BLIND SOURCE SEPARATION BY INDEPENDENT COMPONENT ANALYSIS APPLIED TO ELECTROENCEPHALOGRAPHIC SIGNALS

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Abstract: **Independent Component Analysis (ICA) is a statistical based method, which goal is to find a linear transformation to apply to an observed multidimensional random vector such that its components become as statistically independent from each other as possible.**

Usually the Electroencephalographic (EEG) signal is hard to interpret and analyse since it is corrupted by some artifacts which originates the rejection of contaminated segments and perhaps in an unacceptable loss of data. The ICA filters trained on data collected during EEG sessions can identify statistically independent source channels which could then be further processed by using event-related potential (ERP), event-related spectral perturbation (ERSP) or other signal processing techniques. This paper describes, as a preliminary work, the application of ICA to EEG recordings of the human brain activity, showing its applicability.

I. INTRODUCTION

An important application of multichannel EEG is to try to find the location of a epileptic focus (a small spot in the brain where the abnormal activity originates and then spreads to other parts of the brain) or of a tumor, even when they are not visible in a x-ray or CT scan of the head.

Blind Source Separation (BSS) concerned to signal processing applications is an application area which main goal is the recovering of independent source signals, after they are linearly mixed by an unknown medium. This source separation is achieved by using recordings of several sensors. A classical example of blind source separation is the cocktail party problem, where several people are speaking simultaneously in the same room. The problem is to separate the voices of the different speakers, by using recordings of several microphones in the room.

Some acceptable solutions for the blind source separation problem have been found in the neural network and statistical signal processing fields. The classical application of the ICA model is blind source separation. In contrast with decorrelation techniques such as Principal Component Analysis (PCA), which ensures that output pairs are uncorrelated, the ICA maximizes the degree of statistical independence among outputs using contrast functions approximated by the Edgeworth expansion of the Kullback-Leibler divergence [1]. Therefore when compared with the PCA, ICA imposes the much stronger criterion that the multivariate probability density function of output variables factorizes. Finding such a factorization requires that the mutual information between all variable pairs go to zero. While decorrelation only takes account of second-order statistics, the mutual information depends on all higher-order statistics of the output variables. Although ICA can be seen as an extension of the PCA and factor analysis it is really a more powerful technique, capable of finding the underlying sources when these classical methods fail completely.

As the problem of determining brain electrical source from patterns recorded on the scalp surface is mathematically undetermined the joint problem of EEG source identification, segregation, localization and removing artifacts becomes very difficult. Recent efforts to identify EEG sources have focused mostly on performing spatial segregation and localization of source activity. The problem of both source localization and source identification have been investigated by using the ICA algorithm. Independent sources can be derived from highly correlated EEG signals and without regarding to the physical location or configuration of the source generators, by using the ICA algorithm, however, canceling these noise sources is a central, and as yet unsolved problem in EEG signal processing.

One of the most successful method is mainly based on ICA of an artificial neural network by using an adaptive algorithm. In the adaptive case, the algorithms are obtained by stochastic gradient methods. When all the independent components are estimated simultaneously, the most popular algorithm in this category is natural gradient ascent of likelihood, or related contrast functions like “Infomax”. The experiments described in this paper were obtained by using a kind of extended “Infomax” algorithm for the EEG analysis.

II. RELEVANT ICA THEORY

The ICA algorithm allows to separate N independent sources from N sensors under the constraints that the propagation delays of the unknown “mixing medium” are negligible, and the sources are non-log and have probability density functions (pdf’s) not too unlike the gradient of a logistic sigmoid. Therefore the EEG signal must be recorded by N scalp electrodes and the correlated signals are used to separate N unknown “independent brain sources” that generated these mixtures.

Before proceeding we have to make a clear distinction between ICA, which is a theoretical method with different applications, and blind source separation, which is an application that can be solved using various theoretical approaches, including but not limited to ICA. One of these approaches is the PCA, which is a decorrelation technique, so ensuring that output pairs are uncorrelated $<y_i, y_j=0>$, for all *i* and *j*. Decorrelation only takes account of second-order statistics. In contrast the ICA is based on the much stronger criterion of statistical independence which requires all higher-order correlations of y_i to be zero. The relation between Principal Component Analysis and ICA is evident. Both methods formulate a general objective function that define the 'interestingness' of a linear representation, and then maximize that function. A second relation between PCA and ICA is that both are related to factor analysis, though under the contradictory assumptions of Gaussianity and non-Gaussianity, respectively. The affinity between PCA and ICA may be, however, less important than the affinity between ICA and other methods. This is because PCA and ICA define their objective functions in quite different ways. PCA uses only second-order statistics, while ICA is impossible using only second-order statistics. PCA emphasizes dimension reduction, while ICA may reduce the dimension, increase it or leave it unchanged. However, the relation between ICA and nonlinear versions of the PCA criteria is quite strong.

Suppose $y_1, y_2, \ldots, y_N$ random variables with joint pdf given by $f(y_1, y_2, \ldots, y_N)$. If the random variables y_i are statistically (mutually) independents then the joint pdf can be factorized since

$$f(y_1,...y_N) = \prod_{i=1}^{N} f_{y_i}(y_i) \qquad (1)$$

where $f_{y_i}(y_i)$ denotes the marginal density of y_i. If the random variables y_i are statistically independents, then for any functions g_1 and g_2 one has

$$E\{g_1(y_i)g_2(y_j)\} - E\{g_1(y_i)\}E\{g_2(y_j)\} = 0, i \neq j \qquad (2)$$

which is clearly a stricter condition than the condition of uncorrelatedness given by

$$E\{y_i y_j\} - E\{y_i\}E\{y_j\} = 0, i \neq j \qquad (3)$$

However for the special case of joint Gaussian distribution, independence and uncorrelatedness are equivalent [2] and ICA becomes in these cases not interesting or impossible.

A simple neural network algorithm based on information maximization (Informax) was derived by Bell and Sejnowski [3] and is able to separate super-Gaussian (sparse) independent components. A source s_i can be distinguished from mixtures x_i by considering the activity of each source statistically independent of the other sources. This means that their joint probability density function, measured across the input time ensemble factorizes. Therefore the mutual information between any two sources, s_i and s_j is zero:

$$I(y_1, y_2, ..., y_N) = E\left\{ \ln \frac{f_y(y)}{\prod_{i=1}^{N} f_{y_i}(y_i)} \right\} = 0 \qquad (4)$$

where *E{.}* denotes mathematical expectation. The sources s_i are assumed to be temporarily independent, while the observed mixtures of sources, x_i are statistically dependent on each other, therefore the mutual information between pairs of mixtures, $I(x_i,x_j)$ is in general positive. The problem of blind source separation consists in finding a matrix **W** such that the linear transformation

$$I = Wx = Was \qquad (5)$$

re-establishes the condition $I(y_i,y_j)=0$, for all $i \neq j$.

Consider the joint entropy of two non-linearly transformed components of **u**:

$$H(u_1,u_2) = H(u_1) + H(u_2) - I(u_1,u_2) \qquad (6)$$

where $u_i=g(y_i)$ and $g(.)$ is an invertible, bounded nonlinearity. The nonlinear function provides, through its taylor series expansion, higher order statistics which are necessary to establish independence.

The maximization of the joint entropy is obtained by maximizing the individual entropies, $H(u_1)$ and $H(u_2)$ and minimizing the mutual information $I(u_1,u_2)$. In general the maximization of $H(u)$ minimizes $I(u)$ and when the mutual information reaches the value zero the two variables become statistically independents. The algorithm attempts to maximize the entropy by iteratively adjusting the elements of the square matrix **W**, by using small batches of data vectors drawn randomly from {**x**}. Without substitution, one has

$$\Delta W \propto \frac{\partial H(u)}{\partial W} W^T W = \left[I + \phi y^T \right] W \qquad (7)$$

where

$$\phi_i = \frac{\partial}{\partial y_i} \ln \frac{\partial u_i}{\partial y_i}$$

The term $(W^T W)$ is the natural gradient and avoids matrix inversions speeding up the convergence. The form of the nonlinearity g(u) is crucial in the performance of the algorithm and its ideal form is the cumulative density function (cdf) of the distributions of the independent sources.

Assuming that the complexity of the EEG dynamics can be modelled as a relatively small number of independent brain processes, the EEG source analysis problem satisfies ICA assumption. The foremost problem in interpreting the output of ICA is determining the number of input channels, and the physiological and/or psychophysiological significance of the derived source channels.

III. EXPERIMENTAL RESULTS

The extended ICA algorithm was tested in both simulated data, as shown in figure 1, and in real data as shown in figure 2. Figure 1a) shows four independents generated signals that are then linearly mixed resulting the signals shown in figure 1b). Figure 1c) shows the result of the extended ICA decomposition algorithm applied to the signals shown in figure 1b), which obviously does not take into consideration the linear transform from which the signals obtained in figure 1b) were obtained from the ones shown in figure 1a).

By comparing figures 1a) and 1c) we can conclude that the result of the decomposition is satisfactory since the order, polarity and amplitude of the output only have a simple changing.

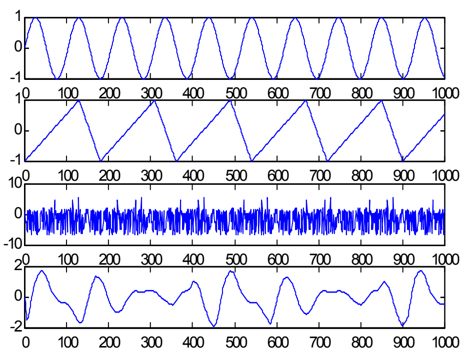

Figure 1a). Four signals generated independently

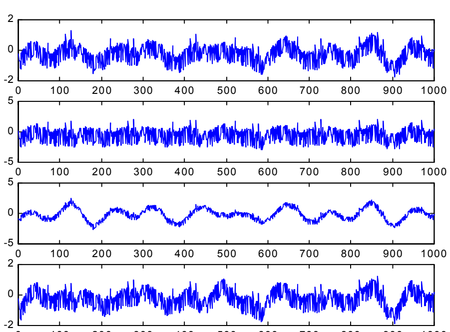

Figure 1b). The Signals shown in figure 1a) after passed through a random mixed matrix.

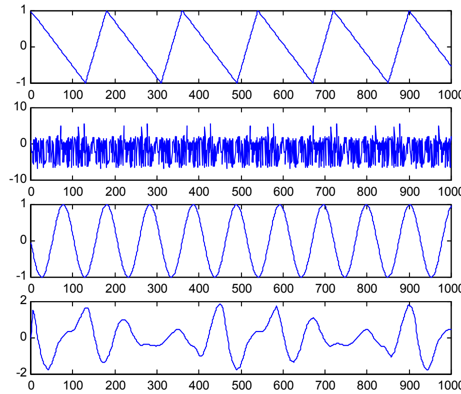

Figure 1c). Signals after ICA decompose

The extended ICA algorithm was also applied to the analysis of 10 EEG recordings of the human brain activity. To ensure signal stationarity the time index was permuted, and the 10-dimensional time vectors were presented to a 10->10 ICA network one at a time. First and second order statistics were removed in order to speed up the convergence, so the data were first pre-whitened. The learning rate was annealed from 0.03 to 0.0001 during convergence. After each pass through the whole training set, the value of correlation between the ICA output channels and the value of change in the weight matrix were checked, and the training was stopped when the mean correlation among all channel pairs was bellow 0.06 and the ICA weights had stopped changing appreciably.

EEG recordings of the human brain generally include either super-Gaussians signals (ERPs for example), or sub-Gaussian signals (for example working frequency disturb and EOG). So ICA appears suited for this kind of applications as shown in figure 2 where the experimentation was done in real EEG data.

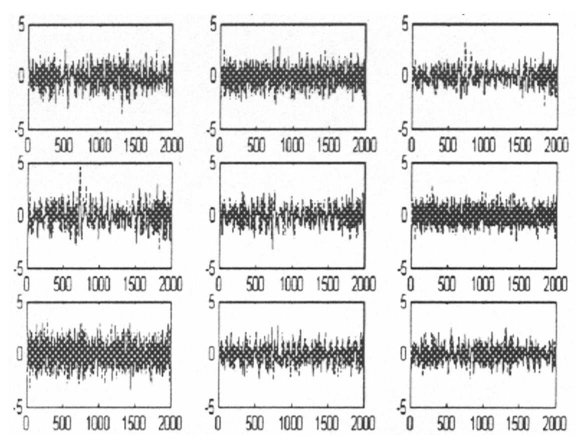

Figure 2. EEG real data separated by ICA

The first row on the left of figure 2 shows a normal EEG data, the second row is a close and open eye's EEG data and finally the third row is a working frequency disturbing. These original signals were mixed as in the last case of synthetic data and the ICA algorithm realized the blind source separation. The results are very promising taking into consideration that the target signals include both super-Gaussian and sub-Gaussian sources.

IV. Discussion

This paper has focused on the application of ICA to the analysis of EEG, which proved a reasonable efficiency.

Apart from the brain signals, signals from other organs, as for example from the heart system have similar problems with artifacts and could also benefit from ICA techniques. In general biomedical signals are a rich source of information about physiological processes, but they are often contaminated with artefacts or noise and are typically mixtures of unknown sources summing differently at each sensor. Besides other interesting questions such as to understand the nature of the sources, ICA seems to hold a great promise, for blindly separating artifacts and decomposing the mixed signals into subcomponents that may reflect the functionality of distinct generators of physiological processes, which must also be interpreted in the near future.

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