Electromyography (EMG) signal classification for wrist movement using naïve bayes classifier

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Abstract. Electromyography (EMG) signal is a myoelectric signal in the muscle layer. It occurs caused by contraction and relaxation muscle activity. This article provides a numerical study of the classifying the electromyography signal for wrist movement combined with open and grasping finger flexor. The EMG signal has been recorded using a device called electromyography. It has acquired by attaching a surface electrode in the skin then the electrode was capturing the raw signal. The volunteer involved were six where each volunteer has ten datasets the EMG signal. The surface electrode are stuck in the lower arm muscles. The EMG raw signal was processed using zero-mean normalization. The feature extraction method is root mean square (rms), mean absolute value (mav), variance (var), and standard deviation (std). This EMG signal has been classified by naïve bayes classifier. Training and testing data was using 5-cross validation. The result indicates that the classification accuracy for classifying the EMG signal for wrist movement combined open finger flexor (OFF) and grasping finger flexor (GFF) is 70% and 75% respectively. Therefore, the EMG signal can be applied for identifying of muscle disorder, prostheses hand and biometric system.

1. Introduction

The development of science and technology in the world has impacted in security system, health and human activity field. The study in electromyography (EMG) signal is a study that was developed rapidly to get solution for human rehabilitation, prostheses hand control and biometric system [1]–[3].

Every human has different muscle size. The EMG signal can help humans to identify the abnormalities muscle. In previous research, we have carried out studies on the movements of opening and grasping fingers extensor using learning vector quantization classifier [4]. Any relevant research about EMG signal has been published. The artificial hand has used the EMG signal for controlling the hand prostheses. Two surface electrode are attached in the lower arm muscles to record the EMG signal. The EMG signal has been extracted and classified using different type of classification [5]–[9]. Flexion movement in a single finger be able to identified using a single channel surface electrode device. This surface EMG device has recorded the EMG signal during flexor movement in different fingers [9]–[11]. Multi channel of EMG electrode surface has used to classify a single and combination movement for...
artificial hand control. The feature extraction method has used time domain auto regression, fuzzy neighborhood discriminant analysis and classification has used linear discriminant analysis [7], [12]. Hence this study aims to extract the feature EMG signal using time domain feature and classify the open and grasping finger flexion movement using naïve bayes classifier.

2. Methods
The methodology of the research is explained by flow diagram in Figure 1.

![Flow diagram](image)

Figure 1. The methodology of the research

2.1. The object and location
This study was involving six participants with male gender. The average of participant’s height and weight is 162.5 cm and 60.5kg respectively. The location of this study was at Politeknik Aceh Selatan.

2.2. Data collection

2.2.1. Preparation. The devices needed for EMG signal data recording are determined. The tools and devices are the EMG myoware sensor, the surface electrodes, arduino, data cable, laptop, coolterm software. The EMG myoware sensor and the surface electrode as shown in Figure 2 and Figure 3. All devices are installed to be a single unit.

![Figure 2. An EMG myoware sensor](image)

![Figure 3. The surface electrode](image)

2.2.2. Data recording. The data recording was performed for the data retrieval process for each participant. Before data recording, the subject must fill the inform consent to become the subjects. The subjects have no injuries and abnormalities in the muscles tissue. The subjects were attached three electrodes in the lower right arm muscles. The illustration of placement electrodes is as shown in Figure 4.
Figure 4. Surface electrode placement in the lower arm muscle

The two types of movement for recording the EMG signal for each participant are open finger flexor (OFF) and grasping finger flexor (GFF) as shown in Figure 5 and Figure 6 respectively.

Figure 5. Open finger flexor movement
Figure 6. Grasping finger flexor movement

The CoolTerm software was used for recording the EMG signal. Every movement was started on the 5th and ends on the 15th second. The 1st to 5th second was named the initial phase of the EMG signal and the 16th to 20th second are named the end phase of the EMG signal. The plotting of EMG signals for OFF dan GFF movement to one participant is shown in Figure 7.

Figure 7. The plotting of EMG signal for OFF and GFF movement

2.2.3. Data processing. The raw EMG signal that has been recorded from each participant was processed to ensure not interference signal. All EMG raw signals have normalized using Equation (1).

\[ \text{zeromean} = a - \bar{x} \]  

(1)

Where \( a \) is the original EMG signal and \( \bar{x} \) is mean value of \( a \).

Mean absolute value (MAV). This method was one of the feature extraction that popularly used in the EMG signal analysis. The MAV equation is using Equation (2).
where $|x_i|$ is absolute value and $N$ is the number of data from the EMG signal.

**Root mean square (RMS).** Root mean square is the root of the mean of the squared the EMG signal. This method aims to obtain the effective value of the EMG signal. The RMS is using Equation (3).

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

where $x_i^2$ the square of the EMG signal amplitude.

**Variance (Var).** The variance is the mean of the two degree value of deviation variables. Variance is using Equation (4).

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

**Standard Deviation (STD).** The standard deviation is the distribution of the EMG signal value. The greater the standard deviation value, the greater the distance of each data to average value. The standard deviation equation is shown in Equation (5).

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

where $s$ is standard deviation, $x_i$ is EMG signal data, $\bar{x}$ is the mean of EMG signal, and $n$ is the number of data.

2.2.4. **The EMG signal classification.** This classification is to get differences in EMG signal patterns for each subjects. The classification method is naïve bayes classifier. The classification performance is evaluated using accuracy, precision, and recall as shown in Equations (6), (7) and (8).

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

$$\text{precision} = \frac{TP}{TP + FP}$$

$$\text{recall} = \text{sensitivity} = \frac{TP}{TP + FN}$$

3. **Results and Discussion**

Based on the research methods that have been explained in section 2, the results of EMG signal classification can be obtained as shown in Table 1 and Table 2. The classification performance evaluation of the naïve bayes classifier as shown in Table 3 and Table 4.
Using the Equation (8), the result of accuracy classification overall is 70% for OFF movement and 75% for GFF movement.

From the Table 1, it shows that the naïve bayes method classifying the EMG signal for OFF movement with true positive (TP) for subject3. It indicates that the EMG signal in open finger flexor combining wrist movement is unique movement. Meanwhile, the naïve bayes classifying the EMG signal with false negative (FN) for subject5 is middle unique movement and for subject1, subject2, subject4 and subject6 is not unique movement. From the Table 2, it shows that the naïve bayes method classifying the EMG signal for GFF movement with true positive (TP) for subject1. It indicates that the EMG signal in open finger flexor movement is unique movement. Meanwhile, the naïve bayes classifying the EMG signal with false negative (FN) for subject2, subject3, subject4, subject5 and subject6 is middle unique movement and for subject6 is not unique movement.
classifying the EMG signal for GFF movement with true positive (TP) for subject1, subject3 and subject5. It indicates that the EMG signal in grasping finger flexor combining wrist movement is unique movement. Meanwhile, the naïve bayes classifying the EMG signal with false negative (FN) for subject2 is middle unique movement and for subject4 and subject6 is not unique.

From the Table 3, it explains that subject3 and subject5 have the best precision and recall value. It indicates that the EMG signal for this subjects have the best classifier testing performance criteria. Meanwhile subject1, subject4, and subject6 have a good classifier testing performance criteria and subject2 has a bad classifier testing performance criteria.

From the Table 4, it shows that subject1, subject3 and subject5 have the best precision and recall value. It indicates that the EMG signal for this subjects have the best classifier testing performance criteria. Meanwhile subject6 has a good classifier testing performance criteria. Subject2 and subject4 have a bad classifier testing performance criteria.

![Figure 8](image1.png)

**Figure 8.** The naïve bayes classifier performance evaluation for OFF movement

![Figure 9](image2.png)

**Figure 9.** The naïve bayes classifier performance evaluation for GFF movement

Figure 8 and 9 show ROC Area, TPR, and FPR for naïve bayes classifier performance evaluation. The total area under ROC curve (AUC) is a single index for measuring the performance evaluation. The larger the AUC, the better is overall performance of naïve bayes classifier.

4. Conclusion
In this investigation has shown that the EMG signal in the lower arm muscle be able to used to identify people’s wrist movement. The EMG signal be able to specify the pattern recognition from one to another
applied to artificial hand. The overall classification accuracy is 70% for OFF movement and 75% for GFF movement. The finding of this study suggest that the feature used in this study and naïve bayes classifier was appropriated method for studying the EMG signal classification. A further study could assess reducing the number of instances in each subjects to achieve better accuracy.

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