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OVERFIT PREVENTION IN HUMAN MOTION DATA BY ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Motion analysis has been an active research area for the past decade. Several approaches had been proposed to detect and recognize motion activity for different applications such as motion estimation, modeling, and reconstruction. However, a suitable classifier is required to be embedded with the surveillance system to ensure accurate motion recognition. During these processes, the recognition system compares the captured motion with the motion database in order to recognize the motion activity. However, the classifier can only recognize the motion activities that are closely fit with the database, and overfitting has been an issue in this process. Hence, this paper is aimed at resolving overfitting problem by using Artificial Neural Network (ANN) for motion classification. The motion data was transformed into numerical data with an aid of Kinovea. Data mining software called WEKA was used to perform motion classification. Multi-Layer Perceptron (MLP), which is known as ANN, was modified to recognize different motion activities in the classification process. It was observed that MLP is able to yield classification accuracy of 97.62%. Overfitting issues were also solved by manipulating learning rates in the ANN classifier. A reduced learning rate from 0.3 to 0.1 improved the classification accuracy of jumping motion by up to 12.04%.

Keywords: *overfitting, data pre-processing, classification, multi-layer perceptron, recognition, WEKA.*

INTRODUCTION

Human motion analysis has been one of the most active researches in robotics, computer vision, and artificial intelligence with its applications in various fields such as surveillance, information retrieval, medical analysis, and criminal detection. The analysis helps understand the human behavior from video captured or image sequence. According to Ijjina and Chalavadi [1], human motion recognition is an approach to analyze human motion by using video or photo captured via camera or CCTV. There are different methods used by previous researchers in predicting human motion, including ANN [2], back propagation neural networks [3], and Field Programmable Gate Array cum neural network [4]. Data mining has been introduced recently to analyze human motion. There are three main stages involved in supervised data mining: pre-processing, classification, and post-processing. This depends on the information related to statistics, mathematics, and computing which should be used as an overall holistic approach for knowledge discovery [5].

Statistics suggested that data pre-processing would take up to 60% of the time in a complete process of data mining [6]. In the pre-processing stage, there are numerous methods proposed previously including General Regression Neural Network (GRNN) [7], tree-based imputation [8], reweighing and sampling [9], multiple imputations [10], and Self-Organizing Map (SOM) [11]. For instance, GRNN proposed by Chen et al. [7] consisted of four layers to distribute the input data into pattern layers to generate the estimated data. Meanwhile, the tree-based imputation method introduced by D'Ambrosio et al. [8] assumes the missing data at random mechanism, and incremental variable imputation was adopted to impute the missing data. Besides, Kamiran and Calders [9] utilized reweighing and sampling method to remove discrimination of the data before the classifier is learned. The multiple imputation method of Seaman et al. [10] generally illustrated three imputation methods, including regression imputation, passive imputation, and Just Another Variable (JAV). The SOM developed by Folguera et al. [11] performs imputation with the concept of distance object per one weight.

The complete dataset can then be used to recognize human motion. According to Cao et al. [12], human motion recognition can be considered as a method to allocate a tag to a motion activity. Several methods had been studied by previous researchers to recognize human motion. For instance, Ho et al. [13] used a data mining technique to discover the intention of humans for human-robot interaction. Besides, Hu and Boulgouris [14] combined the construction of templates and measurement of the motion for fast human activity recognition. On the other hand, Shao et al. [15] carried out motion segmentation by the color intensity and motion-based to recognize the action types separately. Meanwhile, Zhou et al. [16] studied image sequence and proposed feature-reduced Gaussian Process (GP) classification to analyze deformable human motion.

It was found that previous researchers often employ Naïve Bayesian filter [17], K-Nearest Neighbor (KNN) [18], and Support Vector Machine (SVM) [19], which usually face overfitting or missing data problem due to uneven distribution in the training data. Besides, it was found that it is hard to treat error that arises from rapid motions within the original video. For instance, Ji et al. [20] carried out human motion recognition efficiency by feature-reduced Gaussian process and depth sequences, respectively where the efficiencies yielded were between 70% and 90%. Besides, the improvement of the data overfitting can be done by modifying the parameter of the classifier which can optimize the outcome of the classification data [21]. However, overfitting of such an approach is still a concern in human motion recognition. Overfitting raises when the recognition system learns the training data too well [22]. Hence, the objective of the present study was, therefore, to identify the overfitting problem in human motion data and resolve it by using ANN. This approach is not only able to handle simple motion activities but also able to work with complex motion activities.

METHODOLOGY

Figure 1 shows the flow chart of the approach followed. Human motion data were collected via two different approaches namely marker-based and marker-less motion capture systems. For the marker-based system, the motion data were collected from the CMU database while marker-less motion data were collected experimentally using HD video-recordings camera. The motion activities involved were walking, running, jumping, waving, and crouching.

The motions captured were pre-processed by performing data transformation and data imputation. Data transformation was performed with an aid of Kinovea in order to transform video data into numerical data. The numerical data were obtained at each of the body joints such as the head, neck, left shoulder, right shoulder, left elbow, right elbow, left wrist, right wrist, left pelvis, right pelvis, left knee, right knee, left ankle, and right ankle. When there is missing data found in the transformation process due to hidden body segment, the data were imputed using the pre-processing method proposed by Chan et al. [23].

The complete dataset without missing data was classified using WEKA. The ANN classifier namely Multi-Layer Perceptron (MLP) was used to classify human motion activities. The CMU database was used as the test set due to its preciseness of the data as compared to experimental data. The manipulated parameter in ANN is the learning rate pre-set to the classifier. First, the default setting was used in WEKA to perform classification and manipulate the parameter when the classification accuracy could not reach 70%. Evaluation of the results was then performed once the accuracy of all motion activities had exceeded 70%.

ANN Classifier

According to Bataineh et al. [21], ANN is a mathematical model inspired by the structure of human biological neural networks and often used to forecast the output

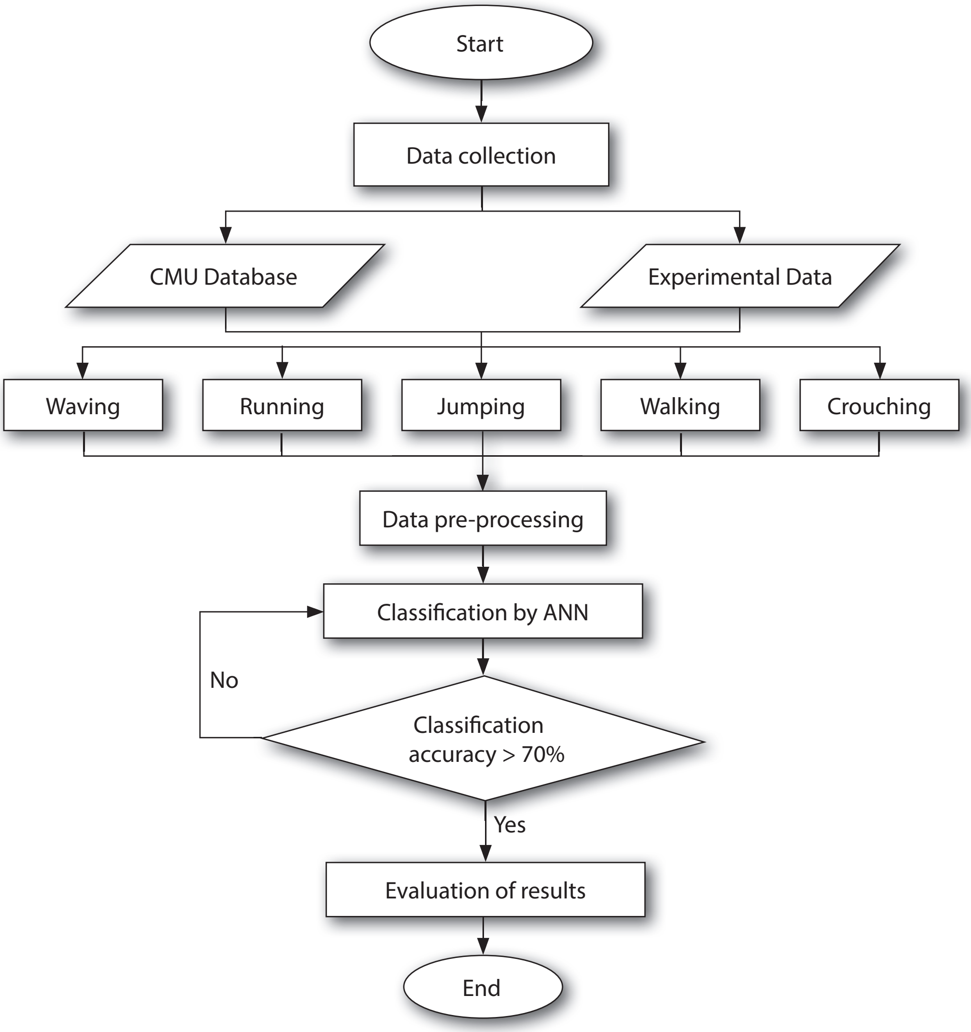


Figure 1 Flow chart of classification analysis by ANN

of the system. In this paper, we have employed ANN in human motion recognition. In WEKA, ANN was treated as a MLP classifier where back propagation will be used in the classification. There is a total of 31 input nodes and 5 output nodes for each of the databases. The sample of the hidden layer generated is depicted in Figure 2.

To generate the hidden layer in order to predict the output class of the motion data, there are two manipulated parameters that need to be considered which are the learning rate and the momentum factor. WEKA has given the ability for the user to manipulate the parameter in order to obtain the optimum classification accuracy. The learning rate and momentum factor indicate the weightage of the output layer is given by:

$$\Delta w_{ij} = \left(\eta \times \frac{dE}{dw_{ij}}\right) + \left(\gamma \times \Delta w_{ij}^{t-1}\right) \tag{1}$$

where

Δw_{ij} = Weight increment

η = Learning rate

$\frac{dE}{dw_{ij}}$ = Weight gradient

γ = Momentum factor

Δw_{ij}^{t-1} = Weight increment for previous iteration

Since there are two-stage of hidden layers in the MLP classifier (Figure 2), there is a total of $(31 \times 2) + (5 \times 2) = 72$ weight and $(5 + 2) = 7$ biases that must be determined. Suppose a set of input values have 31 items and the correct motion class as (1, 0, 0, 0, 0). If the output node values are

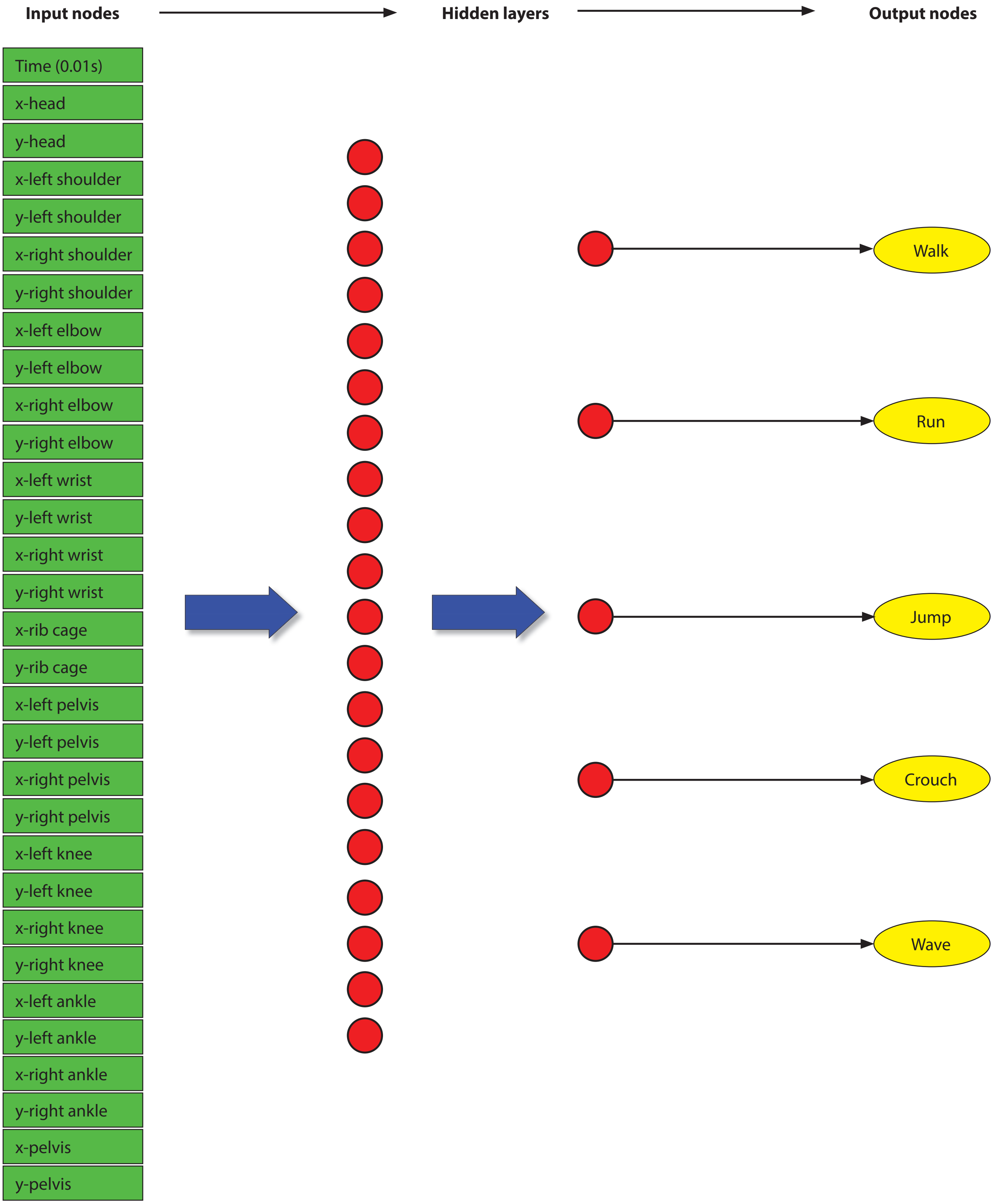


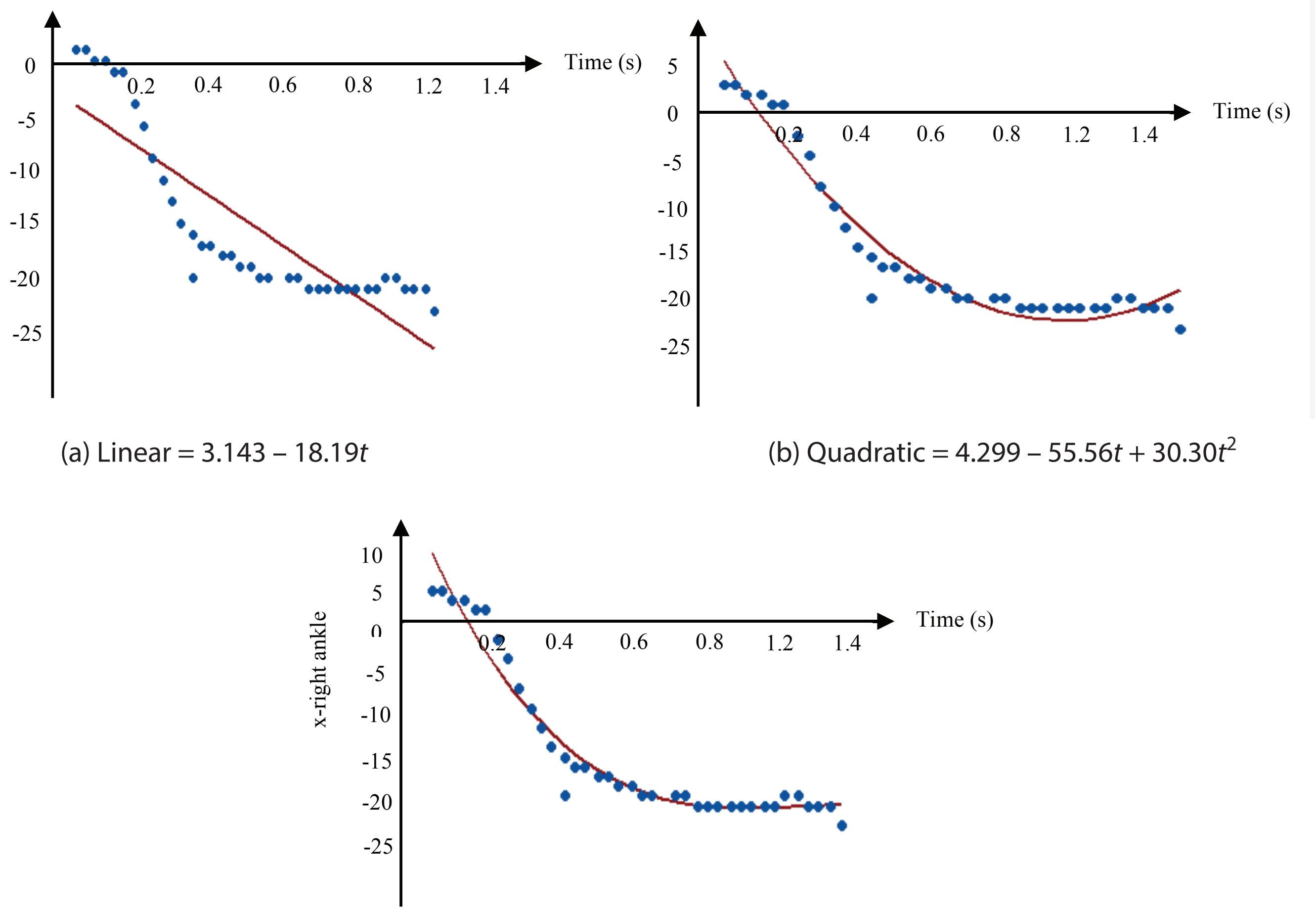
Figure 2 Hidden layer of MLP classifier

(0.8, 0.2, 0.3, 0.15, 0.25), then a training algorithm is required to adjust the 79 weights and biases values to increase the first output node value and decrease the rest of the output node values in order to meet the expected output. The learning rate and momentum factor played an important role in the training process to achieve the required output. For instance, to increase the first output node, the learning rate needs to be increased, and the momentum factor or the learning rate needs to be decreased to lower down the output values. The values of learning rates and momentum factors ranging from 0.1 to 1.0. In this paper, a different set of learning rates and momentum factors will be tested to compute the optimum classification accuracy.

RESULTS AND DISCUSSION

As aforementioned, the coordinate point of the body joint might be missing due to hidden body segments. Hence, the pre-processing method proposed by Chan et al. [20] was carried out to impute the missing data. The method proposed used regression imputation with an aid of Minitab. Figure 3 shows the regression model created on the right ankle of the *x*-coordinate. Linear, quadratic and cubic models were generated to check how fit is the input data with the model. By visual inspection, it was observed that quadratic and cubic models best fit with the input data of the right ankle *x*-coordinate.

The regression model created in Figure 3 only shows how fit is the input data as compared with the model created. To select a suitable model that employs and imputes the missing data, the analysis of R^2 and *p*-values are required. Table 1 shows a sample of the imputation method applied on the right ankle of walking motion.



(a) Linear = 3.143 – 18.19t

(b) Quadratic = 4.299 – 55.56t + 30.30t^2

(c) Cubic = 5.912 – 72.50t + 65.62t^2 – 19.29t^3

Figure 3 Regression model generated on right ankle *x*-coordinate

Table 1 Sample of imputation method on walking motion

Model	Right ankle x-coordinate		Right ankle y-coordinate	
	R^2	p-value	R^2	p-value
Linear	73.4	0.000	56.5	0.000
Quadratic	94.6	0.000	68.6	0.001
Cubic	95.5	0.013	79.7	0.000

Table 3 Confusion matrix generated using ANN classifier

Motion	a	b	c	d	e
a = Walk	82	0	0	2	0
b = Run	4	24	0	0	0
c = Jump	0	0	111	24	22
d = Crouch	0	0	11	115	25
e = Wave	0	0	10	0	62

As shown in Table 1, the R^2 values of the right ankle *x*-coordinate for both quadratic and cubic model are almost similar; however, the quadratic model was selected to impute the missing data due to the low p-value as compared to the cubic model [24]. The cubic model has been chosen for the right ankle *y*-coordinate as it has the highest value and lowest p-value. Similar steps were performed on each of the body joints that contained missing data to obtain complete data. The motion data of walking motion after the imputation method is shown in Table 2. The highlighted columns indicate the missing data imputed by the pre-processing method.

As can be seen in Table 2, the motion activities were captured every 0.03 seconds to get precise data. Once completed data was obtained by the pre-processing method, it was classified by ANN. In the classification process, the CMU dataset was used as a test set to train the experimental data. Table 3 shows the confusion matrix generated using the ANN classifier. There is a total of 490 instances involved in five motion activities. For example, in walking motion, it shows that 82 out of 84 instances were correctly classified into walking motion. However, there were merely 111 instances out of 157 instances correctly classified into jumping motion. The classification accuracy of jumping motion is not efficient when compared to walking motion. This might be due to the rapid motion involved. For rapid motion, the motion data tends to fluctuate and ANN faces difficulty to identify the correct pattern in the motion data.

Table 2 Sample of completed dataset of walking motion

Class	Time (s)	x-Right ankles	y-Right ankles
Walk	0.00	2	–60
Walk	0.03	2	–60
Walk	0.06	1	–61
Walk	0.10	1	–61
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
Walk	2.66	71	356
Walk	2.70	75	382
Walk	2.73	78	402
Walk	2.76	82	422

The classification results by ANN are illustrated in Figure 4. There are two different results shown in Figure 4, where prior improvement is the default setting with a learning rate of 0.3 and a learning rate of 0.1 after improvement. With a lower learning rate, ANN tends to learn the data faster and is able to classify the motion activity efficiently. Generally, the classification accuracy has been improved when the learning rate decreased from 0.3 to 0.1. Jumping motion was the most improved activity with the classification accuracy increased from 57.96% to 70.70%.

In addition, we have also performed an analysis on the computational time once the learning rate is changed. The result of the computational time from ANN is depicted in Figure 5. The time to build a model decreases when the learning rate decreases. This is because the time to learn the input data by the ANN classifier decreased once the learning rate decreased. It is shown that the computational time has been decreased up to 0.12 seconds. The improvement of the computational time is not distinct due to low input data in the classification process.

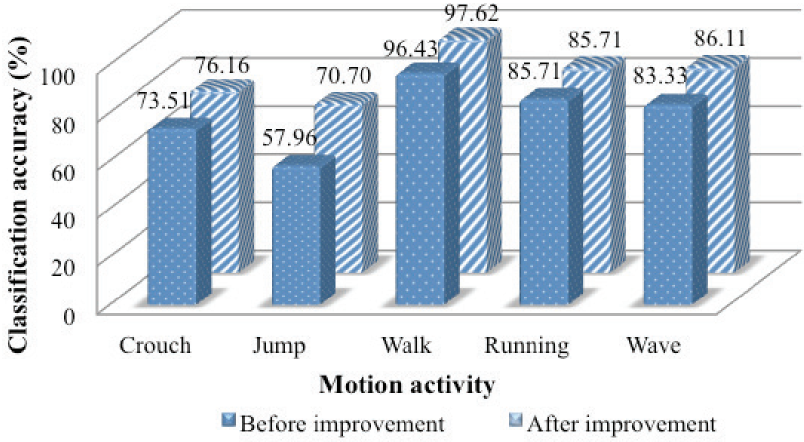


Figure 4 Comparison of the classification accuracy by ANN

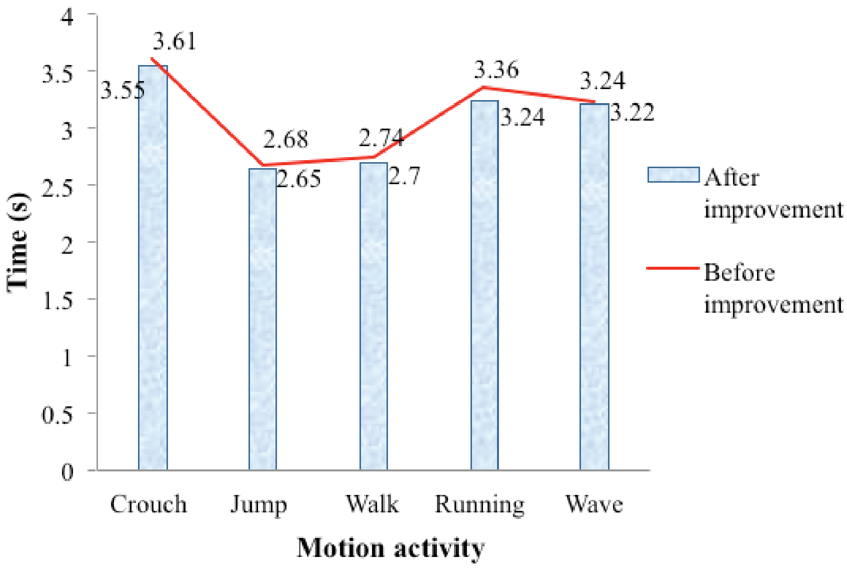


Figure 5 Comparison of the computational time in ANN

CONCLUSION

This study addressed the performance of ANN in different motion activities. The overfitting issue can be solved by manipulating the learning rate in the ANN classifier. Learning rate was found to be one of the parameters affecting the performance of ANN. By using the default parameter in the ANN classifier, the classifier tends to learn its original dataset (CMU database) and is not able to adapt to a new dataset (experimental data). By reducing the learning rate from 0.3 to 0.1, improvement of classification accuracy by up to 12.04% on the jumping motion was observed. The analysis was done on the computational time of the ANN classifier also indicated that the time used to classify motion activity is reduced with a lower learning rate. However, there was merely 0.12 seconds decrease in the computational time. Even though the improvement in computational time is not distinct but it is believed that it would be a great contribution to big data analysis in the future.

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