**Quasi-MVC**

Short-Proposal

**1. Introduction**

There is a need to remotely monitor physical activity at the neuromuscular level to both increase health and to collect data to understand movement disorders outside the clinic. The benefits of remote muscle-based physical activity tracking span a wide variety of patient populations including persons with knee osteoarthritis, stroke patients, patients with obesity, and patients recovering from surgery [1], [2]. Thus, remote monitoring of physical activity using surface electromyography (EMG) has already started to take off [1]–[5]. However, a standard protocol for remote use of EMG has not yet been established.

EMG sensors contain electrodes that, when properly placed on the surface of the skin, detect the electrical signals associated with muscle contractions. However, the use of EMG has many challenges. EMG signals are affected by many factors including electrode placement, skin impedance, orientation of the muscle fibers, perspiration, temperature, individual muscle characteristics, and the amount of tissue between the muscle and the surface of the skin among others [6]. These factors mean that EMG signals vary between and within individuals, and as such, need to be normalized to a reference value at least every recording session.

The gold standard EMG reference value is the mean EMG amplitude resulting from a maximum voluntary contraction (MVC). In this case, an MVC is performed for each muscle of interest, and therefore, each muscle has its own normalization value. Normalization to MVC often provides reliable results with high resolution due to normalization to a maximum value. However, an MVC cannot be performed without the facilitation of a trained assistant, and as such, is not suitable for remote deployment of EMG. Therefore, to deploy EMG for remote use, there is a need to develop a quasi-maximum voluntary contraction (MVC). We aim to develop the quasi-MVC through machine learning, where EMG data collected during walking tasks will be used as the input to predict the mean MVC. This MVC prediction value could then be used as the reference value for normalization.

**2. Problem Definition and Algorithm**

A quasi-MVC needs to be developed to deploy EMG for remote use. MVC is considered the gold standard method for EMG normalization, but is not reliable or appropriate for use in remote settings [7]. Instead of using other normalization methods that may not be as reliable as MVC, we aim to leverage machine learning algorithms to train a model to accurately predict mean EMG values from MVC tasks using EMG values from walking data as the input.

The input to our model will be features extracted from EMG data from known walking bouts in healthy subjects. Features have not yet been selected, but will be motivated by features commonly used in prosthetics control such as the mean absolute value (MAV), root mean square (RMS), variance (VAR), waveform length (WL), median frequency, or percentage of gait cycle [8]. The output of our model will be the predicted MVC value (e.g. mean EMG from an MVC trial). Because our inputs and outputs are continuous, we will use one of the following machine learning algorithms: linear regression, support vector machine regression, decision tree/random forest regression, or neural networks.

Although EMG has become a popular research tool, it is not well known in the general public or in the clinical space, which is hindering its ability to truly benefit society [9]. One step we can take to make EMG more approachable to the public and to clinicians, is to provide methods to use it remotely. It is our hope that if the machine learning approach described above is successful, researchers and clinicians can more readily implement EMG, allowing it to become a ubiquitous tool that benefits society.

**3. Dataset**

Our dataset is comprised of data from wearable sensors (inertial measurement units) worn on 41 healthy subjects for 24 hours per subject. The data is from a study that was conducted in the M-Sense Lab at UVM. This data is available and we have access to it.

The dataset includes EMG, acceleration, and gyroscope data. The data is split into supervised data collected in the lab where known activities are pre-labeled (i.e. we have walking at different speeds and an MVC trial for each subject), and remote data where activities will need to be labeled if that data is to be used. We already have a classifier that can accurately detect walking data from the remote data, however, it is in MATLAB. We plan to translate this to Python if time permits, otherwise, we will only use the lab data.

**4. Related Work**

This is a novel project. The only related work is in regards to using EMG as input to a machine learning algorithm for the control of prosthetics [8], or for early fall detection [10], [11]. We will use these similar references to help us extract appropriate features from the EMG signal.

**5. Bibliography**

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