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Evaluation of the Myo Armband for the Classification of hand motions

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Abstract— **Pattern recognition-based control systems have been widely implemented in prostheses and virtual reality environments to improve amputees' quality of life. Most of these systems use surface electromyography (EMG) to detect user movement intentions. The Myo armband (MYB) is a wireless wearable device, developed by Thalmic Labs, which enables EMG recordings with a limited bandwidth (<100Hz). The aim of this study is to compare MYB's narrow bandwidth with a conventional EMG acquisition system (CONV) that captures the full EMG spectrum to assess its suitability for pattern recognition control. A crossover study was carried out with eight able-bodied participants, performing nine hand gestures. Seven features were extracted from the data and classified by Linear Discriminant Analysis (LDA). Results showed a mean classification error of 5.82 ± 3.63% for CONV and 9.86 ± 8.05% for MYB not significantly different (P = 0.34). This implies that MYB may be suitable for pattern recognition applications despite the limitation in the bandwidth.**

I. INTRODUCTION

The Electromyography (EMG) records the electrical activity from contracting muscles. Changes in the amplitude of these signals can be used to detect motion, but advanced processing like pattern recognition, is usually required to identify the underlying type of gesture. The combination of EMG signals and pattern recognition has been widely studied [1-7] aiming to improve the dexterity of upper-limb prostheses, by restoring control of several degrees of freedom.

In this context, pattern recognition is based on the idea that similar movements produce similar signal characteristics, differentiable from other movement patterns. To analyze the data, processing is divided into segmentation, extraction of characteristic features, dimensionality reduction of the feature space and classification. In this last step, decision boundaries are computed depending on the classifying algorithm such as Support Vector Machines (SVM) [2,6,8,9], K-Nearest Neighbor (KNN) [6,8], Artificial Neural Networks (ANN) [2,6,9] or Linear Discriminant Analysis (LDA) [2,6,8,9] .

Although direct measurement of the electrical activity from the muscles is allowed via inserted electrodes, most studies in pattern recognition have focused on surface EMG [1,10].

The Myo armband (MYB) is a wireless wearable device developed by Thalmic Labs, able to record EMG via eight stainless steel superficial electrodes. In addition, MYB counts with a nine-axis inertial measurement unit (IMU) sensor, haptic feedback and Bluetooth communication [11]. These features combined with a compact design, that easily adjusts to the forearm, maintaining interelectrode distance, could lead to a more user-friendly acquisition system. However, the main disadvantage of MYB is its limited sampling frequency of 200Hz.

Most studies in pattern recognition have used higher sampling frequencies than 200 Hz to capture the whole EMG signal spectrum and feed more information to the classifier. Li et al. [12] studied the influence of the bandwidth in classification accuracy by testing several cutoff frequencies for the high pass filter and sampling frequencies ranging from 1kHz to 100Hz, with decrements of 20Hz. Results showed that classification performance using only four time domain features, slowly decreases as sampling frequency is reduced, until 400Hz where it drastically drops.

Initially designed for entertainment purposes, MYB is becoming more popular in the biomedical scientific community, being applied in fields such as medical imaging [13] or prosthetics for rehabilitation purposes [14]. Nevertheless, these are preliminary studies that do not evaluate the actual capabilities of the MYB in pattern recognition, and the effect of its small bandwidth. Therefore, the aim of this study was to assess the suitability of MYB in the classification of hand motions. To achieve this, the classification performance of MYB data, was compared to the conventional full band EMG acquisition setup (CONV) in a crossover experimental study.

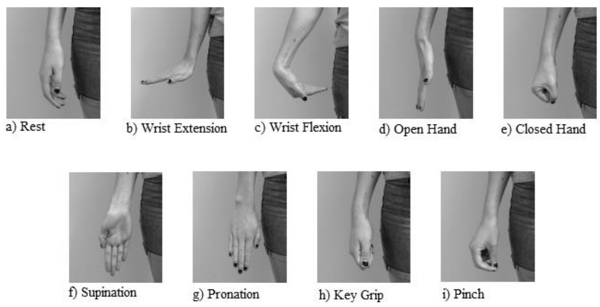

Figure 1: Recorded hand gestures: Rest, Wrist Extension, Wrist Flexion, Open Hand, Closed Hand, Supination, Pronation, Key Grip and Pinch.

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II. METHODS

A. Data Acquisition

EMG signals were obtained from eight able-bodied subjects (five females/ three males, ages: 19-25 yrs.) from the two acquisition systems in a crossover design. The order of each system was randomized per subject. For each subject, the MYB was positioned first and the sites of the six electrodes marked. The six electrodes were chosen to cover the following muscles 2 cm distal to the elbow: *extensor carpi ulnaris, ulna, extensor digitorum, extensor carpi radialis longus, flexor carpi radialis* and *palmaris longus*. The marked areas were used to assure same electrode positions for the CONV system (Ag/AgCl bipolar electrodes) no matter whether the subject was selected to start with one or the other system. CONV Signals were acquired at 2 kHz sampling frequency and analog filtered between 10-500Hz. MYB signals were sent via Bluetooth 4.0 to the acquisition software developed in MATLAB, using Myo SDK MATLAB Mex Wrapper toolbox [15].

Each subject performed five sets of nine movements (see Figure 1) in a randomized order with both acquisition systems. Each movement was held for 4s, with 15s break between movements, and three minutes break between sets to avoid fatigue. The ethical committee of Northern Jutland approved the experiment (N-20160021).

B. Data Processing

The acquired signals were processed in MATLAB for pattern recognition. To fairly compare between CONV and MYB, only six channels of the MYB were analyzed (MYB6). Secondly, MYB6 was compared to the performance obtained with eight channels of the MYB (MYB8).

To focus on the steady-state part of the signal, only the central part of the contraction was analyzed. Steady-state regions, corresponding to constant force contractions, contain more discriminating movement information than transient states, yielding in higher classification performance [16]. Therefore, the middle 3s of each contraction were concatenated into a 15s signal for each hand gesture. Figure 2 shows the raw data obtained after concatenating every motion and removing the transient parts of the contraction.

Resulting data was segmented with an overlapping window of 200ms and 50ms increment. Six-time domain features were selected from the literature [17,18] (WL, MAV, WAMP, CARD, SSC and ZC) and evaluated for correlation. The counting nature of some features requires setting certain thresholds. According to [19], no threshold is required for ZC and SSC, whereas preliminary work [20], prevailed that a threshold of 0.1:1 times the root mean squared of the rest signal is needed for WAMP and CARD. Based on this research, the feature extraction code was implemented using no threshold for ZC, SSC, and the root mean squared of the rest signal as threshold for WAMP and CARD.

The obtained feature set was dimensionality reduced with Principal Component Analysis (PCA) to preserve 95% of the variance. BioPatRec dimensionality reduction function was employed for this processing step [21]. The reduced data was fed into a Linear Discriminant Analysis (LDA) classifier, due to its high performance in previous research [5,21-23] and fast implementation. LDA was built with a 4:1 training and testing ratio, repeated for a five-fold validation of the training data. Finally, the percentages of classification error obtained in each validation step were averaged for each subject.

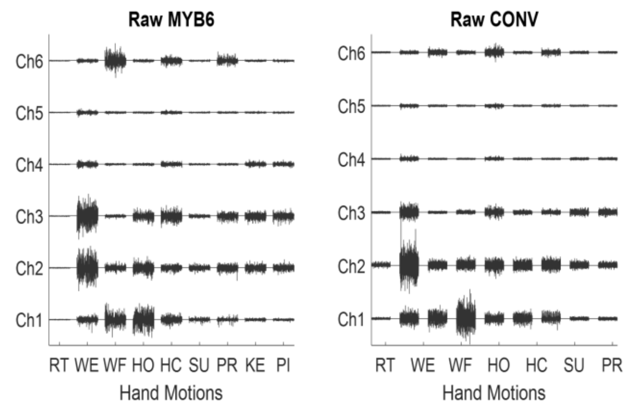

Figure 2: Raw EMG signals of 3s contractions of one subject showing different contraction patterns for each movement (Rest, Wrist Extension, Wrist Flexion, Hand Open, Hand Close, Supination, Pronation, Key Grip and Pinch) and the channels employed for MYB6 and CONV.

Due to the low number of subjects the non-parametric Kruskal-Wallis test was applied to evaluate the performance between MYB6 and CONV, and between MYB6 and MYB8. P-values less than 0.05 were considered significant.

III. RESULTS

Figure 3 shows the normalized power spectral density (PSD) of both the MYB and the CONV computed using the fft function in MATLAB. Figure 3 depicts the limited PSD of MYB with respect to CONV for just one subject and a single movement.

Mean percentage classification error after five-fold validation of the LDA training data, show lower error for CONV data, see Table 1. However, there was no statistical difference in classification error between CONV and MYB6 is not significant (P=0.34).

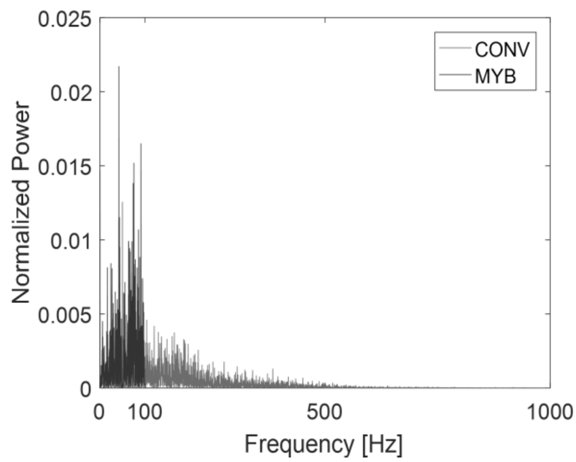

Figure 3: Normalized power spectral density (PSD) of CONV (light blue) and MYB (dark blue), showing the restricted bandwidth of the latest.

TABLE I. CONV AND MYB6 CLASSIFICATION ERROR

	Percentage of classification error		
	CONV	***MYB6***	***MYB8***
Subject 1	4.00	11.67	10.73
Subject 2	2.88	8.83	8.34
Subject 3	5.99	5.13	3.78
Subject 4	7.56	17.81	13.32
Subject 5	0.60	0.41	0.45
Subject 6	7.33	9.73	9.36
Subject 7	12.72	24.02	20.36
Subject 8	5.46	1.27	0.30
Mean ± STD	5.82 ± 3.63	9.86 ± 8.05	8.33 ± 6.80

Increasing the number of channels from six to eight in the MYB yielded in reduction of 1.53 in the mean percentage classification error, see Table 1. Kruskal-Wallis analysis showed no significant difference between MYB6 and MYB8 data performance (P=0.67).

IV. DISCUSSION

The application of pattern recognition-based myoelectric control systems has great potential to restore movement functionality in amputees. Full band conventional acquisition systems for surface EMG (CONV) have shown good performance. On the other hand, MYB is a wearable device that is gaining interest in the research community due to its compact design and ready to use sensors. However, only preliminary studies are available [14] for this purposes, without an assessment of the influence of its limited bandwidth (<100 Hz) in hand gesture classification. The aim of this work was to compare the performance of MYB with CONV system to evaluate its suitability in the classification of multiple motions in a crossover and structured analysis experimental design.

The idea of CONV comparison is to provide a reference framework to MYB performance. The classification error obtained for CONV is alike to the classification error found in other studies with similar processing configuration [21,23,24]. For instance, in [21], Otriz-Catalan et al. acquired 11 movements from 17 able-bodied subjects with four channels at 2kHz. Four features, that were also used in this work were extracted (WL, ZC, SSC and MAV), and fed into an LDA classifier reaching an average classification error of 7.90 ± 0.04%. In [24], the classification error reported for 9 movement classification with 6 channels from 10 able-bodied subjects and 1kHz sampling frequency, using autoregressive features, was approximately 6%. This classification error is close to the one obtained in this study for CONV (5.82 ± 3.63%). However, there are also studies [23] that showed lower classification error owing its variability to the experience of the users and acquisition systems.

With respect to the spectral information, Li et al. [12] evaluated the effect of decreasing the sampling frequency from 1kHz to 100Hz. They showed a decrease in performance with approximately 2 percentage points similar to the current study.

Nevertheless, the non-significant difference between MYB and CONV classification error implies that the limited 100Hz bandwidth, provided by MYB, is not necessarily a drawback in detecting different movements, and thus, suitable for pattern recognition applications.

The non-significant change in classification accuracy between MYB6 and MYB8 is consistent with other studies that showed very little variation after the same increase in channel number [5,23] and assessment about the optimal electrode placement and configuration [25].

Furthermore, when the performance of both acquisition systems was observed, remarkable differences between subjects were noticed. The subjects with largest diameter in the dominant forearm (subjects 3, 5 and 8 with diameters of 31.3, 29.0 and 26.2 cm respectively) had lower classification error with MYB than CONV, despite the lower sampling frequency. This implies that the size of the forearm may play a role in the performance of the MYB, as electrodes have a tighter fit at larger diameters compared to smaller ones. This was confirmed by using the clips to reduce the size of the MYB, in which case two subjects with smaller diameter did increase their performance. These results are consistent with findings in [25] that determined that larger interelectrode distances yielded in lower classification error.

It should be noted subjects 4 and 7 are the major contributors to the high error rates obtained in this study. The main cause is not just the size of the forearm, but also the inconsistency in performing the movements. For example, subject 7 always perform wrist extension with extended fingers. If subject 7 is excluded from the data set, the obtained classification errors will be: 4.83 ± 2.51% for CONV, 7.83 ± 6.11% for MYB6 and 6.61 ± 5.13% for MYB8.

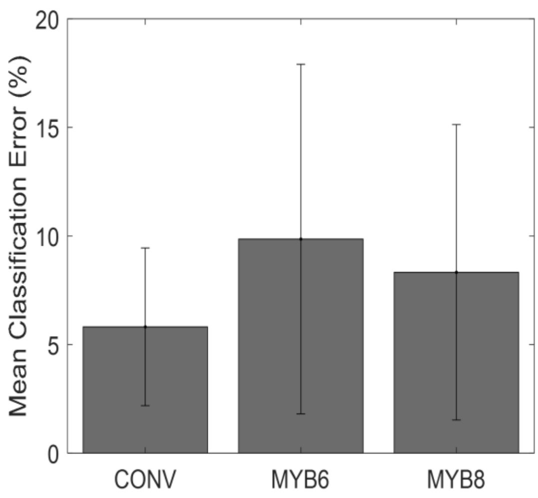

Figure 4: Mean percentage classification error for conventional acquisition system (CONV), Myo armband using 6 channels (MYB6) and Myo armband using 8 channels (MYB8).

V. Conclusion

MYB has proven to be a suitable acquisition system for pattern recognition applications based on LDA classification. However, future work should involve the evaluation of its performance with other classifiers and its behavior in real-time compared to conventional systems, to fully determine MYB potential in pattern recognition, and more specifically, prosthesis and rehabilitation.

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