Fine-Grained Transportation Mode Recognition Using Mobile Phones and Foot Force Sensors

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Abstract. Transportation or travel mode recognition plays an important role in enabling us to derive transportation profiles, e.g., to assess how eco-friendly our travel is, and to adapt travel information services such as maps to the travel mode. However, current methods have two key limitations: low transportation mode recognition accuracy and coarse-grained transportation mode recognition capability. In this paper, we propose a new method which leverages a set of wearable foot force sensors in combination with the use of a mobile phone's GPS (FF+GPS) to address these limitations. The transportation modes recognised include walking, cycling, bus passenger, car passenger, and car driver. The novelty of our approach is that it provides a more fine-grained transportation mode recognition capability in terms of reliably differentiating bus passenger, car passenger and car driver for the first time. Result shows that compared to a typical accelerometer-based method with an average accuracy of 70%, the FF+GPS based method achieves a substantial improvement with an average accuracy of 95% when evaluated using ten individuals.

Keywords: Transportation Mode Recognition, Foot force sensor, GPS, Accelerometer.

1 Introduction

According to a survey of world urbanization, 80% of the EU population lives in cities and this number is still rising [1]. Transportation mode is an important type of urban user context that facilitates several transport context adaptation applications such as maps and navigation that adapt to travel modes and user mobility profiling [2]. Transportation mode recognition in people's daily life can contribute to implicit human computer interaction in terms of reducing the user cognitive load when interacting with services during travel, and can help to enable the hidden computer part of the vision of ubiquitous computing. Automatic transportation mode recognition could also facilitate a range of applications as follows:

- *Physical Activity Monitoring*: The transportation modes of individuals are logged and mapped to locations to enable individuals to plan travel based on physical activity goals and health monitoring [3]. In addition to health-related applications, activity-profiling systems can play a fundamental role in ubiquitous computing

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scenarios [4]. In such applications, information from a variety of sensors is used to determine a mobility context for possible information service adaptation. For example, a mobile phone can detect when a person is driving or involved in vigorous physical activity, and automatically divert a call for safety consideration [5].

- *Individual Environmental Impact Monitoring*: Inferences of the transportation mode and location of an individual are used to provide a personalized environmental scorecard for tracking the hazard exposure and environmental impact of one's activities. Examples include Personal Environment Impact Report (PEIR) and UbiGreen [6, 7] along with commercial offerings such as Ecorio and Carbon Diem [8, 9].
- *User Mobility Profiling*: Transportation annotated mobility profiles (time, location, transportation mode traces) are created for profile based recruitment for gathering distributed user context and for group context awareness [10].

The confluence of advanced wearable sensor technology and widely available portable computing devices offers the opportunity for automatic recognition of a person's activities and transportation modes in daily living [11]. A mobile phone with integrated GPS can provide user spatial contexts (e.g. speed) in an outdoor environment [12, 13]. Wearable foot force (FF) sensors can capture a person's foot force variations from different postures (e.g. between standing and sitting) and activities (e.g. between cycling and driving) in real time [14]. Different transportation modes differ in terms of both the average movement speed (e.g. between walking and taking a bus) and foot activities (e.g. between cycling and driving). The combination of foot force sensors and mobile phone GPS could potentially be useful in enabling more fine-grained transportation mode recognition such as subdividing motorized transportation modes into bus-passenger, car-passenger and car-driver.

The primary aim of this pilot study is to assess how well a combination of mobile phone GPS and wearable foot force sensors can be used to recognise different transportation modes, compared with a more typical accelerometer-based method, i.e., as used in [15].

The main contributions of this paper are: i) we conducted a thorough survey of transportation mode recognition, which exposes two main limitations of current work; ii) we proposed a novel method combining foot force sensors and mobile phone GPS for improved transportation mode recognition; iii) we illustrated substantial improvements of our method through comparing it with an accelerometer-based method.

2 Related Work

Much related work exists to recognise transportation mode by sensing modalities that are viable or available to be used on mobile phones. The related work can be grouped based upon the type of sensors used, mainly the accelerometer and GPS.

-Accelerometer

In [16], Mizzel and his colleagues showed that the accelerometer signal can produce a good estimate of its vertical and horizontal components. The vector in turn holds an estimation of the magnitude of the dynamic acceleration caused by the phone carrying user.

Different human-powered transportation modes, such as walking and cycling, can generate different acceleration components. Dynamic acceleration patterns can be sensed by an accelerometer. A 3D-accelerometer can be used to classify different human daily activities. In [17], Juha utilised a wireless motion band attached to the user ankle to sense the acceleration generated by the ankle. This work has successfully differentiated different human-powered transportation modes such as walking, running and cycling through using a binary decision tree classification method. A personalised classification method also increases the accuracy of detection. In [18], Ravi also found that activities can be recognised with a fairly high accuracy through wearing a single 3D-accelerometer near the pelvic region. The results also showed that the pelvic region placement can recognise everyday activities with an overall accuracy rate of 84%. Similar work has also been done by Brezmes [19].

Accelerometer-based methods can achieve an increased accuracy when people carry their smart phones in a fixed place. However, many people tend to carry their mobile phones more freely, such as near the waist, in a front pocket, in a knee-high pocket, by hand, and so on. These on-body placement variations greatly change the nature of the acceleration signal (which is also impacted by different body motions such as bending, swaying and twitching) during user movement [2]. In [15], Wang et al. have also considered this issue and attempted to differentiate transportation modes without any placement restrictions for accelerometers. They used a smart phone embedded accelerometer to recognise six kinds of transportation modes, but the accuracy is relatively low (at 62% on average).

-GPS

GPS, as a global-wide positioning system, has already been integrated into mobile phones. The potential usability of GPS in profiling user daily outdoor activities has been widely presented, such as in [20] and [21].

In [20], Lin Liao et al. have developed a probabilistic temporal model that can extract high-level human activities from a sequence of GPS readings. Two main types of transportation mode (human powered and motorised) are inferred, based on the Conditional Random Fields model. Though they achieved over an 80% in accuracy, the range of the transportation modes is coarse, as it can only detect two main types of transportation modes: human powered and motorised.

In contrast to [20], Zheng et al. used a supervised learning based approach to infer more fine-grained transportation modes using the raw GPS data [21]. They proposed a change point (between different transportation modes) based upon a segmentation method. The results show that change point based segmentation achieved a better accuracy compared with uniform-duration based segmentation and uniform-length based segmentation. However, GPS information alone cannot detect change points precisely, since on many occasions, a person could take a taxi immediately after he/she gets off a bus and this very short change segment between two transportation modes is easy to be neglected using GPS.

The existing GPS work exposes an inherent limitation. GPS information alone is too coarse to enable fine-grained transport recognition with a good accuracy. For example, GPS performs poorly in the recognition of different transportation modes with similar speeds, e.g., with fast walking, cycling, and slow motorized traveling.

Table 1. Related work for transportation mode recognition

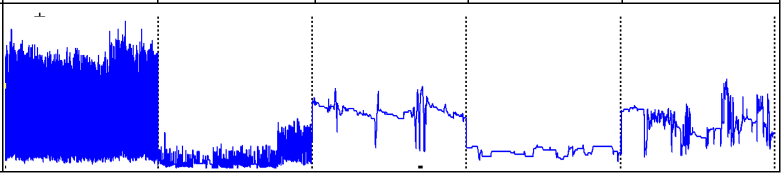
Ref No.	Sensor Type	Classifiers	Feature Used	Transportation Mode	Mobile Placement	Accuracy
[19]	Accelerometer	K-Nearest Neighbours	Raw three-axis vector readings from the Accelerometer	Stationary, Walk, Run	Jacket, chest, and trousers, Pockets	60%
[15]	Accelerometer	Decision tree (J48), K-Nearest Neighbour, SVM	Mean, standard deviation, mean-crossing rate, third-quartile, sum and standard deviation of frequency components between 0~4 HZ, ratio of frequency components (0~4 Hz) to all components, spectrum peak position.	Stationary, Walk, Bike, Bus, Car	Free	62%
[22]	Accelerometer, GPS, and Audio Sensor	Decision Tree (J48)	Mean, standard deviation, and number of peaks of the accelerometer readings ; mean and standard deviation of the DFT power of audio sensor readings	Stationary, Walk, Run	Pocket	78%
[20]	GPS	Hierarchical Conditional Random Fields	Mean GPS speed, Temporal information (time of the day),	Stationary, Walk, Motorised Modes	In-Hand	83%
[21]	GPS	Bayesian Net, Decision Tree, Conditional Random Field, SVM	Mean, maximum, and standard deviation of the velocity, Length of trips	Stationary, Walk, Bike, Motorised Modes	In-Hand	76%

Table 1 shows that the average accuracy for current transportation mode recognition methods is comparatively low, 70%, i.e., only a little over 2/3 of trips are recognised correctly. In addition, most current methods have restrictions with respect to how users should carry their mobile devices, except [15]. Moreover, much of the surveyed work does not support differentiating sub-motorised transportation modes, i.e., into car passenger, bus passenger, and driver. Only [15] has more sub-classes of motorised transportation modes (bus passenger, car passenger) and is closest to one of our aims in this paper - more fine-grained transportation mode recognition. Hence, we decide to reproduce the accelerometer-based method used in [15] as a baseline to evaluate our new method.

3 Method Design and System Overview

In order to solve the limitations of both low accuracy and coarse-grained recognition capability, we propose a novel method that leverages both mobile phone GPS and a set of foot force sensors. The rationale for choosing these two types of sensors is because of the obvious variations in GPS speed and foot force pattern in different transportation modes. Based on our observations (as table 2 shows), given different transportation modes, when the GPS mean speed is similar, the foot force patterns are different, and vice versa.

Table 2. Variations in GPS speed (mean ± standard deviation) and foot force patterns for different transportation modes

	Walking	Cycling	Bus Passenger	Car Passenger	Car Driver
GPS Speed (m/s)	1.3±0.2	2.5±1.2	5.2±2.0	8.5±5.2	7.8±4.9
Left Foot Force (Percentage of user weight)	67%±51%	18%±11%	53%±5%	21%±3%	35%±12%
Left Foot Force Patterns in Time Domain (5 min duration for each mode)					

Based on table 2, we hypothesise that our new method should be able to achieve more fine-grained transportation mode recognition with a higher accuracy compared with a typical accelerometer-based method. In addition, to variations in mean and variance, our new method also relies on basic time-domain features such as mean and standard deviation for transportation mode recognition. Time-domain features tend to consume less computational resources compared with frequency-domain features [23], e.g. those used in [15].

To the best of our knowledge, the potential benefits of using mobile phone GPS in combination with foot force sensors to improve transportation recognition has not been proposed or examined to date. Therefore, we propose the following system architecture to examine whether or not foot force sensors combined with mobile phone GPS can

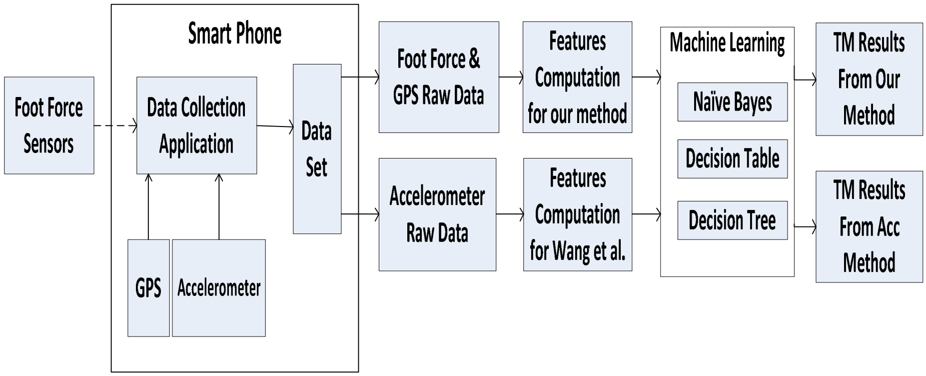


Fig. 1. Architecture of the FF+GPS transportation mode (TM) recognition system

discriminate between the five different transportation modes (walking, cycling, bus-passenger, car-passenger, and car-driver) that are most often used for commute purpose. The following system may answer our primary research question: does the addition of foot force monitoring to GPS improve the recognition of transportation mode beyond which is achieved by using accelerometer data alone.

In order to show the usefulness of our new method, we designed our new transportation modes recognition system using both foot force sensors and GPS as shown in figure 1. In order to evaluate our new FF+GPS based method and to compare it with the accelerometer-based method used in [15], our new transportation mode recognition system also collects the accelerometer data simultaneously with foot force sensor data and GPS data. This simultaneous sensor data collection scheme can minimize the effect of variability from different instances of sample which may affect the comparison results. No noise filtering is carried out on the raw sensor data. Any sensor errors arising via typical daily living environment, e.g., occasional GPS data interruption, are presented to the feature computation phase.

In the feature computation phase, the data window segmentation method used in [15] is applied to both the accelerometer-based and FF+GPS based methods. Eleven different features are extracted from our accelerometer data as used in [15]. For the FF+GPS based method, the following time-domain features are extracted: mean, max and standard deviation of GPS speed; mean, max and standard deviation of foot force readings from both feet.

In the transportation mode recognition phase, three commonly used machine learning schemes: Naïve Bayes (NB), Decision Tree (DT) J48, and Decision Table provided by WEKA toolkit [24] are used to compare the performance of these two methods. A 10-fold cross validation mechanism is used for evaluation.

4 Experiments and Results Evaluation

4.1 Participants

All study procedures were approved by the Research Ethics Committee at Queen Mary, University of London, and all participants signed a written informed consent form.

Data collection took place over a 6-month period from Dec, 2011 to June, 2012. Five transportation modes (walking, cycling, bus passenger, car passenger, and car driver) were performed by 10 volunteers (6 male; 4 female) with an age range from 24 to 56.

During data collection, volunteers had the liberty of carrying the mobile phone device in any orientation and position that was desired, such as near the waist, in a knee-high pocket, in a back-pack, in the top jacket, by hand, and so on. The collected data totals 2023 samples, which is equivalent to more than 7.5 hours of samples.

4.2 Equipment

During the data collection procedures, each participant carried a Samsung Galaxy II smart phone, and wore a pair of special insoles. The special insoles were instrumented by a set of Flexiforce sensors[1]. Four Flexiforce sensors have been mounted on each insole in order to cover the force reaction area of both forefoot and heel for each foot as shown in figure 2. The rationale for choosing heel and forefoot as the focused area of foot force monitoring is stated in [25]. All Flexiforce sensors are interfaced to the smart phone wirelessly but via a wired USB hub that connected to a portable laptop for power, as Flexiforce sensors need to be powered and cannot be powered by a smart-phone. Flexiforce sensor readings are set to 35 Hz, and mobile phone embedded GPS is set to 1 Hz for the Android 2.3.3 OS platform. The smart phone embedded accelerometer[2] frequency is set to 35 Hz according to settings used in [15].

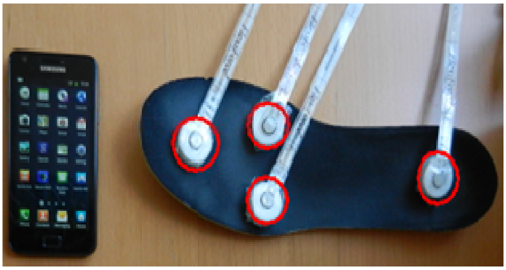


Fig. 2. Experimental equipment

4.3 Results and Evaluation

For each kind of transportation mode, we define true positive, true negative, false positive, and false negative as follows (The walking transportation mode has been chosen as an example to illustrate the point):

- **A true positive** occurs when a sample from a particular kind of transportation mode is classified as the same kind of transportation mode. For example, a sample from walking classified as walking is a true positive.

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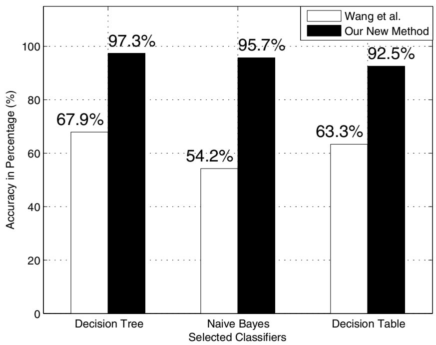
1 The sensitive range of each Flexiforce sensor is from 0kg to 45 kg with a linearity error less than±3%. The response time is less than 5 microseconds.

2 This is a 3-D accelerometer, whose sensitivity is programmed from -2g to +2g (g=9.8).

- **A true negative** occurs when a sample from one other kind of transportation mode is classified as not in this particular kind of transportation mode. For example, a sample from cycling classified as not walking is a true negative for walking.
- **A false positive** occurs when a sample from other kinds of transportation mode is classified as this particular kind of transportation mode. For example, a sample from cycling classified as walking is a false positive for walking.
- **A false negative** occurs when a sample from a particular kind of transportation mode is classified as other kind of transportation mode. For example, a sample from walking classified as cycling is a false negative for walking.

We present the accuracy for each classifier we chose in figure 3 and figure 4. The accuracy is the sum of true positives and true negatives over the total number of classifications. The accuracy tells us overall how good a method is at classifying different kinds of transportation mode.



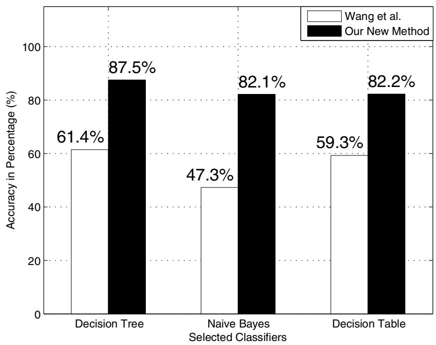


Fig. 3. Comparison of Recognition Results for All Five Transportation Modes

Fig. 4. Comparison of Recognition Results for Three Motorized Modes

The experimental results for all five transportation modes recognition using the different classifiers are listed in figure 3. It is noted that the FF+GPS based method obtains a much higher recognition accuracy than the accelerometer-based method as used in [15]. On average, FF+GPS based method achieves 95% which is 33% higher than that of [15]. In addition, the use of a decision tree (J48) classifier obtains the highest recognition accuracy for both methods.

The experimental results for more fine-grained recognition of three motorized transportation modes (bus passenger, car passenger, and car driver) using different classifiers are listed in figure 4. The FF+GPS based method obtains a substantially higher accuracy than the accelerometer-based method used in [15]. On average, our method achieves an accuracy of 84% which is 28% higher than [15]. This result illustrates that the FF+GPS based method compared to an accelerometer-based method can provide more fine-grained transportation mode recognition in terms of reliably differentiating bus passenger, car passenger, and car drivers.

Since the decision tree (J48) classifier outperforms other classifiers, the precision and recall for each transportation mode from the decision tree classifier are presented in figure 5 and figure 6. Precision is the number of true positives over the total number of true positives and false positives and tells us how well a method is able to discriminate between true and false positives. Recall is the number of true positives over the sum of true positives and false negatives and tells us how well a method is able to recognise one particular transportation mode given all samples from this kind of transportation mode.

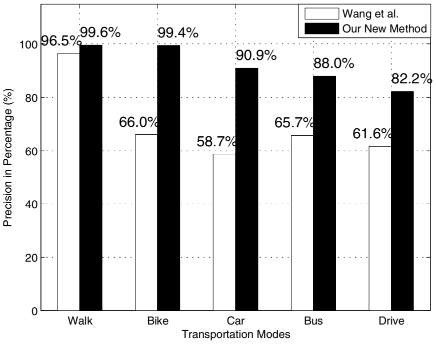


Fig. 5. Precision Results from the Decision Tree Classifier

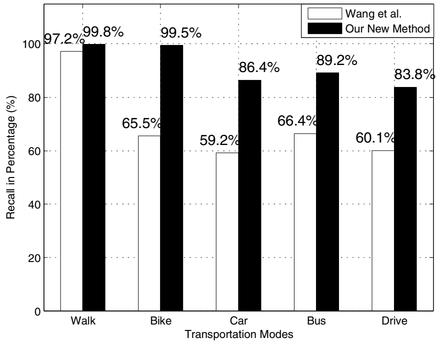


Fig. 6. Recall Results from Decision Tree Classifier

With respect to the precision and recall results, the FF+GPS based method outperforms the typical accelerometer-based method in all aspects, especially in recognising cycling and in sub-differentiating motorised transportation modes into car-passenger, bus-passenger, and car-driver.

It is also noted that both methods perform equally well in detecting walking. This is because there are three stances in a normal human walking motion: which are heel strike, mid-stance, and toe-off [26]. Accelerometer-based method can detect the acceleration generated from these three stances, which differs from other transportation modes in terms of variance. The FF+GPS based method can also detect foot force patterns variations generated when walking, the patterns of which are quite unique in terms of both mean and variance as table 2 shows.

From figure 5 and figure 6, it is also found that our new FF+GPS based method can detect cycling to a very high accuracy (99%) compared with accelerometer-based method (65%). This is because the cycling apparently differs from other transportation modes in terms of both mean GPS speed and foot force patterns. The average speed for cycling is about 2.5m/s which is quite different from both walking (about 1.3 m/s) and motorised transportation modes (about 6.8m/s), see table 2. Besides, as people need to power the bike by pedalling regularly when cycling, the foot force patterns generated are also distinct from other transportation modes (as shown in table 2). For the case of accelerometer, the acceleration during cycling is mainly affected by the road conditions and is sometimes quite similar to those of motorised transportation instances. This introduces errors from false negatives for a typical accelerometer-based method.

For the case of sub-classifying motorised transportation modes using accelerometer, it is noted that the instances from one particular motorised mode are easily misclassified as those of other motorised mode, or even as cycling, using a typical accelerometer-based method. These motorised modes were mistaken as cycling since coasting on a bike is similar with low speed vehicles in terms of acceleration. Moreover, since the acceleration mainly depends on the vehicle and road conditions, the acceleration patterns of the samples from car-driver and car-passenger are almost identical, which can hardly be differentiated by any typical classifiers.

Our new FF+GPS based method in this case achieved an overall 84% accuracy on average. This is mainly because foot force patterns in different sub motorised modes tend to be very different. As in the driving case, people need to step on both the accelerator pedal and the brake pedal regularly in order to control the car. In the bus-passenger case, people may stand and move inside the bus, which would never happen when being a car passenger. Moreover, the GPS speed patterns from bus is also different from samples of private car, since buses need to stop more regularly at bus stops and move slower than private cars for safety consideration.

It is also noted that some instances of driving from the FF+GPS based method have been mistaken as being bus-passenger. This is because in some cases, when passengers move around in a bus, foot force patterns tend to be similar to the patterns of stepping on pedals when driving. Some instances from driving have also been mistaken as being car-passenger. These errors occurred during slow speeds or after stopping for a period of time. In these cases, foot force patterns tend to be similar as drivers were stationary and were not operating the vehicle foot control pedals.

5 Discussion and Future Work

Use of the FF+GPS based method achieves a substantial accuracy improvement and a more fine-grained transportation recognition capability, compared with a typical accelerometer-based method. In a practical system, one must also consider computational and energy costs. A mobile devices cannot dedicate its full computing resources to such (location-based) auxiliary applications given its primary roles are more for user interaction and communication. The FF+GPS transportation recognition method is only based upon an analysis of time-domain features. It can achieve an improved transportation mode recognition capability at a relatively low computation cost (compared to frequency-domain based methods). More specific testing involving computational load analysis will be included in a future study.

With regard to energy efficiency, the FF+GPS based method also showed that foot force sensors also perform very well in recognising human powered transportation modes (such as walking and cycling) without GPS. This means that foot force sensors can be used to reduce the usage of GPS (the most energy consuming sensor in most location determination systems) and its consequent energy consumption. We leave exploring the delicate balance between extendability, computability, and energy efficiency as future work.

6 Conclusion

In this work, the potential benefits of using mobile phone GPS in combination with a set foot force sensors to improve transportation mode recognition have been examined for the first time. Five fine-grained transportation modes, including walking, cycling, bus passenger, car passenger, and car driver, have been performed by ten different users. The results have been investigated in detail, evaluated (by comparing with a more typical accelerometer-based method in [15]), and fully discussed.

Given the sample size of this pilot, and based on the classification algorithms employed, our new FF+GPS based method has improved the transportation mode recognition accuracy from 62% to 95% on average. The key contribution of our work is that the FF+GPS based method provides more fine-grained transportation mode recognition capability in terms of differentiating between bus passenger, car passenger and car driver with an accuracy of 84% on average.

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