Pairwise Classification Using Combination of Statistical Descriptors with Spectral Analysis Features for Recognizing Walking Activities

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***Abstract*—The advancement of sensor technology has provided valuable information for evaluating functional abilities in various application domains. Human activity recognition (HAR) has gained high demand from the researchers to undergo their exploration in activity recognition system by utilizing Micro-machine Electromechanical (MEMs) sensor technology. Tri-axial accelerometer sensor is utilized to record various kinds of activities signal placed at selected areas of the human bodies. The presence of high inter-class similarities between two or more different activities is considered as a recent challenge in HAR. The nt of incorrectly classified instances involving various types of walking activities could degrade the average accuracy performance. Hence, pairwise classification learning methods are proposed to tackle the problem of differentiating between very similar activities. Several machine learning classifier models are applied using hold out validation approach to evaluate the proposed method.**

***Index Terms*—HAR; Accelerometer; Inter-Class Similarities; Pairwise Classification; Random Forest.**

I. INTRODUCTION

The advancement of pervasive computing has drastically garnered demand for various kinds of applications such as in face recognition [1], iris recognition [2], medical imaging [3] and ambient assisted living [4]. The progression of the smart environment has become an emerging field in the Human Activity Recognition (HAR) research area among the researchers to provide better lifestyle environment to the user. Recognition of the human activities [5] or determination of human gait [6] is useful in many ways by providing a better lifestyle to the human. It could also be beneficial nurses by helping them to identify the abnormalities of the Parkinson patients' action during their rehabilitation treatment [7], [8]. In the area of HAR, there are three common sensing approaches that are broadly applied namely, vision-based sensor, environmental-based sensor and wearable-based sensor. A vision-based sensor is applied for monitoring the resident activity in certain areas or buildings. The abnormalities of the resident behaviour could be easily identified by monitoring the actions performed through the camera sensor. Clutter, variable lighting and the camera specification are the aspects that should be taken into account in order to provide a good end-user vision application. The environmental-based sensor is applied by involving various kinds of sensors such as camera, motion, temperature and humidity sensors. This internet-of-things application integrates those kinds of sensors for monitoring the regular activities performed by the residents at homes. Since the cost of the implementation is definitely high, this approach might be impractical to be implemented. Moreover, when the privacy of the residents becomes a major consideration, both of these approaches are unfeasible to be applied as the confidentiality of the residents' personal information may be disclosed. In order to overcome this problem, the wearable-based sensor might become a solution in this HAR. In this approach, several inertial sensors such as accelerometer and gyroscope are attached to several parts of the human bodies [9]. The sensor records the signal for each activity or action conducted and the recorded signal is later used for further analysis.

Theoretically, an accelerometer sensor records the signal in three different dimensions and the signal is produced in different signal patterns depending on the type of the activity performed. Since the recorded signal pattern is diverse, it will help the classifier model to differentiate each of the activity conducted according to the recorded signal. However, when involving various types of stationary and locomotion activities, it might be possible for some of the activities to produce very similar signal patterns due to the effect of the gravitational forces. For instance, walking activity might be categorized into two different classes, 2D walking (walk forward, walk left, walk right) and 3D walking (walk upstairs, walk downstairs) [10]. Previous work on HAR stated that the most difficult activity to be classified is when it involved ascending walking and descending walking [11]–[14]. Both of these activities consist of very similar signal pattern and this issue, on the other hand, contributed to the presence of high inter-class similarities. The occurrence of high inter-class similarities tends to degrade the classification performance. This happens because the probability of the instances is incorrectly classified due to the high rate of confusion between each signal pattern. In this article, several contributions are brought up and explained. Firstly, the features from statistical descriptors and spectral frequency measurement analysis are extracted and combined in order to differentiate between stationary and locomotion activities. Secondly, pairwise classification learning is proposed to tackle the problem of high inter-class similarities activities especially the one involving various types of walking activities. Thirdly, the proposed method is evaluated using several widely known classification models such as random forest, K-Nearest Neighbor (KNN), decision tree (J48) and Support Vector Machine (SVM). We also noticed that the result of this research significantly outperformed the reported result of previous work.

II. Wearable-based Sensor Applications

Many of the previous work had utilized the wearable-based sensor approach and the pioneering work in HAR had been done by Bao and Intille [15]. They recorded the accelerometer signal by using the five bi-axial accelerometers which were placed at several parts of human bodies and evaluate their work using several classifier models; decision tree, decision table, naïve Bayes and nearest neighbour classier. Mannini et al. [16] utilized a single accelerometer sensor placed at human wrist and ankle to record the signal of twenty six activities in their work. Later, they proposed a method that allows automatic detection of sensor positions from the walking activity that had been performed based on five different sensor positions; ankle, thigh, hip, arm and wrist [17]. Fida et al. [18] studied the effect of window size in recognizing the short and long duration activities using single tri-axial accelerometer which was placed at the human waist. Kwapisz et al. [12] on the other hand recorded six daily physical activities using single tri-axial accelerometer which was placed at human thigh. Later, Catal et al. [11] continued Kwapisz work for recognizing the activity using voting ensemble classifier model. The result showed a significant increase in the performance of overall accuracy compared to the previous work by Kwapisz. Walse et al. had proposed several works on activity recognition using the same dataset. They evaluate their proposed method using random forest classifier and the result showed acceptable performance [19], [20]. However, even though plenty of works had been reported previously in HAR, the most difficult activity to be classified is the stairs activity [21]. Most of the work on HAR successfully recognized other activity but failed to differentiate between the 3D walking activities (ascending and descending activities) and 2D walking activities (right, left and forward walking) [11]–[14], [22]. Zheng [10] had claimed their work on HAR involving 2D and 3D walking activities from acceleration signal. Even though other stationary and locomotion activities achieved good performance but the accuracy for 2D and 3D walking activities are definitely lower than the other activities.

III. Proposed Methodology

A. Accelerometer Activity Dataset

The researchers from the Department of Electrical Engineering, University of Southern California had collected human activity dataset (USC-HAD) from various types of subjects including male and female with different ages [23]. Motion Node is a device consists of calibrated inertial accelerometer sensor which is used to record the activity signal. The device is placed on the front hip of fourteen subjects during the data collection. The sampling rate used in this dataset is 100 Hz. In this dataset, each subject is asked to conduct twelve different physical activities involving 2D walking (walk forward, walk left, walk right), 3D walking (walk upstairs, walk downstairs), running, jumping, sitting, standing, sleeping, elevator up, and elevator down. We evaluated the proposed method based on two different experiments. Firstly, all twelve activities are employed in our model to evaluate the effectiveness of the proposed method. Secondly, in order to make a fair comparison with the author, two activities (elevator up and down) are eliminated from the list since the author [10] does not include both of these activities in their present work.

B. Fast Fourier Transform (FFT) Analysis

Accelerometer sensor records the signal for three different axes (x, y and z). Each dimension records the signal from different angle of movement. X-dimension records the right and left movements, y-dimension records the up and down movements, z-dimension records the forward and backward movements. In general, accelerometer sensor captures the acceleration signal in two different acceleration signals; gravitational acceleration (high-frequency component) and body acceleration (low-frequency component). Each acceleration signal captures the sum of gravitational and body acceleration [24]. Gravitational acceleration is presented in high-frequency component and this signal component is not useful for determining the activity classes. Only low-frequency component is required for recognizing the types of the activity conducted. Hence, both of these signals need to be separated before any further calculation is performed. Fourier Transform is used to analyze the signal in the frequency domain by computing a Discrete Fourier Transform (DFT) of a sequence [25]. Hence, Butterworth low-pass filter is utilized in separating the acceleration signal between the high-frequency components and the low-frequency component. Afterwards, only body acceleration signal will remain and use for further analysis.

C. Statistical Descriptors and Spectral Analysis Features

Sliding window segmentation is one of the commonly known segmentation methods used to segment the signal into a series of window segments. This process aims to divide the time series signal into several segments before any calculation is performed. For this experiment, a window size of 6.4 seconds with 50% overlapping between two consecutive window segments is used. Even though the selection of window sizes will affect the number of instances for classification [18] but the selection of window size in this work is considered as sufficient in separating the transition between two different activities. Later, several types of features are calculated and extracted from each window segment that had been generated. In this work, we have combined several features from two different groups; statistical descriptors and spectral frequency measurement analysis features. Easy and less computational complexity, statistical descriptors are useful for determining the postural or stationary activities [24]. In contrast with stationary activities, locomotion activities like running and jumping consist of correlation acceleration pattern relation from each dimension. Thus, several spectral frequency measurement analysis features are extracted. This feature is less susceptible to signal quality variations and correlate to the periodic nature of the specific activity. Table 1 and 2 present the list of the features from statistical descriptors and spectral frequency measurement analysis features used in this work.

D. Random Forest Ensemble Classifier

Ensemble classifier is introduced based on the combination of more than one classifier models to maximize the performance of classification accuracy [26]. Random forest ensemble classifier is introduced by Breiman [27] based on the collection of several randomized decision tree. Each of the decision trees in the forest is learned from a random subset of the training example and the features. The output predictor from each decision tree is averaged until each tree reaches to the leaf node in order to obtain the overall output in the test

Table 1
List of Statistical Descriptors Features

Features	Descriptions
Minimum and maximum	Minimum and maximum values from each window segment for each dimension
Variance	Summation of value of each window segment divided by window size for each dimension
Standard deviation	The measurement of how spread out member are from each window segment for each dimension
Skewness	The measurement of asymmetry of the distributions of the data points of the acceleration data around mean from each window segment for each dimension
Kurtosis	The descriptors of the shape of the distribution of the data points of the acceleration data from each window segment for each dimension
Correlation coefficient	The measurement the correlation among the acceleration in x, y and z directions and among the acceleration sensors from each window segment for each dimension
Harmonic mean	Calculation of harmonic mean from each window segment for each dimension

Table 2
List of Spectral Analysis Features

Features	Descriptions
Power bandwidth	Calculate the power bandwidth of the signal in frequency response from each window segment for each dimension
Band power	Calculate the average power of the input signal in frequency response from each window segment for each dimension
Occupied bandwidth	Calculate the maximum 99% of power bandwidth occupied by the input signal in frequency response from each window segment for each dimension

samples. In order to obtain the final prediction, the class category which has recorded the highest probability is selected. There had been several works in the past involving HAR that utilized ensemble classifier as their class estimator. Tthe result of these works indicated good performance in determining the class of the activities [20], [28]–[30]. With the intention of maintaining the generalization of the proposed methods, several classifier models are utilized to compare the result obtained. KNN, J48 and SVM classifier model are utilized in these experiments. In order to validate our performance result, holdout validation strategy is utilized. In this experiment, the subset is divided into two different sizes of subsets. 30% subset that had been randomly selected is used for training and 70% subset is reserved for testing. This testing subset is useful for evaluating the generated training model in measuring how successful the model could recognize the unseen data. Average accuracy and precision are the two performance metrics used in measuring the performance of this work.

E. Pairwise Classification Approaches

In the past few years, most of the classification models are designed to handle the problem of binary class classification. In order to overcome the multi-class problems, the enhancement of the classifier model is modified to enable the classifier in handling the multi-class classification problems. Initially, SVM is proposed and this method has been shown to be effective in classifying binary class problems [31]. Afterward, the existing SVM has been improved by introducing the kernel that enable it to handle multi-class classification problem. On the other hand, binarization strategies are used for transforming the multi-class classification problems into a series of binary class classification problems. This method is known as binarization classification method [32]. The binarization classification is broadly classified into two different methods; one-versus-all (OVA) and one-versus-one (OVO) methods. OVA is created by categorizing each of the classes into two groups of classes (positive and negative class). The dominant instances belong to the positive class and the negative class instances belong to the union of the other classes. The number of classifier model obtained is equal to n-1 (where n is the number of classes). In contrast with OVA, OVO generates the classifier model by transforming the multi-class problem into a series of the binary class model and the number of classifier model created is equal to n(n-1)/2. This method is also called as the round robin classification. To obtain the final prediction, all the instances need to be trained through the entire model generated and the prediction result from each model is combined. The class which received majority voting is classified as the final prediction [33]. In this work, both of these methods are utilized to cater to the problem of high inter-class similarities between classes as reported in section 1.

IV. Experimental Result and Analysis

The acceleration signal from each dimension is filtered using 5th order Butterworth low-pass filter in order to separate the entire acceleration signals between the body and gravitational acceleration. In this experiment, 0.3 Hz cutoff frequency is used to eliminate the unwanted information from the signal. The amount of the cutoff frequency chosen is considered sufficient to separate the high and the low-frequency components. Thus, the frequency which is above this threshold will be eliminated from the signal for each dimension of the signal. Figure 1 and 2 present the signal example for very similar activities and the filtered signal using Butterworth low-pass filter respectively.

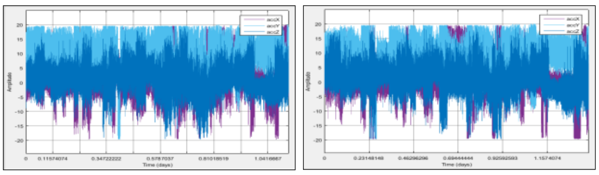

Figure 1: Raw signal for walking down (left) and walking up (right)

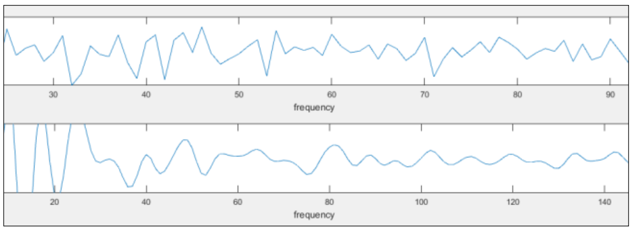

Figure 2: Filtered signal using a Butterworth low-pass filter.

Referring to Figure 1, two activities (walking down and walking up) that contributed to high inter-class similarities are presented. It can be seen clearly that the record for the acceleration signal from each dimension is almost similar even though the activity conducted is different. Furthermore, this will cause difficulty for any classifier model to differentiate between these two activities. The frequency signal presented in Figure 2 (top) clearly showed that the unfiltered signal consisting of noise from the signal is presented in the uneven sine waves. Hence, Figure 2 (bottom) showed the filtered signal which was obtained when the gravitational acceleration signal had been eliminated from the body acceleration signal. The signal from each of the dimensions has undergone the segmentation process before additional features are extracted. The extracted features which were presented as a feature vector afterwards is used for classification. As described in subsection C, the size of the sliding window is 6.40 seconds with 50% overlapping between the adjacent windows is applied for this experiment. Then, each generated window segment had to go through the feature extraction process in order to extract the features as explained in section C. Each dimension will produce a total number of 36 features (from statistical descriptors and spectral frequency measurement analysis features) with an addition of one label to represent the class categories. As mentioned previously in subsection A, two different experiments are conducted in our work. In the first experiment, we utilized all the twelve activities collected in the dataset. Table 3 and 4 present the classification result for two pairwise classification methods using OVA and OVO respectively.

Table 3
Classification Result Using OVA

Activity	Training		Testing	
	Accuracy	Precision	Accuracy	Precision
jump	0.944	0.974	1.000	0.975
liftdown	0.874	0.901	0.917	0.892
liftup	0.897	0.899	0.875	0.924
run	0.985	0.965	0.989	0.989
sit	0.991	0.985	0.991	0.987
sleep	1.000	1.000	1.000	1.000
stand	0.986	0.969	0.988	0.975
walkdown	0.936	0.932	0.950	0.961
walkfor	0.965	0.907	0.967	0.928
walkleft	0.917	0.953	0.933	0.958
walkright	0.912	0.940	0.931	0.950
walkup	0.914	0.948	0.936	0.952
average	0.947	0.947	0.958	0.958

Table 4
Classification Result Using OVO

Activity	Training		Testing	
	Accuracy	Precision	Accuracy	Precision
jump	0.941	0.960	1.000	0.959
liftdown	0.868	0.891	0.902	0.878
liftup	0.891	0.885	0.871	0.905
run	0.980	0.963	0.981	0.991
sit	0.985	0.986	0.985	0.989
sleep	1.000	1.000	0.999	1.000
stand	0.979	0.965	0.977	0.969
walkdown	0.919	0.932	0.929	0.953
walkfor	0.961	0.898	0.965	0.915
walkleft	0.895	0.953	0.911	0.955
walkright	0.905	0.929	0.925	0.939
walkup	0.914	0.927	0.928	0.933
average	0.940	0.941	0.949	0.949

Referring to Table 3, the accuracy for testing subset achieved above 93% for almost all activities excluding the two elevator activities (lift up and lift down) using OVA. Sleeping recorded 100% in which the instances are correctly classified, followed by sitting (99.1%) and standing (98.8%). Jumping I achieved 100% of accuracy and other locomotion activities (running) recorded 98.9% of accuracy. For 2D walking activities (walk forward, walk left and walk right), the accuracy obtained were 96.7%, 93.3% and 93.1% respectively. In contrast with 2D activities, 3D activities such as walking down and walking up had recorded an acceptable performance, in which the accuracy obtained were 95% and 93.6% respectively. The lowest accuracies obtained were from lift down and lift up activities. In OVO, the overall accuracy obtained for training and testing subsets were 94% and 94.9% as presented in Table 4. In this method, all of the testing instances for jumping activities were correctly classified. Overall accuracy reported an acceptable performance in which the accuracy is above 90%, except for lift up which recorded 87% of accuracy. The second highest accuracy is recorded from sleeping (99.9%) and followed by sitting and running. The accuracy result for both of these activities is above 98%. However, the accuracy rate for 2D activities had slightly dropped with 0.2% and 0.1% respectively when OVO is applied. Similarly, with 3D activities, the percentages of average accuracy for all three 3D walking activities decline with the use of OVA. Walk forward showed a decline from 96.7% to 96.5%, followed by walk left which showed a decline from 93.3% to 91.1% and walk right experienced a decline from 93.1% to 92.5%. From this experiment, it can be concluded that the walking activity could be summarized as the most difficult activities to be classified. Elevator activity had also recorded the lowest accuracy among other activities since both of these activities involved very little movement. This also tends to increase the difficulties for the classifier model to differentiate between elevators up and elevators down. In order to validate our proposed method with benchmark study, we followed the experiment as implemented by the author [10]. In this following experiment, two elevator activities (lift up and lift down) were eliminated from our activity class. Only ten numbers of classes remained for the evaluation criteria. Table 5 and 6 present the classification result by using the OVA and OVO methods based on the ten activities respectively.

Table 5
Classification Result Using OVA

Activity	Training		Testing	
	Accuracy	Precision	Accuracy	Precision
jump	0.939	0.962	1.000	0.965
run	0.984	0.964	0.982	0.980
sit	0.986	0.994	0.986	0.992
sleep	1.000	1.000	1.000	0.999
stand	0.992	0.979	0.991	0.981
walkdown	0.937	0.943	0.940	0.956
walkfor	0.967	0.910	0.970	0.925
walkleft	0.927	0.962	0.913	0.971
walkright	0.921	0.937	0.943	0.940
walkup	0.918	0.956	0.935	0.956
average	0.957	0.958	0.964	0.964

Table 6
Classification Result Using OVO

Activity	Training		Testing	
	Accuracy	Precision	Accuracy	Precision
jump	0.939	0.953	1.000	0.954
run	0.982	0.965	0.979	0.981
sit	0.982	0.994	0.978	0.993
sleep	0.999	1.000	1.000	1.000
stand	0.990	0.979	0.989	0.975
walkdown	0.922	0.932	0.909	0.950
walkfor	0.961	0.904	0.962	0.919
walkleft	0.909	0.960	0.908	0.959
walkright	0.915	0.929	0.936	0.932
walkup	0.918	0.939	0.927	0.926
average	0.952	0.952	0.956	0.956

Table 5 presents the classification result for ten activities using OVA method. As we can see, the overall accuracy obtained definitely increases when the two elevator activities had been excluded from the activity list. The average accuracy achieved from the training and testing subset were 95.7% and 96.4% respectively. Similar to the previous experiment, the accuracy for both jumping and sleeping is 100%, followed by standing at 99.1%. The accuracy for two 2D walking activities (walking forward and walking right) also showed an increase. However, other activities like running and sitting had recorded a slight drop. Table 6 presents the classification using OVO and the highest accuracy was obtained from jumping and sleeping. This result is similar to the result which involved the use of OVA. The overall accuracy is 95.6% which showed a decrease of 0.8% compares to the result obtained in OVA. The other activities (stationary and locomotion) showed a decline when OVO is applied. Walking down and walking left have also recorded the lowest accuracy compared to others in which the accuracy is not more than 91%. Hence, we concluded that OVA produced significantly good accuracy performance to recognize various types of activities including 2D and 3D walking activities compared to OVO. Table 7 presents a confusion matrix for the testing subset using OVA.

Table 7
Confusion Matrix OVA Method

AC	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	628	0	0	0	0	0	0	0	0	0
A2	10	922	0	0	0	1	3	1	1	1
A3	0	0	1385	0	16	0	1	0	0	3
A4	0	0	0	1865	0	0	0	0	0	0
A5	0	0	10	1	1282	0	0	0	0	1
A6	2	1	1	0	1	1460	40	9	12	28
A7	2	7	0	0	4	12	2322	11	26	9
A8	4	4	0	0	1	14	54	1353	40	12
A9	0	3	0	0	2	14	37	14	1439	17
A10	5	4	0	0	1	26	53	6	13	1556

According to Table 7, most of the instances of stationary and locomotion activities are almost correctly classified except for the walking activities. As we can see, both of the walking activity groups (2D and 3D walking) are confused with each other as these kinds of activities involved different signal pattern even though those activities are considered as walking. This problem has also been highlighted by the previous works as the most difficult activities to be classified and differentiated due to the fact that the signal recorded is very similar to each other. In order to validate our proposed method, several other classifier models are utilized in this work. J48, KNN and SVM are applied to compare the performance of our proposed method. Table 8 presents the classification result with several other machine learning algorithms.

Table 8
Comparison with Others Machine Learning Methods

Activity	RF - OVA	J48	KNN	SVM
jump	1.000	0.979	1.000	0.457
run	0.982	0.929	0.854	0.542
sit	0.986	0.952	0.859	0.655
sleep	1.000	0.988	0.951	0.914
stand	0.991	0.923	0.787	0.587
walkdown	0.940	0.834	0.737	0.414
walkfor	0.970	0.865	0.815	0.781
walkleft	0.913	0.830	0.756	0.197
walkright	0.943	0.830	0.779	0.214
walkup	0.935	0.840	0.733	0.401
average	0.964	0.890	0.817	0.541

Average accuracy that had been obtained from our work by using the RF-OVA obviously showed the highest accuracy compared to the other classification models. Decision tree model (J48) recorded the second highest accuracy followed by KNN models. However, SVM produced the worst accuracy result in recognizing the activities since the average accuracy obtained is below 55%. This clearly proven that our result promised good achievement in recognizing various types of activities. To assess our results with previous work, a comparison with previously reported work had been carried out. Table 9 presents the comparison between our results with the result of the previous work by the author [10].

Table 9
Comparison with the Previous Result

Activity	Zheng	OVA	OVO
jump	0.971	1.000	1.000
run	0.971	0.982	0.979
sit	0.971	0.986	0.978
sleep	0.986	1.000	1.000
stand	0.986	0.991	0.989
walkdown	0.943	0.940	0.909
walkfor	0.957	0.970	0.962
walkleft	0.929	0.913	0.908
walkright	0.914	0.943	0.936
walkup	0.929	0.935	0.927
average	0.956	0.964	0.956

Average accuracy obtained from OVA is significantly higher compared to OVO and Zheng work. The accuracy performance which had been recorded by OVO is almost similar to our benchmark work. Almost all of the activities recorded by OVA has achieved good performance and outperformed the accuracy reported by the previous author. Two activities (jumping and sleeping) contributed drastically to the average accuracy since all the instances from both of these activities are correctly classified. Other locomotion activities like running have also shown an incline. Three walking activities (walking forward, walking right and walking up) showed an improvement of about 2%. Even though two of the walking activities (walking down and walking left) showed a slight decrease but this accuracy achieved acceptable performance in recognizing the 2D and 3D walking activities especially those involving stationary activities. Hence, we could conclude that our proposed method showed promising results in improving the performance of the classification of the activity using single accelerometer sensor signal.

V. CONCLUSION

This article presents the work on activity recognition for various types of stationary and locomotion activities. In this work, the tri-axial accelerometer which was embedded in Motion Node sensing device had been attached to the front hip of fourteen subjects to record the signal of twelve different types of physical activities. Accelerometer signal is filtered by using Butterworth low-pass filter in order to separate the signal between body and gravitational acceleration. The body acceleration signal the go through the feature extraction process in order to extract several features that represent the characteristic of the class categories. Sliding window segmentation is applied to cut off the signal into series of windows segments. Several features from statistical descriptors and spectral frequency measurement analysis are extracted in order to differentiate between locomotion and stationary activities. The appearance of high inter-class similarities between classes is one of the problems that had been reported as the biggest challenge in HAR. 2D and 3D walking activities had been reported to be difficult to distinguish due to the signal obtained is very similar to each other and might be confusing. Hence, pairwise classification approaches are introduced to tackle the problem of high inter-class similarities activities. Random forest ensemble classifier model shows a good performance in recognizing the activity, using the proposed method as compared to KNN, J48 and SVM classifier models. In comparison with benchmark work, our result shows a significant improvement in recognizing various types of activities. For our future projection, we plan to evaluate our proposed method by selecting the most relevance features from the feature selection model. Hybrid feature selection model needs to be introduced since the hybrid models have recently shown promising and good accuracy for various optimization problems [34].

ACKNOWLEDGMENT

This work is sponsored by Universiti Putra Malaysia and funded by the FRGS research grant (5524660), Ministry of Higher Education Malaysia.

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