Decoding Underlying Brain Activities in Time and Frequency Domains through Complex Independent Component Analysis of EEG Signals

Gaetano Valenza, Nicola Vanello, Matteo Milanesi, Enzo Pasquale Scilingo, and Luigi Landini

Abstract— **Brain activities are often investigated through Electroencephalographic (EEG) data analysis using time-domain Independent Component Analysis (ICA). Nevertheless, the instantaneous mixing model of ICA cannot properly describe spatio-temporal dynamics, such as those related to traveling waves of neural activity. In this work, we exploit the application of the Complex ICA (cICA) to describe the underlying brain activities in time and frequency domain. In particular, we show how to effectively extract the most significant time-frequency structure of cortical activity in order to solve a compelling EEG-based pattern classification problem. The crucial step of independent component selection among frequencies is performed using an objective computational method based on template matching techniques with physiologically-plausible activations. Experimental results are obtained using on-line EEG data from the BCI Competition 2003 and are expressed in terms of confusion matrix after leave-one-out validation procedure. A comparative analysis between ICA and cICA models reveals that cICA estimation gives powerful information and allows to achieve a higher classification accuracy with respect to instantaneous ICA.**

Index Terms— **Complex Independent Component Analysis, Electroencephalogram, Time-Frequency Analysis**

I. INTRODUCTION

The multi-channel Electroencephalogram (EEG) [1] is a powerful multivariate signal, derived from non-invasive recordings, which reflects the synchronized electrical activity of large neuronal populations. Several signal processing techniques have been developed and are still under study to support the diagnosis of brain disorders, tumors, cerebrovascular lesions and problems associated with brain trauma [1], [2].

Independent Component Analysis (ICA) algorithms [3], [4] are a family of unsupervised statistical methods used for decomposing a mixed signals into independent sources. ICA has been proven to be an important tool for EEG analysis for the extraction and separation of statistically independent sources, and reveals more information than classical methods such as Principal Component Analysis (PCA) [4]. ICA can be applied to EEG data in order to find proper combinations of measurement channels, i.e. spatial filters, resulting in temporally independent components. Standard ICA can be applied successfully for artifact removal from EEG signals, such as electrocardiogram, electrooculogram and skeletal muscle activity [4]. The instantaneous mixing model has been applied also to the decomposition of EEG neural sources, under the hypothesis of independence or near independence of the temporal activity of local neural populations, sparsely interconnected [5]. However, the application of instantaneous mixing model to EEG data encounters several theoretical and practical limitations. Firstly, the ICA mixing model assumes that EEG observations result from a linear instantaneous combination of different sources. Since the propagation of electromagnetic waves across the brain tissues may be considered instantaneous at frequencies of interest, this model may properly describe sources at fixed positions within the brain. Such assumptions can be too strong in case of EEG [1], [2], [6] because of the spatiotemporal dynamics of EEG data. In fact EEG may be characterized by traveling waves across the brain due to the propagation of neural activity. In such a case the EEG signal at a given electrode may be seen as a summation of delayed sources. A similar phenomenon can originate when different brain areas are coupled, although with time delays. Another limitation of instantaneous mixing model is that the obtained independent components (ICs) are related to the EEG time-domain structure exclusively. In fact, EEG activity has distinctive characteristics in different frequency bands, as delta, theta, alpha, beta, and gamma bands, which may be associated with different physiological processes [1]. To overcome these limitations, a convolutive mixing model was proposed by Anemuller et al. [6] to extract the underlying EEG complex dynamics through effective estimation of the EEG sources. Such a technique, so-called Complex ICA (cICA), hypothesizes a linear mixing of convolved sources. The convolutive model is solved in the frequency domain by means of a time-frequency representation of the EEG signals and by applying an instantaneous mixing model to each frequency band.

This work aims at validating the suitability of cICA approach to effectively decompose underlying brain activity as recorded by EEG during a compelling task. To this aim, we here describe how to classify EEG trials during a sensorimotor rhythms modulation task, designed for brain-computer interface application [7]. We present a study comparing ICA and cICA spatial filtering as part of a comprehensive processing chain able to distinguish 4 classes referred to different mental states. To objectively choose the ICs useful for classification purposes, an automatic method based on template matching approach is proposed. Experimental results were obtained using the dataset IIa from BCI Competition 2003 [7] records and are shown in form of

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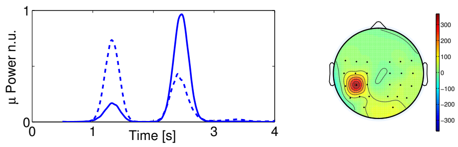

Fig. 1. (Left) Averaged power of the μ sensorimotor rhythm along the time, evaluated among trials belonging to the target top (continuous line) and bottom (dashed line).

confusion matrix [8]. Classification accuracies from Support Vector Machine (SVM) [9] using cICA-based and standard ICA-based methods were compared.

II. Materials and Methods

In this section, we show the proposed approach describing how practical issues regarding the application of ICA models on EEG signals, i.e. EEG channel selection, ICA and cICA spatial filtering and automatic ICs selection, were addressed. Further details will be eventually provided in the extended version. All algorithms were developed using Matlab v7.2, exploiting graphics functions from the EEGLab Matlab toolbox and using LIBSVM for SVM classification.

A. Experimental Protocol

As the experimental protocol was extensively described in [7], [10], in this paragraph we briefly report on the description of the data set IIa of the BCI Competition 2003. The dataset comprises acquisitions on three subjects. To introduce the proposed methodology, we will show the results obtained on one subject (identified as A). 64-channels EEG data were recorded using surface electrodes at a sampling rate of 160 Hz during ten 30-min sessions consisting of a sensorimotor rhythms modulation task. Each session contained 192 trials of 4 seconds each. For each trial, the subject had to control a moving cursor shown in a monitor. The vertical movement of the cursor was determined by a linear combination of the subject's amplitude power in μ $(8-12\text{Hz})$ and β $(18-24\text{Hz})$ frequency bands of signals related to three channels located over sensorimotor cortex (i.e. CP1, CP3, CP5). The goal was to match the final position of the cursor with the target position indicated at the beginning of the trial. Each trial started with one second of blank screen and another second in which the target position appears on the right side of the screen. Such a position was randomly chosen among four possible positions/classes, i.e. top, up (middle-top), down (middle-bottom), bottom. During the last two seconds, a cursor appears in the middle of the left side of the screen and travels at a constant speed to the right, and can be controlled by the subject. Consequently, the screen is cleared and the next trial begins.

Figure 1 shows the averaged power of the μ sensorimotor rhythm along time, estimated from trials belonging to the target top and bottom.

B. Channel Selection and Preprocessing

In order to apply the ICA and cICA algorithms, multivariate data comprised of as many EEG channels as possible is strongly suggested. Nevertheless, high dimension of the data could lead to a high computational load and estimation problems leading, consequently, to an unreliable estimation of the unmixing matrices. Moreover, to achieve reliable components estimates, the maximum number of channels that can be exploited is limited by the number of data time points [5]. Therefore, when a high-resolution EEG acquisition (i.e., ≥ 64 EEG channels) is performed, a channel selection procedure is needed. The selected EEG channels used in this work are 26, namely FC1-6, C1-6, CP1-6, P1-6, PO3-4, according to the standard 10-20 system. This choice is motivated by the engagement of the electrodes upon the sensory motor cortex along with their mirrored channels. Moreover, this choice is based on the correlation study described in [10].

Concerning the preprocessing step, the signal coming from each EEG channel was filtered by means of a fourth-order IIR band-pass filter having cut-off frequencies equal to 1Hz and 40Hz. Data were already provided with artifact-free samples [7], [10].

C. Independent Component Analysis (ICA)

Considering the time-varying artifact-free EEG signals $x(t) = (x_1(t), x_2(t), ..., x_N(t))^T$, where $i = 1, ..., N$ denotes the electrodes, as a linear instantaneous mixture of statistically independent sources $s(t) = (s_1(t), s_2(t), ..., s_M(t))^T$, it is possible to model $x_i(t)$ as $x_i(t) = \sum_{k=1}^{M} a_{ik} s_k(t)$ where the operator T stands for the transpose operator of the matrix, and $A = \{a_{ik}\}_{MxN}$ is the linear mixing matrix. Assuming the statistical independence of the sources, ICA aims to estimate the unmixing matrix W such that $y(t) = Wx(t)$. Therefore, signals $y(t)$ provide an estimation of $s(t)$ being as statistically independent as possible.

Different contrast functions are used in ICA algorithms to maximize the independence among the output signals in order to estimate the unmixing matrix. Here, we adopted the FastICA algorithm using negentropy as a contrast function [3].

D. Complex Independent Component Analysis (cICA)

The cICA assumes a convolutive model where each variable is given by a linear summation of convolved sources $x_i(t) = \sum_{k=1}^{M} a_{ik} \otimes s_k(t)$ where a_{ik} are finite impulse response filters. The cICA procedure consists of two processing stages. First, each signal from a chosen *i*-th electrode, $x_i(t)$, of the measured EEG is decomposed into time-frequency representation $Xi(T, f)$ by using the short-time Fourier transform (STFT). Then, the previously described ICA algorithm is performed on the complex frequency-domain data within each spectral band. Therefore, a set of complex ICs is estimated for each frequency bin [6].

For each frequency, the signals $Xi(f, t)$ are assumed to be generated by independent sources $Si(f, t)$ by multiplication with a frequency-specific mixing matrix $A(f)$ such that $Xi(T, f) = A(f)Si(f, t)$ with $rank\{A(f)\} = N$.

Afterwards, the estimates $\widetilde{X}(T, f)$ of the sources are obtained from the sensor signals by multiplication with frequency-specific separating matrices $W(f)$ such that $\widetilde{X}(T,f) = W(f)X_i(T,f)$. The sources $Si(f,t)$ are modeled as complex random variables with a circular symmetric, super-Gaussian distribution probability density function, and the separating matrix $W(f)$ is obtained by maximizing the log-likelihood of the measured signals $Xi(T,f)$. The detailed mathematical derivation of the cICA is reported in [6]. The cICA estimates M_c ICs which is equal to $M_c = BM(\Delta f)^{-1}$, with Δf and B the frequency resolution and band of the frequency representation, respectively.

An ambiguity of the cICA approach resides in the unknown extraction order of ICs at each frequency. In practice, there is a need to identify the sources $Si(f,t)$ that belong to the same IC in the time domain. This procedure, that is usually referred as alignment of ICs, can be performed exploiting correlations among the different sources [6], [11].

E. Automatic Independent Component selection and Pattern Recognition

The IC selection aims at considering the most significant ICs among the M and M_c when the ICA or cICA is applied, respectively. Retaining all the ICs, in fact, could lead to a non-optimized and redundant information as input for the classification algorithm.

As we are dealing with a large amount of ICs given by the cICA algorithm, an automatic IC selection procedure is needed also to reasonably provide objective and improved results. We propose a method based on template matching between the estimated ICs with a physiologically plausible activation. The template was chosen as the time-domain evolution at a given frequency, extracted from channel CP3. As we are dealing with EEG data gathered during sensorimotor rhythms modulation tasks, we are interested in consistent and significant activations within the μ (8−12 Hz) and β (18−24 Hz) frequency band, i.e. the so-called sensorimotor rhythms. Given the inter-subject variability of the μ and β bands, a power frequency analysis of EEG signals was performed to validate such bandwidths. As an example, figure 1 shows a physiological activation in μ band during two different sensorimotor rhythms modulation tasks (see section II-A for further details).

The Spearman correlation coefficient was selected as metrics for the computation of the matching score and a simple thresholding was applied to identify ICs that should be chosen. It is straightforward to notice that, when using cICA algorithm, the IC selection is performed among ICs related to frequencies belonging to the μ and β bandwidths. While, in the standard ICA approach the correlation coefficient was computed after STFT of the ICs.

Each chosen IC contributes in defining the feature set related to each class. The feature set of the ICA and cICA are comprised of the time evolution of the Power Spectral Density features in μ and β bands. While in the former case these features were obtained by STFT, in the latter were obtained directly from ICs components. We compared the performances given by the ICA and cICA spatial filters using a multi-class Support Vector Machine algorithm [9] with Leave-One-Out (LOO) cross-validation procedure [12]. More specifically, we used ν-SVM ($\nu = 0.5$) having a radial basis kernel function with $\gamma = n^{-1}$, where n is the feature space dimension.

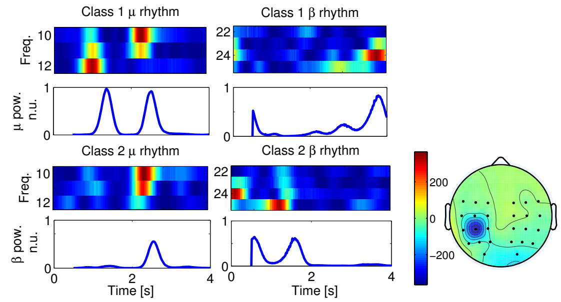

Fig. 2. An example of IC chosen after the application of the ICA algorithm. The STFT representations and the power of the sensorimotor rhythms during the target/class 1 (top) and target/class 2 (bottom) are shown. The topoplot shows that the principal source of such an IC is generated from the sensorimotor cortex.

The results are expressed in terms of confusion matrix [8] in which the element r_{ij} indicates how many times in percentage a pattern belonging to the class i was classified as belonging to the class j. The more diagonal is the confusion matrix, the higher is the accuracy of classification.

III. Results

In this work, the six labelled sessions from the subject A of the data set IIa of the BCI Competition 2003 are taken into account for further evaluation. The EEG signals have been preprocessed as described in paragraph II-B and the last 2 seconds of each trial, when the cursor is controlled by the subject, were analyzed.

Standard ICA results: concerning the application of the standard ICA spatial filtering, PCA was applied to all the available EEG data (six sessions, i.e., 1152 trials) gathered from the selected 26 channels, retaining the first 15 components which explain more than 98% of the total variance. On such data, the FastICA algorithm was applied to estimate the unmixing matrix W. The ICs having correlation coefficient > 0.8 were selected for further analysis, resulting in five selected ICs. The threshold value was empirically chosen as the one giving best classification results. An example of chosen IC is shown in Fig. 2. The feature set was comprised of 288 examples for each target class representing the power in μ and β bands on each selected ICs. The classification result was obtained using an SVM with leave-one-out procedure and expressed in terms of confusion matrix as shown in Tab. I. Having 4 classes, the random guess accuracy is 25%.

Complex ICA results: the application of the cICA spatial filtering was performed on the concatenated time-frequency representations of each trial. As concerns the short-time Fourier representation, a windowing procedure was applied with sliding Hamming time windows of 1 s length overlapped of 0.1 s, so obtaining $\Delta f = 1Hz$. For each frequency within μ and β bands, the PCA was applied to retaining the first 22 components which explain more than 98% of the total

TABLE I

CONFUSION MATRIX OF SVM CLASSIFIER USING STANDARD ICA.

	Target 1	Target 2	Target 3	Target 4
Target 1	**57.10**	23.77	12.35	6.79
Target 2	20.00	**35.00**	27.14	17.86
Target 3	8.33	28.33	**32.50**	30.83
Target 4	8.77	14.61	30.52	**46.10**

Bold indicates the percentage of correct classification for each target class.

variance. As for the ICA, once the unmixing matrix $W(f)$ was estimated, five ICs were chosen showing a correlation coefficient with the template > 0.65. The feature set was comprised of 288 examples for each target class representing the selected IC samples in μ and β bands on each selected ICs. The classification result was obtained using an SVM with leave-one-out procedure and expressed in terms of confusion matrix as shown in Tab. II.

TABLE II

CONFUSION MATRIX OF SVM CLASSIFIER USING COMPLEX ICA.

	Target 1	Target 2	Target 3	Target 4
Target 1	**80.00**	7.17	8.68	4.15
Target 2	5.41	**92.79**	0.45	1.35
Target 3	7.56	3.19	**87.25**	1.99
Target 4	1.97	5.91	1.97	**90.16**

Bold indicates the percentage of correct classification for each target class.

IV. CONCLUSIONS

In this work, we described how to effectively detect the underlying brain activities in time and frequency domains using Complex Independent Component Analysis (cICA) of EEG signals. The EEG electrical activity, in fact, can be seen as a result of a mixing process of the cortical neural sources. Accordingly, standard techniques of blind source separation such as linear instantaneous ICA algorithms are used for the cortical source estimation with several applications ranging from artifact removal to neural activity analysis [4], [5]. Nevertheless, a simple linear mixing model cannot be sufficient to properly model and estimate the cortical sources, because of the complex spatiotemporal dynamics of the brain activity. All these issues can be afforded adopting a more general mixing model, i.e. the convolutive mixing model [6]. Taking advantage of the convolution theorem, the EEG sources are estimated from the complex time-frequency representation of the EEG signals according to the short-time Fourier definition. In this paper, we described the advantages in applying such an approach to solve a practical and difficult EEG classification problem. A comprehensive processing chain involving also preprocessing and pattern recognition steps has been described. Both ICA and cICA algorithms estimate a number of ICs equal to the dimension of the input data. Given the high number of ICs, especially when using cICA on high resolution EEG data, an ICs selection procedure is needed. Therefore, we showed how to objectively select such ICs using data-driven physiologically-plausible templates. Our results are very satisfactory. When using cICA spatial filters, the difficult 4-class problem is effectively solved reaching more than 80% of classification accuracy (see Tab. I). The results obtained with standard ICA, instead, seem to indicate that a simple linear instantaneous mixing model is less suitable for representing the underlying brain activity, at least in this task. Several theoretical and practical issues can still be raised concerning the proposed methodology and could be the topic of an eventual extended version of this manuscript. The first issue is related to the channel selection strategy. In fact, it could be possible to choose electrodes in a way to cover most of scalp surface, at the expenses of sensor density. This alternative strategy could take into account components originating in different areas, as the frontal regions. Another issue is related to the estimation of the unmixing matrices: the shown results were obtained using all the available trials. This operation is allowed since it does not need any trial labeling and does not affect the independency between training and test sets. Results obtained by estimating the unmixing matrices without the test set could be provided. A comparison of the results obtained adopting the two strategies could also serve as an indication of data non-stationarity, i.e. inter-trial variability. Concerning the ICs selection step, we adopted a physiological plausible and data-driven template matching method. Nevertheless, other approaches could be feasible as, for instance, a choice based on the minimization of mutual information among the ICs. This latter approach, could reveal unexpected significant components relevant for the classification.

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