A COMPARISON BETWEEN THREE PATTERN RECOGNITION ALGORITHMS FOR DECODING FINGER MOVEMENTS USING SURFACE EMG

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INTRODUCTION

Classifying surface EMG into different movement types using different pattern recognition algorithms is often used in research in upper limb prosthetics. Several different classifiers have been explored in the literature, however none of them have made it to market for prosthetic hands. Commercially available myoelectric hands are still controlled in a fairly simple open/close manner. As the there are more dexterous hands available for amputees such as the i-Limb by Touchbionics [1], the bebionic by RSLSteeper [2] and soon to be available hands such as the Michelangelo hand by Otto Bock[3], the Vincent hand [4] and the Continoe by Ortocare Innovations [5] the need for robust control algorithms are evident. There has been much research into control of hands using a vast amount of different techniques. Some of the earliest attempts at controlling prosthetic hands using pattern recognition approaches dates back to the 1970’s [6].

Using support vector machines and ten commercial Otto Bock electrodes, Bitzer et al. [7] were able to distinguish six classes of control to the DLR hand II. Sebelius et al. [8] used a virtual reality hand for training the amputees. Pons et al [9] used virtual hands for training amputees to control the MANUS hand prosthesis using a three bit sequential commands based on EMG. Another method proposed by Nan et al.[10] used five EMG-electrodes and a combination of Bayesian and neural networks to classify both location and motion in a cooking task, classifying six motions and six locations. Xinpu et al. [11] used a new method called SLEX (smooth localised complex exponential) to detect EMG features and a LDA (Linear Discriminant Analysis) to reduce the data set and a MLP (Multi-layer perceptron) network to classify eight wrist motions using six electrodes placed on the forearm of healthy participants. Using four channels of EMG signals Jun-Uk et al. [12] used a wavelet packet transform to extract a feature vector. This vector was subsequently dimensionally reduced using LDA and a multilayer perceptron network was used to classify the outputs to nine hand motions. Ning et al. [13] used a signal processing algorithm for extracting proportional control information for multiple DOF control from EMG signals. A nonnegative matrix factorization (NMF) was used to estimate neural control information from the EMG signals. Cipriani et al. [14] used a four command EMG-classifier and state machines to test different control strategies to command the Cyberhand with 14 able-bodied participants and a knn-classifier to control the Cyberhand in [15]. Tenore et al. [16] decoded individual finger movements (extension/flexion) of each finger (10 movements) using 19 electrodes for an amputee using traditional time-domain features and a multilayer perceptron as a classifier with an accuracy greater than 90%. Shenoy et al. [17] performed an online and an offline study using windowed RMS of the EMG-signal as a feature vector and a Support Vector Machine (SVM) as a classifier to control a 4-DOF robotic arm. Castellini et al [18] used two conditions; still arm (SA) and free arm (FA) to evaluate three different grasps using seven electrodes and ten able-bodied participants using SVMs. User-selected intentional movements were decoded in real time using EMG collected from two sites by Momen et al [19]. Features were extracted using the natural logarithm of RMS values and the feature space was segmented using a fuzzy C-means clustering algorithm. Englehart et al [20] using four channels of EMG compared LDA and MLP approaches using different features in a six class task. Hargrove et al [21] compared classifiers and features using both surface and intramuscular EMG. The preceding work has mostly used surface electromyography. For some in-depth reviews on pattern recognition techniques using EMG for control of prosthetic hands see [23],[24].

In this work a comparison between three different pattern recognition algorithms using perhaps the most simple feature set, the Mean Absolute Value, is made.

MATERIAL & METHODS

Ten able-bodied subjects (eight men and two women, aged 25-34) took part in the study. Surface EMG-signals were acquired using an in-house built amplification and data acquisition system. The system acquires 16 channels of EMG, sampled at 2 kHz per channel and with a bandpassfilter between 0.5 Hz and 800 Hz with 16-bit resolution per channel and a gain of 56 dB per channel. A custom-built LabView application (see frontend in Fig. 1) was used to store the data on a PC. A written and visual cue was given as to which movement the participant was meant to perform. The participants were sitting in front of the computer with their arm resting on a pillow during the time of the experiment.
Red Dot Ag/AgCl electrodes (3M Healthcare, Germany) were used in the study. The electrodes were placed on the forearm of the participants as in [8], [15]. Twelve electrodes were placed on the superficial flexor muscles on the volar side of the forearm and four electrodes were placed on the superficial extensor muscles on the dorsal side of the forearm.

The movements used for classification in this study were: thumb flexion, index finger flexion, middle finger flexion, ring finger flexion, little finger flexion, thumb opposition, thumb extension, index finger extension, middle finger extension, ring finger extension, little finger extension, thumb abduction and finally a rest class making up thirteen classes in total. This means flexion and extension of each individual finger as well as thumb adduction/abduction and a rest class. These movements would account for individual control of each digit. In the study after a cue was given the movement was to be held between 4-6 seconds until a rest cue was given. The rest state was of equal length as the movement. Two different datasets each consisting of five repetitions of each movement totalling 60 movements and the rest states were stored on the computer along with the intended class information.

Matlab was used to further process the data. The EMG-data was further bandpassfiltered using a 6th order Butterworth bandpass filter (10-500 Hz) and a 6th order notchfilter (centered at 50 Hz). Each channel of the filtered signals were also normalized. The Mean Absolute Values (MAV) (see top part of Fig. 2) of the filtered EMG-signals were chosen as a feature set. The features were extracted using a window size of 150 ms with a 50 ms overlap. To get an even higher classification accuracy a majority vote filter was used using ten values, five past and five future values. This implies the output of the classifier will be delayed by 250 ms. The delay can be tolerated and the output could still be considered as real-time were it to be applied in such an environment. The whole feature set was chosen as input to the classifiers without cutting rest-periods or performing any additional pre-processing (e.g. PCA).

Three different classifiers were tested: LDA (as has been used in e.g. [20]), k-nn as used by e.g.[8] and a network of multilayer perceptrons as has been used by [16]. All of these classifiers are available in Matlab. The knn classifier used had a k=16 and the Euclidian distance was used as the distance metric. In the MLP network, 16 hidden layer neurons were used and the network was trained using Matlabs scaled conjugate gradient algorithm. Both hidden and output layer neurons had a tansig transfer function. The two datasets were kept separate in the training and testing sessions for all classifiers.

RESULTS

The overall accuracies of the different classifiers can be seen in Table 1. The overall accuracies are not great, but still probably sufficient if using majority voting. Using more features or dimensionality reduction could increase the accuracy of the classifiers.

<p>| Table 1: Accuracy of the different classifiers with and without majority vote filtering |</p>
<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy</th>
<th>Majority vote accuracy</th>
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<tbody>
<tr>
<td>LDA</td>
<td>77.66 %</td>
<td>80.66%</td>
</tr>
<tr>
<td>knn (k=16)</td>
<td>77.98 %</td>
<td>80.77 %</td>
</tr>
<tr>
<td>MLP</td>
<td>79.59 %</td>
<td>82.11 %</td>
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</table>

**DISCUSSION & CONCLUSION**

The results show a that there is no great difference between the classifiers, given this problem and feature set. Expanding the feature set would likely yield a higher accuracy, but this would be at the expense of a more complex system. Each of the classifiers would be possible to implement in an embedded system that would be used to control a prosthetic hand. It should also be noted that this setup would lend itself well to be implemented in an embedded system. Calculating the MAV feature is fairly easy computing wise and the filters are not of a high order. Reducing the amount of channels to eight or even lower would also reduce the computing requirements of an embedded system.

Further work would be expanded to also include amputees as they are the ones who would be ultimate user of a classifier such as this in a sophisticated prosthetic hand system.

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**REFERENCES**