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Preliminary Research of Surface Electromyogram (sEMG) Signal Analysis for Robotic Arm Control

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Abstract. Human-robot interactions have gained popularity in the recent past, particularly in the advent and revolution of industry 4.0 era. There are still open research issues to be addressed, e.g., human-machine interaction, especially in robotic operation using bio-signal. This paper presents surface electromyography (sEMG) signal analysis of the motion of upper limb muscles to control the robotic arm. The objective is to use as few EMG channels to estimate joint angles for application in a robotic arm. The overall target is how this information can be applied to a robot control scheme. Three motions are proposed based on the 2 degrees of freedom (DOF) between joint elbow and shoulder. Three sEMG channel signal is captured using a DAQ unit comprising of pre-amplifier and NI USB 6008 and a laptop running LabVIEW software. The analysis is conducted using Matlab software. The result indicates that the sEMG from three muscles of the upper limb gives useful information and the performance of the sEMG synergy-based model has a good prospect for the controlling robot arm.

INTRODUCTION

In the recent past, robots have played an important role in manufacturing industries and other fields like human support robots. From 2012 up to 2017, robot sales have increased by an average of 19% annually with a reported peak in 2017 of 381,335 units, which is a 30% increment [1]. The human-robot interfaces are attracting more attention particularly since the introduction of robots for daily life tasks, e.g., self-care services [2][3][4]. One of the most important aspects in robotics is control system. Conventional control schemes entail complicated systems with many sensors, and buttons preprogrammed logic. Commonly, the action/motion relation have been mapped by training process (i.e., haptic devices or 3-D motion of a joystick)[4]. The challenge with the system is its reduced adaptability to the user's needs. This necessities a review of the existing control interface. Myoelectric controlled interface is one of the promising substitutes that have been widely applied by researchers in areas like robotic teleoperations, prostheses, and exoskeletons[2]. Electromyography (EMG) is a promising candidate due to its ease of acquisition as well as rich in contextual information like force, torque and, position content that can be derived with minimal signal processing operations.

In a previous study, EMG signal using multiple target muscles was used to estimate joint angles of upper limbs[4][5][6]. The authors in [7] applied Kalman filtering techniques to translate from raw/processed EMG signal to an equivalent angle position[7]. Others researchers investigated the activation patterns, electrode positioning, and other relevant factors for high-density surface EMG (SEMG) mapping from upper-arm and forearm muscle[6]. Another author used biceps muscle only to estimate angle of elbow in flexion-extension motion[7]. Increasing the

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targeted muscles will lead to increased computation costs. A related study was the use of hand and wrist motion for controlling myoelectric prosthesis based on synergy of muscles[8]. In the study, the authors pointed out that EMG signal can be modeled to achieve proportional control in multiple degrees of freedom (DoF).

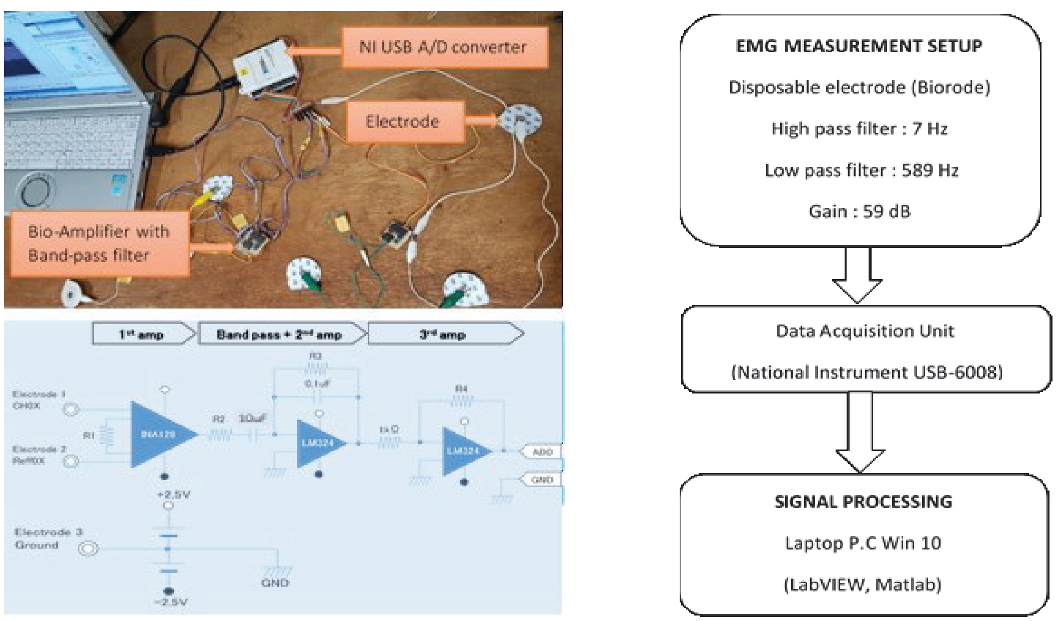
In this paper, we report the preliminary results and methodology of a myoelectric controlled robotic arm. The objective of this research is to use as few EMG channels to estimate joint angles for application in robotic arm. Synergy of the target muscles will be explored to bring out an estimation of elbow and shoulder joint angle to control a robotic arm. We will highlight the difference between several motions of the upper limb and match the motion to control scheme of the robotic arm. In the experiment, custom-made low-cost bio-amplifier circuits were used to capture three EMG signals of the elbow and shoulder muscles as shown in the next section. Signal processing and feature extraction are conducted in order to get useful information for controlling robotic arm. Synergy of the target muscles is explored when conducting individual motion and the model validated by use of motion tracking sensors.

MATERIAL AND METHOD

System Overview

The experiment overview is as shown in Fig. 1. First, three target muscles are selected that will capture representative muscle activity of the entire arm in motion. Data acquisition is performed on muscle surface using electrodes (Ag/AgCl, size: 57 x 48 mm, Biorode, Japan) as shown below. The EMG measurement circuit comprising of an instrumentation amplifier and operational amplifier, bandpass filter all connected in cascade as shown in Fig.1A. The band-pass filter has a high pass filter of approximately 7Hz and low pass filter at 589 Hz with an adjustable gain set to approximately 59-65 dB for each channel.

Data acquisition unit comprises of National Instruments (NI) Corporation USB-6008 for Digital/Analog conversion and a Personal Computer (PC) i5 2.7 GHz Let'note Panasonic. Data was acquired at a sampling rate of 2 kHz. We used Matlab® and LabVIEW software for signal acquisition and processing.



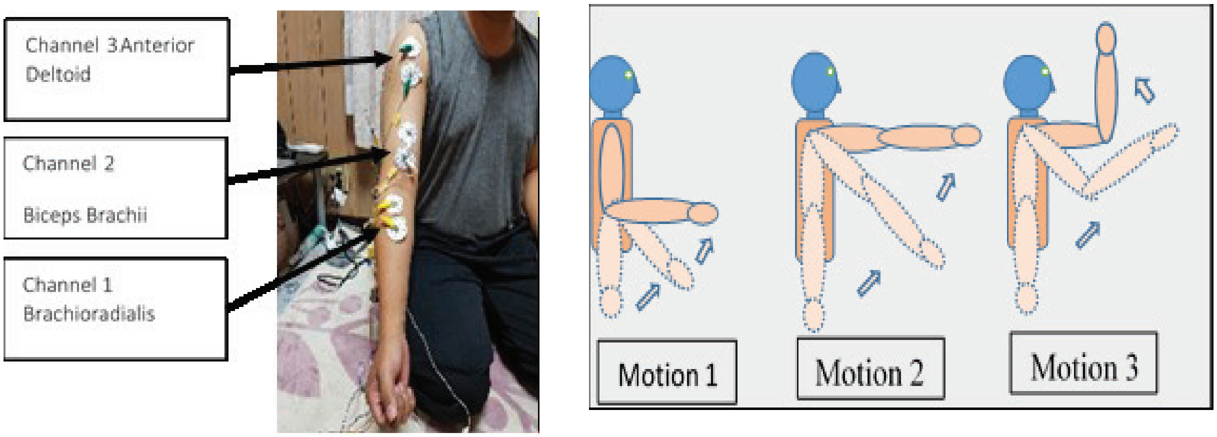
(a) (b)

FIGURE 1. (a) EMG measurement device and circuit. (b) Signal flow overview

Experiment Set Up Protocol

In this study, five healthy male subjects who meet the criteria as follows: 20-40 years old 60-100 kg were selected. All the procedures have been approved by the ethics committee. EMG signals were recorded from

Brachioradialis, Biceps Brachii and Anterior Deltoid muscles using bipolar electrode placement and one common electrode as reference (ground) placed on the bony part of the elbow as shown in Fig. 2a. Mounting and positioning of the electrodes was based on the SENIAM rules [9]. The target motions consisted of: elbow flexion as motion 1, shoulder flexion as motion 2 and a combination of elbow and shoulder flexion movement called the uppercut motion as motion 3. The combination is illustrated in Fig. 2b. In the recording of the EMG signal, the upper limb of motion 1 and motion 2 have limited to a range of up to 90 degrees for modeling of the relation of EMG and joint angle. In the experimental protocols and motion patterns shown in Fig. 2b, the subjects were instructed to perform motion 1, motion 2 and motion 3 which set at 3 second periods respectively.



(a) (b)

FIGURE 2. (a) EMG electrodes placement. (b) Motions setup

For the validation process, we use IMU sensors to capture position of the upper limb (see fig.3). Motion is tracked by nine-axis motion sensor MPU GZ50 connected with microcontroller Mbed LPCI 765 and logged in SD Card at a sampling rate of 500Hz.

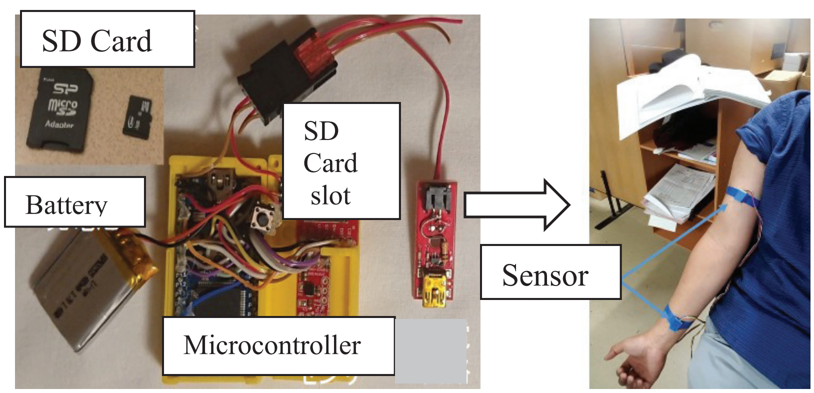


FIGURE 3. Motion sensor setup and placement

Signal Processing

Processing of the raw data is critical to remove baseline noises, motion artifact noises, etc. An essential part of this paper is the analysis of the EMG signal. The acquired signal from fig. 4 is passed through rectification and smoothing as described by moving average smoothing equation below.

$$X^{1,2,3}[i] = \frac{1}{M}\sum_{j}^{M-1}\left\| x[n-j] \right\| \tag{1}$$

Where M is the smoothing window size, and n is the current sampling point, x is the raw EMG signal from DAQ. The output X^1, X^2, and X^3 represent processed EMG signal of Anterior Deltoid, Biceps Brachii, and Brachioradialis muscle respectively.

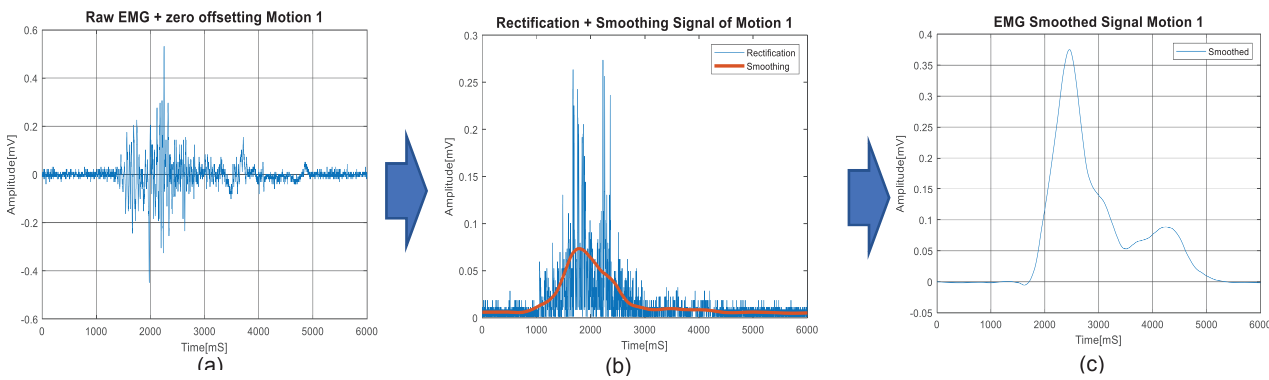


FIGURE 4. EMG Signal processing operations a. Raw EMG +zero offsetting b. Rectified + Smoothing c. Smoothed output signal

Moving average filtering method produced data with bumpy transitions (noisy smoothed data), so we opted for an alternative method, i.e. Savitzky-Golay filtering. The filter can be thought of as a generalized moving average filter shown in (1) above. It differs from moving average filter by performing an unweighted linear least-squares fit of the selected data points using an nth degree polynomial. Due to this feature, it is usually considered as a digital smoothing polynomial filter. The higher the polynomial degree, the better the smoothing function at a higher computational cost. Besides the advantage of smoothing achieved by this method, it also effective in preserving the frequency components of the signal. These are some of the reason why we considered the use of it in our analysis.

Joint angle estimation is the overall target of the research. In this paper, we considered a simple accumulative operation of muscle flex of the elbow and shoulder to be described by the following relation.

$$\theta est = X^1[i] + X^2[i] + X^3[i] \tag{2}$$

The value of θest produced in this operation is validated by measured angle values from the motion sensors. Scaling and conditioning of the EMG signal is performed such that the output reflects the actual joint-angle relation such that the signal can be applied in robot control. The results are shown in the next section.

RESULT AND DISCUSSION

The EMG signal processing was conducted offline, which consisted of several steps as shown in Fig. 4. After acquisition using LabVIEW data acquisition, raw EMG data for motion 1, 2 and 3 as shown in Fig. 5 is exported to Matlab for processing.

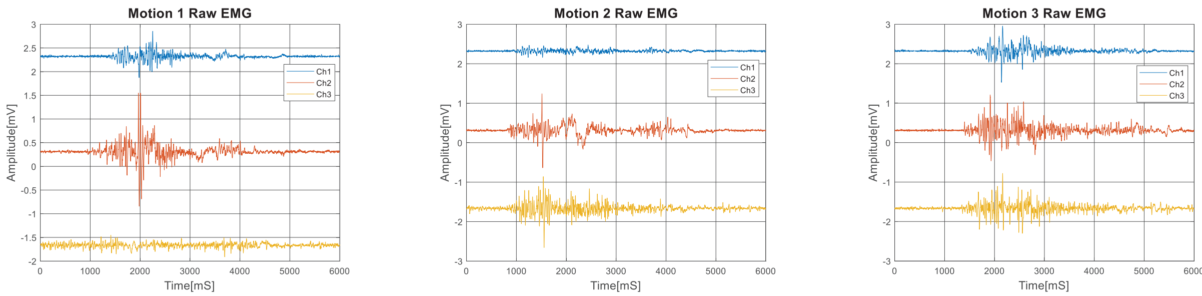


FIGURE 5. Raw EMG motion 1, 2 and 3

EMG data were processed using custom-made Matlab functions. Figure 5 shows the three recorded channels of EMG. From the data, it is noted that during motion 1, channel 1 and 2 are most active, and channel 3 has little muscle activity. In motion 2, channel 2 and 3 showed highest activation and little activation for channel 1. This is as expected when raising hand with no elbow flexion. Motion 3, which is a combination of motion 1 and 2 has all the muscles under consideration showing appreciable activation patterns.

Figure 6 below shows a representative sample of the processed signal or Integrated EMG (IEMG) from each motion repeated in three trials. We considered each motion to be intuitively working as a synergetic scheme as described by (2) above. The results are as expected when raising parts of the hand with no activation and a steady rise in muscle activity as the arm is raised. As the hand is restored to rest, muscle activation is gradual and remains even after rest position is achieved. This point is made clear when motion sensor and EMG activity are considered together. Signal conditioning is thereby recommended particularly threshold conditioning to define when subjects are actively controlling the robot.

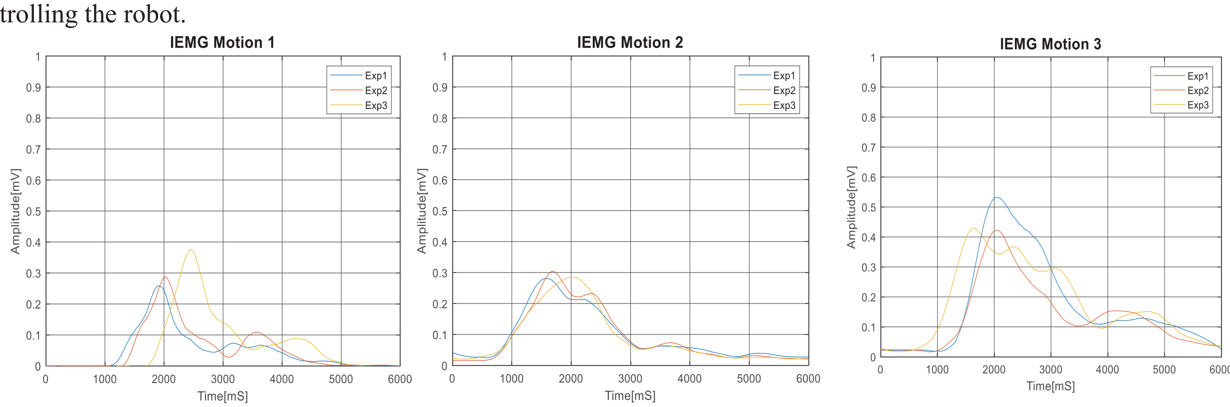


FIGURE 6. Integrated EMG (IEMG) of trials for motion 1, 2, and 3.

Figure 7 below shows the processed EMG signal and measured motion data based on one axis of interest. The result shows that the EMG signal shows activity before motion sensors. This is in agreement with other researchers [xx]. In this case, the difference of signal activity is not very clear which can be attributed to synchronization errors of data logging of EMG and motion sensor. In spite of the mentioned errors, the apparent relation between EMG activity and measured angle is seen clearly. In a control paradigm, the estimated angle relation (synergy-based model of three muscles) can be effectively applied in robotic control. The advantage of the proposed scheme would be the low cost both in computation and setup. Figure 7 shows that the IEMG result obtained from motion 1 is aligned with the estimated joint angle. The same operation would yield similar result for shoulder flexion and combination of all motions.

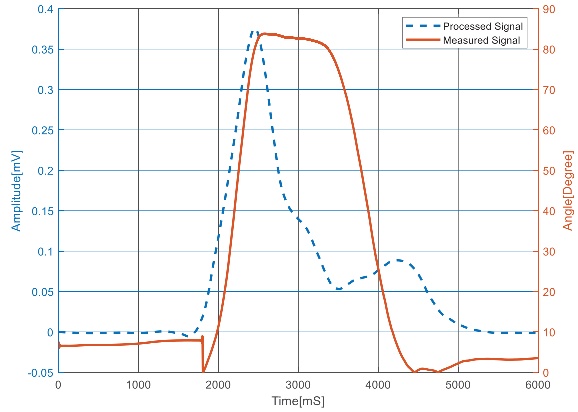


FIGURE 7. Validation between model synergy of motion 1 with 1 degree of freedom

CONCLUSION

This study has shown that sEMG from three muscles of the upper limb gives useful information for the controlling robot arm. Three motions have been attempted that related to the 2 DoF joint construction of the upper limb. The sEMG signals were from Anterior Deltoid, Biceps Brachii, and Brachioradialis muscles. The synergy-based model was to evaluate the motions related to the joint angle for robotic controlling arm. The results show that the performance of the sEMG synergy-based model has a good prospect for controlling robotic arm. Additional modeling is required to capture more complex hand motions and improve motion tracking performance of the EMG signals.

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