ABSTRACT MYOELECTRIC CONTROL WITH AN ARDUINO-BASED SYSTEM

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ABSTRACT

This paper presents the design and evaluation of an Arduino-based system for electromyogram (EMG) signal measurement and prosthesis control with the abstract decoder. It achieves a 2 kHz sampling rate for two EMG channels, processes EMG signals on-the-fly and sends the prosthesis control command via a CAN bus. We tested the accuracy and responsiveness of the system in real-time by playing back previously recorded EMG signals through a Tip, Ring, and Sleeve (TRS) function generator. The correlation coefficients between the mean absolute value (MAV) of the original signals and the measured signals were above 97%.

INTRODUCTION

In clinical settings, myoelectric control is achieved by dual-site bang-bang control. Other methods such as pattern recognition, direct control, regression and abstract decoding have been introduced as alternatives [1]. Pattern recognition extract features from the EMG signals and groups the inputs into discrete movement classes. This technique often entails complex machine learning procedures, and it is normally implemented on high-performance processors [2, 3]. Recently, customised embedded electronic systems have been developed to enable real-time prosthesis control to approximate clinical settings [4, 5]. However, the width of adoption of the embedded system, as a research tool, is slow due to the cost and resources that are required to develop a reliable, flexible system.

In this work, we introduce a simple Arduino UNO-based embedded sensing and processing system for prosthesis control with abstract decoding [6, 7]. We evaluate the function and reliability of the system using previously-recorded EMG signals.

METHODS

System architecture

The conceptual design of the proposed embedded system is presented in Figure 1.

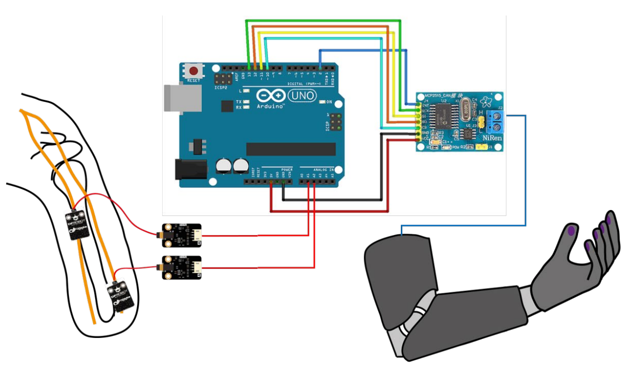


Figure 1: Conceptual design of the proposed embedded system

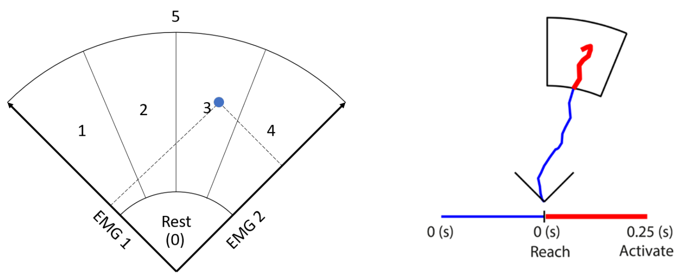
Our Arduino UNO-based system comprises four modules for data collection, EMG signal processing, prosthesis control and data transmission. The data collection module can sample up to two channels of EMG as fast as 2 kHz per channel. The signal processing module works at 100 Hz. It removes the DC bias of the input data, reduces the signal noise through an averaging filter and normalises the EMG signal based on calibration, in accordance with Dyson et al. [8]. The control module determines the grip patterns with an abstract decoder and sends the motor commands to the robo-limb™ prosthetic hand (Össur, Reykjavík, Iceland) via the data transmission module.

Abstract decoder

Unlike machine learning-based approaches, abstract control relies on human learning for the operation of the myoelectric-controlled interface (MCI) [6]. Abstract decoding promotes the co-contraction of muscle groups that are not co-contracted naturally for new functional gains or the utilisation of natural co-contractions. An example of the MCI is as outlined in Figure 2 (a). In our proof-of-concept implementation, we split the control interface into six zones, named the rest zone (zero), grip zones one to four and the outlier zone (five). Users control the instantaneous position of the blue 2D cursor with the control signals that are extracted from the two EMG signals. To activate a grip on the prosthesis, the user should hold the cursor in a grip zone (one to four) for a certain period. Figure 2 (b) shows a representative cursor trajectory for an individual trial.

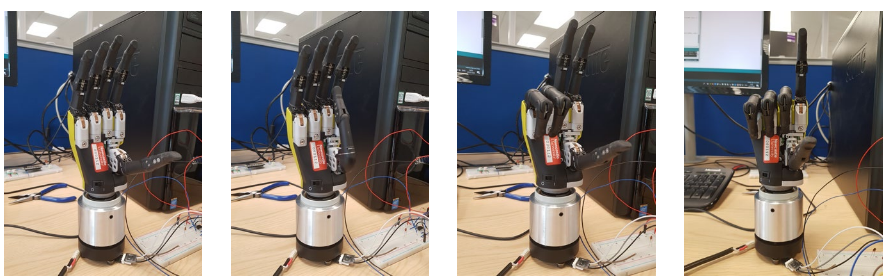
In our implementation, the cursor timer goes to sleep when the cursor stays at the rest zone or the outlier zone. Once the cursor moves to a grip zone, the timer records the period when the cursor is held within it. A grip command associated with the zone is sent to the prosthesis if the cursor stays within the zone for $t = 0.25$ seconds. The movement of the cursor to another zone will reset the timer (base time: 10 milliseconds). The system will not send motor commands to the prosthesis when the cursor stays at the rest zone or the outlier zone so the hand will maintain at the last grip until a new grip is determined.

In this implementation, we considered four grips, the normal grip, the thumb park grip, the three-jaw chuck grip and the pinch grip, and assigned them to zone one to four, respectively (Figure 3).



(a) (b)

Figure 2: The 2D MCI space and a representative cursor trajectory.



(a) (b) (c) (d)

Figure 3: The grips correspond to (a) zone one, (b) zone two, (c) zone three and (d) zone four

RESULTS

We tested the performance of the proposed embedded system. A MATLAB program controlled the stimulation of the signals through the TRJ function generator, as demonstrated in Figure 4. A potential divider and an amplifier circuit processed the signal to mimic the EMG signal measured by the Gravity Analog EMG sensors (OYMotion Technologies, Shanghai, China). The results are presented in two sub-sections. The performances of the data collection module and the signal processing module are in Section one. Section two presents the functional test of the control module and the data transmission module.

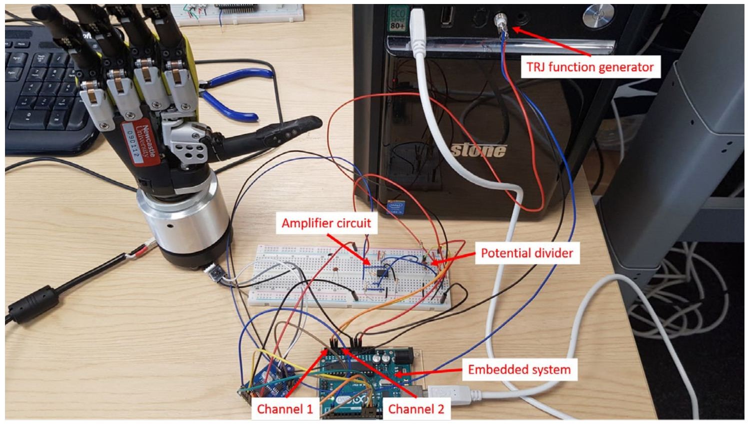
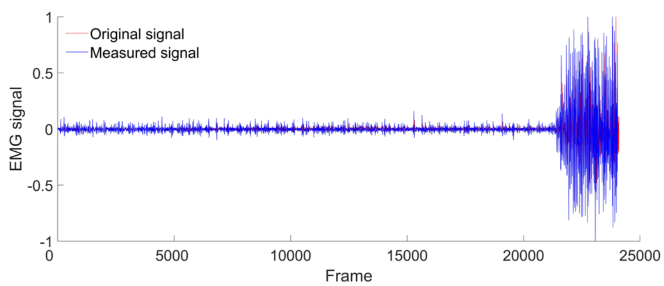


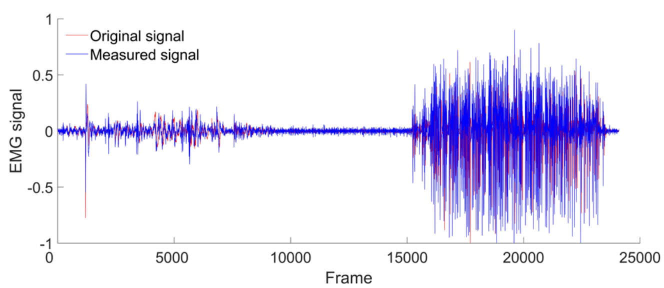
Figure 4: The embedded system connected with a prosthetic hand and TRJ function generator

Analysis of the EMG signal

Figure 5 shows the comparison between the original EMG signals and the signals measured from the embedded system. The original signals were previously recorded by D360 amplifier (D360, Digitimer, UK) at 2 kHz sampling rate for 12 seconds. Since the sampling rate of the embedded system was set to 1 kHz, linear interpolation was applied to the sampled signals to maintain the same length as the original signals. The measured signals closely matched to the original signal. The correlation coefficient between the moving MAV of the original signals and that of the measured signals are 99.43% and 97.58% at two channels.



(a)



(b)

Figure 5: The comparison between the original EMG signals and the measured signals at (a) channel one and (b) channel two.

Evaluation of the control module

The state of the prosthesis controller is changed by the control signals. Figure 6 shows an example in which the embedded system sent two motor commands to the prosthetic hand. The first command was sent at the 856^{th} frame, which was 0.75 second (75 frames) after the increase in the control signal on channel two. It changed the prosthetic hand from the normal grip to the pinch grip. The second command was sent at the 1279^{th} frame, which was 0.37

second (37 frames) after the participant released the muscle on channel 1. The prosthetic hand returned to the normal grip after receiving the command. The time required to change the state of the prosthesis was keeping the cursor position at the same zone for 0.25 second (25 frames) as expected. Although the cursor temporally moved to zone two between the 1243^{th} frame and the 1254^{th} frame, the abstract decoder did not send a command to the prosthetic hand.

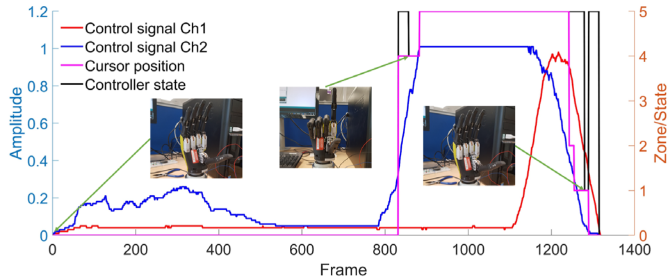


Figure 6: The EMG control signals and the corresponding changes in the state of the prosthesis

DISCUSSION

The analysis of the EMG signals and the controller states demonstrates that the Arduino development board is capable of EMG data collection. The measured signals on both channels maintain high similarity with the original signals generated from the TRJ function generator. The abstract decoder working at 100 Hz can correctly indicate the location of the cursor and control the prosthetic hand with a 10-millisecond temporal resolution. Its simplicity and low computational cost requirement allow it to be implemented on the Arduino board.

This paper presents a new embedded system with off-the-shelf components that allows myoelectric control through the abstract decoder. With a £17 equipment cost, the proposed system can achieve a maximum 2 kHz sampling rate for 2-channel EMG measurement and the real-time prosthesis control. It removes the barrier for many researchers to perform take-home experiments without designing a customised embedded system. We aim to present a demo of this system at MEC2020 and release the design specifications and code in due course.

ACKNOWLEDGEMENTS

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