Gesture Recognition via Electromyograph Signals

1. Problem Description

Much of this section is adapted from my thesis proposal. It has been edited to fit within the scope of this class project.

Skeletal muscles produce electrical impulses when activated. These electrical impulses can be detected and recorded using an electromyograph. There are two primary varieties of electromyograph. The first requires hypodermic needles to be inserted in the area of study. The second version of the device is known as a *Surface* electromyograph ("sEMG"). Surface electromyographs perform the same function but are less invasive at the cost of decreased precision. The quality of readings taken by surface electromyographs are known to be effected by personal characteristics such as perspiration, subcutaneous body-fat content, and jostling or shifting of the sensor array [2].

As sEMG technology has become more available researchers have turned their attention to the information that might be available through these devices [3]. In particular, the problem of classifying movements is now popular enough that several datasets of recorded signals and subject characteristics have been generated and published [1].

Researchers have been successful in gesture classification using EMG sensor data through a variety of means [3]. However, methods employed for this task face two notable considerations:

1) Limited computational resources - processors and memory may be restricted to what can be embedded in a device.
2) Availability of training data - The amount of training data required to achieve satistfactory results without overfitting is limited to the quality and configuration of equipment of a single study. [4]

The artificial neural network ("ANN") is a prime example of a high-performing algorithm that has performed will in-sample but does not generalize well due to these constraints.

This project seeks determine whether or not it is possible to extract latent features common to various classes of gestures in a way that is invariant to minor differences in quality and configuration of sEMG sensors and superficial characteristics of the wearer. This is important because, if successful, a large amount of training data captured in differing studies can be generalized with minimal information loss. I believe this can be achieved using topological methods for feature selection.

Persistence diagrams allow us to inform decisions about high-dimensional geometric properties of data without the information loss associated with other techniques for visualizing features (e.g. principle component analysis). Persistence images use a weighting function emphasize pertinent topological features of a signal and de-emphasize noise. This approach should outperform the typical moving average approach [3] to preprocessing sEMG signals which "bake-in" signal noise and in some cases smooth over potentially important characteristics like medium-sized amplitudes.

2. **Previous Work**

The primary work that inspired this project is *Latent Factors Limiting the Performance of sEMG-Interfaces* by Lobov, *et al.* [2] in which the goal is to control a pac-man style game using gestures. While the subjects were able to control the game character with some success using gestures, they performed the task far better when using a mouse or joystick. The research team preprocessed the sEMG training data using a root mean square (RMS) moving average for smoothing. They employed both a linear discriminant analysis ("LDA") classifier and an artificial neural network ("ANN") classifier.

3. **Data**

The data set I will be using for this project is the *EMG data for gestures Data Set* from the UCI Machine Learning Repository [6]. This data set was collected by Lobov, *et al.* during the study described in the previous section.

This data set consists of 36 subjects performing a series of six distinct gestures. Each subject performed their gestures four times for approximately three seconds per gesture. The motions were captured by a bracelet placed on the forearm and transmitted via Bluetooth to a PC where the data was recorded. The bracelet was equipped with 8 evenly spaced sEMG sensors. The result is a data set of approximately 864 matrices of size $t \times 10$ where t represents elapsed time in milliseconds. The 10 columns of each matrix are time, sensor readings 1 - 8, and a gesture label.

4. **Analysis Methods & Pipeline**

My goal is to develop a data pipeline that consists of a feature extraction component and gesture classification component.

Methods from topological data analysis will be utilized for feature extraction.

Specifically the persistence of topological features in the set of sEMG modalities will be examined independently as well as jointly with the intention of developing a smoothing mechanism for removing variance due to personal characteristics described by Lobov, *et al.* [2]. Topological methods are rarely - if at all - utilized in the problem of gesture identification with most researchers opting for more traditional methods for smoothing EMG signals (e.g. moving averages, RMS, etc.) [3].

The second step in the pipeline is a general classifier capable of reliably differentiating gestures with some degree of invariance to the format of training data. The technique of self-similarity matrices ("SSM") described by Traile, Bendich, and Harer may be used for this task wtih some modification[5].

5. **Software**

6. **Risk Mitigation**

References

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