Recognizing the Activity Daily Living (ADL) of Subject Independent

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Abstract: - Recognition of an Activity Daily Living (ADL) has recently garnered for providing a piece of valuable information to a human. Small and easy to carry, a wearable sensor such as an accelerometer has opened the space for researchers to explore the prior knowledge of pervasive computing. In some ways, the wearable sensor has started to gain attention among researchers to conduct their research in a broad area of human activity recognition. Recent ADL is not only tackling simple activities but also cater to the broad categories of complex activities. However, the recognition accuracy tends to decrease when involving huge numbers of a subject. Even though the same activity has been conducted by a different subject, the acceleration signal obtained significantly differs. This happens due to the action pattern for each subject is different based on several aspects such as subject age, gender, emotion and personality. Thus, this paper is proposing the framework for tackling the subject independent matter by improving the recognition accuracy of ADL. The signal obtained from an accelerometer sensor to undergo a segmentation process to extract additional valuable features. In certain cases, some of the features might irrelevant to determine the class. Hence, we propose feature selection to select the most meaningful features which can lead to accuracy above 90%. On top of that, this paper also highlighted a short empirical review of previous related work. This preliminary work will be evaluated and analyzed using several machine learning algorithms.

Key-Words: - Activity Daily Living (ADL), accelerometer, wearable sensor, machine learning, WISDM, subject independent.

1 Introduction

Nowadays, the majority of the people are owing to a personal smartphone regardless of their age [1]. With the current technology, it is possible to detect the user daily activities based on the smartphone's accelerometer readings and reduce the injury risk. According to the research report, 279 out of 4842 Malaysian elderly who age more than 60 had experience home injuries [2]. This problem could lead to fatal injuries especially when the elderly are alone at home and no action can be provided at the real time. Besides the elderly risk of injuries, the recognition of activity daily living (ADL) can also be used for automated physical therapy where the doctor can observe the daily activities of their patient to identify their recovery status. As a result, high accuracy and efficiency of ADL classification using machine learning model are required. Doctors face difficulty to get track of all their patient's daily activities to monitor their therapy progress as the process is very time-consuming. The same problem also happens in old fork house where the guardian has to take care of many elderlies at the same time. The elderlies, who has ADL disability might hurt themselves when they are trying to complete their daily work alone. This is dangerous if an accident happened and nobody notice and unable to provide assistance in real time.

In the previous research, most of the work regarding ADL classification using machine learning only focus on the subject dependent matter and few numbers of subjects are involved in the data collection. As we know, different people will have a different posture and pattern when doing some activities. Thus, when the machine learning model trained with only a few numbers of subjects, it might be inaccurate to classify and differentiate the activities for other people [3]. Previous research also does not perform feature selection to choose the most relevant features in order to increase the efficiency and accuracy of classification result [4]. This is due to some of the features might irrelevant and less meaningful to describe the activity.

2 Materials and Methods

2.1 Activity daily living (ADL)

The activity of daily living is a term that describes the daily self-care activities of people. There are many activities classified in ADL category, such example included bathing, grooming and dressing, getting to the toilet and moving from one place to another. The basic ADL is not limited to the activities mentioned before; it included all daily activities a person can perform without assistance from others. The previous work of recognizing ADL using machine learning mostly focusing on static activities such as walking, standing, sitting, ascending stairs and descending stairs [4]. There is some research that covers transition activities such as standing up, sitting down, and lying down [6][3].

2.2 Wireless sensor network

A wireless sensor network is a series of sensors installed in a different location in the home to collect occupancy binary data. One popular and commercially available wireless network kit is RFM DM 1810, which often used in research to classify the human activity [7]. The wireless network cannot work alone, it has to be equipped with various binary sensors such as reed switches to measure whether doors and cupboards are open or closed; pressure mats to measure sitting on a couch or lying in bed; mercury contacts to detect the movement of objects (e.g. drawers); passive infrared (PIR) to detect motion in a specific area; float sensors to measure the toilet being flushed [7]. This type of sensors is not suitable to classify activities such as running, walking or sitting. Instead, it can recognize what activity (washing dishes, watching TV, etc.) a subject is doing at the moment based on their location [8].

2.3 Accelerometer

A tri-axial accelerometer is a sensory device that can be found in the majority of modern smartphone or wearable device. It consists of three sensors (x, y, and z-axis) that can simultaneously measure the vibration (acceleration) in three perpendicular axes. The reading of y-axis is usually larger compared to the other two axes due to the Earth. The x, y and z-axes recorded the reading for all three directions as shown in Fig. 1 [5]. In ADL classification, the number of accelerometers and its placement play an important role in obtaining high accuracy performance. According to a paper written by Cleland [9], the best location for single accelerometer placement is at the hip with an average accuracy of 97.8%. In his study, six accelerometers are placed in different location of the human body (lower back, wrist, foot, chest, hip and thigh). As a result, using multiple accelerometers will statistically increase the accuracy of classification even though the differences are not significant. The best classification result can be achieved by using two accelerometers placed at the upper and lower part of the body.

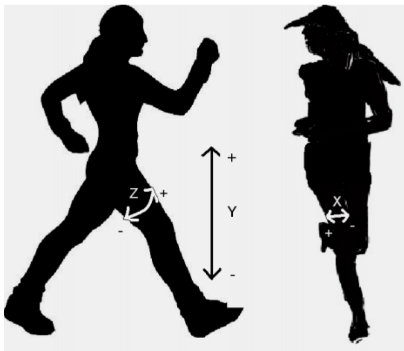

Fig.1 Axes motion relative to subject [5]

3 ADL Classification

There is numerous machine learning model that can be used for ADL classification. In a research lead by Cufoglu in 2016, six machine learning model included Instance Based Learner (IBL), K Nearest Neighbour (KNN), K-Star, J48, Locally Weighted Learning (LWL), and Naïve Bayesian Tree (NB Tree) are used to classify ADL [6]. The experiment was repeated using 9 data points, 15 data points and 30 data points with 11, 15 and 32 attributes respectively. As a result, the highest accuracy for nine data points was obtained by K-Star with an accuracy of 70.86%. When the data points increased to fifteen, K-Star still remains as the best classifier with an accuracy of 70.53. When 30 data points are used, IBL took over the first place with an accuracy of 69.7%. The data used in the study is provided by Bruno et al. [14] at the UCI Machine Learning Repository [15]. However, in his study, Cufoglu only used data from 3 volunteers (2 male and 1 female) out of the 16 provided.

The effect of a machine learning model that is trained by using data from too little people can be observed by a study conducted by Cheng [3]. In his study, Cheng uses dataset collected from four individuals to conduct two types of classification experiment, 1-vs-own and 1-vs-all. The activities involved in this experiment are sitting, sitting down, standing, standing up and walking. For1-vs-own experiment, the training data and the testing data are obtained from the same individual whereas 1-vs-all uses three individual's datasets as training data to test the activity of the remaining one individual. The overall accuracy of 1-vs-own is higher than 90%. On the other hand, the accuracy of 1-vs-all is lower with 61.9% highest accuracy achieved by Neural Network (NN). The low accuracy is a result of overfitting phenomenon where the machine learning model fit too well on the training data [16].

A study conducted by Walse et al. uses human activity recognition (HAR) dataset provided by Wireless Sensor Data Mining (WISDM) Laboratory to classify six activities (walking, jogging, stairs, sitting, standing, and lying down) [4]. Walse et al. successfully achieved an accuracy of 97.83% with J48 using Adaboost.M1 meta-classifier. The other classifier (Random Forest, REP Tree, Random Tree, and Hoeffding Tree) also has a good performance on classifying the activities. However, Decision Stump has a significantly lower performance with an accuracy of 57.31%. This study uses 43 features extracted by Kwapisz et al. [5] from the three axes of accelerometer. The downside of this study is feature selection is not performed to increase the efficiency of the classification process. The use of abundant numbers of features in training data does not necessarily contribute to a better training effect with lower testing error because some of the attributes might be not relevant to the classification process. Instead, when too many features are used it will require more processing time for a computer program to perform the classification [3].

Fida conducted a study on varying different window sizes to classify static and dynamic activities from a single accelerometer [17]. The data was collected from 9 subjects to perform activities such as standing, walking, ascending and descending stairs, sitting and brief walking with an accelerometer attached to their waist. This study also involved dynamic activity where the data of transition between standing and sitting are recorded. The result of this study for 70-30% split subject dependent experiment shows that SVM outperformed KNN, NB, MLP and DT with accuracy over 90% for a window size of 1s and 1.5s. MLP's accuracy comes in second place with window size 1.5s over 90%. The study further experiments the accuracy for subject-independent classification. Turns out, the overall accuracy has a significant drop (average accuracy around 80%) and k-NN has the highest average accuracy.

Cleland conducted an experiment to find out the best location for accelerometer placement for ADL classification [9]. The experiment has collected the data from eight male subjects by placing six accelerometers at various location of their body (chest, lower back, left foot, left hip, left thigh, and left wrist). Four machine learning model included Decision tree (J48), Naïve Bayes (NB), Neural Network (NN), Multilayer Perceptron and Support Vector Machine (SVM) were used to classify the activities. The best accuracy for single accelerometer was achieved with SVM (97.81%) with accelerometer placed at left hip. Similar to past study, Cleland also found that ascending and descending stairs are the most difficult to be classified compared to the other activities.

Subject independent activity classification study was rarely done in the past. However, Awan has conducted a study regarding subject independent human activity recognition with cloud support in 2015 [18]. The study collected training data limited from two people using smartphone accelerometer at a different position (hand palm, trouser pocket, waist-mounted, and armband) for 11 ADL. The classification process in this study is performed in a workstation module using Waikato Environment for Knowledge Analysis (WEKA) to reduce the processing burden for a smartphone. As a result, K-NN achieved the highest accuracy compared to NB, Bayesian Network, J48, Multilayer Perceptron and Logistic Regression. In terms of smartphone position, waist-mounted, and armband position has significantly higher accuracy probably because the smartphone was fixed and more steadied in those positions which can reduce the noise (unwanted data/ outliners) in the collected data.

Nabian conducted a comparative study on machine learning classification models for activity recognition [19]. The study used data provided by Baños [20] which consists of body motion recordings from 10 volunteers using sensors placed on the chest, right wrist, and left ankle. The dataset has 346,000 instances which are separated into 80% training data and 20% testing data. Ridge Logistic Regression, KNN, Random Forest, Decision Tree, NB, SVM, and NN are used as machine learning model to classify activities such as standing, sitting, lying down, walking, climbing stairs, jumping front and back, running, jogging, biking, knees bending, frontal elevation of arms, and waist bend forward. The performance of KNN and random forest is excellent with accuracy of more than 99% followed by Decision Tree and Artificial Neural Network (NN) with accuracy above 98%. On the other hand, SVM, NB and Ridge Logistic Regression performance were relatively poor with an accuracy of 68.9%, 84.2%, and 69.59% respectively. According to Nabian, the low accuracy of linear classifier (NB and Ridge Logistic Regression) is a result of the non-linearity data in different activities. The paper further study on the running time for each classifier. As a result, Random Forest and Decision Tree took a very short time to complete the classification process (19sec and 15.2sec respectively) whereas KNN and SVM took a very long time (149.2sec and 131.2sec).

Kwapisz and his team conducted their WISDM project using android phone's triaxial accelerometer to measure the acceleration in three spatial dimensions for activity recognition [5]. According to Kwapisz, an accelerometer is able to detect the orientation of the device by detecting the direction of Earth gravity, which plays an important role in classifying human activity. The study collects data through smartphone accelerometer with 20Hz (20 samples per second) from 29 subjects to collect 6 different activities (walking, jogging, ascending stairs, descending stairs, sitting, and standing). Four machine learning model including J48, Logistic Regression, Multilayer Perceptron, and Straw Man were used to classify the activities. As a result, Multilayer Perceptron recorded the highest overall accuracy in classifying the activities. The highest accuracy was also achieved by the same machine learning model on classifying jogging with an accuracy of 98.3%. Ascending and descending stairs are the two activities that is hardest to be classified. The highest accuracy achieved in classifying the two activities is 61.5% only by Multilayer Perceptron. On the other hand, Straw Man classifier performance is below average in the study. The highest accuracy is only 37.2% on classifying walking. The detailed accuracy of each classifier and their activities are listed in Table 1.

Table 1. Classification result by Kwapisz [5]

	% of Records Correctly Predicted			
	J48	**Logistic Regression**	**Multilayer Perceptron**	**Straw Man**
Walking	89.9	93.6	91.7	37.2
Jogging	96.5	98.0	98.3	29.2
Upstairs	59.3	27.5	61.5	12.2
Downstairs	55.5	12.3	44.3	10.0
Sitting	95.7	92.2	95.0	6.4
Standing	93.3	87.0	91.9	5.0
Overall	85.1	78.1	91.7	37.2

Ravi [21] conducted a study namely "Activity Recognition from Accelerometer Data" to classify eight human activities including standing, walking, running, ascending and descending the stair, sit-up, vacuuming, and brushing teeth. The study used one accelerometer located at pelvic and 5 machine learning model (Decision Table, Decision Tree, KNN, SVM and NB) to classify human activity. The paper is divided into four settings, the first setting collects data from a single subject over different days and performed mixing and cross-validation. Setting two is identical to setting one but the subject is increased to two people. Setting three used the same subject's data for training and testing but from a different day. Setting four is a subject independent approach where the first subject's data is used for training whereas the testing data comes from a different subject. As a result, setting one and setting two achieved very high accuracy for all classifier but setting three shows a lower accuracy. Setting four, however, its result is not satisfying as the highest accuracy was only 73.33 achieved by boosted SVM and the lowest accuracy is as low as 47.33%. The detailed comparison of each research in the past is tabulated in Table 2 where the first column is the name of the author, followed by their machine learning model (method) and a number of activities involved. The last two column shows if the study involves subject independent work and the highest accuracy achieved in the respective paper.

Table 2. Comparison of ADL classification

Author	Activities	Subject Independence	Accuracy (%)
Cufoglu [6]	11	No	70.86 (K-star with 9 datapoints)
L. Cheng [3]	5	No	99.5 (SVM)
L. Cheng [3]	5	Yes	61.9 (NN)
K.H. Walse [4]	6	No	94.61 (REP Tree)
B. Fida [17]	6	No	96.3 (SVM)
B. Fida [17]	6	Yes	80~90 (SVM)
Cleland [9]	4	No	97.81 (SVM)
Awan [18]	11	Yes	99.07 (KNN)
Nabian [19]	12	No	99.4 (KNN & RF)
J. R. Kwapisz [5]	6	No	98.3 (MP)
N. Ravi [21]	8	No	above 90%
N. Ravi [21]	8	Yes	73.33 (Boosted SVM)

4 ADL Features

In a study conducted by Fida [17], features such as mean, average standard deviation, skewness, and kurtosis were extracted from the 3 axes accelerometer reading using sliding windows method with different window sizes (0.5 s, 1s, 1.5 s, 2 s, 2.5 s and 3 s) to find out its effect on the daily living activity classification. Turns out, 1.5s window size shows the highest overall accuracy in both subject dependent and subject independent experiment. Cleland used a window size of 512 samples with 256 samples overlapping to extract feature from 370,000 samples of raw accelerometer data [9]. The study extracted eleven features from each window to obtain a total of 26 attributes. The list of extracted features is tabulated in Table 3.

Table 3. Example of features

No.	Feature Description
1.	Mean value for each axis (x, y, and z)
2.	Average Mean over 3 axes
3.	Standard Deviation value for each axis (x, y, and z)
4.	Average Standard Deviation over 3 axes
5.	Skewness value for each axis (x, y, and z)
6.	Average Skewness over 3 axes
7.	Kurtosis value for each axis (x, y, and z)
8.	Average Kurtosis over 3 axes
9.	Energy value for each axis (x, y, and z)
10.	Average Energy over 3 axes
11.	Correlations: x_y, x_z, x_total, y_z, y_total, z_total

In a subject independent study conducted by Awan, six features were extracted from an accelerometer placed at four different parts of the body. The extracted attribute in this study included mean, standard deviation, a correlation between axis, variance, mode, and kurtosis. Mean and mode maintained a uniqueness of each axis even in the activities that had steady data patterns. Hence, they provide an adequate result compared to the other extracted feature. The mode, which has overall high accuracy in the classification process shows a surprising low accuracy (13%) using multilayer perceptron classifier. The study uses a sliding windows method with different window sizes in extracting new features. According to Awan, different activities require different span, therefore, the optimal window size cannot be determined. However, using a window size of 2-6s are recommended using smartphone accelerometer according to past research [5][18][22].

Baek conducted an experiment on user activity detection using accelerometer signal processing [23]. In his paper, he studied the relationship of five different attributes and their effectiveness on classifying human activity. Baek selected mean, standard deviation, skewness, kurtosis, and eccentricity as the signal features. According to Baek, mean and standard deviation can distinguish static (stand, sit and lying) and dynamic activities (walking, running, and using stairs) effectively. The x-axis of skewness, however, is able to differentiate walking and running from ascending and descending stairs. The y-axis, on the other hand can differentiate walking and ascending stair from running. Baek also mentioned that walking and running can be distinguish using stairs by the x-axis of kurtosis. Fig. 2 illustrated how each statistical feature distinguishes their respective activity.

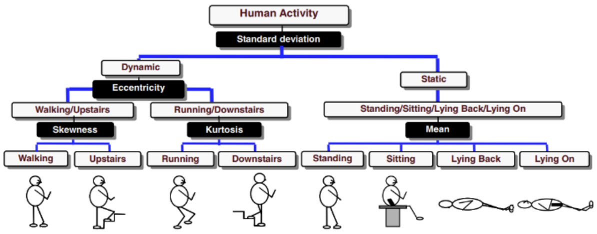

Fig. 2. Features in ADL classification [23]

5 Proposed Framework

As highlighted at the beginning of this paper, we are proposing the work in recognizing of ADL for tackling the subject independent matter. It might incapable to produce high accuracy when it involves a different pattern of a subject with a different action. For example, even though the activity conducted in the same by two different subjects, but it not necessary it will produce the same acceleration pattern. In addition, it tends to increase the complexity of a learning algorithm to learn the characteristic of the activity pattern. Hence, we propose the framework to tackle this issue mentioned above. Fig. 3 shows the entire framework of our proposed work.

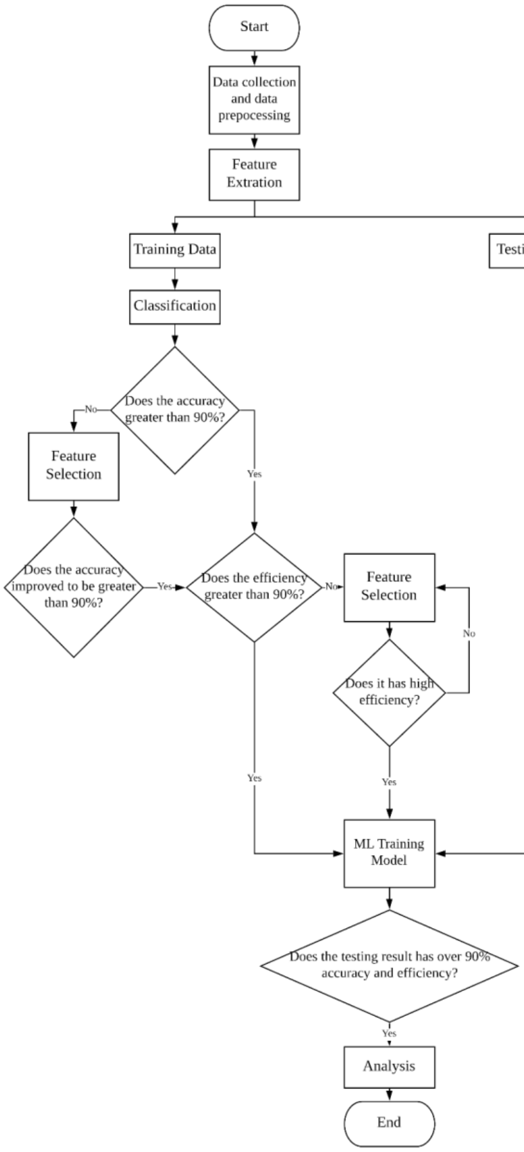

Fig. 3. Overall proposed framework

Fig. 3 illustrates the entire process flow of our proposed algorithm for tackling the problem of recognizing the activity of the independent subject. Initially, the acceleration signal will undergo a preliminary process to filter and remove unwanted information before it will proceed for further process. Next, several additional features by combining from mathematical and statistical features will be extracted and the extracted features subset will be separated into two subsets; training (70%) and testing (30%). The training subset is used for training the learning model, while when it achieves the satisfy performance, the learning model is evaluated using the reserve testing subset. If the result of the classification has over 90% accuracy, the efficiency of the classification will be taken into consideration. However, some of the features might unnecessary to portray the activity. Hence, the selection of good features is taking into deliberation. Afterward, we will evaluate the performance of each features using several feature extraction methods until it reaches desired accuracy performance. Otherwise, the feature extraction process needs to be repeated to extract more relevant attribute in order to increase its accuracy and efficiency. Finally, the process of testing and training is repeated for various machine learning model and is compared in detail.

6 Conclusion

This paper discusses the empirical study of recognizing activity daily living using the wearable sensor. As mentioned in the early section, the use of wearable sensor such as an accelerometer is practical due to low cost and small in sizes. Hence, we obtained the activity recognition data from public dataset to undergo our research. On top of that, we are proposing the framework to recognize the various human activities without relying on the identity of the subject. As mentioned early, much works reported are not considered the subject independent matter. Even though there are a few numbers of works reported tackled the subject independent matter, but the accuracy obtained still considered as below 90%. This matter might be happening due to some of the features may irrelevant to describe the activity of a different subject. The selection of features is considered as critical to cater this issue. Hence, we propose the work for tackling the subject independent matter to improve the recognition accuracy with a various number of subject in our projection work. We also propose a feature selection method in order to evaluate the performance of each extracted features which leads to desired accuracy performance. In future work, we are planning to evaluate the performance of our proposed work by improving the recognition accuracy of subject independent matter using several machine learning models and feature selection models based on a wearable sensor.

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