(Tentative title) MYO Armband for gaming applications

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***Abstract*—**

***Index Terms*—MYO, EMG, LDA, Logistic regression, machine learning, gaming**

I. Introduction

Electromyography (EMG) is a bio-medical signal that is produced by the muscular electrical activity in response to stimuli [1]. A muscle is a set of motor units each composed out of muscular cells innervated by a motor neuron. Muscles are connected to tendons which serve to move skeleton structures. A resting potential between the intracellular and extracellular environments of the muscle is about -80mV. Motor neuron initiates muscle contraction by releasing specific neurotransmitters from the corresponding nerve endings. Increased neurotransmitter concentration is picked up by the muscle cell receptors which in turn initiate a process of membrane depolarization. A wave of polarization and depolarization is propagated across the neighboring muscle fibers causing them to contract [1] [2].

The summation of the action potentials from all fibers in a particular motor unit generates a motor unit action potential (MUAP). Thus, the EMG signal can be observed as a result of the summation of multiple MUAPs [3]. Generally, there are two types of sensors used for EMG signal acquisition: invasive and non-invasive. Invasive sensors are inserted directly into the muscle tissue while non-invasive are placed on the skin above the region of interest [1]. For the purpose of this study non-invasive sensor from the MYO Armband will be used.

MYO armband is a human-computer interface developed by Thalmic labs in 2014. The armband is placed at the upper part of the forearm where it acquires EMG activity through 8 sensory modules. The device communicates with the computer by using Bluetooth. MYO armband supports five hand gestures from the box: wave in, wave out, fist and spread fingers. Those gestures can be then mapped to predefined user commands or application. Additionally, real-time raw EMG data can be acquired via the MYO Armband SDK.

In this paper, we will propose a gesture-based framework which would allow real-time usage of the MYO Armband in different gaming scenarios. In the further section, we will provide performance measurements of the framework in relation to the classification model, train-test split ratio and filtering window size.

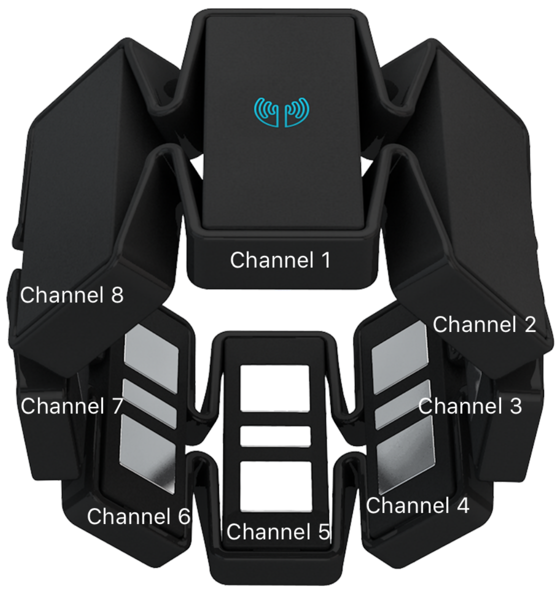

Fig. 1. MYO Armband and labeled channels

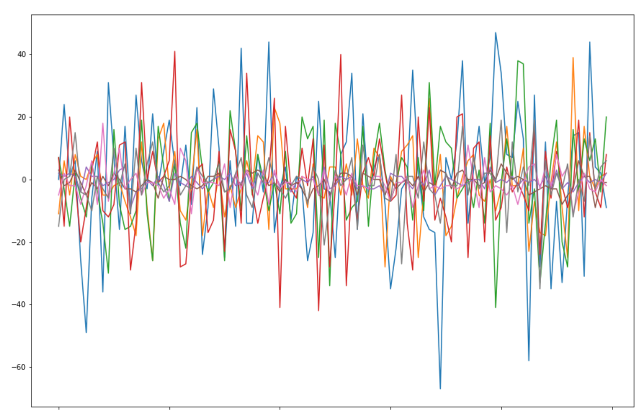

Fig. 2. Raw EMG signal sample

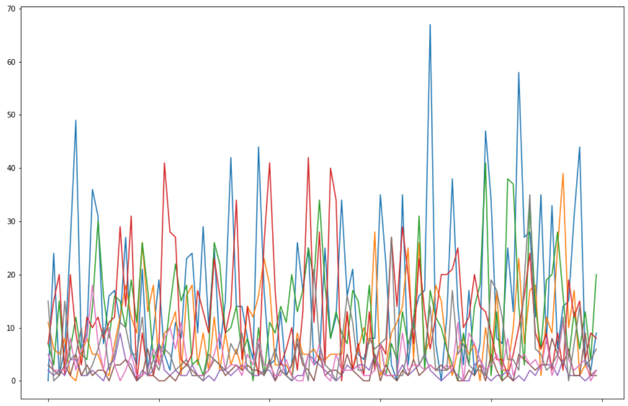

Fig. 3. Rectified EMG signal sample

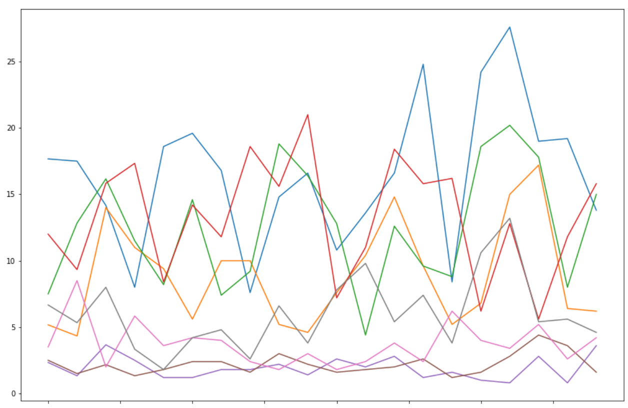

Fig. 4. Filtered EMG signal sample

II. Materials and Methods

A. Materials

In this study we used non-invasive commercial EMG sensor Myo Armband. Small size, portability and relatively low cost, and a proprietary SDK make MYO Armband a great device for quick EMG data acquisition. MYO Armband has 8 dry sensors (Figure 1). Those 8 sensor transfer EMG data through Bluetooth at a rate of 200Hz. The armband should be placed at the upper part of the forearm. Before every experimental trial, MYO had been worn for a period ranging from 5 to 10 minutes for device warm-up and more accurate sensory output. Once the device is connected to the PC, the raw EMG data was acquired by using the official Thalmic Lab SDK.

B. Methods

1) Data acquisition: The raw EMG data from the MYO Armband is collected through the window $W^{N\times 8}$. The window size is adjustable based on the gaming application used. If the window size is 200 samples ($|W| = 200$). Each column of the W is represented by the channel vector $C_i^{200\times 1}$ received from the channel $i = 1, 2, 3, ...8$.

2) Rectification: Preprocessing is a crucial part of EMG signal classification. Raw EMG signal (Figure 2) should be preprocess to eliminate random high-frequency and low-frequency noise [1]. This is usually done by averaging the signal S_n and performing full-wave rectification. The result of the signal rectification is a signal $abs(S_n)$ (Figure 3) where each data point is an absolute value of itself. Full-wave rectification preserves the original EMG dynamic and helps to avoid the situation when the EMG signal can be averaged to zero.

3) Filtering: For real-time EMG filtering the moving average algorithm is used. Each channel C_n of the signal S_n is filtered by unweighted mean of the previous n data points p_i.

$$\overline{C_n} = \frac{p_M + p_{M-1} + p_{M-2} + ... + p_{M-(n-1)})}{n}$$

$$\overline{C_n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i}$$

For offline performance estimation of the classifier models the moving average approach is inadequate since it makes data points dependent of each other. Therefore, to avoid the possible dependency between the train and test sets each channel C_n of the signal S_n is averaged by the number of points N_p (Figure 4).

4) PCA: Principle Component Analysis (PCA) is a very powerful yet simple dimensionality reduction technique. The main idea behind PCA is to project data from a high-dimension space onto low-dimension space with maximum variance. The approach is particularly useful for preliminary analysis of the complex multichannel EMG datasets. The result of the PCA is a set of orthogonal principal components among each the variance of the features is maximized and noise is reduced [4].

The PCA uses the notion of variance and covariance extensively. The variance is measure of the data is spread from the mean in a dataset:

$$Var(X) = \frac{\sum_{i=0}^{n}(X_i - \overline{X})^2}{n-1}$$

Covariance is a measure of how the data dimension vary from the mean with respect to each other. For matrices X and Y the covariance is calculated as follows:

$$Cov(X,Y) = \frac{\sum_{i=0}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{n-1}$$

Although the covariance must be calculated only between two dimensions, it is still possible to get the covariance estimates from a multidimensional dataset. It is done by calculating all possible inter-dimensional covariances and putting them into covariance matrix $C^{N\times N}$ where N is the total number of dimensions.

$$C^{N\times N} = (c_{i,j} = Cov(Dim_i, Dim_j))$$

Before calculating the covariance matrix for the dataset, it is important to subtract mean value $\overline{x}$ from x in all dimensions. The new dataset, therefore, will have a mean of zero.

Next step is find eigenvalues and eigenvectors of the covariance matrix cov. The biggest eigenvalue with a corresponding

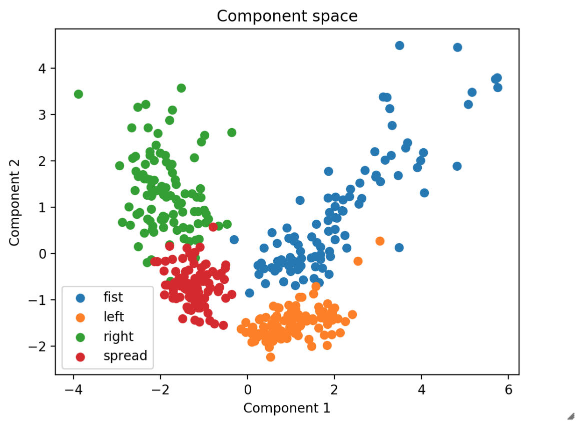

Fig. 5. Four gesture dataset projected on two principle components

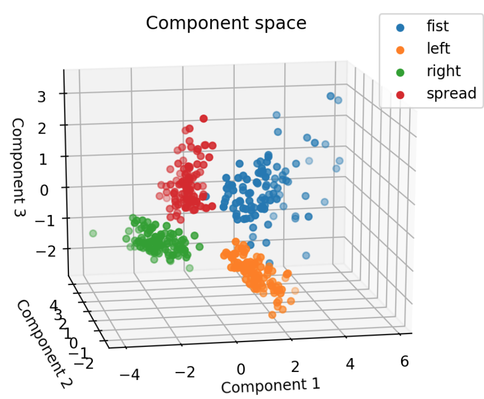

Fig. 6. Four gesture dataset projected on three principle components

eigenvector will be a principle component of the dataset. It is up to us to decide how many principle components to choose from a $ComponentVector$.

$$ComponentVector = [eig_1, eig_2, eig_3, ...]$$

The final step is to project the dataset along the chosen principal components. This is done via simple matrix multiplication where both the principle components matrix P_c and feature matrix X are both transposed.

$$ProjectedData = P_c^T X^T$$

The PCA results on the dataset with 4 prerecorded gestures (wave left, wave right, clenched fist, spread hand) are shown on Figure 5 and Figure 6.

5) Classification:

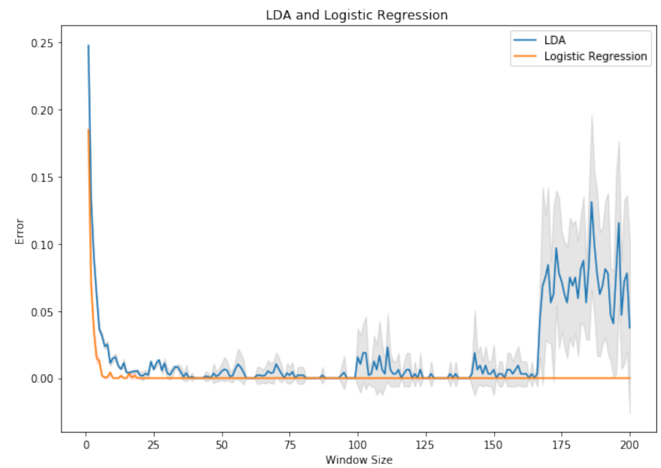

Fig. 7. LDA's and Logistic regression's error in relation to the filtering window size

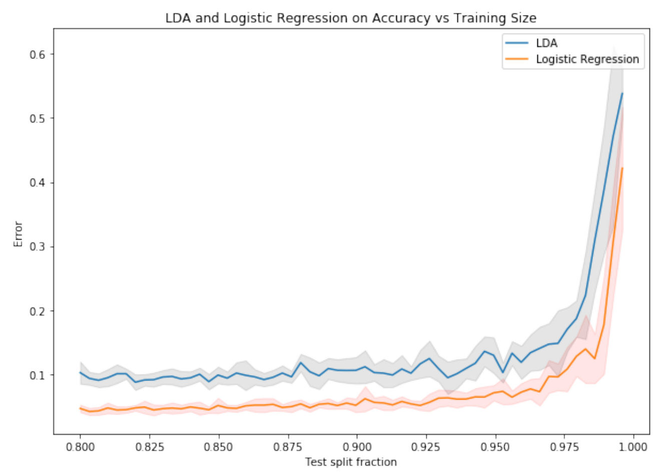

Fig. 8. LDA's and Logistic regression's error in relation to the training size

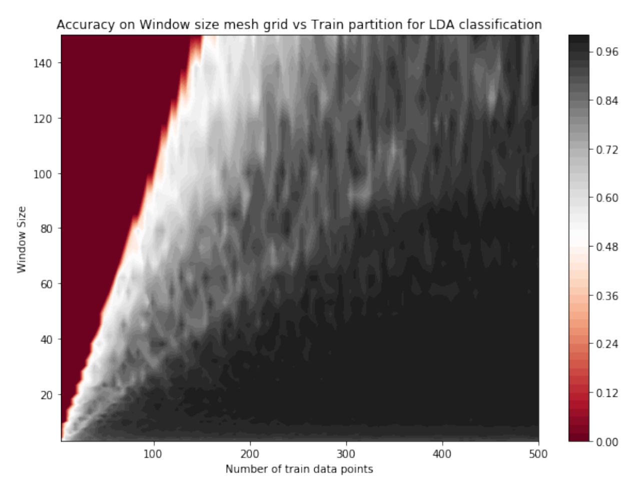

Fig. 9. Window size vs Training data points for LDA classification

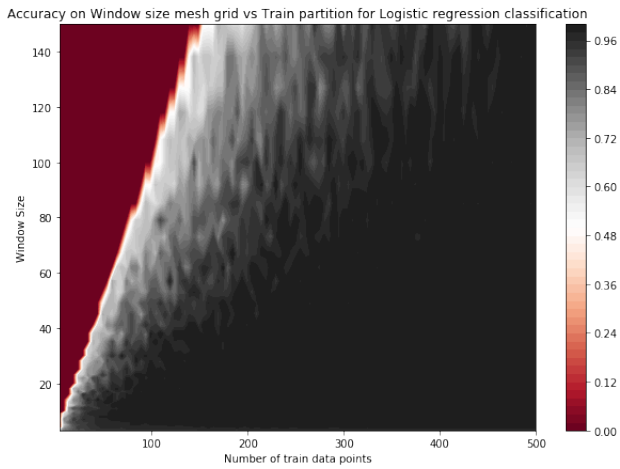

Fig. 10. Window size vs Training data points for Logistic Regression classification

III. Gaming framework

IV. Results

V. Discussion and conclusion

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