Hand Posture and Gesture Recognition using MYO Armband and Spectral Collaborative Representation based Classification

Ali Boyali, Naohisa Hashimoto and Osamu Matsumoto
National Institute of Advanced Industrial Science and Technology

***Abstract*— In this paper, we propose the use of Collaborative based Representation in Spectral Domain to recognize the postures and gestures from the Electromyography (EMG) recordings acquired by a recently introduced sensor; Thalmic Labs' MYO armband. The recognition accuracy obtained for a set of six hand gestures and postures is promising with an accuracy over 97 % which is a competent result in the related literature. The algorithms are developed for creating an intuitive human machine interface for navigating a robotic wheelchair.**

***Index Terms*— EMG gesture recognition, MYO armband, Collaborative based Classification.**

I. Introduction

As the tiny computing technologies such as smart phones and tablets are evolving rapidly and have obtained large public acceptance, little and versatile sensor gadgets which can communicate with these devices in a ubiquitous manner have also been emerging such as MYO armband by Thalmic Labs which can measure the raw Electromyography signals of the worn arm.

The armband measures the EMG signals using eight circularly arranged sensors around the worn arm muscles. In this study we make us the EMG signals obtained by the armband to recognize a set of six hand gestures (Fig. 1).

Fig.1 MYO armband and Hand Gestures, 1- Fist, 2- Hand Relax, 3- Fingers Spread, 4- Wave In, 5- Wave Out, 6- Double Tap

The literature on the classification of EMG signals is fairly rich and vast variety of applications and classification methods have been proposed. The recognition accuracy reported in these studies ranges between 88-99% depending on the EMG features, classification method and number of gestures. We refer the reader for the details in the survey study [1]. Due to the stochastic nature of the EMG signals, the signal processing and classification require tedious efforts. In this study, we describe the methods for training and signal pattern recognition to recognize six different hand gestures and postures on a continuous signal using Subspace Clustering (SC) and the spectral version of Collaborative Representation based Classification (CRC) [2].

II. Building Training Dictionary

Two common challenges in gesture recognition are building a reliable gesture dictionary and spotting the gestures. In this study, unlike reported in the literature we describe procedures and methods which enable the system recognize continuous gestures on a streaming signal real time eliminating the spotting need of the gestures. The training phase is of great importance in building dictionary. Since gestures are dynamic hand movements, EMG signals are the product of stochastic processes, spotting a signal on a streaming signal visually is not an easy task to create a training dictionary.

In order to overcome this drawback, we first perform a hand gesture pair, such as hand fist and hand relax repeatedly for five seconds and collect the hand gesture pairs (Fig. 2).

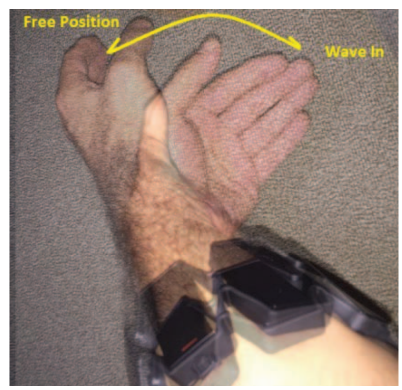

Fig.2 Wave in – Hand Relax Gesture Pair for Training

The recorded eight channel EMG signals for each of the pairs are then put in a 1D column vector form into the training dictionary by a sliding window. The resultant observation matrix thus contains two different signal pattern groups in different column locations. One can cluster this observation matrix into the corresponding classes by employing a SC method.

In this study we employed the Ordered Subspace Clustering (OSC) [3] method. The OSC algorithm is based on the Sparse Subspace Clustering (SSC) [4] with an additional penalty term in the self-representation based objective function. The additional penalty term enforces the neighboring columns to be similar that is the case in building the training dictionary in this study. The OSC methods yields labelled clusters for each gesture sets. In fact, when this

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training scheme is used for the representative gestures, we obtain ten hand gestures because each hand gesture returns the hand relax position after the gesture is performed. For every hand movement the arm muscles produce different EMG signal profiles. We mapped the return hand postures to the hand relax posture in this study.

III. Collaborative Representation Based Classification (CRC)

The CRC, as a recent state of art classification method is based on representation of the observed pattern y as a linear combination of the patterns stacked in the training dictionary A. Thus, the linear system of the equations $y=Ax$ is solved using ridge regression and the coefficient vector x is obtained. Once x is obtained using Eq. 1, the label of the observed pattern is defined using the minimum representation residuals by Eq. (2).

$$x = (A'A + \lambda I)^{-1}A'y \qquad (1)$$
$$\min x = ||y - A\delta i(x)|| \qquad (2)$$

where the selection operator $\delta i(x)$ takes the only coefficients for the i^{th} class and makes the coefficients of the remaining classes zero. The regression operator is only computed once that makes the algorithm very fast compared to the other classification methods in the literature. The Lagrange parameter λ is used to prevent the ill-conditioned matrix operations.

The Least Square Ridge regression employs $l2$ norm in the objective function which is more convenient when there is data fidelity. However, the EMG signals, by the nature of the biological process are complex signals and don't exhibit fidelity. For this reason, instead using the raw signal readings directly, we transform the each recording obtained by a sliding window to a circulant matrix, then compute the eigenvalues of the each signals from each of the channels. A unitary matrix, such as a Fourier matrix (F) diagonalizes a circulant matrix (C) yielding the spectral features; eigenvalues (Λ) of the circulant matrix. The eigenvalues which constitute an invariant subspace capturing the spectral features of the observed signals.

$$\Lambda = FCF^{*} \qquad (3)$$

As we work on the spectral domain, the resulting eigenvalues contain complex conjugate eigenvalue pairs. In the complex domain the Hermitian transpose is used instead of simple matrix transpose in Eq. (3).

IV. Simulation Results and Conclusion

We performed each gesture pairs five times. Only the first gesture pairs from each of the classes are used for building the dictionary matrix. The remaining signals are reserved for testing. The recognition accuracy for each of the gestures are given in Table I.

Table I – Recognition Results

Gesture	Fist	Wave In	Wave Out	Fingers Spread	Double Tap
Accuracy (%)	100	99.34	98.34	97.3	100

The average number of computations for the test experiments is over 1200 which corresponds to the six seconds gesture performance. Fig. 3 shows the recognized labels for the Wave Out- Hand Relax gestures pair.

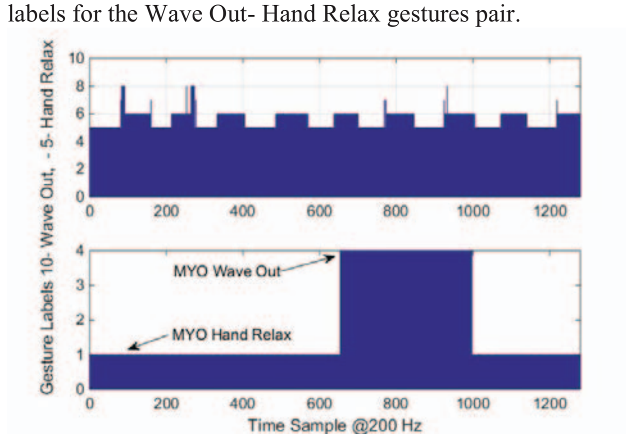

Fig.3 Wave Out – Hand Relax Recognition Results (Upper Figure – CRC Results, Bottom – Reported by MYO)

As seen in Table I, the recognition accuracy for the continuous hand gestures are very high and competent in the related literature where tedious signal processing and classification algorithms are used. We don't employ and pre-processing method and work directly on the raw data. The results can be improved using convenient filtering methods for EMG signals.

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