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Finger Movement Pattern Recognition Method Using Artificial Neural Network Based on Electromyography (EMG) Sensor

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***Abstract*— In this study, the EMG signals are processed using 16 time-domain features extraction to classify the finger movement such as thumb, index, middle, ring, and little. The pattern recognition of 16 extracted features are classified using artificial neural network (ANN) with two layer feed forward network. The network utilizes a log-sigmoid transfer function in hidden layer and a hyperbolic tangent sigmoid transfer function in the output layer. The ANN uses 10 neurons in hidden layer and 5 neurons in output layer. The training of ANN pattern recognition uses Levenberg-Marquardt training algorithm and the performance utilizes mean square error (MSE). At about 22 epochs the MSE of training, test, and validation get stabilized and MSE is very low. There is no miss classification during training process. Based on the resulted overall confusion matrix, the accuracy of thumb, middle, ring, and little is 100%. The confusion of index is 16.7%. The overall confusion matrix shows that the error is 3.3% and overall performance is 96.7%.**

Keywords*— *artificial neural network; electromyography; features extraction; pattern recognition

I. Introduction

Recently, a number of studies in bionics hand have developed significantly. The purpose of the studies is mainly to interpret finger movement. The common used sensor for measuring the activity of muscle is electromyography (EMG). The raw signal from EMG sensor is hard to understand and interpreted by human. Thus, the implementation of pattern recognition method that can interpret the muscle activity or finger movement has important role. This research was focused on the feature extraction and pattern recognition of five finger movement classification using EMG raw signals.

The work reported in [1] developed an algorithmic scheme for multi-channel supervised classification of surface EMG using support vector machine (SVM) and signal based wavelet optimization. The implementation of this scheme to experimental EMG signals to classify six hand movement has the average misclassification rate of 5%. SVM has been implemented for pattern recognition methods for multi stage classification of human voice acquired from patient with Parkinson Disease [2,3]. The method consists of feature extraction and classification steps. The results show that SVM has better accuracy than KNN, AdaBoost, and ART-KNN for PCA feature classification of Parkinson Disease. The SVM pattern recognition method is hard to implement with many features without feature reduction.

The hand gesture recognition using ANN based on EMG signal has been studied in [4,5]. A back-propagation ANN classifier with Levenberg-Marquardt training algorithm was utilized. The network uses conventional features in time domain and frequency domain. From the simulation results, ANN can classify six different hand movements (left, right, up and down) with the rate error of 11.6 %.

An implementation of real time novel pattern recognition for controlling virtual myoelectric hand using four channel EMG signals has been proposed by [6]. The features are extracted utilizing wavelet packet transformation. Features dimensionality is reduced by principal component analysis (PCA) and classified by a multilayer neural network. The experimental results showed that the proposed method is applicable to real-time virtual myoelectric hand control.

In this study, feed-forward ANN will be used to classify five finger movements based on one channel EMG signals. The 16 utilized features in time domain will be fed up to the input of network and will be discussed in Section 2. The classification results and discussion will be presented in Section 4.

II. Methods

A. Feature Extraction

Some research studied the feature extraction of EMG signals divided in two domains: (1) time domain features and

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(2) frequency domain features [7]. Ref [8] proposes a new technique for feature extraction of forearm EMG signals using mother wavelet matrix. Time domain features were used in this paper. The definition and the equation are presented as follows:

- Integrated EMG (IEMG): IEMG is normally used as an onset detection index in EMG non-pattern recognition and in clinical application [9,10].

$$IEMG = \sum_{i=1}^{N} |x_i| \tag{1}$$

- Mean absolute value (MAV): MAV is one of the most popular used in EMG signal analysis. It is similar to IEMG feature which is used as an onset index, especially in detection of the surface EMG signal for the prosthetic limb control [11,12].

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{2}$$

- Modified mean absolute value type 1 (MAV1): MAV1 is an extension of MAV feature [12,13]

$$\begin{gathered} MAV1 = \frac{1}{N}\sum_{i=1}^{N} w_i |x_i| \\ w_i = \begin{cases} 1, & if\, 0.25N \le i \le 0.75N \\ 0.5, & otherwise \end{cases} \end{gathered} \tag{3}$$

- Modified mean absolute value type 2 (MAV2): MAV2 is an expansion of MAV feature which is similar to the [12,13].

$$\begin{gathered} MAV2 = \frac{1}{N}\sum_{i=1}^{N} w_i |x_i| \\ w_i = \begin{cases} 1, & if\, 0.25N \le i \le 0.75N \\ 4i/N, & else\ if\ \ i < 0.25N \\ 4(i-N)/N, & otherwise \end{cases} \end{gathered} \tag{4}$$

- Simple square integral (SSI) or integral square uses energy of the EMG signal as a feature [14].

$$SSI = \sum_{i=1}^{N} x_i^2 \tag{5}$$

- Variance of EMG (VAR): VAR is another power index. Generally, variance is defined as an average of square values of the deviation of that variable; however, the mean value of EMG signal is close to zero (~10-10) [10,15].

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2 \tag{6}$$

- Root mean square (RMS): RMS is another popular feature in analysis of the EMG [16,17]. It is modeled as amplitude modulated Gaussian random process whose relates to constant force and non-fatiguing contraction.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{7}$$

- Waveform length (WL): WL is a measure of complexity of the EMG signal [11,12]. It is defined as cumulative length of the EMG waveform over the time segment.

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i|. \tag{8}$$

- Difference absolute standard deviation value (DASDV): DASDV is look like RMS feature, in other words, it is a standard deviation value of the wavelength [17].

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

- Autoregressive (AR) coefficients: A common approach for modelling univariate time series is the AR model [10,15,16]. follows:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_n y_{t-n} + \varepsilon_t = \sum_{i=1}^{n} a_i y_{t-1} + \varepsilon_t \tag{10}$$

  where a_1 to a_n are the autoregressive coefficients, y_t is the time series under investigation, n is the order of the AR model ($n = 4$) and ε is the residual which always assumed to be Gaussian white noise.

- Hjorth 1 (Activity): The activity parameter represents the signal power, the variance of a time function. This can indicate the surface of power spectrum in the frequency domain[18].

$$Hjorth\_1 = \mathrm{var}(x) \tag{11}$$

- Hjorth 2 (Mobility): The mobility parameter represents the mean frequency, or the proportion of standard deviation of the power spectrum [18].

$$Hjorth\_2 = \sqrt{\frac{\mathrm{var}\left(x\dfrac{dx}{dt}\right)}{\mathrm{var}(x)}} \tag{12}$$

- Hjorth 3 (Complexity): The 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 if the signal is more similar [18].

$$Hjorth\_3 = \frac{mobility\left(x\frac{dx}{dt}\right)}{mobility(x)} \tag{13}$$

B. *Artificial Neural Network*

In this paper, the pattern recognition of the features mentioned before is classified using the standard network as shown in Fig. 1. The standard network that is used for classification method is a two layer feed forward network with a log-sigmoid transfer function in hidden layer and a hyperbolic tangent sigmoid transfer function in the output layer.

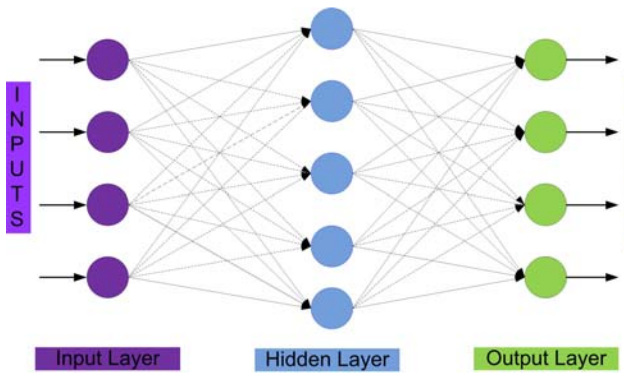

Fig. 1. ANN structure.

The first output neuron of hidden layer can be expressed as

$$a^1 = f^1(IWp + b^1) \tag{14}$$

where a^1 is output vector from input layer, p is an n-length input vector, IW is input weight matrix, f^1 is transfer function of hidden layer, and b^1 is the bias vector of hidden layer.

The first output neuron of the output layer as written in (15)

$$a^2 = f^2(LW(f^1(IWp + b^1)) + b^2) \tag{15}$$

where a^2 is output vector from output layer, LW is output layer weight matrix, f^2 is transfer function of the output layer, and b^2 is the bias vector of the output layer.

The transfer function in hidden layer and output layer is written as in equation (16) and (17). The function of log-sigmoid generates outputs between 0 and 1 while hyperbolic tangent sigmoid function generates ouputs beetwen -1 and 1, as the neuron's net input goes from negative to positive infinity. The description of transfer function can be seen in Fig. 2.

$$f^1(n) = \frac{1}{1+e^{-n}} \tag{16}$$

$$f^2(n) = \frac{2}{1+e^{-2n}} - 1 \tag{17}$$

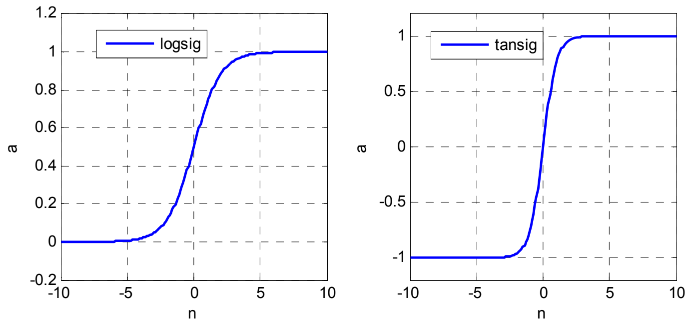

Fig. 2. Neuron activation function.

The Levenberg-Marquardt training algorithm is used in this study. It was designed to approach second-order training speed without having to compute the Hessian matrix. As typical training feedforward networks, the performance function of this training algorithm has the form of a sum of squares, and the Hessian matrix can be approximated using equation (18).

$$H = J^T J \tag{18}$$

and the gradient can be calculated as

$$g = J^T e \tag{19}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors.

The Levenberg-Marquardt training algorithm uses equation (20) to approximate the Hessain matrix

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{20}$$

when the scalar μ is zero, the equation (20), using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size.

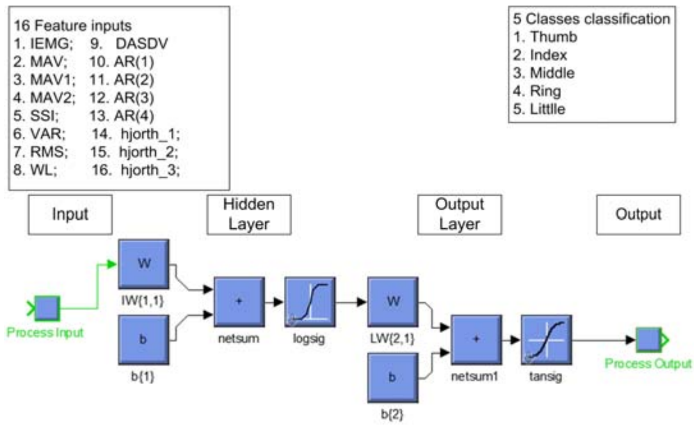

Fig. 3. ANN input and output for pattern recognition.

The ANN for classification use Mean Square Error (MSE). The MSE measures the magnitude of the forecast errors as shown in (21). Better model will show the smaller values of MSE.

$$mse_{error} = \frac{\sum(y_1 - y_2)^2}{m} \quad (21)$$

where y_1 is the real output in classification, y_2 is the output from ANN classification, and m is the total number of samples in classification. The used ANN has 16 input features and has the 5 class classification results for thumb, index, middle, ring, and little as shown in Fig. 3.

III. MATERIALS

A. Electromyography (EMG) Datasets

In this paper, electromyography data from EMG datasets repository [19] are used. Eight subjects, consist of six males and two females. Fifteen fingers movements are acquired from each subject. The age of subjects are varied between 20 to 35 years. The subjects were all normally limbed with no neurological or muscular disorders. The subjects were seated on an armchair, with their arm supported and fixed at one position to avoid the effect of different limb positions on the generated EMG signals[19,20].

B. Five Movements Selection

Five out of fifteen electromyography data are selected. The description of five finger movements are shown in Fig. 4. The finger movement datasets which consists of thumb (T), index (I), middle (M), ring (R), and little (L) were used and processed in this paper. Six data is acquired for each of finger movement. The total processed raw EMG data is thirty dataset.

C. Five Movement Signal

In Fig. 5 five finger movements signal is plotted using MATLAB. It shows that each individual movement has different signal than each other. Further, these signals are processed using 16 features calculation. The 16 features are used as input vector in ANN pattern classification method that results 5 class classification.

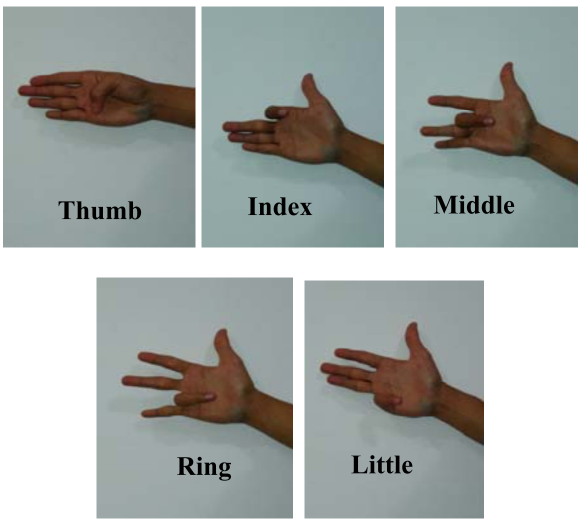

Fig. 4. Five individual movements of fingers.

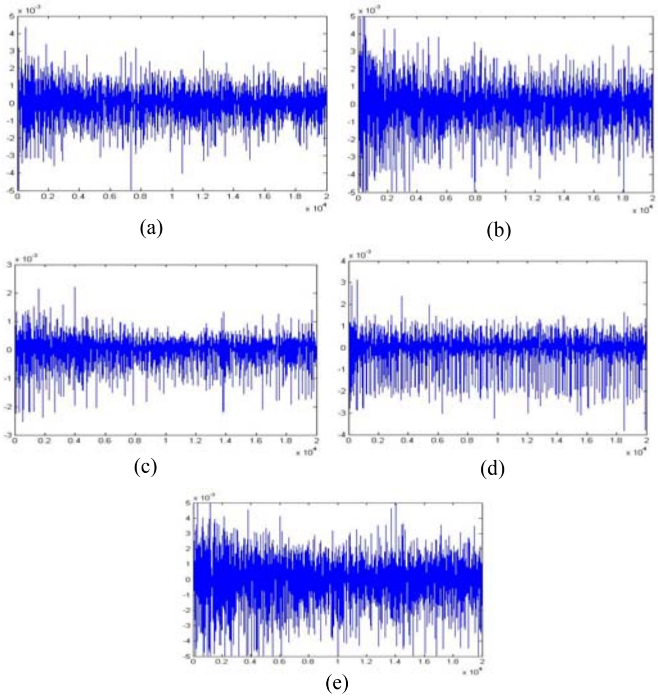

Fig. 5. EMG raw signal of (a) Thumb, (b) Index, (c) Middle, (d) Ring, and (e) Little.

IV. RESULTS AND DISCUSSION

The finger movement classification pattern recognition is designed by arranging the 16 features as rows and 30 data samples as column in matrix 16 x 30. That matrix is used as input vector in ANN. The target vector has 5 elements/classes that each of elements consists of the value 0 or 1. The 30 dataset samples of finger movement are divided into three sub-set i.e. training, testing, and validation using specified samples. 18 data are used in training, 6 data are used in test, and 6 data are used in validation. The ANN uses 10 neurons in hidden layer and 5 neurons in output layer as shown in Fig. 6.

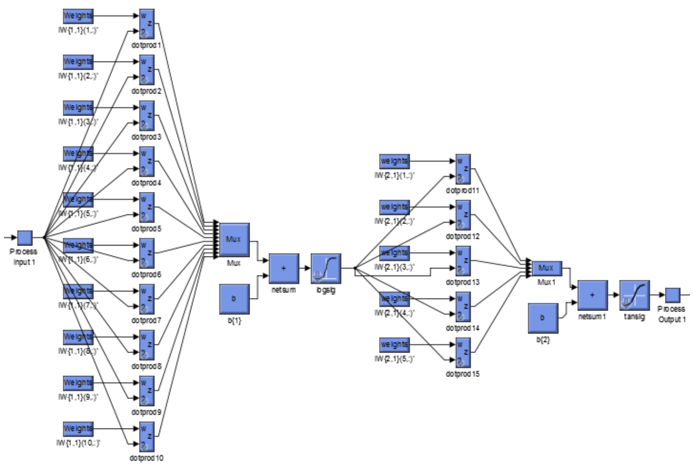

Fig. 6 ANN with 10 neuron hidden layers in Simulink.

The training of ANN pattern recognition uses Levenberg-Marquardt training algorithm and the perfomance utilizes

MSE. In Fig. 7 and Table 1, at 22 epochs the MSE of training, test, and validation is 0.00079, 0.0407, and 0.0521 respectively. At about 22 epochs the MSE of training, test, and validation get stabilized and the MSE is very low. This means that the network giving very high accuracy of pattern recognition in finger movement classification.

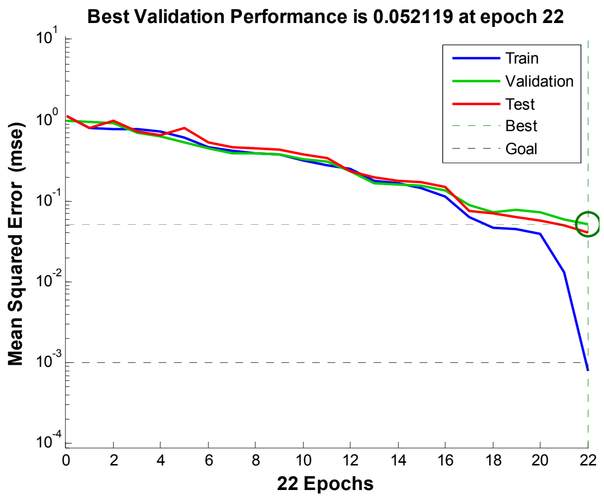

Fig. 7. MSE graph during training, validation, and testing.

TABLE 1. ANN PERFORMANCE

	ANN performance and epoch		
	Train	***Validation***	***Testing***
Peformance	0.00079	0.0521	0.0407
Epoch	22	22	22

The output of pattern recognition in finger movement classification is presented in the two following table. Table 2 presents confusion matrix result during training. The accuracy of each finger movement is 100%. The confusion of each finger movement is 0% that means there is no miss classification during training process. The overall performance is 100 % and overall error is 0 %.

TABLE 2. CONFUSION MATRIX OF FINGER MOVEMENT RESULT DURING TRAINING

Finger movement	**True Classification**				
	Thumb	***Index***	***Middle***	***Ring***	***Little***
Thumb	3	0	0	0	0
Index	0	4	0	0	0
Middle	0	0	4	0	0
Ring	0	0	0	3	0
Little	0	0	0	0	4
Movement sample	3	4	4	3	4
Accuracy (%)	100	100	100	100	100
Overall accuracy (%)	100				

Table 3 presents confusion matrix result all of training, validation and testing together. The accuracy of thumb, middle, ring, and little is 100 % . The the confusion of index is 16.7%. The overall confusion matrix shows that error is 3.3% and overall performance is 96.7 %. Based on the confusion matrix results, it can be said that the network can classify the finger movement with very high accuracy and minimal error.

TABLE 3. OVERALL CONFUSION MATRIX

Finger movement	**True Classification**				
	Thumb	***Index***	***Middle***	***Ring***	***Little***
Thumb	6	1	0	0	0
Index	0	5	0	0	0
Middle	0	0	6	0	0
Ring	0	0	0	6	0
Little	0	0	0	0	6
Movement sample	6	6	6	6	6
Accuracy (%)	100	83.3	100	100	100
Overall accuracy (%)	96.7				

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