Improved Use of Foot Force Sensors and Mobile Phone GPS for Mobility Activity Recognition

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***Abstract*— Recent advances in the development of multimodal wearable sensors enable us to gather richer contexts of mobile user activities. The combination of foot force sensor (FF) and GPS is able to afford fine-grained mobility activity recognition. We derive and identify 12 (out of 31) maximally informative FF features, and the minimal most effective insole positions (two per foot) for sensing, to improve the use of FF + GPS methods for mobility activity recognition. We tested the improved FF + GPS method using over 7000 samples collected from ten volunteers in a natural, unconstrained, environment. The results show that the improved FF + GPS can achieve an average accuracy of over 90% when detecting five different mobility activities, including walking, cycling, bus-passenger, car-passenger, and car-driver.**

***Index Terms*— Foot force sensors, activity recognition, mobile phone sensing.**

I. Introduction

USER mobility or activity can be used as a user context to better tailor a raft of rich applications to users' needs, in different mobility-related situations [1]. Many different types of sensors have been used to gather rich datasets of user motion during different activities [2]–[4]. Among these, foot force monitoring seems to be very useful in detecting different user activities with a fairly high accuracy [5] and can outperform accelerometer-based monitoring [1].

The earliest foot force monitoring systems used foot-force plates which are fixed into a specific indoor environment for gait analysis [4], [6]. However, for the purpose of pervasive monitoring in people daily life, these fixed environment systems have been surpassed by wearable foot force sensors in recent years [5], [7]. Different FF sensor configurations can be used, either single sensor, multiple homogeneous sensors or multiple hybrid sensors. The main drawback of using multiple homogeneous sensors, e.g., FF, is that these may not capture enough information to detect some fine-grained mobility activities such as riding a bus [1]. Our prior work has shown that a hybrid FF+GPS can outperform typical accelerometer-based methods in detecting fine-grained mobility activities with a both higher accuracy and a lower computational cost, but it did not investigate the effect of the FF sensor configuration on transport mode classification accuracy [1].

For the same sensor configuration, there are different detailed sensor settings in how to use foot force sensors, e.g. different monitoring plan (both-feet-monitoring [5], [7] or single-foot-monitoring [8], [9]), different numbers of sensors for each foot, ranging from one [10] to sixteen [9], and different sensor placements on the foot (heel, middle, forefoot, or toe). Methods that use fewer sensors have potential benefits, such as system simplicity and a lower cost. However, methods that use more sensors are expected to be superior in terms of a better accuracy. How to find the trade-off between the number of FF sensors, their configuration and maintaining accuracy at classifying common transport modes is the main research challenge investigated in this paper. Additional challenges concern how to perform finely-grained mobility activity recognition, in the wild, using hybrid FF sensors and whether or not we need to monitor the FF in both feet versus just one, e.g., to differentiate between pedalling a bike versus the use of pedals to control a car whilst driving it. To the best of our knowledge, no other work has examined these research challenges for FF.

The remainder of the paper is organised as follows: Section 2 provides a review of the current FF-based activity recognition systems. Section 3 describes the method and presents an overview of the system. Section 4 describes experiments and evaluates the experimental results. Section 5 discusses the further work. Section 6 draws conclusions.

II. Related Work

The study of human activity using foot force monitoring has a long history in computer science terms, dating back to about 30 years ago when Dion and his colleagues first made use of a thin force transducer to monitor walking [6]. Similar foot force plate based research of gait analysis was also performed later by Hoyt and his colleagues in 1994 [4]. Though these early laboratory-based approaches are accurate in terms of gait analysis, they are not applicable to monitor mobility activities in daily living environment e.g., due the high cost and lack of feasibility of deploying a foot force plate for ubiquitous use. The use of suitable wearable force sensors can achieve the same level of accuracy as using a foot plate [5], [7].

Veltink et al. [5] used two six-degrees-of-freedom movement sensors under each shoe to measure ambulatory ground reaction forces and centres of pressure. This work also demonstrated that the heel and forefoot are the two key positions

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for ambulatory foot force monitoring. However, this work only measured the foot ground reaction force during walking-other mobility activities were not considered. In addition, the FF sensors (15.7mm in thickness) that instrument the experimental shoe (on the inside sole) are too cumbersome to be worn daily. Another limitation of this work is that only one test subject was monitored.

Zhang et al [9] assessed activities such as walking, jogging, and running by using a small, non-intrusive insole pressure measurement device. They studied 40 subjects and achieved a high accuracy for activity recognition of 95%. They showed that different subjects tend to generate similar foot force patterns when performing the same activity and that in addition to heel and forefoot, the toe is also a potential key position for activity recognition. However, one main drawback is that only different sub-types of walking and running are considered. Other important mobility activities, such as cycling, are not considered. Another limitation is that for one test subject, 32 foot force sensors (16 per foot) are used to instrument both insoles. This is inefficient and costly for pervasive use.

Tracie et al [7] designed and implemented a more efficient Wireless In-shoe Force System (WIFS) to acquire, process, and transmit foot force information. This pilot study showed that 4 force sensors (per foot) are able to obtain accurate foot monitoring information when compared with using force plate monitoring as the ground truth, providing the FF sensors are arranged properly under the supporting bones of each foot. In addition, this work also promoted the feasibility of using a wireless foot force monitoring system, which is more suitable for ubiquitous use. However, the key limitation of this work is that only one foot, the left one, was considered for FF monitoring. The justification for sensing one rather than both feet is not clear. Further, this work only considered basic mobility activities such as walking and standing, other human-powered and motorised mobility activities were not studied.

The above work focussed on using only FF sensors. Other work has investigated using FF combined with other sensors to improve user activity recognition [1], [8]. Tao et al. [8] combined FF with accelerometer and gyroscope sensors for fine grained gait analysis. Though this combination achieved improved results in gait detection, this cannot detect motorised activities [1] solved this problem by combining FF with mobile phone GPS. By comparing this with a typical accelerometer-based method, it was shown that GPS speed is a useful combination with FF monitoring to detect fine-grained mobility activities. This work achieved a 95% overall accuracy in detecting walking, cycling, car (or taxi)-passenger, bus-passenger, and car (or taxi)-driver. The motivation for selecting these 5 modes is that they are 5 of the most common urban transportation modes and they require different types of navigation views, hence we need to be able to differentiate these.

Table I illustrates that current FF based methods achieved a level of about 90% accuracy on average in detecting various foot-related mobility activities, e.g., walking. However, some mobility activities cannot be recognised by using force sensor alone, e.g., driving a car [1]. We also found that most of the work monitored the FF in both feet. The most commonly monitored insole positions are heal, forefoot, and toe. The number of sensors for one foot ranged from 4 to 16. Hence, we decide to extend the work [1] to further improve the FF+GPS method for use in mobility activity recognition through investigating the effect of different FF sensor configurations.

TABLE I
CLASSIFICAION OF RELATED WORK USED FOR FF-BASED ACTIVITY RECOGNITION

Ref	Sensor Configuration	Insole positions	One or both feet	No. of sensors / foot	Mobility Activity	Accuracy
[7]	FF	Heel, Fore, Toe	Left	4	Stand, Walk	90%
[9]	FF	Heel, Middle, Fore, Toe	Both	16	Walk, Run	97%
[5]	FF	Heel, Fore	Both	2	Stand, Walk	93%
[8]	FF + ACC + Gyroscopes	Heel, Middle, Fore, Toe	Right	5	Walk (gait analysis)	97%
[1]	FF + GPS	Heel, Fore, Toe	Both	4	Walk, Cycle, Car, Bus, Drive	95%

III. METHOD DESIGN AND SYSTEM OVERVIEW

In our previous work [1], it was found that foot force patterns for some different mobility activities, e.g., between different motorised activities, are quite similar [1]. This is why GPS speed (in m/s) is used to complement the use of FF to detect motorised activities. This achieved a higher accuracy.

It is noted that the FF patterns are quite unique for classifying walking, cycling, bus passenger, car passenger and car driver [1]. This is because in human powered activities, the feet generate unique force patterns. Hence, we hypothesize that if when using FF only (i.e., without GPS) we should be able to recognize human powered mobility activities (walking and cycling) at a fairly high accuracy as well. However, sometimes single FF patterns, e.g., from cycling, are similar to those of another mobility activity, e.g., car-driver pedal use for driving control, or when a bus-passenger rocks his or her foot. This can introduce FF misclassification errors. This is the motivation to monitor the FF in both feet to see if the patterns were different.

A. Correlation Coefficient Between Left and Right Foot

In order to solve the challenges mentioned above to detect human-powered activities using FF only, we use the correlation coefficient between left foot force and right foot force to capture the characteristic of regular force shifting between left and right feet during different mobility activities (walking and cycling). It is also observed that such periodic force shifting between the left and right feet does not frequently exist in motorized activities.

The correlation coefficient between left and right feet is calculated as follows. For each window of FF values, ‘L_x’

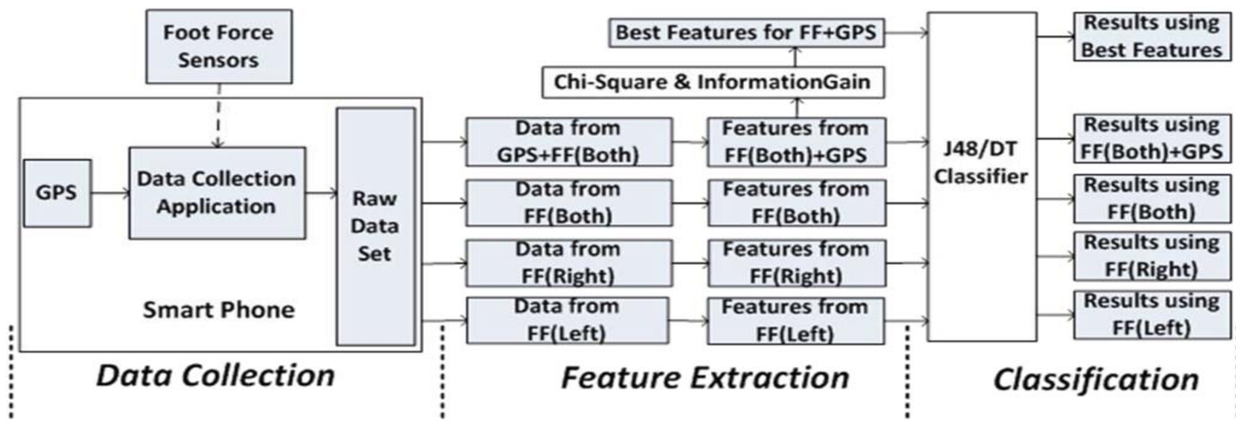

Fig. 1. Architecture of the FF+GPS system with different sensor configurations for mobility activity recognition.

is used to denote the force values from the left foot sensors and 'R_x' is used to denote the force values from the right foot sensors. 'X' represents the sequential number of the sampled value. For a data window with N samples (N is the window size), we get the following set of foot force value pairs (L_1, R_1), (L_2, R_2), …, (L_N, R_N).

The equations for generating the mean values of left foot force ($\bar{L}$) and right foot force ($\bar{R}$) are as follows:

$$\bar{L} = \frac{\sum_{i=1}^{N} L_i}{N}; \qquad \bar{R} = \frac{\sum_{i=1}^{N} R_i}{N} \tag{1}$$

The equations for generating the standard deviation of left foot force (S_L) and right foot force (S_R) are as follows:

$$S_L = \sqrt{\sum_{i=1}^{N} \left(L_i - \bar{L}\right)^2}; \qquad S_R = \sqrt{\sum_{i=1}^{N} \left(R_i - \bar{R}\right)^2} \tag{2}$$

Based on the equations mentioned above, the correlation coefficient (γ_{LR}) between the left foot force and the right foot force is computed using the following equation:

$$\gamma_{LR} = \frac{\sum_{i=1}^{N} \left(L_i - \bar{L}\right)\left(R_i - \bar{R}\right)}{S_L S_R} = \frac{\sum_{i=1}^{N} (L_i - \bar{L})(R_i - \bar{R})}{\sqrt{\sum_{i=1}^{N} (L_i - \bar{L})^2 \sum_{i=1}^{N} (R_i - \bar{R})^2}} \tag{3}$$

In the equation above, γ_{LR} is the correlation coefficient between the left foot force and the right foot force. The range of γ_{LR} is between -1 and 1. In a positive relationship, as the left foot force increases, the right foot force tends to increase too. The value range is between 0 and 1. In a negative relationship, as the left foot force increases, the right foot force tends to decrease. The value range is between -1 and 0. If the left foot force and right foot force are independent, then the coefficient will tend to be zero, e.g., this value tends to be zero for a car-passenger. This feature can increase the accuracy in using FF alone to detect human-powered activities e.g., walking and cycling.

B. System Overview

We propose to answer the following research questions: Is monitoring both feet better than monitoring just one? Where are the most effective and minimal insole positions (as fewer sensors make it more energy efficient) to monitor FF? Which features are the maximal informative ones in differentiating mobility activities? How can we reduce the use of GPS, when we use FF, in order to further improve the energy-efficiency?

In the data collection phase when deploying our system, see Fig. 1, data is acquired from both smart phone GPS and a set of foot force sensors. In total, 8 foot force sensors are used for foot force monitoring from both feet. The insole positions of sensors are clearly labelled (Fig. 2). The data from foot force sensors and mobile phone GPS are collected simultaneously to form the raw data set. All the results generated at the classification phase originate from the same raw data set.

In the feature extraction phase (Fig. 1), a uniform-duration (8 seconds window) segmentation (without overlap) as used in [1] is applied to all methods. It has been shown that time domain features are more computational light than frequency domain features [11], [12]. We focused on using the following time domain features: mean, max, and standard deviation. Hence, the following 31 features form the features pool of this paper: mean, max, and standard deviation of GPS speed, mean, max, and standard deviation of force readings from positions P0, P1, P2, P3, P4, P5, P6, and P7 (see Fig. 2). The correlation coefficient between counterpart sensors from both feet are represented as: γ (P0, P4); γ (P1, P5); γ (P2, P6); γ (P3, P7) (see Equation 3). In the same order, numbers from 1 to 31 are used in the following paragraph to denote these features as shown in Table II.

The usefulness of these features for mobility activity recognition has been proven in our previous research [1]. The mean and max value of foot force readings can be used to determine whether whole body weight is supported by the feet during different activities, e.g., between walking and car-passenger. The standard deviation value of foot force readings can be used to specify whether or not an activity involved dynamic foot force variations e.g. cycling. The mean and max value of GPS speed can be used to differentiate between human powered activities and motorised activities. The standard deviation of GPS speed can be used to determine whether the motorized

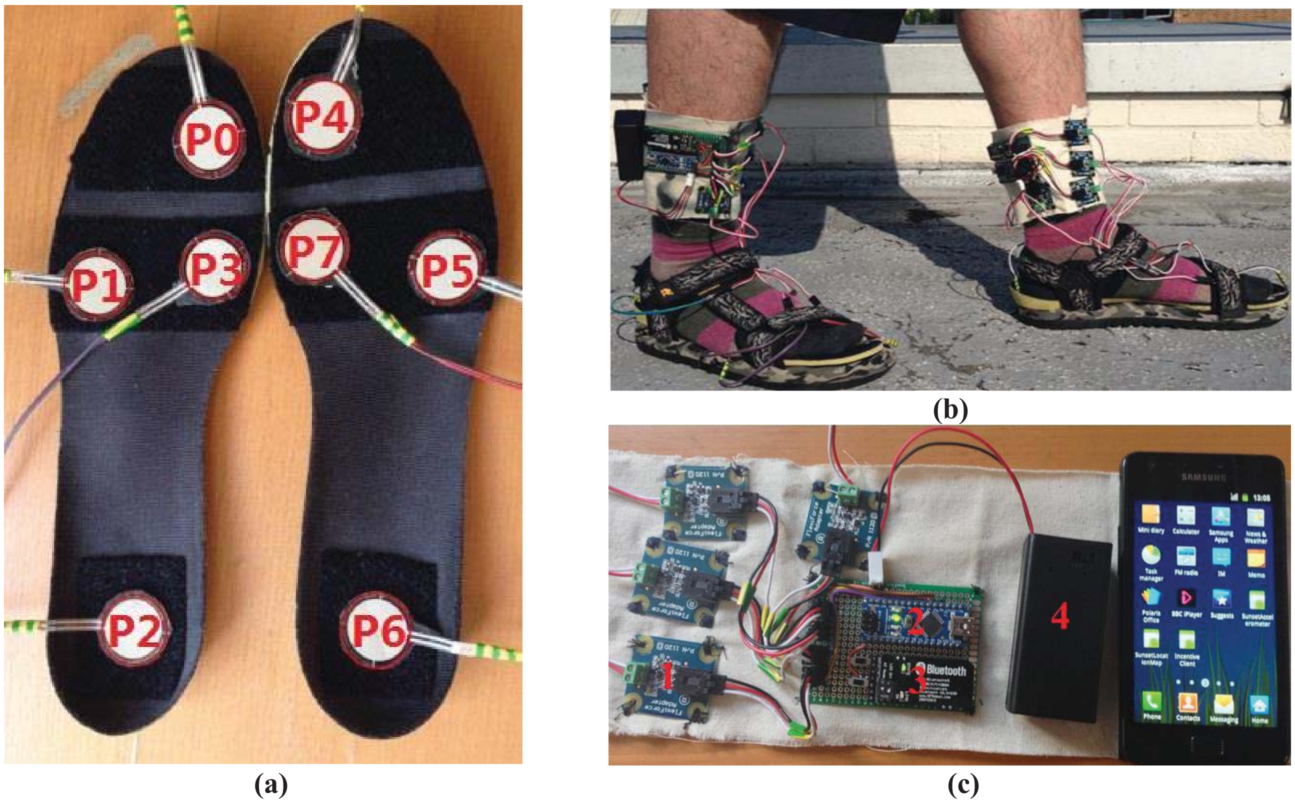

Fig. 2. Experiment equipment: (a) experimental insoles with 8 Flexiforce sensors instrumented; (b) the scene of foot force measurements; and (c) the foot force sensing system and a Samsung galaxy II smart phone.

TABLE II
FEATURE NUMBERS AND CORRESPONDING FEATURES

Number	Feature	Number	Feature
1	GPS Mean Speed	17	P4 Max Force
2	GPS Max Speed	18	P4 STD Force
3	GPS STD Speed	19	P5 Mean Force
4	P0 Mean Force	20	P5 Max Force
5	P0 Max Force	21	P5 STD Force
6	P0 STD Force	22	P6 Mean Force
7	P1 Mean Force	23	P6 Max Force
8	P1 Max Force	24	P6 STD Force
9	P1 STD Force	25	P7 Mean Force
10	P2 Mean Force	26	P7 Max Force
11	P2 Max Force	27	P7 STD Force
12	P2 STD Force	28	Cor-Coe of P0 & P4
13	P3 Mean Force	29	Cor-Coe of P1 & P5
14	P3 Max Force	30	Cor-Coe of P2 & P6
15	P3 STD Force	31	Cor-Coe of P3 & P7
16	P4 Mean Force		

activity involved frequent speed variations e.g., to differentiate between car and bus. The correlation coefficient between left foot force and right foot force can be used to determine whether the activity involved regular force shifting between left foot and right foot e.g., to differentiate between cycle-pedalling and drive-pedalling.

As Fig. 1 shows, different sensor configurations have been employed, including FF(left), FF(right), FF(both), and FF(both)+GPS.

TABLE III
DIFFERENT SENSOR CONFIGURATIONS AND CORRESPONDING FEATURE SET

Sensor Configurations	Features used (in number)
FF(both) + GPS	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18, 19,20,21,22,23,24,25,26,27,28,29,30,31
FF(both)	4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20, 21,22,23,24,25,26,27,28,29,30,31
FF(Right)	16,17,18,19,20,21,22,23,24,25,26,27
FF(Left)	4,5,6,7,8,9,10,11,12,13,14,15

The comparisons between FF(left), FF(right), and FF(both) configurations are used to prove the usefulness of using sensors on both feet and correlating a coefficient between the left foot and right foot force to detect human powered activities (see Section IV-C-1).

The combined FF (from both feet) plus GPS speed is used to identify the maximally informative features and the corresponding best insole positions to detect the required mobility activities (more details in IV-C-2 and IV-C-3).

Table III shows the different features extracted for different sensor configurations. These are used to generate the classification results used for comparison and evaluation.

In the classification phase of Fig. 1, a decision tree classifier which proved to be the most effective classifier in mobility activity recognition was used to generate the final classification results [1]. All experimental data collected (from 10 volunteers) were equally divided into 10 folds so that a 10-fold cross validation mechanism is used for validation [13].

IV. Experiments and Results Evaluation

A. Participants

All study procedures were approved by the Research Ethics Committee at Queen Mary, University of London. All participants signed a written informed consent form. Data collection took place over an 8-month period from Oct, 2012 to June, 2013. Five mobility activities (walking, cycling, bus passenger, car passenger, and car driver) were performed by 10 volunteers (6 male; 4 female) with ages ranging 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. They were instructed to perform different activities in daily life environment, and a researcher observed them to take notes about the actual activity being performed. The data collected totalled 7536 samples, of which 1643 samples were from walking, 1521 samples were from cycling, 1597 samples were from riding buses, 1403 samples were from taking car/taxi, 1372 samples were from driving. Each sample contains sensor data collected during 8 second time duration.

B. Equipment

During the data collection procedure, each participant carried a Samsung Galaxy II smart phone, and wore a pair of special insoles. The special insoles were instrumented by eight Flexiforce sensors (4 in each sole). This number was chosen as the baseline number of sensors because it was show that this can obtain accurate ground reaction force values [7]. Hence, four Flexiforce sensors have been mounted directly under the major weight-bearing points of each foot in order to cover the force reaction area of heel, forefoot, and toe for both feet as shownn Fig. 2(a). All Flexiforce sensors are interfaced to the smart phone via a Bluetooth connection (see Fig. 2 (b)). The foot force sensing system (see Fig. 2 (c)) is implemented with four adaptors (marked as 1), one Arduino Nano Board (marked as 2), one Bluetooth module (marked as 3), and one 9v battery box (marked as 4). Flexiforce sensor reading frequency is set to 35 Hz, and mobile phone embedded GPS is set to 1 Hz according to settings used in [1].

C. Results and Evaluation

Accuracy is defined as the sum of correctly classified instances of all mobility activities over the total number of classifications. Precision for activity (A) is defined as the number of correctly classified instances of activity (A) over the number of instances classified as activity (A). Recall for activity (A) is defined as the number of correctly classified instances of activity (A) over the number of instances of activity (A).

1) Mobility Activity Recognition Using Different FF Configurations (Without GPS): From Fig. 3 and Fig. 4, it is noted that all three settings (FF-Left, FF-Right, and FF-Both) perform equally well in detecting walking. This is because there are three stances used in normal human walking, heel strike, mid-stance, and toe-off [14]. The foot force patterns from either left or right are quite unique in terms of both mean and standard deviation [1]. Sensing both feet can achieve a better accuracy in detecting cycling than sensing either one of them (Fig. 3 and Fig. 4). This is because by knowing the correlation coefficient between left and right feet, noise arising from body motion, e.g., leg rocking, can be ruled out. It is also found that by using the correlation coefficient between left and right feet, cycle-pedalling can be differentiated from drive-pedalling with a higher accuracy.

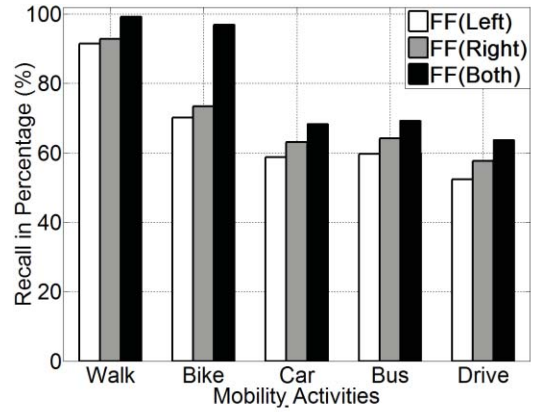

Fig. 3. Recall results from using foot force sensors only.

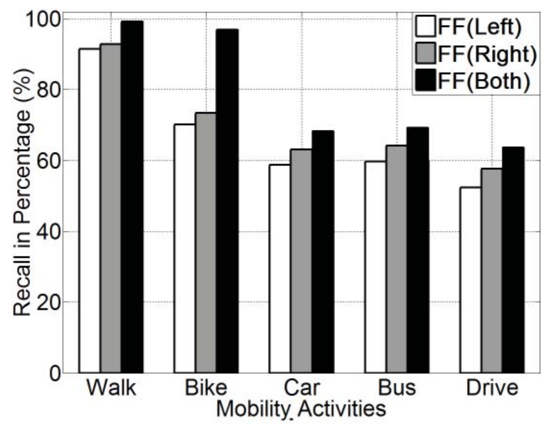

Fig. 4. Precision results from using foot force sensors only.

However, use of FF only cannot classify motorised mobility activities at a high accuracy. This is because on many occasions, the foot force patterns from motorised modes are quite similar, e.g., seated bus passengers have quite similar foot force patterns to car passengers. It is also noticed that sensing the FF in only one foot may mislead the system into inferring false user postures during travel, which in turn affects the accuracy in differentiating mobility activities. For example, a standing bus passenger may lean, putting the majority of weight on one foot, which makes his right FF patterns similar to that of a car passenger. Also a car passenger sitting with crossed legs may also be misclassified as a standing bus passenger or even a car driver if we only sense the weight-bearing foot force. The majority of these misclassifications can be resolved by sensing both feet plus GPS-speed. Hence, we propose a hybrid GPS use-plan to reduce the use of GPS of the FF+GPS method.

In the proposed hybrid GPS use-plan, GPS is only activated when detecting motorised mobility activities. For the majority

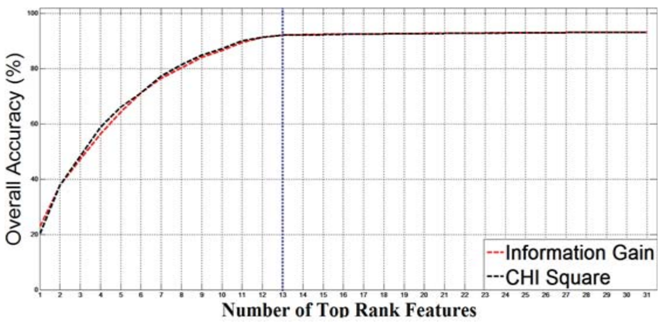

Fig. 5. Overall accuracy as a function of the number of top rank features.

of foot related activities such as walking and cycling, only FF is used. The merit of using this hybrid GPS use-plan is to reduce the use of the most energy hunger sensor, GPS, but without significantly affecting the overall accuracy. The final results of employing this new GPS use-plan are presented in section IV.C.4.

2) Best Feature Selection: Although sensing both-feet is better than single-foot-sensing to detect walking and cycling (Section IV.C.1), GPS speed is also useful to help better differentiate different motorised mobility activities. However, we hypothesize that, given the range of features and insole positions we considered, whether or not there are less informative features and less useful insole positions when detecting mobility activities that can then be pruned to improve (simplify) the FF+GPS method. Hence, the following two commonly used feature selection algorithms, Chi Square and Information Gain [15], have been employed to identify the best feature set.

From the results as shown in Fig. 5, we can see that the accuracy tapers off for about the top 13 features for both feature selection algorithms (Table V). If we were to pick more features beyond the top 13, the performance only improves slightly, <1% for all 31 features. From Table V, It is also noted that although the order of the 13 top rank features is not the same, the set of 13 top rank features (as marked in grey) is the same for both Chi Square [15] and Information Gain [15]. This indicates that the 13 top rank features are the maximally informative features within our pool of 31 features.

3) Best Insole Positions Selection: The practical advantage of best insole positions selection is that we can significantly reduce the equipment cost, without drastically affecting the performance. Our best insole position selection is based upon the best features selection, as we need to select the insole positions that provide the maximally informative features.

Table IV shows that within the range of 13 top rank features identified in section IV.C.2, no feature is selected from insole positions P0 and P4. This is because little force is generated on both toes during the required mobility activities, so P0 and P4 are pruned.

In addition, the insole positions P3 and P7 only contribute to one feature (No. 31), which is the correlation coefficient between P3 and P7. Moreover, it is also discovered that the overall accuracy only decreased 1% by removing this feature (31). This is because the information provided by this feature is also covered by other similar features such as feature 30, which is the correlation coefficient between P2 and P6. Hence, feature 31 is also removed from the selective feature set. The corresponding insole positions (P3 and P7) are also pruned.

TABLE IV

The Percentage of Features From the Top 13 That Originated From Different Sensor Positions

Sensor	Related Top 13 Features	Percentage
GPS	1, 2, 3	18.9%
FF Sensor P0	None	0%
FF Sensor P1	9,29	12.4%
FF Sensor P2	10, 12, 30	18.9%
FF Sensor P3	31	6%
FF Sensor P4	None	0%
FF Sensor P5	20, 21, 29	18.9%
FF Sensor P6	22, 24, 30	18.9%
FF Sensor P7	31	6%

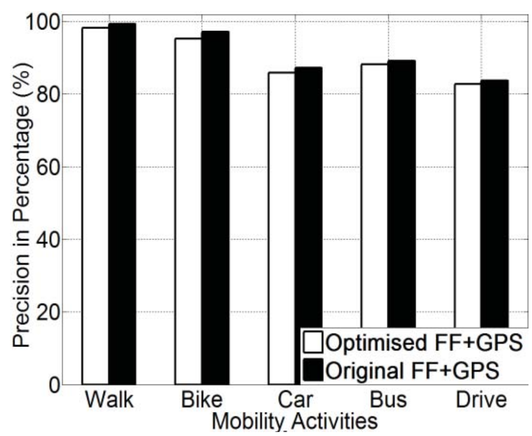

Fig. 6. Precision accuracy for the improved FF+GPS method.

Finally, the following 12 top ranking features are selected as the optimum feature set: 1 (GPS mean speed), 2 (GPS max speed), 3 (std. dev. of GPS speed), 9 (std. dev. of P1 force), 10 (P2 mean force), 12 (std. dev. of P2 force), 20 (P5 max force), 21 (std. dev. of P5 force), 22 (P6 mean force), 24 (std. dev. of P6 force), 29 (correlation coefficient between P1 and P5), and 30 (correlation coefficient between P2 and P6). The following insole positions are selected as the optimum insole positions: P1, P2, P5, and P6.

4) The Improved FF+GPS Method: According to the results we get from IV-C.1, IV-C.2 and IV-C.3, we propose the following improved FF+GPS method that employed the 12 best features (out of 31), 4 best insole positions (out of 8), and the proposed hybrid GPS use-plan.

Fig. 6 and Fig. 7 show the results of using the improved FF+GPS method (white bars) for detecting the 5 predefined mobility activities. Compared with the original FF+GPS method (black bars), the precision and recall accuracy of using the new improved FF+GPS hardly changes. For the decision tree classifier, only a 1.8% reduction in overall accuracy is noticed when using the improved FF+GPS method.

TABLE V
CLASSIFICATION FEATURE RANKING AND SELECTION

Selection Algorithms	Features Rank in Number (from left to right is the order from 1st to 31st)
InfoGain	02,12,10,24,21,30,20,01,03,09,22,29,31,11,23,08,05,15,18,19,17,06,04,28,16,26,25,27,14,13,07
ChiSquare	12,02,30,21,10,24,22,03,01,29,20,31,09,16,06,19,17,26,13,27,14,18,25,11,23,08,04,05,15,07,28

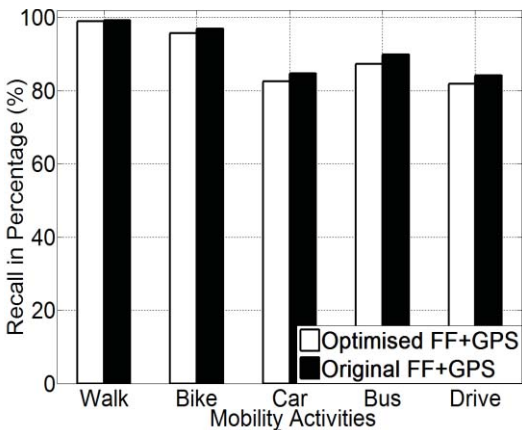

Fig. 7. Recall accuracy when using he improved FF+GPS method.

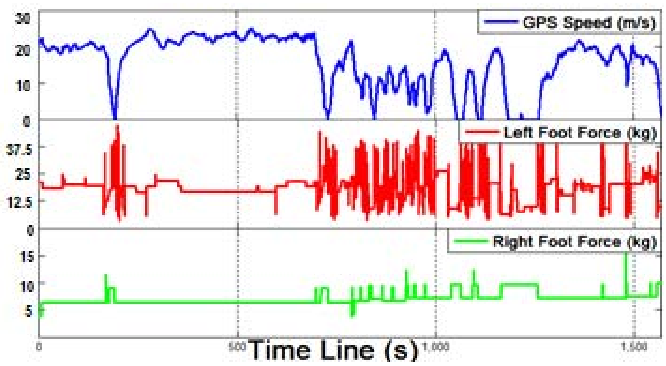

Fig. 8. GPS speed, foot force variations during a 30 minutes driving process.

TABLE VI
BEST INSOLE POSITIONS AND OVERALL ACCURACY FOR DIFFERENT NUMBER OF FF SENSORS USED

Number of FF sensors per foot	Best insole Positions	Overall Accuracy
1 (2 in total)	P2 and P6	75%
2 (4 in total)	P1, P2, P5, and P6	91%
3 (6 in total)	P1, P2,P3, P5, P6, and P7	93%

V. DISCUSSION AND FUTURE WORK

It is shown that the number of foot force sensors in the FF+GPS method can be reduced to four (two sensors per foot) to still achieve the same level of accuracy. In addition, the minimal most effective insole positions with respect to accuracy for different (number of foot force sensors) configurations are also of interest, as the resources in practical systems may be limited.

As Table VI shows, given the configuration of using only one sensor per foot, the overall accuracy of FF+GPS method is lower, 75%. This is mainly because of the lack of sensing in the fore part of the foot. Though, P2 and P6 in the heel can detect walking with a high accuracy and can indicate whether or not a user is sitting in a car versus standing on a bus, heal sensing still cannot sense the force variations of pedalling e.g., during cycling or driving. Given the configuration of using only two sensors per foot, the overall accuracy has been increased to 92%. This is because by adding two forefoot sensors P1 and P5, most of the foot force variations during different mobility activities can be sensed and contribute to the classification results. However, the configuration of using three sensors per foot only leads to a 1% gain in accuracy. This is because the information gained by adding the insole sensor position P3 and P7 do not contribute much to detect mobility activities.

It is also discovered that by adding the correlation coefficient feature, to sense the FF in both feet, walking and cycling can be detected more accurately. The potential correlation between other features is also of interest. The foot force variation of the driver relates to speed variations when driving the car, e.g., step on the accelerate pedal to speed up; step on the brake pedal to slow down.

We also investigated if a study of foot force variations can be used to better understand driver behaviour. However, there is no obvious correlation between GPS speed and foot force value (Fig. 8), i.e., while driving, an increment/decrement of vehicle speed does not correspond clearly to an increment/decrement of the foot force. However, our experiments do show that dips in GPS speed do correspond to variations in left (shifting) foot force. The right (accelerating/breaking) foot force also varies with GPS speed dips, however with a smaller amplitude. This is mainly because the pressures used on different pedals are different.

If one could find a valid correlation function between foot force and car speed, this could be used to help improve car driving. However, since driving is a complex behaviour and FF is only partially sensing the driving behaviour, e.g., driving behaviour depends on many other factors such as the type of the car, driving habits, traffic/road condition, etc. More specific experiments and data analysis of FF for car-driving behaviour is considered as future work.

With regard to energy efficiency, the new improved FF+GPS method reduces the use of GPS and reduces the number of required foot force sensors to 4 (50% more efficient than the original FF method in [1]). However, a detailed energy consumption analysis of the current hybrid GPS use-plan and 4 sensors based foot force monitoring sensors is not included in this work. We leave exploring the energy efficiency of the improved FF+GPS method as part of future work.

We selected car and bus as the most representative motorised transportation modes. Further work will also investigate if FF patterns can be used to differentiate train versus bus versus car. This is especially challenging because: of the greater variations of types of train in terms of acceleration and speed; the greater freedom variations of movement for passengers in trains and the lack of GPS availability for position and speed determination when travelling underground or in tunnels.

VI. Conclusion

We researched and developed an improved FF+GPS method to detect mobility activities. Our contributions are fivefold. First, we investigated whether or not we could reduce the number of FF sensors (compared to [1], we reduced the no. from 8 to 4 for both feet) and second, where we could most effectively position these sensors without affecting the transport mode classification accuracy. Third, we investigated if monitoring the FF in both feet versus one foot improves transport recognition accuracy (it does). The correlation coefficient between left foot force and right foot force can improve the accuracy in detecting walking and cycling. Forth, we investigated if could identify the most important features used for classification and omit some features (we reduced the no. from 31 to 12 compared to [1]), whilst maintaining an overall detection accuracy of about 90%. When a decision tree classifier is employed, only a 1.8% reduction in overall accuracy occurs when using the improved FF+GPS method compared to the original FF+GPS method [1]. The reduction in both the number of sensors and derived features computed improve the energy efficiency of the sensing. Fifth, we further improved the energy efficiency of our proposed FF+GPS method for mobility detection by improving the plan to reduce the use of (the most energy hunger sensor) GPS sensor.

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