Evaluation on EMG Electrode Reduction in Recognizing the Pattern of Hand Gesture by Using SVM Method

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Abstract. Understanding the pattern of hand gesture on research which designs a prosthetic hand has been popular subject in recent years. The hand gesture recognition relies heavily on the sensors, with electromyograph (EMG) sensor electrode being used the most. Previous researches have been using various recognition methods with different number of electrode. But, many of them used 12 to 4 electrodes. In this paper, we experimented the use of 3 to 2 electrodes to recognize hand gesture in open (HO), close (HC) wrist flexion (WF), and wrist extension (WE) condition. It used SVM method to recognize the extracted features from electrode signal. In this research, two scenarios between the use of 3 electrodes and then with the reduction to 2 electrodes are compared. SVM classification showed 96.35% as the best accuracy on experiment that used 3 electrodes and 97.16 % when it used 2 electrodes. Mean, standard deviation, and root mean square were being the best statistical features in recognizing HO, HC, WE and WF hand gesture.

1. Introduction
The research of electromyograph (EMG) electrode usage on recognizing any pattern of hand gesture has been done by some researchers. It is very often that researchers use various electrode numbers between 12 to 4 [1]. The problem is that the development of classification method developed by those researchers cannot be compared with the number of electrodes used [2]. The less number of electrode usage, the lower economical cost it gets, even easier when it comes to electrode placement [3]. In previous researches, many of them have explored to use myo arm band with 8 EMG electrodes by using classification method of support vector machine (SVM), neural networks (NN) and linear discriminant analysis (LDA) [4], [5]. However, the use of myo arm band had the weakness of placement shift [6], hence the electrodes could be misaligned from the intended muscle. This problem could result to noise increase in data sampling on EMG signal. Further, classification method by SVM and NN had been used to identify hand gesture [7]- [9] which shows that SVM method had a better accuracy compared to NN.

In this paper, signal from electrodes is feature extracted by using statistical features namely mean, variance, standard deviation (SD), entropy, skewness, kurtosis, and root mean square. Three electrodes were attached on extensor carpi radialis longus, flexor carpi ulnaris, and flexor carpi radialis muscles. The recognition was then conducted through SVM method. In previous
research, scientists used 12 to 8 electrodes to recognize the hand gesture, but in this research, it only took 3 electrodes and statistical feature as its extraction feature by taking 3 test scenarios to find the dominant muscle that worked out on 4 movements. The fewer electrode used, then the lesser cost of the system. The experiment scenarios was focused to compare the use of 3 electrodes and 2 electrodes with fewest and best statistical features to achieve highest accuracy. It used carpi radius longus extensor, flexor carpi ulnaris, flexor carpi radialis muscles as the most outer muscles which acts as hand mover. In big picture, the scenarios in the experiment aimed to reduce the number of electrode as best as possible without degrading performance significantly with fewer features.

2. Methodology

The block diagram of the research is shown at Fig. 1. This research was conducted using three electrodes which generated 3 EMG signal data on each HO, HC, WE and WF hand gesture pattern. The signal data then extracted by using mean, variance, SD, skewness, entropy, kurtosis and RMS statistical features. Finally, the extracted features from each signal are classified using the SVM method.

![Figure 1. Research block diagram.](image)

2.1. Signal Acquisition and Preprocessing

EMG signal has frequency between 20 Hz and 200 Hz [10] so that this research used AD620 amplifier instrumentation as signal power. This filter was using high pass filter (HPF) and low pass filter (LPF) by 20 Hz and 400 Hz cut off. Further, nocth filter 50 Hz was used to omit frequency noise on the made instrumentation. The filtered EMG signal was then inputted into ADC internal STM32F4 through DMA facility [11]. It took 1 KHz of EMS signal sampling which was inputted to ADC, sent to PC by using Delphi 7. During the research, extensor carpi radialis longus, flexor carpi ulnaris and flexor carpi radialis muscles signal EMG were identified. Those signals being saved into feature extraction process by using statistical feature.
2.2. Feature Extraction
Figure 3 showed the using of 3 EMG electrodes placed on muscles (carpi radius longus extensor, flexor carpi ulnaris, and flexor carpi radialis). Some patterns were identified on this research such as Hand Open (HO), Hand Close (HC), WF (Wrist Flexion), and WE (Wrist Extension) as shown on Figure 4. Every movement of HO, HC, WF and WE were collected to txt file while those saved EMG signals then being proceeded by taking Matlab R2017b analysis as its feature extraction.

There were 8 subjects of 19 to 36 year old aged people, whether men or women. Every subject contributed 8 times of data taking with 5 minutes break time. Here, the analysis of feature extraction on Matlab 2017b were Mean, Variance, Standard Deviation (SD), Entropy, Skewness, Kurtosis, and RMS. These results were then tested through SVM with Weka 3.8 tool to recognize Hand Open (HO), Hand Close (HC), WF (Wrist Flexion), and WE (Wrist Extension) based on the observed muscles.

Fig. 5 shows each EMG electrode signal in all three muscles. Every signal was extracted by using statistical features namely mean, variance, SD, skewness, entropy, kurtosis and RMS.

3. Experiments and Results
The experiment consists of two scenarios. First scenario was to test and find highest accuracy of hand gesture recognition using SVM based on extracted features from three electrodes. In second scenario, the number of electrodes was reduced to two.

3.1. Scenario I
On Scenario I, all saved data related to HO, HC, WE and WF on the 3 muscles (carpi radius longus extensor, flexor carpi ulnaris and flexor carpi radialis) were used to test further through
Figure 4. The condition of hand.

Figure 5. Feature extraction by using statistical extraction.

SVM by using Cross Validation Folds 20 to find the accuracies. Figure 4 showed the result of collected data sampling from HO (Hand Open) when 3 EMG electrodes were used on those muscles. The feature extractions such as mean, variance, standard Deviation (SD), entropy, kurtosis and RMS on statistical feature can be seen on Figure 5. It showed the feature extraction was applied to 8000 data.

Table 1 showed the result of classification of EMG signal by using statistical feature on Mean, Variance, SD, Entropy, Skewness, Kurtosis and RMS. While by using SVM Method, seen on Table, the best features were Mean, SD and RMS with 96.35 % of value.
Table 1. The result of feature extraction by using 3 electrodes on carpi radius longus extensor, flexor carpi ulnaris, and flexor carpi radialis

| Feature Extraction                           | Accuracy % |
|----------------------------------------------|------------|
| Mean, Variance, SD, Entropy, Skewness, Kurtosis, RMS | 71.35      |
| Mean, Variance, SD, Entropy                  | 70.37      |
| Mean, Variance, SD, Entropy                  | 70.37      |
| Mean, SD, RMS                                 | 96.35      |
| Mean, SD                                     | 93.94      |
| Mean                                         | 72.85      |

3.2. Scenario II

Scenario II used 2 electrodes on every movement of HO, HC, WE, and WF of carpi radius longus extensor - flexor carpi ulnaris, flexor carpi ulnaris-flexor carpi radialis and carpi radius longus extensor - flexor carpi radialis muscles. Those data were then tested with various combination of managed feature extractions. In the very first of Scenario II, it used 2 electrodes on the muscles of carpi radius longus extensor and flexor carpi ulnaris. The EMG signal data gained from those further being extracted on statistical feature and being classified by taking SVM Method. Table 2 showed its accuracy and it obtained the best accuracy on Mean, SD and RMA features with 96.8 % of value.

Table 2. The result of feature extraction of 2 electrodes on carpi radius longus extensor- flexor carpi ulnaris

| Feature Extraction                           | Accuracy % |
|----------------------------------------------|------------|
| Mean, Variance, SD, Entropy, Skewness, Kurtosis, RMS | 72.65      |
| Mean, Variance, SD, Entropy                  | 69.82      |
| Mean, Variance, SD, Entropy                  | 69.33      |
| Mean, SD, RMS                                 | 96.87      |
| Mean, SD                                     | 95.89      |
| Mean                                         | 75.78      |

Later, the second Scenario II was using EMG signal on two muscles of flexor carpi ulnaris and flexor carpi radialis. Those muscles had close position on the same hand. Table 3 showed the highest accuracy of mean, SD and RMS with 97.16 %.

Table 3. The result of feature extraction of 2 electrodes on flexor carpi ulnaris - flexor carpi radialis

| Feature Extraction                           | Accuracy % |
|----------------------------------------------|------------|
| Mean, Variance, SD, Entropy, Skewness, Kurtosis, RMS | 83.49      |
| Mean, Variance, SD, Entropy, Skewness         | 80.76      |
| Mean, Variance, SD, Entropy                   | 80.85      |
| Mean, SD, RMS                                 | 97.16      |
| Mean, SD                                     | 94.33      |
| Mean                                         | 80.95      |

Now, the third one on Scenario II, was using data of carpi radius longus extensor dan flexor
carpi radialis muscles. Those muscles had different side on hand. On the condition of Wrist Flexion and Wrist Extension, the condition of carpi radius longus extensor muscles had different EMG signals.

Table 4. The result of feature extraction of 2 electrodes on carpi radius longus extensor and flexor carpi radialis muscles

| Feature Extraction                                      | Accuracy % |
|--------------------------------------------------------|------------|
| Mean, Variance, SD, Entropy, Skewness, Kurtosis, RMS    | 77.14      |
| Mean, Variance, SD, Entropy, Skewness                  | 71.87      |
| Mean, Variance, SD, Entropy                            | 70.80      |
| Mean, SD, RMS                                         | 96.09      |
| Mean, SD                                              | 94.33      |
| Mean                                                   | 82.12      |

Table 4 showed the accuracy from SVM Method classification which figure out the features of Mean, SD, and RMS as the highest accuracy with 96.09% of value.

The best performance was achieved when feature extraction was as less as it could but it got the highest accuracy. In this research paper, it had two scenarios. The first scenario was observing all muscles data of carpi radius longus extensor, flexor carpi ulnaris and flexor carpi radialis. The second one was combining the two muscles data on every test. It consisted three tests. The first test was applied to carpi radius longus extensor and flexor carpi ulnaris muscles. The second test was applied to flexor carpi ulnaris and flexor carpi radialis muscles. The last test was applied to carpi radius longus extensor and flexor carpi radialis muscles.

The use of those two scenarios could reduce the number of electrode from 3 electrodes to 2 electrodes of EMG without reducing the performance on pattern recognition. The result of this research also were shown on Table 1 to Table 4 with the best feature on Mean, SD and RMS with 96.35%-97.16% accuracy value. Those also showed that the reducing of electrode number from 3 to 2 were not reducing the recognizing of hand gesture of HO, HC, WE, dan WF and further, the muscles of flexor carpi ulnaris and flexor carpi radialis were the best alternatives on recognizing them because they were on the same position on hand. The muscles of flexor carpi ulnaris and flexor carpi radialis had 97.16% of accuracy value with its best features on Mean, SD and RMS.

4. Conclusion
The placement of EMG electrode in this research is proven to be effective in achieving high accuracy hand gesture recognition on HO, HC, WE and WF pattern. Three muscles were chosen in the experiment because they are the most outer muscles on hand to be easily placed with electrode on, namely carpi radius longus extensor, flexor carpi ulnaris and flexor carpi radialis. The best statistical features were mean, standard deviation and root mean square which resulted 97.16% accuracy with two electrodes on flexor carpi ulnaris and flexor carpi radialis muscles under SVM classifier. The use of two electrodes on flexor carpi ulnaris and flexor carpi radialis muscles is a very good alternative to the three electrodes scenario without sacrificing accuracy. For future works, the use of one electrode is interesting to be applied and evaluated. Fewer number of electrode means more efficiency in production and computation cost.

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