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COMPARISON OF EMG SIGNAL CLASSIFICATION ALGORITHMS

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Abstract— *Vast information regarding muscle activity for clinical and engineering applications can be obtained via the EMG (Electromyogram). EMG signal are acquired through surface electrodes which are placed on target muscle set of healthy subjects aged between 23 to 30 years. In this work, six forearm movements have been chosen for classification purpose for both left and right hand. With Hilbert Huang Transform method a total of 21 features of time-frequency domain are extracted for 10 healthy subjects and classified using conjugate gradient method of supervised learning technique using artificial neural networks (ANN). The average accuracy at IMF-1 level obtained is 85.8% for left hand movements, and 86.2% for right hand movement classification. The results of using the Hilbert Huang Transform based ANN classification are quite promising when compared to another classification techniques as K-NN, QDA, LDA and Mahdi Khezri et al. different signal acquisition and classification techniques. The technique can be used for practical implementation of prosthesis for movement classification.Machine Learning algorithms (Decision Trees and Support Vector Machines) are proposed and compared to select a classification system for EMG signals to improve the performance of pattern recognition for the control of a prosthesis prototype. The training, validation and signal classification were made using the Classification Learner application of the MatLab software, using a database captured with the commercial myoelectric armband MYO which contain the information of eight different hand movements. The results show that Support Vector Machines algorithms have a better performance than the decision trees, reaching the 99.8% of accuracy with linear and quadratic kernel and the 99.9% using a cubic kernel.*

Keywords— classification, machine learning, EMG, Artificial Nural Networks, prosthesis

INTRODUCTION

In recent decades, research into finger movement pattern recognition for bionic hand applications has grown dramatically. The rise of amputees is to blame for this. The World Health Organization (WHO) reports that there were 8,4 million cases of diabetes mellitus (DM) in Indonesia in 2000, 13,8 million cases in 2003, and 21,3 million cases are expected by 2030. With a frequency of 8,6% over the entire population, this places Indonesia in fourth place overall, above of nations like India, China, and the United States. Many biomedical engineering disciplines, including teleoperation of devices [1], exoskeletons and rehabilitation tools [2, functional electrostimulation [3, prostheses [4], and others, have utilised electromyographic signals. With the advancement of electromyographic prostheses, patients will soon be able to restore the necessary functionality to operate items in their everyday surroundings. Processing the EMG signals is required to extract their characteristics and perform pattern recognition for this. It has been commonly reported that machine learning techniques are used to control upper limb prosthetics [5]. Russo et al[6] .'s classification of three separate hand movements to govern robotic hand movement makes use of a commercial artificial hand (Open Bionics) and a commercial muscle sensor (MyoWare) in conjunction with an Arduino Nano board.With the use of EMG signal characteristics in the time domain, they created classifiers based on Support Vector Machines (SVM) and neural networks, achieving a performance of almost 90%. [7] describes the development of a pattern recognition system that uses two channels of electromyographic signals to classify signals and recognise four different human hand postures. For the recognition of eight human hand motions, the anthropomorphic robotic hand developed in [8] uses a classifier based on Extended Associative Memories (EAM). To complement and enhance the performance of the prototype developed in [8] identifying 8 movements (different from those recognised by the

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bracelet through this document, which uses different algorithms for pattern classification),

II. MATERIAL AND METHODS

The techniques employed in this paper are feature extraction, PCA-based dimensionality feature reduction, and ANN-based classification. Extraction of Features The feature extraction method used in this paper is time-domain. The majority of them were taken from vibration signals, whereas some were frequent features in EMG signals. Integrated EMG 1. (IEMG) A simple EMG signal characteristic is IEMG. It can be determined by adding up the absolute values of the digital EMG signal.

$$IEMG = \sum_{i=1}^{N} |x_i| \quad (1)$$

2. Mean Absolute Value (MAV) MAV is a mean value of IEMG feature.

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i| \quad (2)$$

3. Modified MAV type 1 (MAV1) MAV1 is a modified version of MAV. The absolute value of digitized EMG signal is multiplied by the weight, w prior to the sum and mean calculation. The conditional weight is presented below.

$$MAV1 = MAV = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i| \quad (3$$

$$w_1 = \begin{cases} 1, \text{ if } \; 0.25N \le i \le 0.75N \\ 0.5, \text{ otherwise} \end{cases}$$

4. Modified MAV type 2 (MAV2) MAV2 is similar to MAV2 with the change the conditional weight.

$$MAV1 = MAV = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i| \quad (4)$$

$$w_1 = \begin{cases} 1, \text{if } \; 0.25N \le i \le 0.75N \\ 4i/N, \text{else if}^{i} \; i < 0.25N \\ 4(i-N)/N, \text{otherwise} \end{cases}$$

5. Variance of EMG (VAR) VAR calculated the variance of digitized EMG signal.

$$VAR = \frac{1}{N-1} \sum_{i=1}^{N} x_i^{\,2}, \quad i = 1, \ldots, m \quad (5)$$

6. Root Mean Square (RMS) RMS is a common statistical feature that has been used widely in vibration signal. RMS modeled as amplitude modulated Gaussian random process whose relates to constant force and non-fatiguing contraction [3, 4].

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^{\,2}} \quad (6)$$

7. Waveform Length (WL) WL measures the complexity level of the EMG signal. It is defined as cumulative length of the EMG waveform over the time segment [5, 6].

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \quad (7)$$

8. Simple Square Integral (SSI) is the sum of square digitized EMG signal

$$SSI = \sum_{i=1}^{N} x_i^{\,2} \quad (8)$$

9. Difference absolute standard deviation value (DASDV) is a standard deviation value of the wavelength [4].

$$DASDV = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_{i+1} + x_i)^2} \quad (9)$$

10. Autoregressive (AR) is a common approach for modelling univariate time series [3, 7, 8]

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_n y_{t-n} + \varepsilon_t = \sum_{i=1}^{n} a_i y_{t-i} + \varepsilon_t$$

where a1 to an are the autoregressive coefficients, yt is the time series under investigation, n is the order of the

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AR model (n = 4) and ε is the residual which always assumed to be Gaussian white noise.

11. Hjorth 1 (Activity) parameter represents the signal power, the variance of a time function. This can indicate the surface of power spectrum in the frequency domain [9].

$$H1=var(x) \quad (11)$$

12. Hjorth 2 (Mobility) parameter represents the mean frequency, or the proportion of standard deviation of the power spectrum [9].

$$H2=\sqrt{\frac{\operatorname{var}\left(x\frac{dx}{dt}\right)}{\operatorname{var}(x)}} \quad (12)$$

13. Hjorth 3 (Complexity) parameter represents the change in frequency. The parameter compares the signal's similarity to a pure sine wave, where the value converges to 1 represent the high level of similarity [9].

$$H3=\frac{mobility\left(x\frac{dx}{dt}\right)}{mobility(x)} \quad (13)$$

Principal Component Analysis (PCA)

The two commonly used techniques for data classification and dimensionality reduction are principal component analysis (PCA) and linear discriminant analysis (LDA) [8]. PCA is selected in this study. PCA in general term, is a technique using sophisticated underlying mathematical principles to transforms a number of possibly correlated variables into a significant smaller number of uncorrelated variables called principal components [3]. PCA technique lies in multivariate data analysis, but it has a wide range of applications, such as signals de-noising, blind source separation, cluster analysis, visualization of high-dimensionality data, regression, data compression and pattern recognition. The new extracted components are called principal components. The number of principal components can be reduced using only the first several eigenvectors sorted in descending order of the eigenvalues.

EXPERIMENTAL SET-UP

The Instrumentation and Control Research Laboratory, Institute of Technology Bandung, was the site of the experiment. The experiment included fifteen subjects. Each volunteer's EMG signals for 8 movements were recorded during the experiment. Part B provides a detailed explanation of how the EMG data for eight movements was acquired.
Experimental Devices

The experiment was conducted at the Instrumentation and Control Research Laboratory at the Institute of Technology Bandung. There were fifteen participants in the experiment. EMG signals from each volunteer were captured over the course of the experiment for 8 movements. The method used to collect the EMG data for eight movements is explained in full in Part B.

Fig. 1. Infinity thought technology hardware [8, 9].
Data Acquisition.

Fig. 2 illustrates sensor mounting at 1 Myo channel scan of flexor carpi radialis. The area of reference for positive and negative values are in the range of 2 cm.

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Figure 2.The location of EMG sensor on flexor carpi radialis.

The procedure of data acquiring from subject was done with the subject sitting and relaxing about 3 meter from PC and 1 meter from power and frequency controller. Each of the data acquiring process was done using the procedure such as sensor on – data acquiring from one subject – sensor off and continue with the next subject.

a) The first hand movement is Hand Close. Subjects were asked to close their hand from hand open mode for 5 seconds and break for 3 seconds. The process of data acquiring is repeated for 5 times.

b) The second hand movement is Hand Open. This experiment is similar to Hand Close but the subjects were asked to open their hand from the hand close mode.

c) The third hand movement is Power Grip. Subjects were asked to hold the glass and lift it 5 cm for 6 seconds and break for 3 seconds. The experiment is repeated for 5 times.

d) The fourth hand movement is Tripod. Subjects were asked to hold the pen marker for 6 seconds and break for 3 seconds. The experiment is repeated for 5 times.

e) The fifth hand movement is Pinch. Subjects were asked to hold the key using thumb and point finger for 6 seconds and break for 3 seconds. The experiment is repeated for 5 times.

f) The sixth hand movement is Handforce. Subjects were asked to shake hand for 6 seconds and break for 3 seconds. The experiment is repeated for 5 times.

g) The seventh hand movement is Mouse. Subjects were asked to hold and click the right of mouse using point finger for 6 seconds and break for 3 seconds. The experiment is repeated for 5 times.

h) The eighth hand movement is Keyboard. Subjects were asked to do usual typing on the keyboard of PC using index finger for 6 seconds and break for 3 seconds. The experiment is repeated for 5 times.

The photographs for the aforementioned 8 hand movements are presented in Fig. 3 and the EMG signals of 8 hand movements acquired from Subject 2 are depicted in Fig. 4.

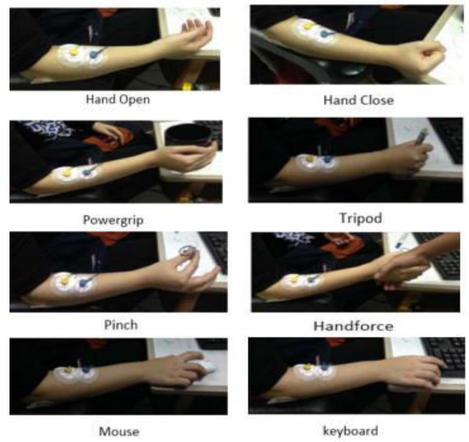

Fig. 3. Eight hand movement for EMG experiment.

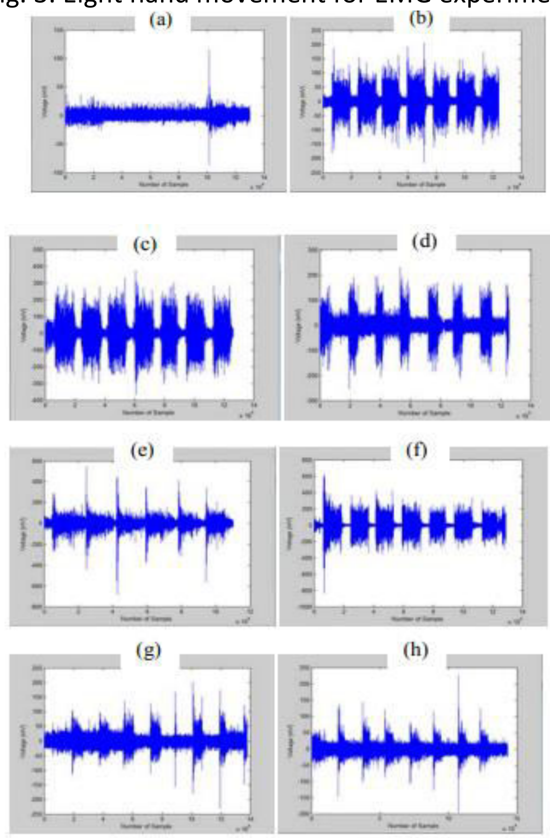

Fig. 4. EMG signals of 8 hand movements (Subject 2): (a) Hand open; (b) Hand close; (c) Powergrip; (d) Tripod; (e) Pinch; (f) Handforce; (g) Mouse; (h) Keyboard.

Robotic Hand.

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The master-slave architecture provides the foundation for the robotic hand. The EMG armband created by Thalmic Labs Inc. is connected to a Raspberry Pi in the master subsystem, which is in charge of collecting data and processing it to categorise the user's muscular activity. The robotic hand's movements are defined by the slave device, an ATmega328 microcontroller, depending on the data analysed by the master device [8].

The electromyographic armband, which has 8 EMG sensors, is in charge of gathering the data from the user's arm muscles and processing them somewhat before sending them over Bluetooth 4.0 technology. Communication with the wristband and access to the provided data are capabilities of the Raspberry Pi 3. The classification is completed in this manner after obtaining the signals from each of the 8 EMG sensors. Once the gesture has been recognised, it is sent to the microcontroller via the Raspberry Pi 3's GPIO pins. The microcontroller gets the information from the gesture recognition and, using a database, determines where each finger of the robotic hand should be in order to carry out the appropriate gripping technique. The microprocessor instructs each motor controller what speed and which direction to rotate at using an output pin and a PWM signal.

The motor generates the movement and transmits it to the mechanisms of the hand, producing the movement of the fingers. The gestures carried out by the prosthesis prototype are those shown in Fig. 1.

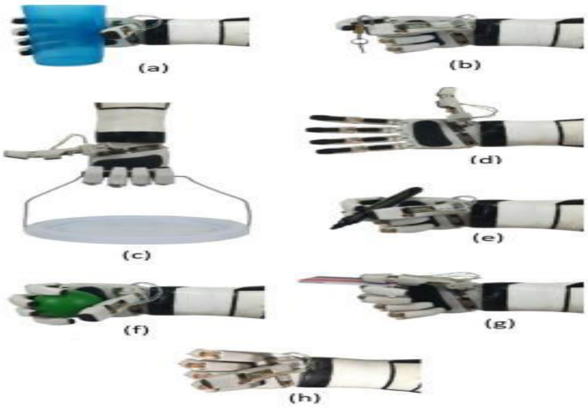

Figure. 1. Types of grasp implemented on the robotic hand: (a) Cylindrical grasp, (b) Tip grasp, (c) Hook grasp, (d) Open hand, (e) Palmar grasp, (f) Spherical grasp, (g) Lateral grasp, (h) Fist.

The classification algorithm used for gesture recognition is based on the Extended Associative Memories (EAM) method, proposed by Sossa et al. in [9]. The purpose of this method is to establish a relationship between an input x with an index μ of the class cμ and in this way determine to which class a performed gesture belongs In [8] it is reported that the performance percentage achieved using this classifier to recognize the 8 defined gestures is 95.83%.

Databases

The Myo myoelectric bracelet gathers the EMG signals that it uses to function. At a rate of 200 samples per second, these signals are sampled with an eight-bit precision. The bracelet amplifies the value collected from each of the EMG sensors and encodes the potential created by muscle movement into integer values with a range of 0 to 1023 [10]. Given that a gesture has a cycle duration of roughly 0.5 seconds, the gesture being performed at any given moment will be represented by a collection of 100 discrete sensor readings [11]. The database found in [12] was created in this manner. Eight files make up the dataset, one for each class and gesture. Each file has 50 readings, and each reading has 800 readings.forming a base of 40,000 data per gesture. In Fig. 2 you can see the hand gestures used to generate the classes that produce the different grips on the robotic hand.

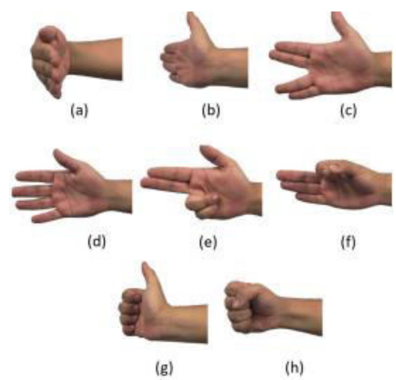

Figure 2. Hand gesture actions or classes used for generating the grasp types of the prosthesis: (a) Cylindrical grasp, (b) Tip grasp, (c) Hook grasp, (d) Open hand, (e) Palmar grasp, (f) Spherical grasp, (g) Lateral grasp, (h) Fist.

Classification And Pattern Recognition

The database [12] was split into two sets for the training and classification processes. For the training of each classification algorithm, the initial data set consists of 8000 data points for each of the eight motions, randomly selected from 10 readings of each gesture. The second data set contains 80 reads (10 different reads for each motion), which are used to validate and confirm how each classifier behaves.

A decision tree and Support Vector Machines, both of which have various variations, are the two classification methods that have been implemented. Though decision trees can have low prediction accuracy, they are simple to understand, quick to forecast and fit, and need little memory [13]. Support Vector Machines categorise the data

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by identifying the best hyperplane that divides it into classes; the best hyperplane is the one where the margin between two classes is largest. Binary predictions using Support Vector Machines can be made quickly, while multiclass classifications typically have faster predictions [13].

The MatLab software's Classification Learner programme was used to examine the classifiers' behaviour in relation to data from the database. You can select from a variety of techniques in this programme to train and validate classification models for binary or multiclass situations [13]. After training, validation errors can be compared to determine which model performs the best. The below list includes the modifications made to the various classifiers. Three versions of the decision tree were put into practise: Coarse Tree, which uses a maximum of 4 divisions and only a few leaves to make thick distinctions across classes. With a maximum of 20 divisions, the Medium Tree uses a medium amount of leaves to draw slightly finer distinctions between classes.

Different kernels were utilised for Support Vector Machines, including linear, quadratic, and cubic SVMs, which produce linear, quadratic, and cubic separations between classes, respectively. Additionally, three distinct scales of the Gaussian kernel were implemented: Fine Gaussian SVM, Medium Gaussian SVM, and Coarse Gaussian SVM.

RESULTS

PCA To enhance the classification accuracy, the 16 features are reduced into 3 principal component (PC) features using PCA. The pair of 3 PCs of Subject 2 is presented in Figs. 5-7. It can be seen that the 8 hand movements can be distinguished from the pair combination of three PCA features.

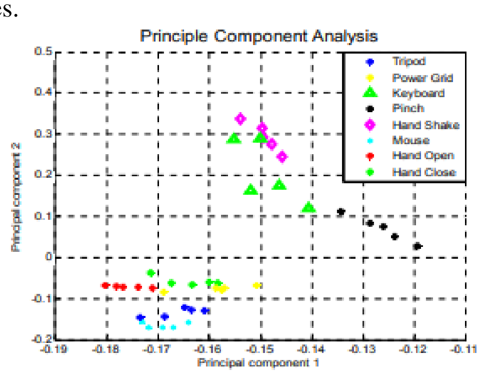

Fig. 5. Plot of PCA (Subject 2): Principal component 1 vs Principal component 2.

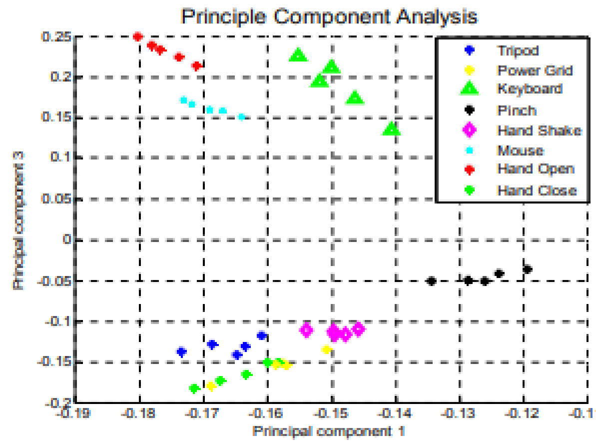

Fig. 6. Plot of PCA (Subject 2): Principal component 1 vs Principal component 3

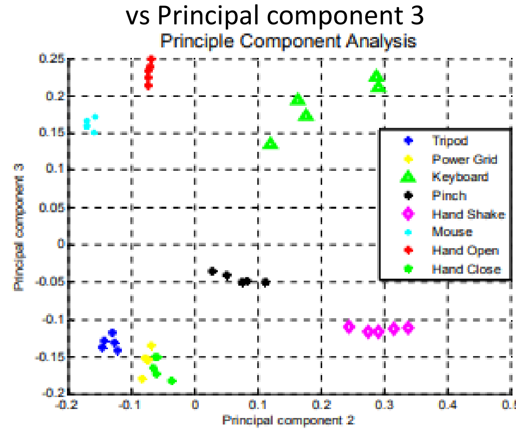

Fig. 7. Plot of PCA (Subject 2): Principal component 2 vs Principal component 3.

ANN In this paper, the Neural Network tool (nntool) from MATLAB is employed. The extracted features of all subjects are used as the ANN input. The ANN used 20 hidden layers and the "trainlm" for the training algrithm. The hidden layer employed "tansig" transfer function and the output layer used "softmax" transfer function. The data were divided into 3 i.e. traning, validation and testing. The training, validation and testing process used 70%, 15%, and 15% of total number of data, respectively. Mean square error is employed as the error performance function to calculate the accuracy. Fig. 8 shows the classification result of data training and data testing for 8 hand movements (classes). The overall accuracy of 8 classes for training is 85.7%. Fig. 9 shows the result of classification or data testing. The overall accuracy of eight classes for testing is 81.2%.The performance of each algorithm for the recognition of patterns in the database can be seen in Table I. Each percentage represents the quantification of the number of gestures classified correctly by algorithm, corresponding 100% to the 80 data reads used to check

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performance. In Fig. 3 the confusion matrix of the Support Vector Machine with cubic kernel is shown, with which the performance of the algorithm can be visualized.

TABLE I CLASSIFICATION PERFORMANCE PERCENTAGE FOR EACH ALGORITHM.

Algorithm	Performance (%)
Coarse Tree	49.2%
Medium Tree	96.4%
Fine Tree	99.1%
Linear SVM	99.8%
Quadratic SVM	99.8%
Cubic SVM	99.9%
Coarse Gaussian SVM	99.5%
Medium Gaussian SVM	99.7%
Fine Gaussian SVM	99.1%

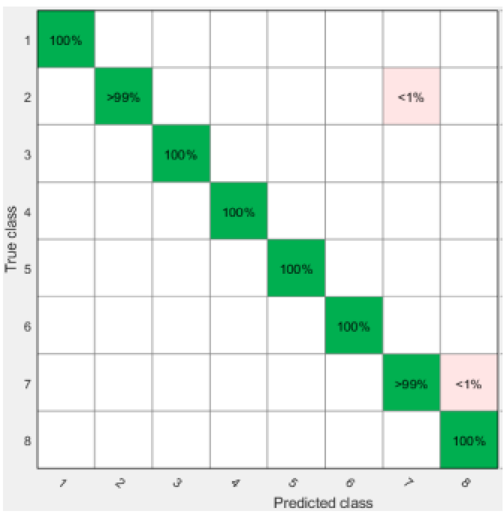

Figure 3. Confusion matrix for the SVM algorithm classification with cubic kernel

Each column in the matrix represents the number of predictions for each class, while each row represents the instances in the actual class. IV. DISCUSSION According to the information presented in Table 1, we can see that the decision tree algorithms have a lower performance than Support Vector Machines, however the fine decision tree can be considered as a viable option as it has a classification percentage 99.1% accurate. In turn, we can observe that in general Support Vector Machine algorithms respond in a more appropriate way than decision trees, having a higher percentage of performance when linear, quadratic and cubic kernels are used, obtaining the best result with the use of the Support Vector Machine with cubic kernel with 99.9% performance.

From Fig. 3 we can see that the recognition made by the Support Vector Machine with a cubic kernel was not correct in all the tests, showing failures when recognizing gesture 2 when in fact it was gesture 7, and recognizing gesture 7 when the real class was 8. The percentage of each error is shown in Fig. 3 in the red shaded boxes. Despite this, the percentage of incidence of the error in each case is less than 1%.

CONCLUSIONS

This paper has presented a classification method for multi-class classification of electromyography (EMG) signals from eight hand movements. The proposed method uses principal component analysis (PCA) and artificial neural network (ANN) to enhance the classification accuracy. It was found from experiments that the proposed method achieves a training accuracy of 85.7% and a testing accuracy of 81.2%.

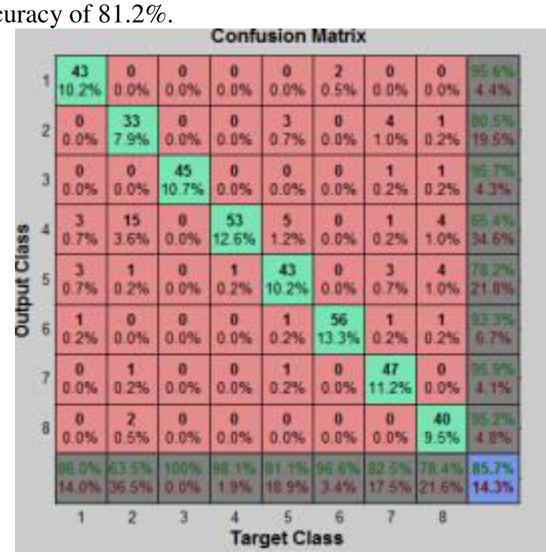

Fig. 8. The result of training of EMG signal data using ANN method

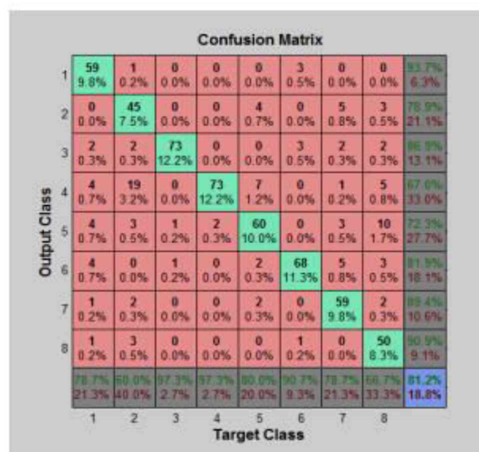

Fig. 9.The result of testing of EMG signal data using ANN method.

The use of a single board computer (Raspberry Pi) in the prosthesis prototype developed in [8], gives great versatility to implement various classifiers for pattern recognition and thus improve system performance.

The training and verification of Machine learning algorithms (SVM and decision trees) for classification through MatLab's Classification Learner application is great to test the performance of these algorithms and thus choose the that best results provide the required application. In this particular project, the decision trees offered lower performance percentages than those obtained with SVM; however, they should be taken into account due to their higher execution speed and ease of interpretation.

The Support Vector Machines algorithms show a very good performance percentage, with the highest percentage being those with the linear (99.8%), quadratic (99.8%) and cubic (99.9%) kernel. One of the advantages that MatLab offers over SVM classifiers is that it is possible to generate the C code of the model trained to perform classifications using the MatLab Coder application, making it possible to export the classifier to run on the robotic hand system.

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