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# Independent Component Analysis of EEG Signals

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**Abstract:** Independent component analysis (ICA) technique is applied to the analysis of Electroencephalographic (EEG) signal. The main task of ICA for a random vector includes searching for a linear transformation which minimizes the statistical dependence between the components involved in the signal. In practice, some artifacts problems limit the interpretation and analysis of clinical EEG signals since the rejected contaminated EEG segments results in an unacceptable data loss. In this contribution, ICA filters were trained based on the EEG data during these sessions were identified statistically independent source channels, which could then be further processed using other signal processing techniques. Finally, the applications of ICA to the multichannel EEG recordings from the human brain were investigated and compared. The experimental results indicated that the proposed ICA method for analyzing EEG significantly cancels the additive background noise and separate the mix signals.

## I. Introduction

The blind source separation has been widely used in many practical areas of modern signal processing. Based on the blind source separation, the independent source signals can be recovered after the signals are linearly mixed with an unknown medium and recorded at N sensors. The concept of independent component analysis (ICA) was described as maximizing the degree of statistical independence among outputs using contrast functions approximated with the Edgeworth expansion of the Kullback-Leibler divergence [1]. In contrast with de-correlation techniques such as Principal Component Analysis (PCA) which ensures that the output pairs are uncorrelated. ICA imposes the much stronger criterion that the multivariate probability density function of output variables factorizes. To find such a factorization, it is required that the mutual information between all variable pairs become zero. The decorrelation only takes account of second-order statistics, but the mutual information depends on all higher-order cumulants of the output variables.

To deal with the problem of EEG signal preprocessing, artifacts cancellation and source localization, it is always difficult due to the fact that the determination of brain electrical source from patterns collected from the scalp is mathematically underdetermined. Recent efforts to identify EEG sources have focused mostly on performing spatial segregation and localization of source activity. Using the ICA algorithm, the problem of both source identification and source localization have been investigated. The ICA algorithm derives independent sources from highly correlated EEG signals statistically and does not regard to the physical location or configuration of the source generators of EEG signals.

Recently, more and more attention has been paid to the ICA techniques. As a noteworthy and decomposed method, ICA was more successful like an artificial neural network and adaptive scheme. For our purpose, the extended Infomax algorithm of ICA is employed to investigate the multichannel EEG signals. As a matter of fact, ICA method is much suited for performing signal source separation if the source are statistically independent and satisfied with some other conditions [1]. It is also assumed that the number of the independent signal source is the same as the number of the N sensors. Thus, N sources signals can be separated with ICA technique. For the problem of separating multichannel EEG signals, N scalp electrodes pick up N correlated signals from the scalp and we need to know what effectively 'independent brain sources' generated these mixtures signals. If we assume that the complexity of the EEG dynamics can be modeled, at least in part, as a collection of a modest number of statistically independent brain processes, the EEG source analysis problem satisfies ICA assumption. The foremost problem in interpreting the output of ICA is, therefore, to determine the proper dimension of the input channels and the physiological and/or psychophysiological significance of the derived ICA source channels. The ICA model of the EEG ignores the known variable synchronization of separate EEG generators by common subcortical or cortical influences [3,4]. However, it appears promising for identifying concurrent signal source that are either situated too close together or too widely distributed to be separated by current localization methods. To solve this problem, an ICA algorithm is proposed to study the N-channels EEG signals and ERPs recordings when subjects were tested with certain task like performing an auditory detection task. The experimental results suggested that the presented scheme provided a useful method for separating multichannel EEG source signals.

## II PROPOSED SCHEME

In fact, ICA is mainly connected with the area of statistical signal processing. The concept of independent component analysis is defined as the procedure of maximizing the degree of statistical independence among outputs based on the contrast functions approximated using the Edgeworth expansion of the Kullback-Leibler divergence [2]. It is different from the decorrelation methods like Principal Component Analysis (PCA) which ensures that output pair signals are uncorrelated with each other. It can be expressed as $\langle u_i u_j = 0 \rangle$. However, ICA algorithm impose the much stronger criterion which has the following multivariate probability density function of **u** factorizes given as [6,7]

$$f_u(u) = \prod_{i=1}^{N} f_{u_i}(u_i) \qquad (1)$$

As we know, the concept of statistical independence means all higher-order correlations of the $u_i$ become zero. In contrast, the second-order statistics is used for dealing with the problem of signal decorrelation. A simple neural network algorithm based on information maximization ("infomax") was developed, which enables us to blindly separate the super-Gaussian sources [5,6]. Moreover, the important fact that we can distinguish a source, $s_i$ , from mixtures, $x_i$ , is that the activity of each source is statistically independent from the other sources. This means that their joint probability density function is measured from the input time ensemble. It can also be understood that the mutual information between any two sources, $s_i$ and $s_j$ , is zero such as

$$I_s(u_1, u_2, \cdots, u_N) = E[\ln \frac{f_u(u)}{\prod_{i=1}^{N} f_{u_i}(u_i)}] = 0 \qquad (2)$$

where E[ • ] denotes expectation operation. Unlike the sources s that are assumed to be temporally independent, the observed mixtures of sources x are statistically dependent with each other. Hence, generally, the mutual information between the pairs of the mixtures, $I(x_i, x_j)$, is positive [7]. The main task of blind separation problem is to compute a matrix, **W**, so that the following linear equation established:

$$\mathbf{I=Wx=Was} \qquad (3)$$

if re-establishing the condition $I_s(u_i, u_j) = 0$ for all $i \neq j$.

Let us consider the joint entropy of two nonlinearly transformed components of **y** such as

$$H(y_1, y_2) = H(y_1) + H(y_2) - I(y_1, y_2) \qquad (4)$$

where $y_i = g(u_i)$ and $g(\ )$ is an invertible and bounded nonlinear function which provides, through its Taylor series expansion, the higher-order statistics that are necessary to establish independence condition. The procedure of maximizing the joint entropy includes maximizing the individual entropies $H(y_1)$ and $H(y_2)$. So maximizing $H(y)$, in general, is equivalent to minimize the $I(y)$. If the latter become zero, the two variables are regarded as statistically independent with each other. We try to maximize the entropy $H(y)$ by iteratively adjusting the elements of the square matrix **W** via the small batches of data vectors drawn randomly from $\{\mathbf{x}\}$ without substitution. In this way, the following relationship can be developed as

$$\Delta W \propto \frac{\partial H(y)}{\partial W} W^T W = [I + \phi u^T] W, \qquad \phi_i = \frac{\partial}{\partial u_i} \ln \frac{\partial y_i}{\partial u_i} \tag{5}$$

In the expression above, $(W^T W)$ is the "natural gradient" term which avoids the matrix inversions and speeds convergence. The nonlinear function $g(u)$ plays an essential role in performing the algorithm well. The cumulative density function of the distributions of the independent sources is always suggested as the nonlinear function [8].

## III Experimental Results

In this section, a simulation was implemented for the purpose of testing the effectiveness of the extended ICA algorithm used in this paper. First of all, 4 signals were generated and passed a linear system with random mixed matrix. To evaluate the performance of the ability of decomposition, the mix signal was processed with the proposed ICA algorithm. The simulation result was shown in Fig.1. It can be seen that the ICA method effectively separate the independent sources although the order, polarity and amplitude of the sources may be different.

In addition, we applied the presented ICA technique to investigate the 14 channel EEG spontaneous signals. The signal segments to be analyzed were assumed to be stationary. Thus, the 14-dimensional EEG time series vectors were presented to a $14 \rightarrow 14$ ICA network. Before separating the signals, the technique of pre-whitening the time series was carried on to remove first- and second-order statistics and to guarantee the convergence of the algorithm. The learning rate was set from 0.03 to 0.0001 when keeping the convergence established. After each data pass through the whole training set, we tested the amount of correlation between the ICA output channels and the amount of change in weight matrix and stopped the training procedure when the mean correlation among all channel pairs was less than 0.05. Then the ICA weights stop changing appreciably. And the processing procedures finish.

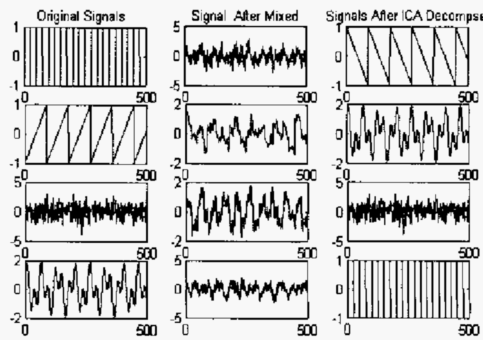


Fig. 1 A typical simulation of separating the mix sources using independent component analysis.

In practice, real EEG signals either include super-Gaussian's noise, especially for ERPs, or sub-Gaussian background such as EOG or other power frequency. We validated feasibility of the extended Informax ICA algorithm which processes our problems. Based on the presented ICA procedure in the simulation, several clinical EEG signals were carried out to separate the mix EEG into a set of independent sources. The experimental result was demonstrated in Fig. 2 which provides us a significant example. From the Fig. 2, we can see that the first row denotes a normal EEG data in the left panel while the second represents another EEG data with eye's close and open alternatively. Similarly, the third row denotes a additive Gaussian noise. The mixed signals output after a linear system was obtained in the middle of the Fig.2. Finally, the decomposition result using ICA algorithm was demonstrated in the right panel. By comparing the inputs with the outputs, it is proved that the extended ICA algorithm allow us to perform the blind source separation of the clinical EEG signals. The corresponding background noise of EEG signals were therefore automatically cancelled.

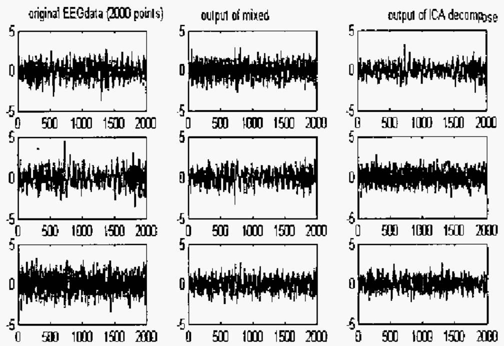


Fig. 2. One of experimental results of ICA decomposition of clinical noisy EEG signals with 20 seconds segment.

## IV DISCUSSION AND CONCLUSION

Real EEG signals include very important information regarding the physiological conditions and the brain function. However, since these kinds of signals are always quite weak and easy corrupted with the artifacts or undesired noise, we often regard these signals as the typical mixtures of unkown combinations of sources summing differently from each sensor. In practice, the nature of the sources for many EEG data sets is still an open question. As a technique, we have focused on applications of ICA algorithm to study both EEG signals and the ERP's. The primary results have shown that the proposed ICA method was effective in processing EEG signals and ERP's when performing the sources separation from only the observed EEG data. Other clinical research applications of ICA may include the analysis of EEG recordings during epileptic seizures and cognitive processing.

In addition to the EEG signals that were presented in this contribution, other physiological signals such as the phonocardiogram and surface EMG signals have similar problems of canceling the artifacts that could also benefit from the ICA. It is true that blind source separation holds great promise for effectively decomposing the artifacts from the relevant signals and further separating the mixed signals into a series of subcomponents. The ICA enables us to understand the activities of functionally distinct generators of physiological process and other mechanism.

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