Using estimation uncertainty to improve prosthesis control

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Introduction

Electromyography (EMG) is the recording and utilization of muscle generated electric potentials, widely used in control of functional prosthetics. The electric potentials recorded from the muscles are action potentials generated by the activation of a muscle contraction. The contraction force a muscle produce is related to the intensity of an EMG recording. The recorded EMG signals are processed through several steps of amplification, filtering and feature extraction before they are used as input in the control for a myoelectric prosthesis. [1, 2]

Myoelectric prosthetics are becoming increasingly advanced, however they still suffer commercial success due to lack of usability outside clinical environments. [3, 4, 5] Thus, many users reject the use of the prosthetics. In recent years development in myoelectric prosthetics have been greatly focused on refining classification accuracy, while other research areas have been more or less neglected [4]. However, there still exist a challenge for the users to be able to consistently produce distinguishable muscle patterns, and the better these muscle patterns the better the system will function. [6] Far fewer studies have been made on user training when compared to studies on system training, though the significance of user training is not doubted [7]. Powell et. al conclude that in order for amputees to understand the significance of producing consistent and distinguishable muscle patterns, the need for user training is important [8].

Fang et. al [7] evaluated the progress of the human learning ability in a pattern recognition based control scheme when providing classifier-feedback during user training. Here, a clustering-feedback method based on Principal Component Analysis (PCA) was used to provide users with real-time visual feedback, to guide users to correctly perform movements based on the recorded EMG signals. The visual feedback consisted of a map with dots representing centroids of classes. Through control based on an Linear Discriminant Analysis (LDA) classifier, users could match the control input to these centroids to best perform a movement to be classified correctly. The study showed great improvements for user training, and an ability to quicken the learning for amputees who are unfamiliar with EMG controlled prosthetic use. [7] Powell et. al [6] demonstrated, by using an LDA classifier, an increase in movement completion percentage from 70.8% to 99.0%, a decrease in movement completion time from 1.47 to 1.13, as well as a significant improvement in classifier accuracy from 77.5% to 94.4%, for users undergoing user training for a two week period. This study provided feedback through a virtual animated prosthesis. Pan et. al [9] provided a visual feedback of an arrow to be moved on a 2D plane. Pan et. al also tested the effect of stimulating the subjects' brain with transcranial direct current stimulation (tDCS). The study concluded that tDCS together with user training provided significantly better results than user training alone. [9]

The general challenge of user training is for the user to be able to consistently produce distinguishable muscle patterns. [6] Therefore further research in user training could provide a vital leap towards more precise classification using current methods, as well as a faster user adaptation of myoelectric controlled prosthetics, but an effective way to properly provide feedback to the user have yet to be developed. Further studies should for now concentrate on developing different feedback methods which should later be compared to determine an ideal method. This study will seek to develop a new method of feedback during user training, by providing the users with the estimation uncertainty of the classification. To the authors knowledge, user feedback has not been provided with this method before.

Methods

Data acquisition will be done with a Myo armband (MYB) from Thalmic Labs. The MYB contains eight surface EMG electrodes, which has a sampling rate of 200 Hz. For **feature extraction** four features will be extracted from the acquired data; slope-sign changes (SSC), waveform length (WL), zero crossings (ZC) and mean absolute value (MAV). The features will be extracted from a window of 200 ms (40 samples) with a 50% overlap. For **classification** LDA will be used. LDA is a supervised classification method used to separate classes of data by linear decision boundaries. Classification methods attempt to classify similar patterns in EMG signals, between previously acquired data and new data [10]. In LDA each decision boundary is a hyperplane from which the minimum distance from the classes it separates is maximized, and the distance from the means of the classes are maximized. A decision boundary is defined as a linear combination of the feature values. Evaluating the certainty that a feature value belongs to a given class can be done by computing the posterior probability of each class. The posterior probability is a value between 0 and 1. The posterior probability is given as the product of the class conditional probability and the prior probability divided by a normalization term that guaranties that the posterior probabilities for all classes sums to one. The class conditional probability is the probability of obtaining a feature value when selecting samples randomly from a class. The prior probability is the likelihood that a sample from a class appears when compared to the other classes before it actually has appeared.

The effect of user training with and without providing uncertainty estimations during the user training, will be tested through a target reaching test. The test will executed in a virtual environment. During the test the user must reach targets of varying size and distance to each other. The test evaluates users speed to reach targets, accuracy, overshoot and overall completion rate [11]. Lastly a **statistical** analysis will be used to compare results of the target reaching test between users training with and without provided estimated uncertainty during user training.

Study protocol

Research question/hypothesis

Using uncertainty estimation as visual feedback during user training will improve the users performance in a linear discriminant controlled target reaching test based on electromyography recordings.

Ethical considerations

The investigators do not foresee any obstacles of ethical nature during the proceedings of this experiment. No test subjects will be exposed to any physical interventions besides being asked to wear the Myo armband. No part of this experiment should put the subject in danger.

Session time

The experiment consist of one session divided into two sub-sessions with an estimated total duration of 2-3 hours.

Inclusion criteria

The subject needs to be:

- able bodied.
- between 18 and 35 years of age.

- able to understand and speak Danish and/or English.

- assessed by the investigators to understand and perform the instructions given during the experiment.

Exclusion criteria

The subject must not have:

- diseases that, assessed by the investigators, might influence subject performance.

Experiment procedure

The experiment is divided into two sessions: 1) training data acquisition, user training and performance test and 2) new training data acquisition and performance test. During the training data acquisition EMG data will be recorded from the subject with an EMG-electrode armband (Myoband from Thalmic Labs) when performing four different wrist movements (flexion, extension, radial deviation and ulnar deviation). The data is subsequently used to fit a classification model used in the myoelectric control scheme for the following user training and performance test. Before the performance test the user is given a training period to get familiar with wrist movements used in the performance test. During the performance test the subject will perform a target-reaching task in a cartesian coordinate system of reaching a number of targets using wrist movements, where each axis represent a one of four wrist movements. The aim for the subject is to reach as many targets as quickly as possible. The subject will perform the target-reaching task twice - one in each session. The subjects are divided into two groups: a test group and a control group. As the study is single-blinded the subject will not be informed which group he/she belongs to.
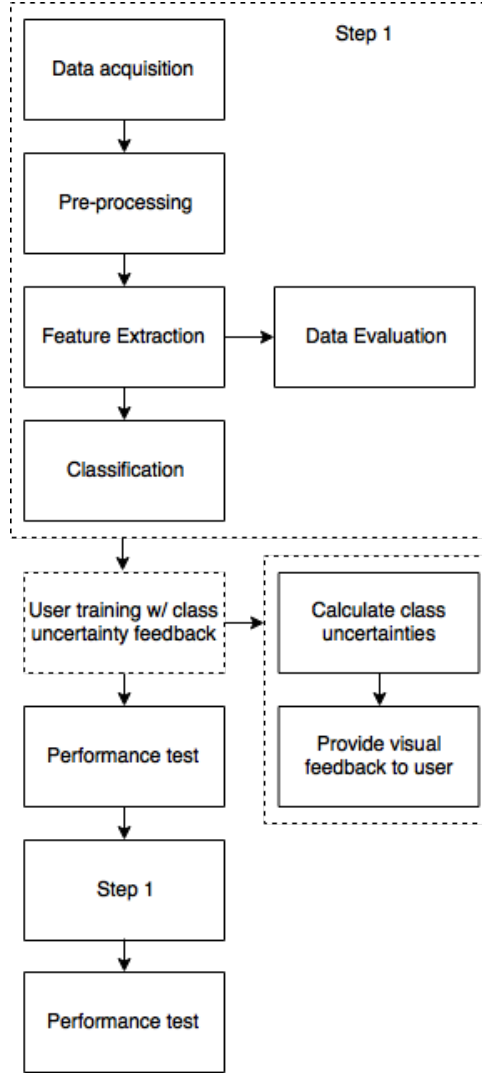
Figure 1: System pipeline for the test group. The following chronology describes the steps in greater detail.

Chronology of session 1, for subjects in the test group:

1. Apply Myoband on dominant forearm at the thickest part.

2. Synchronize Myoband by performing wrist extension until three distinct vibrations are felt.

3. Perform 15 seconds of maximum voluntary contraction (MVC) of instructed movement. Following the MVC the subject will be given a 30 resting period to avoid fatigue.

4. Perform 15 seconds contractions of respectively 40%, 60% and 70% of MVC. During these contractions the subject will control a green marker representing the EMG signal and try to follow a trapezoidal trajectory a precise as possible. The trapezoidal trajectory consists of two five second transition phases and one five second plateau phase. Between each trial the subject will be given a 15 seconds resting period to avoid muscle fatigue.

5. Repeat step 3-4 until training data from all four wrist movements has been recorded.

6. The subject will train the four wrist movements. Each movement will be performed 10 times, where each single movement consists of a five second movement with increased intensity. To improve the precision of movements the subject will receive visual feedback consisting of the probability the movement to belong to based on the classifier. The ideal probability during the training is a 100% probability of belonging to the trained movement and a 0% probability of belonging to the remaining movements.

7. The subject will perform a target-reaching test. The subject will control a cursor in a cartesian coordinate system representing the output of the LDA classifier. To complete a target the subject must dwell the cursor within the target for 0.5 seconds. If this is achieved the target will disappear. The target will similarly disappear if the subject fails to achieve this within 15 seconds. When a target disappears a new target appears for the user to reach. This procedure is continued until no more targets are shown. After finishing the performance test the subject will be given a 2 minutes resting period.

Chronology of session 2, for subjects in the test group:

1. Perform step 3-5 from session 1.

2. Perform step 7 from session 1.

The sessions for subjects in the control group will follow that of the test group with the exclusion of the provided estimation uncertainties during step 6.

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