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# EMG finger movement classification based on ANFIS

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**Abstract.** An increase number of people suffering from stroke has impact to the rapid development of finger hand exoskeleton to enable an automatic physical therapy. Prior to the development of finger exoskeleton, a research topic yet important i.e. machine learning of finger gestures classification is conducted. This paper presents a study on EMG signal classification of 5 finger gestures as a preliminary study toward the finger exoskeleton design and development in Indonesia. The EMG signals of 5 finger gestures were acquired using Myo EMG sensor. The EMG signal features were extracted and reduced using PCA. The ANFIS based learning is used to classify reduced features of 5 finger gestures. The result shows that the classification of finger gestures is less than the classification of 7 hand gestures.

## 1. Introduction

Cerebral vascular accident, well-known as stroke is a major cause of long-term disability in the world, with over 775,000 cases in United States alone in 2014 [1]. The main cause of stroke is the damage in the brain cells as a result of an interruption in the blood flow that supplies nutrient and oxygen to the brain, causes paralysis on one side of the body (hemiparesis). Relearning the basic movement is one way to treat this disability. Repetitive training is highly suggested as to speed up the recovery of the paralyzed limbs. However, the conventional treatment method is labour intensive as it requires at least one assistant to guide the patient while using the treatment equipment. Many research has been done to create an independent rehabilitation equipment as a method to increase the treatment frequency and reduce number of assistant needed. One solution that has current been developed is by creating an exoskeleton to guide and control the movement of the paralyzed limb[2].

The previous research that introduced the exoskeleton equipment was an actuated finger exoskeleton (AFX) that provided treatment specifically only to the joints of the index finger and thumb [3]. It was designed to provide independent control of pinch and reach-to-pinch of each joint of both fingers. Another exoskeleton device that provide control to all five fingers was Hand EXOskeleton Rehabilitation Robot (HEXORR), which used electric motors and a low-friction gear-trains[4].

This paper is the preliminary study of finger exoskeleton design that allows the non-paralyzed fingers to guide, control and enable self-therapy the paralyzed fingers in order to recover the motor



function. The first stage of study is identifying the characteristics of EMG signal acquired from 5 finger gestures. Previous studies has analysed the EMG signals for the purpose of the classification of several hand movements[5-8]. Methods such as ANN[5], SVM[6] and ANFIS[7] has been employed and examined. The result show that ANFIS is over performed than other methods. Therefore this paper used ANFIS as a classification method for EMG signals.

## 2. Methods

### 2.1. Features extraction

This paper employed sixteen feature extraction methods as presented in table 1.

**Table 1.** EMG and time-domain feature extraction methods.

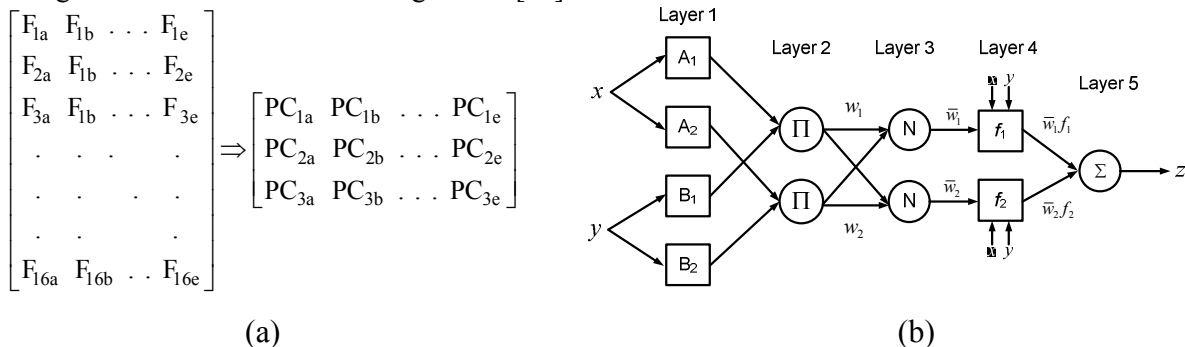
No	Method	Equation
1.	Integrated EMG Integrated EMG (IEMG) is used as an onset detection index in clinical application [9, 10].	$IEMG = \sum_{i=1}^N  x_i $
2.	Mean absolute value Mean absolute value (MAV) is also used as an onset index, especially in detection of the surface EMG signal[9, 10].	$MAV = \frac{1}{N} \sum_{i=1}^N  x_i $
3.	Modified mean absolute value type 1 Modified mean absolute value type 1 (MAV1) is an extension of MAV feature [9, 10].	$MAV1 = \frac{1}{N} \sum_{i=1}^N w_i  x_i $
4.	Modified mean absolute value type 2 Modified mean absolute value type 2 (MAV2) is an expansion of MAV feature which is similar to MAV1 [9, 10].	$MAV2 = \frac{1}{N} \sum_{i=1}^N w_i  x_i $
5.	Simple square integral Simple square integral (SSI) or integral square uses energy of the EMG signal as feature [9, 10].	$SSI = \sum_{i=1}^N x_i^2$
6.	Variance of EMG Variance of EMG (VAR) is defined as an average of square values of the deviation of the EMG signal[9, 10].	$VAR = \frac{1}{N-1} \sum_{i=1}^N x_i^2$
7.	Root mean square Root mean square (RMS) is a measure that relate to constant force and non-fatiguing contraction [9, 10].	$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$
8.	Waveform length Waveform length (WL) is a measure of complexity of the EMG signal[9, 10].	$WL = \sum_{i=1}^{N-1}  x_{i+1} - x_i $
9.	Difference absolute standard deviation value (DASDV) DASDV is a standard deviation of the wavelength [9, 10].	$DASDV = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_{i+1} + x_i)^2}$
10.	Autoregressive Autoregressive (AR) is a common approach for modeling univariate time series as AR model follows [9, 10].n= 4.	$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_n y_{t-n} + \varepsilon_t$ $= \sum_{i=1}^n a_i y_{t-i} + \varepsilon_t$
11.	Hjorth activity Hjorth activity (H1) can indicate the surface of power spectrum in the frequency domain [11].	$HI = \sigma_x^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2$

- |   |   |
|---|---|
| 12. Hjorth mobility<br>Hjorth mobility (H2) parameter represents the proportion of standard deviation of the power spectrum [11]. | $H2 = \frac{\sigma_{x'}}{\sigma_x}$                           |
| 13. Hjorth complexity<br>Hjorth complexity (H3) parameter represents the change in frequency[11].                                 | $H3 = \frac{\sigma_{x''}/\sigma_{x'}}{\sigma_{x''}/\sigma_x}$ |

### 2.2. Dimensional features reduction and feature classification method

This paper employed principal component analysis (PCA) for dimensional features reduction and adaptive neuro-fuzzy inference system (ANFIS) for reduced features classification. The PCA is a technique using sophisticated underlying mathematical principles to transform a number of possibly correlated variables into a significant smaller number of uncorrelated variables called principal components[12]. The visualisation of dimensional features reduction using PCA used in this paper is presented in figure 1(a). Where  $F_1, F_2, F_3, \dots, F_{16}$  is the number of features and a subscript index a, b, ..., e is the number of finger gestures (there are 5 finger gestures in this paper). It can be seen from figure 1(a) that the PCA reduced 16 features into 3 new features namely principal components (PCs). We can select how many new features are required, in this paper three PCs are obtained which are PC1, PC2 and PC3.

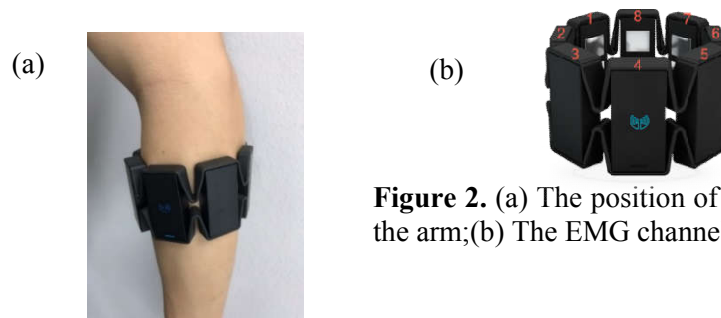
The adaptive neuro-fuzzy inference system (ANFIS) [13] is a specific kind of neuro-fuzzy classifier approach which integrates the ANNs adaptive capability and the fuzzy logic qualitative approach. The ANFIS architecture consists of five layers as shown in figure 1(b). A detail of PCA and ANFIS algorithm is presented in previous study [12]. Both PCA and ANFIS method is used for pattern recognition method of seven hand gestures [12].



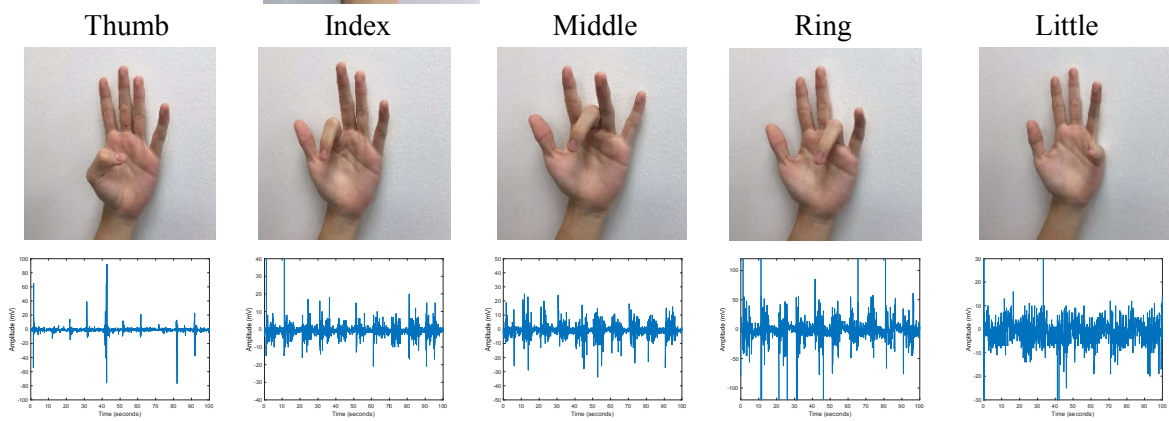
**Figure1.** (a) Dimensional feature reduction using PCA; (b) Two-input ANFIS architecture with first-order Sugeno fuzzy model and two rules.

### 2.3 Experimental setup

The EMG datasets were collected from each individual finger. The subject is person with no neurological or muscular disorders. The participant was seated on an armchair with his arm supported on the armchair, and levelled with the heart to avoid the variation generated by the arm position on the EMG signal. EMG signals were acquired by using Myo gesture controlled armband with 200 Hz sampling rate. The EMG electrodes were attached near to the flexor digitorum superficialis. The photograph of Myo device attached on the arm during the measurement is presented in figure 2. The Myo device consist of 8 EMG sensors. This paper discussed the result of EMG sensor 1. The participant was instructed to elicit a contraction (flexor) from the rest and hold on that position for the period of 5 seconds, continued with the relaxation (extensor) for about the same 5 seconds. The data collection was repeated ten times, until we collected 10 flexor and 10 extensor data. The example of EMG signals and the 5 fingers gesture are shown in figure 3.



**Figure 2.** (a) The position of the armband on the arm; (b) The EMG channel assignments.

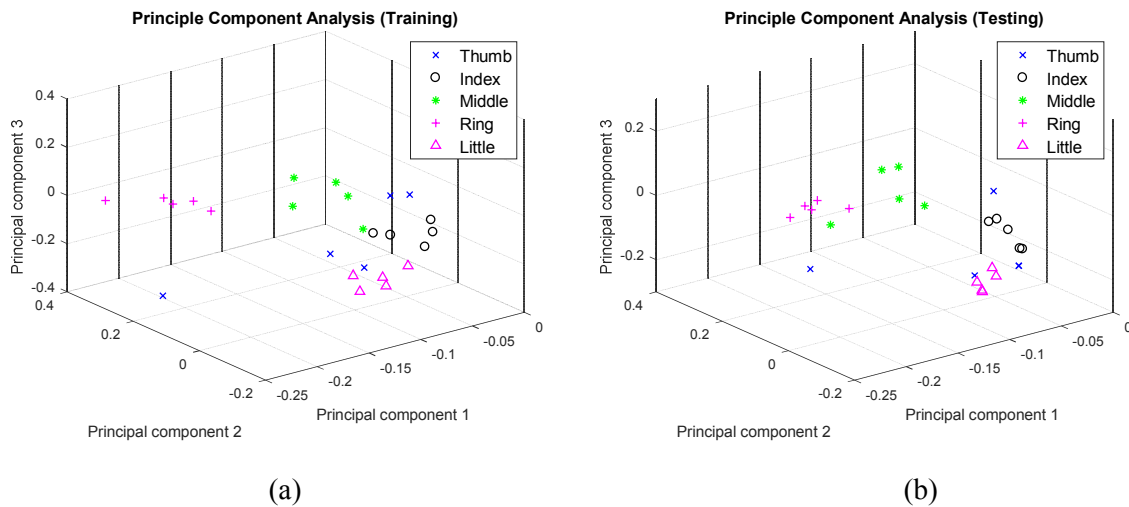


**Figure 3.** Finger gestures during EMG signal data acquisition.

### 3. Results and discussion

#### 3.1. Dimensional features reduction using PCA

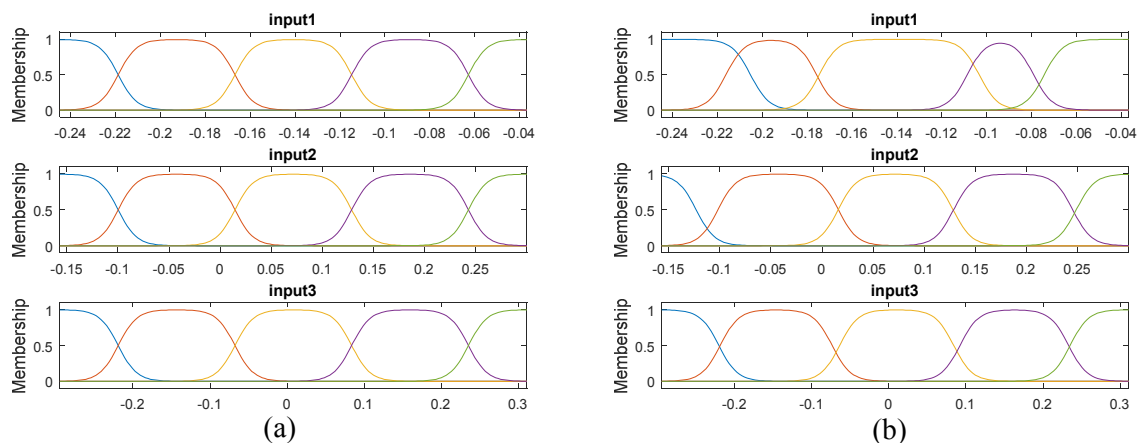
This paper employed As mentioned in Section 3 that 10 EMG signals were acquired for each finger gesture. We used 5 signals for training and another 5 signals for testing. Sixteen features were extracted from each EMG signal. Both training and testing feature dataset from features extraction process is 16 by 25. Where 16 indicate the number of features and 25 is the number of EMG data resulted from 5 finger gestures times 5 measurement. Prior to the feature classification, the feature datasets were reduced using PCA to obtain more sensitive features for each finger gesture. The three new features are computationally calculated from 16 features namely principal component1 (PC1), principal component2 (PC2) and principal component3 (PC3). The feature dimensional reduction using PCA for training and testing data is presented in figure 4 and 5. Compare to previous study in [11], the PCA plot for 7 hand gestures are easier to identify rather than the PCA plot of 5 finger gestures. The features of 7 hand gestures are groups in certain area and there is no overlapping between one feature group to other feature groups. In contrast, the PCA of five finger gestures are grouped in close distance between one group and others, for instance index finger group, middle finger group and little finger group. Only the ring finger group that located in far away from other groups. In addition there is one obvious scattered group i.e. thumb finger. This is because the muscle of one finger to other fingers in the arm are anatomically closed, therefore, once the EMG signal is acquired, there are influenced each other.



**Figure 4.** Three principal components plot resulted from PCA feature reduction method: (a) for training process; (b) from testing process.

**3.2. Reduced features classification using ANFIS**

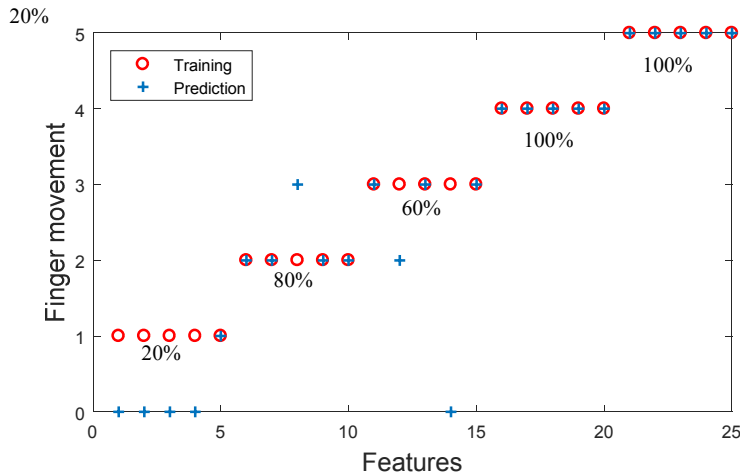
The first-order Sugeno type ANFIS was trained with new three features obtained from PCA result. The reduce dataset for training process is 3 x 25. Where 3 is the dimension of principal component and 25 is the result from 5 finger gestures by 5 EMG signal acquisition. The membership function (MF) result from training process is presented in figure 5(a). Three input was indicate the number of PCs and the five membership indicate the finger gestures (classes). Once the ANFIS was trained, the ANFIS model was then tested using another datasets (testing datasets) and the MF is presented in figure 5(b). Input1, input2 and input 3 in figure 5 represent the PC1, PC2 and PC3 respectively. It can be seen from figure 5 that some MFs of finger gestures were obviously changed, particularly in PC1 i.e. class #1 to #4 and PC2 i.e. class #1



**Figure 5.** ANFIS MFs for 3 PCs and 5 finger gestures: (a) training process; (b) testing process.

The classification result of five finger gestures is presented in figure 6. The ANFIS training parameters used in this paper such as number of training and testing set, membership function, learning rules and number of epoch are similar to the parameters used in [11]. The x-axis and y-axis of figure 6 represents the number of features for each finger gesture and the number of class (finger gestures) respectively. Where 1, 2, 3, 4 and 5 is thumb finger, index finger, middle finger, ring finger and little finger. The classification accuracy is presented on each finger gesture. Where the thumb finger has lowest accuracy result of 20% and ring and little fingers achieved 100% accuracy. The average classification

accuracy of 72%. The missed classification are occurred one in index and middle finger and most of missed classification are occurred in thumb finger. This result is corresponding to the MF result where the class #1 to class #4 in PC1 were changed from training MF and testing MF. In addition, the class #1 in PC2 was also changed.



**Figure 6.** ANFIS classification result for 5 finger gestures.

#### 4. Conclusions

A study of pattern recognition on 5 finger gestures based on EMG signal analysis has been presented. Finger therapy is the most difficult part in post-stroke rehabilitation and physical therapy. The EMG signal of finger gestures is more difficult to be analysed than the EMG signal from hand gestures that conducted in previous study. This is because the position of muscles that connect to certain finger are close each other. Once a certain finger was moved, the other muscle may also be moved. Therefore the accuracy result of classification of finger gestures especially for thumb finger is less than the classification accuracy of hand gestures. However, there is a future work that will be done in the future that is to identify the proper muscle position for each finger movement through the Myo EMG sensor. Through the study to find the appropriate sensor corresponding to certain finger, the classification accuracy will be improve.

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