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Genetic Programming Based Activity Recognition on A Smartphone Sensory Data Benchmark

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***Abstract*—Activity recognition from smartphone sensor inputs is of great importance to enhance user experience. Our study aims to investigate the applicability of Genetic Programming (GP) approach on this complex real world problem. Traditional methods often require substantial human efforts to define good features. Moreover the optimal features for one type of activity may not be suitable for another. In comparison, our GP approach does not require such feature extraction process, hence, more suitable for complex activities where good features are difficult to be pre-defined. To facilitate this study we therefore propose a benchmark of activity data collected from various smartphone sensors, as currently there is no existing publicly available database for activity recognition. In this study, a GP-based approach is applied to nine types of activity recognition tasks by directly taking raw data instead of features. The effectiveness of this approach can be seen by the promising results. In addition our benchmark data provides a platform for other machine learning algorithms to evaluate their performance on activity recognition.**

I. Introduction

Activity recognition refers to detecting human behaviours often from time series stream input. Machine vision and body sensor networks are two traditional ways for activity recognition. However, both of these approaches have drawbacks. To identify one's behaviours from videos, the subject needs to be extracted from the backgrounds, distinguished from other people, and tracked. Each step before the actual recognition is a difficult problem on its own. Furthermore, dealing with high dimensional video data in real time may impact on accurate recognising of human. In comparison, body sensor networks can be much less sensitive to the surroundings. However sensor networks are less practical in real world scenarios as it is inconvenient for human wearing wired sensor-equipped devices around the body all day, not mentioning the interference from domestic appliances. Mobile phones with multi-modal sensors and reasonable computational capability open an opportunity to a light-weight, affordable but still effective alternative for Activity Recognition.

Recognising human activities is usually formulated as a time series classification problem which associates a vector of extracted features from a fixed time period with a certain activity label. To construct an useful feature set, carefully studying the activity is often a necessary step. Firstly the length of the time series pattern has to be identified. This length is used in windowing process which takes meaningful segments out of an input stream. Secondly a set of feature values need to be extracted to facilitate the separation between interesting patterns and all the rest of time series. Such processes are usually time consuming, and often require priori knowledge. Moreover, the effectiveness of a features set is determined by the nature of time series patterns and therefore not transferable from problem to problem. For example, frequency domain features will be more suitable for periodical activities such as running and walking. However, they may not be suitable for static activities such as sitting and standing. Therefore a classifier requiring no manual feature extraction process can be more problem independent. We propose a Genetic Programming based method that takes raw data as input and conducts feature extraction and activity recognition in one step.

Another issue associated with mobile phone based Activity Recognition is that no established benchmark dataset is available. Different groups maintain their own data sets and report the performance based on these data. Such data sets are often gathered under different environments, using different protocols. The collection processes are also usually tailor-made for specific research purposes. So even if the classification tasks are the same, fairly assessing different approaches is still difficult. A unified platform for evaluating various action recognition methodologies would be desirable. Moreover, as experimental setups can be expensive and time consuming, a reusable data set will be beneficial to the research community. This data set should be collected in naturalistic environment rather than a constrained lab because people may not behave as normal when being monitored in a lab setting. Also, situations frequently occurring in real-world such as turning a corner, uneven ground and bumping into another person may not be captured under laboratory environments.

To address these issues, in this paper we present a GP method and the study on a dataset collected from mobile phones placed on different positions on a range of subjects. This dataset is consisted of most common daily activities data collected under naturalistic environment, including: sitting, standing, walking, running, lying down, going upstairs and going downstairs. A benchmark study that using GP to detect each of the 7 activities from raw, multi-channel sensory data is carried out. In a broader sense, going upstairs and going downstairs can be considered as walking. Consequently, combining these two with walking on plain ground as one class is sensible. GP is applied on two additional tasks: one is detecting all these three walk gaits and the other is to identify static status of the subjects. The experimental results show that GP can achieve consistently good performance for individual validation, i.e. training and testing on the subject. On activities of standing, running, being still and walking (3 gaits), the GP programs are tolerant to the variabilities across arbitrary subjects to some extent. Other three classical machine learning algorithms(J48 [23], Naïve Bayes [12] and SVM [13]) were used for comparison.

II. Related Work

1) Vision Based Activity Recognition: The KTH data [26] and the Weizmann dataset [5] are the two earliest well-known datasets for vision-based activity recognition. Low-resolution videos are taken under lab environment with a static and clear background. Moreover, camera motions are totally not involved and all the activities are performed following the scripts. On both datasets, over 95% accuracy has been achieved by state-of-art techniques.

Recently, researchers have turned to more realistic videos. Laptev et al. [15] proposed Hollywood-1 datasets including video fragments from different movies. This dataset is further extended to Hollywood-2 dataset by adding more activities and videos [19]. These two datasets still pose a challenge to all existing techniques. Sport videos are another source of activity dataset [21]. In these datasets, the videos are all of high quality and taken from some particular viewpoints. The least constrained data set by now is constructed in 2009 [17] which consists of a big collection Youtube videos.

Although substantial efforts have been made to improve the performance, recognising human behaviours based on camera input remains an unsolved problem. The challenges include cluttered background, moving cameras, poor illumination, varying appearance of subjects and frequent occlusions.

2) Body Sensor Based Activity Recognition: Body-wore sensors are not affected by the surroundings and lighting conditions. They are more suitable than cameras when multiple people appear within a close proximity. Past works on wearable sensor system first relied on one sensor only [2], [20], [24] and then became more interested in multimodal sensors [1], [22], [30]. Sensors can also be placed on daily-used objects such as doors, cabinets and micro-ovens to obtain further contextual information [9].

In 2004, Bao and Intille [2] collected inertial data from 20 subjects by five bi-axial accelerometers placed tightly on limbs and hip. The major part of the data is obtained without any supervision or monitoring in a natural environment and the rest in a controlled laboratory. All the subjects recorded the start time and the end time of each activity themselves in a dairy. As it takes time for the subjects to make notes, some records can not be well aligned to the activity labels. To minimise mislabelling, the records within 10s to start/end points have been discarded. Overall, the accuracy rate reported by this study is 84%. Intille et al. [11] designed and operated a laboratory called PlaceLab for subjects to live in and do their daily activities. To build such a lab is time consuming and expensive. At the same time, the artificial environment makes the research less applicable in real world.

Another well-known public dataset is OPPORTUNITY activity recognition dataset [25]. A total of 72 sensors are integrated in the controlled environment by placing on objects and humans. This research mainly interested in the recognition of both locomotion(sit, stand,walk and lie) and gestures. Additive and rotative noises are added to the test sets to simulate real-world scenarios.

Overall, in wearable sensor network system, subjects are required to take multiple devices on different parts of the body, which hinders normal activities. This obstructive configuration makes these techniques less practical to long-term and large-scale real-world applications. In addition, the data are usually collected in a non-naturalistic environment, which makes the assessment less realistic.

3) Mobile-based Activity Recognition: One may argue that the information gathered from a single position can not be sufficient for accurate activity recognition. However, the experimental results show that reasonable results can be achieved even when only one accelerometer is used [3], [7], [14], [18]. The performance can be further improved by employing sensors of multiple types. Lester et al. [16] demonstrated by using extra audio and barometric pressure sensor the accuracy can be improved by $30 \sim 50\%$ approximately. Moreover, GPS is useful to decide travel modes of users [27] by implying their velocity.

The sensor readings can be very different when a mobile phone is placed at different body positions. For example, the time series recorded in pant pocket appears periodical patterns but the one recorded in the backpack shows patterns of vibration [18]. One straightforward way to address this issue is always using a pre-defined placement [14]. Recently, more researches are devoted to investigate how different mobile phone placements affect on the performance, including constructing placement-independent features [18], dynamically determining phone placement in run time [16] and finding a placement that is optimal for all activities[4] .

Like other time series classification tasks, features play a very important role in mobile phone based activity recognition. Firstly a suitable window size should be defined to extract meaningful time series segments from streams. Then a set of features are to be constructed based on these segments. The window size and the features are usually learnt from intuitions, empirical experience and domain knowledge [3], [14], [16], [18], [27], [28]. However, whether a feature set is proper is dependent on specific activity to be recognized [8]. There is no universally useful feature set for all activity recognition task. Our GP method avoids the feature extract process and hence can be problem independent.

III. Data Collection

A. Hardware

Three Android smart phones are used in this data collection: Samsung Galaxy S4 GT-I9505, Sony Xperia C6903 and HTC One. All these mobile devices have 3-axis inertial sensors: accelerometer, gyroscope and magnetic sensor. All the details are shown in Table I. We use a sample rate of 30Hz which is less frequent than the maximum sample rate of all sensors.

B. Data Collection Protocols

The data collection is a naturalistic process as all the subjects are allowed to do activities in public places or at home rather than a built up laboratory. A researcher stays a distance within the subjects to observe their activities. This researcher may give instruments such as “please sit down on the couch

TABLE I. CONFIGURATION OF PHONES

Phone	Sensor	Type	Maximum Sample Rate (HZ)
Samsung Galaxy S4 GT-I9505	Accelerometer	STMicroelectronics K330 Accelerometer	100
	Gyroscope	STMicroelectronics K330 Gyroscope	100
	Magnetic Field	Yamaha YAS532	100
Sony Xperia C6903	Accelerometer	BOSCH BMA255	200
	Gyroscope	BOSCH BMG160	200
	Magnetic Field	BOSCH AK8963	50
HTC One	Accelerometer	BOSCH BMA250	100
	Gyroscope	ST Group R3GD20	83
	Magnetic Field	AKM AK8963	100

for a rest" or "please go the level 4 by stairs" to enable each session covers more activities.

The subjects are told that standard behaviours are preferred but not mandatory. They are allowed to conduct any activities freely, such as standing still or turning around, sitting upright or relaxed, walking fast or slowly. All activities can be interrupted as they are taken in real-world scenario. For example, a subject gives the way to others or opens a door. So even for the same activity that is conducted by the same subject, the variations can be substantial. This generates great realistic difficulties for recognition.

A web server is used for continuously storing time series data, marking labels and synchronizing data with labels. These sensory data are stored in mobile devices and sent to the server through wireless connection. This eliminates the possibility of data loss caused by unstable internet connection. The other function of the server is providing an user interface to correctly record the labels (see details in Section III-B1). Data and the corresponding labels are then combined for supervised learning. Figure 1 demonstrates the infrastructure of data collection, each phone for data collection is connected to the server individually and so is the portable device for labelling. They are all synchronised using the server time.

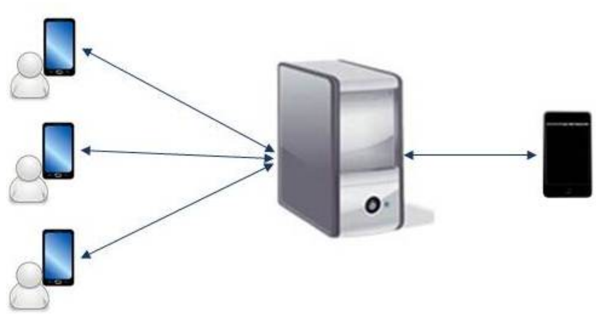

Fig. 1. The infrastructure for Data Collection

1) Labelling: The subjects control the start and the end of whole recording by a phone application. It starts to record sensory readings when the "Start" button is pressed. This process can be terminated by pressing "End" Button. However, the subjects do not label those data themselves, because self-report can be error-prone. It is also inconvenient and aggravating for the subjects because taking pens around and making notes time to time can severely disrupt their activities. In addition, the labels near the start and end points would not be accurate and need manual adjustment [2], which makes the data less realistic. Another labelling method is to take videos and check the labels frame by frame. This method costs much time and human efforts and therefore is not suitable for large scale data set collection. In this study, a researcher is responsible for observing the subjects and marking the ground truth. The researcher can access the server by a given web URL and record the on and the off of every activity. Any activities not falling in any target categories will go to "Others".

2) Synchronization: The smart phones can be synchronized to the server time by the application mentioned in Section III-B1. By pressing "Set time" Button, the phones will first record the current device time T_m and then send a http request to acquire current server time T_s. As the duration of internet connection D_c can be easily obtained, the difference of time system between the phone and the server will be $|t_s - t_m + D_c|$. The timestamps will then be adjusted according to this difference and sent back to the server together with sensor data.

The sensor data is sampled over regular time intervals while the according labels could be marked at any time points during the recording. So even after the synchronization, the start time and the end time of an activity label may not be perfectly matched to all timestamps in the sensor data recording. Hence, closest match is used here.

C. Data Set

This data set is acquired from 5 healthy subjects of both genders, all around 28 years old. For each subject three sessions are taken, each session is around 10 minutes. In total, there are about 2.5 hours of recording. For each subject, two sessions are randomly chosen for training and the rest one for testing. Three mobile placements are available: A. Coat Pocket, B. Front Pant Pocket and C. Back Pant Pocket, recorded by Samsung, Sony and HTC respectively. All the placements refer to the right side of the body. Table II shows the gender, the environment of the data collection and the placements of mobile phones. The subjects are allowed to only use the preferred placements. The data is collected in various environments: in domestic houses or some public places. Subject 4 is recorded under an environment unfamiliar to her.

TABLE II. THE INFORMATION OF SUBJECTS AND DATA COLLECTION

Subject	Gender	Environment	Phone Placements
1	male	domestic house	A,B
2	female	office buildings	A,B
3	male	office buildings	A, B, C
4	female	office buildings	A, B, C
5	female	office buildings	A, B, C

IV. GP-BASED ACTIVITY RECOGNISER

Genetic Programming based method is the main learning paradigm for this task. With proper computational model language, GP is capable to operate on a collection of raw data points and construct features automatically. The key for GP to evolving good solutions is an effective set of functions and terminals. In this study, we present a GP representation specifically designed for time series classification.

A. Function Set and Terminal Set

The function set contains four basic arithmetic operations and three functional operations that are introduced for multiple channel time series classification:

Function Temporal_Diff(double input) takes one parameter as the input. The output of this function is the difference between the current data point and its previous reading. Despite being a simple operator, this function shows both the intensity and the direction of temporal changes.

Function Window(double input, int temporal_index, int temporal_operation) stimulates a sliding window which segments short time series pieces from the data stream. The first parameter reads numeric values and reserves most recent 12 readings. The value of 12 is learnt from empirical studies. The second parameter does a closer search for relevant time points by selecting only a subset of them. The third parameter decides the characteristic that are taken out from raw readings. The last two parameters come from special terminals (*Temporal_Index* and *Temporal_Operation* respectively) whose values are tuned throughout the evolutionary process. **Terminal Temporal_Index** ranges from 1 to $2^{12}-1$. Arbitrary points within a segment can be selected by the equivalent binary string of this integer value. **Terminal Temporal_Operation** selects one of four available operations: AVG(average), STD(standard deviation), DIF(the sum of difference between consecutive points) and SKEWNESS(skewness). This function and ''Temporal_Diff'' function are essentially searching for useful features along time axis.

Function Multi_Channel(int channel_index, int channel_operation) works similar as function *"Window"*, but on channels rather than time points. The two terminals for this function are *Channel_Index* and *Channel_Operation*. **Terminal Channel_Index** is an integer between 1 and $2^M - 1$ (M is the number of channels). It functions similarly to Temporal_Index. **Terminal Channel_Operation** indicates an operation for its parent *"Function Multi_Channel"*. It has 4 optional values: MED(medium),AVG(average), STD(standard derivation) and RANGE(the distance between the maximum and minimum values.

Only one terminal called **Terminal Channel[X]** is general to multiple functions. It reads the latest value of the Channel No. X. More details of our GP representation can be found in [29].

B. Fitness Function

In this study GP is applied to a range of binary classifications, distinguishing one activity (marked as positives) from all others (marked as negatives). So the data can be highly unbalanced. We use Area Under Curve(AUC [6]) rather than accuracy for evaluation during training phase, against the possible negative affect caused by skewed data distribution. The threshold corresponding to the top left corner of AUC curve is used in test as boundary between the positive class and the negative class.

C. GP configuration

The GP runtime parameters are shown in Table III, the population size is set to 1000 due to the complexity of the problem. The other parameters follow a standard GP setting (shown in Table III).

TABLE III. GP CONFIGURATION

Population Size	1000
Generation	50
Minimum Depth	2
Maximum Depth	8
Mutation Rate	0.05
Crossover Rate	0.85
Elitism Rate	0.1

V. RESULTS

The proposed GP method is applied on a range of binary time series classification tasks as mentioned previously including sitting, standing, walking, running, lying, going upstairs and going downstairs. GP has to find a classifier to distinguish each activity from all the other classes. Aside from this, two tasks including the recognition of being still and walking (3 gaits) are conducted additionally. Being still refers to a subject stays relatively stationary even compared to some of the "inactive" activities, i.e. sitting,standing and lying. In walking (3 gaits), we include going upstairs and going downstairs with normal walking as one class. We expect these recognition can be handled by GP as the intensity of acceleration for these activities may form patterns distinguishable enough for GP to build accurate classifiers.

For each task GP runs for 10 times to compensate the variations across runs. We report the best of the 10 runs on test data as the final output. Three traditional algorithms are used for comparison: J48, Naive Bayes and SVM, all from the Weka machine learning system [10]. They all use default parameter settings. These three classifiers are provided four features, that is, for each channel the average, standard deviation, maximum value and minimum value of a sliding window (size 12). The window size is also used by GP to ensure they gain the same amount of information.

Table IV shows the test accuracy, True Positive rate (TP) and True Negative rate (TN) when 3 traditional classifiers and GP are trained and tested at the front pant pocket for each subject. GP is highlighted if GP achieves better or at least comparable results with its comparisons. Otherwise, the best performer is highlighted instead. We can see that GP can obtain good performance in task of detecting sitting, standing, running, lying and being still. For these 5 activities, the test accuracy is above 95%, with reasonable accurate recognitions of the positives. The detection rate decreases when three walk gaits are treated separately, only around 85% of instances can be correctly recognised. The overall performance increased around 5%-10% when they were considered as one class.

Compared to GP, the traditional algorithms occasionally work similarly or slightly better than GP. However, none of those three algorithms can achieve consistently good results over all activities across various subjects. For example, the results of using SVM to detect walking and walking (3 gaits) are very promising. It outperforms GP for all subject expect for subject 2. While in detecting going upstairs and going downstairs, SVM fails to recognise most of positive instances. The high accuracies are only caused by unbalanced data. The low TP rate reveals that those classifiers did not actually capture any patterns. Decision tree and Naïve Bayes perform even worse. Overall, GP is superior than the others. Note that traditional classifiers are provided with manually extract features while GP works on raw data.

GP obtained the similar performance (shown in Table V) as Table IV at back pant pocket. One interesting observation is that overall the recognition performance on going upstairs is better than the other two walking gaits. It may be because going upstairs involves more energetic movements on thighs and therefore induces distinguishable patterns i.e. greater rotations and higher accelerations on the phones. Also, detecting walking in gaits seems easier to GP than any of its three subclasses. It is sensible as the differences between the subclasses are more subtle and consequently the patterns are more difficult to capture.

It is slightly different when phone being placed at coat pocket. As Table VI shown, recognition of sitting does not maintain the consistent good performance as at the other two placements. It is even worse when the subjects lying down, for Subject 3 and Subject 4 nearly no positives can be identified. A possible reason is that the coat can be unzipped and unbuttoned so the pocket can swing around and move unconstrained inside of pocket. When a subject lying down, the phone may remain in the status from the last movement. The orientations, angles and the relatively position to the subject become unpredictable. For example, a subject can be on top of the phone or the other way around. In future work we will conduct statical tests verify these analysis. Furthermore, going upstairs does not perform well. A possible reason can be that movement from the leg can hardly be sensed from the coat pocket. In spite of that, GP still shows a higher success rate.

The test file of Subject 5 does not include any sitting instances. A hyphen is placed in the tables for clarification. However, it should be noted that nearly all negatives have been successfully classified.

Table VII shows how GP programs that are trained based on Subject 1 can work well on all other subjects. For Subject 1 with phone placed at front pant pocket, the results are duplicated from Table IV. No results for coat pocket are presented here as Subject 1 did not use that placement in data collection. We can see that in detecting activity of standing, running, being still and walking (3 gaits), GP can find programs that are relatively generic to different people. It is unexpected to see that among three static activities standing, sitting and lying, only standing appears in this case. The reason can be that when people are standing the thighs are vertical while it is almost horizontal when sitting or lying. Hence standing is more differentiable than the other two activities. The performance of traditional methods is even much worse in comparison. In Table VII, a ($\simeq$) symbol appearing after the accuracy value indicates that one of three traditional classifiers is comparable with or better than GP (the classifiers should also be reusable of which the accuracy, TP and TN above 80%). In other detection tasks, they could be slightly better than GP but the classifiers remain unusable. In most of failure cases, no positive instances can be detected. Such outcome shows that GP method is more generalizable and suitable in finding features suitable across different subjects. The other 4 tables demonstrating the cross-person results share similar content with Table VII so they are not presented here.

Table VIII presents the cross-placement results for each subject. We can see from that the evolved classifier only achieve the some reusability on some tasks, for example recognising running and staying still. The three traditional methods achieve better or comparable results on these two tasks. However, they are less effective than GP on detecting standing and going upstairs. Note that GP is compared to the best of three classifiers. Still, a considerable number of traditional classifiers resulted in very poor true positive rate ($< 5\%$).

VI. Conclusion and Future Work

Activity Recognition is a research topic with increasing importance. In comparison with the tradition machine vision based and body sensor network approaches, the ubiquitous smart phones bring a novel way that is non-obstructive and effective for human activity recognition. However it also pose a new challenge as the signals are often collected at only one place on a person and there are significant variation in phone's position. Moreover a phone usually have more freedom in movement inside owner's pocket, which introduces more uncertainty.

Based on our study we argue that a GP-based method is more suitable for this complex recognition problem as it requires no manual feature exaction and can be applied on real world stream data set various recognition tasks. In comparison with three traditional classifiers with manually constructed features on these tasks, GP is more successful to find accurate classifiers for each subject over all tasks. The evolved programs are also more general as they can be applied on subjects that have not be seen during the training. We conclude that with a proper representation i.e. a set of functions and terminals, GP can effectively extract time series features and achieve good recognition performance.

Moreover, this study provides a publicly available activity data set which can serve as an evaluation benchmark for measuring the performance of activity recognition methods. The data collection employs a natural protocol and allows great diversity among different sessions of the same subject. The data set can become a unified testbed for researchers to evaluate their algorithms and conduct fair comparisons.

In the near future we will expand the data collection to include more subjects and more activities. In addition we will extend the GP methodology itself to include more effective function and terminal sets, especial functions which can better identify the duration of an activity. Methods to improve cross-subject and cross-position performance will also be investigated to improve the usability of our GP method for complex real world activity recognition.

TABLE IV. TEST RESULTS: ACCURACIES, TRUE POSITIVE AND TRUE NEGATIVE RATES (%) OF INDIVIDUAL TRAINING AND TESTING FOR EACH SUBJECT WITH THE PHONE PLACED AT FRONT PANT POCKET

	Sitting				Standing				Walking			
	J48	NBayes	SVM	GP	J48	NBayes	SVM	GP	J48	NBayes	SVM	GP
Subject 1	91.94 TP: 22.8 TN: 99.3	87 TP: 51.8 TN: 90.7	90.4 TP: 0 TN: 100	**96.5** **TP: 74.4** **TN: 98.9**	94.96 TP: 50.9 TN: 99.4	99.36 TP: 94.4 TN: 99.9	99.17 TP: 93.8 TN: 99.7	**99.1** **TP: 96.5** **TN: 99.4**	81.97 TP: 79.7 TN: 83.6	78.43 TP: 87.6 TN: 72	88.62 TP: 83.9 TN: 91.9	**87.4** **TP: 95.3** **TN: 81.8**
Subject 2	96.15 TP: 95.8 TN: 98.6	88.62 TP: 0 TN: 100	77.31 TP: 70 TN: 99.5	**99.6** **TP: 99.7** **TN: 99.5**	99.32 TP: 96.4 TN: 99.7	87.27 TP: 0 TN: 1	99.67 TP: 99.6 TN: 99.7	**99.2** **TP: 94.7** **TN: 99.9**	85.01 TP: 78.2 TN: 88.2	69.85 TP: 6.2 TN: 99.7	76.28 TP: 98.4 TN: 65.9	**87.5** **TP: 93.7** **TN: 84.5**
Subject 3	89.55 TP: 72.6 TN: 94.8	80.19 TP: 98.7 TN: 74.5	99.34 TP: 99.3 TN: 99.4	**97.8** **TP: 99.0** **TN: 97.4**	99.49 TP: 92.3 TN: 100	99.46 TP: 95.8 TN: 99.7	99.57 TP: 95.4 TN: 99.9	**99.3** **TP: 94.4** **TN: 99.7**	**89.30** **TP: 83.0** **TN: 91.3**	76.54 TP: 97.3 TN: 69.9	90.19 TP: 88.3 TN: 90.8	85.1 TP: 86.1 TN: 84.8
Subject 4	87.72 TP: 35.4 TN: 98.3	93.9 TP: 65.4 TN: 99.6	93.6 TP: 64 TN: 99.6	**96.0** **TP: 87.0** **TN: 97.8**	99.76 TP: 96.9 TN: 99.9	99.66 TP: 93.7 TN: 99.9	99.49 TP: 90.9 TN: 99.9	**99.6** **TP: 98.8** **TN: 99.7**	90.14 TP: 90.9 TN: 89.7	78.00 TP: 96.4 TN: 66.7	**90.52** **TP: 91.3** **TN: 90**	85.9 TP: 87.6 TN: 84.8
Subject 5	-	-	-	-	99.28 TP: 86.6 TN: 99.7	99.51 TP: 92.7 TN: 99.8	99.26 TP: 81.5 TN: 99.9	**99.0** **TP: 98.8** **TN: 99.0**	84.47 TP: 79.9 TN: 87.3	76.27 TP: 94.2 TN: 65.2	**87.77** **TP: 84** **TN: 90.1**	83.3 TP: 87.1 TN: 80.9

	Running				Lying				Going Downstairs			
	J48	NBayes	SVM	GP	J48	NBayes	SVM	GP	J48	NBayes	SVM	GP
Subject 1	97.96 TP: 98.2 TN: 97.9	78.74 TP: 99.3 TN: 72.7	93.94 TP: 98.8 TN: 92.5	**99.4** **TP: 98.3** **TN: 99.8**	97.7 TP: 98.8 TN: 97.6	92.66 TP: 0 TN: 100	88.94 TP: 100 TN: 88.1	**96.8** **TP: 100.0** **TN: 96.6**	91.58 TP: 12.6 TN: 94.1	84.89 TP: 52.6 TN: 85.9	91.64 TP: 30.6 TN: 93.6	**92.7** **TP: 87.4** **TN: 92.9**
Subject 2	99.24 TP: 97.1 TN: 99.4	99.57 TP: 97.7 TN: 99.7	97.58 TP: 99.1 TN: 97.4	**98.0** **TP: 98.4** **TN: 98.0**	88.12 TP: 0 TN: 100	88.12 TP: 0 TN: 100	98.58 TP: 100 TN: 98.4	**99.4** **TP: 100.0** **TN: 99.4**	89.98 TP: 0 TN: 99.7	91.45 TP: 22 TN: 99	90.25 TP: 0 TN: 100.0	**89.4** **TP: 48.2** **TN: 93.9**
Subject 3	99.02 TP: 95.4 TN: 99.3	90.61 TP: 97.4 TN: 90.2	99.63 TP: 96.5 TN: 99.8	**99.2** **TP: 96.9** **TN: 99.3**	80.7 TP: 0 TN: 100	76.61 TP: 98.9 TN: 71.3	99.03 TP: 98.8 TN: 99.1	**99.2** **TP: 98.2** **TN: 99.4**	94.17 TP: 52.9 TN: 98.1	64.89 TP: 92.7 TN: 62.3	95.32 TP: 60 TN: 98.6	**87.7** **TP: 72.7** **TN: 89.1**
Subject 4	**98.68** **TP: 93.0** **TN: 99.1**	92.50 TP: 99.0 TN: 92.1	99.66 TP: 95.4 TN: 100	94.5 TP: 99.1 TN: 94.2	88.86 TP: 2.2 TN: 99.2	89.33 TP: 0 TN: 100	**99.44** **TP: 97.5** **TN: 99.7**	94.9 TP: 98.0 TN: 94.5	95.37 TP: 60.6 TN: 98.6	83.88 TP: 80.3 TN: 84.2	94.97 TP: 56.1 TN: 98.6	**91.2** **TP: 79.7** **TN: 92.3**
Subject 5	98.16 TP: 90 TN: 99	95.28 TP: 96.7 TN: 95.1	99.20 TP: 94.2 TN: 99.7	**98.8** **TP: 93.8** **TN: 99.3**	94.92 TP: 78.7 TN: 100	76.1 TP: 0 TN: 100	76.23 TP: 7 TN: 99.9	**99.7** **TP: 99.5** **TN: 99.8**	91.08 TP: 54 TN: 95.6	58.87 TP: 89.9 TN: 55.1	92.01 TP: 45 TN: 97.7	**81.3** **TP: 89.5** **TN: 80.3**

	Going Upstairs				Being Still				Walking (3 gaits)			
	J48	NBayes	SVM	GP	J48	NBayes	SVM	GP	J48	NBayes	SVM	GP
Subject 1	97.41 TP: 19.6 TN: 99.9	94.97 TP: 5.2 TN: 97.8	98.42 TP: 59.2 TN: 99.7	**98.0** **TP: 80.4** **TN: 98.6**	93.88 TP: 82.9 TN: 97.8	97.61 TP: 97 TN: 97.8	97.77 TP: 97.2 TN: 98	**97.7** **TP: 97.5** **TN: 97.8**	83.53 TP: 79.6 TN: 87.1	82.22 TP: 87.4 TN: 77.6	**94.44** **TP: 94.6** **TN: 94.3**	86.2 TP: 95.0 TN: 78.2
Subject 2	72.65 TP: 57.2 TN: 74.4	63.38 TP: 76.1 TN: 61.9	72.6 TP: 99.5 TN: 69.6	**83.5** **TP: 90.6** **TN: 82.6**	74.56 TP: 32.1 TN: 98.4	98.84 TP: 99.4 TN: 98.5	98.23 TP: 99.9 TN: 97.3	**98.9** **TP: 99.8** **TN: 98.4**	94.77 TP: 92.2 TN: 97.6	72.93 TP: 48.4 TN: 99.4	95.08 TP: 91.4 TN: 99	**95.1** **TP: 95.0** **TN: 95.2**
Subject 3	93.05 TP: 60.8 TN: 96.6	75.16 TP: 95 TN: 73	94.16 TP: 50.1 TN: 98.9	**92.9** **TP: 94.4** **TN: 92.7**	91.02 TP: 82.9 TN: 98.9	98.85 TP: 98.8 TN: 98.9	99.04 TP: 98.7 TN: 99.3	**98.8** **TP: 98.4** **TN: 99.1**	95.79 TP: 96.1 TN: 95.5	90.37 TP: 97 TN: 85.4	**97.82** **TP: 98.6** **TN: 97.2**	92.4 TP: 96.2 TN: 89.6
Subject 4	95.44 TP: 72.4 TN: 98.1	89.45 TP: 77 TN: 90.9	93.73 TP: 59.8 TN: 97.7	**93.7** **TP: 95.2** **TN: 93.6**	97.82 TP: 95.4 TN: 99	98.24 TP: 97.7 TN: 98.5	98.32 TP: 96.6 TN: 99.1	**98.1** **TP: 98.0** **TN: 98.2**	96.65 TP: 97.9 TN: 95	90.82 TP: 96.2 TN: 83.7	97.33 TP: 99.5 TN: 94.5	**95.1** **TP: 96.7** **TN: 92.8**
Subject 5	92.81 TP: 63.2 TN: 96.6	59.56 TP: 91.7 TN: 55.4	92.17 TP: 49.9 TN: 97.6	**94.2** **TP: 91.8** **TN: 94.5**	79.12 TP: 27.6 TN: 98.6	98.86 TP: 97 TN: 99.6	98.99 TP: 99 TN: 99	**99.2** **TP: 99** **TN: 99.2**	97.26 TP: 98.6 TN: 95.2	93.15 TP: 96.6 TN: 87.8	97.51 TP: 98.8 TN: 95.6	**96.2** **TP: 95.9** **TN: 96.6**

TABLE V. TEST RESULTS: ACCURACIES, TRUE POSITIVE AND TRUE NEGATIVE RATES (%) OF INDIVIDUAL TRAINING AND TESTING FOR EACH SUBJECT WITH THE PHONE PLACED AT BACK PANT POCKET

	Sitting	Standing	Walking	Running	Lying	Going Downstairs	Going Upstairs	Being Still	Walking (3 Gaits)
Subject 1	96.0 TP: 98.0 TN: 95.8	99.4 TP: 96.7 TN: 99.7	88.0 TP: 93.7 TN: 84.0	99.1 TP: 99.2 TN: 99.1	99.9 TP: 99.7 TN: 99.9	89.6 TP: 47.4 TN: 91.0	92.6 TP: 70.9 TN: 93.3	97.8 TP: 97.3 TN: 98.0	94.5 TP: 95.3 TN: 93.8
Subject 2	99.5 TP: 98.6 TN: 99.6	99.1 TP: 95.9 TN: 99.6	83.5 TP: 80.2 TN: 85.1	99.3 TP: 97.4 TN: 99.4	98.6 TP: 97.2 TN: 98.8	83.0 TP: 60.8 TN: 85.5	87.4 TP: 84.0 TN: 87.8	97.4 TP: 97.2 TN: 97.6	95.9 TP: 99.1 TN: 92.4
Subject 3	99.5 TP: 99.0 TN: 99.7	99.4 TP: 97.1 TN: 99.6	87.7 TP: 91.5 TN: 86.6	97.3 TP: 97.9 TN: 97.3	99.4 TP: 99.8 TN: 99.2	89.5 TP: 74.4 TN: 90.9	94.0 TP: 95.6 TN: 93.8	98.6 TP: 98.3 TN: 99.0	94.8 TP: 94.4 TN: 95.1
Subject 4	98.6 TP: 97.8 TN: 98.8	99.1 TP: 82.9 TN: 99.9	84.8 TP: 89.8 TN: 81.8	95.4 TP: 98.1 TN: 95.2	99.9 TP: 99.4 TN: 100.0	91.0 TP: 82.1 TN: 91.8	94.3 TP: 94.9 TN: 94.2	98.3 TP: 98.3 TN: 98.3	95.5 TP: 97.6 TN: 92.8
Subject 5	-	99.0 TP: 99.8 TN: 98.9	85.2 TP: 88.7 TN: 83.1	99.0 TP: 95.2 TN: 99.4	99.6 TP: 99.5 TN: 99.6	87.7 TP: 84.6 TN: 88.1	94.1 TP: 94.2 TN: 94.0	98.7 TP: 98.1 TN: 98.9	94.8 TP: 95.0 TN: 94.5

TABLE VI. TEST RESULTS: ACCURACIES, TRUE POSITIVE AND TRUE NEGATIVE RATES (%) FROM INDIVIDUAL TRAINING AND TESTING FOR EACH SUBJECT WITH THE PHONE PLACED AT COAT POCKET

	Sitting	Standing	Walking	Running	Lying	Going Downstairs	Going Upstairs	Being Still	Walking (3 Gaits)
Subject 3	79.7 TP: 97.6 TN: 74.2	98.4 TP: 96.7 TN: 98.6	82.1 TP: 81.3 TN: 82.3	96.8 TP: 98.3 TN: 96.8	80.7 TP: 0.0 TN: 100.0	85.4 TP: 73.0 TN: 86.6	84.3 TP: 86.8 TN: 84.0	98.5 TP: 98.7 TN: 98.4	96.6 TP: 96.2 TN: 96.9
Subject 4	98.0 TP: 97.7 TN: 98.0	97.3 TP: 42.7 TN: 99.9	81.9 TP: 84.1 TN: 80.5	97.6 TP: 97.5 TN: 97.6	89.4 TP: 0.5 TN: 100.0	93.1 TP: 93.5 TN: 93.1	83.2 TP: 85.0 TN: 83.0	98.2 TP: 97.5 TN: 98.6	93.4 TP: 94.3 TN: 92.2
Subject 5	-	97.6 TP: 99.4 TN: 97.5	84.0 TP: 86.2 TN: 82.7	98.8 TP: 95.0 TN: 99.2	99.4 TP: 99.2 TN: 99.5	87.4 TP: 83.9 TN: 87.8	93.6 TP: 89.9 TN: 94.0	98.1 TP: 98.5 TN: 97.9	95.8 TP: 96.2 TN: 95.2

TABLE VII. TEST RESULTS: ACCURACIES, TRUE POSITIVE AND TRUE NEGATIVE RATES (%) FROM CROSS-PERSON TESTING - TRAINING ON SUBJECT 1 AND TESTING ON OTHER SUBJECTS WITH THE PHONE PLACED AT FRONT PANT POCKET AND BACK PANT POCKET RESPECTIVELY

Training on Subject 1 and Testing on all five subjects (at Front Pant Pocket)									
	Sitting	Standing	Walking	Running	Lying	Going Downstairs	Going Upstairs	Being Still	Walking (3 Gaits)
Subject 1	96.5 TP: 74.4 TN: 98.9	99.1 TP: 96.5 TN: 99.4	87.4 TP: 95.3 TN: 81.8	99.4 TP: 98.3 TN: 99.8	96.8 TP: 100.0 TN: 96.6	92.7 TP: 87.4 TN: 92.9	98.0 TP: 80.4 TN: 98.6	97.7 TP: 97.5 TN: 97.8	86.2 TP: 95.0 TN: 78.2
Subject 2	11.4 TP: 100.0 TN: 0.0	96.7 TP: 80.9 TN: 99.0	68.1 TP: 86.5 TN: 59.4	98.5 ($\simeq$) TP: 81.8 TN: 100.0	87.7 TP: 0.0 TN: 99.6	90.2 TP: 0.0 TN: 100.0	89.3 TP: 0.0 TN: 99.4	97.1 TP: 99.9 TN: 95.5	88.0 TP: 96.2 TN: 79.2
Subject 3	71.6 TP: 65.3 TN: 73.6	94.6 TP: 98.6 TN: 94.3	78.2 TP: 94.2 TN: 73.1	99.2 ($\simeq$) TP: 96.8 TN: 99.3	99.1 TP: 97.4 TN: 99.4	74.5 TP: 12.6 TN: 80.4	55.9 TP: 98.4 TN: 51.3	98.3 ($\simeq$) TP: 98.7 TN: 97.8	91.7 TP: 93.2 TN: 90.5
Subject 4	16.8 TP: 100.0 TN: 0.0	97.4 TP: 97.1 TN: 97.4	73.1 TP: 95.7 TN: 59.2	97.2 ($\simeq$) TP: 56.0 TN: 100.0	89.3 TP: 0.0 TN: 100.0	91.5 TP: 0.0 TN: 100.0	46.6 TP: 94.5 TN: 41.1	95.7 TP: 99.0 TN: 94.1	90.6 TP: 98.5 TN: 80.1
Subject 5	-	97.5 TP: 42.4 TN: 99.6	63.7 TP: 80.5 TN: 53.3	97.1 TP: 69.4 TN: 100.0	99.7 ($\simeq$) TP: 99.8 TN: 99.7	89.2 TP: 0.0 TN: 100.0	88.6 TP: 0.0 TN: 100.0	97.0 TP: 99.2 TN: 96.1	85.2 TP: 92.0 TN: 74.8
Training on Subject 1 and Testing on all five subjects (at Back Pant Pocket)									
	Sitting	Standing	Walking	Running	Lying	Going Downstairs	Going Upstairs	Being Still	Walking (3 Gaits)
Subject 1	96.0 TP: 98.0 TN: 95.8	99.4 TP: 96.7 TN: 99.7	88.0 TP: 93.7 TN: 84.0	99.1 TP: 99.2 TN: 99.1	99.9 TP: 99.7 TN: 99.9	89.6 TP: 47.4 TN: 91.0	92.6 TP: 70.9 TN: 93.3	97.8 TP: 97.3 TN: 98.0	94.5 TP: 95.3 TN: 93.8
Subject 2	88.6 TP: 0.0 TN: 100.0	87.8 TP: 98.4 TN: 86.3	56.7 TP: 96.9 TN: 37.8	99.4 TP: 96.7 TN: 99.7	88.1 ($\simeq$) TP: 0.0 TN: 100.0	33.8 TP: 100.0 TN: 26.7	88.2 TP: 2.0 TN: 97.9	97.0 ($\simeq$) TP: 98.2 TN: 96.4	82.5 TP: 89.4 TN: 75.1
Subject 3	76.4 TP: 0.0 TN: 100.0	95.4 TP: 96.4 TN: 95.3	70.7 TP: 94.1 TN: 63.3	98.9 TP: 96.4 TN: 99.1	80.7 TP: 0.0 TN: 100.0	48.5 TP: 100.0 TN: 43.6	90.0 TP: 0.1 TN: 99.8	98.4 ($\simeq$) TP: 98.5 TN: 98.4	88.6 TP: 90.4 TN: 87.3
Subject 4	83.3 TP: 0.0 TN: 100.0	96.4 TP: 82.1 TN: 97.0	68.9 TP: 87.0 TN: 57.8	98.1 TP: 98.9 TN: 98.0	90.2 ($\simeq$) TP: 8.9 TN: 99.9	35.1 TP: 100.0 TN: 29.1	89.5 TP: 0.0 TN: 99.9	97.6 ($\simeq$) TP: 98.4 TN: 97.3	87.5 TP: 90.5 TN: 83.6
Subject 5	-	90.8 TP: 99.0 TN: 90.5	71.5 TP: 98.0 TN: 55.0	98.4 TP: 93.9 TN: 98.9	75.5 ($\simeq$) TP: 0.0 TN: 99.2	36.7 TP: 100.0 TN: 29.0	87.5 TP: 0.0 TN: 98.8	97.7 TP: 99.9 TN: 96.8	87.0 TP: 88.1 TN: 85.4

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TABLE VIII. Test Results: Accuracies, true Positive and true Negative rates (%) from cross-placement testing - training at front pant pocket and testing at other phone placements

	Sitting	Standing	Walking	Running	Lying	Going Downstairs	Going Upstairs	Being Still	Walking (3 Gaits)
Training at Front Pant Pocket and Testing at Coat Pocket									
Subject 3	62.9 TP: 26.8 TN: 74.0	($\simeq$) 89.9 TP: 99.8 TN: 89.2	66.8 TP: 18.1 TN: 82.3	($\simeq$) 96.8 TP: 63.7 TN: 98.9	($\simeq$) 68.6 TP: 0.0 TN: 85.0	70.2 TP: 79.5 TN: 69.3	86.1 TP: 67.7 TN: 88.1	($\simeq$) 98.3 TP: 98.2 TN: 98.5	($\simeq$) 59.0 TP: 11.5 TN: 94.2
Subject 4	81.3 TP: 67.2 TN: 84.1	82.7 TP: 100.0 TN: 81.9	62.9 TP: 4.0 TN: 99.1	99.4 TP: 96.0 TN: 99.6	55.3 TP: 7.8 TN: 61.0	46.6 TP: 100.0 TN: 41.7	81.9 TP: 0.0 TN: 91.4	($\simeq$) 72.7 TP: 97.9 TN: 60.9	($\simeq$) 72.7 TP: 60.5 TN: 88.9
Subject 5	-	46.6 TP: 100.0 TN: 44.6	52.3 TP: 10.3 TN: 78.3	($\simeq$) 97.3 TP: 94.6 TN: 97.6	98.9 TP: 98.2 TN: 99.2	76.9 TP: 73.2 TN: 77.4	87.8 TP: 0.0 TN: 99.1	($\simeq$) 28.2 TP: 100.0 TN: 1.0	($\simeq$) 61.8 TP: 38.3 TN: 97.8
Training at Front Pant Pocket and Testing at Back Pant Pocket									
	Sitting	Standing	Walking	Running	Lying	Going Downstairs	Going Upstairs	Being Still	Walking (3 Gaits)
Subject 1	90.4 TP: 0.0 TN: 100.0	71.6 TP: 10.0 TN: 77.9	66.1 TP: 71.1 TN: 62.5	($\simeq$) 99.2 TP: 97.5 TN: 99.8	92.7 TP: 0.0 TN: 100.0	96.8 TP: 1.6 TN: 99.8	97.5 TP: 93.4 TN: 97.6	($\simeq$) 97.4 TP: 97.7 TN: 97.3	78.2 TP: 78.9 TN: 77.6
Subject 2	88.6 TP: 0.0 TN: 100.0	($\simeq$) 98.7 TP: 97.8 TN: 98.8	86.0 TP: 89.0 TN: 84.6	($\simeq$) 83.2 TP: 98.6 TN: 81.8	81.3 TP: 16.8 TN: 90.0	76.0 TP: 55.1 TN: 78.2	81.5 TP: 66.2 TN: 83.3	($\simeq$) 97.2 TP: 97.5 TN: 97.0	93.4 TP: 96.2 TN: 90.4
Subject 3	76.4 TP: 0.0 TN: 100.0	97.6 TP: 99.2 TN: 97.5	74.5 TP: 81.9 TN: 72.2	($\simeq$) 98.4 TP: 79.4 TN: 99.6	67.8 TP: 9.7 TN: 81.7	80.5 TP: 65.5 TN: 81.9	94.7 TP: 80.3 TN: 96.3	($\simeq$) 98.6 TP: 98.7 TN: 98.5	($\simeq$) 57.5 TP: 0.2 TN: 99.9
Subject 4	83.2 TP: 0.0 TN: 100.0	79.6 TP: 100.0 TN: 78.7	62.0 TP: 0.2 TN: 100.0	($\simeq$) 93.5 TP: 0.0 TN: 100.0	63.3 TP: 52.0 TN: 64.7	39.6 TP: 100.0 TN: 34.0	89.8 TP: 32.9 TN: 96.4	($\simeq$) 53.4 TP: 100.0 TN: 31.6	68.2 TP: 45.7 TN: 98.0
Subject 5	-	20.1 TP: 100.0 TN: 17.1	70.8 TP: 86.6 TN: 61.0	97.1 TP: 94.8 TN: 97.3	75.8 TP: 0.0 TN: 99.7	59.1 TP: 67.3 TN: 58.1	88.5 TP: 0.0 TN: 99.9	($\simeq$) 28.6 TP: 100.0 TN: 1.6	($\simeq$) 51.7 TP: 24.8 TN: 93.0

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