Human-Machine Interface: Myoelectric Control Scheme to Restore Upper Extremity Motor Function

Yuni Teh\textsuperscript{1,2}, Ed Richter\textsuperscript{1}, and Arye Nehrari, PhD\textsuperscript{1}
\textsuperscript{1}Department of Electrical & Systems Engineering, \textsuperscript{2}Department of Biomedical Engineering
Washington University in St. Louis, Saint Louis, MO

Introduction

Peripheral neuropathies, most commonly caused by physical trauma, affect approximately 20 million people in the United States. In many cases, they cause motor nerve damage, which results in muscle weakness that restricts motor tasks. However, electromyograms (EMG), which measure the electrical activity of a muscle, can still be acquired from weak muscles, as long as they show some degree of response to innervation.

This project aims to use patterns from EMG signals to control a FANUC robotic arm that replaces basic arm functions in patients with upper extremity neuropathies. In specific medical applications, a cutoff frequency of 20 Hz, then amplified again with an instrumentation amplifier (INA118), high pass filtered with infra spinatus along the shoulder: biceps, triceps, trapezius, pectoralis major, and pectoralis minor, and... and B. Hudgins, "A real-time pattern recognition based myoelectric control usability study implemented in a virtual environment,” presented at the Engineering in Medicine and Biology Society, 2007. EMBS 2007.

Data Acquisition

Bipolar dry electrodes were attached to five muscle groups along the shoulder: biceps, triceps, trapezius, pectoralis major, and infraspinatus. Each electromyographic signal was pre-amplified with an instrumentation amplifier (INA118), high pass filtered with a cutoff frequency of 20 Hz, then amplified again with an operational amplifier (TL072).

The circuit was built on an NI ELVIS II board and the signals were acquired through the built-in analog-to-digital converter (ADC) at a sampling rate of 1 kHz.

Data Processing and Classification

The raw EMG signals were processed in 500 ms segments, or extraction windows. Four features were calculated for each muscle channel: mean absolute value (MAV), number of zero crossings, number of slope sign changes, and waveform length.

\[
MAV: \bar{x}_i = \frac{1}{N} \sum_{k=1}^{N} |x_k| \quad \text{Waveform Length: } l_k = \sum_{k=1}^{N} |x_{k+1} - x_k| \]

The classifier training data was comprised of $5 \times 4$ feature vectors for each movement and 20 feature vectors for the resting state. Based on this data, linear discriminant analysis (LDA) classifiers corresponding to each movement (and resting state) were built with the classify function in Matlab. Score thresholds for each classifier were set using the training data so that there would be no more than 1% false negative errors and 0.1% false positive errors.

FANUC Robot Implementation

An adjustable mode control scheme was employed to obtain a versatile work envelope with 3 degrees of freedom and a gripper using only five movements. A sample of allocated control signals is shown below.

Results and Discussion

The data acquisition hardware obtained EMG data with a sufficiently high signal-to-noise ratio (SNR). The gains of each muscle channel were varied to avoid clipped signals. The gain values should be customized based on the user’s muscle strength.

The five chosen movements were found to be linearly separable, as shown below on the right. Using recorded data, a 100-fold cross validation test with 3:2 training to testing ratio yielded an average false positive error of 0% and an average false negative error of 2.08%, indicating a very robust classifier. With this system, the user successfully controlled the robot to grab a cup.

Conclusions and Future Work

The proposed human-machine interface successfully replaced natural arm movements with a robot through a robust myoelectric classification system. There is room for further investigation, starting with testing the system on a person with a motor nerve damage. For a more convenient setup, the EMG hardware should be miniaturized and the number of muscle groups should be minimized without sacrificing classifier accuracy. Furthermore, the FANUC robot should be replaced with a less cumbersome device.

References

[2] Forbes T., "Mouse HCI Through Combined EMG and IMU," Department of ELECTRICAL ENGINEERING, University of Rhode Island

Acknowledgments

• Ed Richter
• Arye Nehrari, PhD
• Dennis Mell
• Mianzhi Wang
• Yen Shih-Cheng, PhD
• Thanawin Trakoolwilaiwan
• Alexander Lim
• Claire Poulard