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Performance Analysis of ICA Algorithms against Multiple-Sources Interference in Biomedical Systems

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Abstract— **This paper evaluates the performance of some major ICA algorithms like Cardoso's Joint Approximate Diagonalization of Eigen matrices (JADE), Bell and Sejnowski's Infomax algorithm and Comon's algorithm in a biomedical blind source separation problem. Independent signals representing Fetal ECG (FECG) and Maternal ECG (MECG) generated and then mixed linearly to simulate a recording of electrocardiogram. ICA has been used to extract FECG, but very less literature is available on the performance, i.e., how does it behave in clinical environment? Therefore, there is a used to evaluate performance of these algorithms in biomedical. To quantify the performance of ICA algorithms, different samples values of simulated maternal and fetal ECG investigated. Separation performance of ICA algorithms measure by performance index. The performance of algorithms are compared and discussed.**

Index Terms—**ICA, BSS, Biomedical Signal Processing**

I. INTRODUCTION

The ECG of an adult describes the electrical activity of the heart. It is an important tool for the physician for identifying abnormalities in the heart activity. In the same way, it is important to obtain the FECG and to trace problems in its heart activity. Most methods for acquiring the FECG are invasive which require placing an electrode on the fetal scalp. This procedure is available during delivery time only. It is important to try to find non-invasive techniques for earlier diagnosis. Obtaining FECG from recordings of electrodes on the mother's skin is fundamentally equivalent to the adult ECG but there are more difficulties arise. The FECG is generated from a very small heart so the signal amplitude is low. Noise from electromyograpic activity affects the signal due to its low voltage. Another interesting source is the maternal ECG (MECG), which can be 5-1000 times higher in its intensity. The MECG shows in all the electrodes, thoracic and abdominal. There is no place to put an electrode on the mother's skin and to receive just the fetal signal without the mother signal. In all cases where the FECG is observed, the MECG is higher in magnitude. So eliminating the MECG from the recorded signal is very important [1].

Technically, the above problem can be thought of as a set of desired and undesired signals linearly mixed to produce another set of body surface signals. It is assumed that these signals are non-Gaussian (except the random noise signal) and independent. ICA decomposes the mixed signals into as statistically independent components as possible. ICA has been used to extract FECG [2][3][4], but very less literature is available on the performance, i.e., how does it behave in clinical environment. This needs an evaluation of its performance in clinical environment. Several ICA algorithms have been proposed. In this paper, we evaluates the performance of some major ICA algorithms like Cardoso's joint approximate diagonalization of Eigen matrices (JADE) [5], Comon's algorithm [7] and Bell & Sejnowski's infomax algorithm[9] in a biomedical blind source separation problem. The signals, which are best suited for ICA, are designed to be biologically motivated for independent FECG and MECG. They are linearly mixed. The ICA separation produces independent FECG and MECG estimates.

II. METHODOLOG

Consider the classical ICA model with instantaneous mixing

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{n} \qquad (1.1)$$

where the sources $\mathbf{s} = [s_1, s_2, \ldots, s_n]^T$ are mutually independent random variables and $\mathbf{A}_{nxn}$ is an unknown invertible mixing matrix and noise $\mathbf{n} = [\mathrm{n}_1, n_2, \ldots, n_n]^T$. The goal is to find only from observations, **x**, a matrix **W** such that the output

$$\mathbf{y} = \mathbf{W}\mathbf{x} \qquad (1.2)$$

is an estimate of the possible scaled and permutated source vectors.

Jutten and Herault provided one of the first significant approaches to the problem of blind separation of instantaneous linear mixtures [10]. Since then, many different approaches have been attempted by numerous researches using neural networks, artificial learning, higher order statistics, minimization of mutual information, beam forming and adaptive noise cancellation, each claiming various degrees of success.

Several algorithms exits for blind source separation. This paper describes the performance of some major ICA algorithms. This section presents a brief description of the respective approaches of the compared ICA algorithms.

A. JADE Algorithm

The JADE algorithm [5] relies on second and fourth-order cumulants to separate the sources. SOS is used to obtain a whitening matrix **Z** from the sample covariances. To reduce the computational load, only the ***n*** most significant eigen pairs of fourth order cumulants obtained from the whitened process are joint diagonalized by unitary matrix **U**. The separated matrix can be estimated as $\mathbf{U}^{\dagger}\mathbf{Z}$, where † represents pseudo inverse. The JADE contrast function [6] is the sum of squared fourth order cross cumulants

$$\phi^{JADE}(Y) = \sum_{ijkl \neq iikl} (\mathbf{Q}_{\mathrm{ijlk}})^2 \tag{1.3}$$

As this algorithm uses cross-cumulants, there is no need to go for gradient descent and hence there is no chance of divergence. In addition, there is no problem of updating the weights and tuning the parameters as in Bell and Sejnowski's infomax algorithm.

B. Comon's Algorithm

A specific contrast function is proposed in[7], based on minimization of mutual information between the components at the output of separator (which is directly related to Kullback-Leibler divergence between the output vector probability density function (pdf) and it's pdf if it was made of independent components). After some manipulations on the Edgeworth expansion [8] of the source joint pdf, the contrast function simplifies into sum of the output squared *r*th-order marginal cumulants:

$$\Psi_{\mathrm{r}}\left(\hat{\mathbf{Q}}\right) = \sum_{\mathrm{i}=1}^{\mathrm{q}} \left(\mathrm{k}^{\mathrm{s}}_{\underbrace{ii...i}} \right)^2 \tag{1.4}$$

Note that the criterion depends on $\hat{\mathbf{Q}}$ through $\mathbf{s} = \hat{\mathbf{Q}}^{-1}\mathbf{z}$. At 4th-order, the above contrast becomes the output-squared kurtosis:

$$\Psi_4\left(\hat{\mathbf{Q}}\right) = \sum_{\mathrm{i}=1}^{\mathrm{q}} \left(\mathrm{k}^{\mathrm{s}}_{\underbrace{iiii}} \right)^2 \tag{1.5}$$

C. Bell and Sejnowski's Algorithm

Bell and Sejnowski have developed an unsupervised learning algorithm (Infomax algorithm) [9] based on entropy maximization in a single layer feed-forward neural network. The main idea is that maximizing the joint entropy **H**(y) of the outputs of a neural processor can approximately minimize the mutual information among the output components. It is proved that infomax is equivalent to maximum likelihood [9]. The joint entropy of n variables, $y_1, y_2, ..., y_n$, which are the outputs of the neural network, may be written as:

$$\mathbf{H}\left(y_{1,...,}y_n\right) = \mathbf{H}(y_1) + \ldots + \mathbf{H}(y_n) - \mathbf{I}\left(y_{1,...,}y_n\right) \tag{1.6}$$

If the nonlinear transfer function of a neural network matches the probability density function of the inputs, and the joint entropy $\mathbf{H}(y_{1,...,}\ y_n)$ of the outputs is maximized, the mutual information $\mathbf{I}(y_{1,...,}\ y_n)$ among the outputs is then minimized. The output signals are assumed independent. The learning rule for a single layer feed-forward neural network to implement the separation is

$$\Delta \mathbf{W} \alpha \ \left[\mathbf{W}^T\right]^{-1} + \left(1-2y\right)\mathrm{x}^T \tag{1.7}$$

$$\Delta \mathbf{w}_0 \alpha \left(1-2y\right) \tag{1.8}$$

where $y = f(u)$, $u = \mathbf{Wx} + \mathbf{w}_o$ and $f(u)$ is a sigmoid contrast function. Usually $f(u) = 1 + e^{-(u-1)}$ or $f(u) = tanh(u)$. Here **W** is the weight matrix and $\mathbf{w}_o$ is the bias vector.

III. EXPERIMENT SETUP

As the number of signals in the biomedical system grows, it becomes necessary to improve the efficiency of common biomedical resources. Independent Component Analysis (ICA) use as an advanced tool for blind suppression of interfering FECG and MECG signals. The role of ICA is to provide a mitigated FECG signal to the conventional analysis. As the number of signals in the biomedical system grows, also, the duration of FECG and MECG varies in time, it becomes necessary to measure the performance of these ICA algorithms.

A. Signal Generation

Simulations have been done using artificially generated data to observed different signals in biomedical systems. In order to test the performance of the ICA algorithms, the period of signals were varied for 1000, 5000 and 10000 samples. In the first setup, all signals were linearly mixed with 1000 samples period of each. In another experimental setup, 5000 samples of signals were taken. Finally, simulations were done with 10,000 samples. These biomedical are linearly mixed and different ICA algorithms carry out separation.

B. Linear Mixing

We use a mixing matrix since this approximates the fading resulting in a linear, isotropic medium. We have set the mixing coefficient randomly between input users and fixed for all practical.

C. Performance Evaluation

To quantify the higher order performance of the demixing use the performance index, *PI*. This is a measure on the global system matrix **P=WA** suitable for the degeneracy conditions $\mathbf{W} = \mathbf{A}^{-1}$ and is calculated

$$PI = \sum_{i=1}^{n} \left\{ \left(\sum_{k=1}^{n} \frac{|P_{ik}|^2}{\max_j |P_{ij}|^2} - 1 \right) + \left(\sum_{k=1}^{n} \frac{|P_{ki}|^2}{\max_j |P_{ji}|^2} - 1 \right) \right\} \tag{1.9}$$

where p_{ij} is the $(i, j)^{th}$ element of the global system matrix **P =WA** and $max_j p_{ji}$ represents the maximum value among the elements in the i^{th} row vector of **P,** $max_j p_{ij}$ does the maximum value among the elements in the i^{th} column vector of **P**. When perfect signal separations carry out, the performance index *PI* is zero.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The Performance Index results from the ICA algorithms separation of our simulation are shown in Fig 1and comparisons are shown in Fig 2. The performance index of the performance matrix **P=WA** indicates the same decay in higher order separation. As the number of sources interference become dominant, the demixing performance is poorer between 5 to 10 sources. Performance index is zero means good separation. Fig 1 (a) show output Performance Index using JADE algorithm for 1000, 5000 and 10000 samples values respectively. The result indicates that as the number of sources increases, performance of JADE algorithm degrades. As the number of samples increase, JADE algorithm least affected but computational complexity also increase. The plot of performance index vs. number of sources is given in Fig 1 (c) extracted by Infomax algorithm. The result indicates that as the number of sources increases, performance of Infomax algorithm also degrades. Infomax algorithm least affected as the number of samples increase but computational complexity also increase. Fig 1 (b) shows the performance index results using Comon's algorithm. As the number of samples and sources interference increase, the performance of Comon's algorithm degrades.

The ICA algorithms separations of our simulation are shown in Fig 2 for comparisons. It is evident that the performance of the algorithms badly degrades as the no of sources increase, but JADE and Infomax least affected compared with Comon's algorithm. In addition, JADE and Infomax have good performance index against number of samples increase. The performance of the Comon's algorithm again slightly less compared to other two algorithms. JADE algorithm has the least computational cost and no parameters to tune.

V. CONCLUSIONS

In this paper, we have calculated the performance of the JADE, Infomax and Comon's ICA algorithms in a simple electro physiologically motivated BSS problem to extract the FECG. Using simulated independent signals from the pregnant woman skin (FECG and MECG); we observe that number of interference sources increase affects the BSS performances of the algorithms. As time duration of sources increase, JADE and Infomax algorithms least affected but performance of comon's algorithm degrades. By processing the data, we clearly achieve a better estimate of the FECG independent of the other interference sources. For number of interference sources and duration of sources increase, all algorithms are able to extract the sources but with different performance index. Even for high value of performance index, quality of separated signals is quite satisfactory for all algorithms. The JADE and Infomax algorithms give better performance compare to the Comon's algorithm.

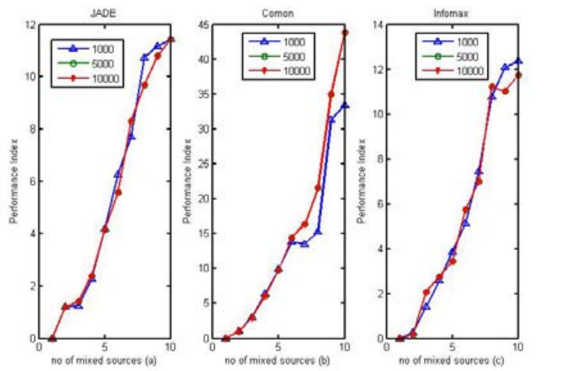

Figure 1. Output *PI* for (a) Jade (b) Comon (c) Informax algorithms for comparison of 1,000, 5000 and 10,000 samples.

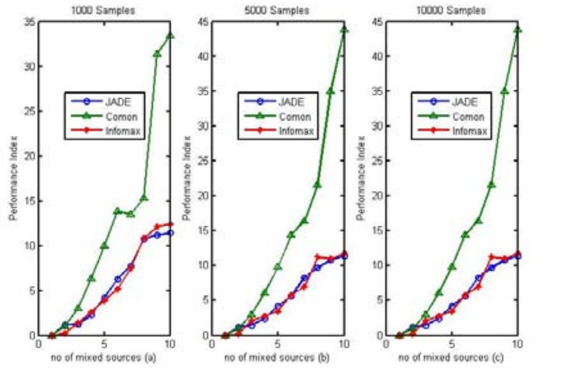

Figure 2. Output *PI* for (a) 1000 (b) 5000 (c) 10000 samples for comparison of Jade, Comon , and Infomax algorithms.

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