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Activity Recognition using Accelerometer Sensor and Machine Learning Classifiers

A.S Abdull Sukor[1], A. Zakaria[2], N. Abdul Rahim[1],
[1]School of Mechatronic Engineering, Universiti Malaysia Perlis, 02600 Arau, Perlis, Malaysia
[2]Centre of Advanced Sensor Technology (CEASTech), UniMAP, 02600, Arau, Perlis, Malaysia
E-mail: abd.syafiq@gmail.com

***Abstract*—Activity recognition is considered as an important task in many applications, particularly in healthcare services. Among these applications include medical diagnostic, monitoring of users' daily routine and detection of abnormal cases. This paper presents an approach for the activity recognition using an accelerometer sensor embedded in a smartphone. This approach uses a publicly available accelerometer dataset as the raw input signal. The features of the signal are selected based on the time and frequency domain. Then, Principal Component Analysis (PCA) is used to reduce the dimensionality of the features and extract the most significant ones that can classify human activities. A comparison process is performed between the original raw data and PCA-based features and additionally, time and frequency-domain features are also compared using several machine learning classifiers. The obtained results show that the PCA-based features obtain higher recognition rate while frequency-domain features have higher accuracy, with the rate of 96.11% and 92.10% respectively.**

Keywords—accelerometer dataset, activities of daily living, classification, machine learning, principal component analysis

I. INTRODUCTION

Activity recognition plays a vital role in healthcare services and has been studied as a part of solutions to reduce the costs and workloads currently being placed on professional caregivers [1]. The capability of performing activities is usually associated with the physical and mental health of people and can be considered as a primary indicator to determine their quality of life [2]. Activity recognition is regarded as a challenging task due to the fact that each activity has their unique characteristics. It is indeed a well-researched problem and can be associated with many applications. Among these include falling detection [3], [4], abnormality detection [5]–[7] and prediction of human behaviour [8]–[10].

Studies in this area are usually conducted in a highly controlled environment [11]. Often, the results do not represent the condition in a real-world application. However, activity recognition using mobile-based devices have shown to generate high quality results in a real-world setting [12]. In particular, activity recognition using accelerometer sensor shows a good potential due to the ability of the sensors to consume low power which enables continuous sensing over a day [11]. These sensors are usually embedded in various types of smartphones or it can also be strapped to human body using strip or belts. In fact, the computing capabilities of smartphones have increased in recent years, which allows the function to be extended to other applications such as capturing human body movement rather than supporting only voice communications [13]. Using the accelerometer sensor data, a mobile phone device can analyze and interpret that a user is performing some activities such as running or walking. With the advancement of today's technologies, activity recognition can be used to monitor human daily activities and identify any unusual changes in their daily routine [14].

One aspect that needs to be considered is the number of sensors. The use of multiple sensors has resulted in the problem of movement obstruction as well as practicality in the long-term wearing [15]. In addition, the cost will also be increased with the addition of more sensors. With this respect, more researchers are focusing to apply activity recognition approaches by using only one accelerometer sensor in order to collect the body movement signal [3], [16].

However, several issues are associated with the activity recognition approaches using accelerometer sensor. These include data processing, feature extraction methods and high-performance classification support techniques [13]. For example, if the features are not properly selected from the raw signal, it will degrade the activity recognition accuracy and decrease the computational efficiency. Several studies have applied feature extraction methods to select the most significant features that can classify human activities [16]-[18]. Furthermore, dimensionality reduction process also can be applied to reduce the dimensionality of raw data and transform original features to a lower dimensional space [13]. These processes are often expected to meet several requirements, such as high accuracy, short training time and real-time data generalization [19].

The paper presents an approach to recognize activities of daily living using a publicly available accelerometer sensor dataset [20]. It also highlights several issues such as signal pre-processing, feature selection, dimensionality reduction and classification. The comparison process is performed using several machine learning classifiers, which consist of Decision Tree (DT), Support Vector Machine (SVM) and Multi-Layer Perceptron Neural Network (MLP-NN).

The paper is organized as follows: Section II explains the related work on activity recognition approaches. Section III discusses the methodology used in this method. Section IV presents the experimental results as well as discussion and Section V summarizes the conclusion and future work.

II. Related Work

Various activity recognition approaches have been proposed in several research studies. Most of these studies are composed of two categories of methods. The first category involves the use of probabilistic models to infer the types of activities [21]. This method uses statistical modelling to represent the activity model structure and train the data based on large-scale datasets. Among the major models used in the activity recognition in this category include Hidden Markov Models (HMM) [17], Dynamic Bayesian Network (DBN) [22], hierarchical clustering [23] and Partially Observable Markov Decision Processes (POMDPs) [24]. An overview of these probabilistic tools can be found in [25], which gives the explanation in terms of learning-based methods. For example, in a study conducted by [17], activity recognition is performed using Hidden Markov Model (HMM). The features are extracted from video camera sensors, where Genetic Algorithm (GA) and Best First Search (BFS) are used to select the best features that may describe the activities to be recognized. The results show that HMM is able to classify human activities with the support from feature extraction from GA with the accuracy of 75%. This category often offers an efficient way of representing activity models in probabilistic values. Therefore, they can infer activities in ambiguous conditions. However, the major disadvantage of these tools is that they are mostly in a static condition and thus, it is difficult to adapt the models in different environments due to the incompleteness of training model.

The second category uses classification techniques which map inputs of sensory data to the desired output [26]. This alternative approach uses machine learning techniques to extract patterns of activities from the data observation. Examples of classification technique in this category include Random Forest (RF) [27], Support Vector Machine (SVM) [18], Decision Trees (DT) [28], and Artificial Neural Network (ANN) [7]. Generally, these methods produce individual activity models by comparing the data input from sensor observations to a set of template model in the training dataset. The training is done by closely matching the sensor dataset with the models produced by the tools. The advantages of this method are that it can handle noisy, uncertain and incomplete datasets [29]. For example, Fan (2013) recognizes human activities from 3 different models, namely behaviour, position and activity. Decision Tree is used to compare the performance of these models and it is found that the behaviour model has the highest accuracy of 80.29%.

Other approaches to activity recognition include using threshold-based classifier. This method uses predefined threshold values, which are generally defined by the designer [10]. It is usually sufficient to recognize static postures, such as standing, sitting and lying. The limit of this approach is that the user needs to find the suitable threshold values as they can be very sensitive to the defined activities. Meanwhile, another approach is to use fuzzy logic reasoning to identify human activities. For example, Medjahed et al. (2009) propose to use fuzzy rules in recognizing several ADLs using physiological sensors, microphone, infrared and state-change sensors. It shows a great potential when working with vague, imprecise and noisy information. This method is sufficient if the activities are defined in the membership functions, however, it only applies to a narrow range of adaptation. It only works well if the activities are clearly defined by the fuzzy rules.

This focus of this paper is to use the classification technique in identifying human's daily activities. It addresses several issues in classifying the model such as feature extraction and dimensionality reduction. Then, a comparison process using machine learning classifiers is performed to find which types of features that can classify human activities effectively.

III. Methodology

This section provides the methodology involves in performing activity recognition from the accelerometer sensor data, which has been embedded in a smartphone. This section is divided into two subsections, where each section describes how data is collected and steps taken in the data preprocessing method.

A. Data Collection

A publicly available dataset is used in this study [20]. The dataset is composed of sensory data from a tri-axial accelerometer and a gyroscope. However, for this study, only accelerometer dataset is used to identify human activities. This is because previous studies show many disadvantages of using multiple sensors in identifying human activities [15]. Furthermore, it has been shown that one accelerometer is sufficient in analyzing human body movement [31]. The dataset is composed of nine types of ADLs and four types of falls. Each signal is stored in time (ns), acceleration values (ms^{-2}) in x, y and z-axis as well as the activity labels. The mean sampling rate for the signal is 87 Hz and the range of the acceleration value is between 20 to -20. For this study, six activities are chosen, namely Standing (STD), Sitting (SIT), Lying (LYI), Stairs Up (STU), Stairs Down (STN), and Walking (WAL). These activities are selected as they represent the most common body movement in human's daily lives.

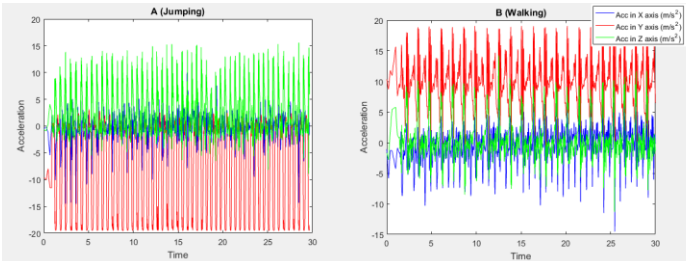

Figure 1. Raw Signal Captured by Accelerometer

Fig 1 shows the raw signal of two activities: A (jumping) and B (walking), which have been captured by the accelerometer sensor in thirty seconds. The blue, red and green lines represent the acceleration values in x-axis, y-axis and z-axis respectively. Pre-processing is then applied to the raw signal in order to generate several features.

B. Data Pre-processing

In the classification technique, data processing is among the most important steps. It consists of a signal segmentation, feature selection, feature extraction and dimensionality reduction process. Fig 2 presents the steps taken in the data pre-processing.

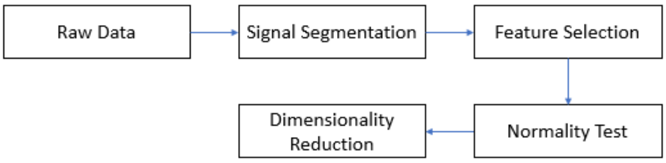

Figure 2. Steps in Data Pre-processing

Firstly, the segmentation technique is used to divide sensor signals into small time window segments so that the feature can be easily extracted in each segment. In this work, a sliding window with 50% overlap is chosen as the method of segmentation, since it has been proved as well-suited in many studies. The features are computed from 600 sampling points, which represent a 3-second time window. This duration is considered sufficient, as most existing studies use different size duration between one and three seconds [11]. Fig 3 shows the example of segmentation window for three activities.

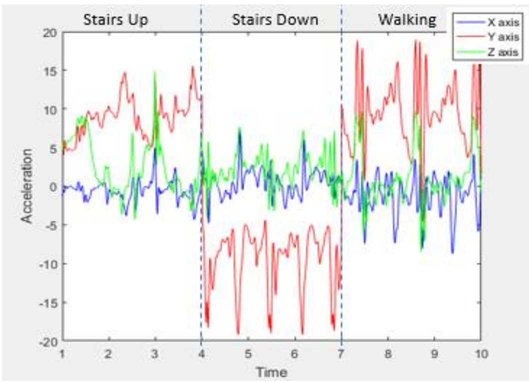

Figure 3. Segmentation of Raw Signal

Then. the feature selection process allows several signal characteristics from raw sensory data to be extracted. Time-domain and frequency-domain features are widely used for feature calculation. Table 1 lists down a number of common features used, which are extracted from each window. Examples of the features in the time-domain include min, max, mean average, standard deviation, Signal Magnitude Area (SMA) and Signal Vector Magnitude (SVM) [13]. SMA is calculated using (1), where x_u, y_u and z_u are referred as the signals from the sample of the tri-axial accelerometer. Meanwhile, SVM is calculated using (2), where x_i is the ith sample of x-axis, y_i is the ith sample of y-axis and z_i is the ith sample of z-axis accelerometer signals. Additionally, tilt angle is also calculated using (3).

$$SMA = \frac{1}{i}\left(\sum_{u=1}^{i}|x_u| + \sum_{u=1}^{i}|y_u| + \sum_{u=1}^{i}|z_u|\right. \tag{1}$$

$$SVM = \sqrt{{x_i}^2 + {y_i}^2 + {z_i}^2} \tag{2}$$

$$TA = \arcsin\left(\frac{y_i}{\sqrt{{x_i}^2+{y_i}^2+{z_i}^2}}\right) \tag{3}$$

Meanwhile, power spectral density (PSD), signal entropy and spectral energy are included in the frequency-domain features. Thus, in total, a 60-dimensional feature vector is generated for each time window.

Table 1. Time and Frequency-domain Features

Types of Features	Methods
Time-domain	Min, Max, Mean, Standard Deviation, Signal Magnitude Area (SMA), Signal Vector Magnitude (SVM), Tilt Angle
Frequency-domain	Power Spectral Density (PSD), Signal Entropy, Spectral Energy

The next step is to use normality test to determine whether the acquired features can be fitted in a normal distribution pattern. The aim of this test is to determine whether to use parametric or non-parametric classification tools. There are three common tests that are usually performed: Shapiro-Wilk (SW), Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) [32]. These three tests are used to calculate the probability values (*p-values*), where the significance level (α) for these three tests is set at 0.05. If the *p-values* are less than 0.05, the null hypothesis is rejected. The hypothesis of these normality tests is stated as below:

Null hypothesis, H_0: Data is in normal distribution
Alternative hypothesis, H_1: Data is not normal

Finally, the dimensionality reduction process is a technique to transform original features in high-dimensional data into a meaningful representation data in the form of reduced dimensionality. This process facilitates classification process and visualization of high-dimensional data. PCA is considered as one of the popular approaches that can reduce the dimensionality of data by converting original features into new mutually uncorrelated features [33]. These new features are called as principal components, where they are arranged according to their variances and the components that contribute to the lowest variances are usually omitted. The steps taken in the PCA can be represented as below:

i. Normalize the data by subtracting the mean value
ii. Calculate the covariance matrix
iii. Calculate the eigenvectors and eigenvalues of the covariance matrix
iv. Choose the components and form a feature vector
v. Derive a new dataset

IV. Results and Discussion

In this section, the results from the conducted experiments in the methodology section are presented and discussed. Firstly, the results of the normality test are presented in Table 2. From this table, it can be seen that some features which are taken from the time and frequency-domain have probability values (*p-value*) less than 0.05. Based on this result, the null hypothesis can be rejected and thus, it can be concluded that the acquired features are not fitted in a normal distribution with a 95% confidence. Therefore, based on this conclusion, non-parametric classification tools can be chosen as they are well-suited to be applied for the classification process.

Table 2. Normality Test for Extracted Features

Types of Features	**AD**	**SW**	**KS**
Mean	p-value<0.05	p-value<0.05	p-value<0.05
Standard Deviation	p-value<0.05	p-value<0.05	p-value<0.05
SMA	p-value<0.05	p-value<0.05	p-value<0.05
SVM	p-value<0.05	p-value<0.05	p-value<0.05
PSD	p-value<0.05	p-value<0.05	p-value<0.05

Fig 4 presents the dimensionality reduction process using PCA. The three-dimensional plot is used to calculate the most important principal component values, where the first three principal component's variations was accounted for 94.81% (PC1 was 71.85%, PC2 was 14.97% and PC3 was 7.99%) of the total data which contain useful information. This clearly shows that each activity is successfully clustered into their own groups.

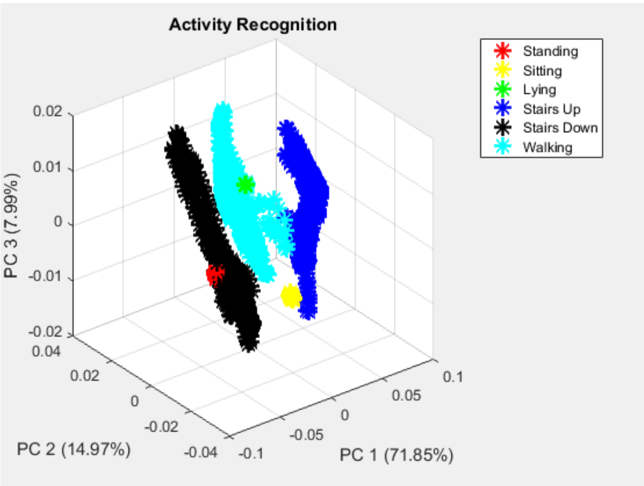

Figure 4. PCA-based Dimensionality Reduction Process

The next process is to classify the activities and compare their performance. The comparison process are performed in terms of Precision, Recall, F-score and Accuracy. The first comparison is between the original features extracted from the raw data and PCA-based features. Additionally, time-domain and frequency-domain features are also compared. It uses several non-parametric machine learning classifier tools, namely DT, SVM and MLP-NN. These machine learning tools are chosen as they have been proven to give better results as stated by [19]. The dataset is divided into two sets, where 70% is used for training and 30% for the testing process. In this experiment, all features have been normalized into the range of [0,1].

Table 3 shows the results from the comparison of classification performance between the original features and the features after the dimensionality reduction process. The classification is obtained using 3600 samples, where each activity contains 600 samples of data. It can be observed that the calculated rates are all higher than 90%. MLP-NN gives the best results compared to other classifiers, with the individual mean accuracy of 98.77%. On the other hand, SVM gives relatively the worst results, with the individual mean accuracy of 91.53%. From this table, the results also show that the total average accuracy is increased by 4.21% when dimensionality reduction using PCA is applied to the original features. This can be explained by the fact that PCA has reduced the data dimensionality and only the highest variances (PC1, PC2 and PC3) are chosen as the dataset for the classification process. Thus, it can be seen that the dimensionality reduction process using PCA facilitates the classification process and improves the classification rates.

Table 3. Comparison of Classifiers between Original Features and Features after Dimensionality Reduction

Classifier Types	Precision	Recall	F-score	Accuracy
Original Features				
DT	98%	98%	98%	95.36%
SVM	91.3%	90.2%	90%	90.19%
MLP-NN	99.6%	99.5%	99.5%	97.54%
Total Average Accuracy				94.36%
Features after Dimensionality Reduction				
DT	96.9%	96.9%	96.9%	96.85%
SVM	94.2%	92.9%	92.8%	92.87%
MLP-NN	100%	100%	100%	100%
Total Average Accuracy				98.57%

Meanwhile, Table 4 shows the comparison of classifiers between features that are divided into the time-domain and frequency-domain. From this table, the frequency-domain features have shown higher total average accuracy compared to the time-domain features, with the difference of 8.90%. DT has the highest mean accuracy in the time-domain, while MLP gives the highest mean accuracy for the frequency-domain features. Based on this result, it can be concluded that the frequency-domain features give a more meaningful data representation compared to the time-domain features. This is because the frequency-domain uses Discrete Fourier Transform (DFT) to transform the features in the time-domain. This gives better characteristic of the signal and able to characterize well different human activities.

Table 5 shows the example of confusion matrix from one of the machine learning classifiers, which is the MLP-NN. The input of this classifier is based on the data after dimensionality reduction process (PCA-based features). The confusion matrix is performed between six classes of activities, namely standing (STD), sitting (SIT), lying (LYI), stairs up (STU), stairs down (STN) and walking (WAL). The row in the table represents the actual class and the column represents the recognized class by the classifiers. The value in the table shows the probability of the recognized actual class. From the table, it can be seen that the activities are accurately recognized with 100% accuracy.

Table 4. Comparison of Classifiers between Time-domain and Frequency-domain Features

Classifier Types	Precision	Recall	F-score	Accuracy
Time-domain Features				
DT	93.8%	93.5%	93.5%	93.52%
SVM	74%	69.7%	66%	69.72%
MLP-NN	88.3%	87.2%	87%	87.2%
Total Average Accuracy				83.48%
Frequency-domain Features				
DT	95%	94.4%	94.4%	94.35%
SVM	83%	87.8%	87.5%	86.3%
MLP-NN	96.7%	96.5%	96.5%	96.48%
Total Average Accuracy				92.38%

Table 5. Example of Confusion Matrix based on MLP-NN Classifier

	Predicted Activity					
	STD	SIT	LYI	STU	STN	WAL
STD	186	0	0	0	0	0
SIT	0	178	0	0	0	0
LYI	0	0	166	0	0	0
STU	0	0	0	167	0	0
STN	0	0	0	0	194	0
WAL	0	0	0	0	0	189

V. Conclusion and Future Work

This paper presents an approach for the recognition of activities of daily living based on a publicly available accelerometer dataset. The dataset uses an accelerometer sensor which has been embedded in a smartphone. A number of features from the time-domain and frequency-domain are extracted from the raw accelerometer signal. PCA is performed on the original features to distinguish low and high variances and reduce the dimensionality of data. This approach is evaluated by comparing the precision, recall, F-score and accuracy of four different types of machine learning classifiers.

In particular, this paper investigates which features that can contribute to the higher classification rate of activity recognition. Based on the normality tests, it is proven that the data is not in a normal distribution, therefore non-parametric classification tools are used to classify the activities. A considerable improvement can be observed by using PCA-based features which can better classify and improve the recognition rate rather than using original features extracted from raw data as the input classifiers. Furthermore, features that are selected from the frequency-domain have shown to have higher accuracy rather than the time-domain features. In another word, frequency-domain features have more robust performance than the selected time-domain features. From the overall results, Multilayer Perceptron Neural Network shown to has the highest accuracy compared to other classifiers. Experimental results also show that a three-second time window with 50% overlap is well-suited for the feature extraction process.

In the previous work, researchers have achieved lower or equivalent recognition rates and they are also considered multiple sensors to recognize activities. For example, [13] only considers three types of activities: walking, running and jumping with the average accuracy below than 85%. Furthermore, [12] uses multiple sensors on the human body, which may cause the problem of movement and practicality in the long-term wearing. However, as presented, this paper uses one accelerometer sensor which performs significantly better where people can easily change the orientation and device position at all time.

As for the future work, the activity recognition can be performed using another approach such as probabilistic methods and the accuracy can be compared with this classification-based method. Moreover, the recognition of ADL can also be extended to other types of activities including context-based activities such as watching television, toileting and cooking. This application can be used to help caregivers in monitoring the health of elderly people, particularly the ones who are living independently in their own homes and identify any abnormalities regarding their daily lives.

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