Identifying typical physical activity on smartphone with varying positions and orientations

Fen Miao[1,2]*, Yi He[3]*, Jinlei Liu[1,4], Ye Li[1 §], Idowu Ayoola[5]

[1]The Key Lab for Health Informatics of Chinese Academy of Sciences, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China.

[2]Shenzhen College of Advanced Technology, University of Chinese Academy of Sciences, China

[3] High-field Magnetic Resonance Department, Max Planck Institute for Biological Cybernetics, Tuebingen, Germany.

[4]School of Electrical & Mechanical Engineering, Guangdong University of Technology, Guangzhou, China.

[5]Industrial Design, Technische Universiteit Eindhoven, the Netherlands.

*These authors contributed equally to this work

[§]Corresponding author

Email addresses:

Fen Miao: fen.miao@siat.ac.cn

Yi He: yi.he@tuebingen.mpg.de

Jinlei Liu: 2007liujinlei@163.com

Ye Li: ye.li@siat.ac.cn

Idowu Ayoola: i.b.i.ayoola@tue.nl

Abstract

Background

Existing activity recognition approaches were either of high price, dependent on a structured environment or not convenient to use. This paper aims to automatically detect whether the smartphone is worn in the pocket before activating physical activity recognition without any limitation of firm attachment via built-in sensors.

Methods

By introducing a method to judge whether the phone is in a pocket, we investigated the data collected from six positions of seven subjects, chose two signals that are insensitive to orientation for classification. Decision trees (J48), Naive Bayes and Sequential minimal optimization (SMO) were employed to recognize five activities: static, walking, running, walking upstairs and walking downstairs.

Results

Compared the classification results of three classifiers, the results demonstrated that the J48 classifier produced the best performance (average recognition accuracy: 89.6%), and then we chose the J48 classifier as online classifier.

Conclusions

The utilization of the built-in sensors of the smartphone to recognize typical physical activities without any limitation of firm attachment is feasible.

Background

As modern lifestyle has shifted to more sedentary work and leisure activities, it has become important to have a comprehensive understanding of the relationships between physical inactivity and health [1]. Daily activities can provide additional information for medical doctors to accurately diagnose chronic disease [2], for example, by providing contextualized meaning in analyzing vital-signs of patients over distance. The physical activity recognition technique not only can be used to increase physical activity [3], but also can improve the treatment and differential diagnosis of neurological, degenerative and respiratory disorders [4, 5]. Mobile activity monitoring opens up opportunities for indoor and outdoor applications that can be used to support social interaction [6].

Although many activity recognition approaches [7, 8] have been developed and shown their good performance, they were either of high price, dependent on a structured environment or not convenient to use. Moreover, wearable sensors had been proved in many experiments for its feasibility and effectiveness [9-12], but people maybe forget to wear the clothes with micro sensors. However, smartphone provides several built-in sensors, which can be used to monitor motion. In addition, the smartphone has the capacity to quantify gait parameters with a degree of accuracy that is comparable to that of the tri-axial accelerometer [13]. Until now, several physical activity recognition methods have been proposed using smartphone sensors. In 2012, Cho et al proposed a linear discriminant analysis based activity recognition method using support vector machine to classify five activities including walking, going upstairs, going downstairs, running and static [14]. Anjum et al evaluated 4 machine learning algorithms including Naiive Bayes, Decision tree, K-Nearest Neighbour and Support Vector Machine classifiers to recognize seven activities (walking, running, climbing/descending stairs, driving, cycling, and inactive) using smartphone accelerometer and gyroscope [15]. The decision tree was demonstrated to be the best classifier with the average AUC (area under the ROC curve) larger than 0.9. Arif et al proposed to track physical activities with acceleration sensor incorporated in the smartphone in front pants leg pockets [16]. Six activities were recognized based on the extracted 105 features and then reduced to 30 using K-Nearest Neighbour classifier. To make the activity recognition solution more flexible, a phone-position independent algorithm was developed in [17] to recognize seven activities based on a complex method to analyze movement periodicity and a decision tree classification. In addition, some unsupervised learning algorithms were used for human activity recognition to avoid generating a large number of labeled activities for the training dataset [18, 19, 20]. Compared with supervised learning method, unsupervised algorithms are often weak in accuracy and little number of activities recognized.

In built-in sensors of smartphone, three of them are always hardware-based (the accelerometer, gyroscope and magnetic sensor), while these sensors can be either hardware-based or software-based (the gravity, linear acceleration, and rotation vector sensors). Moreover, the software-based sensors derive their data from the accelerometer, magnetic sensor or gyroscope. The software-based sensors are more varying because they often rely on one or more hardware sensors to derive their data. Therefore, in this paper hardware-based sensors are chosen for monitoring movement, such as tilt, shake, rotation, or swing. In another aspect, as previous studies [21, 22] that smartphones were fixed in a certain position and orientation of the body would restrict normal behaviours while using the device, we will dedicate to a flexible activity recognition solution with the phone in our pocket or bag, dependent on the users' habits. It was demonstrated that when we place a mobile phone in our pocket or bag, it moves with the pace of our body, thus it appears to be an ideal location to detect the activities of the user [23].

In the study herein, the smartphone was freely placed in a user-determined pocket and we chose five most representative daily activities that are strongly linked to physical exercises. Data generated by the accelerometer and gyroscope were used to train a set of classifiers, which include decision tree (J48), Naive Bayes classifier and SMO found in the WEKA Machine Learning Toolkit [24]. We also investigated the influence of positioning the smartphone in six pockets with 4 orientations.

The main purpose of this paper is to automatically detect whether the smartphone is worn in the pocket before activating physical activity recognition without any limitation of firm attachment. The structure of this paper is as follows: Section 2.1 describes Device and Study population. Section 2.2 describes how to identify the location of mobile phone, followed by data collection in Section 2.3. Section 2.4 and 2.5 describe how the system works, the experimental results and discussion are presented in Section 3 and Section 4, respectively. We conclude the work in Section 5 with suggestions for future work.

Materials and Methods

The built-in accelerometer, gyroscope, proximity sensor, light sensor and the orientation sensor of a smartphone was used to collect information that reflected acceleration, angular velocity, distance, light changes and orientation of physical activities. Signals were extracted from the data and the optimal signals were selected in order to classify activities. Due to the loose placement of the smartphone with varying orientations, we aim to extract signals that are independent or insensitive to orientation change for the activity classification. The challenges of this research are that the location and positioning (orientation) of the smartphone are additional variables. These variables are also influenced by the size, material and style of the hosting pocket. The block diagram of the proposed recognition scheme of this work is illustrated in Figure 1.

Device and study population

A smartphone (Samsung, I9100GALAXYSII, 125.3x66.1x8.49mm3, 116g, Android OS 2.3) was worn on six body positions without affixing it, the positions were the two front and back pockets on the trousers and the two front pockets on the coat, as shown in Figure 2. The smartphone has a built-in proximity sensor, a light sensor, a triaxial accelerometer (STM K3DH) with 19.6 m/s2 resolution, a triaxial gyroscope sensor (STM K3G) with 34.9 rad/s maximum range and 0.0012 rad/s resolution, and a triaxial magnetic field sensor (Asahi Kasei AK8973) with 2000 μT maximum range and 0.0625 μT resolution.

Because the signals have large difference between individuals for different activities, a population of 7 healthy volunteers (4 males and 3 females) were recruited to gather a representative dataset for algorithm development. The characteristics of the subjects were: age 30 $\pm$5 years (range 25 - 36), body weight 65 $\pm$20 kg (range 44 - 83), and body mass index 22.0 $\pm$2.8 kg/m2 (range 18.2 - 25). Prior to the trial, every subject was informed and provided informed consent.

Identify the location of mobile phone

As our study aims to recognize human activity based on the smartphone in the user's pocket, we will automatically identify whether the mobile phone is in the user's pocket before analysis with the help of proximity and light sensors. It is also presented in [25] that the proximity and light sensors of the phone can realize simple forms of context recognition associated with the user interface. Information about light and proximity sensors is shown in Table 1. The proximity sensor lets you determine how far an object is from a device. It is usually used to determine how far a person's head is from the front of a handset; for example, when a user is making or receiving a phone call. Most proximity sensors return the absolute distance, in cm, but some return only near and far values. Therefore, we will use the light and proximity sensors to determine whether the phone is in the user's pockets. Take Samsung I9100 for example, if an object is within a close range or out of range, it will read 0.0 or 5.0 values respectively (see Figure 3 (a)). The light sensor measures the ambient light level in lux. The android platform supported eight different luminance values, as shown in Table 2.

From table 1 and table 2 we can see, the phone can be considered as in a pocket when the luminance value is less than 100 lux and the proximity sensor returns 0.0. But there is a special case that the user is making or receiving a phone call at night. In order to judge the special case, we register a Phone State Listener event to monitor the phone state change in our application. The performance of identifying the locations of the smartphone using light and proximity sensors and Phone State Listener event will be given in the Results part.

Data collection

An application of physical activity management was developed and installed on the investigator's smartphone that measure distance, intensity of light, acceleration, angular velocity and orientation, as shown in Figure 3(a). As shown in Figure 3(b), the standard sensor coordinate system of the smartphone is defined relative to the screen. The X-axis is horizontal and points to the right. The Y-axis is vertical and points up, and the Z-axis points toward the outside of the screen. The coordinate system of the accelerometer is the same as the standard sensor coordinate system, so the acceleration of A_x, A_y, A_z, show the accelerometer of X, Y, Z direction, respectively. The software-based low pass filter with 0.25 Hz cutoff frequency was employed to separate acceleration due to gravity (GA) and linear acceleration (LA). So A_x was separated to GA_x, and LA_x , the same for A_y and A_z . And the coordinate system of the gyroscope is the same as the accelerometer.

In Android operating system, there are four different sensors sampling frequencies (fastest, game, normal, and UI). The values of the four frequencies are not constant and depending on the computational workload of the smartphone. In order to facilitate data collection, we adopted the light and proximity sensors to automatically control the data acquisition. Once the phone was put into subject's pocket, the light and proximity sensors would start working, if it was taken out it would stop collecting data. The raw acceleration, gyroscope and orientation signals were sampled at 25 Hz and stored in text format on Secure Digital (SD) card in the smartphone and later transferred to computer for analysis. The data at the first and last 5 seconds were cut off since subjects need time to put the phone inside the pocket and also take it out.

Each subject performed a range of daily activities which are listed in Table 3. We collected data using smartphone's built-in sensors for everyday activities that involve normal physical movement and range in level of intensity. The activities that were classified were: static, walking, running, ascending stairs, descending stairs.

Seven healthy subjects performed each activity and position listed above for 1 minute. In an effort to simulate real living conditions, the test protocol was designed to be very flexible. For example, the subjects were asked to perform the activities in their own style and in a random order and were not restricted on how the activities should be performed. For this reason, there are inter-subject variability in the speeds and amplitudes of some activities. In order to mark the data, the subject was kept stationary for 5 seconds between two different activities. All the activity data collected from the seven subjects' six pocket positions were mingled together to establish an independent dataset. The overall data sizes collected for the 5 activities listed in table 3 were 1697, 2531, 2080, 675 and 1114 separately.

The original physical activity data, accompanied with the corresponding multiple features extracted from the sensors of the smartphone, are freely available at https://github.com/fenmiao/ActivityData for further study.

Feature extraction

The proposed feature extraction process can be expressed as Figure 4. Firstly, to reduce bias due to sensor sensitivity and noise, sliding window approach was employed to divide the signal into smaller time windows. At a sampling frequency of 25 Hz, each window with 50% overlap represents 1.6 seconds.

Most previous works on activity recognition use body-worn sensors, which are fixed on a specified body location and orientation. However, in this work, the device orientation varies to allow for normal phone usage. We chose two magnitude signals that are insensitive to orientation and position, LA_{3a} and gyr_{3z} for classification. LA_{3a} is the signal magnitude vector (SMV) of linear acceleration. LA_{3a} can be represented as:

$$LA_{3a} = \sqrt{LA_x^2 + LA_y^2 + LA_z^2} \qquad (1)$$

Likewise, gyr_{3z} uses the same computational method as LA_{3a} with the gyroscope sensor.

In another aspect, Ore1, Orel2 and Orel3, which represents the X, Y, Z direction value of the magnetic sensor, were collected as the 3 independent signals. Combined with LA_{3a} and gyr_{3z}, 5 signals were collected in our study.

The above signals were extracted for each sliding window to develop classification algorithms. And six kinds of statistical features for all the windows were computed due to their high popularity and usefulness in many pattern recognition and machine learning problems. They are defined as follows:

• Mean: the average value of the signal over the window

• Standard Deviation: the standard deviation value over the window

• Median: the median value over the window

• Skewness: the statistic to describe the overall distribution of all values in the form of steep slow degree,

$$Skewness = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} (x_i - Avg)^3 / std^3 \tag{2}$$

Where Avg is the mean of x_i, std is the standard deviation of x_i.

• Kurtosis: the degree of peakedness of the distribution over the time window,

$$Kurtosis = \frac{n(n+1)\sum (x_i - Avg)^4 - 3(\sum (x_i - Avg)^2)^2 (n-1)}{(n-1)(n-2)(n-3)std^4} \tag{3}$$

Where Avg is the mean of x_i, std is the standard deviation of x_i.

• Inter-quartile-Range (IR):

$$IR = Q_3 - Q_1 \tag{4}$$

Where Q_3, Q_1 is the 75th and 25th percentiles over the window, respectively.

At last, a 30 feature vector was obtained for classification.

Classification

We classified activities from daily life data, employing three different classifiers in WEKA environment [24]. The data classification process is presented in Figure 5. We compared and evaluated the performance of several activity recognition classifiers:

decision trees (J48), Naive Bayes and Sequential minimal optimization (SMO). In order to give insights on how the models will generalize to an independent dataset with large number of features (overall 30 features) and relatively small size of data, cross validation [26] were employed. In k-fold cross-validation, the original sample is randomly partitioned into k equal size subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k-1 subsamples are used as training data. The cross-validation process is then repeated k times, with each of the k subsamples used exactly once as the validation data. The k results from the folds can then be averaged to produce a single estimation. In general, 10-fold cross-validation is commonly used in most of situation. Therefore, 10-fold cross validation was used to optimize the three classifiers in our study.

1) The decision tree was created using the J48 algorithm with 10-fold cross validation. In order to develop a binary decision tree, the following design elements should be considered in the training phase:

• At each node, a set of candidate questions to be asked has to be decided. Each question corresponds to a specific binary split into two descendant nodes. Each node, *t*, is associated with a specific subset X_t of the training set X. Splitting of a node is equivalent to the split of the subset X_t into two disjoint descendant subsets, X_{tY}, X_{tN}. The first of the two consists of the vectors in X_t that correspond to the answer "yes" of the question and those of the second to the "no". The first node of the tree is associated with the training set X. For every split, the following is true:

$$X_{tY} \cup X_{tN} = X_t \tag{5}$$

• A splitting criterion must be adopted according to which the best split from the set of candidate ones is chosen.

• A stop-splitting rule is required that controls the growth of the tree, and a node is declared as a terminal one (leaf).

• A rule is required that assigns each leaf to a specific class.

If a smaller tree structure was able to achieve performance comparable to a larger one, the smaller one was chosen. It should be noted that the size of the tree might be different in each training session.

J48 was chosen to give results in tree model, which can be easily transformed into real-time applications. And it has been successfully applied to activity recognition earlier. The selected parameters for the J48 decision tree are:

(i) confidence factor = 0.25;

(ii) minimum number of objects = 30, numFolds = 3;

(iii) unpruned = True.

2) In the Naive Bayes [27] classification scheme, the required estimate of the probability density functions (PDF) at a point $x = [x(1),...,x(l)]^T \in \Re^l$ is given as

$$p(x) = \prod_{j=1}^{l} p(x(j)) \tag{6}$$

That is, the components of the feature vector x are assumed to be statistically independent. In order to safeguard good estimates of the PDF the number of the training samples, N, must be large enough. Instead, with the Naive Bayes classifier, although the independence assumption may not be valid, the final result turns out to be that the Naive Bayes classifier can be very robust. And it has been reported to perform well for many real-world data sets.

3) Instead of previous SVM learning algorithms that use numerical quadratic programming (QP) as an inner loop, SMO uses an analytic QP step. SMO decomposes the overall QP problem into QP problems, using Osuna’s theorem to

ensure convergence. SMO chooses to solve the smallest possible optimization problem at every step. For the standard SVM QP problem, the smallest possible optimization problem involves two Lagrange multipliers, because the Lagrange multipliers must obey a linear equality constraint. At every step, SMO chooses two Lagrange multipliers to jointly optimize, finds the optimal values for these multipliers, and updates the SVM to reflect the new optimal values. The advantage of SMO lies in the fact that solving for two Lagrange multipliers can be done analytically. Thus, numerical QP optimization is avoided entirely. The inner loop of the algorithm can be expressed in a short amount of C code, rather than invoking an entire QP library routine. Even though more optimization sub-problems are solved in the course of the algorithm, each sub-problem is so fast that the overall QP problem is solved quickly [28].When the training data set is very large the running speed will be very slow, and its operation is time-consuming. So we just employ this method as a comparison.

Classification performances were measured by the performance of correctly classified instances and the complete confusion matrix.

Results

The result of recognizing whether the phone is in the pocket

Motion sensors start to collect data only when the phone has been put inside the pocket. In order to judge whether the phone is put inside the pocket or not, we set the following rules:

1) The proximity sensor: If the proximity sensor returns near, we use the value 0 to indicate the near state, otherwise we use the value 1 to indicate the far state.

2) The light sensor: Normalize the intensity value of light sensor of Table 3 to the range [0, 1].

3) The Listener for Call State: The Android system provides

LISTEN_CALL_STATE in the class of PhoneStateListener which is the listener for monitoring changes in call state on the device. When the phone is calling, the value 1 is used to indicate the call state, otherwise the value 0 is utilized to indicate the uncalled state.

From the classification result demonstrated in Figure 6, we can see the in-pocket case can be well identified according to the proposed rules in our study.

The activities recognition results

As the features were extracted from the sliding windows, classification was done with 0.8 seconds time resolution. One subject's LA_{3a} curves from three different positions are shown in Figure 7. The value of LA_{3a} in coat pocket is smaller than that in trousers pockets. The moving human lower limbs will produce a bigger acceleration than that of the trunk part. As the differences of acceleration produced by two legs, the phone in trousers pockets will shake more severe than that in coat pockets. So the waveform of the coat pocket seems to be more regular.

As shown in Figure 8, the scatterplot of five activities were employing a combination of gyr3zStd, gyr3zMean and LA3aMean. The action segmentation result as follows: the star-shape scatter area represents static, the plus sign scatter area represents walking, the circle scatter area represents running, the diamond scatter area represents downstairs and the square scatter area represents upstairs. Much of our classifier confusion seen in the results can be explained with transitions from one activity to another. Because the subject needs time to switch form one activity to another, the reading of sensors will be consecutive. And this reason causes the confusion of action segmentation. In addition, when subject walking upstairs or downstairs s/he will produce nearly the same acceleration magnitude, so the resulting inaccuracy is visible especially in the recognition of walking upstairs and downstairs.

Moreover, distributions of walking, walking upstairs and walking downstairs partly overlap when using the two magnitude features. But static and running will not confuse with other activities.

Table 4 shows the confusion matrix of the J48 classifier. Walking upstairs represents walking upstairs, down represents walking downstairs, each row shows how the model classified one class and each column shows which classes one type of classification by the model actually belong to.

The average recognition accuracy of the three common classifiers across five activities is listed in Table 5. Decision tree classifiers showed the best performance, recognizing activities with an overall accuracy of 89.6%. In the application of physical activity recognition, the J48 classifier was chosen to recognize activities at real-time.

Discussion

Most previous studies [15-22, 29-31] have focused on recognizing activities with wearable sensors. However, most of these works required accelerometers to be attached to a specific location. Table 6 gives the comparison between the previous typical studies the proposed method in our study. From the table we can see, the proposed solution in our study can automatically identify the locations of the smartphone and realize convenient activity recognition from the smartphone at any pockets with quite good accuracy. Even though in-pocket case in this paper is an ideal position to realize quite high accuracy, we believe that an efficient solution in the future study to deal with more cases, such as in the hand and making a call, is needed to adapt to more situations.

Based on the observation for a large number of people, we find that people usually put the mobile phone into the coat pocket vertically, which can result in four possible orientations: upward facing in, upward facing out, downward facing in, downward facing out. There are three axis linear acceleration curves from two different smartphones worn in different orientations but the same rear trousers (Figure 9(a)). The curves of X, Y, Z axis linear acceleration from two smartphones are quite different due to the different orientations. However, the orientation of the mobile phone is relatively vertical and the acceleration magnitude is chosen which is a measure for the quantity of acceleration and has no directions, it is insensitive for the orientations of the smartphones. Therefore, as shown in Figure 9(b), there were 2 similar LA_{3a} curves from two different mobile phones worn in the same rear trousers pocket with 2 different orientations. From the plot we can conclude that the two mobile phone orientations have no influence on the features that we used for classification.

Conclusions

In this study, we investigated the physical activity recognition issue on a built-in kinematic sensor smartphone. In contrast to previous studies in which the phone must be attached to the subject's body with fixed orientation and location. Our approach is more convenient for that orientation and position of smartphone are varying no matter the material and style of the hosting pocket. In order to improve classification quality, data processing technique was used to reduce the noise present in raw data. We explored orientation-independent features extracted from magnitudes as well as three axis direction components for five typical physical activities. Two different smartphones indicated that the classification algorithm has generality, and several typical activities can be recognized with good accuracy by using feature extraction and classification algorithms. Although there are limits on what can be achieved in daily life activity recognition using a mobile phone without posing any pre-conditions on its position and orientation, the system we proposed is more feasible for long-term activity monitoring because of its convenience, lower cost, and the ability to classify several typical activities in daily life with a relatively high accuracy.

However, as the dataset is with large dimensional features and relatively small size of data, cross validation were used to assess the classification performance, the performance will be varying while applied in external validation data. In the future, we will validate the proposed models in more external validation datasets. In addition, with the rapid development of wearable sensors such as embedded sensors in smart watch and clothes, a new kind of human activity recognition solution would be studied to monitoring the user’s activity at any time and any place. We also plan to develop a sport management application that can merge the physical activity collected from different wearable sensors based on a private cloud platform [32], and thus calculate the user's physical activity and help them formulate a daily exercise program. In addition, security of data [33, 34] will be considered in our future system. Speaking of formulating a daily exercise program, it is inevitable to include the influence of social actors in our day-to-day activities too. It is interesting to also analyze peak social and private moments during the daily activity routines in order to develop a meaningful activity program and tips for the individual involved.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

Fen Miao participated in the classification study, performed the statistical analysis and made important revision on the draft. Yi He participated in the design of the study and carried out the experimental data acquisition of the study. Jinlei Liu carried out the feature extraction study and drafted the manuscript. Ye Li conceived of the study, and participated in its design and coordination and revised the manuscript. Idowu Ayoola participated in the design of the study and made the language revision. All authors read and approved the final manuscript.

Acknowledgements

This work acknowledged Huhe Dai for the interpretation of data. This work was supported in part by the National Natural Science Foundation of China (No. 61379136), the Basic Research Program of Shenzhen (No. JCYJ20130401170306884), and the Promote Program of Low-Cost Health Lab (No. CXB201104220026A).

References

1. S. N. Blair: **Physical inactivity: the biggest public health problem of the 21st century**. *British journal of sports medicine* 2009, 43:1-2.
2. F. Pitta, M. Y. Takaki, N. H. d. Oliveira, T. J. Sant'Anna, A. D. Fontana, D. Kovelis, *et al.*: **Relationship between pulmonary function and physical activity in daily life in patients with COPD**. *Respiratory medicine* 2008, 102:1203-1207.
3. R. M. Steele, E. Van Sluijs, S. J. Sharp, J. R. Landsbaugh, U. Ekelund, and S. J. Griffin: **An investigation of patterns of children's sedentary and vigorous physical activity throughout the week**. *Int J Behav Nutr Phys Act* 2010, 7:88.
4. 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* 2009, 30: R1-R33.
5. M. Lotan: **Quality physical intervention activity for persons with Down syndrome**. *The Scientific World Journal* 2007, 7: 7-19.

6. T. Nelson, C. Megens, and M. Peeters. **Bouncers: a design exploration into sharing and triggering personal activity amongst friends**. *Persuasive Technology* 2012:33.
7. J. Ben-Arie, Z. Wang, P. Pandit, and S. Rajaram: **Human activity recognition using multidimensional indexing**. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2002, 24:1091-1104.
8. I. Maglogiannis and C. Doukas: **Emergency Fall Incidents Detection in Assisted Living Environments Utilizing Motion, Sound and Visual Perceptual Components**. *IEEE Trans. Information Technology in Biomedicine*, 2011, 15:277-289.
9. I. Gyllensten and A. G. Bonomi: **Identifying Types of Physical Activity With a Single Accelerometer: Evaluating Laboratory-trained Algorithms in Daily Life**. *IEEE Transactions on Biomedical Engineering* 2011, 58:2656-2663.
10. D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler: **Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring**. *IEEE Transactions on Information Technology in Biomedicine* 2006, 10:156-157.
11. M. Ermes, J. Parkka, J. Mantyjarvi, and I. Korhonen: **Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions**. *IEEE Transactions on Information Technology in Biomedicine* 2008, 12:20-26.
12. A. M. Khan, Y. K. Lee, S. Y. Lee, and T. S. Kim: **A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a**

hierarchical recognizer. *IEEE Transactions on Information Technology in Biomedicine* 2010, 14:1166-1172.

13. S. Nishiguchi, M. Yamada, K. Nagai, S. Mori, Y. Kajiwara, T. Sonoda, *et al.*: **Reliability and Validity of Gait Analysis by Android-Based Smartphone**. *Telemedicine and e-Health* 2012, 18:292-296.
14. J. Cho, J. Kim, T. Kim.: **Smart phone-based human activity classification and energy expenditure generation in building environments**. *Proceedings of the 7th international symposium on sustainable healthy buildings* 2012: 97-105.
15. Anjum, Alvina, and Muhammad Usman Ilyas: **Activity recognition using smartphone sensors**. *IEEE conference on Consumer Communications and Networking* 2013:914-919.
16. M. Arif, M. Bilal, A. Kattan, S.I. Ahamed: **Better Physical Activity Classification using Smartphone Acceleration Sensor**. *Journal of medical systems* 2014, 38: 1-10.
17. R. Guidoux, M. Duclos., G. Fleury, P. Lacomme, N. Lamaudi èr, P. Manenq et al: **A smartphone-driven methodology for estimating physical activities and energy expenditure in free living conditions**. *Journal of biomedical informatics* 2014, 52:271-278
18. Lee, Young-Seol, and Sung-Bae Cho: **Activity recognition with android phone using mixture-of-experts co-trained with labeled and unlabeled data.** *Neurocomputing* 2014, 126:106-115.
19. K. Yongjin, K. Kyuchang, and B. Changseok. **Unsupervised learning for human activity recognition using smartphone sensors**. *Expert Systems with Applications* 2014, 41:6067-6074.

20. S. Bhattacharya, P. Nurmi, N. Hammerl, T. Plötz: **Using unlabeled data in a sparse-coding framework for human activity recognition**. *Pervasive and Mobile Computing* 2014, 15:242-262.

21. Y. He, Y. Li, and S.-D. Bao: **Fall Detection by built-in tri-accelerometer of smartphone**. *IEEE-EMBS International Conference on Biomedical and Health Informatics* 2012:184-187.

22. Y. He and Y. Li: **Physical Activity Recognition Utilizing the Built-In Kinematic Sensors of a Smartphone**. *International Journal of Distributed Sensor Networks* 2013, Article ID: 481580.

23. L. Sun, D. Zhang, B. Li, B. Guo, and S. Li: **Activity recognition on an accelerometer embedded mobile phone with varying positions and orientations**. *Ubiquitous Intelligence and Computing* 2010, 6406:548-562..

24. M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, I.H. Witten: **The WEKA data mining software: an update**. *ACM SIGKDD explorations newsletter* 2009, 11:10-18.

25. A. Pantelopoulos and N. G. Bourbakis: **A survey on wearable sensor-based systems for health monitoring and prognosis**. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 2010, 40:1-12.

26. Kohavi R.: **A study of cross-validation and bootstrap for accuracy estimation and model selection.** *International Joint Conference on Artificial Intelligence* 1995, 14:1137-1145.

27. S. Theodoridis, A. Pikrakis, K. Koutroumbas, and D. Cavouras: **Introduction to Pattern Recognition***: A Matlab Approach: A Matlab Approach*: Academic Press, 2010.

28. J. Platt: **Sequential minimal optimization: A fast algorithm for training support vector machines**. 1998.

29. J. Staudenmayer, D. Pober, S. Crouter, D. Bassett, and P. Freedson: **An artificial neural network to estimate physical activity energy expenditure and identify physical activity type from an accelerometer**. *Journal of Applied Physiology* 2009, 107:1300-1307.

30. H. Vathsangam, A. Emken, D. Spruijt-Metz, E. Schroeder, and G. Sukhatme: **Determining Energy Expenditure from Treadmill Walking using Hip-Worn Inertial Sensors: An Experimental Study**. *IEEE Transactions on Biomedical Engineering* 2011, 58:2804-2815.

31. J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, and I. Korhonen: **Activity classification using realistic data from wearable sensors**. *IEEE Transactions on Information Technology in Biomedicine* 2006, 10:119-128.

32. C. He, X. Fan, and Y. Li: **Toward ubiquitous healthcare services with a novel efficient cloud platform**. *IEEE Transactions on Biomedical Engineering* 2013, 60:230-234.

33. F. Miao, S.-D. Bao, and Y. Li: **Biometric key distribution solution with energy distribution information of physiological signals for body sensor network security**. *IET Information Security* 2013, 7:87-96.

34. A. Drosou, D. Ioannidis, K. Moustakas, and D. Tzovaras: **Unobtrusive behavioral and activity-related multimodal biometrics: the ACTIBIO authentication concept**. *The Scientific World Journal* 2011, 11:503-519.

Figures

Figure 1 - Block diagram of the recognition scheme.
(a) The part to determine whether the phone is in a pocket. (b) In WEKA environment offline activities classification (c) In real-time online activities classification.

Figure 2 - Pocket locations.
For each pocket shown, there is a corresponding one in the left side of the body.

Figure 3 - (a) Data collection interface on Samsung I9100. (b) The coordinate system of the smartphone.
For each pocket shown, there is a corresponding one in the left side of the body.

Figure 4 - Feature extraction process

Figure 5 - Data classification process

Figure 6 - Classification result of the phone’s position

Figure 7 - Acceleration data collected from three different positions.

Figure 8 - The scatter graphs of five activities, employing a combination of gyr3zStd, gyr3zMean and LA3aMean.

Figure 9 - (a) The three axis linear acceleration of the two phones (b) The LA_{3a} and the average value of LA3a of the two phones with 2 different orientations in rear trousers pocket.

Tables

Table 1 - Description of Light Sensor and Proximity Sensor

Sensor	Type	Description	Common Uses
LIGHT	Hardware	Measures the ambient light level (illumination) in lux.	Controlling screen brightness
PROXIMITY	Hardware	Measures the proximity of an object in cm relative to the view screen of a device. This sensor is used to determine whether a handset is being held up to a person's ear.	Phone position during a call.

Table 2 - Eight luminance values supported by Android platform

Type	Description	Constant Value (lux)
LIGHT_NO_MOON	luminance at night with no moon in lux	0.0010

LIGHT_FULLMOON	luminance at night with full moon in lux	0.25
LIGHT_CLOUDY	luminance under a cloudy sky in lux	100.0
LIGHT_SUNRISE	luminance at sunrise in lux	400.0
LIGHT_OVERCAST	luminance under an overcast sky in lux	10000.0
LIGHT_SHADE	luminance in shade in lux	20000.0
LIGHT_SUNLIGHT	luminance of sunlight in lux	110000.0
LIGHT_SUNLIGHT_MAX	Maximum luminance of sunlight in lux	120000.0

Table 3 - Activities Performed in this experiment

Number	Activity task	Activity Description
1	Static	Standing still / sitting on a sofa / sitting at a desk
2	Walking	Walking on a treadmill [a] / walking on the playground
3	Running	Running on a treadmill [a] / running on the playground
4	Walking downstairs	Walking downstairs at a normal pace
5	Walking upstairs	Walking upstairs at a normal pace

Table 4 - Confusion matrix of J48 decision tree

Actual \ Model	walking upstairs	walking downstairs	walking	running	static
walking upstairs	**915**	18	160	21	0
walking downstairs	22	**454**	158	41	0
walking	127	85	**2268**	51	1
running	23	51	68	**1938**	0
static	0	0	16	0	**1681**

Table 5 - Classification results

Methods	Accuracy (%)	Root mean squared error	Time taken to build model (s)
J48	89.6	0.1804	0.65
Naive Bayes	75.3	0.283	0.12
SMO	81.1	0.332	1.74

Table 6 - Comparison with the reported activity recognition methods

Reference	Smartphone position	Activities numbers	Contributions	Algorithm and accuracy	Limitations
Anjum et al [15], 2013	Pant pocket, hand, hand bag, shirt pocket	7	Activity recognition with smartphone at multiple positions including pant pocket, hand, hand bag and shirt pocket	Decision tree (AUC 0.985)	Limited activity traces and thus would tradeoff the performance in external verification
Arif [16], 2014	Leg front pants pocket	6	Demonstration of better activity classification accuracy	10-fold KNN (98.2%)	Position is fixed in front pants leg pockets
Romain Guidoux et al [17], 2013	Leg front pants pocket	9	Estimation of total energy expenditure with phone-position independent by transform	Total energy expenditure (73.6%)	Low accuracy
Yongjin Kwon et al [19], 2014	Pants pocket	5	Unsupervised learning without labels	Hierarchical clustering or DBSCAN (above 90% accuracy)	Some important activities including going upstairs and downstairs were

					not studied
Sourav Bhattacharya [20], 2014	Jacket pockets, pants pockets, backpack	8	Deal with unlabeled data	Sparse coding (80%)	Important activities including going upstairs and downstairs were not studied
This paper	Any pockets	5	Automatically identify the locations of the smartphone and conveniently activity recognition with smartphone at any pockets	10-fold J48 (89.6%)	More situations, such as in the hand, should be further studied