Reduction in Classification Errors for Myoelectric Control of Hand Movements with Independent Component Analysis

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***Abstract*—Myoelectric control has been an important area of investigation by researchers during the past forty years. An important role has been played by myoelecric signals in prosthetic control, since it targets the amputees who lost their body limb either in an accident or in the war. Remarkable advances were achieved with the number of movements to be classified with a high accuracy. This paper presents Independent Component Analysis (ICA) as a pre-processing technique for myoelectric control. Three different window lengths were investigated in the current study (64 ms, 128 ms and 256 ms). Two classification schemes were applied based on Time Domain-Auto Regression (TDAR) features with Uncorrelated Linear Discriminant Analysis (uLDA) and Principle Component Analysis (PCA) for dimensionality reduction, and Linear Discriminant Analysis (LDA) classification. The ICA pre-processing technique increased the classification accuracy for different window lengths used from 88% to 93%. The results suggested that FastICA consistently improves the performance across all window lengths and classification schemes.**

***Keywords*—Myoelectric Control, Surface Electromyography, ICA, TDAR and LDA**

I. INTRODUCTION

It has been reported that EMG recorded from the amputee forearm muscles after hand amputation are similar to EMG of healthy subjects [1, 2]. Therefore, there is still an EMG signal when the amputee intends to perform a movement. This fact has inspired researchers to develop myoelectric signal processing algorithms for the control of a prosthetic hand [3].

Myoelctric signal is the measurement of the electrical activity of the closely spaced muscles from the surface of the forearm in which the muscles are responsible for finger and hand movements located in the anterior (flexor) and posterior (extensor) compartments [4]. The signals from deep sources are filtered by a tissue filter function (low pass) between the deep muscles and the surface electrodes [5].

An important role has been played by myoelecric signals in rehabilitation because of its non invasive nature as well as ease of recording from the surface. In addition to its role in prosthetic control, it plays an important role in functional electric stimulation and assistive device control such as exoskeleton devices [6].

The general stages for pattern recognition based myoelectric control are signal conditioning, feature extraction, dimensionality reduction, and classification. To reduce classification errors, researchers added a pre-processing step to the myoelectric control stage. Hargrove et. al [5] proposed a PCA tuning technique as a pre-processor for their 11 class myoelectric control system. Significant reductions in the error values were obtained for different window lengths after application of PCA tuning. However, PCA tuning increased the dimensionality of the input by a factor, which equals to the total number of motion classes to be classified. To overcome this problem, a sequential backward selection algorithm was added to the pre-processing step to reduce the number of channels obtained with PCA tuning.

Independent component analysis (ICA) or Blind Source Separation (BSS) is powerful statistical method applied to the field of biomedical signal processing for identification of statistically independent signal sources, based on the assumption of linear mixing. ICA has been widely applied for source extraction to isolate brain activity related to specific brain functions and artifact removal from Electroencephalogram (EEG), and Magnetoencephalogram (MEG) data [7].

For the EMG signals, Ganish et. al [8] compared the performance of different BSS algorithms for isometric hand gesture identification using 4 channel surface EMG (sEMG). The Temporal Decorrelation Source Separation (TDSEP) technique was the best performer for an analysis window of 1s duration. Nevertheless, the 1 sec analysis window is not suitable for myoelectric control since the analysis window length should not exceed the optimal controller delay, which is within the range of (50-400 ms) [9].

This work presents an ICA based pre-processing technique for source extraction from EMG measurements as an additive step to the pattern recognition based myoelectric control such that the most relevant information is extracted. This will in turn increase classification accuracy for different window lengths that proposed.

II. INDEPENDENT COMPONENT ANALYSIS

An easy Independent component analysis (ICA) is a computational, statistical technique applied to reveal hidden factors that underlie sets of incidental signals and measurements [10]. It assumes that the measured signals are an approximately linear combination of the independent sources with no delay between the signals. For the original sources, the assumption is that they have a non-Gaussian distribution and their number is the same or less than the number of measurements.

The assumption for the noise is that it is statistically independent from the source signals of interest, and it is this property which enables artifact removal from biomedical signals such as EEG and MEG [7]. However, ICA doesn't retrieve the order of the

independent components or the exact amplitude and sign of the independent components [8].
ICA has been shown to extract underlying sources when traditional methods such as factor analysis and PCA have failed [10].
ICA is somehow related to factor analysis and principal component analysis where ICA is a more powerful technique than the earlier mentioned techniques. Nevertheless, it is proven able to find the underlying sources when traditional methods fail [10].
The process of source separation and source estimation with ICA is shown in fig. 1. The ICA assumption is that process of mixing is linear which can be expressed as

$$\boldsymbol{x}=\boldsymbol{A}\boldsymbol{s} \qquad (1)$$

where $\boldsymbol{x} = [x_1(t), x_2(t), ..., x_n(t)]$ are measured signals , $\boldsymbol{s} =[s_1(t), s_2(t), ..., s_n(t)]$ are the original sources and A is the mixing matrix.
To separate the measured signals from the original sources, the ICA algorithm will search for the un-mixing matrix W where the measured signals can be linearly translated to compute Independent components such that:

$$\mathbf{s} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s} \qquad (2)$$

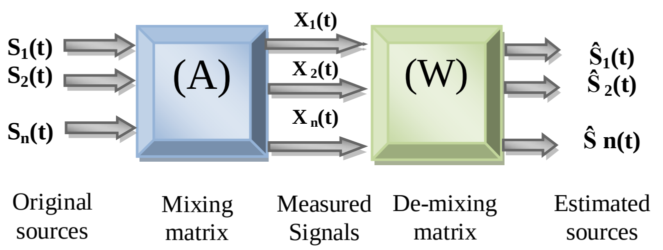

Figure 1. The block diagram of blind source separation, S_n (t) is the nth original source, x_n (t) is the measured signal and $\hat{S}_n(t)$ is the estimated source

METHODOLOGY

The general block diagram of our proposed system is shown in fig. 2 with the added ICA pre-processing step for myoelectric control.
The EMG data sets used in the current work were acquired originally by Hargrove et. al [11]. Sixteen bipolar surface EMG electrodes were mounted around the upper part of the forearm around the circumference as shown in Fig. 3.
The subjects were asked to perform ten combinations of wrist movements and hand grips, namely, forearm pronation, forearm supination, wrist flexion, wrist extension, radial deviation, ulnar deviation, key grip, chuck grip, hand open, and rest state. The 10 class wrist movements and handgrips are shown in Fig 4.
The sEMG signals were collected from 6 participants. Each trial consisted of performing a medium force isometric contraction of the nine movements for duration of 5 seconds followed by a rest period. The recordings consisted of 5 trials for each subject. The signals were sampled at 1024 Hz sampling frequency and band pass filtered (10-500) Hz. For additional details, refer to [11].
To reduce computational complexity, the authors decided to choose the first 5 channels shown in red in Fig.3 to perform the analysis. In addition, L. Hargrove showed that a reasonable classification accuracy range (91-97%) could be achieved with the use of 4 EMG electrodes only [11].

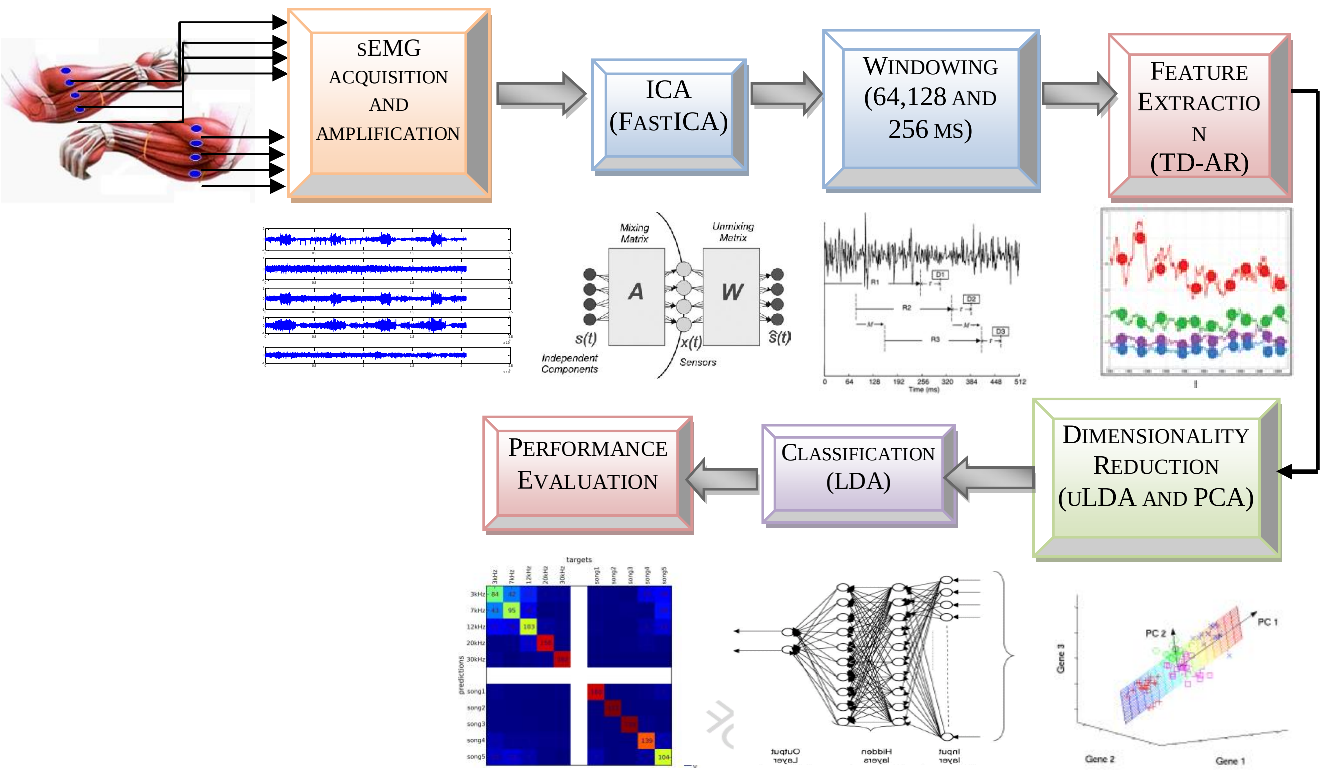

Figure 2. Block diagram of the myoelectric control system

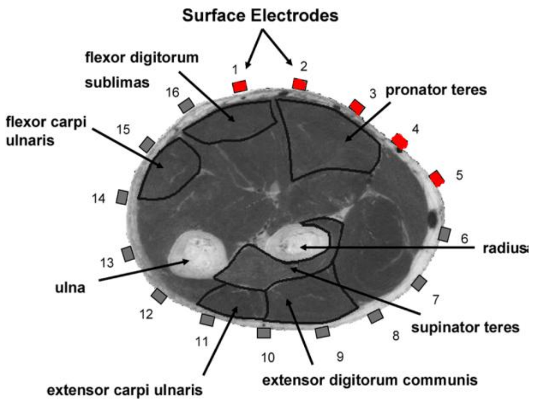

Figure 3. Surface electrodes locations on human forearm on a cross-section of the upper forearm

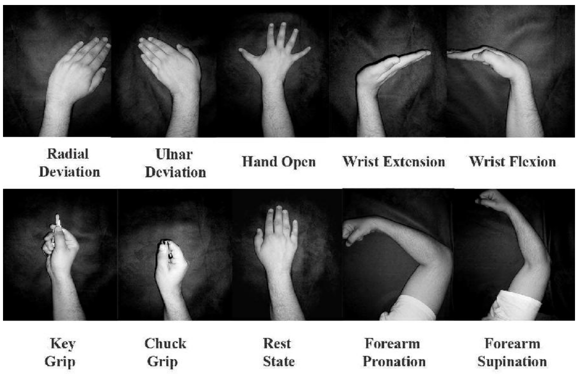

Figure 4. Ten classes of wrist movements and handgrips

A. *Pre-processing with FastICA*

There are many developed ICA algorithms in the literature, such as, second-order blind identification (SOBI) [12],TDSEP[13], FastICA [14] and information maximization algorithm(Infomax) [15].
The authors decided to use FastICA for the pre-processing step because it is relatively simple, has very fast convergence as well as the possibility to estimate the ICs one by one or all at the same time and no step-size parameters are required to be chosen. In addition, the histogram of the EMG data showed that their distribution is super Gaussian which matchs FastICA assumption about the non-gaussianity.
FastICA is a fixed point ICA algorithm that employs higher order statistics to recover independent sources. It tries to decompose the signals based on their non-gaussianity. It is a fast fixed-point iterative algorithm which searches projections that maximize the non-gaussianity of components by their kurtosis [16].
The simplest cost function for an algorithm based on the kurtosis, J (W), is defined as [17]

$$J(w) = -\frac{1}{4}|\mathrm{kurt}(y)| = -\frac{\beta}{4}\mathrm{kurt}(y) \qquad (3)$$

where y is an estimated component and β is the sign of the kurtosis [17].
This cost function can be minimised using the standard gradient descent approach, which leads to:

$$W(k+1) = W(K) - \mu \frac{\partial J(W)}{\partial W}\bigg|_{W(k)} = W(k) + \mu(k)\varphi\big(y(k)\big)x(k) \qquad (4)$$

where μ(k) is the learning rate and φ (y (k)) depends on the second, third and fourth order moments of y [17]. Since this algorithm extracts one source at a time, a deflationary process must be followed to exclude the extracted source from the remaining mixtures. This kind of gradient descent approach enables a fast adaptation in a non-stationary environment. However, its convergence can be slow and depends on a good choice of the learning rate sequence [16].

B. *Classification schemes*

Two classification schemes with three different window lengths (64ms, 128ms and 256ms) were used in this study. The window overlap for the three different window lengths was 32 ms.
The first classification scheme consisted of feature extraction performed by Time Domain-Auto Regression (TDAR) features with PCA for dimensionality reduction. Hudgins et. al [18] showed that TDAR features achieved the highest performance for their experiment. TDAR features consisted of sixth-order AR models, Root Mean Square Value (RMS), Zero Crossings (ZC), Integral Absolute Value (IAV) and Slop Sign Changes (SCC).
For the second scheme, the same feature extraction as in scheme one was used with uLDA dimensionality reduction [19]. The feature sets for both schemes consisted of 50 features (10 features by 5 channels). Afterwards, with PCA and uLDA dimensionality reduction, the feature set size was reduced to 40 features.
Classification was performed with an LDA classifier for both classification schemes since the problem of training iteratively could be avoided with the use of LDA giving a low chance of under and over training [3].

IV. Results and Discussion

The classification errors for both schemes proposed are shown in fig. 5 and fig. 6. Error bars show the standard deviation across 6 subjects.
Fig. 5 displays the classification error for three different window lengths (64ms, 128 and 256 ms) of ICA per-processor for classification scheme 1 (uLDA used for dimensionality reduction). While fig. 6 shows the same results in fig. 5 for classification scheme two (PCA used for dimensionality reduction).
From fig. 5 and fig. 6, ICA improves the classification accuracy for all windows and classification schemes proposed. This represents relative improvements for the first classification scheme of 32%, 44%, and 47 % for window length of 64, 128, and 256 ms respectively. For the second one, the relative improvements were 33%, 44%, and 50% for the 64, 128, and 256 ms windows, respectively.
The error reduction rate for classification schemes 1 was 4 % whereas for the for the second scheme, the error reduction rates was 5%, for three different window lengths.

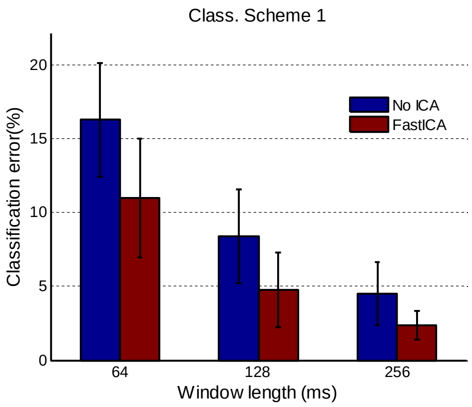

Figure 5. Classification errors with and without ICA pre-processing across 6 subjects for classification scheme 1. Standard deviation of the inter-subject variability is shown with error bars

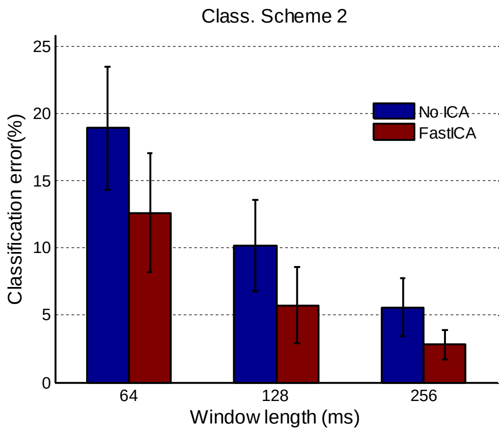

Figure 6. Classification errors with and without ICA pre-processing across 6 subjects for classification scheme 2. Standard deviation of the inter-subject variability is shown with error bars

Table 1 shows the confusion matrix for subject 2 using 256 ms data analysis windows for classification scheme 2 (PCA algorithm for dimensionality reduction). The values in white (left columns shows the classification accuracies without ICA pre-processing while the accuracies in grey (right column) displays the classification accuracies with ICA pre-processing.

The accuracies for wrist extension and radial deviation were (76.25% and 72.81%) respectively. After pre-processing with ICA, the accuracies increased to 99% for both movements.

It is remarkable that FastICA consistently improves the performance across all window lengths and classification schemes. In addition, better classification accuracy was achieved with ICA pre-processing technique.

V. Conclusion

The addition of ICA as a pre-processing step to the myoelectric control block diagram was proposed. Five channel EMG signals for ten hand movements were tested with two classification schemes for with three different window lengths.

The classification schemes consisted of feature extraction performed by Time Domain-Auto Regression (TDAR) features with PCA for dimensionality reduction for the first classification scheme and uLDA for the second one. LDA used as a classifier for both schemes.

The ICA pre-processing technique increased the classification accuracy by 5 % for different window lengths used from 88% to 93%. The results suggested that FastICA consistently improves the performance across all window lengths and classification schemes.

Additional data collection from more subjects to take in to account the inter-subject variability on a large scale is being done to test them with ICA.

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Table 1. confusion matrix in percentages for subject 1 with classification scheme 2 (with and without FastICA) for a 256ms analysis window

Output class

	Pronation		Supination		Flexion		Extension		Radial dev		Ulnar dev.		Key		Chunk		Open		Rest	
Pronation	97.2	99.1	0.62	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.2	0
Supination	2.81	0.31	95.9	98	0.62	0.62	0	0	0	0	0	0	0	0	0	0	0	0	0.62	0.62
Flexion	0	0	0.94	0	89	99.4	0	0	0	0	9	0.31	0	0	0.3	0.3	0	0	0.62	0
Extension	0	0	0	0	0.31	0	76.25	99	23.12	0.93	0.31	0	0	0	0	0	0	0	0	0
Radial dev.	0	0	0	0	0	0	26.9	0.31	72.81	99	0	0	0	0	0.3	0.62	0	0	0	0
Ulnar dev.	0	0	0.31	0	2.812	0	0.3	0.31	0.3	0	95	99.37	0	0	0	0.3	0	0	1.25	0
Key	0.62	0	0	0	0	0	0	0	0	0	0	0.31	91.8	96.9	1.56	0.62	1.56	0.62	4.37	1.56
Chunk	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0.31	97.18	99.4	0.93	0.31	1.56	0
Open	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0	0.3	99.3	99	0.3	0.6
Rest	3.14	0	0.3	0	0	0	0	0	0	0	0.3	0	0	0	0	0	0.9	0	95.3	100

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