Data extraction from impulsive muscle under preplanned gesture

A.Y. Bani Hashim[1], Z. Fu[1], Z. Jamaludin[1] and I.S. Mohamad[2]

[1)] Faculty of Manufacturing Engineering, Universiti Teknikal Malaysia Melaka,
Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
[2)] Faculty of Mechanical Engineering, Universiti Teknikal Malaysia Melaka,
Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

[*]Corresponding e-mail: yusairi@utem.edu.my

Keywords: Electromyography; raw EMG; muscle contraction; forearm

ABSTRACT – Electromyography signals are obtainable from the contraction of the human muscles, based on the human movements. The human forearm muscles consist of Brachioradialis muscle, Pronator Teres muscle, Flexor Carpi Radialis muscle, Palmaris Longus muscle, Flexor Carpi Ulnaris muscle and Extensor Carpi Ulnaris muscle. All those muscles are responsible for the movement of the human forearm. By performing specific hand gestures, the contraction of the muscles was captured through the raw electromyography signals. The study aimed to learn from the raw signals by looking at how each burst was unique from another about a muscle that was producing the signal. The Myonator—an in-house developed device that collects and reads the signals, was used to record the muscle contrac-tion from hand gestures of four subjects. The plots from the recorded data were obtained through LabVIEW. The results show that specific burst patterns distinctively identify specific muscles contraction. Therefore, mapping the burst patterns to some muscles is proven viable.

1. INTRODUCTION

The data extraction of electromyography (EMG) signal is obtainable from the movement of the forearm which results in the contraction of the muscles. The human-machine interface will be satisfied when the signals are attainable where the signals are used as an input means to control a particular machine, for example, a robot arm.

The method is required to obtain the electromyography signals is by placing the electrodes on the experimental subject's forearm to extract the surface electromyography (sEMG) signals. Whenever the forearm moves, some EMG signals will be captured.

The affecting factors in this study is that a person has a different type of skin type and muscle composition that affect the reading of the EMG. Therefore, this study sought to learn from the raw EMG signals that how each burst was unique from another about a muscle that was producing the signal. It was hypothesized that mapping the burst patterns to some muscles is possible.

The classification and extraction of individual motor unit action potentials from intramuscular electromyographic signals show that EMG raw signals are needed to be extracted first to proceed to the classification of the signals [1]. In fact, the accuracy of EMG classification could be improved further by the inclusion of an accelerometer to monitor wrist movement [2].

A low-cost testing system was developed to perform the pattern-recognition-based control strategies, which can be used in the real-time operation [3]. There is a mutual relationship between electroencephalogram and electromyogram signals due to the time delay of information flow [4]. It shows that a shorter time delay was obtained when subjects were performing the active exercise with movement intention rather than performing the passive activity without movement intention.

The integration between electroencephalogram and electromyogram could benefit the patients with a nerve disorder. Electromyography signals have long been used for the benefits of sports science [5]. It is stated that electromyographic fatigue threshold is a correlation of critical power and torque or force limits. It establishes general exercise intensities below which neuromuscular fatigability is negligible and unpredictable. Moreover, usage of EMG signals are found in the medical field where the signals were used as the examined signals in EMG-EMG coherence function analyses and EMG-EMG transfer function. In some other study [6], while chewing gum, the physiological features of the rhythmically coordinated jaw and neck muscle EMG activities were studied using EMG-EMG transfer function and EMG-EMG coherence function analyses in 20 healthy subjects.

On the other hand, investigation done by [7] supports the sports field. During the golf swing, it explores the relationship between the patterns of EMG signals recorded from eight muscle regions of forearms and shoulders, and the patterns of peak rotational speed of thorax, pelvis, and arm, and. By doing so, golfer's injuries could be minimized by learning the EMG signal patterns. In [8], the extraction of the motor unit profile which is the representation of the trajectories of negative and positive turns of a scanning-EMG signal was studied. With the success of motor unit profile extraction, an algorithm was developed that has been able to detect turns of the scanning-EMG signal and would then link them by using point tracking techniques. Also, analyzing the algorithm's behavior and the influence of the algorithm's parameters and determining which parameter values provide the real scanning-EMG signals did the best performance.

The current pattern recognition and machine learning using EMG signals have several inherent problems regarding the gait subphase detection [9]. It is shown that electromyogram with a signal graph matching algorithm has good timing characteristics of EMG signals as compared to the algorithm for time-domain feature extraction.

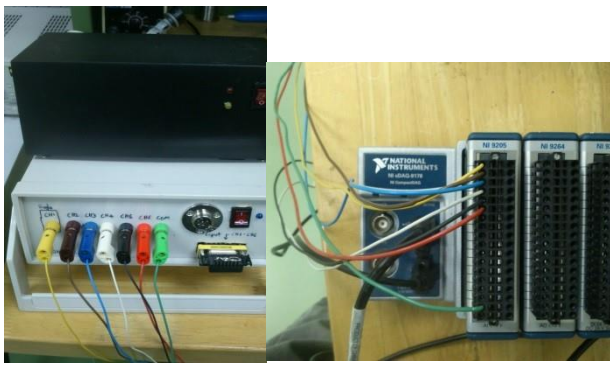
Human body gestures play an important role in determining the EMG signals as gestures such as wrist flexion, double wrist flexion, hand closing and hand opening. All of these gestures are found to be important and can be used to control a prosthetic terminal based on the hand gestures [10]. In [11], a combination of surface and intramuscular recordings are used so that investigation could be done to compare the action potentials from gastrocnemius and soleus which are represented in sEMG with various inter-electrode distances. The results stated that by reducing inter-electrode gap could result in the detection of sEMG to be insensitive to gastrocnemius activity without substantial attenuation of soleus crosstalk.

In [12], a regression model which relates the multichannel surface EMG signals to human lower limb flexion/extension joint angles was constructed. They have proved that their proposed model can form human-machine interaction interface which will then lead to continuous bioelectric control and not to mention further improve human and machine motion stability such as for lower limb wearable, intelligent equipment.

2. RESEARCH METHODOLOGY

The first step of analyzing the electromyography signals is to obtain and record the signals before examining them. Different hand gestures are required so that experiment could be done to secure the electromyography signals. The order of performed hand gestures throughout the test was, starting from the flex, extend, abduct, adduct, open and close finger, an 'OK,' and a thumb up. The approach to get the EMG signal is by using a named Myonator which will be connected to the electrodes that are placed on the skin of the experimental subjects.

The experiments were conducted by using gel electrodes attached to Myonator (an in-house developed EMG measurement tool, see Fig. 1(a)), which was connected to Ni-DAQ LabVIEW (see Fig. 1(b)). There were more subjects participated but for simplicity, this study reported the results obtained from four subjects, two of whom were female.



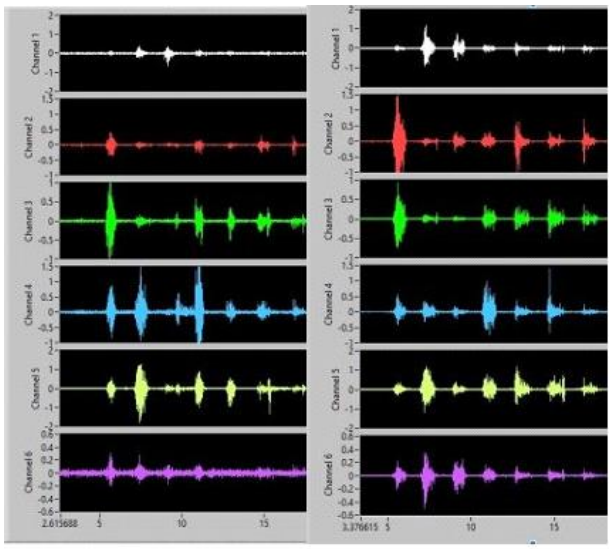
(a) (b)

Figure 1 (a) The Myonator has six channels where each channel is connected to a set of three electrodes, (b) Ni-DAQ LabVIEW is a data acquisition device that allowssmooth data transmission between hardware and dynamic signal analyses using its computational tools.

The subjects were taught on the preplanned gestures. They would act the gestures upon instructed. They were prepared for the electrodes installation on their forearm where their skin of the essential areas would be clean before the arrangement took place. The electrodes (six sets) were placed at the selected locations encasing the forearm.

3. RESULTS AND DICUSSION

Results showed that there were nine bursts of EMG signals following the order of hand gestures. Figures 2(a), 2(b), and 3(a) exhibited somewhat similar patterns, whereas Fig. 3(b) showed distorted signals.

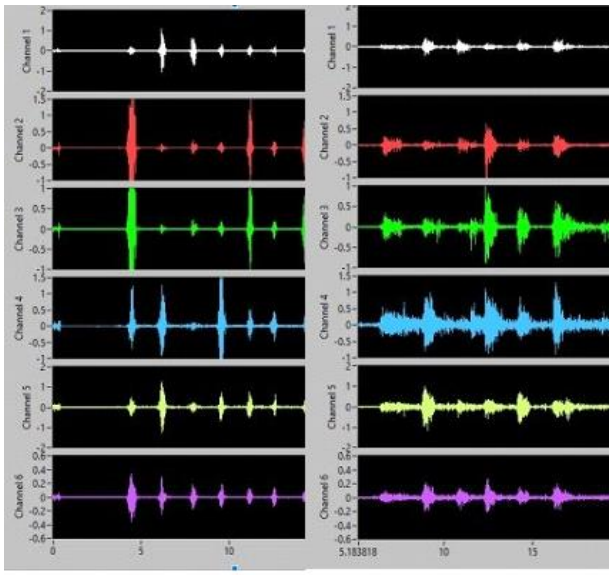


(a) (b)

Figure 2 (a) Raw EMG recorded from subject-1 (male), (b) subject-2 (male). It is noticed that although both subjects acted the same preplanned gestures, the data showed that each subject produced a unique set of burst, especially the spikes.

The apparent cause of EMG signal from Fig. 3(b) was due to subject-4 herself. It was suspected that the subject who is a female did not apply enough energy when performing the hand gestures. Because the subject has thin arms, the electrodes were placed very close to one another. Signal chattering could have had happened resulted in the strange bursts at channel 4 (see Fig. 3(b)). The apparent burst of signals seen in Fig. 3(a), Fig. 2(b), and Fig. 3(a) was from the flexing hand gesture, which contracted the Flexor Carpi Radialis and Palmaris Longus muscles. The burst train (successive bursts) of the digital-analog code of 011000 was noticed in Fig. 2(a), Fig. 2(b), Fig. 3(a).

The second noticeable burst train was the extending hand gesture that contracted the Brachioradialis muscle yielded the digital-analog code of 100111 for Fig. 2(a), Fig. 2(b), Fig. 3(a), which was opposite of flexing hand gesture. It was believed that the reverse digital-analog code was the effect of the particular muscles that are situated at the different end of the forearm. The muscles contract oppositely from one other.



(a) (b)

Figure 3 (a) Raw EMG recorded from subject-1 (male), (b) subject-2 (male). It is noticed that although both subjects acted the same preplanned gestures, the data showed that each subject produced a unique set of burst, especially the spikes.

4. SUMMARY

The EMG signals were successfully collected using the Myonator. The results showed that on different body gestures would produce unique EMG signals where specific burst patterns distinctively identify particular muscle contraction. Therefore, mapping the burst patterns to some muscles was proven viable.

ACKNOWLEDGMENT

This work was supported in part by the Universiti Teknikal Malaysia Melaka under Grant FRGS/2/2013/ SG02/ FKP/02/2/F00176.

REFERENCES

[1] Katsis, C. D. (2006). A novel method for automated EMG decomposition and MUAP classification. *Artificial Intelligence in Medicine*, 37(1).

[2] Khushaba, R.N., Al-Timemy, A., Kodagoda, S., & Nazarpour, K. (2016). Combined influence of forearm orientation and muscular contraction on EMG pattern recognition. *Expert Systems with Applications*, vol. 61, pp. 154-161.

[3] Akhmadeev, K., Rampone, E., Yu, T., Aoustin, Y. (2017). A testing system for a real-time gesture classification using surface EMG. *IFAC-PapersOnLine.* 50(1), pp. 11498–11503

[4] Kim, B., Kim, L., & Kim, Y.H. (2017) Cross-association analysis of EEG and EMG signals according to movement intention state. *Cognitive Systems Research.* 44, pp. 1–9.

[5] McCrary, J.M., & Ackermann, B.J. (2017). EMG amplitude, fatigue threshold, and time to task failure: A meta-analysis. *Journal of Science and Medicine in Sport*. In press.

[6] Ishii, T., Narita, N., & Endo, H. (2016). Evaluation of jaw and neck muscle activities while chewing using EMG-EMG transfer function and EMG-EMG coherence function analyses in healthy subjects. *Physiology & Behavior*, vol. 160, pp. 35-42.

[7] Verikas, A., Parker, J.,& Bacauskiene, M. (2017). Exploring relations between EMG and biomechanical data recorded during a golf swing. *Expert Systems with Applications*. 88, pp. 109–117.

[8] Corera, I., Malanda, A., Rodriguez-Falces, J., & Porta, S. (2017). Motor unit profile: A new way to describe the scanning-EMG potential. *Biomedical Signal Processing and Control*. 34, pp. 64–73.

[9] Ryu, J. (2017). Real-time gait subphase detection using an EMG signal graph matching (ESGM) algorithm based on EMG signals. *Expert Systems with Applications*. Pergamon, 85, pp. 357–365.

[10] Tavakoli, M., Benussi, C., & Lourenco, J.L. (2017). Single channel surface EMG control of advanced prosthetic hands: A simple, low cost and efficient approach. *Expert Systems with Applications*, vol. 79, pp. 322-332.

[11] Vieira, T. M., Wakeling, J.M., & Hodson-Tole, E. (2016). Is there sufficient evidence to claim muscle units are not localised and functionally grouped within the human gastrocnemius? *J Physiol*, 594: pp. 1953-1954.

[12] Chena, J., Zhanga, X.,& Cheng, Y. (2017). Surface EMG based continuous estimation of human lower limb joint angles by using deep belief networks. *Biomedical Signal Processing and Control*. 40, pp. 335–342.