Common Sport Movement Recognition from Wearable Inertial Sensor

Norazman Shahar, Nurul Fathiah Ghazali, NurAkmal Yahya, Muhammad Amir As'ari

Abstract: Common sport movements are the fundamental movements in all kind of sports. There are lots of researches done on classifying sports movements but very few are focused on common sport movement which is the focus of this project. The main aim is to develop an automated algorithm that can detect the common sport movements into walking based and jumping based movement from the wearable inertial sensor. The inertial sensor signals obtained from ten subjects were processed and grouped into walking-based and jumping-based movements. Time-domain features were extracted from the signals. Finally, the classification and performance evaluation process is done by using three different classification models (Support Vector Machine (SVM), k Nearest Neighbor (k-NN) and Decision Tree) with fixed window size of 1.28 seconds at the first stage. At the second stage, the best model from the first stage was used to determine the best window size in extracting the features that represent the walking and jumping based movement. As a result, SVM algorithm with window size of 2 seconds produced the highest overall accuracy of 95.4 % which proved to be the best classification algorithm to classify the common sport movements into walking-based and jumping-based movements. It is hoped that the outcome from this project can be used as a part of developing the overall automated sport movement recognition which is useful for the analyst, coach or player to analyse the performance of the player as well as predicting total energy consumption in preventing the injury among the player.

Keywords : Common Sport Movement Recognition, Decision Tree, k-Nearest Neighbors, Inertial Sensor, Support Vector Machine.

I. INTRODUCTION

"Sport" can be defined as a type of movement that involve physical skills, under set of certain rules to be taken competitively to gain results [1]. According to Lindsay Broomfield, there are three main groups of basic physical skills which are body management skills, locomotor skills and object control skills [2]. Body management skills involve balancing the body whether during movement or in still condition such as static and dynamic balancing. Meanwhile, locomotor skills are the skills that involve transportation of the body in any direction from a point to another including walking, running, jumping and lastly, sprinting. The last one, which is object control skills, are skills that involve the handling of objects such as throwing balls and ribbon in hands. The common sport movement that this project is focusing on falls under locomotor skills.

Common sport movements are also defined as basic or general movements for all type of sports. This is in contrast with specific sport movements whereby these types of movement only exist in single type of sport. For example, in a badminton game, the specific movements are smashing, drop shooting and the serving [3]. While, in a fencing, attack, beat and lunge can be considered as specific movement [4].

The researchers worldwide used many types of sensors and methods to automatically recognize the body movements. The famous sensor used is known as inertial sensor which consists of motion sensors (accelerometer and gyroscope) and magnetic sensor (magnetometer). Accelerometer is a sensor used to measure acceleration meanwhile gyroscope to measure angular velocities and magnetic sensor to detect magnetic fields [5-7]. The most commonly proposed technology in movement recognition is by solely using accelerometer which has been used to detect different sports exercises such as fencing and ball's games like badminton, tennis and ping pong [8, 9]. Nowadays, the technology of activity recognition is not just using external sensor attached to the body, but also used accelerometer sensor inside a mobile phone and even smartwatch [10-12]. Apart from solely depend on accelerometer, there are few studies on movement recognition proposed the combination of accelerometer and gyroscope to monitor the rehabilitation of elders and specific sport detection like badminton and ski jumping [6, 13-16]. Another one is the accelerometer, gyroscope and magnetometer combination which are commonly used in daily movement recognition and also in detecting the joint kinematics for rehabilitation purposes [7, 11, 12, 17, 18]. Signal obtained from these sensors were processed by using machine learning in interpreting the activities of daily living (ADLs) performed by the user.

Machine learning especially supervised learning is part of Artificial Intelligence whereby the machine, the computer, will perform tasks with the training provided by human [19].

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Classification using supervised learning approach is conducted by assigning class labels to the instances in datasets which is represented by the predictor features [20]. Since the early stages of machine learning until now, there have been a lot of classification algorithms or classifiers that have been introduced to classify the given data. For examples, k Nearest Neighbor (k-NN), Decision Tree, Support Vector Machine (SVM), Naïve Bayes and Artificial Neural Network (ANN) [17, 19, 21].

Though there have been a lot of studies conducted to monitor human body movements which focused on classifying specific sports movements, unfortunately, there has been lack of research on classifying the common sport movements.

Therefore, an automated algorithm that can detect the common sport movements and classified into walking based and jumping based movement from the wearable inertial sensor has been proposed in this project. Time-domain features consisted of mean, variance, minimum and maximum values were extracted from the accelerometer and gyroscope signals before classifying them using three machine learning model which are SVM, k-NN and Decision Tree. By selecting the best classifier and window size combination based on the performance accuracy, an automated algorithm was developed. This project will potentially be a part of developing the overall automated sport activity or movement recognition which is useful for the analyst, coach or player to analyse the performance of the player as well as predicting total energy consumption in preventing the injury among the player.

II. LITERATURE REVIEW AND RELATED WORKDS

2.1 Existing Works in Inertial Sensor Based Movement Recognition

In general, the most well-known sensor used for movement recognition are called inertial sensor which consists of accelerometer, gyroscope and magnetometer. Different from each other, accelerometer is an electromechanical device used to measure acceleration forces which means the change in velocity, or speed divided by time [5]. In simple words, it is commonly used to gain raw acceleration data in the three-axis (x, y, and z axes). Meanwhile, gyroscope provides the angular value in the x, y and z axes while magnetometer has the function to detect magnetic fields [6]. Most of the existing studies in movement recognition can be folded three categories based on different sensing combinations which are:

i. Solely accelerometer

ii. Combination between accelerometer and gyroscope

iii. Combination between accelerometer, gyroscope and magnetometer

Most of researches preferred to use accelerometer as the main technology in movement recognition [23]. There is a survey conducted by Oscar D. Lara regarding human activity recognition using wearable sensors. This survey stated that accelerometers are the most widely used sensors to recognize movement [24]. For example, Fajri Nurwanto et.al proposed a light sport exercise movement detection system by using accelerometer sensor on smart phone and smartwatch [10]. In the study, time series pattern of the accelerometer data was discovered to detect the sport exercise movement. This is almost similar to the work that was done by Filip Malawski and Bogdan Kwolek which proposed an effective method for recognizing the fencing footwork using a single body-worn accelerometer [8]. The study utilized the time domain features from the inertial sensor which was attached to the subject's knee before performing specific actions on a command to identify the fencing footwork. Another example is the study in [9] that used the accelerometer to classify ball games' postures such as tennis, badminton and ping pong. The study was conducted by using two triaxial accelerometers on the user's front arm and upper arm to track the motion data [9]. Similarly, a single triaxial accelerometer was also used in [25] for classifying four daily activities which are walking, going upstairs, going downstairs, and sitting [25].

For combination between accelerometer and gyroscope, the approach was implemented in several applications such as medical monitoring and rehabilitation of the elders, and sports game monitoring such as badminton game [6, 13]. The work in [16] proposed these combination sensors for ski jumpers' movements detection while work in [14] proposed for badminton movement recognition and analysis system to enhance the performance of badminton players. Moreover, the work in [15] was focused on the recognition of six different human activities which are standing, sitting, laying down, walking, walking downstairs and upstairs.

There are also several works introduced the combination between the accelerometer, gyroscope and magnetometer sensors in classifying the human movement. For instance, work in [17] used this approach to identify nineteen daily activities which are standing, lying, sitting, walking on different environments, cycling, exercising and also sports like rowing and basketball while the work in [7] focused on recognizing different type of gesture movement.. Moreover, there was also an attempt to implement this combination sensors for rehabilitation purpose such as the work in [18] that formulated the signal from body segment in obtaining the join kinematics. Other than that, there are also several trial in implementing this combination sensors from mobile in detecting the human movement such as the studies in [11][12] that recognize the movements such as walking, running, sitting, standing, jogging, biking, walking and standing.

In general, existing works proposed the use of three inertial sensor combinations for movement recognitions which consists of solely accelerometer, combination of accelerometer and gyroscope, and combination of accelerometer, gyroscope and magnetometer. Each sensor combination contributed not only to sports movements recognition, but other movements recognition as well. Thus, this project used the second combination which is the combination of accelerometer and gyroscope for the common sport movements recognition. This combination is chosen because previous researches are still lack of focus on common sport movements. Another reason is that this combination is the least commonly used for movement recognition compared to the other two combinations.

By using this combination, the outcome is hoped to be as reliable as the previous works done for movement recognition.

2.2 Effect of Window Size in Movement Recognition

Apart from sensors, movement recognition also involved feature extraction, specifically the use of window sizes to sample the signals. A window size can be defined as a representation of the number of samples, and a duration [26].

The most commonly used window size approach in movement recognition is sliding window approach where the process is called "windowing". During windowing process, the signals are split into windows of a fixed size with either overlap or non-overlapped adjacent windows [27].

Previous studies have used various range of window sizes which can be as small as 0.1 second [28] to 12.8 seconds [29] and more [30] with overlapping or non-overlapping windows. There was a research done by Emily Walton et. al. which included the evaluation of different window sizes (3s, 5s and 7s) with 50% overlap between two adjacent windows. In the research, the research involved two stages which were first to determine the best window sizes and second to obtain the highest performance of classifier used [31]. Based on previous researches also, it is mentioned that the shorter the window size, the faster a movement detection and at the same time improve the energy expenditure while larger window sizes are more suitable for complex movement recognition [27, 30].

In short, previous researches had proposed variety ranges of window size either with or without overlapping between the adjacent windows. Thus, as window size is playing a big role in determining the accuracy of a movement recognition, this project used smaller window sizes ranging from 0.25s to 2s to segment the signals obtained from wearable inertial sensor as it involved only the common sport movements, unlike the previous researches which involved complex movements.

2.3 Supervised Machine Learning Classification Techniques

Machine learning is part of Artificial Intelligence whereby the machine performed tasks with the training provided by human. Training is given by compiling the data that human observed for the program to learn to generate useful information [19]. It is categorized into two fields which are supervised and non-supervised machine learning. Non-supervised machine learning is known for clustering the dataset provided while supervised machine learning is known for its classification and regression types. This project is focusing on classifying the data into different class by using different classification algorithms. Classification using machine learning approach is conducted by assigning class labels to the instances in datasets which is represented by using predictor features. The predictor features may be continuous, categorical or binary. If the machine gives correct output (predicted class) in correspond with the input (true class) trained to them, then the learning is called supervised [20, 21].Usually, the given dataset is divided into training and test sets, with training set was used to build the model, and test set was used to validate it and at the same time to determine the accuracy of the model.

The crucial part in classifying the data is feature selection or extraction which is to extract only useful information from the raw data. Machine will use the selected features to do classifying process [20]. The performance of this machine learning can be evaluated by the classifiers' prediction accuracy which equals to the percentage of correct prediction divided by the total number of predictions. One of the techniques proposed to calculate the classifier's prediction accuracy is by splitting the training set into three subsets where two-thirds are used for training and the other third is used to estimate performance. However, this technique is said to be inefficient and not preferable [20]. Another technique is known as cross validation where the training set is divided into mutually exclusive and equal-sized subsets and for each subset, the classifier is trained on the union of all the other subsets [21].

The easiest method to understand and most widely used is leave-one-out (LOO) cross validation. In LOO cross validation, each observation is left out in turn. The left-out observation, n is treated as the test set while the remaining, n−1 observations are used as the training set [20].

Common LOO cross validation used is 10-fold cross validation. In an experiment of comparing learning algorithms, 10-fold cross validation was used to conduct the tests where each of the tests was run ten time for each classifier used. By repeating the same test on the same data with ten repetitions, they then counted how often the outcome is the same [32]. From the outcome, the classifiers' accuracy can be predicted by dividing the percentage of correct prediction to the total number of predictions [20]. Another example is an experiment conducted to classify human activities where a total of 9120 features were divided into 10 equal partitions. All features were used for both training and testing, and each feature was used for testing exactly once in each of the 10 runs [17].

Since the early stages of machine learning until now, there have been a lot of classification algorithms or classifiers that have been used to classify the given data. There are five most commonly used classifiers which are k Nearest Neighbor (k-NN), Decision Tree, Support Vector Machine (SVM), Naïve Bayes and Artificial Neural Network (ANN). The differences between each of these classifiers are summarized in Table 1.

Table 1: Summary of differences between five commonly used classification models

Classifier	ANN	SVM	KNN	Naïve Bayes	Decision Tree
Training Time	Fastest	Faster	Fast	Slower	Slowest
Processing Time	Slowest	Slow	Fast	Faster	Fastest
Complexity	Highest	High	Low	Lower	Lowest
Prediction Accuracy	Highest	Higher	High	Low	Lowest
Computational Cost	High	High	High	High	High

From Table 1, it is clear that even though ANN provided the highest accuracy for classification process, unfortunately it requires the longest processing time and the most complex model compared to the other classification models.

In general, previous researchers have proposed these five classification algorithms in classifying the movements which are Naïve Bayes, k-NN, Decision Tree, SVM and ANN. For this project, the best choices of classification models are SVM, k-NN and Decision Tree because all three of them have the shorter training time compared to ANN and Naïve Bayes.

III. MATERIAL AND METHOD

The workflow for this project is based on the following Fig. 1 which comprised of five steps.

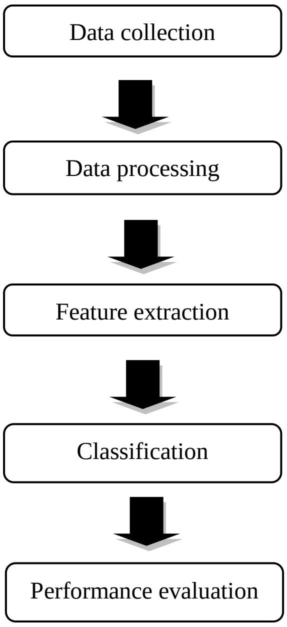

Fig. 1.Methodology workflow

2.4 Data Collection

The data was collected by having ten subjects to wear the accelerometer sensor. The subjects were required to do two main categories of movements which are walking-based and jumping-based physical movements. Walking-based movements are divided into three which are walking, running, and sprinting. Meanwhile, for jumping-based movements, there are three movements which are low jump, high jump, and long jump. Each walking-based movement required the subject to repeat the motion for two times repetition. Meanwhile, for jumping-based, each movement required three times repetition continuously from the subject. In total, the recorded data was consisted of 15 motions from six different activities which were classified into two categories of movements (walking-based and jumping-based).

The device which was used to collect and process the data is known as Physilog® 4 Silver by Gait Up (see Fig. 2(a)). It was used to collect 3-axis accelerometer data (x, y, and z-axis). This sensor comes with 3D accelerometer, 3D gyroscope, 3D magnetometer and barometer. The 3D sensor is needed for this project as it functions to measure linear acceleration [23]. For the purpose of this project, only the data from accelerometer and gyroscope were considered. The sampling frequency for this device has been set to 100 Hz by using the software as shown in Fig. 2(b). The device was placed at the chest areas of the subjects as in Fig. 3.

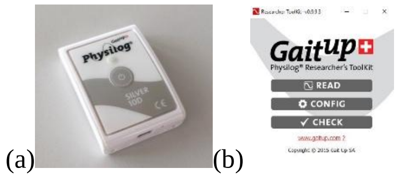

Fig. 2.(a) Physilog® 4 Silver by Gait Up, a device used to collect and process the data (b) Physilog® software used to read the data or signal collected by the device.

Fig. 3.Physilog® device placement on subject's chest area (a) Front view (b) Back view.

After the device was placed on subject's chest area, the subject was required to do six different movements as shown in Fig. 4 for (a) walking, (b) running, (c) sprinting, (d) low jump, (e) high jump and (f) long jump.

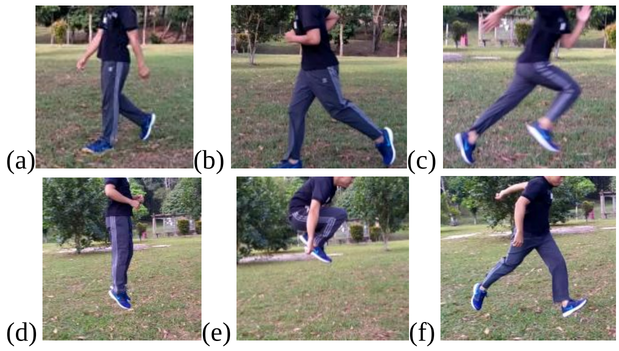

Fig. 4.Movements of subjects during data collection process for walking-based movements (a) Walking (b) Running (c) Sprinting; and jumping-based movements (d) Low jump, (e) High jump and (f) Long jump.

2.5 Data Processing

The recorded raw data was transferred to Physilog software for processing step. During this step, the raw signal was undergoing segmentation and labelling processes in preparing the dataset for training and testing session. The main purpose of labelling process is to prepare the dataset for training the machine learning by giving it both questions and answers in the next step. The established dataset was saved as .csv file for further processing in MATLAB.

Under segmentation and labelling, the data are segmented and labelled into "Walking-based" and "Jumping-based" categories. From the six activities, walking, running and sprinting are labelled as "Walking-based" movements meanwhile low, high and long jumps are labelled as "Jumping-based" movements.

2.6 Feature Extraction

In MATLAB, the processed data will undergo feature extraction process to extract only useful information from the raw data. This step is to make sure only important and needed data will be used later. The features that have been extracted from the data would be the time-domain features which consist of mean, variances, minimum and maximum values. The following equations represent these time-domain features:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} a_i \tag{1}$$

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n} |a_i - \mu|^2 \tag{2}$$

$$a_{min} = \min_{i \in [n]} a_i \;, [n] = \{1, 2, 3, \ldots, n\} \tag{3}$$

$$a_{max} = \max_{i \in [n]} a_i \;, [n] = \{1, 2, 3, \ldots, n\} \tag{4}$$

Whereby the n is the total number of sample in a fixed window size N. The relation between n and N is described in the following equation:

$$n = N \times f_s \tag{5}$$

Whereby fs is the frequency sampling rate.

As mentioned previously, as the sensor used was to collect 3-axis data from both accelerometer and gyroscope, the total data that would be extracted for every sliding window during feature extraction were 24 features from one subject.

2.7 Classification and Performance Evaluation

The extracted features later undergone the classification process using the Classification Learner App embedded in MATLAB software. This project used three classification algorithms which are k-NN, Decision Tree and SVM in classifying between the walking-based and jumping-based movement.

To evaluate the performance of each classifier, cross validation of 10-folds is used to formulate the accuracy which will determine the best classification model in representing the walking and jumping-based movement recognition. After that, confusion matrix was produced for the purpose of analysing the classifier performance in detail. The evaluation process was divided into two stages. In the first stage, the extracted features were formulated with window size, N=1.28s before trained with different classification model (k-NN, Decision Tree and SVM) and select the best classification model based on the accuracy value. After that, the second stage was executed by using the selected classification model from the first stage and trained with extracted features from various window size (N=0.25s, 0.5s, 1s, 1.25s, 1.5s and 2s). The best classifier from the various window sizes was selected before confusion matrix of this classifier was generated for performance analysis.

Regarding confusion matrices, there are two views of confusion matrices that were used to show the result of performance evaluations for both stages. The function of confusion matrix is to show how well the classifier can perform and classify the given data into their true classes correctly. The first view is the default one which is known as Number of Observations where it shows the number of correctly classified and misclassified data. Meanwhile, the second view is known as True Positive Rates and False Negative Rate confusion matrix. In this type of confusion matrix, it shows the percentage of the correctly classified and misclassified data. In short, the difference between these two views of confusion matrix is just how the data was presented whether in number of observations or percentage. For this project, both views were being used.

IV. RESULTS AND DISCUSSION

2.8 Result from Data Collection and Data Processing

Fig. 5 and 6 shows the raw accelerometer and gyroscope signals obtained from one subject. From the signal, there are clearly six movements that have been done by the subjects which are two repetitions each for walking, running and sprinting; and three repetitions each for low, high and long jumps.

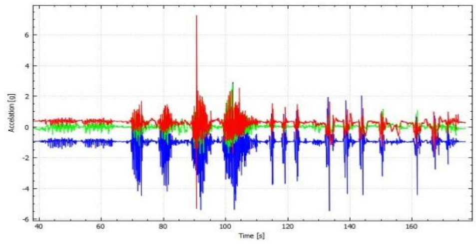

Fig. 5.Raw accelerometer signal obtained from one subject before segmentation process.

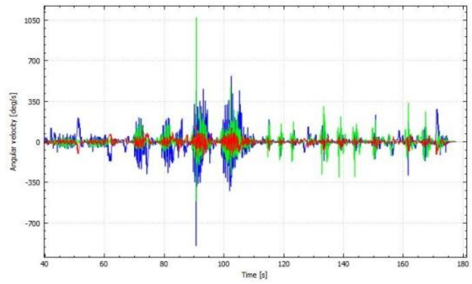

Fig. 6.Raw gyroscope signal obtained from one subject before segmentation process.

This signal is then segmented or labelled into its respective movements which are walking, running, sprinting, low jumping, high jumping and long jumping. The result of segmentation process can be seen in Fig. 7.

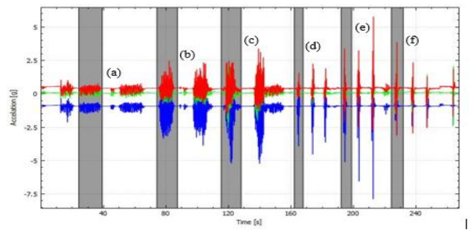

Fig. 7.Signal after segmentation process into (a) Walking (b) Running (c) Sprinting (d) Low jumping (e) High jumping (f) Long jumping.

Even the signal is segmented into six different movements, these movements are grouped into walking-based and jumping-based movements in which 2, 3 and 4 (walk, run, sprint) are labelled as "Walking-based" and 5, 6 and 7 (low jump, high jump, long jump) are labelled as "Jumping-based" respectively. The first three activities are categorized as walking-based as they have the similarities in foot movement in which all of them involved moving by lifting and setting down each foot in turn and never having both feet off the ground at once. Meanwhile, the last three activities are under jumping-based as they all agreed with the basic definition of jumping which is pushing human's body off a surface and into the air by using the muscles in the legs and feet.

2.9 Result from classification and performance evaluation process

As mentioned in previous chapter, the performance evaluations were done in two stages to determine the best classification model for developing an automated algorithm in classifying common sport movements into walking-based and jumping-based movements. This section is to show and discuss the results from both stages.

Table 2 shows the result obtained from classification process by using three different classification algorithms which are k-NN, Decision Tree and SVM in the first stage whereby the window size N is fixed with 1.28s. The performance of these three algorithms was evaluated according to the true positive rate in classifying movements into walking-based and jumping based movements, and the overall accuracy. Fig. 8-10 illustrate the confusion matrices in terms of True Positive Rate and False Negative Rate for the three classification algorithms used in this stage.

Table 2: Performance evaluation for three classification algorithm used in this study in classifying movements into walking-based and jumping based

Classifier Model	True Positive Rates (%)		Overall Accuracy (%)
	Walking-based	Jumping-based	
SVM	97	90	94.4
k-NN	98	85	93.7
Decision Tree	93	88	91.6

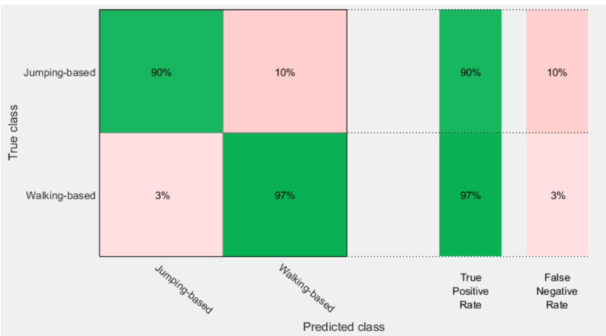

Fig. 8.Confusion matrix (True Positive Rate and False Negative Rate) for SVM classification model used in this study.

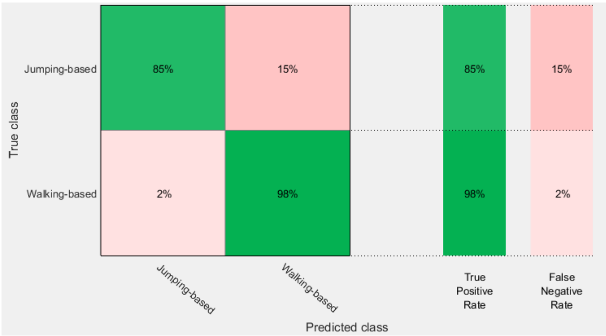

Fig. 9.Confusion matrix (True Positive Rate and False Negative Rate) for k-NN classification model used in this study.

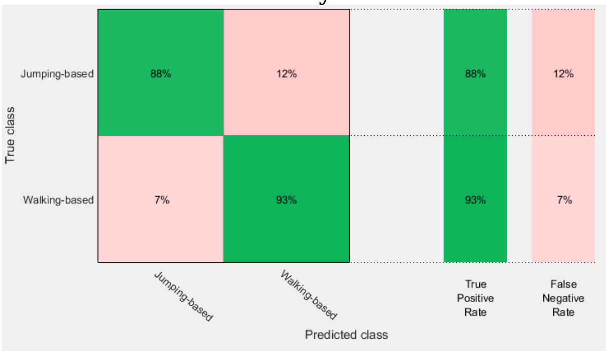

Fig. 10.Confusion matrix (True Positive Rate and False Negative Rate) for Decision Tree classification model used in this study.

As shown in the table and figures, SVM algorithm produced the highest true positive rate in classifying the movements with the percentage of 97% for walking-based class, 90% for jumping-based class and 94.4% for the overall accuracy. Following SVM is k-NN with less true positive rates which are 98% for walking-based class, 85% for jumping-based class and 93.7% of overall accuracy. Otherwise, Decision Tree is the classification algorithm with the lowest true positive rates which are 93% for walking-based class, 88% for jumping-based class and 91.6% for overall accuracy. This result complies with the researches done by previous researchers [17, 19, 34] which concluded that between these three algorithms, SVM and Decision Tree, have the highest and lowest accuracy, respectively. Thus, from this first stage SVM is chosen to be proceed to the second stage of this process.

Table 3 shows the result obtained from the second stage where by classification process by using the chosen classification algorithm which is SVM and tested with different window sizes. The performance of each combination was evaluated according to the true positive rate in classifying movements into walking-based and jumping based movements, and the overall accuracy. Fig. 11-12 illustrate the confusion matrices in terms of True Positive Rate and False Negative Rate, and Number of Observation for the best combination of classification algorithm and selected window size.

Table 3: Performance evaluation of the chosen classifier model, SVM with different window sizes

Window Size, *N* (s)	True Positive Rates (%)		Overall Accuracy (%)
	Walking-based	Jumping-based	
0.25	92	76	86.3
0.50	95	85	91.0
1.00	97	86	92.9
1.25	97	89	94.2
1.28	97	90	94.4
1.50	99	86	94.1
2.00	**99**	**89**	**95.4**

Table 3 presents the performance in term of accuracy for the selected SVM model that has been trained with extracted features with various window sizes. Fig. 11-12 show the confusion matrices of this model in terms of True Positive Rates, False Negative Rates and Number of Observations.

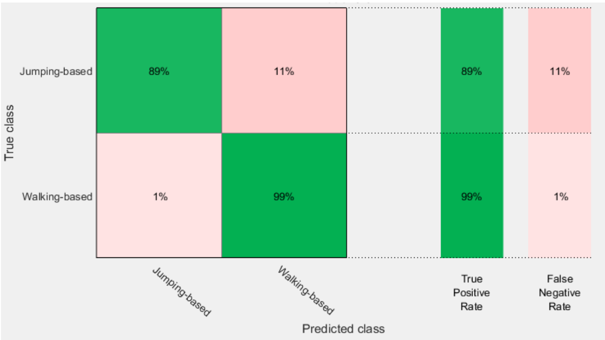

Fig. 11.Confusion matrix (True Positive Rates, False Negative Rate) with the highest accuracy for SVM algorithm with window size, N of 2s.

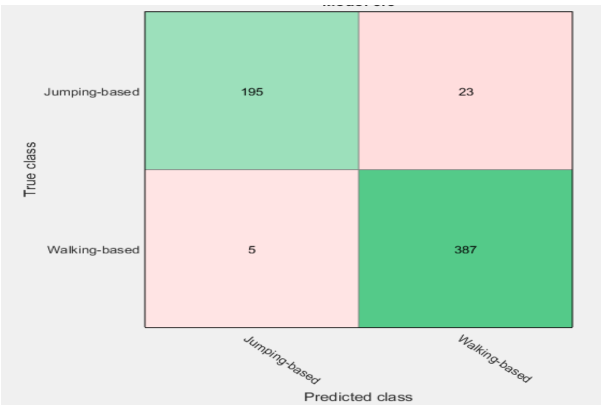

Fig. 12.Confusion matrix (Number of Observation) with the highest accuracy for SVM algorithm with window size, N of 2s.

From Table 3 and Fig. 11-12, it can be seen that the window size, N=2s is the most appropriate to be used in developing the automated algorithm for recognizing the walking and jumping based recognition using SVM and time domain based features. By using SVM from previous performance evaluation process, the combination of the best classifier and selected window size produced an overall accuracy of 95.4% which is 1.0% higher than the previous window size, N=1.28s. For each class, the one using window size, N=2s has the true positive rates of 99% for walking-based class and 89% for jumping-based class, which are among the highest values recorded as compared to the other window sizes.

By the end of this study, it is found that the end result is a successful classification between walking-based and jumping-based physical activities. The outcome from the performance evaluation of the three algorithms would prove that SVM and Decision Tree are the most and least accurate among the three algorithms. In overall, it is found that SVM with window size, N=2s provided the highest accuracy in the classification between walking-based and jumping-based physical activities.

V. CONCLUSION

In conclusion, common sport movements are fundamental movements in all sports. This study has successfully presented an algorithm for detection the common sport movements into walking based and jumping based movement using a wearable inertial sensor with different window sizes. From the performance evaluation of SVM with various window sizes, it is found that SVM with window size of 2s provided the highest accuracy, 95.4% in classifying the common sport movements into walking-based and jumping-based movements. The findings of this study show that having a large window sizes are necessarily improving the recognition performance for walking and jumping based study. From this algorithm, it is hoped that the outcome from this project can be used as a part of developing the overall automated sport movement recognition.

In future, there are several developments need to be done to further expanding this project. One of the suggestions is more sensor placements to increase the complexity and accuracy of the collected data. Second suggestion is to expand feature extraction process which can be achieved by adding more time domain based other than the ones used in this project and also by including frequency-domain. Last but not least, it is suggested for the classification process to involve classifying of more movements. Rather than only classifying them into two classes done in this project, it is suggested to classify the movements into their separate classes.

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