Gesture Recognition via Electromyograph Signals

1. **Problem Description**
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.

   The 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**
5. **Risk Mitigation**

Applications of machine learning and signals processing techniques to human-computer interface ("HCI") problems have seen a significant rise in interest in the past decade. In particular, the problem of identifying hand and wrist gestures via electromyography ("EMG") sensors has become popular enough that several datasets of recorded signals and subject characteristics have been generated and published [1] [2].

Electromyography is a method by which electrical impulses produced by muscles can be recorded. *Surface* electromyographs ("sEMG") are sensor devices capable of recording these electrical impulses on the surface of the skin as opposed to their intramuscular counterparts. A drawback to surface EMGs is the effect of personal characteristics such as perspiration, amount of subcutaneous body-fat, and jostling or shifting of the sensor array [2].

The primary goal of researchers in this area has been to improve upon non-invasive, robotic prosthetic hands and forearms. Researchers have seen success in gesture classification using EMG sensor data through a variety of means [3]. However, methods employed for this task face two notable considerations: the first of these is computational cost - processors and memory may be restricted to what can be embedded onboard a prosthetic. The second consideration is the amount and availability of training data required to achieve satistfactory results without overfitting [4]. The artificial neural network ("ANN") is a prime example of a high-performing algorithm in this space that is subject to these constraints.

This second consideration regarding training data contains some subtleties worth noting. Although there are a number of publicly available databases for sEMG training data, it is usually not possible to combine this data for training a single model. As described by Phinyomark [4], this is due to the measurements being taken in different manners using equipment differing equipment quality.

The intention of this research project is to develop a data pipeline consisting of a feature extraction step and a subsequent gesture classification step capable of addressing these constraints. Ideally this pipeline will be capable of operating on streaming data as would be encountered by a prosthetic device or other HCI devices while in use. This hypothetical pipeline would address the concerns described above as follows.

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].

References

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