Recognizing Hand Movements from a Single sEMG Sensor using Guided Under-determined Source Signal Separation

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Abstract—**Rehabilitation devices, prosthesis and human machine interfaces are among many applications for which surface electromyographic signals (sEMG) can be employed. Systems reliant on these muscle-generated electrical signals require various forms of machine learning algorithms for specific signature recognition. Those systems vary in terms of the signal detection methods, the feature selection and the classification algorithm used. However, in all those cases, the use of multiple sensors is a constant. In this paper, we present a new technique for source signal separation that relies on a single sEMG sensor. This proposed technique was employed in a classification framework for hand movements that achieved comparable results to other approaches in the literature, but yet, it relied on a much simpler classifier and used a very small number of features.**

I. Introduction

Electromyographic signals collected at the surface of the skin (sEMG) have been used in many applications, including rehabilitation, prosthesis, computer interfacing, etc. [1], [2], [3]. Several sEMG-based systems have been proposed to date and they vary widely in terms of: the classification approach employed; the feature selection criteria; and the number of sensors used.

In terms of the classification algorithm, Artificial Neural Networks (ANN) [4], [5], [6], Fuzzy Logic and Fuzzy Control systems [4], [7], are possibly the most common methods used to classify muscle activity – i.e. classify motor unit action potentials trains (MUAPT). The ability to recognize MUAPT can be applied, for example, to hand gesture recognition, control of electro-mechanical prosthesis, computer mouse movement, etc. [3]. One such example can be found in [4], where an ANN was compared to a Fuzzy Inference System (FIS) for classification in a hand prosthesis control. In this work, the authors concluded that for their application the best performance was achieved using the FIS classifier, with an 83% accuracy for 8 different hand movements.

In another work presented in [6], several techniques for classification were employed in order to identify hand gestures using sEMG signals extracted from the forearm of human subjects. The authors reported good performance using ANN, Random Forest (RF), 1-Nearest-Neighbor (1NN), Support Vector Machine (SVM), Decision Tree (DT) and Decision Tree with Boosting (DT/B) as some of the different classification techniques used. In that case, the ANN approach presented a better performance than the other methods.

In terms of feature selection, the features can be extracted from the *time* or the *time-frequency* domains [4], [5], [3]. These features typically include: number of Zero Crossings (ZC), Mean Absolute Value (MAV), Slope Sign Changes (SSC), coefficients of Auto-regressive models (AR) [4], [5]; Absolute Maximum/Minimum, Maximum minus Minimum, Median Value (Med), Variance, Waveform Length (WL) [3]; coefficients of the Short Time Fourier Transform (STFT) [3]; Wavelets Transform (WT) [3], [2], etc.

Given the wide range of features and their large dimensionality, many systems also employ dimensionality reduction techniques to the set of features. In those cases, Class Separability (CS), Principal Component Analysis (PCA), Analysis of Variance (ANOVA) or Multivariate ANOVA (MANOVA) are the techniques frequently used. In [4], for example, the authors developed a feature selection that employed CS and PCA for dimensionality reduction. In that system, as well as in [6] where ANOVA was the technique of choice, the main concern is always to reduce dimensionality without affecting the classification in a significant manner.

Finally, in terms of number of sensors used, as far as we know all systems developed to date have made use of two or more sEMG signals derived from multiple sensors. For example, in [4], the authors reported using only two differential sEMG electrodes placed on the forearm of the test subjects. As we mentioned earlier, their system used multiple features and a FIS+PCA classifier to achieve 83% accuracy. A better performance (93.3% for six movements) was obtained in [6], but with the cost of relying on more sensors – 5 to be more specific – and using ANN as the classification algorithm.

As it can be inferred from the literature review, the use of multiple electrodes and of sophisticated classification algorithms help coping with a major disadvantage of surface EMG: the occurrence of cross-talk from adjacent muscles [1]. It is exactly this cross-talk of MUAPTs that makes the use of a single sensor a quite challenging problem.

In this paper, we propose a system for recognizing hand movements that utilizes a single sEMG source. In our framework, we propose a new technique to separate *"cross-talked"* MUAPTs called "Guided Under-determined Source Signal Separation" (GUSSS). This technique was inspired on Independent Component Analysis (ICA), but unlike other methods based on ICA ([7]), our method relies on a single sEMG source. Also, using a simple distance classifier and with just two features, our method achieved 85% accuracy for 3 hand movements– which demonstrates that the use of a larger number of features and a more complex classifier could lead to an even better performance.

II. Background and Related Work

As we explained above, in our method two features extracted from a single differential sEMG signal are used for classification. Similar to [4], [5], the first feature used is based on the Mean Absolute Value (MAV). However, it is the second feature that holds the ability to deal with cross-talk originated from multiple MUAPTs. Since this new method is based on ICA, in this section we present a quick overview of traditional Blind Source Signal Separation using ICA [8], [9]. In Section III, we explain the proposed technique, which we named "Guided Under-determined Source Signal Separation" (GUSSS).

Traditional Blind Source Signal Separation using ICA (BSSS-ICA) is a powerful technique for sEMG signal separation [7]. In those scenarios, it is assumed that the sEMG signals contain various motor unit action potential trains (MUAPT) due to cross talk [1], and that the MUAPTs are statistically independent [7]. It is important to notice that each MUAPT actually originates from a different muscle, but in order to apply BSSS-ICA, each sEMG signal must be captured by a specific sensor placed close to the muscle responsible for that MUAPT.

Mathematically, the goal of BSSS-ICA is to recover N source signals, $S = [s_1(t), \ldots, s_N(t)]^T$ which were linearly mixed, producing the observed signals $X = [x_1(t), \ldots, x_M(t)]^T$. A typical example would be N independent sounds emanating from different objects and being detected as mixed signals by M microphones spread over the space [9]. Figure 1 depicts this idea for three sources and one microphone.

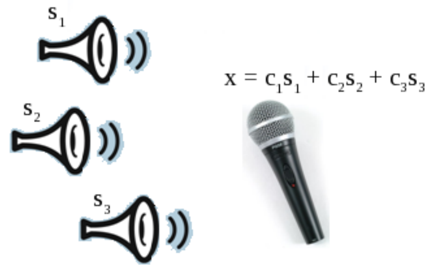

Figure 1. Three independent sources mix together and the linear combination is collected by a sensor.

Traditional ICA methods are able to separate the signals whenever $M \geq N$, that is, the number of observed signals is at least equal to the number of independent sources. In those cases, the sources and the signals can be related in a matrix form such as $X = AS$, where A is called the mixing matrix and contains the coefficients of the linear combination of the observed sources. The fact that M is greater or equal to N allows for BSSS-ICA to solve an overdetermined system of equations through the expression $S = A^{-1}X = WX$. The solution is found using a constrained optimization algorithm that maximizes the independence of the signals in S.

For the under-determined cases, that is, when the number of sensors is smaller than the number of independent sources ($M < N$), methods for signal separation have been proposed [10], [11] and referred to as Under-determined BSSS. However, these methods produce losses in the recovered (separated) signals which increase with the reduction of the number of sensors.

III. Proposed Method

In this work, we propose a framework for recognizing hand movements using a new technique called Guided Under-determined Source Signal Separation (GUSSS). In our method, we handle an extreme case of under-determination where the number of sensors is actually equal to one – i.e. $M = 1$. As we will explain in greater detail later, unlike BSSS-ICA, where the source signals to be separated are unknown – that is the reason for the term "*blind*" in BSSS – in our method, it is assumed that the signals are one of the many expected *signatures* captured by the sensors – and that is the reason for the term "guided" in GUSSS.

The proposed framework for our method is illustrated in Figure 2 and it consists of three parts: 1) signal acquisition and pre-processing; 2) feature extraction; and 3) classification.

As the name implies, the first module of our framework is responsible for acquiring, amplifying and filtering the sEMG signal. The next module in the flow, and presented in Figure 2, extracts the features that are used for classification of the hand movements. These features are the Mean Absolute Value (MAV) and the GUSSS ratio, which we will introduce shortly. Finally, the classification module used for this work was based on a simple distance classifier.

A. Guided Under-determined Source Signal Separation

As in other systems that use BSSS-ICA, here we also assume that sEMG signals are a mixture of electrical signals (MUAPT) originating from different muscles [1]. In other words, as we mentioned earlier, the sensed signals are linear combinations of independent MUAPTs that become mixed due to cross-talk.

In the proposed Guided Under-determined Source Signal Separation, we let x_1 be such linear combination of N independent MUAPTs. That is, x_1 represents a sensed signal from the single sensor in the framework. Next, we let s_p be a particular known signal, or signature, that the system is trying to identify within the observed signal x_1. Since the sensor captures not only s_p, but also various other MUAPTs s_i, we can write:

$$\begin{aligned} x_1 &= c_1 s_1 + c_2 s_2 + \cdots + c_p s_p + \cdots + c_N s_N \\ &= c_p s_p + \sum_{i \neq p} c_i s_i \\ &= c_p s_p + \tilde{s} \end{aligned} \quad (1)$$

where c_i, $i = 1, \cdots, N$ are unknown mixing coefficients. The expression above is simply to stress the fact that x_1 can be considered a linear combination of the desired signature and an unknown mixture of other MUAPTs $\tilde{s}$. Since initially we are interested in separating or identifying only s_p from the observed signal, we will require that $\tilde{s}$ be independent from s_p. This assumption is an obvious consequence of the assumption that all N MUAPTs are independent – i.e. if N MUAPTs can be regarded as independent, any linear combination of $N-1$ MUAPTs must also be independent of the remaining MUAPT. Moreover, the algorithm for GUSSS will successfully identify s_p within x_1 whenever $c_p \neq 0$. So, the question remaining becomes how to determine c_p.

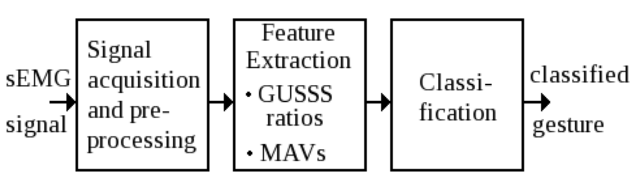

Figure 2. Framework of the proposed classification system.

In fact, two situations may arise: the desired signature is indeed present in the mixed signal x_1, or it is not. In order to distinguish between those two situations, the algorithm creates a second synthesized signal x_p by injecting an weighted copy of the particular signature s_p into the sensed signal x_1. That is:

$$x_p = w_1 x_1 + w_p s_p \quad (2)$$

where w_1 and w_p are arbitrarily chosen constants. Substituting eq. (1) in eq. (2), we obtain:

$$x_p = w_1 (c_p s_p + \tilde{s}) + w_p s_p = w_1 \tilde{s} + (w_1 c_p + w_p) s_p \quad (3)$$

which leads to

$$x_1 = \tilde{s} + c_p s_p$$

$$x_p = w_1 \tilde{s} + k_p s_p$$

where $k_p = w_1 c_p + w_p$. Finally, we can express these equations in matrix form as

$$X_p = AS$$

where

$$X_p = \begin{bmatrix} x_1^T \\ x_p^T \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & c_p \\ w_1 & k_p \end{bmatrix}$$

$$S = \begin{bmatrix} \tilde{s}^T \\ s_p^T \end{bmatrix}$$

The last step of the algorithm is to solve for S. Since we now have two independent components and two linear equations on s_p and $\tilde{s}$, we can apply any traditional ICA algorithm to separate the s_p and $\tilde{s}$ components. Moreover, a sub product of the ICA algorithm is the mixing matrix A. The coefficients of such matrix can be used to infer whether or not a particular signature was present in the sensed signal x_1. For example, if we consider the case where the particular signal s_p is not present in the mixture signal x_1, the mixing coefficient c_p would be in theory zero. On the other hand, if s_p is indeed present in the mixture x_1, that coefficient must be different from zero.

In practice, mainly due to noise, the coefficient c_p is never exactly zero. However, it will be very "small" whenever the particular signature is not present in x_1 – otherwise, c_p should be "large". In the proposed framework, we define the GUSSS ratio as:

$$r_p = \frac{1}{c_p} \tag{4}$$

Finally, while what constitutes a "large" or a "small" value for the coefficient c_p may not be obvious, it is clear that the derived GUSSS ratio can be used as a criterion for determining if a particular signature is present or not in the sensed signal. In the proposed framework, the GUSSS ratio is used as a feature for the distance classifier.

Identifying multiple signatures in x_1: In the previous discussion, we explained how a particular signature can be identified or separated from x_1. In order to identify the presence or not of all possible signatures, the framework employs an iterative method. That is, first, we assume that the system needs to identify N sEMG signatures corresponding to the N possible hand gestures[1]. Next, from the test signal x_1, we obtained N ratios by injecting iteratively the desired signature into x_1 – equations (2)-(4) . That is, we find

$$x_p = x_1 + s_p \qquad for\ p = 1\ to\ N$$

and once again, we apply the ICA algorithm to each

$$X_p = \begin{bmatrix} x_1^T \\ x_p^T \end{bmatrix} \qquad for\ p = 1\ to\ N$$

to obtain the ratios r_1, r_2, ..., r_N. Finally, it should go without saying that if r_i is the smallest of the N ratios found by the GUSSS, it is likely that the sensed signal x_1 is the signature s_i, and thus, the hand gesture i is the one being sought.

B. Mean Absolute Value as a Classification Feature

We considered a second feature for the classifier: the Mean Absolute Value (MAV) of the signals. The MAV of a signal $x(t)$ is obtained by calculating the average of the absolute values of x at all instants t. If $x(t)$ is continuous in time, then

$$MAV = \frac{1}{T}\int_T |x(t)|\,dt$$

where T is the time interval for which $x(t)$ is defined. If the signal is discrete, then

$$MAV = \frac{1}{K}\sum_{k=1}^{K} |x(k)|$$

where K is the number of samples that constitute $x(k)$.

[1]We will explain how to obtain the signatures in Section IV

C. Classification Module

As we pointed out earlier, the goal of the GUSSS is to identify which signature is present in the observed sEMG signal x_1. In order to do so, the same signature must be injected to synthesize a secondary signal x_p. Our framework uses a training set of sEMG signals to learn those signatures and in the results section we will explain two approaches used for this purpose. Here, we assume that the signatures are available.

Furthermore, from the training signals we also learn the average MAVs for the different signatures, i.e. for the different gestures or classes of gestures. In mathematical terms, let μ_1, μ_2, ..., μ_N be the average MAVs obtained from the training set and corresponding to N different gestures to be recognized. Let σ_1, σ_2, ..., σ_N the corresponding standard deviations. Given the input signal x_1, the algorithm calculates its MAV, m_1, and based on this value, it computes the Mahalanobis distances to the average MAVs of the gestures. That is:

$$d_p = \frac{|m_1 - \mu_p|}{\sigma_p} \qquad for\ p = 1\ to\ N$$

It should be noted that if x_1 is the result of gesture i, it is likely that m_i is similar to μ_i. In that case, d_i would also be the smallest of the N distances above.

Using both the GUSSS ratios and the MAVs distances above, we can define the distance classifier. The only missing step is the normalization of both features. That is, we define the normalized GUSSS ratio and the normalized MAV distance as, respectively:

$$\bar{r}_p = \frac{r_p}{\sum_{j=1}^{N} r_j}$$

$$\bar{d}_p = \frac{d_p}{\sum_{j=1}^{N} d_j}$$

Those features are group in the feature vector:

$$\overrightarrow{v_p} = \begin{bmatrix} \bar{r}_p \\ \bar{d}_p \end{bmatrix}$$

for $p = 1, \ldots, N$, corresponding to each of the N gestures to be identified. The classification is obtained by assigning x_1 to that gesture (to the class) for which the correspondent feature vector $\overrightarrow{v_i}$ is closest to the origin. The reason for the normalization of the ratios and distances is, of course, to allow both features to have the same weight in the classification process.

IV. RESULTS

In this section, we explain how we applied the proposed classification framework and how we tested the new technique, GUSSS, to separate MUAPTs. For these experiments, we worked with one test subject and we used three hand gestures, which are illustrated in Figure 3. The sEMG signals of interest are those generated in the transition from a rest position of the hand to the actual gesture. All the sEMG signals were obtained using a Tinkertron EMG switch. This device consists of circuitry for detection and amplification of sEMG signals. The signals from the Tinkertron were sampled at 6.25 kHz using a National Instruments digitizer. In order to reduce undesired noise coming from the power lines, we implemented a digital filter to remove the 60 Hz component.

Since our framework relies on a single sEMG source, we placed a pair of differential electrodes on the extensor carpi radialis muscle along the subject's forearm. The use of this muscle has been previously reported [4], [5]. A reference (ground) electrode was also placed on the wrist of the opposite arm.

As we mentioned earlier, three different hand gestures were considered in our experiments (Figure 3). As we have also explained, the proposed GUSSS technique requires a signature associated to each of the gestures to be recognized. The classification module also needs the average MAVs and the standard deviations. All of them were obtained by analyzing 20 training sample signals for each of the gestures. Once the signatures, the mean average MAVs and the corresponding standard deviations were learnt, an additional set of 40 testing signals per gesture were used and the results are reported below. However, before we present the performance of our framework, we must explain the two methods used to learn the signatures: average and ICA-based.

A. Obtaining the Signature Signals

Given a training set with 3x20 samples – i.e. 20 samples from each hand gesture in Figure 3 – two approaches were used for obtaining the corresponding signatures. The first approach consisted of averaging the training signals grouped per hand gesture. That is, each of the 20 samples belonging to the same gesture were averaged creating a single time signal $s_p(t) = \sum_{i=1}^{20} y_i(t)$ for $p = 1, 2, 3$.

The second approach was a little more elaborated, and involved, once again, the application of ICA. However, this time ICA was used as a learning algorithm for the signatures. That is, consider a training set with samples y_1, y_2, ..., y_{20}. If all 20 signals were identical, applying ICA to the matrix

$$Y = \begin{bmatrix} y_1^T \\ y_2^T \\ \vdots \\ y_{20}^T \end{bmatrix}$$

would lead to a single independent component, that is, $s_1 \neq \vec{0}$ and $s_2 = s_3 = \cdots = s_{20} = \vec{0}$. In fact, since in practice the samples are not exactly the same, the application of the ICA algorithm to Y will lead to various, but small independent components. Our second method for learning signatures relied on the above extracted components from the ICA of Y.

It is important to mention that the training process is subject dependent. The signatures, the average MAVs and the corresponding standard deviations would need to be specifically calculated for another subject.

Table I presents the confusion matrix for the classification results using the average method for learning signatures, while Table II shows the results for the case where the ICA approach for signature learning was used. As the tables indicate, using the ICA approach led to the highest accuracy (85%), although both results were quite similar.

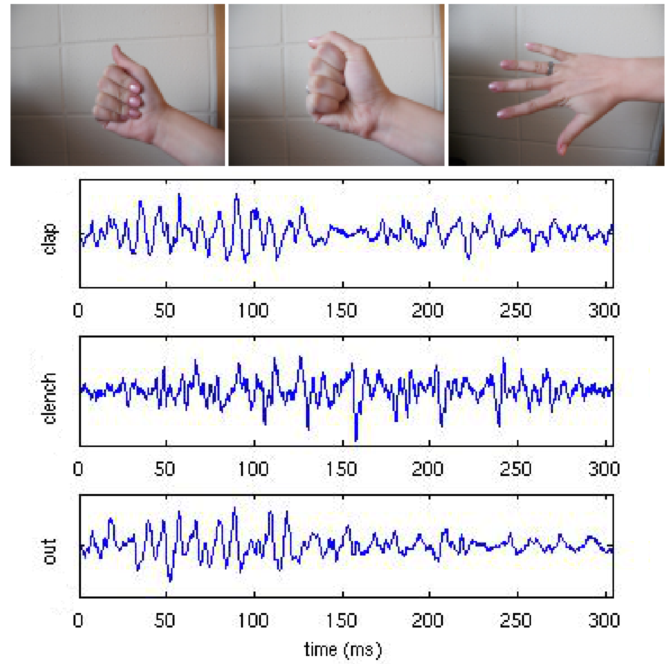

Figure 3. *The three hand gestures considered, "clap", "clench" and "out", and corresponding sample sEMG signals. The signals are generated in the transition between rest and the actual gesture.*

Averages as signatures		Assigned gestures		
		clap	clench	out
Real gestures	clap	32	0	8
	clench	2	38	0
	out	8	1	31
Correct classification: 84.2%				

Table I
CONFUSION MATRIX FOR CLASSIFICATION USING THE AVERAGE APPROACH TO LEARN SIGNATURES.

ICA for getting signatures		Assigned gestures		
		clap	clench	out
Real gestures	clap	33	0	7
	clench	3	37	0
	out	8	0	32
Correct classification: 85.0%				

Table II
CONFUSION MATRIX FOR CLASSIFICATION USING THE ICA APPROACH TO LEARN SIGNATURES.

V. DISCUSSION AND CONCLUSIONS

This paper introduced a novel technique for an extreme case of under-determined source signal separation – i.e. one single observation and multiple sources. The proposed classification framework was demonstrated for detecting specific hand gesture signatures using a single sEMG source. Compared to other systems found in the literature which use multiple sEMG sources for classification, our proposed framework employed a much simpler classifier using only two features. Yet, the classification accuracy obtained with our method, 85%, was quite comparable to previously reported methods. At the same time, it still required fewer sensors, fewer features, and a very straightforward classification algorithm.

In summary, our proposed GUSSS technique shows much promise for classification tasks using, for example, a larger number of hand gestures.

VI. FUTURE WORK

Many practical applications, such as prosthetic hands, wheelchairs, etc require high classification indices. Also, a larger number of recognizable gestures is usually required for a *"real-world"* application. In that sense, our framework must be enhanced by the addition of techniques used in other systems. One such example is the use of more elaborate classifiers. Another certain improvement of the proposed framework may derive from the use of a larger set of features. Finally, new ways of obtaining signatures should be explored in search of better performances. In any event, we believe that our results support the claim that the introduction of GUSSS presents a new and very powerful method for separation and identification of patterns in MUAPT signals. In other words, GUSSS can revolutionize the common use of PCA and ICA not only in the context of sEMG signals, but in other areas, and that is certainly a research we plan to conduct in the future.

REFERENCES

[1] J. G. Webster, ed., *Encyclopedia of Medical Devices and Instrumentation. Electromyography.* John Wiley, 2006.

[2] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of emg signal analysis: detection, processing, classification and applications," *Biol. Proced. Online*, vol. 1, pp. 11–35, March 2006.

[3] M. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, "Advances in electromyogram signal classification to improve the quality of life for the disabled and aged people," *Journal of Computer Science*, vol. 7, no. 6, pp. 706–715, 2010.

[4] M. Khezri and M. Jahed, "A novel approach to recognize hand movements via semg patterns," in *29th Annual International Conference of the IEEE EMBS*, pp. 4907–4910, Aug. 2007.

[5] M. Khezri and M. Jahed, "Real-time intelligent pattern recognition algorithm for surface emg signals," *BioMedical Engineering OnLine*, 2007.

[6] G. Shuman, "Using forearm electromyograms to classify hand gestures," in *IEEE International conference on Bioinformatics and Biomedicine*, pp. 261–264, 2009.

[7] Y. Guangying, "Study of myoelectric prostheses hand based on independent component analysis and fuzzy controller," in *Eighth International Conference on Electronic Measurement and Instruments*, pp. 1–174–1–178, Aug. 2007.

[8] A. Hyvaerinen, "Survey on independent component analysis," *Neural Comput. Sur.*, vol. 2, pp. 94–128, 1999.

[9] T. Jung, S. Makeig, M. J. McKeown, A. J. Bell, T. Lee, and T. J. Sejnowski, "Imaging brain dynamics using independent component analysis," in *Proceedings of the IEEE*, vol. 89, pp. 1107–1122, Jul. 2002.

[10] Y. Li, S. Amari, A. Cichocki, D. W. C. Ho, and S. Xie, "Underdetermined blind source separation based on sparse representation," in *IEEE Transactions on Signal Processing*, vol. 52, pp. 423–437, Feb. 2006.

[11] S. Araki, H. Sawada, R. Mukai, and S. Makino, "Underdetermined blind sparse source separation for arbitrarily arranged multiple sensors," *Signal Processing*, vol. 87, pp. 1833–1847, Mar. 2007.