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Human-Machine Interfacing via Epidermal Electronic Systems

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ELECTRICAL AND COMPUTER

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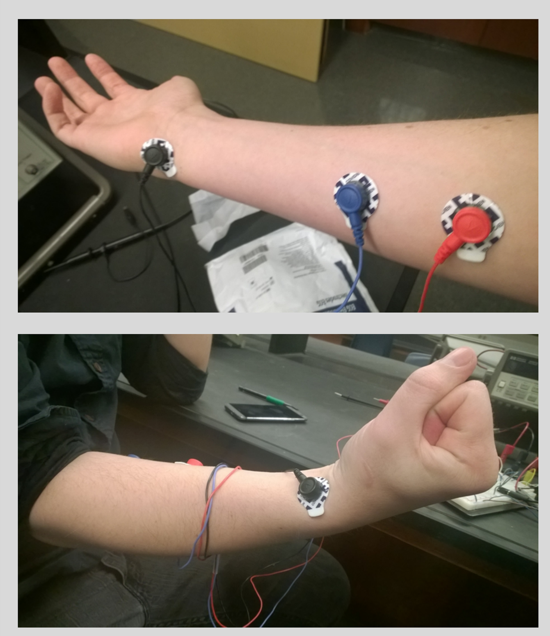
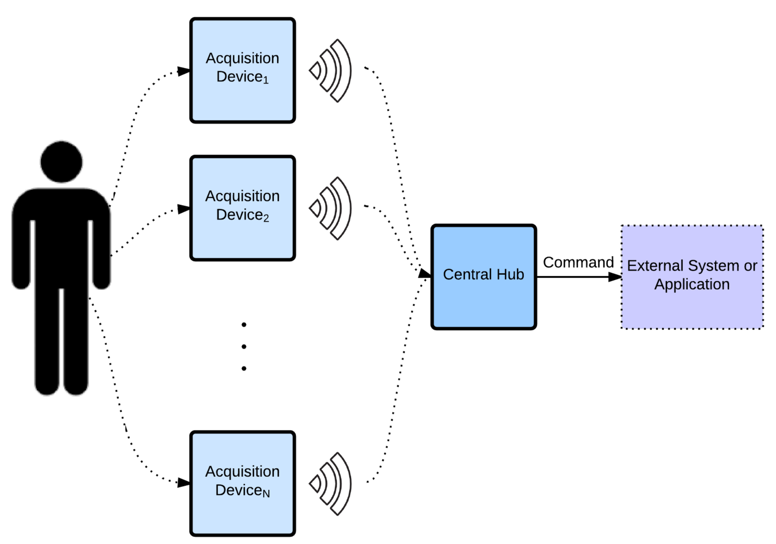
CAPSTONE DESIGN EXPO 2015

Introduction

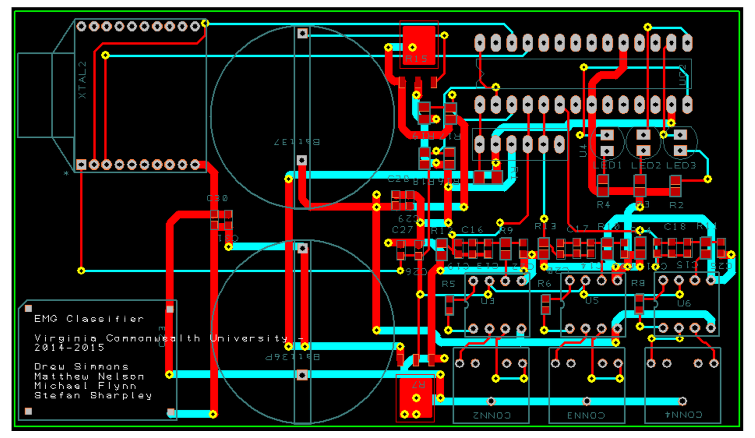
Surface electromyography (EMG) is quickly becoming a reliable and cost-effective way for interfacing with external systems. While EMG equipment is becoming cheaper and more sophisticated, the technology is still difficult to utilize effectively. This project's aim is to provide a simple, extensible system to assist researchers, developers, and hobbyists with applying this technology for practical use.



System Overview



High-level diagram with multiple acquisition devices sending EMG information to the hub



PCB layout for the data acquisition device

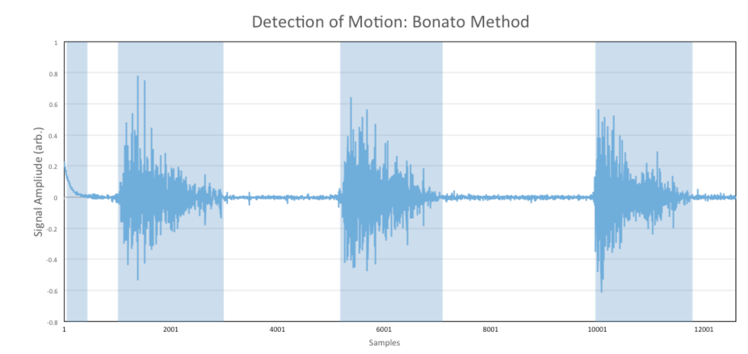
This system involves a network of data acquisition devices transmitting information wirelessly to a central hub. These acquisition devices are placed on the user and can each measure up to three muscles from a single muscle group, connecting directly to the EMG sensors and handling all of the signal processing and analysis. Devices can be added as needed to analyze motion in different areas of the body and are are compatible with most EMG sensors.

As the central hub receives data from a given acquisition device it classifies the signal and sends a command to an external system according to the gesture identified. These commands and gestures can be configured by the user, allowing this system to be easily adapted for many situations.

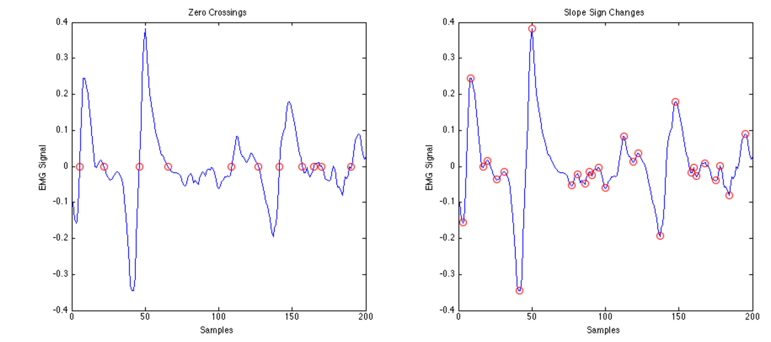
EMG Signal Processing

For optimal signal analysis and classification, the system needs to be able to detect onset of motion quickly and efficiently. A double threshold comparator that adjusts for baseline variance in the signal (Bonato method) is used to determine where the gesture begins.

Once motion has been detected, features of the signal can be analyzed. Temporal features are utilized so that they can be calculated as the signal is received. Selection of features to observe is determined by examining which features provide the most discrimination for used gestures.



Signal with highlighted portions showing motion detected with the Bonato Method



An EMG signal annotated with two temporal features

Gesture Classification

$$D_M(x) = \sqrt{(x-\mu)^T S^{-1} (x-\mu)}$$

Equation for Mahalanobis distance, with mean vector of observations μ and covariance matrix S

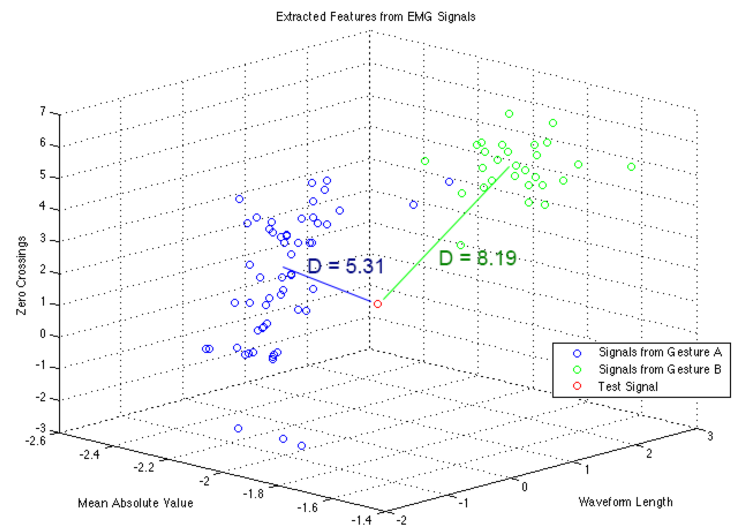


Illustration of classification with three features between two gestures

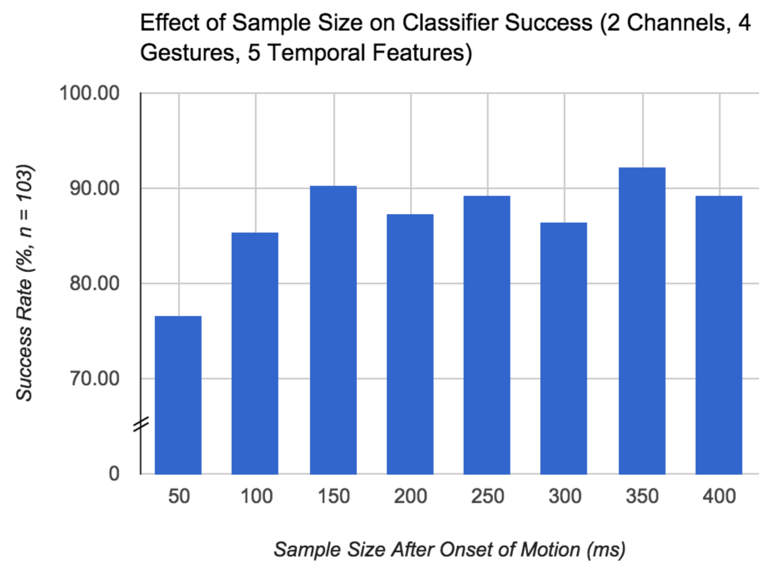
Classification of an EMG signal is done by extracting features and comparing them with a known set of signals. Before the device can be used, the user undergoes a short training session to teach the system how to differentiate between gestures that they want to use.

Once trained, whenever onset of motion is detected the system extracts features from a short sample of the signal and calculates its Mahalanobis distance from the classifier's trained classes. The system identifies the signal as the class with the shortest distance and emits the corresponding command.

Results

When discerning between four gestures and measuring two muscles on a user's forearm, the classifier was able to achieve a 90.29% success rate with a sample size of 150ms. This sample size was chosen for being the most accurate while still feeling responsive to the user. Larger sample sizes showed only nominal improvement while introducing additional latency.

As more gestures are defined, the accuracy of the classifier decreases with a success rate of only 71.90% between six gestures. To increase accuracy, additional sensors can be added to the acquisition device and placed effectively at critical muscles for the gestures involved. In one case, accuracy was able to improve by 27.79% with the addition of another sensor and better muscle placement.



Number of Gestures	Success Rate	Number of Trials
2	100.00%	59
3	97.50%	80
4	90.29%	103
5	80.47%	128
6	71.90%	153

Accuracy of classifier decreases as gestures are added (sample size 150ms, 2 channels, 5 temporal features)

Conclusions / Future Work

The initial prototype of this system was successful, demonstrating high accuracy while being responsive enough for real-time use. With this complete, work can begin towards fitting the acquisition device for wearable use and packaging the system to be easily configurable by the end user. Additional work can also go towards further optimization of the system, such as tightening motion detection and autonomously determining optimal parameters for signal analysis. As it currently stands, this system is ready for practical use, with possible applications in areas such as prosthetics, vehicle control, or simulation interfacing.