A New Post Correction Algorithm (PoCoA) for Improved Transportation Mode Recognition

Zelun Zhang
School of Electronic Engineering and Computer Science
Queen Mary, University of London
London, UK
zelun.zhang@eecs.qmul.ac.uk

Stefan Poslad
School of Electronic Engineering and Computer Science
Queen Mary, University of London
London, UK
stefan@eecs.qmul.ac.uk

***Abstract*—Transportation mode plays an important role in enabling us to derive a mobile user's context, and to adapt intelligent services to this. However, current methods have two key limitations: a low recognition accuracy and coarse-grained recognition capability. In this paper, we propose a new Post Correction Algorithm (PoCoA) that is applied after the use of typical classifiers to address these limitations. We evaluated the use of PoCoA for the following transportation modes, walking, cycling, bus passenger, metro passenger, car passenger, and car driver. PoCoA enhances a typical accelerometer-based transportation recognition method with a more accurate sub-classification of motorized transportation modes when tested on a dataset obtained from 15 individuals. Overall accuracy improved from 69% to 88% when comparing with a state of the art two-stage classifier (Decision Tree + Discrete Hidden Markov Model).**

Keywords- Transportation mode recognition; Accelerometer; Post Correction Algorithm; Hidden Markov Model (HMM)

I. INTRODUCTION

Transportation mode is an important type of user context that denotes someone's mobility status while travelling. In this research, we are interested in recognizing the urban transportation modes of normal adults. The transportation modes include walking, cycling, bus passenger, tube (London's Metro or Underground Train) passenger, car/taxi passenger, and car driver. Such transportation mode recognition could facilitate a range of applications as follows.

Human-Centered Activity Monitoring: Transportation modes of individuals can be logged and mapped to locations to enable individuals to plan travel based on physical activity targets and use in health monitoring [1], e.g., a mobile phone may detect how many hours a person walks every day and to provide personalised health advice [2].

Individual Environmental Impact Monitoring: The transportation mode can be used to provide a personalized environmental scorecard for tracking the environmental impact of one's activities. Examples include Personal Environment Impact Report (PEIR) and UbiGreen [3, 4], along with commercial offerings such as Ecorio and Carbon Diem [5, 6].

Distributed Intelligent Services Adaptation: In-situ information can be adapted to mobility profiles (time, location, transportation mode traces), which can contribute to distributed user-context and group context-awareness [7], e.g., to automatically adapt a navigation map from a bus-route view while someone is on a bus, to a pedestrian view triggered by starting to walk from the destination bus stop to a meeting place.

Implicit Human Computer Interaction: Transportation mode recognition in people's daily life can help to enable the hidden computer part of the vision of intelligent transportation system in terms of reducing a user's cognitive load when interacting with services while travelling, e.g., a mobile phone may detect when a person is driving or involved in vigorous physical activity, and automatically divert a call for safety considerations [8].

The confluence of advanced wearable sensor technology embedded in widely available mobile phones offers the opportunity for automatic recognition of a person's activities and transportation modes in daily life [9]. Mobile phone integrated accelerometer and GPS can provide spatial user contexts (e.g. acceleration and speed) during different activities in real time [10]. Typically, thresholds for speed and acceleration are often used to differentiate transportation modes [8]. However, under certain traffic conditions, i.e., congestion, speed and acceleration for different transportation modes can coalesce making the modes hard to be differentiated using such thresholds alone, e.g., to sub-differentiate motorised modes with a high accuracy. Hence, additional post-acquisition analysis is needed to supplement threshold-based analysis, to possibly reclassify transportation modes (two-stage classifier).

The main contributions of this paper are: First, we reproduced the results of a best practice method (an accelerometer-based method identified in the survey) to be used as a baseline method to evaluate our method through observing 15 different individuals' daily mobility patterns. Second, we proposed a novel Post Correction Algorithm that is applied after the use of typical classifiers. We then evaluated this experimentally through comparing PoCoA with a more typical two-stage classifier (DT+HDMM). Third, after generating more comprehensive datasets by simulating the classification process of the accelerometer-based method, we further demonstrated the potential usefulness of our new Post Correction Algorithm.

II. RELATED WORK

Recognising transportation mode through sensing modalities that are available on mobile phones, mainly the accelerometer and GPS, has been the subject of much research.

978-1-4799-0652-9/13/$31.00 ©2013 IEEE

The accelerometer can produce a good estimate of the magnitude of the dynamic acceleration of any human mobile host that wears such a device [11]. Different human-powered transportation modes, such as walking and cycling, generate acceleration patterns that are differentiable. Thus, Juha [12] has successfully differentiated different human-powered transportation modes, such as walking, running and cycling, using a motion band attached to the user's ankle. Ravi [13] also found that these activities can be recognised with accuracy of 84% when wearing a single 3D-accelerometer near the pelvic region. Similar results have also been achieved in [10, 14].

Accelerometer-based methods can achieve an increased accuracy when people carry their smart phones in a fixed place. However, people normally 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 variations greatly change the nature of the motion signal, which eventually impacts the comprehensive use of a specific trained classifier [15]. Wang et al. [16], have also considered this issue and have attempted to differentiate transportation modes without any placement restrictions for accelerometers. Using the magnitude[1] of three axis mobile phone accelerometer readings (which avoids placement restrictions by eliminating the influence of direction along a specific axis), Wang et al. recognised six kinds of transportation modes, but the accuracy is relatively low (at 62% on average).

The potential usability of GPS in profiling user daily outdoor activities has been widely presented. Liao et al. [17], 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 use of the Conditional Random Field model. On the other hand, Zheng et al. used a supervised learning based approach to infer more fine-grained transportation modes from the raw GPS data combined with GIS (Geographic Information System) in [18]. They proposed a so called change-point (when transportation modes change) based upon a segmentation method. Their results show that the change-point based segmentation achieves a better accuracy (over 80%), but the types of transportation modes recognised are coarse. In addition, GIS-based methods tend to exhaust the mobile device power level as they need frequent data transmission.

Table I shows that the average accuracy achieved by using GPS alone (at a level of 80%) is higher than that achieved by using accelerometer alone (at a level of 70%). Nonetheless, classification of all GPS-based methods is coarse. Work [19] which uses both GPS and accelerometer achieved the best accuracy. Clearly, the accuracy of transportation mode detection maybe higher if one utilises more sensors. However, the objective of our work is to determine the value add of PoCoA using a mobile phone accelerometer rather than a GPS method for ubiquitous use because: First, compared to GPS, the accelerometers consume much less energy [20]. Second, an accelerometer can obtain sensor data continuously, while GPS mainly works outdoors (open sky environment) [21], e.g., for passengers seated away from an overground vehicle window or travelling underground, the GPS signal is blocked. Third, the accelerometer needs far less time to start, while a mobile phone GPS can require several minutes to start [22].

[1]The Magnitude M is calculated by: M= $\sqrt{x^2 + y^2 + z^2}$

Table I. Sensor based transportation mode recognition related work

Ref	Sensor Type	Transport Modes	Placement	Accuracy
[13]	Accelerometer	Walk, Run, Bike	hip	84%
[10]	Accelerometer	Still, Walk, Run	pockets	60%
[16]	Accelerometer	Still, Walk, Tube, Bike, Bus, Car	FREE	62%
[23]	Accelerometer	Still, Walk, Run	pocket	78%
[17]	GPS	Walk, Motorised	hand	83%
[18]	GPS	Walk, Bike, Motorised	hand	77%
[19]	Accelerometer, GPS	Still, Walk, Bike, Motorised	FREE	92%

Table I also shows that the average transportation mode recognition accuracy, using accelerometer-based methods, is relatively low, at a level of 70%. This offers a good opportunity to increase its accuracy. In addition, most of the current methods have restrictions with respect to how users should carry their mobile devices, except for [16]. Moreover, only [16] uses sub-classes of motorised transportation mode, i.e., bus passenger and tube passenger. This is closest to one of our aims in this paper - more fine-grained transportation mode recognition. Hence, we decided to reproduce the accelerometer-based method used in [16] as a baseline from which to extend and evaluate PoCoA.

PoCoA is applied after typical classifiers and can also be considered as the 2nd stage of a two-stage classifier. A two-stage classifier is normally an instance based classifier followed by an outlier detection model [9, 22, 24, 25]. Among all existing two stage classifiers, we chose a state of the art two-stage classifier as used in [19], which is a DT+DHMM (Decision Tree + Discrete Hidden Markov Model) system. This is considered as the most accurate two-stage classifier since a DT is tuned to differentiate between the boundaries of transportation modes, and DHMM eliminates noise based on temporal knowledge of the previous transportation mode and the likelihood of a transition to the next mode. Thus, the most popular two stage classifier (DT+DHMM) as used in [19] is selected to validate our new Post Correction Algorithm.

III. EXPERIMENTAL RESULTS FOR THE ACCELEROMETER BASED METHOD

We reproduced a typical accelerometer-based transportation mode recognition method [16] according to the three typical phases (see Fig. 1): Raw Sensor Data Collection, Feature Extraction, and Machine Learning and Classification.

A. Raw Sensor Data Collection

Studies were approved by the university, and all participants signed a written informed consent form. Data collection took place over a 10-month period from Dec, 2011 to Oct, 2012. Six transportation modes (walking, cycling, bus passenger, tube passenger, car passenger, and car driver) were performed by 15 volunteers (9 male, 6 female) with an age range from 20 to 56. A Samsung Galaxy II smart phone (with Android OS version 2.3.3) has been used as the equipment. Its smart phone embedded accelerometer[2] is set to operate at 35 Hz according to the settings used in [16]. An Android application has been designed and implemented to enable volunteers to clearly label the accelerometer data with the transportation mode. During data collection, volunteers had the liberty of carrying the mobile phone device in any orientation and position they desired. The data collected totalled 13507 samples, of which 2158 samples are from walking, 2371 samples are from cycling, 2637 samples are from riding buses, 2086 samples are from taking a car/taxi, 1996 samples are from driving, and 2259 samples are from taking the Tube (London Underground).

B. *Feature Extraction*

In the feature computation phase, a uniform-duration (8 seconds window) segmentation is applied to the accelerometer data collected as described in [16]. Following this, 11 features are also extracted (as in [16]): mean, standard deviation, mean crossing rate, third quartile, sum and standard deviation of frequency components between 0~2 HZ, ratio of frequency components between 0~2 HZ to all frequency components, sum and standard deviation of frequency components between 2~4 HZ, ratio of frequency components between 2~4 HZ to all frequency components, and spectrum peak.

C. *Machine Learning and Classification*

In the transportation mode recognition phase, 3 commonly used machine learning schemes: Naïve Bayes, Decision Tree (J48), and Decision Table that are provided by the WEKA toolkit [26] are used. All experiment data collected from 15 volunteers are equally divided into 10 folds and a 10-fold cross validation mechanism is used for evaluation [27].

D. *Initial Experimental Results and Discussion*

We present the accuracy for each classifier we chose (see Table II). Accuracy is defined as the sum of correctly classified instances of all modes over the total number of classifications.

Table II. Overall Recognition Results when repeating the work of [16] using three typical classifiers

Classifiers	Decision Tree	Naïve Bayes	Decision Table
Overall Accuracy	**66.9%**	**53.7%**	**63.9%**

From table II, it is noted that the results of the accelerometer method reproduced by us (average accuracy of 61.5%) matches the results presented in [16] (62% accuracy). This gives us evidence that the accelerometer-based method used in [16] has been successfully reproduced. In addition, it is also found that decision tree (J48) classifier obtains the highest overall recognition accuracy, so the precision and recall for each transportation mode from the decision tree classifier are presented in Table III.

Precision for mode **(M)** is defined as the number of correctly classified instances of mode **(M)** over the number of instances classified as mode **(M)**. Recall for mode **(M)** is defined as the number of correctly classified instances of mode **(M)** over the number of instances of mode (**M)**.

Table III. Original Precision and Recall results of the accelerometer-based method reproduced according to [16]

Mode	Walk	Bike	Car	Bus	Drive	Tube
Precision	**96.9%**	**61.2%**	**56.3%**	**64.6%**	**63.7%**	**66.8%**
Recall	**97.4%**	**63.7%**	**53.2%**	**63.4%**	**58.3%**	**65.9%**

The accelerometer-based method performs very well in detecting walking. Precision and recall are both over 95% according to table III. This is because there are mainly three obvious stances for the normal human walking motion: heel strike, mid-stance, and toe-off [28, 29], which generate quite unique acceleration patterns compared with other non-walking transportation modes.

When cycling, people power the cycle by pedalling. An accelerometer can detect this particular acceleration pattern. However, the accelerometer-based method only achieved around 62% accuracy for both recall and precision. This is because in some cases, e.g. when coasting by bike, the acceleration patterns are mainly affected by the road conditions. Instances from these cases exhibit similar feature characteristics with motorised modes instances. For the case of sub-classification of motorised modes, there are also differences within different motorised transportation modes. When driving, people need to step on both the accelerator pedal and the brake pedal regularly in order to control the car. A bus-passenger may stand and move inside a bus, whereas a car passenger does not do this. Moreover, buses need to stop more regularly at bus stops and travel slower than private cars for safety consideration. On the other hand, underground trains, as they are rail based, normally travel more smoothly than road vehicles and exhibit different vibration patterns. Such discrepancies lead to differences in the sensed acceleration which make it possible to sub-differentiate motorised modes. However, it is also noted that the average accuracy for sub-differentiating motorised modes is only around 62%. This is because, for many cases, instances from one particular motorised mode can be misclassified as being those of another motorised mode (or even as cycling) using the accelerometer data, e.g. steady-state cycling sometimes exhibits the same acceleration patterns as a low speed motorised mode on congested roads.

These results and analysis illustrate that accelerometer-based methods are capable of recognising the six required transportation modes: walking, cycling, car-passenger, bus-passenger, tube-passenger, and car-driver. However, the accuracy still needs to be improved to increase the reliability for the potential applications that adapt to these recognised transportation modes (see chapter I).

IV. THE POCOA ALGORITHM DESIGN

A. *Rationale and Motivation*

Table III shows that the current accelerometer-based method already achieves a relatively high accuracy (97%) when recognising walking. However, for other transportation

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

modes (cycling, car-passenger, car-driver, tube-passenger and bus-passenger), the accuracy is much lower (62%).

It is also observed that most occurrences of misclassified transportation modes samples are surrounded by correct-classified samples (Fig. 4). We hypothesize that if an algorithm can find these misclassified samples and correct them according to knowledge about the current mobility context, then the overall accuracy can be improved greatly.

B. Assumptions

PoCoA first exploits the fact that an individual's daily travelling pattern consists of a sequence of moderately-long lasting transportation modes. Second, based on our experiments and context analysis, we also found that people tend to walk when transferring between two non-walking transportation modes during daily activities, e.g. people have to walk to a bus station to get on a bus even if they first cycle to a bus-stop. Normally, one cannot transfer between two non-walking transportation modes without walking a short or longer distance. Hence, we specify the following heuristic: walking is performed by normal adults in transition between any two non-walking travelling periods. Each non-walking period contains only one type of transportation mode, as it is impossible for one to transition between two non-walking transportation modes (e.g. from bus to bike) without walking.

C. Algorithm Design and Description

In addition to the assumption, it is also illustrated in table III that the current accelerometer-based method already achieved 97% accuracy for both recall and precision when classifying walking samples. This means during typical daily travel, the majority of samples from walking can be correctly recognized. This means that walking periods are useful to work as delimiters to separate other non-walking periods. PoCoA is only applied to each non-walking period which (according to our assumption) is supposed to contain only one type of transportation mode. PoCoA is not applied to walking periods as these are used as delimiters between different non-walking periods in a sequence.

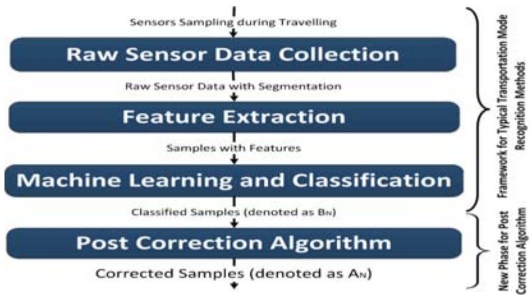

Fig. 1. PoCoA Framework for Transportation Mode Recognition

For the purpose of separating a sequence of classified samples into two subsets: walking segments and non-walking segments. The following rule is applied: the classified sample that depicts a transition from "walking" to a non-walking transportation mode is the start point for applying PoCoA. The classified sample that depicts a transition from any non-walking transportation mode to "walking" is the end point for applying PoCoA.

For PoCoA, we also define another concept "Correction Window". Correction Window is a set of previously classified samples that is used to determine which transportation mode a current misclassified sample should be corrected to. The size of correction window needs to be determined beforehand.

The Pseudo code for the Post Correction Algorithm is presented below: 'B_N' is used to denote the type of transportation mode classified before applying PoCoA. 'A_N' is used to denote the corrected transportation mode after applying PoCoA. Annotation 'N' represents the sequence number of the classified samples. Each B_N and A_N could be one type of non-walking transportation mode: cycling, bus-passenger, tube-passenger, car-passenger, or car-driver. For one particular classified sample B_N and predefined correction window size 'M', the correction window consists of all the classified samples B_{N-M}, B_{N-M+1}, …, B_{N-1}. The appearance percentage value of mode X within the correction window is denoted as P(X).

```
while Transportation_Mode_Recognition_Running do
 if CurrentClassifiedSample (B_N) != 'walking'
 //The size of CorrectionWindow is predefined with size 'M'
   for all Sample in the correction window (B_N-M, B_N-M+1,……, B_N-1) do
     if Sample == 'Bus'
        NoofBus = NoofBus + 1 //increment NoofBus by 1
     end if
     if Sample == 'Bike'
        NoofBike = NoofBike + 1 //increment NoofBike by 1
     end if
     if Sample == 'Car'
        NoofCar = NoofCar + 1 //increment NoofCar by 1
     end if
     if Sample == 'Drive'
        NoofDriver = NoofDrive + 1 //increment NoofDrive by 1
     end if
     if Sample == 'Tube'
        NoofTube = NoofTube + 1 //increment NoofTube by 1
     end if
    end for
  //calculate appearance probability for each of non-walking mode
   P(Bus) = NoofBus / M
   P(Bike) = NoofBike / M
   P(Car) = NoofCar / M
   P(Drive) = NoofDrive / M
   P(Tube) = NoofTube / M
  //CorrectedSample is set to the mode appeared most frequently
   if P(Bus) = MAX(P(Bus),P(Bike),P(Car),P(Drive),P(Tube))
     CorrectedSample(A_N) = 'Bus'
   end if
   if P(Bike) = MAX(P(Bus),P(Bike),P(Car),P(Drive), P(Tube))
     CorrectedSample(A_N) = 'Bike'
   end if
   if P(Car) = MAX(P(Bus),P(Bike-M),P(Car),P(Drive), P(Tube))
     CorrectedSample(A_N) = 'Car'
   end if
   if P(Drive) = MAX(P(Bus),P(Bike),P(Car),P(Drive), P(Tube))
     CorrectedSample(A_N) = 'Drive'
   end if
   if P(Tube) = MAX(P(Bus),P(Bike),P(Car),P(Drive), P(Tube))
     CorrectedSample(A_N) = 'Tube'
   end if
  else (if CurrentClassifiedSample (B_N) == 'walking')
     Do nothing and Continue to next sample
  end if
end while
```

V. RESULTS OF APPLYING POCOA TO REAL DATA

In addition to the accelerometer-based method reproduced according to [16] (see chapter III), the Discrete Hidden Markov Model (as described in [19]) has also been reproduced by applying the DHMM model to the results we generated in section III. This finally forms the following DT+DHMM classification results in Fig. 2 and 3.

The comparison between the original DT classification results (reproduced according to [16]), the DT+DHMM classification results (reproduced according to [19]), and the DT+PoCoA classification results are presented in Fig. 2 and 3.

According to the comparison between results from DT (white bars) and the results from DT+DHMM (grey bars), the overall accuracy has been improved from 62% to 69% after applying DT+DHMM. This is because the DHMM can eliminate outliers from the states transition matrix, which contains the likelihood of a transition between different states in the training set. For example, instances of cycling/tube-passenger are misclassified as being a car-passenger by DT, but (according to the state transition matrix) it is unlikely that there will be transitions from cycling/tube-passenger to car-passenger, so this inference is corrected by DHMM. However, DHMM still does not work properly in differentiating car-passengers and car-drivers. The precision and recall accuracy for car-driver increased little after applying DT+DHMM. This is because misclassifications between car-drivers and car-passengers frequently exist even in the training process. Thus, DHMM fails to eliminate outliers from the trained states in the transition matrix.

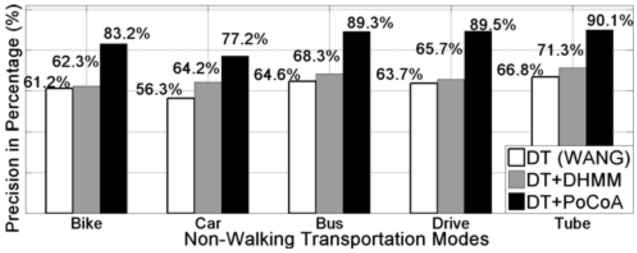

Fig. 2. Precision results for the reproduced accelerometer-based method [16], after applying the DT+DHMM [19], and after applying DT+PoCoA (correction window size: 4)

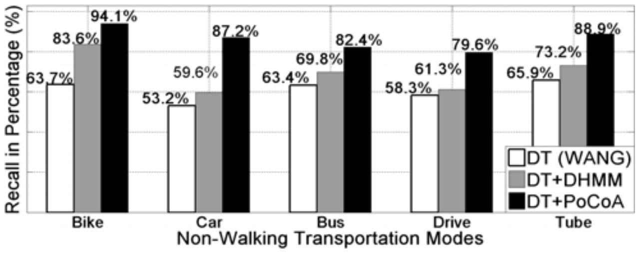

Fig. 3. Recall results for the reproduced accelerometer-based method [16], after applying the DT+DHMM [19], and after applying DT+PoCoA (correction window size: 4)

On the other hand, it is noted that the overall accuracy of the DT method (white bars) has been significantly improved (from 62% to 88%) after applying PoCoA (DT+PoCoA, black bars). This result also illustrates that PoCoA clearly outperforms the state of the art data outlier detection model (DT+DHMM) when used for transportation mode recognition. This is because in the PoCoA model, the transitions between any two non-walking transportation modes are strictly eliminated. As one non-walking period only contains one type of transportation mode, most misclassified samples are corrected according to such a context in the correction window.

The correction window size applied in Fig. 2 and Fig. 3 is 4. In our experiments, a correction window size with 4, not only enables a good accuracy improvement (over 25%), but also requires less time to cache previous samples. However, it is also found that larger correction windows lead to a higher accuracy improvement after applying DT+PoCoA. For example, 95% accuracy can be achieved for sub-differentiating motorised modes when a correction window size of 10 is applied.

All of the observations above are based on the experimental dataset collected. Although this dataset includes mobility data collected from 15 different subjects, it is still limited in terms of sample size and the variability of the original accuracy. In order to better evaluate PoCoA, we generated a larger data set based on proper simulations (see chapter VI).

VI. RESULTS OF APPLYING POCOA TO SIMULATED DATA

In this section, we synthesized a more generalised dataset from simulations to further validate PoCoA. Since PoCoA is applied after the use of typical classifiers (as Fig. 1 shows), we need to generate a larger number of original classified samples (denoted as B_N in Fig. 1). Based on this, the simulation needs to generate both correct-classified samples and misclassified samples to mimic real recognition process.

In probability theory, the count of the number of events and the time interval in which these events occur is normally a Poisson process [30]. The 'events' in our case are the transportation modes samples that are misclassified by typical classifiers. As it is a stochastic process of classification in reality, we thus hypothesize that such a transportation mode recognition process is a Poisson process and the inter-arrival times between consecutive misclassified samples follow an exponential distribution.

Using the following segment of classification results from WEKA as an example:

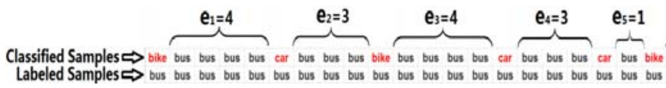

Fig. 4. An example of J48 classification results from WEKA.

For the sample of classification results (from WEKA) presented in Fig. 4, the "classified samples" whose modes are different from their "labelled samples" are considered as misclassified samples (as marked in red). In this case, the data set of the intervals between two consecutive misclassified samples is $E_{N=5} = [4, 3, 4, 3, 1]$, where $e_1 = 4$; $e_2 = 3$; $e_3 = 4$; $e_4 = 3$; and $e_5 = 1$. Also $p(e_1) = p(4) = 2/5 = 0.4$

Based on this, we applied the above calculation to all our experimental data to generate the blue dotted line in Fig. 5, and compared this with a cumulative distribution function of the standard exponential distribution (as shown in the red line in Fig. 5).

From Fig. 5, the X-axis (horizontal) is the interval between two misclassified samples. The Y-axis (vertical) is the probability of the occurrence of intervals that are equal to or smaller than the value of x. The equation for the blue dotted line is $Y = F(x) = P(X<=x)$ where $x = [1, 2, 3, 4,……]$.

The equation for F(x) is given in (1).

$$F(x) = P(X <= x) = \sum_{0}^{x} p(X) \quad (1)$$

The red line is the theoretical cumulative distribution function of a standard exponential distribution which is Y = F(x; λ). The equations for F(x; λ) are given as (2) and (3)

$$F(x;\lambda) = 1 - e^{-\lambda x} \quad (2)$$

where $\lambda = Var(E_N)^{-1/2}$ (3)

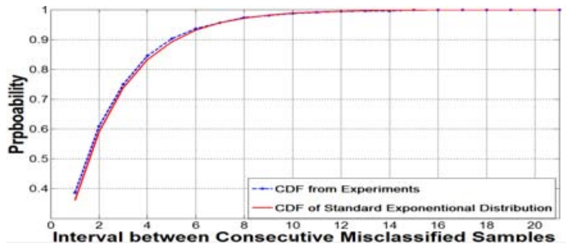

Fig. 5. Cumulative Distribution Function of intervals between two consecutive misclassified samples

From Fig. 5, it is observed the red line and blue dotted line match each other well. This result provides strong evidence (which also proves our hypothesis) that the transportation mode recognition process for urban commuters is a Poisson process.

Then, we conducted the whole simulation (data generated according to Poisson Process) as follows: First, a 100 sets of original data (which are denoted as classified samples B_N in Fig. 1) with different original accuracy (before applying PoCoA) are generated. The accuracy ranges from 1% to 100% with 1% as the interval. Each set contains one million samples. Second, for each data set generated, different correction window sizes ranging from 2 to 20 (with 2 as the interval) are tested. For each particular dataset (with original accuracy ranging from 1% to 100%) with each particular size of correction window (with size ranging from 2 to 20), the PoCoA algorithm has been applied according to the Pseudo code in chapter IV. The results of all combinations (100 different datasets * 10 different correction window sizes) have been presented in Fig. 6.

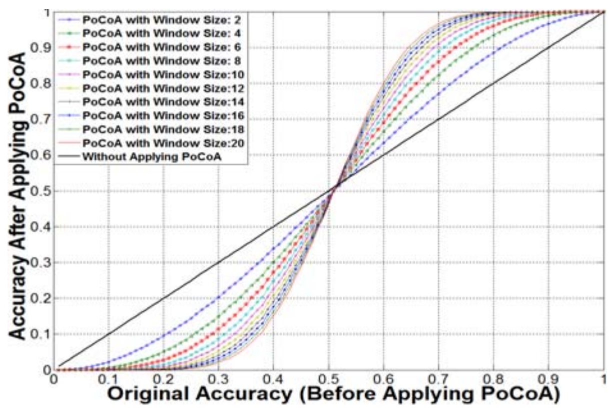

Fig. 6. The Simulation Results of Post Correction Algorithm with a Different Correction Window Size

The black straight line in the middle of Fig. 6 is the result without applying PoCoA, so it is used as a baseline to illustrate the accuracy changes after applying PoCoA using different correction window sizes.

Fig. 6 shows a tendency to have a central symmetry with a central point. A larger correction window size corresponds to a larger accuracy variation that either decreases or increases after applying PoCoA. The original accuracy of the data set needs to be higher than a baseline for PoCoA to be effective (to improve the original accuracy) after applying PoCoA. It is observed that this baseline accuracy is around 50%. For all data sets with an original accuracy higher than 50%, a larger correction window size corresponds to a larger accuracy improvement. This is because given the same original accuracy (higher than 50%), the larger the correction window size, the greater the chance that there will be more correct-classified samples than misclassified samples. Thus, PoCoA can correct misclassified samples according to the knowledge about the current mobility context. It is also found that given the same correction window size, the higher original accuracy leads to a higher accuracy after applying PoCoA. This is because given the same size of correction window for samples, a higher original accuracy leads to more correct-classified samples than misclassified ones. Thus, the majority misclassified samples will be corrected. The accuracy improvements tend to be zero as the original accuracy reaches 100%. This is because the absolute number of misclassified samples tends to be zero as the original accuracy reaches 100%.

VII. Discussion

In a practical system, one must consider both computational and energy costs. Mobile devices cannot dedicate their full computing resources to auxiliary applications given that its primary use is for interactive and communication type applications. This makes PoCoA even more feasible than DHMM, since, as the pseudo code shows in section IV, the core algorithm used for PoCoA is quite computationally light. However, the Viterbi algorithm (the core algorithm for DHMM) is too computational heavy to be applied on mobile devices [31]. A more quantitative estimation of computational load forms part of future research.

Though we found that a larger correction window size leads to a higher accuracy improvement, one also needs to balance time-efficiency against accuracy improvements when applying PoCoA in real-time systems. For the accelerometer-based method used in [16], one classified sample corresponds to around 8 seconds in real time, which means a correction window of size “4” would require about 30 seconds for the system to start up and to cache results to facilitate the reuse in real time. We leave exploring this delicate balance between efficiency and accuracy to future work.

VIII. Conclusion

In this work, the potential benefits of applying a new Post Correction Algorithm (PoCoA) to improve transportation mode recognition, after applying typical classifiers have been examined. In addition PoCoA has been compared against a state of the art (DT+DHMM) classifier [19] based on an accelerometer-based method used in [16]. Data from six transportation modes, (walking, cycling, bus passenger, tube passenger, car passenger, and car driver), undertaken by 15 different users represents our experiment data. The results show that PoCoA method enables a higher accuracy (88%) and a more fine-grained recognition capability (sub-differentiate motorised mode) when applied to an accelerometer-based method. PoCoA also outperforms the DT+HDMM system [19] in terms of both higher accuracy and less computational complexity. Finally, additional simulated results illustrate the potential usefulness of PoCoA to improve other transportation mode recognition methods with original accuracy higher than 50%.

ACKNOWLEDGMENT

This work was made possible in part thanks to the financial support of a scholarship from Queen Mary University of London. This work also has been carried out as part of the ASSET (Adaptive Security for Smart Internet of Things in eHealth) research project funded by The Research Council of Norway VERDIKT program (Grant No: 213131/O70).

REFERENCES

[1] S. Consolvo, P. Klasnja, D.W. McDonald, D. Avrahami, J. Froehlich, L. LeGrand, R. Libby, K. Mosher, and J.A. Landay, "Flowers or a robot army?: encouraging awareness & activity with personal, mobile displays", in 10th Int. Conf. on Ubiquitous computing, pp. 54-63, 2008, ACM.

[2] N. Streitz and P. Nixon, "Special issue: The disappearing computer", in Communications of the ACM, pp. 32-35, 2005, ACM.

[3] M. Mun, S. Reddy, K. Shilton, N. Yau, J. Burke, D. Estrin, M. Hansen, E. Howard, R. West, and P. Boda, "PEIR, the personal environmental impact report, as a platform for participatory sensing systems research", in 7th Int. Conf. on Mobile systems, applications, and services, pp. 55-68, 2009, ACM.

[4] J. Froehlich, T. Dillahunt, P. Klasnja, J. Mankoff, S. Consolvo, B. Harrison, and J.A. Landay, "UbiGreen: investigating a mobile tool for tracking and supporting green transportation habits", in 27th Int. Conf. on Human factors in computing systems, pp. 1043-1052, 2009, ACM.

[5] "CarbonHero. Carbon diem - Is that knowledge now", Available from: http://carbondiem.com. (last retrieved on April 2013)

[6] J. Kao, Lam, R., Pong, G., Talukdar, T., AND Wong, J. "Ecorio - Track Your Mobile Carbon Footprint", 2008; Available from: http://ecorio.org. (last retrieved on April 2013)

[7] E. Agapie, G. Chen, D. Houston, E. Howard, J. Kim, M. Mun, A. Mondschein, S. Reddy, R. Rosario, and J. Ryder, "Seeing Our Signals: Combining location traces and web-based models for personal discovery", in 9th workshop on Mobile computing systems and applications, pp. 6-10, 2008, ACM.

[8] S.J. Preece, J.Y. Goulermas, L.P.J. Kenney, D. Howard, K. Meijer, and R. Crompton, "Activity identification using body-mounted sensors—a review of classification techniques", Physiological measurement, pp. R1-R33, 2009.

[9] A. Subramanya, A. Raj, J. Bilmes, and D. Fox, "Recognizing activities and spatial context using wearable sensors", in Proceedings of the Twenty-Second Conference on Uncertainty in Artificial Intelligence, 2006.

[10] T. Brezmes, J.L. Gorricho, and J. Cotrina, "Activity recognition from accelerometer data on a mobile phone", Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living, pp. 796-799, 2009.

[11] D. Mizell, "Using gravity to estimate accelerometer orientation", in 7th IEEE International Symposium on Wearable Computers, pp. 252-253, 2003.

[12] J. Parkka, L. Cluitmans, and M. Ermes, "Personalization algorithm for real-time activity recognition using PDA, wireless motion bands, and binary decision tree", Information Technology in Biomedicine, IEEE Transactions on, Vol. 5, pp. 1211-1215, 2010.

[13] N. Ravi, N. Dandekar, P. Mysore, and M.L. Littman, "Activity recognition from accelerometer data", in American Association for Artificial Intelligence, pp. 1541-1546, 2005, MIT Press.

[14] H. Cho, S. Kim, J. Baek, and P.S. Fisher, "Motion recognition with smart phone embedded 3-axis accelerometer sensor", IEEE Int. Conf. in Systems, Man, and Cybernetics (SMC), pp. 919-924, 2012.

[15] J. Liu, M. Goraczko, A. Kansal, D. Lymberopoulos, S. Nath, and B. Priyantha, "Subjective Sensing: International Awareness for Personalized Services", NSF Workshop on Future Directions in Networked Sensing Systems: Fundamentals and Applications, 2009.

[16] S. Wang, C. Chen, and J. Ma, "Accelerometer based transportation mode recognition on mobile phones", in 2010 Asia-Pacific Conference on Wearable Computing Systems (APWCS), pp. 44-46, 2010, IEEE.

[17] L. Liao, D. Fox, and H. Kautz, "Extracting places and activities from gps traces using hierarchical conditional random fields", The International Journal of Robotics Research, Vol. 1, pp. 119-134, 2007.

[18] Y. Zheng, L. Liu, L. Wang, and X. Xie, "Learning transportation mode from raw gps data for geographic applications on the web", in Proceedings of the 17th Int. Conf. on World Wide Web, pp. 247-256, 2008, ACM.

[19] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, "Using mobile phones to determine transportation modes", ACM Transactions on Sensor Networks (TOSN), Vol. 2, pp. 13:01-13:27, 2010.

[20] Y. Wang, J. Lin, M. Annavaram, Q.A. Jacobson, J. Hong, B. Krishnamachari, and N. Sadeh, "A framework of energy efficient mobile sensing for automatic user state recognition", in Proceedings of the 7th Int. Conf. on Mobile systems, applications, and services, pp. 179-192, 2009, ACM.

[21] J.R. Blum, D.G. Greencorn, and J.R. Cooperstock, "Smartphone sensor reliability for augmented reality applications", in Mobiquitous --- 9th Int. Conf. on Mobile and Ubiquitous Systems: Computing, Networking and Services, 2012.

[22] H. Lu, J. Yang, Z. Liu, N.D. Lane, T. Choudhury, and A.T. Campbell, "The Jigsaw continuous sensing engine for mobile phone applications", in Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, pp. 71-84, 2010, ACM.

[23] E. Miluzzo, N.D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S.B. Eisenman, X. Zheng, and A.T. Campbell, "Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application", in Proceedings of the 6th Int. Conf. on Embedded network sensor systems, pp. 337-350, 2008, ACM.

[24] J. Lester, T. Choudhury, N. Kern, G. Borriello, and B. Hannaford, "A hybrid discriminative/generative approach for modeling human activities", in Proceedings of the 19th Int. joint Conf. on Artificial intelligence, 2005.

[25] A. Bulling, J.A. Ward, H. Gellersen, and G. Tröster, "Robust recognition of reading activity in transit using wearable electrooculography", pp. 19-37, 2008, Springer.

[26] I.H. Witten, E. Frank, and M.A. Hall, "Data Mining: Practical machine learning tools and techniques", Second Edition (Morgan Kaufmann Series in Data Management Systems), 2005, San Francisco, CA: Morgan Kaufmann Publisher Inc.

[27] G.J. McLachlan, K.A. Do, and C. Ambroise, "Analyzing microarray gene expression data", Vol. 422, pp. 37-53, 2004, John Wiley & Sons.

[28] Y. Makihara, B.S. Rossa, and Y. Yagi, "Gait recognition using images of oriented smooth pseudo motion", IEEE Int. Conf. in Systems, Man, and Cybernetics (SMC), pp. 1309 - 1314, 2012.

[29] S. Yeh, K.H. Chang, C.I. Wu, H. Chu, and J.Y. Hsu, "GETA sandals: a footstep location tracking system", Personal and Ubiquitous Computing, Vol. 6, pp. 451-463, 2007.

[30] S. Katti and A.V. Rao, "Handbook of The Poisson Distribution", Technometrics, Vol. 2, pp. 412-412, 1968.

T.S. Jaakkola and D. Haussler, "Exploiting generative models in discriminative classifiers", Advances in neural information processing systems, pp. 487-493, 1999.