EEG-EMG based bio-robotics elbow orthotics control

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Abstract. Brain-computer interface (BCI) or also its advancement, hybrid brain-computer interface (hBCI), is a technology that is vastly developed. This technology has been used in many fields. BCI is a system that directly changes a human's mind into data that can be extracted to information that can be meaningful to people. The development of this technology has applications as a rehabilitation aid for someone suffering from an inability to move his limbs, such as the arms. Through this research, it is hoped to be able to design an orthosis control system as a rehabilitation device by using a classification method with EEG and EMG signals, so that subjects who use this tool can carry out rehabilitation in upper arm movements especially in the elbow joint. The system utilized Raspberry Pi 3 B+ as the computer and ADS1299 EEG-fe as analog front end for EEG and EMG. EEG frequency band power and EMG Vrms feature are extracted using Wavelet Transform and the model used for movement classification is Support Vector Machine. The results of the movement classification using both signals, using delta alpha ratio and root mean square features, obtained training accuracy for three movements namely relax, flexion, and extension of 90.3% and for testing accuracy of 85.2%. The combination of EEG and EMG signals are considered a promising approach for developing rehabilitation device of right arm limb.

1. Introduction

Patient that suffer from numerous disease that are affecting brain, such as stroke, spinal cord injury, or ALS, may have problem with controlling their limb’s voluntary muscle. Brain-computer Interface (BCI) is a technological interface of human brain and computer which provides external interface between the brain and their body system to control their body. It has been substantially developed by researchers for application such as spellers, virtual environment control, or powered orthotics. BCI may detect mental task by recording signal activities from brain’s neuron, which is an electroencephalography signals [1]. The development of BCI can be divided into four steps, i.e. data acquisition, data segmentation, feature extraction, classification, and actuator interface [2]. While this may look as an effective way to simulate brain command to limb, a BCI system method may not work on all subjects, so we can combine the BCI with other biosignals, such as EMG, EOG, ECG, or kinematic properties of the bodies, to develop more effective control system, which is the hybrid brain-computer interface (hBCI).

There are numerous researches regarding EEG that studies on motoric information. These methods usually called mental imagery which describes motoric commands coming from the brain when a person is trying to imagine moving their limbs. Mental imagery can be extracted from EEG that have a potential of around 0.5 to 100 µV, after which by extracting frequency bands from the signal, we can acquire data for extracting features, that is Delta (0.5–4 Hz), Theta (4–7 Hz), Mu (7–12 Hz), Beta (13–30 Hz), and
Gamma (above 30 Hz) [3]. When a person doing motor action or motor imagery, the EEG signals are dominant in motor cortex part of the brain and by utilizing event related synchronization or event related desynchronization, the signals showed up at Mu and Beta Frequency based on previous research [4].

In this research, we develop control system of right arm’s elbow orthotics, utilizing EEG and EMG signals that were recorded using Raspberry Pi 3 B+ and Front-End Analog to Digital Converter (ADC) ADS1299EEG-FE. The signals analyzed and classified using Support Vector Machine (SVM) on an offline machine and then the model is extracted to be used on the Raspberry Pi 3 B+ to predict the movement intention, and give driving signals to the orthotics actuator.

2. Methodology and Data

2.1. Data Acquisition

This research uses Raspberry Pi 3 B+ as the computer to send data acquisition command and save the data as file, and ADS1299EEG-FE connected to the Raspberry Pi through Serial Peripheral Interface (SPI) communication protocol to convert EEG and EMG signals as ADC data. This acquisition system was developed based on previous research [5]. This research utilizes the ADS1299 capability of signal acquisition with 8 channels of 24-bit Delta-Sigma ADC, and the register settings to have simultaneous sampling of each ADC channels with the operating data rate of 500 sampling per second. The Programmable Gain Amplifier (PGA) used for each channel is configured to 24. The drive code to acquire data from ADS1299EEG-FE is implemented in C, which is then will be called in main program for the control system implemented in Python.

![Figure 1. Elbow Orthotics Hardware System Design.](image)

The control system for the orthotics is shown in Fig. 1. In this figure, there are non-invasive passive EEG electrodes and non-invasive passive EMG electrodes that are connected to the ADS1299EEG-FE. The ADS1299EEG-FE is connected to Raspberry Pi for the data acquisition, which is powered with DC power supply bank. The Raspberry Pi 3 B+ is then connected to the brushless DC motor with built-in driver that is the PWM and direction pin, which is mediated by logic level converter because the driver receives 5 V logic level while Raspberry Pi have 3 V logic level. There are also two safety switches...
placed on orthotics so that the movement of the orthotics can be limited to human degree movement. The orthotics brushless DC motor is powered externally using lithium polymer battery.

Figure 2. Stimulation video.

The subject for recording the signals is a healthy person with age of 21 years old by directly wearing the orthotics. The signal acquisition was taken with duration of 12 seconds utilizing stimulus of a video display of the right hand elbow movement. The purpose was to move the subject’s elbow in relation to the stimulus movement as show in Fig. 2, and the process is shown in Fig. 3. The data that has been recorded as a file with Raspberry Pi 3 B+ and ADS1299EEG-FE system is moved to PC for offline processing.

There are three movement that are recorded, the first 4 seconds is relax which the video is shown as idle, to acquire signal when the brain is not thinking of motor imagery. The next 4 seconds is flexion, and the last 4 seconds is extension. The recording of the signals is taken repeatedly for 10 minutes. The subject motoric movement EEG and EMG signals were recorded for a total of 30 minutes. EEG signals were recorded using the standard 10-20 system by American EEG Society [6], C3, C4, F3, and F4, while the EMG electrode is placed on the biceps brachii and triceps brachii.

2.2. Pre-Processing
There are pre-processing steps for filtering the signals from noise such as DC offset, noise from body movement, and interference from signal from other electrodes.

The first step to filter the signals is removing DC offset from signals of each electrodes with the mean value of their own signals by a time frame, that is, each of trials time frame signal’s mean value of each electrodes were obtained. The next step is using high pass filter with cut off frequency of 2 Hz, to filter
the signal for preparation of the next step. The filter used for this is 10th-order Butterworth filter. The next step is to acquire independent component of each electrodes using Independent Component Analysis (ICA) method, to separate and denoise the signals [7]. Before the feature extraction, EEG and EMG signals is labelled by doing epoch on the data with the time it took for each of the movement from one trial.

2.3. Feature Extraction

There are main frequency bands for extracting the feature of EEG signals for motor imagery/action task. These frequencies can be extracted by using Discrete Wavelet Transform (DWT) of Daubechies waveform. DWT will decompose the EEG and EMG signals into levels of frequencies that relates to EEG and EMG signal frequency. On EEG signals, by using DWT we can find the Power Spectral Density (PSD) of each frequency. From the PSD, this research calculated the Relative Power Ratio (RPR) of each frequency band, because EEG signals is non-stationary as it will differ in the amplitude with each trial. Since the motoric function occurs mainly on mu and beta frequency band, this research use Delta-Alpha Ratio (DAR) for features used in classification. For the EMG signals, this research use root-mean square (RMS) of the signals at range of 62.5 Hz-125 Hz as it is the frequency range the EMG signal occur.

The phenomena of event-related synchronization (ERS) and event-related desynchronization (ERD) of elbow motoric movement occurs in these frequency bands, and the EEG power is known decreasing in the alpha and beta band from relax state to movement state while performing motor imagery or voluntary contraction, based on previous research by [12-14]. Support Vector Machine (SVM) is used for the signal classification. The classification uses the features extracted from EEG Delta Alpha Ratio Power and EMG rms as the input and the output is the movement classification, relax, flexion, and extension.

3. Results and Discussion

From this study, it was found that the filtering process which consist of substracting DC offset and high pass filter will get decent signal that remove some of the unwanted noise. ICA also able to acquire decomposed signal of each electrode. The EEG signal between movement class is hard to differentiate even when extracting the power ratio of each electrode. The EMG signal of each movement class can be seen clearly distinct between movement class, so those signal can help the EEG signal to achieve better classification accuracy result.

Table 1 shows the classification accuracy for three feature combination. Using Delta-Alpha Ratio only, the accuracy for training and testing only reach 46.8% and 41.6%. DAR feature only can’t differentiate between three classes. It can predict relax class more than 63%, but when predicting flexion and extension class it fails to reach even 50%. Using EMG Vrms feature only, the system able to predict relax class, while differentiating between flexion and extension movement still have some error, with the most falsely predicted is extension movement. By using both feature, the difference with using only EMG Vrms is just a bit.

Table 2, 3, and 4 shows the validation of accuracy of each feature combination. The EEG DAR only feature get 37.5% average accuracy, the EMG Vrms get 88.5% average accuracy, and using both feature get 88.9%.

| Table 1. Classification Accuracy |
|----------------------------------|
| Feature Combination | Training Accuracy (%) | Testing Accuracy (%) |
|----------------------|-----------------------|----------------------|
| EEG (Delta-Alpha Ratio) | 46.8 | 41.6 |
| EMG (Vrms) | 90.3 | 84.5 |
| EEG + EMG | 90.3 | 85.2 |
In comparison to recent studies of motor imagery/action classification of elbow movement [15-16], the performance of this system still below their research, this is to be expected because in this research the classification is divided into three movement (relax, flexion, extension) for the elbow movement. This research also uses in-house system which utilize Raspberry Pi 3 B+ and the aim for this research is doing the signal processing and classification directly in the board, which have limited computational power, to build affordable rehabilitation system which requiring the system cost to be as low as possible. The next possible research is to measure the resource usage of the single board computer to utilize it more effective and efficient.

4. Conclusion
The use of signal filtering using mean DC offset, high pass filter can approximate motor imagery/action signals, and ICA can get original signal from each electrodes. The best accuracy for this research is by utilizing the combination of EEG and EMG, with the accuracy of 90.3% for training data and 85.2% for testing data. The accuracy is mainly dominated by the EMG RMS features.

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