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Stop Detection in Smartphone-based Travel Surveys

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Abstract

Future Mobility Sensing (FMS) is a smartphone-based travel survey system that employs a web-based prompted-recall interaction to correct automatically inferred information. A key component of FMS is a stop detection algorithm that derives the users' activity locations and times based on the raw data collected by their phones. Output of this algorithm is presented in the Activity Diary for the users to validate, and its accuracy has a significant impact on user burden. In this paper, we present FMS' stop detection algorithm and its performance during testing by volunteers and public users during a large-scale field test.

1. Introduction

GPS-based travel surveys have gained popularity in the recent years as they can record accurate time and geographic information of users' travel. While such surveys have many advantages over traditional surveys, they suffer from several limitations: high costs, users might forget to bring the logger when they travel, and unavailability of GPS signal in certain areas [Bohte and Maat (2009), Stopher *et al.* (2007), Oliveira *et al.* (2011), Stopher and Wargelin (2010)]. With the advancement of mobile technology, smartphones are becoming an attractive alternative

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to GPS loggers for travel surveys. Besides GPS sensor, many smartphones nowadays are equipped with multiple other sensors, such as Wi-Fi, GSM, and accelerometer, that can provide additional information on the user's travel behaviour. The phone is almost always charged and carried by the user. And as the device belongs to the user, the cost of conducting such surveys is lower. These attributes make smartphones ideal "life-loggers".

We developed the Future Mobility Sensing (FMS) system, a smartphone and web prompted-recall based travel and activity survey system [Cottrill *et al.* (2013)], which uses an app (available for both Android and iPhone) to automatically log and upload sensor data from users' phones. The uploaded raw data is processed in the backend to construct the user's activity diary, i.e., we infer users' stops, modes of transportation, and activities. The activity diary is then presented in a user-friendly web-interface in a prompted-recall manner for user validation. FMS is a next-generation travel behaviour survey system that leverages pervasive smartphones, advanced sensing and communication technologies, and machine learning architecture. It delivers previously unobtainable range of data reflecting what people do, not what they say they do. We field tested FMS in Singapore in conjunction with Singapore Land Transport Authority's (LTA's) Household Interview Travel Survey (HITS) 2012. The test recruited more than 1500 users and produced a large set of rich and detailed travel/activity data that has been validated by the respondents [Carrion et al., 2014].

From our usability tests as well as the field test, it is observed that the accuracy in stop detection is key to users' validation quality [Ghorpade et al., 2014]. A user's comprehension and correct usage of the activity diary depend mainly on the list of stops presented, and most users are reluctant to change system-generated stops. In addition, the detected stops segment the GPS traces into "trips", and errors in them will impact the mode detection algorithm.

The problem of stop detection is a very challenging one. With perfect GPS information, the task of detecting stops would be straightforward. However, in practice, there are many cases, such as densely built up areas, indoors or underground areas etc., where there is only noisy low-accuracy GPS signal or even no GPS signal. In addition, in order to preserve battery power, we choose not to continuously acquire GPS signal even when it is available. In the past GPS-based travel surveys, stop detection were done by heuristic rule based algorithms [Bohte and Maat (2009)] or with the help of visual inspection [Stopher and Wargelin (2010)]. On the other hand, research work has been carried out on detecting the "places of interest" for individual users based on smartphone data [Montoliu and Gatica-Perez (2010), Wan and Lin (2013)], although they are not specifically designed for the purpose of travel surveys. Montoliu and Gatica-Perez (2010) proposed a two-level clustering algorithm for detecting the stops, and tested it with Nokia N95 phones by eight users. More recently, Wan and Lin (2013) focused on "life-space" characterization and proposed a processing procedure to estimate user's life-space. This procedure was tested using data collected by one subject in four months.

In FMS, we need to generate user stops in real time and cater for a wide range of phones available in the market. We started with a simple rule-based approach, then introduced various heuristic methods to overcome issues encountered in the practical settings. We take into consideration inputs from GPS as well as GSM, Wi-Fi, and accelerometer. In this paper, we present the stop detection algorithm used in FMS, discuss some of the practical considerations, and demonstrate its effectiveness in the field test.

The rest of this paper is organized as follows. Section 2 gives an overview of the FMS system. Details of the stop detection algorithm are presented in Section 3. The performance of the algorithm in our field test is discussed in Section 4, followed by the conclusions in Section 5.

2. FMS overview

FMS consists of three separate but inter-connected components – the smartphone app that collects the sensing data; the server that includes the database as well as the data processing and learning algorithms; and the web interface that users access to view and validate the processed data and respond to additional questions to supplement the validated data. The three components and the flows of data among them are shown in Fig. 1.
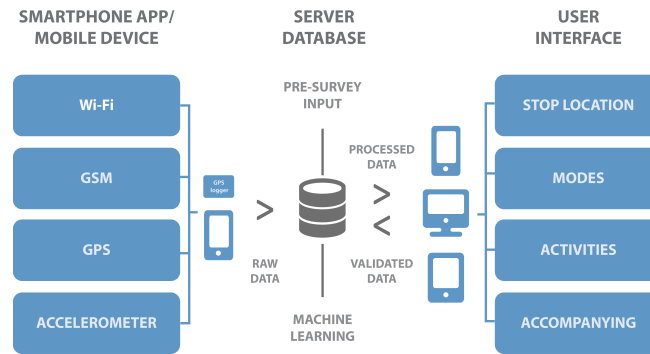
Fig. 1. FMS architecture

2.1. Smartphone app

The smartphone app, available for both Android and iOS platforms, collects data from a multitude of sensors available on the phones including GPS, GSM, accelerometer and Wi-Fi. One of the main objectives of the FMS app design is non-intrusiveness, i.e., the app runs in the background of the phone and silently collects the sensor data without user intervention. Participants would therefore not be influenced in anyway by the application during their normal daily activities. In addition, the application is designed to be light-weight and easy to use. A major concern for location-based applications is battery consumption, and we have made various efforts to minimize battery consumption [Nawaranthne et al., 2014]. The sensor data collected on the phone are transferred to the back-end server through either the cellular network or Wi-Fi, based on the user's preference.

2.2. Backend server

Raw data collected via the app are uploaded to a database where a series of algorithms are used to process the data and make inferences about stops, travel modes and non-travel activities. To minimize the user's interaction burden, the backend algorithms translate raw data into trips and activities. The first round of stop detection is made based on location and point-of-interest (POI) data. GSM, Wi-Fi and accelerometer information are used to merge stops that would otherwise be interpreted as distinct stops. More details on the stop detection algorithm are presented in Section 3. Travel modes are detected based on GPS and accelerometer features, as well as public transit network information. Non-travel activities (e.g. home, work, change mode/transfer) are also detected based on previous validations by the user, POI data and other contextual information.

2.3. Web-interface

The web interface provides a platform that enables users to review their processed data in the form of a daily timeline (Activity Diary) and "validate" their data for a limited number of days (Fig. 2). Validation involves filling in missing information and amending incorrectly inferred data about stop locations and times, modes of travel used for particular trips, and specific activities engaged in at locations deemed to be non-travel time segments or "stops". The validated data are uploaded and the backend algorithm learns to make better inferences as the user interacts with the interface. Also, the website is flexibly designed to enable supplementary data to be collected from users. Supplemental data pertaining to a specific trip (e.g. how many people the user travelled with or what, if any, fee was paid for parking) are collected within the activity diary validation stage. A helpdesk was available for users to interact with through chat or phone call and users are encouraged to have a session with a helpdesk representative for assistance during their first data validation.
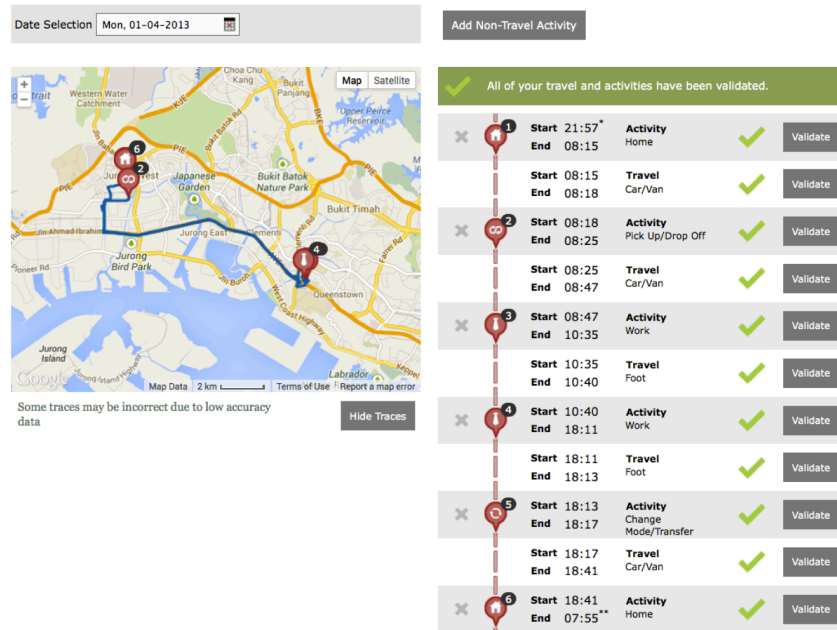
Fig. 2. FMS web-interface – Activity Diary

3. Stop detection algorithm

As mentioned in Section 1, the challenge of stop detection in smartphone based travel surveys lies in the absence of continuous high quality location data. GPS signal is not accurate or even missing in densely build up areas due to the urban canyon effect, and we observe this often in the downtown areas of Singapore. Also, when the user is indoors or underground, there is no GPS reading. In such cases, the phones will provide low accuracy location data based on GSM cell tower information and Wi-Fi information (if Wi-Fi is switched on on the phone). This leads to very noisy and jumpy location data when a user is at an indoor stop. In addition to these physical limitations, we also purposely introduced time gaps in location readings to reduce the burden of our app on the smartphone battery. As continuous sampling with GPS drains battery very fast, we introduced duty cycle for GPS sensor to preserve battery (phased-sampling) [Nawaranthne et al., 2014]. We also stop GPS collection when the phone is stationary. All these have impact on the availability and quality of the location data we collect, and pose a challenge to the stop detection algorithm.

In FMS, a stop is defined as a single instance of a user spending some time in a place performing an activity that is relevant to travel behaviour modelling. For example, we want to detect stops where users change transportation mode or transfer bus/trains, although they can be very short. On the other hand, we do not want to include stops at traffic lights, traffic jams, or bus/train stops where the user did not get on/off. As we do the stop detection almost in real-time, i.e., users are able to view and validated their activities and trips soon after they have performed them, we decided to start with a rule-based approach for stop detection. There are six main steps in this algorithm, which are explained in detail below.

Step 1: Filter raw data – The first step is to filter the noisy raw location data to remove the points that are likely to be very far from the real location of the user's. This happens frequently when GPS signal is not available and the location is deduced from GSM cell tower information, but we have also come across scenarios when the GPS reading is very far off (distance error of tens of kilometres). Most of these points can be identified by checking the accuracy level of the location points provided by the phones. In addition, we note that erroneous GPS readings typically has wrong altitude readings as well. Since Singapore is near sea level and relatively flat, we also remove the readings with exceptionally high altitudes.

Step 2: Generate candidate stops – We perform the first round stop detection by matching the GPS location sequence to spatial/temporal windows to generate candidate stops [Hariharan and Toyama (2004)]. A stop is generated if the location data indicates that the user has been within in an area of 50 meters in diameter for at least one minute. When GPS is unavailable, we use the less accurate location estimation based on GSM cell tower information. Candidate stops with duration as short as one minute were generated in order to capture small stops such as mode change and pick-up/drop-off, which are typically ignored in traditional travel surveys. Information on such stops can play an important role in transportation modelling and planning.
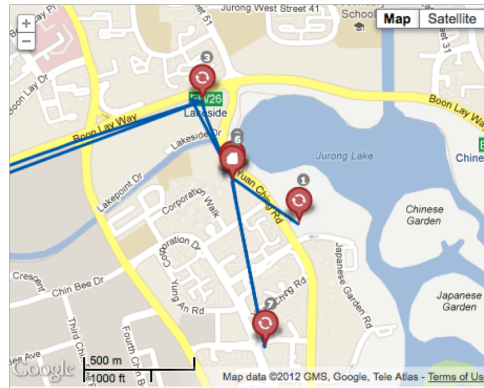

Fig. 3. An example of location jumps due to GSM cell tower handover.

Step 3: Check against frequent place signatures – With real life smartphone data, the quality of the candidate stops varies greatly, and one of the main problems is that a long stop by the user at a particular location can be broken into several candidate stops far away from each other due to the hand-over of the phone among several GSM base stations. Fig. 3 shows an example of such GSM location jumps. This problem is especially prominent at home and work locations, as users stay for extended periods of times indoors at these locations. To improve the quality of these stops, we used *GSM signatures* of frequently visited places for each user. User's frequently visited places, such as home or office, are recorded in the system after registration or when they are validated by the user in the activity diary. The backend algorithm then records all the GSM cell towers that have been "seen" by the phone while at these locations. The list of GSM cell towers associated with a frequent place is called its *GSM signature*. When a new candidate stop is generated, the algorithm checks if the phone is using any of the cell towers in the *GSM signatures*. If a match is found, the candidate stop is moved to the recorded home or office location. This method effectively reduces the "jump" in stops at these locations. Similar signatures can also be generated for Wi-Fi access points at frequently visited places.

Step 4: Merge stops – To further consolidate the candidate stops, we go through a round of stop *merging* for consecutive candidate stops for the following scenarios.

- When there is no GPS data between two consecutive candidate stops and there is overlap between the sets of Wi-Fi access points "seen" by the phone during these stop – This check again aims to deal with the cases when a user is indoors for a long time, and there are jumps in the location data. Since Wi-Fi access points typically have a range of less than 50 meters indoors, it is safe to assume that the user stayed in the same building throughout the two stops.
- When the time lapsed between two consecutive candidate stops is less than 3 minutes and the distance between them is less than 150 meters – These are the cases when users are making small stops while performing one activity, e.g., visiting a park.
- When the two candidate stops before and after a data gap are less than 50 meters away from each other – For example, if a user switches off his phone at night before going to bed and turns it back on in the morning, there would be two candidate stops, and it would be difficult for the user to understand and validate in the activity diary. Merging these two stops makes it consistent with user's real activity behaviour.

Step 5: Detect *still* mode – This applies to the cases when location data is missing between two stops but accelerometer data is available. If the phone is stationary, this state can be detected through accelerometer data with high confidence. We make use of this information to revise the start and end times of candidate stops or even merge them. To perform still/move detection, the gap between two stops is divided into one-minute segments and for each segment the standard deviation of the L-2 norm of the 3-axis accelerometer readings is compared against a threshold. The threshold was determined using a decision tree algorithm on ground truth data collected by volunteers, and it is set to 0.057 for Android phones and 0.013 for iPhones. Whenever standard deviation of a segment is less than this threshold, it is classified as a still segment. A majority voting for all the segments in an interval classifies the entire interval into either still or moving type. The still/move detection procedure is applied for every five-minute segment from the end of the first stop to the start of the second stop or till first move segment that is identified. If no move segment is identified, the two stops are merged. In case a move segment is identified then the current stop is extended till the beginning of the move segment and the still-move detection procedure is applied backwards to every 5 minute segment from the start time of the next stop to determine the end of move segment.

Step 6: Remove extra stops after mode detection – After the previous steps, mode detection is performed on every travel segment between the stops. There can be spurious stops (false positives) in the traces, where the user didn't stop on purpose to perform an activity, such as the ones at traffic light, in traffic jams, or at bus/train stations during the user's transit travel. To minimize this problem, we developed rules to remove short stops between two motorized modes. This has proved effective to remove a large number of spurious stops, and reduces user's validation burden. However, it may delete some of the short drop- off/pick-up stops, which the users will have to add in the activity diary during validation. One possible way to improve on this is to incorporate user history in stop detection. If a user has validated a drop-off/pick-up stop at a certain location before, the algorithm does not remove candidate stops at that location in the future.

After the above six steps, the final set of stops are determined. The detection of activity type for each stop based on user history and contextual information takes place after this. Figs. 4 and 5 show an example of input, intermediate stops and final output of the stop detection algorithm for a sample of 12 hours of user data. Using this relatively simple algorithm, we could kick start the project and collect real world data. The collected data are being used for developing more sophisticated machine learning algorithms to be used in the next version of FMS.

4. Experimental results and discussion

In this section, we present experimental results of the FMS stop detection algorithm in two tests, one with student volunteers, and one with public users.

4.1. Test with volunteers

One difficulty in testing the accuracy of the stop detection algorithm is finding out the ground truth of the users' stops. Through our own experience and also during various tests, we found that users are reluctant to change the stops generated by the system. Particularly, if the stop detection algorithm misses a stop, it is very rare that a user would add it back during validation. This may be due to memory issues or due to the extra effort required to add a new stop in the interface. Hence, we prefer to err on the side of false positives rather than false negatives. In order to better evaluate our algorithms, we engaged student volunteers to collect data and used various methods to find out the ground truth.

A custom version of FMS application was developed for collecting annotated data and given out to the volunteers. In this custom version, the FMS application is modified to allow the volunteers to annotate start and end times of their stops and trips, as well as their modes of transportation. Volunteers carried the phones with them for more than 4 months all the time. To ensure the quality of the data the volunteers were asked to carry a paper diary and register the start and end of each trip in it. The participants were issued travel cards (EZLink cards) to make payments for the train, bus and taxi trips. The transaction logs from the EZLink cards were later used to filter the

erroneously annotated trips. In addition, the volunteers were asked to validated their activity diary everyday, and all these sources of information are considered in generating the ground truth of the user's stops and trips.

Overall, after processing, we have 5807 hours of data from 15 phones collected by 8 volunteers. The stop detection accuracy is 91.24% and 13.3% of the detected stops are false positives.

4.2. Field test with HITS

FMS was also field tested in conjunction with Singapore Land Transport Authority's Household Interview Travel Survey (HITS) from October 2012 to September 2013. More than 7800 user-validated days of travel data were collected from more than 1500 users. Based on user validations, the true positive rate of our algorithm is 95.5% and 12.3% of the detected stops were false positives. As mentioned earlier, users tend to trust the system generated stops more than they should, and the actual stop detection accuracy is probably lower than these numbers, as shown above. In fact, designing a meaningful and consistent measure to truly reflect the stop detection accuracy and its
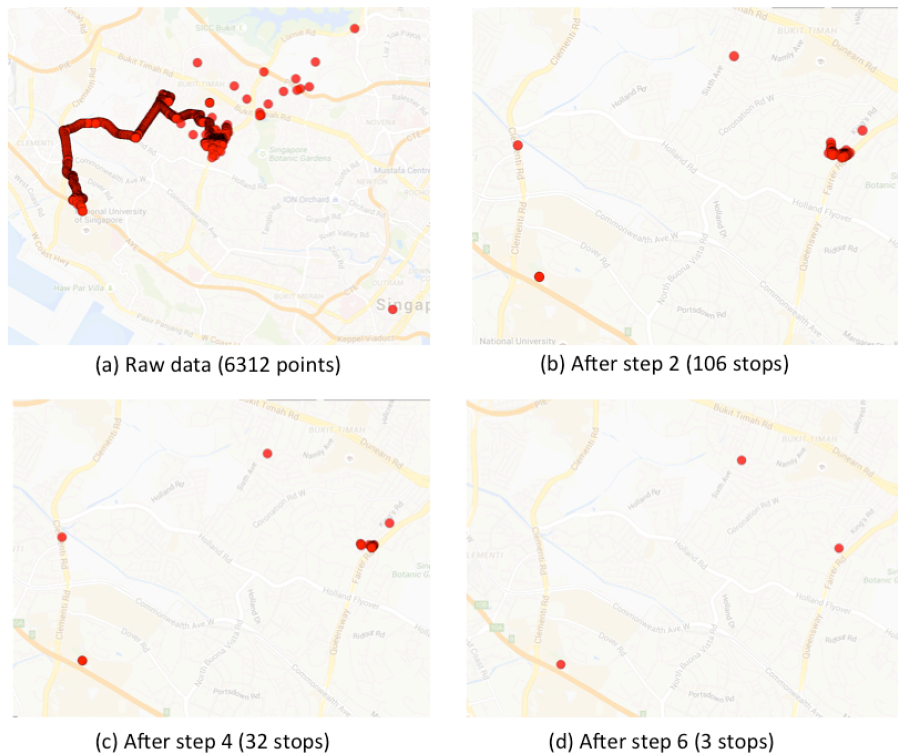

(a) Raw data (6312 points) (b) After step 2 (106 stops)

(c) After step 4 (32 stops) (d) After step 6 (3 stops)

Fig. 4. Raw data and stop detection output after Steps 2, 4, and 6 for one user's data (12 hours).
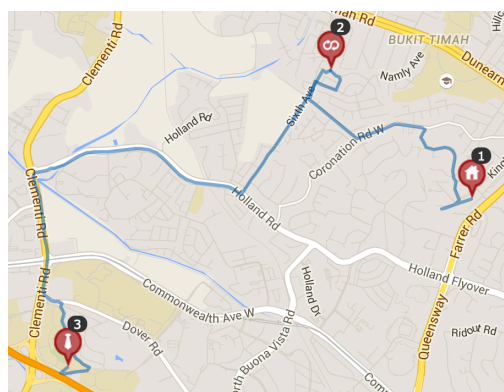

Fig. 5. Final output of the example in Fig. 4 in FMS Activity Diary.

effect on user burden is a difficult problem in itself, and is part of our on-going work.

4.3. Discussion

Although the stop detection algorithm had high detection accuracy, we observed several problems that can impede users' understanding of the activity diary and make the validation process cumbersome and error-prone.

One main problem is the "jumps" in long in-door stops. For example, if a user stays at work for 8 hours, FMS might detect it as two stops with an erroneous short trip in between. This is mainly due to the fact that GPS reading is not available when the user is indoors, and the location readings based on GSM cell towers will jump due to the hand overs. Also, we have observed cases where there appears to be GPS data outside the stop for some time during the stay, and the algorithm mistakenly conclude that the user took a short trip before returning to the same location. As mentioned in the previous section, this problem can be partially rectified by using the GSM and Wi-Fi signatures of the frequent places that the user has validated before. Still it remains as one of the main issues in stop detection.

The second issue relates to the detection of change mode/transfer stops. From a transportation modelling/planning point of view, it is important to collect information regarding the location and waiting times at stops where users transfer or change transportation modes (e.g., from walking to bus etc.). However, this kind of detailed information is typically missed in traditional travel surveys, and in FMS, we strive to recover them from users' raw data. We found that, in general, it is easier to detect users' boarding stops, as they would usually wait for a short period of time before boarding a bus/train. The alighting stops, on the other hand, are very difficult to capture, as passengers would move away immediately after leaving the bus/train, and we cannot infer the "stop" based on the location data. One possible solution for this problem is to examine the accelerometer data closely. Since there is typically a distinct feature for walk segments in the accelerometer data, we can use "change point detection" to locate the alighting stops.

Finally, when we compared the data collected in FMS with data collected in HITS, it is observed that FMS fails to detect some of the pick-up/drop-off stops. This is expected as we delete short stops if the transportation mode before and after the stop are the same motorized mode, as we explained in Section 3. It is done to reduce the spurious stops due to traffic light and/or transit stops en route the user's trip. Therefore, there is a trade-off between detection accuracy of the "valid" short stops by the users and the false positives.

The above problems can be improved by incorporating Point of Interest (POI) information, such as road junctions, bus and train stops etc. In addition, one main advantage of the FMS system is that it acquires individual history data through the validation process. Our system can learn from the personal history and make better inferences over time. For example, if a user has previously validated a pick-up stop at a certain location, the algorithm should not delete a stop at this location even if it is very short. The current rule-based stop detection algorithm is not making full use of this valuable information, and as part of our on-going work, we are developing an integrated stop mode detection algorithm using machine learning techniques with features based on POI information and user history [Ghorpade et al., (2015)]. This novel algorithm is more robust to noise in the raw data, and has higher stop/mode detection accuracy. In addition, we are exploring the usage of accelerometer change point detection to find the small stops which would be otherwise missed by looking at the location data solely. The large amount of data collected in the field test with HITS is being used for training the models for this improved algorithm.

5. Conclusions

To the best of our knowledge, FMS is the first smartphone based travel survey system that has gone through large-scale field test with public users. The huge amount of raw and validated data collected as well as user feedback gathered are valuable inputs that can help us further improve the system. As mentioned above, the stop detection accuracy is vital to ensure the quality of user validated data. A few erroneous stops would increase the user-burden tremendously, and in general, false positives are preferred over false negatives. In this paper, we present the stop detection algorithm we employed in the FMS field test, which achieved an accuracy of 95.5%. To further improve the stop detection algorithm, we are working on an integrated stop mode detection algorithm using matching

learning techniques, which incorporates other inputs such as context data (POI, events, traffic condition etc.) and user history.

Acknowledgements

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