Electromyography Signal Pattern Recognition for Movement of Shoulder

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Abstract. Pectoralis major and deltoid are two muscles that are associated with the movement of the shoulder. Electromyography (EMG) signal acquired from these two muscles can be used to classify the movement of the shoulder based on pattern recognition. In this paper, an experiment for EMG data collection involves eight healthy male subjects who perform four shoulder movements which are flexion, extension, internal rotation and external rotation. Feature extraction of EMG data is done using root mean square (RMS), variance (VAR) and zero crossing (ZC). For pattern recognition, the classifiers that are used are Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA). Classification results show highest accuracy on ZC feature using an SVM classifier with cubic kernel. The study on shoulder movement using EMG of pectoralis and deltoid muscles could be extended on arm amputees based on hypothesis that the EMG signal could be utilized for control of robotic prosthetic arm.

1. Introduction
Electromyography (EMG) signal is the most vital pointer of the muscle execution related with neuromuscular activation. It is additionally a critical idea to comprehend the connection between muscle activation and limb movements. By utilizing EMG information of human limbs as control signals that related to movement for the prosthetic device, EMG-based human arm prosthesis can be produced to compensate the lost function of severed individuals [1]. The purpose of the work in this paper is to classify EMG signal of deltoid muscles based on several shoulder movements. For hypothesis, the fact that movement of shoulder corresponds also to movement of arm bears an idea of using the deltoid muscles to activate certain EMG controlled device such as prosthetic arm. This then could be extended for on prosthetic arm for upper limb amputees.

Studies on classification of human shoulder movement had been done previously by several literatures. González et al. had published a work on classification of motions from around-shoulder based on EMG activity [2]. This work tends to investigate the possibility to associate the around-shoulder muscles’ EMG activities with the different hand grips and arm directions movements. Using k-means classifier with 70% accuracy is set as effective point, this work concluded that it is possible to distinguish different arm direction motions and hand grips, using EMG signals from the around-shoulder muscles activities when reaching and grasping objects.
A literature by Zhang et al. had worked on evaluating the feasibility to estimate 4-degrees of freedom (DoF) kinematics at shoulder and elbow [3]. In this work, a more complicated movement classification had been performed in the experiment which involves simultaneous and continuous estimation of four joint angles across shoulder and elbow in four coordinated arm movements based on EMG signal. With certain arm movement period, the result yields average estimation accuracy up to 91.12% using independent component analysis (ICA) with artificial neural network (ANN).

Another example of related study is by Rivela et al. on classification of eight shoulder movements through EMG pattern recognition [4]. Using linear discriminant analysis (LDA), classification accuracy obtained is 92.1%. Then there is also a paper by Zhou et al. on real-time EMG pattern recognition for shoulder motion [5]. Using support vector machine (SVM), this paper provides average accuracy of 85.3% in real-time validation. Implementation of shoulder movement classification on EMG-based wearable device had been studied by Gini et al. with a novel classifier [6]. Result of classification is 96.9% with computation time of 16 ms.

Several works in classification of shoulder movement based on EMG signal are aimed for application in human-machine interface particularly for prosthetic arm [7-9]. This paper is also determined at such hypothesis with use of minimal EMG channel, less type of shoulder movements and recruitment of normal human subjects for EMG data collection.

2. Methods
The work in this paper involves several stages where it begins with EMG data acquisition followed by EMG signal conditioning. Feature extraction is then performed on the EMG signal to reduce the amount sampled data based on window segmentation technique. Finally, classification is performed to the EMG feature data to obtain the average accuracy of data that is classified correctly.

2.1. EMG Signal Data Acquisition
EMG signal data acquisition is a process to collect raw EMG data signal from human to be processed. The raw EMG data signal is collected from eight normal and intact male subjects on the upper limb part of the body. Reason for choosing only male gender is because the subjects are required to expose their torso part during data collection. This is improper if subjects are chosen from female gender due to issue on private part of the body. The subjects are instructed to perform four movements which are shoulder flexion, shoulder extension, external rotation and internal rotation. Each movement is performed in three trials where duration for one trial is 10 seconds. The collection of the raw EMG signal is done using Ag/AgCl disposable EMG electrodes, ADInstrument PoweLab data recording device and ADInstrument LabChart software.

For each movement, EMG signal were acquired from two muscles. Muscles used in shoulder flexion are deltoid and pectoralis major muscle. For shoulder extension, EMG are taken from deltoid and latissimus dorsi. For external rotation, the muscles used are deltoid and infraspinatus. Finally, the muscles involved in internal rotation are again deltoid and pectoralis major. Figure 1 shows illustration of the four shoulder movements.

2.2. EMG Signal Conditioning
Signal conditioning is the process where the raw EMG signal will be processed to remove the noise mainly by using filtering method. The filtering method is used by MATLAB program with a proper coding programming. In this process, third order Butterworth filter has been chosen as it has the best filtering method for EMG signal processing.
Figure 1. The four shoulder movements for the EMG data collection [10].

2.3. Feature Extraction
Feature extraction is the method to extract further the characteristics or features in the data to be analysed and classified. Three features are used in this work which is root mean square (RMS), variance of EMG (VAR) and zero crossing (ZC). This process has been executed using command in MATLAB software. All the data has been divided into 25 windows or segments which equivalent to 25 seconds for both channels. From the observation results from the command execution, the data pattern is great to be classified into the next method.

2.3.1. Root Mean Square
RMS is modelled as an amplitude modulated Gaussian random process whose RM is related to the constant force and non-fatiguing contraction. Equation 1 shows the expression for RMS where \( n \) is data point number, \( x_n \) is data at point \( n \) and \( N \) is total number of data.

\[
RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x_n^2}
\]  

(1)

2.3.2. Variance of EMG
VAR uses the power of the EMG signal as a feature. Generally, the variance is the mean value of the square of the deviation of that variable. However, mean of EMG signal is close to zero. VAR can be calculated using Equation 2 where \( n \) is data point number, \( x_n \) is data at point \( n \) and \( N \) is total number of data.

\[
VAR = \frac{1}{N-1} \sum_{n=1}^{N} x_n^2
\]  

(2)

2.3.3. Zero Crossing
ZC is the number of times that the amplitude value of EMG signal crosses the zero y-axis. In EMG feature, the threshold condition is used to abstain from the background noise. This feature provides an approximate estimation of frequency domain properties. It can be formulated by using Equation 3 \( n \) is data point number, \( x_n \) is data at point \( n \) and \( N \) is total number of data.

\[
ZC = \sum_{n=1}^{N-1} [ \text{sgn}(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \geq \text{threshold} ]
\]  

(3)

2.4. EMG Signal Classification
The purpose to classify the EMG signal is to get the percentage accuracy of combined movements and subjects from the features that has been extracted to be implemented into the robotic arm. Ten
classifiers are used to train the features. There are linear Support Vector Machine (SVM), quadratic SVM, cubic SVM, fine Gaussian SVM, medium Gaussian SVM, coarse Gaussian SVM, fine k-Nearest Neighbour Classifier (KNN), medium KNN, linear discriminant and quadratic discriminant. This process has been done using Classification Learner in MATLAB software.

3. Results and Discussions

3.1. Data Collection Results
The raw EMG data signal has been collected from all subjects on four movements. The contraction and relaxation of muscles can be observed clearly on all movements. There are some errors during data collection due to longer time usage of the instrument, unstable force used by subject and improper time management in data collection. Figure 2 shows the EMG raw signal.

![Figure 2. Raw EMG data for (a) shoulder flexion (deltoid – green, pectoralis major – violet), (b) shoulder extension (deltoid – green, latissimus dorsi - violet) (c) external rotation (deltoid – green, infraspinatus - violet) and (d) internal rotation (deltoid – green, pectoralis major – violet).](image)

3.2. EMG Signal Classification
The EMG signal classification has been done using MATLAB software. Each feature has been divided into four classes to determine the classification. Scatter plot has been chosen in order to observe the classification pattern as shown in Figure 3.
Figure 3. An example of scatter plot for zero crossing feature using cubic SVM.

Table 1. Classification accuracy of three features using various classifiers.

| Classifier             | Accuracy (%) | RMS  | Variance | Zero-Crossing |
|------------------------|--------------|------|----------|---------------|
| Linear SVM             | 47.4         | 47.0 |          | 43.8          |
| Quadratic SVM          | 43.1         | 45.1 |          | 62.5          |
| Cubic SVM              | 33.0         | 38.6 |          | 78.1          |
| Fine Gaussian SVM      | 60.5         | 61.4 |          | 71.9          |
| Medium Gaussian SVM    | 53.4         | 54.6 |          | 65.6          |
| Coarse Gaussian SVM    | 42.8         | 42.9 |          | 31.3          |
| Fine KNN               | 67.9         | 69.1 |          | 75.0          |
| Medium KNN             | 61.3         | 62.5 |          | 46.9          |
| Linear Discriminant    | 41.6         | 41.5 |          | 46.9          |
| Quadratic Discriminant | 48.5         | 48.3 |          | 59.4          |

Result of average classification accuracy for all features with all classifiers is shown in Table 1. The highest accuracy for RMS, VAR and ZC are 67.9%, 69.1% and 78.1% respectively. In term of classifier, fine KNN provides highest accuracy for RMS and VAR while for ZC highest accuracy is given by cubic SVM. Fine KNN shows the best accuracy across all three features with average of 70.67%. On the other hand, ZC has highest average accuracy across all classifiers with 58.14%.

4. Conclusion
In this paper, EMG data collection is performed to obtain the data from deltoid and pectoralis muscles during several shoulder movement activity. Data collection is successfully done with the subject and the EMG signal also can clearly be observed. Classification of EMG signal depends on how the signal processing been conducted and the EMG feature that has been chosen. Based from the results, the highest accuracy classifier that suitable for this project is fine KNN which have average accuracy of
70.67% across all features. However, when looking at specific feature and classifier, the highest accuracy is 78.1% that is shown by ZC with cubic SVM.

Comparing these results with other previous works, it is below par. This is due to limitations on number of muscles that is chosen for EMG acquisition and also number of movements which is few. There are other previous works that make use up to eight shoulder movements such as in Rivela et al. [4]. The work in this paper also implemented simple type of movement compared to other work that involved complex experiment protocol such as in Zhang et al. [3]. Duration of segmentation window is another significant element in EMG pattern recognition. As this paper used 1000 ms as fixed segmentation window size, previous work such as Zhou et al. focused on analysis for real-time implementation with smaller window size [5]. This provides more data for clustering where with proper classification algorithm could provide higher accuracy. Then there is also other previous work that implemented novel classifier which requires certain adjustment on the conventional classifier to provide better accuracy [6]. On the other hand, the work in this paper only used conventional classifiers that are available as toolbox in the computer programming platform.

As conclusion, the work in this paper requires adjustment in classifier parameters, feature extraction method or segmentation window size to provide higher classification accuracy. However, the accuracy of 78.1% as provided by the ZC feature and cubic SVM could provide good performance for EMG controlled prosthetic arm implementation.

References
[1] Karabulut D, Ortes F, Arslan YZ, and Adli MA 2017 Comparative evaluation of EMG signal features for myoelectric controlled human arm prosthetics. *Biocybernetics and Biomedical Engineering*, 37(2) 326-335.
[2] González J, Horiuchi Y, and Yu W 2010 Classification of upper limb motions from around-shoulder muscle activities: hand biofeedback. *The Open Medical Informatics Journal* 4 74-80.
[3] Zhang Q, Liu R, Chen W, and Xiong C 2017 Simultaneous and continuous estimation of shoulder and elbow kinematics from surface EMG signals. *Frontiers in Neuroscience* 11 280.
[4] Rivela D, Scannella A, Pavan EE, Frigo CA, Belluco P, and Gini G, 2015 Processing of surface EMG through pattern recognition techniques aimed at classifying shoulder joint movements. *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* 2107-2110.
[5] Zhou Y, Chen C, Cheng M, Franovic S, Muh S, and Lemos S, 2020 Real-Time Surface EMG Pattern Recognition for Shoulder Motions Based on Support Vector Machine. *Proceedings of the 2020 9th International Conference on Computing and Pattern Recognition* 63-66.
[6] Gini G, Mazzon L, Pontiggia S and Belluco P 2017 A Classifier of Shoulder Movements for a Wearable EMG-Based Device. *Journal of Medical Robotics Research* 2(02) 1740003.
[7] Laksono PW, Matsushita K, Suhaimi MSAB, Kitamura T, Njeri W, Muguro J, and Sasaki M 2020 Mapping three electromyography signals generated by human elbow and shoulder movements to two degree of freedom upper-limb robot control. *Robotics* 9(4) 83.
[8] Sharba GK, Wali MK, and Al-Timemy AH 2019 Real-time classification of shoulder girdle motions for multifunctional prosthetic hand control: A preliminary study. *The International Journal of Artificial Organs*, 42(9) 508-515.
[9] Bai D, Xia C, Yang J, Zhang S, Jiang Y, and Yokoi H 2016 Shoulder joint control method for smart prosthetic arm based on surface EMG recognition. *2016 IEEE International Conference on Information and Automation (ICIA)* 1267-1272.
[10] https://cruxconditioning.com/gettin-all-sciency-edition-2/