Multimode Trip Information Derivation from Personal Trajectory Data

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ABSTRACT
Handheld GPS devices can serve as a new tool to retrieve individual’s trip information by providing personal trajectory data. In this paper, an innovative method is proposed to detect and extract trip information, including trip modes, trip begin and end locations, etc., from personal trajectory data. A neural network based module is used first to identify walk, bicycle and motorized trip (bus and car) modes. A second module, using critical points on the trajectories, is developed to distinguish car and bus modes, incorporated with GIS map information. The proposed method was tested using field data. Results indicate that the proposed method has good performance in both accuracy and consistency.

Keywords: Multimode Trip Information, Trip Mode Detection, Neural Network, GIS, Personal Trajectory Data
INTRODUCTION

Precise travel behavior analysis is the guiding basis of feasible urban transportation planning. Traditional data collection methods such as paper forms or questionnaire, telephone interview and mail inquiry seem hardly adequate to satisfy planners’ need in various aspects. These traditional survey methods are expensive and time consuming. In addition, these methods rely on human recall and therefore have data quality issues, such as missing short trips (1,2), reporting trips out of sequence (2,3), and rounding up the departure and arrival times (4). Therefore, it is necessary and meaningful to develop survey methods with lower costs and higher data quality.

Nowadays, with the fast development of wireless communication technology, wireless service providers developed numerous location based services, and the number of GPS-enabled smart phone users is growing fast. All these devices are generating enormous personal trajectory data, with almost no additional costs. It has brought new opportunities for the development of GPS-based survey methods.

Since the mid-1990s, many field tests have been conducted to assess the performance of personal trajectory based travel surveys, especially for the GPS trajectory based survey. Results showed that the GPS-based travel survey has better representative results of travel behavior, and higher data quality than traditional survey methods, especially in accuracy, dynamic and real-time features (3,5,6). Due to the increased accuracy of the collected data to examine variability in personal trips, it’s potentially to reduce sample sizes of travel surveys (7,8). Besides, the GPS-based survey can also reduce respondents’ burden, as it automatically collects real-time data by using sophisticated devices instead of respondents’ recall memory (9,10). The main disadvantage of the GPS-based survey technology is the signal loss or degradation problem which is particularly noticeable in densely built central business districts (CBDs) and in underground areas (3).

To further explore the potential of GPS-based travel survey, GPS data are embedded in GIS, GSM or Internet applications. Many field tests successfully obtained trip OD, travel time, travel speed, travel purpose et al. parameters (2,11-13). Furthermore, they discussed the feasibility of substituting the traditional survey based on evaluation result. However, (Bohte and Maat (11)) suggested that the GPS-based survey should be the aid and promoting parts of traditional survey, since travel modes were difficult to be obtained from GPS data and most of the existing studies were performed in developed countries where private car is the primary travel mode, the small scale test may also limit the data quantity.

In order to explore the possibility to identify travel modes from GPS data, an early study by Nielsen and Hovgesen (14) designed some experiments and found that GPS data had different time-space features for different travel modes. Because GPS signal is lost while travelling in subway, detection of the subway mode needs other data. Chung and Shalaby (15) developed 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, the average mode detection accuracy was 91.7%, however, they did not use real GPS-based travel survey data, but used reconstruct trips sampled from a prior Toronto travel survey. Tsui and Shalaby (16) developed an GPS-GIS based
fuzzy logic algorithm for mode detection, however Byon et al. (17) compared the
detection performance of the neural network and fuzzy logic algorithms and pointed out
that the neural network which can be further improved was better for travel mode
detection, because neural network adapt better to future mode mix changes of the road by
simply adding or subtracting a new mode in the output layer, whereas FL-based classifiers
require the modification of membership functions and running optimizations for the
multiple components of the system. Many other studies adopted different imputation
methods to improve the detection results, including ad hoc rules (11, 18, 19), regression
models (20) and learning-based algorithms (21, 22), these studies shown that all the
methods are only partially successful in correctly identifying transportation modes,
especially for bus mode detection, whose detection rate are mostly below 70%.

In summary, the previous researches have done a lot of GPS-based travel mode
detection work. However, many of these efforts have focused on detecting one single
mode of travel, which does not reflect the multimodal nature of travel behavior. What’s
more, most previous efforts for mode identification used simple rules of travel speeds,
which in some cases results in misclassifications. The nature of multimodal trips and
transfer time between modes required a more advanced identification algorithm. In this
paper, we proposed GPS-based multi-mode travel information detection and collection
method, to obtain trip modes, traveler’s departure time, travel time, mode-changing time
and location. In the study, a neural network is firstly built to identify walk, bicycle and
motorized trips modes (bus and car) after analyzing the time-space trajectory features of
the multi-mode travel experiments, and then based on the matter of fact that the GPS
streams of bus and car are very similar and the result of neural network detection is not
satisfying, we further proposed a GIS-based critical point matching algorithm for bus and
car mode detection. In the end, a case study was carried out to display the better
performance of the proposed method.

METHODOLOGY
This paper proposes an innovative method to detect trip information, including trip modes,
mode transfer time, trip begin and end locations from personal trajectory data. A neural
network based module is used first to identify walk, bicycle and motorized trips modes
(bus and car); A second module, using critical points on the trajectories, is developed to
distinguish car and bus modes, incorporated with GIS map information. The personal
GPS trajectory data used in this paper includes speed, displacement, latitude and
longitude per second.

Artificial Neural Network Model
Back Propagation (BP) neural network is one of the artificial intelligence techniques that
can be used to classify the trip modes. A BP neural network contains input layer, hidden
layer, output layer three modules. It can adapts to input–output data pairs and learns their
underlying patterns during cycles of training in the hidden layer. In subsequent recall, the
trained network predicts the output (mode) based on new input GPS measurements.

During the training of the neural network, the calculated output is compared to the
known correct output of the used training data set. If the calculated output is incorrect, the
weights between the input nodes, hidden layer nodes, and output nodes are adjusted accordingly with a method known as ‘back propagation’. The training process is repeated until the accuracy of the network reaches thresholds defined by the user or until a certain number of training iterations known as “epochs” are completed. The weights representing the trained neural network are then used to evaluate future data for which the correct output is not known.

In the proposed NN algorithm, the spot speed and the maximum speed per minute are used as the first two neural network input attributes to capture the general speed difference between trips by motorized vehicles and those by walking and bicycling. Meanwhile, travels by motorized-vehicles are much more influenced by traffic congestion compared to other modes, so the speed variance per minute represents the difference of each mode under congested traffic. Finally, together with the displacement per unit collected by the GPS devices, these four attributes are used as the neural network input attributes. Data preprocessing should be conducted first to calculate the input attributes before the training of the neural network. Travel modes are selected as the output attributes in this paper. For convenience, travel modes are coded as shown in TABLE 1.

<table>
<thead>
<tr>
<th>Travel mode</th>
<th>Walk</th>
<th>Bicycle</th>
<th>Bus</th>
<th>Car</th>
<th>Motorized-vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Code</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>

The detailed neural network topology for mode detection is shown in FIGURE 1.

Critical Point Matching Algorithm
Since walk, bicycle and bus/car have great difference, the BP neural network aforementioned can distinguish walk, bicycle from bus/car travel with a high successful rate, but not quite successful for bus and car. Therefore, a secondary algorithm based on matching trajectory critical points and bus stop locations is further proposed.

Critical points are defined as the “change” points in the travel trajectory (23). In this study, this “change” is referred to the travel mode transition. There two kinds of critical points in the neural network detection results, the first kind are the true mode transfer points, and the second kind are the misidentified mode transfer points which are mainly
caused by the travel stops at signal intersections or under traffic congestion. As shown in FIGURE 2, the blue circle points denote the real mode transition points separating a bus trip with two walk trips. The red square points, on the other hand, indicating the stops at signal intersections, would be “false” critical points misidentified by the neural network.

In order to eliminate false critical points and therefore detect actual trip modes, we compare the locations of the critical points with the bus stops, that is, calculating the distance “L” between critical point and bus stop, if the distance equals to or is smaller than a preset threshold value R, then we recognize that the vehicle makes a stop at the bus stop.

\[ L_i = \sqrt{(x_i - \hat{X}_k)^2 + (y_i - \hat{Y}_k)^2} \]  

(7)

in which, \((x_i, y_i)\) denotes the coordinate of critical point \(i\), and \((\hat{X}_k, \hat{Y}_k)\) denotes the real coordinate of bus stop \(k\).

Meanwhile, if the ratio of the vehicle stop number at bus stops versus the total bus stop number along the trip “W” equals to or is larger than the preset value \(P\), we recognize this vehicle as a bus.

\[ W = \frac{\sum n_i}{N} \]  

(8)

in which, \(n_i = \begin{cases} 0, & (r_i \geq R) \\ 1, & (r_i < R) \end{cases}\), \(n_i = 1\) denotes the vehicle stops at bus stop \(i\), and \(N\) denotes the total number of bus stops along the trip.

**Methodology Summary**

FIGURE 3 shows the processing flow chart for mode detection. The neural network is firstly used for classification of walk, bicycle and motorized travel modes (bus and car), then the trajectory critical points matching algorithm is further used to distinguish car and bus modes, incorporated with GIS map information. After BP neural network and critical points matching algorithm application, we can then classify different travel modes in a multi-mode trip, and meanwhile, according to the space-time information of critical points, traveler’s departure time, travel time, mode changing time and location information etc. can be collected.
FIGURE 3 Flow chart for mode detection.

MODEL CALIBRATION

Neural Network Training
A training process is needed before the neural network model can be applied to detect trip mode. Before the training, unreasonable GPS data whose travel speed exceeds the road speed limitation should be removed. Based on this, the number of hidden neurons, training algorithm, training epoch, learning ratio et al. should be calibrated.

In this paper, different hidden neurons, e.g. 10, 20, 30, 40, 50 et al. were chosen. As a rule of thumb, having too many hidden nodes forces the neural network to memorize the input–output training data and hence can lead to poor generalization. Too few hidden
nodes, on the other hand, can be insufficient for the neural network to identify and isolate the different classes. Therefore, it is desirable to keep the number of hidden nodes to a minimum without sacrificing the discriminate power. The testing results show that the performance in terms of Mean Square Error for the case of 10, 20, 30 and 50 neurons is not as good as that of 40 neurons. Therefore, 40 hidden neurons were used to build the network. Levenberg-Marquardt algorithm was chosen so that the over fitting phenomenon could be avoided. Besides, the Levenberg-Marquardt algorithm can provide fast convergence even for large networks that contain a few hundred weights. Based on same rule, the learning ratio is set to 0.05.

As for the training epoch setting, classification performance during the training process seemed to stabilize after 3000 epochs or 60 failure times, so the training epoch chooses 3000 and the maximum failure time chooses 60.

Matching Thresholds for Critical Points Matching Algorithm
Bus or car mode detection accuracy mainly depends on the critical points matching algorithm parameter settings. Experiment results show that as the distance threshold \( R \) between critical point and bus stop increases, the detection rate of travel by bus becomes higher, and meanwhile the detection rate of travel by car becomes lower; As the ratio threshold \( P \) of the vehicle stop number at bus stops versus the total bus stop number along the road increases, the detection rate of car increases and the detection rate of bus decreases. TABLE 2 and TABLE 3 list the detection rates for different \( R \) and \( P \) values. From the tables we can see that when the matching radius \( R \) equals to 60 meters and \( P \) equals to 70\%, both the car and bus detection rates reach a higher level.

**TABLE 2 Detection Rate of Travels by Car**

<table>
<thead>
<tr>
<th>R (m)</th>
<th>60%</th>
<th>70%</th>
<th>80%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>30</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>40</td>
<td>50%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>50</td>
<td>25%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>60</td>
<td>25%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>70</td>
<td>13%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

**TABLE 3 Detection Rate of Travels by Bus**

<table>
<thead>
<tr>
<th>R (m)</th>
<th>60%</th>
<th>70%</th>
<th>80%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>36%</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30</td>
<td>82%</td>
<td>55%</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>40</td>
<td>91%</td>
<td>73%</td>
<td>45%</td>
<td>0</td>
</tr>
<tr>
<td>50</td>
<td>91%</td>
<td>82%</td>
<td>73%</td>
<td>0</td>
</tr>
<tr>
<td>60</td>
<td>91%</td>
<td>91%</td>
<td>82%</td>
<td>0</td>
</tr>
<tr>
<td>70</td>
<td>91%</td>
<td>91%</td>
<td>82%</td>
<td>9%</td>
</tr>
</tbody>
</table>
EXPERIMENT DESIGN

It is common that a single trip may contain several travel modes. However, walk mode is always act as an intermediate in a multi-mode travel, and common trips can always be divided into several Walk-X-Walk segments. In this paper, trip experiments are designed including three patterns, Walk-Bicycle-Walk, Walk-Car-Walk, and Walk-Bus-Walk, under peak hours and non-peak hours and along different types of roads.

Data Collection

The data collection was conducted at Shaxi Lin (urban rural express way) and North Renmin Road (urban main arterial road) in Chengdu, China. Twenty volunteers from Southwest Jiaotong University participated in the data collection. During the tests, the travelers are asked to carry handheld GPS loggers and travel on the planned routes. The GPS logger is able to collect speed, displacement per second, latitude and longitude for every second. The sample size of each multi-mode travel segment, Walk-Bicycle-Walk, Walk-Bus-Walk and Walk-Car-Walk, is 50 trips. Meanwhile, the traveler is also asked to take travel logs to record his detailed travel information including departure time, travel modes, travel routes, and the time arriving at bus stops etc in time. The travel log information is used for final error analysis of the proposed method.

Multi-mode Travel Features Analysis

Different travel modes have different travel trajectory features. Travel by walk makes the densest GPS positioning points, as walk has the lowest speed. Travel by bus makes overlap GPS location points at the bus stops, otherwise is similar to travel by car. FIGURE 4 shows different speeds of multi-mode travels. The walking speed ranges from 5 to 10 km/h, the bicycling speed is from 10 to 20 km/h, and the speeds of travels by bus and car both have large amplitudes. In addition, the fluctuating frequency of bus speed is obviously larger than car speed, which is mainly because bus stops at bus stops.

FIGURE 4 Speed examples of multi-mode travels.

(a) Walk-Car-Walk; (b) Walk-Bus-Walk; (c) Walk-Bicycle-Walk
RESULTS ANALYSIS

In this section, the mode detection rate (defined as the successful ratio of mode detection), and the mode changing time error (defined as the difference between the detected modes changing time and the true modes changing time from the travel logs) is calculated to verify the proposed methods.

Verification of the Critical Points Matching Algorithm

In order to verify the feasibility of critical points matching algorithm for bus and car mode detection, an example is shown in the following part. FIGURE 5 gives the critical points detecting process and result of one Walk-Bus-Walk trip. FIGURE 5 (a) shows the original GPS travel speed of the trip; FIGURE 5 (b) shows the neural network detection result for bus/car mode, as shown in the figure, bus and car mode are difficult to separate; FIGURE 5 (c) illustrates the motorized-vehicle detection result; and FIGURE 5 (d) points out the modified result after using of the mode-transition time error correction model and the unreasonable trip trajectory removing model. By comparing to original data, our proposed method has detected all the critical points of this travel example.

FIGURE 6 shows the critical points matching and travel information detection results. FIGURE 6 (a) describes the comparison between the critical points and the detected bus stops, in which blue dots are critical points and red squares are the successfully matched points; FIGURE 6 (b) describes the comparison of the matching result with the actual bus stops, in which red squares are detected bus stops, green squares are actual bus stops, and the matching rate is larger than 85%; FIGURE 6 (c) illustrates the travel information detection results, that is Walk (0-557s)-Bus (558-2694s)-Walk (2695-2761s); FIGURE 6 (d) shows the bus stop matching result of a Walk-Car-Walk trip, according to it, the matching ratio is very low (only one bus stop is matched), these results suggest that our proposed method can successfully detect bus and car mode.

FIGURE 5 Walk-Bus-Walk test result.

(a) Original speed; (b) Neural network detection result; (c) Motorized-vehicle detection;
(d) Modified result.
FIGURE 6 Bus stop matching result and travel information detection result.

(a) Bus stop detection of Walk-Bus-Walk travel; (b) Comparison of detected bus stops and actual bus stops of Walk-Bus-Walk travel; (c) Travel information detection result of Walk-Bus-Walk travel; (d) A sample of Walk-Car-Walk detection result.

Analysis of Mode detection Error

TABLE 4 displays the accuracy rates of multiple mode detection. Statistical results show that the correct mode detection rates are all over 80%, among which, Walk-Bicycle-Walk achieves the highest success rate, that is 92%, Walk-Bus-Walk and Walk-Car-Walk travels have similar success rates, 80% and 82% respectively, these results demonstrate that the proposed BP neural network and the critical point matching method can achieve good performance for multi-mode travel detection. Sometimes, the bicycle mode has low speed as the walk mode, and the bus or car mode also have low speed as the bicycle or the walk mode in congested traffic, so some misrecognitions appear in the experiment, such as Walk-Bus-Walk is misclassified as Walk-Bicycle-Walk. It should be noted that two Walk-Bus-Walk trips are misclassified as Walk-Car-Walk trips and one Walk-Car-Walk trip is misclassified as Walk-Bus-Walk trip in the misrecognition, which happens because of the failure of the critical point matching method. The “Other” column in TABLE 4 includes the mode combinations excluding the three listed ones (Walk-Bicycle-Walk, Walk-Bus-Walk, Walk-Car-Walk), like Walk-Walk-Walk or Walk-Bicycle-Car-Walk etc..

<table>
<thead>
<tr>
<th>Multi-mode</th>
<th>W-Bicycle-W</th>
<th>W-Bus-W</th>
<th>W-Car-W</th>
<th>Others</th>
<th>Detection Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>W-Bicycle-W</td>
<td>46</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>92%</td>
</tr>
<tr>
<td>W-Bus-W</td>
<td>3</td>
<td>40</td>
<td>2</td>
<td>5</td>
<td>80%</td>
</tr>
<tr>
<td>W-Car-W</td>
<td>2</td>
<td>1</td>
<td>41</td>
<td>6</td>
<td>82%</td>
</tr>
</tbody>
</table>

NOTE: W=Walk.
Analysis of Mode Changing Time Error

TABLE 5 displays the error statistical results of mode changing time. According to TABLE 5, the majority of detection error falls within 20 second, that is 78%, 92%, 94% for Walk-Bicycle-Walk, Walk-Bus-Walk and Walk-Car-Walk respectively. All the mean error of mode transition time is smaller than 30 seconds, and the error is especially low (less than 15 seconds) for Walk-Bus-Walk and Bus-Car-Walk travels, this is mainly because it is easier to identify accuracy mode changing time when the speed difference between the two modes is relatively larger, for example, the usually speed difference between walk and bicycle is smaller than that between walk and bus, experiment results show that the mean error for Walk-Bus-Walk travels is 13.6s, and it increases to 28.6s for Walk-Bicycle-Walk travels. Finally, TABLE 5 also demonstrates that the proposed method reaches a good performance in mode changing time detection, the errors are relatively small compared to the travel times which usually last tens of minutes, it’s acceptable for travel surveys.

<table>
<thead>
<tr>
<th>Multi-mode Trips</th>
<th>Absolute Error Distribution (%)</th>
<th>Absolute Error (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0~10s</td>
<td>10~20s</td>
</tr>
<tr>
<td>W-Bicycle-W</td>
<td>32.0</td>
<td>46.0</td>
</tr>
<tr>
<td>W-Bus-W</td>
<td>44.0</td>
<td>48.0</td>
</tr>
<tr>
<td>W-Car-W</td>
<td>34.0</td>
<td>60.0</td>
</tr>
</tbody>
</table>

NOTE: W=Walk, Stdev=standard deviation.

CONCLUSIONS AND FUTURE WORK

In this paper, a GPS-based multi-mode travel information detection method is proposed and evaluated. Compared with the previous research, remarkable improvements include: (1) Most previous research mainly focuses on single mode travel information detection, in this paper, special field tests of multi-mode travels are designed and experiment results show detailed traffic information such as travel modes, traveler’s departure time, travel time, mode-changing time and location can be collected. (2) In this study, the personal GPS travel trajectory data is integrated with GIS information to develop the method based on the neural network and trajectory critical points. Experiment results demonstrate that the proposed method has better performance in both feasibility and consistency. The mode detection ratios all reach 80%, and it is especially high for walk and bicycle mode detection, whose detection ratios are all over 90%. The detection errors of mode transition time are mainly within 20 seconds.

Our future research will focus on detection of more complicated travel mode combinations, especially travel by subway where GPS signals are unavailable. Meanwhile, further tests will be conducted to explore the influence of traffic conditions. Another focus will be integration of other models of travel information, such as traffic volume, OD and mode share.

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