Effective application of independent component analysis to the task of gradual EMG control

M O Shamshin\textsuperscript{1}, V A Makarov\textsuperscript{1,2}, S A Lobov\textsuperscript{1}

\textsuperscript{1} Lobachevsky State University of Nizhny Novgorod, Gagarin Ave. 23, 603950 Nizhny Novgorod, Russia
\textsuperscript{2} Instituto de Matemática Interdisciplinar, Applied Mathematics Dept., Universidad Complutense de Madrid, Avda Complutense s/n, 28040 Madrid, Spain

Abstract. In this work, the possibility of a reliable application of the independent component analysis to the problem of EMG interfaces is studied. The developed algorithm takes advantage of the experimental training procedure and enables a computationally efficient identification of gradual finger movements in real time by using inexpensive EMG sensors with a low sampling rate. Experimental data show that the algorithm improves the separation of motor units by 55\% as compared to raw EMG signals.

1. Introduction

Nowadays electromyographic (EMG) interfaces find applications in many areas of our life including the game industry, bionic prostheses, exoskeleton devices, and electric wheelchairs among others. Reliable EMG control in these applications requires an accurate automatic analysis of EMG data providing high-fidelity recognition of gestures made by the user. The quality of classification of EMG patterns is primarily defined by the features extracted from the signals, rather than by the classification algorithm itself [1-3]. Therefore, in the literature an extensive attention has been paid to the development and analysis of different methods of feature extraction from EMG signals. Among the most popular approaches we can mention the fitting of autoregressive models [4,5], Fourier transform [6], and wavelet analysis [7].

Recently, the wavelet analysis has received a great attention due to its flexibility and applicability to non-stationary signals [8]. Using the wavelet transform one can isolate the motor unit action potentials (MUAPs) from EMG signals and hence identify the motor units participating in a given muscle contraction. This, in turn, enables classification of EMG patterns in a human-machine interface (HMI). Besides HMI applications, the analysis of individual MUAPs is applied in medical diagnostic of muscle injuries [9]. However, the wavelet approach requires high-quality EMG recordings. Since the duration of MUAP is about 5 ms, estimation of their shapes requires the sampling rate of at least 5 kHz. Moreover, preamplifiers with high SNR and high-resolution analog-to-digital converters (ADC) are also necessary, which leads to additional requirements to the analogue part of the EMG recording devices. In addition, the dimension of the data flow increases due to multisensor recordings. These factors demand a relatively high processor power from the on-board computers for processing EMG data in real time, a condition that is hardly met by inexpensive standard equipment widely used in practice.

In this work we explore the independent component analysis (ICA) as a computationally efficient method for the analysis of MUAPs generated by muscle contraction. Instead of the analysis of signal waveforms, the proposed method searches for statistical relationships (beyond linear correlations) among multiple EMG signals recorded simultaneously. It enables separating recorded signals into MUAPs activity by a simple computationally inexpensive linear transformation. Moreover, the synchrony in online reading of MUAPs reduces significantly the requirements to the sampling rate, which can be relaxed to 1 kHz or even less. This makes the approach applicable to practically all commercially available devices.
2. Materials and methods

The experiments were carried out by using a myographic Thalmic Myo armband bracelet with the voltage resolution of 25 μV and sampling rate set to 200 Hz. For the sake of simplicity, in this work we aimed at identification of two types of finger movements: bending of ring and pinky fingers. The bracelet was put on the subject’s forearm and located in such a way that two sensors were located over muscle flexor digitorum superficialis that participates in movements of these fingers (Fig. 1). The subject was gradually bending his fingers one by one. Note that most people cannot bend their pinky finger separately from the ring finger, which produces additional experimental complexity.

The collected data have been processed by an ICA-like algorithm (see below) and then finger gestures have been classified. To quantify the classification fidelity we evaluated the root mean square (RMS) signals both from raw EMG data and from the processed data over 100 ms windows:

\[ R(t) = \sqrt{\frac{1}{N} \sum_{\tau=0}^{N-1} y(t - \tau)}, \]

where \( y \) is the detrended original signal (either raw EMG or processed EMG) and \( N = 20 \) is the number of samples in a window. The RMS signals were then additionally smoothed by a low-pass second order Butterworth filter with a cutoff frequency of 10 Hz. To measure the quality of the gradual measurement of finger bending we used Pearson correlation coefficients evaluated over RMSs of raw and processed EMG data.

![Figure 1. Sketch of the model of the recording of EMG activity from flexor digitorum superficialis muscle contributed by two motor units responsible for bending of different fingers.](image)

3. Results

It is convenient to represent the raw EMG data recorded from two sensors \( x_1(t) \) and \( x_2(t) \) (Fig. 1) in the matrix form:

\[ X = \begin{pmatrix} x_1(t) \\ x_2(t) \end{pmatrix}, \]

where \( t \in \{1, 2, \ldots, T\} \) is the discrete sampling time. Figure 2a shows a representative example of the data obtained while a subject performed the two types of movements: bending his ring and pinky fingers one by one. We observe that such movements produce two characteristic clouds of points aligned along two inclined axes on the \((x_1, x_2)\)-plane. Such a situation is typical for application of ICA.
Earlier ICA was applied to EMG signals for source separation [3,10]. We then can introduce the 
MUAPs space as a matrix of two unknown vectors \( \mathbf{F} = (f_1(t), f_2(t))^T \) describing activation of two motor units driving the ring and pinky fingers, respectively (Fig. 1). Then, the recorded data can be represented as a mixture of MUAPs with some weighting matrix \( \mathbf{A} \):

\[
\mathbf{X} = \mathbf{A}\mathbf{F}.
\]

(3)

ICA estimates the mixing matrix and MUAPs from the EMG data, by assuming that MUAPs are statistically independent variables (i.e., their joint probability can be factorized). There exist a number of ICA algorithms: Infomax, KernelICA, JADE, FastICA, etc. These algorithms employ different numerically friendly criteria of statistical independence and optimize them through iterative searching algorithms.

In general, all algorithms proceed in two steps: 1) Data whitening and 2) Rotation of the whitened data. The whitening can be achieved by applying a linear transformation \( \mathbf{Y} = \mathbf{W}\mathbf{X} \), where \( \mathbf{W} = \mathbf{D}^{-1/2}\mathbf{V} \) and \( \mathbf{D} \) and \( \mathbf{V} \) are the eigenvalues and eigenvectors matrices of the data covariance matrix, respectively. On the second step we rotate the data by an angle \( \phi \): \( \tilde{\mathbf{F}}(\phi) = R(\phi)\mathbf{Y} \), where \( R \) is the standard rotation matrix. The angle \( \phi \) is selected by minimizing Gaussianity of the projection. Thus obtained \( \tilde{\mathbf{F}}(\phi_{\text{min}}) \) approximates the original MUAPs up to a constant. Figure 2b shows the ICA estimated MUAPs for the EMG data set represented in Fig. 2a. We note that each separate movement of one finger is represented along one single axis.

**Figure 2.** Example of extraction of MUAPs from an EMG recording. 
\( a) \) Experimental data collected from two electrodes while a subject was bending his ring and pinky fingers one by one (see also Fig. 1). Orange arrows correspond to vectors \( \mathbf{b}_1, \mathbf{b}_2 \) found be linear regression. 
\( b) \) ICA estimated MUAPs. A standard algorithm and the simplified strategy based on vectors \( \mathbf{b}_1, \mathbf{b}_2 \) provide the same result.

Although ICA can deal well with the blind source separation problem, we, however, aim at simplifying the procedure by designing an adequate experimental protocol and straightforward data analysis technique. We assume that the movement of each finger is caused by individual MUAPs activating flexor digitorum superficialis muscle (Fig. 1). Then, the muscle contraction produces an electric potential recorded by electrodes. The amplitude of an EMG signal generated by individual MUAP depends on the distance from the sensor to the innervated zone [12]. Then, following the derivation by Naik and colleagues [10] and taking into account different locations of the sensors we can write the data model:
\[ x_i = \sum_{m,n} a_{i,m} f_m(t - \tau_{m,n}), \quad i \in \{1,2\}, \]  

where \( f_m(t) \) represents the \( m \)-th MUAP, \( a_{i,m} \) is its amplitude at the \( i \)-th electrode, and \( \tau_{m,n} \) is the \( n \)-th time instant of occurrence of the \( m \)-th MUAP.

Figure 2a suggests that only MUAPs of two main types participate in the finger movements. In an experiment, we now can ask the subject to move only one finger. Then, MUAPs of only one form will prevail in the EMG and hence we can reduce (4) to:

\[ x_1 = a_{1,1} \sum_n f_1(t - \tau_{1,n}) + n_1(t), \quad x_2 = a_{2,1} \sum_n f_1(t - \tau_{1,n}) + n_2(t), \]  

where \( n_{1,2}(t) \) are the signals due to residual MUAPs, interpreted as noise. Then, assuming that the noisy terms are small enough, such signals will generate a cloud in the \((x_1, x_2)\)-plane similar to one of those shown in Fig. 2a. Applying the standard least square fit in this case we will get the straight line:

\[ x_1 = k_1 x_2, \]  

where \( k_1 \) is the slope. Next, the subject will move another finger, and then we will record the activity generated by MUAPs of another type (second type of movements). Similarly we get:

\[ x_1 = k_2 x_2. \]  

From (5) we have the ratios \( k_1 = \frac{a_{1,1}}{a_{2,1}} \) and \( k_2 = \frac{a_{1,2}}{a_{2,2}} \). Therefore, we can construct two basis vectors \( b_1 = (1, k_1)^T \) and \( b_2 = (1, k_2)^T \) and use them to construct mixing matrix \( \hat{A} = [b_1, b_2] \). Finally, to unmix the data and obtain MUAPs we apply:

\[ \hat{F} = \hat{A}^{-1} X. \]  

Such an experimentally assisted procedure is much more robust than a blind ICA on mixed data.

We tested the algorithm in 5 male subjects. The collected data had been processed and then we evaluated Pearson correlations among RMS signals (see methods). The Pearson correlation obtained with raw data was \( 0.80 \pm 0.08 \). After application of the algorithm it decreased significantly to \( 0.25 \pm 0.14 \) (\( p < 0.00001 \), t-test). Thus, application of the linear transformation found by our algorithm to raw EMG data improves the separation of motor units by 55 %.

4. Conclusion

In this work we have studied the applicability of ICA to EMG data collected from an inexpensive armband bracelet. For online processing of EMG data we proposed and tested a computationally efficient ICA-like algorithm. It also works at relatively low sampling rates, which is important for designing wearable low-power devices. To develop the algorithm we introduced a model of EMG signals contributed by only one motor unit at a time. Such a situation can be easily achieved experimentally during the algorithm tuning. We have shown that the mathematical model agrees with the recorded EMG data, which enables recognition of dexterous motor activity. The algorithm helps reduce the Pearson correlation of RMS signals by 55%. This enables effective identification of the activity of motor units and identification of finger movements.

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