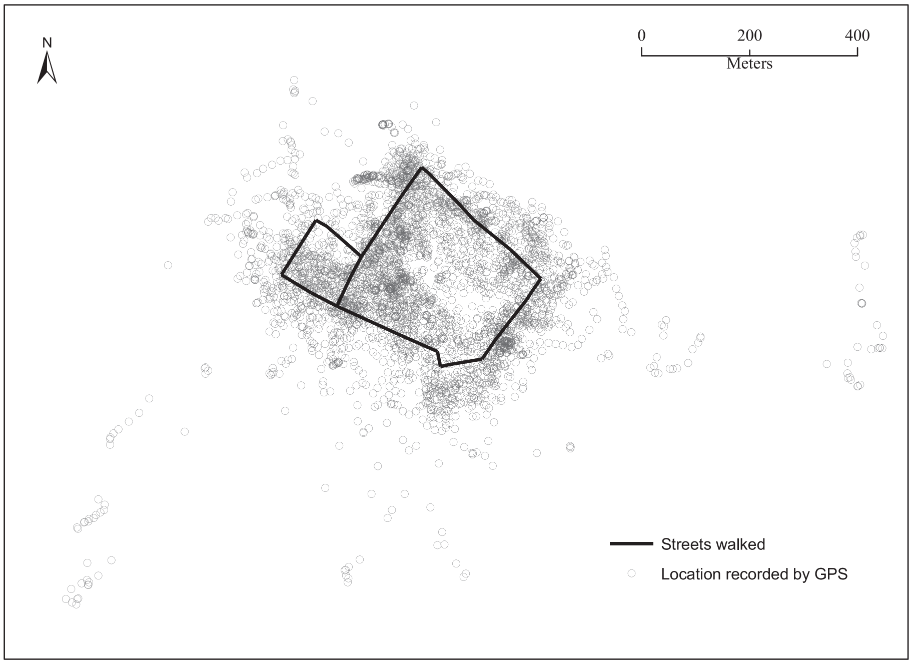

Fig. 3. Field test of urban canyon effect in Lower Manhattan.

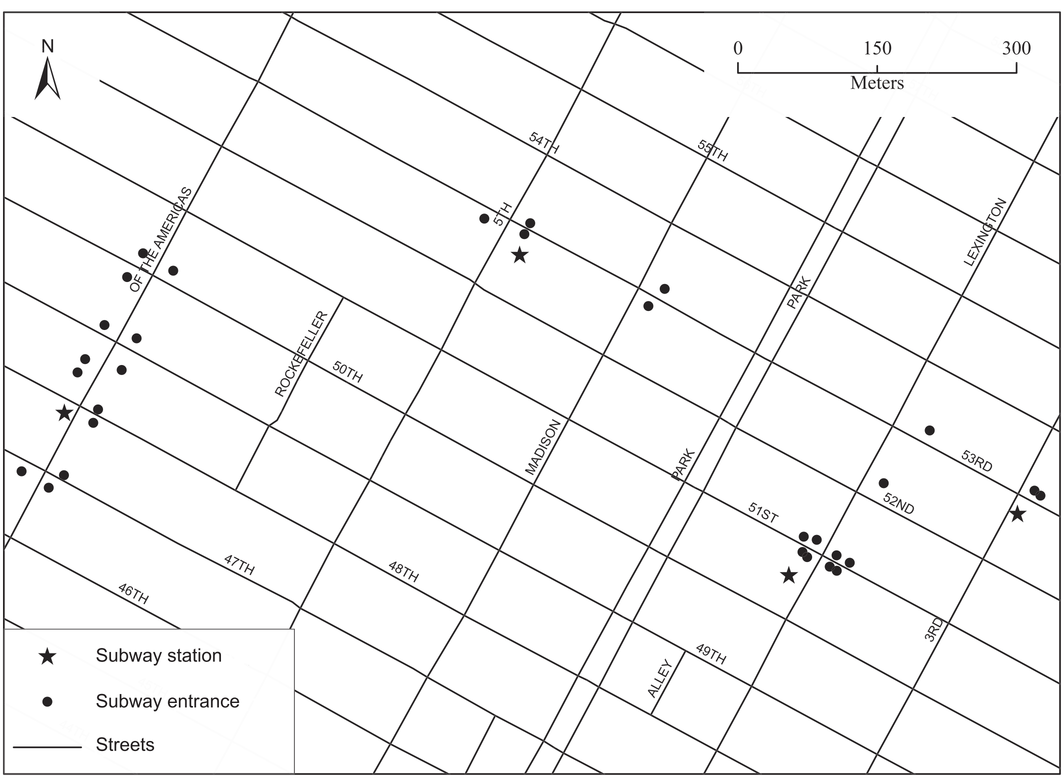

Fig. 4. Sample subway stations and entrances in Manhattan.

matching the GPS traces, or interpolate the underground subway mode. The 65.6% success rate for the subway mode detection (Table 3) demonstrates of the power of our multimodal transportation network. If the same kind of high-quality transportation network data becomes available for the suburban areas outside of NYC in the future, the success rate for detecting the commuter rail mode will be greatly improved.

5.2.4. Traffic congestion

Traffic congestion is a byproduct of the high-density urban environment in NYC and makes it a delicate task to differentiate among walk, bus, and car modes. In most cities, bus is expected to have a faster speed than walking and a slower speed than driving. In NYC, the differences are reduced by frequent traffic congestions. Bus mode can be easily identified as car mode, or even walk mode, as indicated in Tables 3–5. This explains the 62.5% success rate for bus mode (Table 3), much lower than we expected.

Although the network of bus routes in the multimodal transportation network helps in identifying the bus mode, urban canyon effect can often cause a parallel shift of GPS traces from one street segment to another street segment in NYC's dense street network. If the misidentified street segment is not part of the bus route, the GPS traces from a bus ride may be identified as driving or walking. This provides an example of how the different challenges in NYC can interact to complicate the bus mode detection.

In dealing with the challenge caused by traffic congestion, we added an extra step to recheck the walk segments for possible car or bus mode in traffic congestion. We learn that the success rates for bus and car modes could be sensitive to the rules used to identify these modes. Our first run of the 49 GPS traces had a much higher success rate for car mode (95.8%) and a much lower success rate for bus mode (53.3%) than the results in Table 3 from our second run of the same data through a revised GIS algorithm. Because of the tradeoff among the street modes (bus, car, and walk modes), establishing the appropriate rules for each mode is an important step in successful mode detection. We hope that the rules we developed for mode detection in NYC will be helpful for similar tasks in other cities.

6. Conclusions and future research

A GIS algorithm is developed in our study to detect five travel modes in NYC. The overall success rate is 82.6%, ranging from 35.7% for commuter rail to 92.4% for walk mode. Challenges to achieve a high success rate in NYC, including urban canyon effect, sophisticated transportation network, warm start, and traffic congestion, are discussed and some of our ways to meet the challenges are provided.

Future research can improve the GPS/GIS method in several areas. One area of improvement is to expand the GIS algorithm to process multiple-day GPS traces and take advantage of the repetitive patterns of travel modes over multiple days. Another area of improvement is to add the Internet technology into the method and allow verification and modification of the mode detection results over the Web by the survey respondents. Considering the challenges in NYC to achieve a 100% success rate, this may become a necessary and practical step to generate accurate data on travel modes. Still another area of improvement to the GPS/GIS method is to add the mobile technology and use smartphones with GPS and accelerometer (such as iPhones). These smartphones can take advantage of assisted-GPS, Wi-Fi and cellular radio signals to compensate for the satellite signal loss underground or satellite signal degradation in urban canyons as well as to provide a quicker fix after a warm or cold start. The accelerometer in smartphones can output readings of acceleration to help differentiate travel modes, especially underground commuter rail and subway modes in Manhattan.

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