International Journal of Innovative Technology and Interdisciplinary Sciences
www.IJITIS.org
ISSN: 2613-7305
Volume 3, Issue 1, pp. 381-394, 2020
DOI: https://doi.org/10.15157/IJITIS.2020.3.1.381-394
Received January 22, 2020; Accepted February 27, 2020

Window Selection Impact in Human Activity Recognition

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ABSTRACT

Signal segmentation is usually applied in the pre-processing step to make the data analysis easier. Windowing approach is commonly used for signal segmentation. However, it is unclear which type of window should be used to get optimum accuracy in human activity recognition. This study aimed to evaluate which window type yields the optimum accuracy in human activity recognition. The acceleration data of walking, jogging, and running were collected from 20 young adults. Then, the recognition accuracy of each window types is evaluated and compared to determine the impact of window selection in human movement data. From the evaluation, the overlapping 75% window with 0.1 s length provides the highest accuracy with mean, standard deviation, maximum, minimum, and energy as the features. The result of this study could be used for future researches in relation to human activity recognition.

Keywords: Activity recognition; signal segmentation; windowing; window selection; human movement.

1. INTRODUCTION

Signal segmentation is typically required to analyse the nonstationary signal data such as human movement signals. In most signal processing techniques, the signal is initially segmented into fixed length epochs to consider the signal as piece-wise stationary. Window selection is a crucial stage in the human activity recognition. Banos et al. [1] evaluated different non-overlapping window sizes ranging from 0.25s to 7s. However, window size is not the only factor affecting the accuracy of human activity detection. In non-overlapping window, the data are segmented into fixed size windows without considering the information loss between adjacent windows.

The windowing approach could be categorized into three groups: event-defined [2,3,4], activity-defined [5,6,7,8], sliding window [6, 9, 10, 11, 12, 13]. The frequency of the accelerometers in those studies were: 20 Hz [6], 32 Hz [2], 50 Hz [12], 64 Hz [10,11], 76.25 Hz [9], 80 Hz [7], 95 Hz [13], 100 Hz [4,5,8], and 320 Hz [3]. The sampling frequency to assess human physical activities should be at least 20 Hz [14].

The sliding window approach is the most widely used as the segmentation technique in activity recognition due to its simplicity and lack of pre-processing. It has been proven to be beneficial for the periodic activities such as walking and running. The signal data are segmented into fixed-size and with no inter-window gaps. Previous studies have been used various window sizes from 0.1s [15] to 128s [16]. In certain applications, an overlap between adjacent windows is used to avoid the missing information caused by the segmentation [9,10].

This study aimed to evaluate and determine the optimum window type and size in detecting the human activity. The characteristics of overlapping and non-overlapping windows are different, and it is unclear which window type is better for human activity recognition. In addition to the window type, the length of window size could also affect the accuracy of the activity recognition.

This paper is organized as follows. Section 2 describes the methods in conducting the experiment protocol and a brief description of the theoretical background behind windowing, feature extractions, and classification techniques. Section 3 presents the results of the study and section 4 describes the discussion. Finally, the conclusion is presented in section 5.

2. METHODS

Acceleration data were acquired from 20 (10M, 10F) healthy young adults (age 24.1 ± 0.91) recruited from the National Taiwan University of Science and Technology, Taiwan. The National Taiwan University Review Board approved the study and written informed consent was obtained from all subjects before participation. All subjects are free of any balance-related disorder based on self-report. The wearable accelerometer (Cavy-Tech) were attached to each subject's ankle and knee. The acceleration data were acquired at 30 Hz and sent using the Bluetooth wireless protocol that were plugged to the computer.

The subjects were asked to perform walking, jogging, and running on the treadmill for 60s. The treadmill speeds were set to 4 km/h, 6 km/h, and 10 km/h for walking, jogging, and running respectively. The raw data were imported into the MATLAB R2016a [17] environment, which was used for feature extractions. The classifications were evaluated using Weka 3.7 environment [18] with naïve Bayes, k-Nearest neighbours, decision table, and decision tree as the classifiers.

2.1 Windowing

Accelerometers usually deliver a stream of unprocessed signals which may be disturbed by the noises. These noises can be removed through a filtering process. However, this may imply a certain information loss. In order to capture the dynamics of the signals, windowing method partitions the signal into segments of data. There are several approaches in windowing, such as event-defined, activity-defined, and sliding windows. In the event-defined windows, the specific events are employed to define the segment of the data. The size of the segments is not fixed, since the events may not be uniformly distributed. Previous studies determined the events by heel-strike [2,4], toe-off [4], or using the start and end lines [3], which the first event is when the foot first crossed the start and the last event is when the foot first crossed the end.

The activity-defined windows segment the signal data based on the detection of the changes in the activities. The start and end points are determined for each activity through the frequency characteristics. Figo et al. [5] segmented the activities into 60s duration segments, while Dernbach et al. [7] asked the subject to set the start and end points of the activities. Heuristic method could also be used to distinguish the dynamic from static actions [8].

Both event and activity-defined windows are able to segment the signal data based on its unique movement characteristics. However, the pre-processing steps to determine the segments could be tedious. The sliding window is the most widely used in human activity recognition due to its simplicity, the signal data are segmented into fixed-size windows. Since the human movement signal such as walking and running are periodic, the sliding window approach is more beneficial than the event and activity-defined windows. There are two types of sliding windows: non-overlapping and overlapping windows. Although the non-overlapping window is a simpler approach, there may be some information loss between the adjacent windows. In the overlapping window, consecutive segments of data are overlapped by the designated percentage. Intuitively, high overlap percentages provide the highest accuracy but take longer to process the data. Previous work has demonstrated the success with the overlapping window with 50% overlap percentage [9].

In addition to the window type, determining the window size is also important to get better results in activity recognition. Short window size, such as 0.1s, translates into a faster detection of the activity. However, short window size could also lead to more false positive detection and longer time processing. Therefore, the optimum type and size of the window are crucial step in the signal pre-processing.

2.2 Feature Extractions

The appropriate acceleration features are extracted in order to get more informative form of data for the evaluation. Selecting the features is important due to the computational cost consideration. There are two different modes of features that can be extracted to analyse the acceleration data: time- and frequency-domain features.

2.2.1 Time-domain Features

The time-domain features describe the behaviour of the signal over time, it can be used to the patterns of data over a time period. This feature mode avoids the complexity of pre-processing such as Fourier transformation and filtering. This mode does not require high computational cost. The time-domain features selected in this study are as the following:

a. Average

   The average of acceleration data describes the overall effects of the activity. This feature gives an indication of net accelerations lasting from time period equal to or greater than the interval parameter. The subtle shifts in the DC-level (static accelerations) are best captured using the average value of the acceleration [19].

b. Maximum and Minimum

   Basically, this is the value of the peak of the signal. In the step detection, the value of the peak is used to distinguish footstep from standing still. The higher the intensity of an activity, the larger the value of the peak. Minimum value of acceleration is the valley of the signal. It represents the initial contact of the foot on the ground [20]. Maximum and minimum yield the most precise accounting of the variation of the acceleration as a function of time [19].

c. Standard Deviation and Variance

   Standard deviation describes how the measurement of a group is spread out from the average value. Low standard deviation shows that most of the values are very close to the average, while high standard deviation shows the values are spread out. Variance is the squared deviation of a group from its average. It is used to characterize the stability of a signal [21].

d. Root Mean Square

   It describes the changes in the activity [19]. It is computed by squaring the amplitude of the signal to eliminate the negative values.

e. Mean Absolute Deviation
   Mean absolute deviation is the average of the absolute deviations from the central point (in this case, the average acceleration). It can be used as the summary of the variation or statistical dispersion.

2.2.2 Frequency-domain Features

Frequency-domain features describe how much signals lie within the frequency signal range. It requires pre-processing such as Fast Fourier Transform. However, this mode is more robust to measurement and calibration errors compared to the time-domain mode [22]. The frequency-domain features selected in this study are energy and entropy.

a. Energy
   Energy captures the data periodicity; it is computed as the sum of squared discrete FFT component magnitude of a signal, as shown in Equation (1). It can distinguish the low intensity activity such as standing from the high intensity activity such as walking [23].

$$F(k) = \frac{1}{N}\sum_{k=0}^{N-1} b(j).e^{i2\pi k\frac{j}{N}} \qquad (1)$$

   where, k = (0, 1, …, N-1)

b. Entropy
   Due to its sensitivity in detecting changes in human movement signals, entropy methods are able to quantify gait dynamics [24] and useful to discriminate repetitive activities with similar energy values [23]. In this study, Shannon entropy is used as the feature. It evaluates the repetitions within a signal by measuring the probability of the signal occupying discrete states [25], as shown in Equation (2).

$$H = -\sum_{i=0}^{N-1} p_i log_2 p_i \qquad (2)$$

   where, p is the probability of the event.

All features were evaluated for the X-axis, Y-axis, Z-axis, and resultant acceleration. The total number of 36 features was extracted from the raw acceleration data. These features were mean, maximum, minimum, standard deviation, variance, root mean square, mean absolute deviation, Shannon entropy, and energy in X-axis, Y-axis, Z-axis, and the resultant acceleration.

2.3 Classification

In this study, 4 different activity recognition classifiers were compared: Naïve Bayes, k-Nearest neighbours (KNN), decision table, and decision tree (J48). In each case, the raw data were processed in the same way to obtain comparable results.

2.3.1 Naïve Bayes (NB)

Naïve Bayes is a simple technique that assume the value of a particular feature is independent of the value of other features [26]. A naïve Bayes classifier considers each of the features to contribute independently, regardless of any possible correlations between the values. This assumption does not hold in the physiological signals such as acceleration signals from human movement [27].

2.3.2 K-Nearest Neighbours (KNN)

KNN is an instance-based classifier based on the majority voting of its neighbors, it calculates the class with the highest frequency from the k-most similar instances. Each instance in essence votes for their class and the class with the most votes is taken as the prediction. In general, KNN is par with decision tree in terms of performance and the computational complexity in the pattern recognition. In a comparative study using 10-fold cross validation in different experiment settings, KNN achieves a better overall accuracy [28].

2.3.3 Decision Table (DT)

Decision table is a table of rules and classes. Given an unlabelled example, it searches for the exact match in the table and returns the majority class label among all matching instances, or reports no matching is found [9,29,30] tested different classifiers including decision table in daily activity recognition. Compared to decision tree, decision table is easy to program and maintain because of its straight-forward structure but does not have a hierarchical structure. In the context of activity recognition, the activities are sometimes classified with a hierarchy. For example, an activity can be first classified into still vs moving and then within each category, a more detailed category is generated. Decision table is not able to capture such a hierarchy.

2.3.3 Decision Tree (J48)

Due to its low complexity in implementation and excellent interpretation, decision tree is adopted as the main classifier in many activity recognition researches. J48 is one of decision tree algorithms, used by many activity recognition researches as an off-line classification model. The disadvantage of decision tree lies in model updating. Once the decision tree model is built, it might be costly to update the model to accommodate the new training examples. Thus, in the online learning settings, decision tree is not a popular classifier for activity recognition. A comparative study of classifiers showed that decision tree performed the best in detecting the activity [31].

3. RESULTS

To determine the optimum window to recognize and classify the activities (walking, jogging, and running), the signals from the sensors were divided into equal-sized smaller sequences. The accuracy of the classifiers to classify the activities was used to evaluate the data. In this study, the sliding windows overlap percentages were of the 0% (non-overlapping), 25% overlapping, 50% overlapping, and 75% overlapping. All of the data were evaluated using Weka environment with 10-fold cross validation. Figure 1 shows the comparison results of different window types with the sizes of 0.1s, 0.2s, 0.3s, 0.4s, 0.5s, 1s, 2s and 3s. Overall, the overlapping 75% with 0.1s window size outperformed the other window types. In general, the accuracy increases as the window size decreases. However, in the 75 % overlapping window, the accuracy of the window size of 0.5s for all classifiers were higher than the size of 0.4s.

In order to get better understanding on which features have more contribution on the classification accuracy, the sensitivity analyses as shown in Figure 2 were calculated based on the overlapping 75% with 0.1s window size. Firstly, the determination of which axis contributes more on classifying the activity was calculated. This step was done by comparing the accuracy of the modified data sets to the data with all features. There were 4 modified data sets used: all features minus the data of x-axis, all features minus the data of y-axis, all features minus the data of z-axis, all features minus the data of the magnitude. The comparison showed that the deletion of magnitude data increased the accuracy. The next step of the sensitivity analysis was comparing the accuracy of the data without the magnitude data. There were 17 combinations used in this comparison:

1. All features: Mean, standard deviation, maximum, minimum, energy, root mean square, mean absolute deviation, Shannon entropy
2. Combination 1: Mean, standard deviation, maximum, minimum, energy, root mean square, mean absolute deviation
3. Combination 2: Mean, standard deviation, maximum, minimum, energy, root mean square
4. Combination 3: Mean, standard deviation, maximum, minimum, energy
5. Combination 4: Standard deviation, maximum, minimum, energy
6. Combination 5: Mean, maximum, minimum, energy
7. Combination 6: Mean, standard deviation, minimum, energy
8. Combination 7: Mean, standard deviation, maximum, energy
9. Combination 8: Mean, standard deviation, maximum, minimum
10. Combination 9: Mean, maximum, minimum
11. Combination 10: Mean, maximum, energy
12. Shannon entropy
13. Mean
14. Standard deviation
15. Maximum
16. Minimum
17. Energy

4. DISCUSSION

Selecting the window type and size is a crucial step in analysing human movement data. Since, the human physiological signals are not stationary, segmenting the data with windowing could clarify the characteristics of the signal data without the filtering process. Filtering out the noises from the raw data may not always be useful since it would cause some information loss. Due to its simplicity and benefit in detecting the activity in human movement data, sliding window is chosen in this study.

The overlapping percentage of 0% (non-overlapping), 25%, 50%, and 75% were evaluated and it turned out the overlapping 75% with window size of 0.1s outperformed the other overlapping percentages for all classifiers but NB. The non-overlapping window with window size of 0.1s gave the highest accuracy for NB classifier. However, they were only 66.83% and 70.18% on ankle and knee respectively. Whereas the highest accuracy (90.64% on ankle and 90.08% on knee) based on KNN classifier was by the overlapping 75% with window size of 0.1s. This could happen due to NB neglects the correlations between the values of the acceleration signal. This result is in agreement with the previous study by Lara and Labrador [27], which found that NB is not suitable for the data from physiological signals.

Generally, the overlapping window yielded to higher accuracy in classification. The higher the overlapping percentage, the higher the accuracy. This might happen due to many jogging activities were incorrectly classified into walking and running in the lower overlapping percentage. As the overlapping percentage increased, jogging was more correctly classified. The characteristics of jogging could be close to either walking or running. Since the window size is determined by the time, there could be some information loss between the adjacent windows that could not be detected by the non-overlapping window and the other small percentage of overlap.

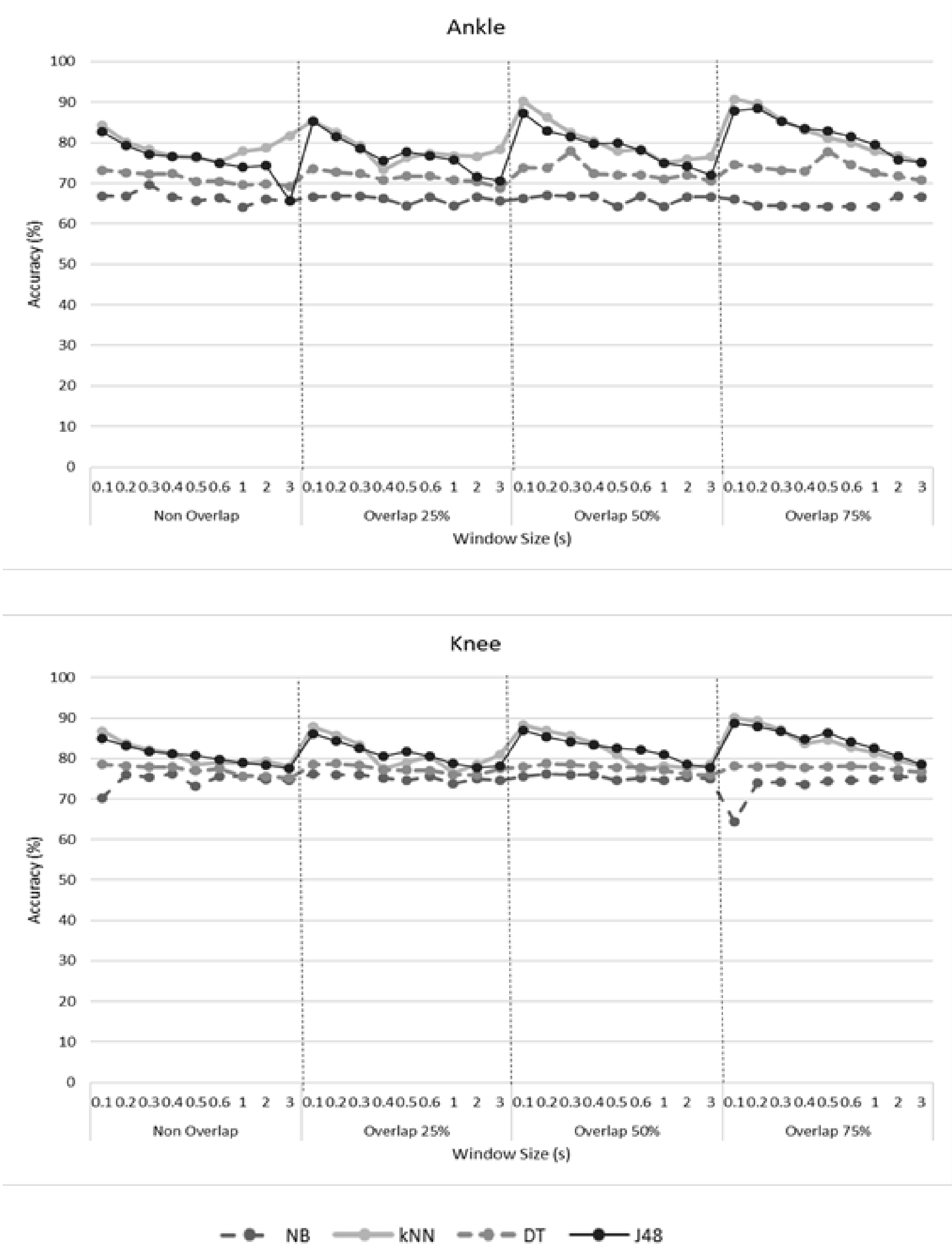

Figure 1. Accuracy comparison of different window types and sizes on ankle and knee using classifiers: NB (naïve Bayes), kNN (k-Nearest neighbors), DT (decision table), J48 (decision tree).

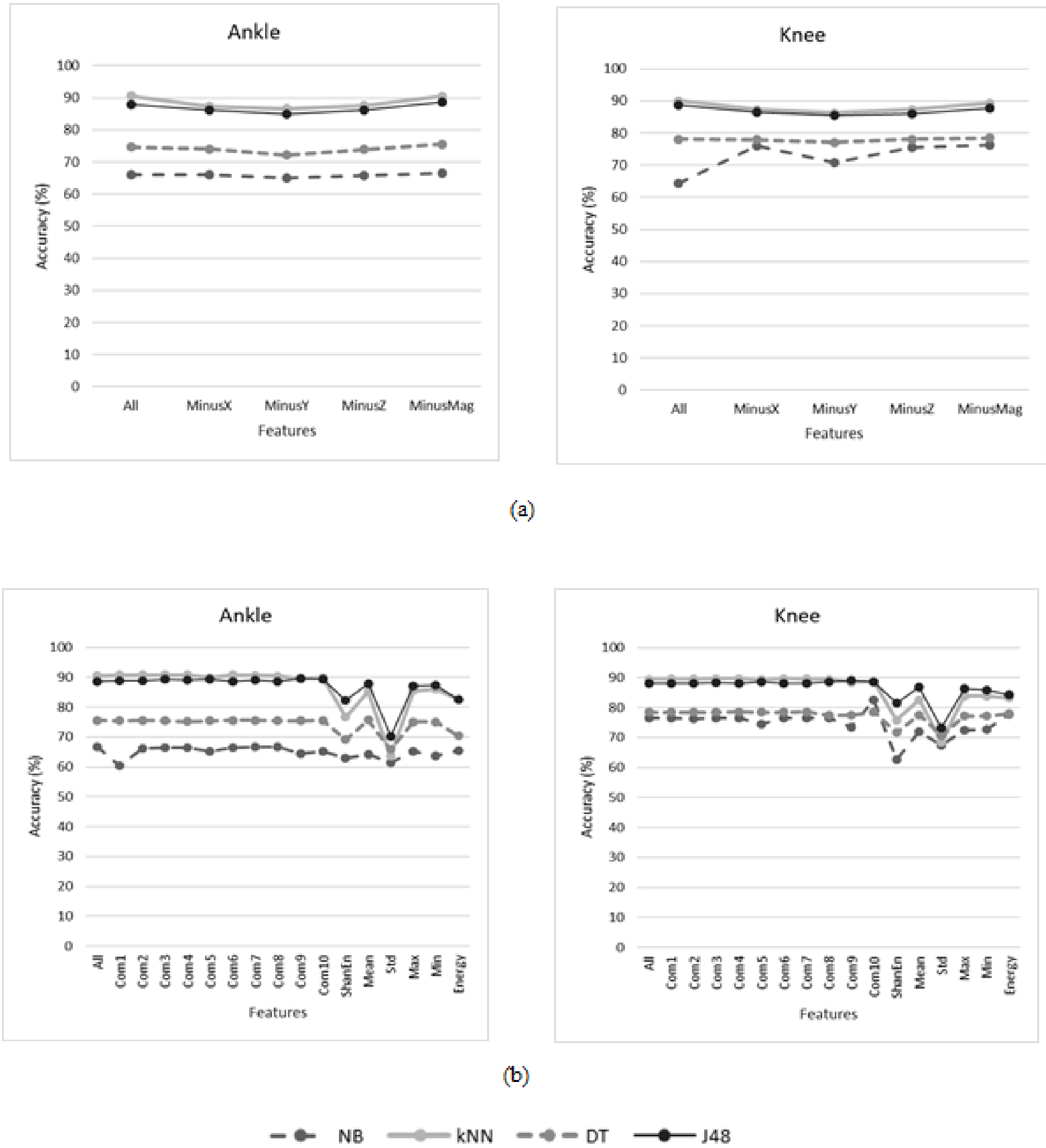

Figure 2. Sensitivity Analyses.

(a) Accuracy comparison of all features by deleting the data sets of the axis: MinusX (without the features from x-axis), MinusY (without the features from y-axis), MinusZ (without the features from z-axis), MinusMag (without the magnitude data).

(b) Features comparison of MinusMag: Com1 (Combination1) to Com10 (Combination 10), ShanEn(Shannon entropy), Mean, Std (standard deviation), Max (maximum), Min (minimum), Energy.

Although the accuracy increases as the window size decreases, there were the exception which the accuracy for 75% overlapping window with size of 0.5s for all classifiers were higher than the size of 0.4s. This happened because even though there were more jogging activities correctly classified with the window size of 0.4s, more walking and running activities were correctly classified on window size of 0.5s.

The 75% overlapping window with the size of 0.1s yielded the highest accuracy, but this window type needed longest processing time which might not be suitable for large data. In addition to this, the results were not so different from the 50% overlapping window with the size of 0.1s, as shown in Table 1.

Table 1. Comparison between 50% and 75% overlapping window with the size of 0.1s

	50% overlap		75% overlap	
	Ankle	Knee	Ankle	Knee
KNN	90.20	88.22	90.64	90.08
DT	73.78	77.87	74.64	78.10
J48	87.29	87.00	87.91	88.71

As for the classifier, the KNN outperformed the other classifiers in the short window size (0.1s and 0.2s) in terms of accuracy. The J48 performed better than KNN in the wider window size (≥0.3s) as shown in Figure 3. However, it needed more iteration time than the other classifiers due to the large number of features (36 features) and the nature of J48 classifier in creating decision trees by dividing the data into smaller subsets and this dividing procedure only stops when all instances in a subset belong to the same class. Both KNN and J48 can be memory intensive for large data sets that will result in long processing time.

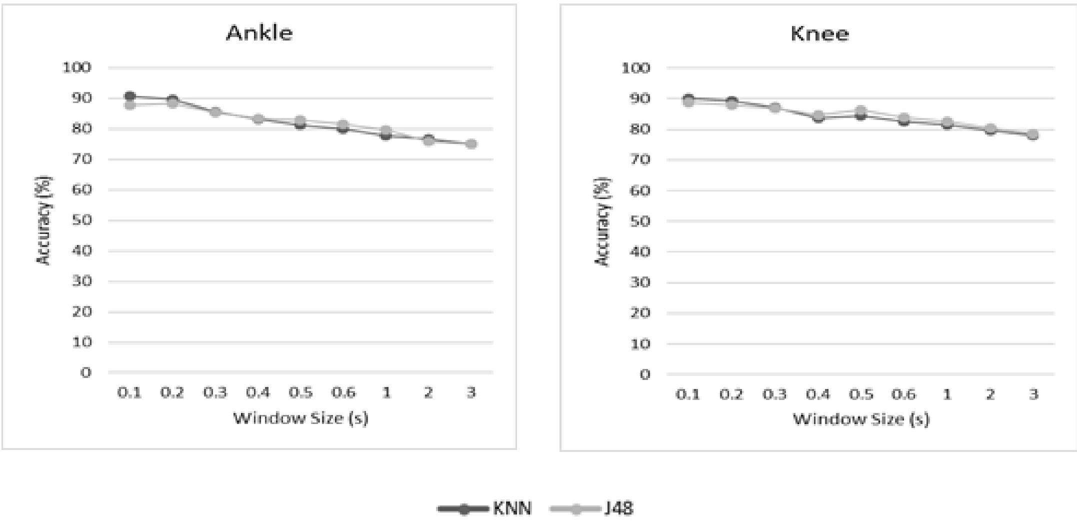

Figure 3. Comparison between k-Nearest neighbour and J48 on 75% overlapping window

In order to determine which feature contributes to the classification accuracy, the sensitivity analysis was calculated by eliminating some features and then comparing its accuracy to the baseline, which included all of the features. The comparison showed that the deletion of magnitude data increased the accuracy. Magnitude data were acquired by calculating the resultant of x, y, and z-axes. The increase of accuracy after the deletion of magnitude data means the resultant values of x, y, and z-axes of the activities are close to each other, especially the jogging data. Therefore, the magnitude data were deleted for the next step of the sensitivity analysis.

The comparison of features combinations on the sensitivity analysis showed that combination 3 (mean, standard deviation, maximum, minimum, and energy) yielded higher accuracy than the data sets with all features. The individual feature accuracy calculation showed that mean, maximum, and minimum contributed almost equally. However, the accuracy of single feature was lower than the accuracy of 5 features altogether. Although standard deviation and energy resulted in low accuracy when used as single feature, the deletion of standard deviation and energy resulted in lower accuracy based on KNN classifier. This could have happened because in KNN, the higher number of features reduce the effect of noise on classification. Thus, KNN is not suitable to evaluate the performance of a single feature [32].

4.1. Shannon Entropy as Feature

Entropy methods have been used in quantifying the complexity human physiological signal including human movement data. Human physiological signals are highly complex and non-linear. Thus, the traditional linear time-domain and frequency-domain methods cannot fully describe its interactions [24]. Previous works showed promising activity recognition results using entropy as one of the features [9,30].

The results of sensitivity analyses showed that the optimum features in order to obtain the highest accuracy based on KNN was the combination 3 (mean, standard deviation, maximum, minimum, and energy). The comparison of the accuracy using single feature, as shown in Table 2, shows that Shannon entropy as a single feature performed better than the standard deviation. Combination 5 is the combination 3 after removing standard deviation. The comparison between combination 3 and combination 5 showed that based on standard deviation increased the accuracy of KNN classifier but decreased the accuracy of J48. Whereas, the addition of Shannon entropy to combination 5 yielded to slightly lower accuracy of KNN and higher accuracy of J48 compared to combination 3. Thus, it can be concluded that standard deviation is the better feature for KNN, while Shannon entropy works better with J48.

Table 2. Comparison of Features Based on k-Nearest Neighbours and J48

Features	KNN	J48	KNN	J48
Shannon Entropy	76.70	82.36	75.81	81.66
Mean	85.31	87.90	82.67	86.94
Standard Deviation (std)	63.61	70.28	68.35	73.17
Maximum	85.55	87.18	83.82	86.33
Minimum	86.03	87.30	83.82	85.78
Energy	82.65	82.63	83.26	84.38
Combination 3 (mean, max, min, energy, std)	90.80	89.22	89.66	88.27
Combination 5 (mean, max, min, energy)	89.93	89.39	89.22	88.66
Combination 3 + Shannon Entropy	90.40	88.99	89.25	88.11
Combination 5 + Shannon Entropy	89.71	89.35	88.74	88.52

Although entropy methods have been widely used and proven as better approach for human physiological analyses compared to the traditional methods, Shannon entropy is not the optimum feature in terms of accuracy to classify human movement. This might have happened because Shannon entropy examines the frequency throughout the signal without considering its path and varies with data length, which makes it not appropriate to measure the complexity on short data [33]. The more developed entropy method such as multiscale entropy (MSE) might be more suitable as the feature in evaluating human movement, since it examines the probability of particular values occur within a signal with considering the paths [34].

5. CONCLUSION

This paper has presented the comparative study of using different overlap percentages of sliding windows with various window sizes. The results of the evaluation showed that the higher overlap percentage of the window, the better the accuracy. In this study, the 75% overlapping window outperformed the other overlap percentages, since the lower overlap percentages led to more missing information between adjacent windows. However, the 75% overlapping window needed longer iteration time which is not suitable for large data sets. Intuitively, shorter window size yields in faster detection of the activities and this study proved that indeed shorter window size performed better than the wider window size. This could be happened since the characteristics of jogging are somewhere in the middle of walking and running. The wider window size incorrectly classified jogging into either walking or running. As for the classifier, KNN performed as the best classifier in short window size (0.1s and 0.2s), while J48 performed better in wider window size (≥0.3s). The sensitivity analysis showed that using 5 features (mean, standard deviation, maximum, minimum, and energy) resulted in highest accuracy. Although as Shannon entropy performed better than standard deviation as single feature, the addition of Shannon entropy decreased the accuracy based on KNN. Shannon entropy works better than standard deviation if J48 were the classifier. Future studies might consider employing other entropy methods such as multiscale entropy in feature extraction, instead of Shannon entropy.

ACKNOWLEDGMENT

This study was financially supported by the Ministry of Science and Technology (MOST) of Taiwan (MOST 105-2221-E-011-104-MY3).

CONFLICT OF INTERESTS

The authors would like to confirm that there is no conflict of interests associated with this publication and there is no financial fund for this work that can affect the research outcomes.

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