Classification of Finger Extension and Flexion of EMG and Cyberglove data with modified ICA weight matrix

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Abstract— **This paper reports the classification of finger flexion and extension of surface Electromyography (EMG) and Cyberglove data using the modified Independent Component Analysis (ICA) weight matrix. The finger flexion and extension data are processed through Principal Component Analysis (PCA), and next separated using modified ICA for each individual with customized weight matrix. The extension and flexion features of sEMG and Cyberglove (extracted from modified ICA) were classified using Linear Discriminant Analysis (LDA) with near 90% classification accuracy. The applications of this study include Human Computer Interface (HCI), virtual reality and neural prosthetics.**

I. Introduction

In recent years, there has been an increasing number of research conducted towards myoelectric control of individual fingers for prosthetic devices [1, 2]. Control of finger flexion and extension is of particular importance, especially to prosthetics. From initial investigations in using surface Electromyography (sEMG) for classifying individual finger flexions and extensions, researchers have acknowledged the growing importance of controlling finger flexions and extensions [1, 3, 4] in prosthetics and rehabilitation applications.

The finger extension and flexion are performed using both extrinsic and intrinsic muscles of the hand. The former one stretch over the forearm and latter one is responsible for all the actions of the hand. The pattern recognition process of simple and complex gestures can be broken down into three main phases: feature extraction, feature reduction, and classification. In the recent past, researchers have explored the classification of various finger and hand gesture movements using different feature extraction and classification techniques, which include support vector machines [5], linear discriminants and neural networks [3, 4, 6].

Matrix factorization techniques such as Independent Component Analysis (ICA), Principal Component Analysis (PCA) and Nonnegative Matrix factorization (NMF) have been used for several pattern recognition and data mining applications [7-9]. ICA is a multivariate data analysis technique having most promising results not only in general Blind Source Separation (BSS) problem but also in source separation and identification of sEMG [3, 5]. ICA converts a multidimensional vector into statistically independent components (ICs). For ICA algorithm, it is the requirement that the sources must linearly mixed and be highly independent. BSS techniques using ICA have been widely used in biomedical and sEMG signal processing applications [3, 9, 10]. One of the advantages of using ICA is that it decomposes these physiological signals into different ICs, which can be used for further processing.

This paper presents a research study conducted on classification of sEMG and Cyberglove data for various finger extension and flexion movements using modified ICA weight matrix. The initial research study conducted on 10 participants has shown promising results and efficacy of ICA in identifying various Cyberglove and sEMG gestures.

The rest of the paper is organized as follows. The brief introduction of EMG and Cyberglove is introduced in section II. The ‘‘Methods’’ section describes the experimental design and feature extraction methods while the ‘‘Results” section explains the results for the proposed scheme in detail and ‘‘Discussion and Conclusion’’ section discusses the future research related to sEMG and Cyberglove classification scheme.

II. EMG and Cyberglove

Surface EMG is the electrical recording of the muscle activity from the surface by the muscle cells when these cells are electrically or neurologically activated [3, 5, 11-13]. It is detected from superficial muscles by using surface electrodes, has rich motor control information and is closely related to the strength of muscle contraction. Surface EMG has been used in various applications which include myoelectric control, prosthetics, neuropathy and other related applications [1, 2, 13, 14].

The Cyberglove is a more advanced glove that was developed specifically for the recognition of sign languages. It uses proprietary resistive bend sensing technology to accurately transform finger motions into real time diagonal joint angle data [15]. In a Cyberglove the 22 sensors are distributed as follows: three flexion sensors for each finger, four abduction sensors, a palm arch sensor, and two sensors for wrist (one for flexion and one for abduction) [15]. A typical Cyberglove sensor placement is shown in Fig. 1.

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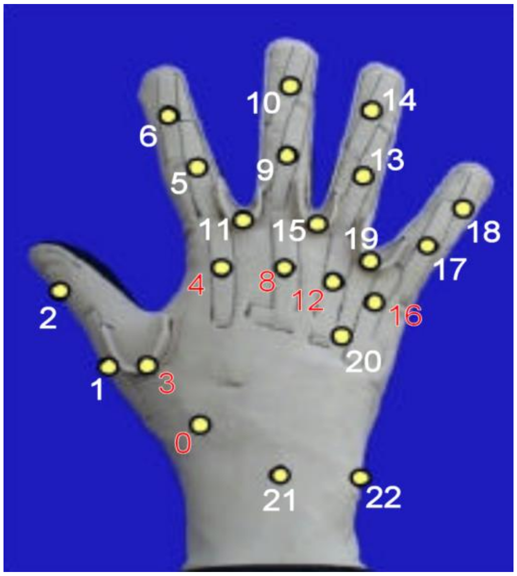

Fig. 1. Cyberglove with 22 sensor data [16]

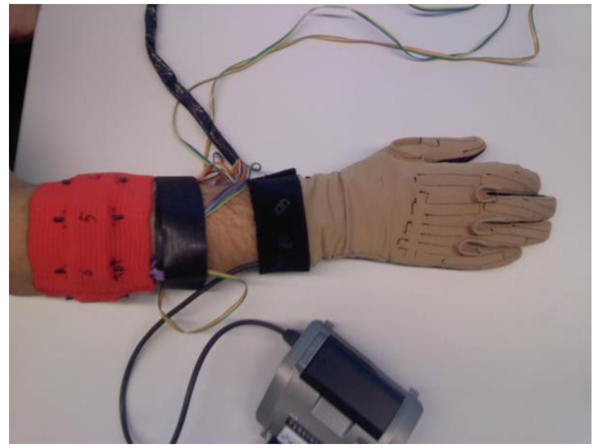
Fig. 2. Cyberglove with sEMG sensors used for the experiment [16]

III. METHODS

A. Data acquisition

For this study, the required Cyberglove and sEMG data were obtained from NINAPRO database[16]. NINAPRO database consists of both kinematic (Cyberglove) and sEMG data from the upper limbs of 27 intact subjects while performing 52 finger, hand and wrist actions. For the purpose of this study, we used 10 flexion and extension movement from 10 subjects, which include, 1) Index finger flexion 2) Middle finger flexion 3) Ring finger flexion 4) Little finger flexion 5) Thumb flexion 6) Index finger extension 7) Middle finger extension 8) Ring finger extension 9) Little finger extension and 10) Thumb extension. One of the examples of the Cyberglove and sEMG sensor set up used for the experiment is shown in Fig. 2.

As explained in [16], sEMG data was acquired using OttoBock MyoBock 13E200 surface EMG electrodes with an amplification factor of 14000. The raw sEMG signals were recorded with a sampling frequency of 500Hz and the bandwidth of sEMG was around 25Hz-500Hz.

Similarly, 22 sensor Cyberglove data was recorded using sampling frequency of 50Hz. The experimental protocol for the whole process is explained as follows: During the data acquisition, the subjects sit comfortably on an adjustable chair, in front of a table with a large screen. The subjects are presented with short movies appearing on the screen and are asked to simply replicate the movements depicted in the movies as accurately as possible. Each subject first undergoes a "training phase" to get familiar with the procedure, during which each movement of the first three classes and three movements of the fourth class are repeated three times (no data are recorded). After the training phase, a sequential series of ten repetitions of each class of movements is presented to the subject while data are recorded [16].

B. Feature extraction using PCA and ICA

Initially, 22 sensor data was processed through PCA. From the experimental analysis it was found that for Cyberglove data, 85% of the variances are found in the first 6 Principal Components (PCs). On the other hand for sEMG data, 4 PCs were found to be having variances greater than 85% (Refer to Fig. 3 and Fig. 4). For ICA analysis, 6 and 4 PCs were selected (6 for Cyberglove and 4 for sEMG). The advantage of PCA is that pre-applying PCA enhances ICA performance by (1) discarding small trailing Eigen values before whitening and (2) reducing computational complexity by minimizing pair-wise dependencies. PCA decorrelates the input data; the remaining higher-order dependencies are separated by ICA [17].

For ICA, let x and s be PCs that contain the linear mixtures of (Cyberglove and sEMG) $x_1, x_2, \dots, x_n$ and $s_1, s_2, \dots, s_n$, respectively, and let A be the matrix with entries $a_{ij} = A_{ij}$. The above-mentioned mixing model can then be written as

$$x = As \qquad (1)$$

where x is an observed data vector, A is an unknown full rank mixing matrix, s, is an unknown non-Gaussian source process. The goal of ICA is finding the weight matrix, $W = A^{-1}$, so that the sources can be estimated from the vector x by optimizing a statistical independence criterion.

$$\hat{s} = Wx = W(As) \qquad (2)$$

where $\hat{s}$ are the estimated sources up to permutation and scaling ambiguity. However in this process the quality of the separation would also depends on the recorded signals; x. i.e. the quality of separation might be poorer for very low quality of recordings. Hence, in this research study, we propose a novel method to reconstruct the weight matrix based on the threshold value. After several empirical analysis (spectrum and frequency), threshold value of 0.1 was found to be

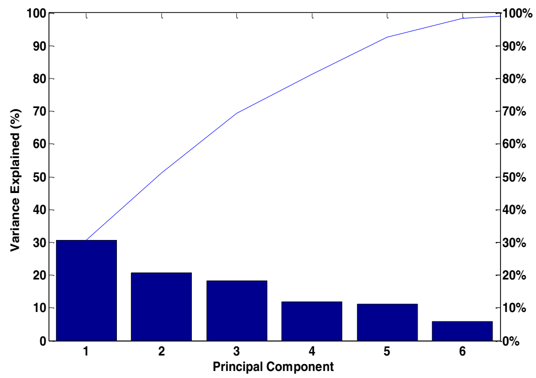

Fig. 3. Principal Components plot for the Cyberglove data

suitable for further analysis. Hence, the rows in the weight matrix W that corresponded to independent component (ICs) with $ICs \leq 0.10$ (10%) were set to zero. The new weight matrix that was obtained, denoted by $\hat{W}$, is similar to the original weight matrix W ($\hat{W} \approx$ W), with the difference that $\hat{W}$ does not contain information relating to ICs that contribute no or little to the content of the original signals x. This weight matrix ($\hat{W}$) was kept constant for each individual and the new sources ($\tilde{s}$) were estimated as:

$$\tilde{s} = \hat{W}\, x \tag{3}$$

For this study, we based our work on a simple feature extraction strategy and calculated the Root Mean Square (RMS) features using the windowed sEMG and Cyberglove data. For the sEMG data, we empirically used 256 samples as the window size with 25% overlapping, whereas for the Cyberglove data, 128 samples were chosen as the window size, shifted 25 samples each time. The feature extraction and classification were implemented using Matlab software under the Windows platform.

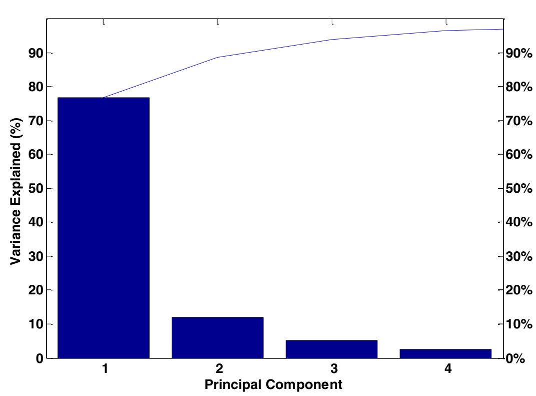

Fig. 4. Principal Components plot for the sEMG data

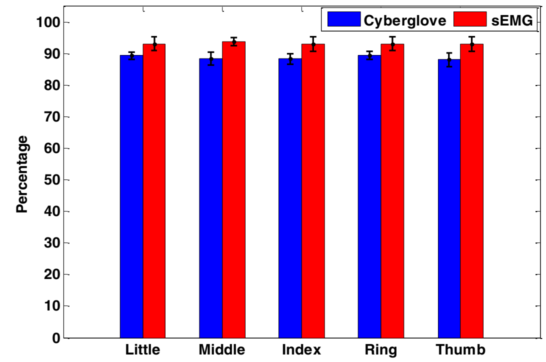

Fig. 5. Finger flexion results (Mean±SD) for sEMG and Cyberglove data

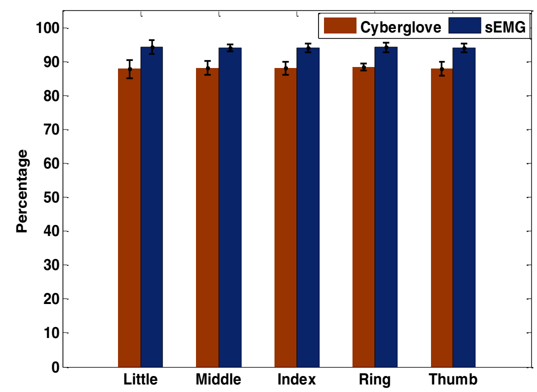

Fig. 6. Finger extension results (Mean±SD) for sEMG and Cyberglove data

C. Classification of features using LDA

The RMS feature set was computed for windowed sEMG and Cyberglove ICA data. These feature sets were provided to train a subject specific Linear Discriminant Analysis (LDA). The advantage of this classifier is that it does not require iterative training, avoiding the potential for under or over-training [18]. The main objective of LDA is to minimize the distances among the vectors belonging to the same class and to maximize the distances among the class centres. For the Cyberglove and sEMG gesture recognition task, the LDA classifier is implemented by calculating linear discriminant functions and selecting the maximum one as the classification rule.

In the classifier evaluation sessions, pattern classification of sEMG and Cyberglove was performed on data analysis windows. In each classifier evaluation session, a subject specific LDA classifier constructed on the preceding training session was applied to determine the motion of the individuals. In order to evaluate the performance of the proposed myoelectric and Cyberglove classification scheme, confusion matrices were calculated.

IV. RESULTS

The classification results of finger flexion and extension features for both the sEMG and Cyberglove features are given in Table I. The average classification results (Mean and Standard Deviation (SD)) plots for the finger flexion and extension sequences are shown in Fig. 5 and Fig. 6 respectively.

TABLE I. FLEXION AND EXTENSION CLASSIFICATION (AVERAGE) RESULTS

Gestures	Classification Accuracy % (Mean±SD)	
	Cyberglove	sEMG
Little finger flexion	89.4±1.2	93.2±2.1
Middle finger flexion	88.5±2.1	93.8±1.3
Index finger flexion	88.4±1.6	93.1±2.3
Ring finger flexion	89.4±1.3	93.2±2.2
Thumb flexion	88.2±2.2	93.1±2.4
Little finger extension	87.9±2.7	94.3±2.1
Middle finger extension	88.2±2.0	94.1±1.1
Index finger extension	88.1±1.9	94.2±1.3
Ring finger extension	88.5±1.1	94.3±1.4
Thumb extension	87.9±2.1	94.1±1.3

V. DISCUSSION AND CONCLUSION

In this research study a simplistic pattern recognition system for finger extension and flexion using sEMG and Cyberglove is presented. The system uses PCA for dimensional reduction followed by modified ICA weight matrix designed for the individual. The ICA separated RMS features were classified using simple LDA system. The system shows promising results for both sEMG and Cyberglove.

The proposed classification scheme is tested only for 10 subjects. In order to test the robustness of the proposed method, the system needs to be tested for more number of hand finger movements using numerous subjects. Also, several key areas need to be further investigated to demonstrate the robustness of the system. The sEMG signals used in the present classification effort were recorded about 2 hour period. It is unknown whether the classifier will remain stable in response to the changing muscle conditions that may happen over the course of time. Moreover, it will be challenging task to device a similar classification scheme for transradial amputees and stroke survivors.

In future authors would like to combine both sEMG and Cyberglove data to produce better gesture recognition system for complex hand and finger movements. Moreover, it is interesting to explore the feasibility of the proposed approach to motion dependent and user dependent gestures/actions.

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