Pattern recognition of electromyography (EMG) signal for wrist movement using learning vector quantization (LVQ)

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Abstract. EMG is an electric signal in the human muscle layer. This signal is caused by muscle contraction activity. The main purpose of this study was to explore the pattern of electromyography signal for wrist movement in open finger extensor. The EMG can be recorded using a device called electromyography (EMG). It can be acquired by attaching an electrode to the surface of the skin and the electrode was capturing the raw of EMG signal. Volunteers involved in this study were six people where each individual have 10 datasets the EMG signals. The electrodes are installed in the lower arm muscles. The EMG raw signal was processed by normalizing zero-mean. After pre-processing, the EMG signal has been done a feature extraction process to get the EMG data which was be an input vector in Learning Vector Quantization (LVQ). The feature extraction method was mean absolute value (MAV), root mean square (RMS), minimum value (Min), maximum value (Max), variance (Var), standard deviation (STD), and length of data (LoD). This study indicates that the classification accuracy for training and testing data of the EMG signal for wrist movement in open finger extensor (OFE) and grasping finger extensor (GFE) was 70.83% and 83.33% respectively. Therefore, the EMG signal can be used for identifying muscle disorder, artificial hand control and biometric identity.

Keywords: EMG signal, LVQ, human muscle layer, muscle contraction activity

1. Introduction

The development of science and technology that has occurred currently had a significant impact on the biomechanics [1-8] and biomedical fields (biomechanics and biomedical engineering) [9-11]. Biomechanics is a study of human body movements while biomedical is a science that uses technical concepts applied in the medical and health fields.

Research on the signal electromyography (EMG) [12-19] is one of the existing studies in the biomedical field. Research in this field has developed rapidly which is shown by the solution to the problems in human rehabilitation and treatment.

Every human has a unique EMG signal. This EMG signal can help humans to identify abnormalities that occurs in muscles for the rehabilitation of patients and artificial hand control [20-24]. Some relevant research that have been published discussed about basic components in artificial hands that use EMG signals are used to control the artificial hand. Two electrodes are attached to the lower arm muscles used to record EMG signals. The EMG signal has been obtained then it has been extracted and classified to get a different types of classification [12, 25-26]. Flexion movement in a single finger can be identified with a single channel surface EMG device. This surface EMG device has recorded signals from the
muscles during flexion in different fingers [21-22, 27]. The use of multi-channel EMG electrode surface is used to classify the combination and single finger movements for artificial hand control. Feature extraction method is using time-domain-auto regression. Feature reduction method uses orthogonal fuzzy neighborhood discriminant analysis and classification method using linear discriminant analysis [28-29]. Pattern recognition in finger movements using artificial neural networks is extracting EMG signals using the time domain feature to classify finger movements. The network training process using the Lavenberg-Marquardt algorithm and performance measurement uses a mean square error (MSE).

The researches stated above explain that the classification of EMG signals in the lower arms is only in flexion and extension of the fingers while the flexion and extension of the wrist are ignored. On the other hand, flexion and extension of the wrist was affected EMG signals in the lower arm muscles.

Hence the present study aims to investigate the finger recognition for opening or grasping combined with flexion and wrist extension by classifying EMG signals in each of these movements.

2. Methods
The research method in this study based on the flow diagram shown in figure 1.

2.1. Object and research location
Six male participants have been chosen for this research. The average of participant’s weight and height is 60.5kg and 162.5cm respectively. The research was held at Politeknik Aceh Selatan’s Multimedia and Programming Laboratory.

2.2. Data collection
The EMG signal data collection techniques used in this study includes preparation, collecting data, and processing data stage.

2.2.1. Preparation stage. The preparation stage was the initial stage before the data collection stage was carried out. In this stage, the needs of the equipment needed for EMG signal data are determined. The tools and equipment needed are the surface electrode, the EMG myoware sensor, arduino uno minicomputer, cable, and laptop. The physical of the surface electrode and the EMG sensor used as shown in figure 2 and figure 3. All devices and materials required are installed into a single unit.
2.2.2. Data recording stage. The data recording stage is carried out to retrieve the data for each subject. Before data collection, the subject must first fill out the inform consent to become the participants. The participants were normal subjects who had no abnormalities and injuries in the muscles. Subjects were attached to three electrodes in the lower right arm muscles, namely the wrist extensors and the wrist flexors. The figure of the attached electrodes as shown in figure 4.

The two types of movement for recording EMG data for each individual are open finger extensor (OFE) and grasping finger extensor (GFE) as shown in figure 5 and figure 6.

The process of recording EMG signals was using the CoolTerm software. Every movement starts on the 5th second and ends on the 15th second. The 1st to 5th seconds was called the initial stages of the EMG signal while the 16th to 20th seconds are called the end stages of the EMG signal. The recording of EMG signals on one of participant for OFE and GFE movements was shown in Figure 7.
2.2.3. Data processing stage. In this stage, the raw EMG signal that has been recorded from the subject will be processed by the EMG signal. The EMG signal processing was to ensure that the EMG signal recording results do not contain interference. All EMG raw signals has normalized so that the raw EMG signal was within the same standard. Normalization method uses the zero mean methods as shown in equation (1).

$$\text{zero mean} = a - x$$  \hspace{1cm} (1)

Where \(a\) is EMG signal data and \(x\) is the average value of \(a\).

After normalizing the EMG raw signal, the EMG signal from the normalized feature extraction was used as input data in the classification process. This EMG signal feature was used to get the accuracy of the classification results. In this study, the feature extraction method used was time domain features. The reason for choosing time domain feature is due to the fact that the feature does not require mathematical transformation.

2.2.4. Mean absolute value (MAV). This method was one of feature that popularly used in EMG signal analysis. The MAV feature was the average absolute value of the EMG signal amplitude. MAV equation is as shown by equation (2).

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

Where \(|x_i|\) is the absolute value of the EMG signal and \(N\) is the amount of data from the EMG signal.

2.2.5. Root mean square (RMS). Root mean square is the root of the average value of the squared EMG signal. This aims to get the effective value of the EMG signal. The equation of the RMS is as shown in equation (3).
Where $x_i^2$ is the square of the EMG signal amplitude value and $N$ is the amount of data from the EMG signal.

2.2.6. Minimum value (Min). The minimum value is the minimum amplitude value of the EMG signal.

2.2.7. Maximum value (Max). The maximum value is the maximum amplitude value of the EMG signal.

2.2.8. Variance (Var). The variance is the average of the two-degree value of deviation variables. Variance equation is as shown in equation (4).

$$
Var = \frac{\sum_{i=1}^{N} x_i^2}{N - 1}
$$

Where $x_i^2$ is the square of the EMG signal amplitude value and $N$ is the amount of data from the EMG signal.

2.2.9. Standard Deviation (STD). The standard deviation is the distribution of the value of the EMG signal and how closed each EMG value is to the average value line of the EMG signal. The greater the standard deviation value, the greater the distance of each data with the average value. The standard deviation equation is shown in equation (5).

$$
\sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}}
$$

Where $\sigma$ is standard deviation, $x_i$ is the EMG signal data, $\bar{x}$ is the average value of EMG signal, and $n$ is the amount of data.

2.2.10. Length of Data (LoD). Length of data is the length of EMG signal data. LoD equation as shown in equation (6).

$$
LoD = \text{length}(N)
$$

Where $N$ is the data of EMG signal.

2.2.11. Stage of EMG signal pattern recognition. In this stage, the pattern recognition method is used to classify the EMG signal. This classification is to determine the level of differences in EMG signal patterns in each participant. The classification method used in this study is Learning Vector Quantization (LVQ). This method works determining the initialization vector or reference vector taken in each class. This reference vector will be updated by calculating the difference between the input vector and the reference vector to obtain an input vector in a stable (convergent) state. In the LVQ algorithm, the input vector $x$ calculates the shortest distance to the reference vector $w_c$ using the Euclidean distance as shown in equation (7). If the reference vector $w_c$ and the input vector $x$ are in the same class, the reference vector $w_c$ will be updated using equation (8) so that the distance $w_c$ will be closer to $x$. If the reference vector $w_c$ and the input vector $x$ are in different classes, the reference vector $w_c$ will be updated using equation (9) so that the distance $w_c$ will be further away from $x$.

$$
d_c = \sum_{j=1}^{n} (x^j - w_c^j)^2
$$
\begin{align*}
  w_c(t+1) &= w_c(t) + \alpha (x(t) - w_c(t)) \\
  w_c(t+1) &= w_c(t) - \alpha (x(t) - w_c(t))
\end{align*}

(8) \hspace{1cm} (9)

Where \( t \) is a time and \( \alpha \) adalah learning rate where \( 0 < \alpha < 1 \). The LVQ network simulation uses Weka software[30]. Ten EMG data for each individual was selected. This data was divided into two parts; six data as learning data and four data as testing data. The method for learning and testing uses supplying testing sets, where test data was separated by learning data. The number of features involved in the input vector is seven units. The LVQ type used is the LVQ1 network. The total codebook vector in the competitive layer is six units where one codebook vector states one class. The network performance is measured using accuracy, precision, and recall as shown in equations (10), (11) and (12).

\[
  \text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]

(10)

\[
  \text{precision} = \frac{TP}{TP + FP}
\]

(11)

\[
  \text{recall} = \text{sensitivity} = \text{TPR} = \frac{TP}{TP + FN}
\]

(12)

3. Results and Discussion

From the research methodology that has been explained above, the results can be obtained as shown in the confusion matrix in table 1 and table 2. To measure the performance of the LVQ classifier network as shown in table 3 and table 4.

| Actual (%) | Subject1 | Subject2 | Subject3 | Subject4 | Subject5 | Subject6 |
|------------|----------|----------|----------|----------|----------|----------|
| Subject1   | 100      | 0        | 0        | 0        | 0        | 0        |
| Subject2   | 0        | 100      | 0        | 0        | 0        | 0        |
| Subject3   | 0        | 33.33    | 66.67    | 0        | 0        | 0        |
| Subject4   | 0        | 0        | 0        | 66.67    | 0        | 33.33    |
| Subject5   | 0        | 0        | 66.67    | 0        | 0        | 33.33    |
| Subject6   | 0        | 33.33    | 0        | 0        | 0        | 66.67    |

| Subject1   | 66.67 | 0 | 0 | 0 | 0 | 33.33 |
| Subject2   | 66.67 | 0 | 0 | 0 | 0 | 33.33 |
| Subject3   | 66.67 | 0 | 0 | 0 | 0 | 33.33 |
| Subject4   | 66.67 | 0 | 0 | 0 | 0 | 33.33 |
| Subject5   | 66.67 | 0 | 0 | 0 | 0 | 33.33 |
| Subject6   | 66.67 | 0 | 0 | 0 | 0 | 33.33 |
By using equation (10), the result of accuracy classification average is 70.83% for OFE movement and 83.33% for GFE movement.

From table 1, it show that the LVQ network classify the EMG signal for OFE movement with true positive (TP) for subject 1 and subject 2. It indicates that the EMG signal in open finger extensor combining wrist movement is unique. Meanwhile, the LVQ network classifying the EMG signal with false negative (FN) for subject 3, subject 4, subject 5 and subject 6 indicates that the EMG signal for this subject is not unique. Table 2 shows that the LVQ network classifies the EMG signal for GFE movement with true positive (TP) for subject 3, subject 5 and subject 6. It shows that the EMG signal in grasping finger extensor combining with the wrist movement is unique. Meanwhile, the LVQ network classify the EMG signal with false negative (FN) for subject 1, subject 2 and subject 4 then the EMG signal for this subject as not unique.
Table 3 explains that subject 1 has the best precision and recall value. It indicates that the EMG signal for this subject has the best performance of testing network criteria. The subject 2, subject 3, subject 4 and subject 6 have a good performance. Meanwhile, the subject 5 has a poor performance. Table 4 shows that the subject 3 and subject 5 have the best precision and recall value. It indicates that the EMG signal for these subjects have the best performance of testing network criteria. Meanwhile subject 1, subject 2, subject 4 and subject 6 have a good performance of testing network criteria.

![Figure 8. LVQ network performance evaluation for OFE movement](image)

Figure 8 and 9 shows ROC Area to TPR for LVQ network performance. Total area under ROC curve (AUC) is a single index to measure the performance a test. The larger the AUC, the better the overall performance of LVQ network test is.

4. Conclusion
The results of the present of the study also suggest that the EMG signal in the lower arm muscle can be used to identify person’s wrist movement. The EMG signal in lower arm muscle can also be used to determine the level of movement pattern variation from one to another. The accuracy of the classification
process is 70.83% for OFE movement and 83.33% for GFE movement. This study has shown that the feature used in this research and the LVQ network classifier was sophisticated method in studying the EMG signal pattern. Further research might investigate the EMG signal in lower arm muscle involving more participants so that the classification process can achieve better accuracy.

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