Blind source separation of multiplicative mixtures of non-stationary surface EMG signals

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Abstract *– Electromyographic (EMG) signals detected over the skin are mixtures of signals generated by many active muscles due to the phenomena related to volume conduction. Separation of the sources is necessary when single muscle activity has to be detected. Signals generated by different muscles may be considered uncorrelated but have a largely overlapping bandwidth. When many muscles are active, no a priori information is available about the mixing matrix. Under certain assumptions, mixtures of surface EMG signals can be considered multiplicative. In this study we apply blind source separation (BSS) methods to separate the signals generated by two active muscles. An algorithm based on cross time-frequency representations will be used on simulated and experimental non-stationary EMG signals. The experimental signals were collected from muscles which could be activated selectively. The contractions performed by the subjects allowed objective validation of the methods. From the simulated signals, optimal performance was obtained. Correlation coefficients between the reference and reconstructed sources were higher than 0.9 even for sources whose spectral and temporal support largely overlapped. In the experimental case, in the reconstructed source the contribution of the other source was significantly decreased after the application of the BSS methods. The ratio between root mean square (RMS) values of the signals from the two sources increased from (mean ± standard deviation) 2.33 ± 1.04 to 4.51 ± 1.37 and from 1.55 ± 0.46 to 2.72 ± 0.65 for wrist flexion and rotation, respectively. This increment was statistically significant. It was concluded that BSS approaches are promising for the separation of surface EMG signals, with applications which go from the muscle assessment, detection of muscle activation intervals, and prosthetic control.*

1. Introduction

Blind source separation consists of recovering a set of signals of which only mixtures are observed. Neither the structure of the mixtures nor the source signals are known to the receivers. The aim is to identify and decouple the mixtures.

Surface electromyographic (EMG) signals are the resultant of the electric activity of the muscle fibers. The signals detected over the skin are mixtures of contributions generated by many active muscles. Indeed, the electric potential distribution generated by a motor unit (MU), the smallest function unit of the muscle, covers a large region over the skin due to the blurring effect (basically a low pass filtering) of the tissues separating the sources (the muscle fibers) and the recording electrodes. In case of muscles close to each other, it is often impossible to distinguish, from the interference EMG signal, the activity of the different muscles. Separation of these activities is important for a number of applications, including the control of prostheses or the assessment of muscle coordination.

The EMG signals generated by different muscles may have overlapping frequency bandwidths, thus classic linear filtering approaches can not be applied for the purpose of source separation. Moreover, no a priori information is available on the relative activation of different muscles. In general, we face off with convolutive mixtures of non-stationary, wide-band signals. In specific cases, however, multiplicative mixtures can be considered instead of convolutive ones. For detection systems at distances of 10-20 mm over small muscles, the effect of the tissues interposed between the two detection points can be approximated as an attenuation of signal amplitude. The degree of attenuation depends on the subcutaneous layer thickness, on the depth of the source, on the distance between detection systems, and so on. Thus, there is no way to have a priori information on the attenuation factor. Under these conditions, the surface EMG signals detected over the muscles of interest can be regarded as multiplicative mixtures of contributions from different sources.

Multiplicative mixtures of non-stationary surface EMG signals were considered in this work. A blind source separation approach based on Spatial Time-Frequency Distributions (STFDs) of the signals will be applied to both simulated and experimental surface EMG signals.

2. Methods

2.1 Blind source separation method

The signal model adopted is the following :

$$\mathbf{x}[t] = \mathbf{A}\,\mathbf{s}[t] + \mathbf{n}[t]$$

where $\mathbf{x}[t]$ is the vector of size m containing the mixtures (called the *observations*), $\mathbf{s}[t]$ is the vector of size n containing the sources, $\mathbf{A}$ is the full rank mixing matrix of dimensions m x n with $m \geq n$, $\mathbf{n}[t]$ is the additive noise vector of equal power σ^2 on each observation. We will briefly describe the BSS method used. Further details can be found in [2,4].

The method is based on the *joint diagonalization* of several STFD matrices of the *whitened* observations for *(t,f)* locations corresponding to source *single auto-terms*. First, a

whitening matrix is computed from the empirical correlation matrix of the observations. Under unitary sources power assumption, this is a *n* x *m* matrix **W** with orthogonal rows such that

$$\mathbf{W}\,\mathbf{A}\,\mathbf{A}^{H}\,\mathbf{W}^{H} = \mathbf{I}$$

where **I** is the *n* x *n* identity matrix and the superscript ^{H} denotes the complex conjugate transpose of a matrix. With $\mathbf{z}[t] = \mathbf{W}\mathbf{x}[t]$, and $\mathbf{U}=\mathbf{W}\mathbf{A}$, it can be shown that $\mathbf{A}^{\#}=\mathbf{U}^{H}\,\mathbf{W}$, where $\mathbf{A}^{\#}$ denotes the pseudo-inverse of **A**.

The second step is to estimate **U**. Let $\mathbf{D}_{zz}[t,f]$ be a STFD of the whitened observations **z**[t] for an arbitrary kernel. Neglecting the noise for the ease of demonstration we have:

$$\mathbf{D}_{zz}[t,f]=\mathbf{U}\,\mathbf{D}_{ss}[t,f]\,\mathbf{U}^{H}$$

Since **U** is unitary, it can be estimated from the joint-diagonalization of a set of matrices $\mathbf{D}_{zz}[t,f]$, correspponding to several time-frequency locations, where $\mathbf{D}_{ss}[t,f]$ is diagonal.

Thus, the way the time-frequency locations are selected is an important issue. Several selection methods exist, two of them are presented in [2,4] and [3]. The first is based on the selection of source *single auto-terms* and the second one is based on the selection of (*t,f)* locations where $\mathbf{D}_{zz}[t,f]$ has high energy. See [2,4,3] for details.

2.2 Simulation model

Surface EMG signals have been simulated by an analytical model for the description of the generation and detection EMG systems [1]. The tissues are layered parallel planes which describe the muscle (anisotropic), the fat (isotropic), and the skin (isotropic) layers. Thus, the volume conductor is a non-homogeneous, anisotropic medium. The sources of signal are the intracellular action potentials which travel along the muscle fibers from the end-plates towards the tendon junctions. A MU is comprised by a number of muscle fibers which are innervated by the same motoneuron. The electrical activity of the muscle fibers is detected over the skin. The MU action potentials are generated as the summation of the action potentials produced by the fibers belonging to the MU.

A MU is recruited when the force developed by the muscle exceeds a given threshold which is typical of each unit (recruitment threshold). After the force exceeds the recruitment threshold, the rate of activations of the MU (number of activations per second) increases linearly with force. Given the force profile, the recruitment thresholds of the MUs, and the relationship between activation rate (firing rate) and force, the complete interference EMG signal is generated.

Surface EMG signals were simulated as produced by Gaussian force profiles. Representative synthetic EMG signals are reported in Figure 1.

2.3 Experimental protocol

The main issue when testing blind source separation algorithms on experimental surface EMG signals is that the sources are not known. This determines difficulties in objectively evaluating performance. We designed an experimental protocol in which two muscles were involved. These muscles could be controlled rather selectively by the subjects, thus it was possible to produce contractions in which only one muscle was active at a time. The contractions were thus cyclic with parts in which one of the two muscles was active and parts in which the other was active. It was thus known a priori in which intervals of time one muscle was active and the other not. The BSS method was applied to the entire signal in which the two sources were mixed, without information on the instants of time of presence of one or the other source. We thus were able to record signals with two sources present, having the reference sources (i.e., the time intervals in which they were present) for performance assessment. In this way the two sources had different temporal supports but the signals processed contained cyclically the activity of both muscles.

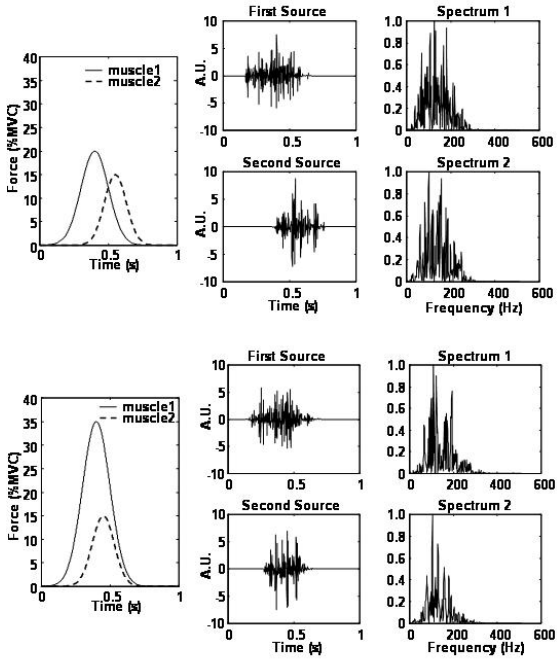

FIG. 1 : Examples of simulated force profiles with the corresponding surface EMG signals and power spectral densities. The force profiles of the two simulated muscles have a Gaussian shape and are temporally overlapped. The frequency content of the signals from the two muscles is almost the same. A.U. stands for arbitrary units.

The muscles selected for the experimental validation were the pronator teres and the flexor carpi radialis and 8 subjects participated to the experimental protocol. The movements were a rotation and a flexion of the wrist, which selectively activated the two muscles. Surface EMG signals were recorded by three single differential systems (10 mm interelectrode distance), one placed over the first muscle, one over the second and one in the middle. The subject seated on a chair with the arm 90° flexed and the forearm completely extended. The maximal force in rotation and flexion of the wrist was measured. After this, a first contraction lasting 100 seconds and consisting in a cycle of 3 second flexion at 50%

of the maximal voluntary contraction (MVC), 1 second rest, and 3 second rotation at 50% MVC was performed. After 5 minutes of rest, a second 100 second long contraction with a cycle of 2 second flexion at 50% MVC and 2 second rotation at 50% MVC was performed.

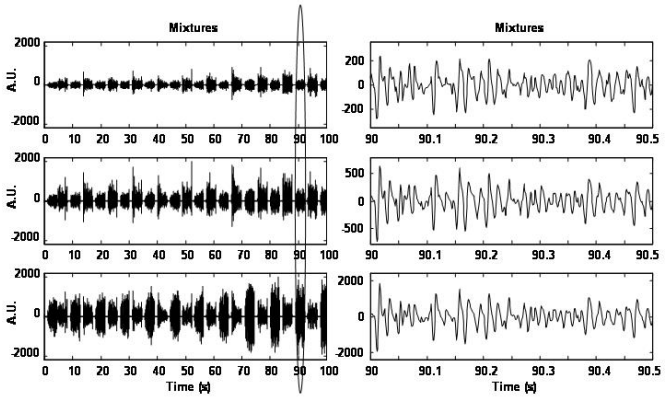

FIG. 2 : Examples of experimental signals recorded from the three locations over the two muscles. A cyclic task, consisting of 3 second flexion at 50% MVC, 1 second rest, and 3 second rotation at 50% MVC was performed. The two sources are detected by three sensors and the mixture can be approximated as multiplicative, as shown on the right. The entire recording lasts 100 seconds. The BSS algorithm was applied to the entire 100 second recording. A.U. stands for arbitrary units.

Figure 2 shows representative signals recorded during one of the experimental sessions. The experimental signals were analysed by the BSS approach described above with Choi-Williams Kernel ($\sigma = 1$) and the selection of *(t,f)* points based on the single auto-terms criterion. The kernel was selected on the basis of the results obtained in simulation (see below). The entire signal recordings (100 seconds) were processed by the BSS algorithm. The reference and reconstructed sources could be identified from the activation intervals of the muscles (given by the recorded forces in flexion and rotation). The mean frequency (MNF) of the power spectral density of the reference and reconstructed source was computed over time to assess changes in the frequency content of the signals. The ratio between root mean square (RMS) values of the reconstructed and reference source with respect to the other source detected at the same sensor was used as performance index. RMS was computed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

with N the number of samples and x_i the signal samples.

3. Results

3.1 Simulated signals

Two representative cases were simulated. The first (DYN1) considered two muscles which were active with Gaussian shaped forces (bursts of activity). The first burst (source 1) had a peak force corresponding to 20% MVC and was located at 400 ms with a standard deviation of 130 ms. The second burst reached a force of 15% MVC, was located at 550 ms and had a standard deviation of 100 ms (Figure 1). In the second case (DYN2), the first burst reached 35% MVC, was located at 400 ms, and had a standard deviation of 130 ms. The second burst corresponded to 15% MVC peak force, had location at 450 ms and standard deviation of 100 ms (Figure 1).

The simulated surface EMG signals were generated by MUs randomly located in the muscle. The activity of a MU was simulated at the skin surface in a reference position by the model described [1]. Then the electric activity of the same MU recorded in other locations over the skin was obtained from the reference activity by a scaling factor accounting for the distance between the muscle fibers and the detection point.

There were no significant differences among performance of the different investigated kernels (Bessel, Wigner-Ville, Choi-Williams, Spectrogram), although the Choi-Williams with $\sigma = 1$ led to slightly better results. In the following only the results from the Choi-Williams ($\sigma = 1$) will be reported. Performance in simulated signals were evaluated by the cross-correlation coefficient between the reference and the reconstructed sources. Since there was no significant difference between performance related to the first and the second source reconstruction, only results for the first source will be reported. In all cases, 50 simulations were performed, corresponding to random MU locations within the muscle, thus results are reported as mean and standard deviation of the 50 trials.

The BSS method based on STFDs was applied varying the number of *(t,f)* points for the joint diagonalization. Moreover, three criteria for the *(t,f)* points selection were compared. *(t,f)* points were randomly selected (Rand) or selected by the criteria proposed in [2] (Single Auto-terms) and [3] (Bel).

Table 1 reports the cross-correlation coefficient between the reconstructed and the reference first source. In general, the performance were good, with cross-correlation coefficient always higher than 0.8. The single auto-terms criterion for the *(t,f)* selection led to the best performance. With this criterion, the selection of the number of *(t,f)* points is not critical. Increasing the number of sensors from 3 to 5 slightly improves the performance. In general, the second condition (DYN2) led to lower correlation coefficients than the first (DYN1) but the difference was very small, indicating that overlapping of the temporal support is not critical for the source separation method used.

3.2 Experimental signals

The cross-correlation between signals generated during rotation and flexion was not significantly different from zero, indicating that the hypothesis of uncorrelated sources could be applied to the signals generated by the two investigated muscles.

The initial MNF value for the extensor carpi radialis was 101.4 ± 21.8 Hz and for the pronator teres 85.6 ± 15.3 Hz.

After source reconstruction, MNF initial values were 104.4 ± 20.4 Hz and 84.9 ± 14.1 Hz for the two muscles, respectively. There was no statistical difference (Student t-test for dependent samples) between MNF initial values in the reference and reconstructed sources. The rate of decrease of MNF was, for the two reference sources, -0.23 ± 0.16 Hz/s and -0.17 ± 0.10 Hz/s, indicating that the signals changed spectral content with time. The two reconstructed sources led MNF rate of change of -0.23 ± 0.16 Hz/s and -0.17 ± 0.08 Hz/s. The rates of decrease of MNF were not statistically different between the reference and reconstructed sources.

TAB. 1 : cross-correlation coefficient between the reconstructed and the first source in the two simulated conditions and for different choices of the number and selection of the *(t,f)* points for joint-diagonalization

		3 sensors		
		10 pts	**100 pts**	**1000 pts**
DYN1	Rand	0.89±0.08	0.94±0.05	0.96±0.00
	Bel	0.84±0.09	0.84±0.09	0.84±0.09
	LM	0.96±0.00	0.96±0.00	0.96±0.00
DYN2	Rand	0.88±0.09	0.87±0.08	0.91±0.07
	Bel	0.85±0.09	0.84±0.09	0.84±0.08
	LM	0.94±0.05	0.94±0.04	0.94±0.05
		5 sensors		
		10 pts	**100 pts**	**1000 pts**
DYN1	Rand	0.92±0.08	0.95±0.05	0.98±0.00
	Bel	0.88±0.09	0.84±0.09	0.88±0.09
	LM	0.98±0.00	0.98±0.00	0.98±0.00
DYN2	Rand	0.89±0.10	0.88±0.10	0.91±0.09
	Bel	0.86±0.09	0.84±0.09	0.88±0.08
	LM	0.96±0.05	0.95±0.05	0.95±0.05

The average ratio between RMS values of the reference source and of the other source activity detected at the first sensor was 2.33 ± 1.04 while it increased to 4.51 ± 1.37 after BSS. For the second source the ratio increased from 1.55 ± 0.46 to 2.72 ± 0.65. In both cases of flexion and rotation, the increase in RMS ratio with respect to the original condition was statistically significant. Figure 3 shows an example of source reconstruction for experimental signals.

4. Discussion and conclusions

The BSS approach is particularly suited for separation of surface EMG signals generated by different muscles. Indeed, in this case, no a priori information is available about the mixture matrix and the sources. Moreover, no assumptions can be made on the frequency content of the sources which in general have a bandwidth largely overlapped.

In some cases it is impossible, with surface EMG measures, to separate the activities of closely located muscles, due to the poor selectivity of the recording (see Figure 3 for example).

In this work we applied a BSS approach to surface EMG signals and we validated the performance by both simulations and experimental signals. The simulations well represented the generation system but did not provide indication if the assumption of multiplicative mixtures was met in real cases. The experimental protocol designed had the specific aim of allowing objective validation of the method. It was shown that the method can to some degree separate the activity of sources which are mixed in an approximately multiplicative manner. When analysing a selective movement, the reduction of EMG activity detected over the non active muscle by BSS was significant with an improvement of approximately twice.

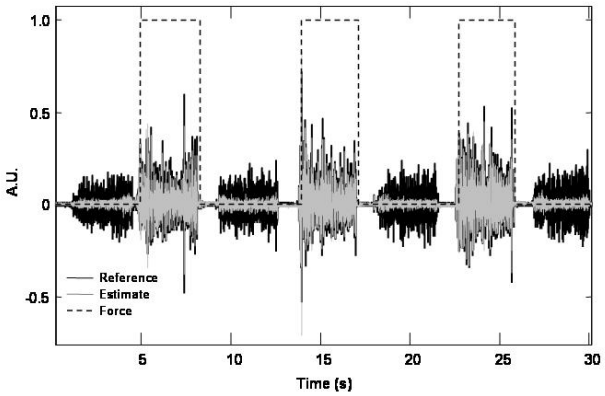

FIG. 3 : Example of signal recorded from the sensor located over the pronator teres during wrist rotation (black line). A threshold has been applied to the force signal related to rotation and the values exceeding 15% of the maximal force are shown (dashed line). The intervals defined by the force signal are those during which the pronator teres is active. From the original signal it is clear that a large contribution from the activation of the extensor carpi radialis is also present. After source separation, the relative amplitude of the second source in the reconstructed signal (grey line) significantly decreases. A.U. stands for arbitrary units.

The method proposed is limited to multiplicative mixtures. The application proposed in this study considered small muscles very close to each other. For larger muscles, this assumption may not be met since different MUs contribute to the signal detected at different locations over the same muscle and the convolutive effect of the tissues can not be neglected. However, in the conditions analysed, the method performed satisfactorily, indicating promising applications.

References

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