Hand Gesture Recognition Using Mechanomyography Signal Based on LDA Classifier

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Abstract: The growing number of amputees in Iraq with multiple degrees of amputations makes it necessary to provide them with prosthetic hands with an easy to use control system that meets their aspirations. The Mechanomyography (MMG) signal has been proposed as an alternative or assisting method for hand gesture recognition. Electromyography (EMG) which is used as control signal in the commercial prosthetic hands faces many challenges such as electrical interference, non-stationery and electrode displacement. The MMG signal has been presented as a method to deal with the existing challenges of EMG. In this paper, MMG based hand gesture recognition is proposed with Pattern Recognition (PR) system. MMG signal have been collected from six healthy subjects, using accelerometers and microphones, which performed seven classes of hand movements. Classification accuracy of approximately 89% was obtained with PR method, consisting of time domain and Wavelet feature extraction and Linear Discriment Analysis (LDA) for classification. The results showed that the proposed method has a promising way for detecting and classifying hand gestures by low-cost MMG sensors which can be used for the control of prosthetic hand.

1. Introduction
Many people around the world lose their hand for many reasons such as wars, accidents and diseases. The role of the hands in daily life is vital since it is controlled by muscles which consist of smaller building blocks called motor units. Contraction of motor units can produce muscle vibration that named Mechanomyography (MMG) [1].

The lateral changes in the muscles during contraction is measured at frequency between 5-100Hz [1,2]. This MMG can be used as a control signal for prosthetic devices [3]. It can be detected by a contact sensor on the surface of the skin which makes it noninvasive technique that do not demand any surgical intervention [4]. This signal can be detected by many kinds of sensors that can sense the vibrations such as microphone, accelerometer, laser distance sensor and piezoelectric sensor [1, 5] or any other sensor that can sense a pressure generated from vibrations [6].

Researchers have investigated these sensors individually or in combination. Siddiqui and Chan [7] investigated the measurement of the acoustic wave from the wrist of human hand. Their developed prototype composed of 5 microphones which is hold on by wristband. The microphones were directly placed in contact with the skin of the subject. In another study, Wilson and Vaidyanathan [8] proposed a
framework for control upper-limb prostheses by using MMG sensors. These sensors consisted of Micro Electro Mechanical (MEM) microphone and one inertial measurement unit (IMU) [8]. Other researchers investigated hybrid approach of EMG and MMG to get the benefits of both systems.

Xiloyannis et al. [9] proposed a novel framework by combining the signals of EMG and MMG. They used 9 sensors, 5 sensors for EMG and 4 sensors for MMG. The experiment was carried out on six healthy males. Change et al. [10] proposed a method based on the hierarchical procedure, by combing IMU and EMG sensors to classify six hand motions. They suggested that using multi sensors can increase the accuracy of classification. All the previous studies have adopted systems of many sensors or some kind of complicated algorithms which make the processing is more complicated. The main problem of the EMG based system is that the signal is affected by electrical interference from the surroundings, changing in skin impedance due to sweat and also its high cost as compared to MMG sensors [11,12].

The control system of the commercial prosthetic devices which use on-off and other control strategies are slow and may be exhausting for the patient [13]. For this reason, the Pattern Recognition (PR) was proposed as a solution for this problem which can control multiple degrees of freedom in response to brain order [14]. In general, PR system consists of number of stages which are data acquisition, preprocessing (include filtering and windowing), feature extraction, classification and control [15]. In this paper, the usability of low-cost MMG sensors for hand gesture recognition by utilizing PR chain consisting of time domain and Wavelet feature extraction and also Linear Discernment Analysis (LDA) as classifier will investigated. LDA is considered as a simple classifier and does not required iterative training which will increase the processing speed [16].

2. Materials and Methods

2.1. The participants

Six healthy subjects, aged between (22-39) years, were recruited in this experiment. They were asked to sit on chair and their back on backrest of the chair toward the screen of laptop; situate their forearms in upright position on table. The subjects have no history of muscle’s disease. The experimental protocol and data collection were performed according to the declaration of Helsinki and its later amendments.

2.2. Sensors’ location

Two types of sensors were used to record the signals. These are MPU6050 (digital accelerometer) and ADMP401 microphone (MEMs microphone). Two accelerometers were used, the first one is located on anterior side of the forearm below the elbow and the second one is located on the opposite side of the first as shown in Figure 1. Two microphones were located on the front side of the wrist muscle. The sensors are positioned by wristband to avoid the movement of the sensor which could lead to motion artifact that distorts the signals.

Figure 1. The sensors position on the forearm (A) sensor position on the backside of forearm (B) sensor position on front side of the forearm. Accelerometers are placed under the yellow band and microphone under the red one.
2.3. Data acquisition
The data are recorded from the sensor to Arduino (Mega2560) microcontroller board which is connected to laptop computer (Core i5 1.8 GHz and 8GB RAM) through serial port, as shown in Figure 2. The Arduino has 16MHz internal clock and 12-bit A/D resolution. The accelerometers are connected to I2C port of the Arduino and the microphones are connected to analogue port. These signals are sent to laptop through Matlab Simulink (2018) with support package for Arduino which then processed by Matlab, as shown in Figure 3. The sampling frequency was set to 1 kHz. Then, the signal is filtered by second order Butterworth pass-band filter which is programmed by Matlab.

![Data collection method](image)

**Figure 2.** Data collection method

![Signals](image)

(A) and (B) represent accelerometer signals at front side and back side of forearm respectively, and (C) represent microphone signals.

**Figure 3.** The signals that are collected by Arduino (A) and (B) represent accelerometer signals at front side and back side of forearm respectively, and (C) represent microphone signals.

2.4. Experiment protocol
Each subject was asked to perform 7 movements’ classes. Each movement lasted for 3 seconds therefore, the length of the set of movements was 21 seconds. The recorded movements are: 1- Rest or no movement, 2- hand open, 3- hand close, 4- pinch, 5- tripod grip, 6- thumb flexion, 7- index flexion, as shown in the Figure 4. Each subject repeated these set of movements six times where each repetition is named as a trail. Each trail is recorded separately. Four of the six trails are chosen for training and the other two are chosen for testing.
Figure 4. The seven movement classes performed by the subjects during each trial

Pattern recognition was used as the based protocol for analysis of the signal. The pattern recognition is divided into 4 stages as shown in Figure 5. The first stage is the preprocessing stage which includes filtering and windowing. The filtering is a process to remove the noise from the signal. The main source of noise is the moving artifact which induced by the subject motion. Other source of noise that affects the accelerometer is due to gravity [17]. The other potential source of noise is a noise that comes from crosstalk which has effect on the microphone in spite off that the experiment is carried in a quiet environment. The widowing step divided the signal into specific segments over time. There is a relationship between the length of the window and the classification accuracy of PR [18]. The window size chosen for this study is 256ms and window increment is 128ms. These window has been suitable for this experiment to get the best accuracy [18]

Figure 5. Pattern Recognition stages

The second stage is the feature extraction which is defined as the information taken from the signal. This information is useful for analysis the data. There are two kinds of feature extraction which are Time Domain (TD) features such as Root Mean Square(RMS), Zero Crossing (ZC), Slope Sign Changes (SSC) and time-frequency domain features [19] such as wavelet packet transform. In this study, four types of features have been utilized which are RMS, ZC, SSC and wavelet packet transform.
The third stage is the feature reduction which is used when there is a large data which proposes a challenge when analyze it. Principal Component Analysis (PCA) is the most common feature reduction that is used by researchers where a specified number of data are extracted, called the principal components. These represent a linear combination of extract from original data and are orthogonal to each other, for that reason, there is no redundant information [20].

The fourth stage is classification stage. Linear Discernment Analysis (LDA) was the classifier used in this study since it has simple implementation and does not require tuning. LDA classifier can characterize two or more different classes by finding linear combination of features [18].

3. Results
In this study, seven hands gestures are classified for 6 subjects as shown in Figures 6 and 7. The average error is equal to 11.72% across 6 subjects, in spite of these results above are taken from healthy subjects. As the results in Figure 7 show that some classes such as third class (hand open) which is weaker than other movement classes. This may be the subject is not trained well to perform the motion in right way according to accurate time and right position at each trail. Other potential reason is that the subject was moving during experiment that affects the result of some movements. Subjects one, five and six (with red color) in bar plot (Figure 6) are trained well after many sessions which make these results are better from other subjects, as shown in Figure 6.

In this study, only low-cost accelerometer and microphones were utilized to collect the MMG signals from healthy subjects. Future research will tackle collecting data from amputee subjects with MMG.

![Figure 6. Bar plot for the resulted classification errors for 6 subjects](image-url)
Figure 7. Confusion matrices (A-F) of errors resulted from 6 subjects for 7 hand classes which are: 1. Rest, 2. Hand close, 3. Hand open, 4. Fine pinch, 5. Tripod grip, 6. Thumb flexion, 7. Index flexion.

4. Conclusion
MMG based pattern recognition has been proposed in this study to classify 7 classes of hand movements utilizing low-cost microphones and accelerometers. An overall classification accuracy of approximately 89% was obtained across 6 subjects was obtained. It had been concluded that MMG signal could be utilized as a promising method in PR control. These results are determined from low-cost sensors, good performance of the proposed PR system can be achieved.

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