International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 4, April - 2014

Comparison and Performance Analysis of various ICA Algorithms for ECG signals

Hemant Kasturiwale
Assistant Professor,Electronics Engineering Department,
Thakur College of Engineering & Technology,
Kandivali (E),

Zainab Mizwan
Senior lecturer,Shree L.R.Tiwari college of Engineering,
Mira Road (E),

***Abstract*--The Electrocardiogram (ECG) is useful for clinical diagnosis and in biomedical research. The signals recorded are observed visually and hence can lead to wrong diagnonsis. ECG recordings are distorted by artifacts like blinking of eyes, movement of hands, dislocation of leads and so on causing serious problem for ECG interpretation and analysis. Independent component analysis is a new technique suitable for separating independent component from ECG complexes. This paper compares the various Independent Component Analysis (ICA) algorithms like FASTICA, JADE, and EFICA with respect to their capability to remove noise and artifacts from ECG. We compare the signal to interference ratio (SIR), performance index (PI), separation of semi orthogonality of these algorithms.**

***Keywords:* ECG, FASTICA, JADE, EFICA**

I. INTRODUCTION

Biomedical signals from many sources including hearts, brains and endocrine systems pose a challenge to researchers who may have to separate weak signals arriving from multiple sources contaminated with artifacts and noise. The analysis of these signals is important both for research and for medical diagnosis and treatment [3]. Electrocardiogram (ECG or EKG) is a non-invasive test that records a nd displays the electrical activities produced by heart muscle during a cardiac cycle [4]. The ECG test is a standard clinical tool for diagnosing abnormal heart rhythms and to assess the general condition of a heart, such as myocardial infarctions, atrial enlargements, ventricular hypertrophies, and bundle branch blocks. ECGs appear to satisfy some of the conditions for ICA: 1) Current from the different sources is mixed linearly at the ECG electrodes; 2) Time delays in signal transmission are negligible; 3) There appear to be fewer sources than mixtures; and 4) Sources have non-Gaussian voltage distributions [1]. However, movements of the heart such as contraction of the chambers during beating violate the ICA assumption of spatial stationarity of the sources. The presence of moving waves of electrical activity across the heart also means that the activity of a single chamber may be taken for multiple sources by ICA. Independent component analysis (ICA) is a method for finding underlying factors or components from multivariate (multidimensional) statistical data [6]. What distinguishes ICA from other methods is that it looks for components that are both statistically independent and non-Gaussian.

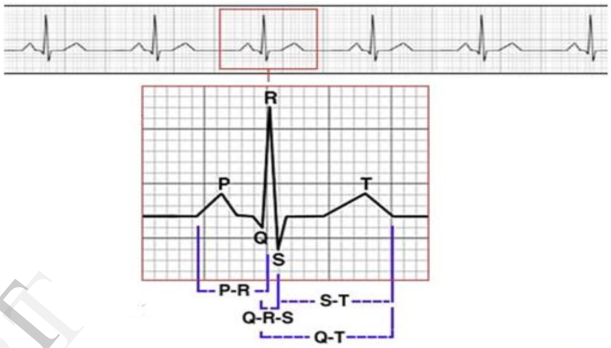

Fig 1: ECG Wave

Wavelet analysis is a method which relies on the introduction of an appropriate basis and a characterization of the signal by the distribution of amplitude in the basis. The Wavelet Transform (WT) gives us a powerful tool to confront very diverse problems in applied sciences. It also helps to analyze the complex events occurring in different scales in the signal. Wavelet transforms are widely applied in many biomedical engineering fields for solving various real-life problems.

II. INDEPENDENT COMPONENT ANALYSIS

ICA is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples [1][5]. Independent Component Analysis (ICA) involves the task of computing the matrix projection of a set of components onto another set of so called independent component. ICA requires the fulfillment of two assumptions: 1) the measured signals are linear combinations of independent source signals, and 2) the independent source signals are nongaussian.

A. ICA Model

The ICA model is defined as follows,

$$x(t) = A\,s(t) \qquad (1)$$

where the sources $s = [s_1, s_2, s_3 \ldots\ldots\ldots, s_n]^T$ are mutually independent random variables and $A_{n \times n}$ is an unknown invertible mixing matrix [2][12]. The goal is to find only from observations, x,a matrix W such that the output y=W xan estimate of the possible scaled and permutated source vector s.

B. ICA Algorithms

In order to calculate the de–mixing matrix **W**, numerous ICA algorithms have been developed with various approaches [11]. The various algorithms have been studied and their performance is compared. The algorithms studied in this paper are FASTICA, EFPICA, and JADE .A brief description of algorithms is given below.

I) JADE: Another signal source separation technique is the Joint Approximation Diagonalization of Eigen matrices (JADE) algorithm. This approach exploits the fourth order moments in order to separate the source signals from mixed signals [15].

At the beginning, the whitening matrix **P** and the signal z = **P** x are estimated [10]. After that, the cumulates of the whitened mixtures $Q_i^z$are computed. An estimate of the rotation matrix **R** is obtained by $\lambda_i V_i$ by means of the joint digitalization. The operation of JADE includes optimization of orthogonal contrast by finding the rotation matrix R such that the cumulant matrices are as diagonal as possible [15]. JADE estimates very rapidly the unmixing matrix and works in batch mode, has no need for formal parameter tuning and is particularly useful in low dimension problems [9].

II) FASTICA: Fast ICA is an efficient and popular algorithm for independent component analysis .The algorithm is based on a fixed point iteration scheme maximizing non Gaussianity as a measure of statistical independence [7] [8]. It can be also derived as an approximate Newton iteration. It belongs to family of fix point algorithms of ICA, which is based on the iteration to search for maximum of non gaussianity of variables.

The basic form of the Fast ICA algorithm is as follows: Choose an initial (e.g. random) weight vector w

1. Let $w^+ = E\{xg(w^T x)\} - E\{g'(w^T x)\}w$
2. Let $w = w^+ / \|w^+\|$
3. If not converged go back to one

The FastICA algorithm and the underlying contrast functions have a number of desirable properties when compared with existing methods for ICA.

1. The convergence is cubic (or at least based on (stochastic) gradient descent methods, where the convergence is only linear. This means a very fast convergence, as has been confirmed by simulations and experiments on real data.
2. Contrary to gradient-based algorithms, there are no step size quadratic), under the assumption of the ICA data model. This is in contrast to ordinary ICA algorithms parameters to choose. This means that the algorithm is easy to use.
3. The algorithm finds directly independent components of (practically) any non Gaussian distribution using any nonlinearity *g*. This is in contrast to many algorithms, where some estimate of the probability distribution function has to be first available, and the nonlinearity must be chosen accordingly.
4. The performance of the method can be optimized by choosing a suitable nonlinearity *g*. In particular, one can obtain algorithms that are robust and/or of minimum variance. In fact, the two nonlinearities in have some optimal properties.

a) Pre-processing by Centering and Whitening

To make the model zero mean centering is performed. The mathematical expression for centering is

$$x = x - E(x) \qquad (2)$$

Similarly, to make the system variance equal to unit, whitening is performed [14]. Whitening reduces the number of parameters to be calculated and hence the complexity. The mathematical expression for whitening is:

$$E\{\hat{x}\hat{x}^T\} = I \qquad (3)$$

III)EFICA: The algorithm EFICA is a version of the FastICA algorithm that features adaptive choice of the FastICA non-linearity.An efficient variant of FastICA algorithm, EFICA which is asymptotically efficient.The algorithm is taylored to achieve the efficiency when the probability distribution of the independent signal components belongs to the class of generalized Gaussian distributions.

III. PERFORMANCE PARAMETERS OF VARIOUS ALGORITHMS

Signal to Interference Ratio (SIR) is an engineering term for the power ratio between a signal (meaningful information) and the background noise. SIR is the quotient between the average received modulated carrier powers *S* or *C* and the average received co-channel interference power *I*, i.e. cross talk from other transmitters than the useful signal. SIR is always expressed in decibels. SIRs are usually expressed in terms of the logarithmic decibel scale[12]. In decibels, the SIR is 20 times the base-10 logarithm of the amplitude ratio, or 10 times the logarithm of the power ratio.

Performance Index gives performance aspect related to database.

$$PI = \sum_{i=1}^{n} \left\{ \left[\sum_{k=1}^{n} \frac{|g_{ik}^{z}|}{max_j g_{ij}} - \right] + \left[\sum_{k=1}^{n} \frac{|g_{ik}^{z}|}{max_j g_{ji}} - 1 \right] \right\} \qquad (4)$$

Where, g_{ij} is an ij^th^ element of the global matrix G

$G = W * A_0$ whereW calculated demixing matrix.

Psi is one of the forms of judging the performance

Psi ={sum(sum(G.^2))/sum(max(G.^2))-1} (5)

IV. RESULTS AND DISCUSSION

The figure 2 shows the plot of mixed signals of two ECG source signals with block length of 1400

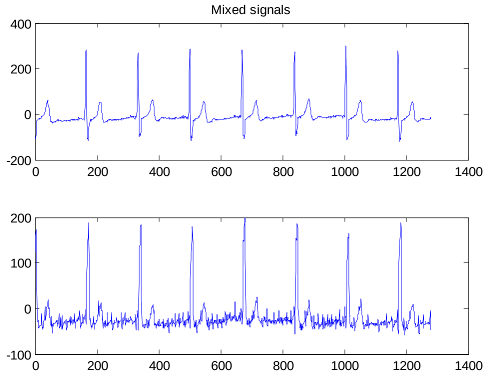

Fig 2: Mixed signals from two sources

The figure 3 shows the whitened signal of the ECG data obtained using fast ICA .The approaches used to obtain the whitened signal is deflation and symmetric,we found the result using symmetric approach. The nonlinearities that can be used are tanh, pow3, gauss and skew.

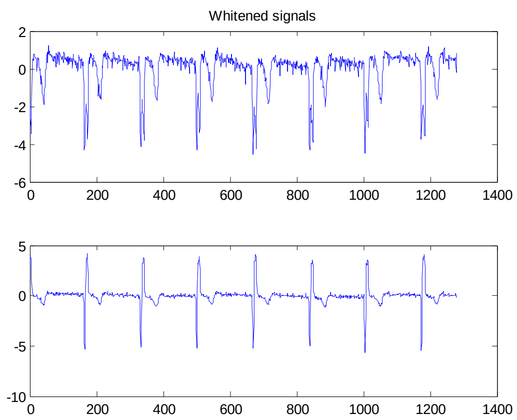

Fig 3: FASTICA plot Whitened signal

TABLE 1
PERFORMANCE COMPARISON ON THE BASIS OF APPROACH & NONLINEARITY

Database	Parameters			
	Eigen Values		Approach	Non-Linearity
	Largest	Smallest		
Source 1	1602.3	53.5308	Symmetric	tanh
Source 2	2532.93	398.36	Symmetric	tanh
Source 3	1899.99	72.2805	Symmetric	tanh

The table II shows the comparison of various sources for fixed point ICA like Psi, SNR and block length of various signals. The parameters are calculated to measure the performance of the full ICA algorithm.

TABLE II
PARAMETER COMPARISON FOR FAST ICA

Database	Parameters		
	Psi	Blocklength	SNR
Source 1	0.4474	10000	-5.7088
Source 2	0.067	1280	-5.7111
Source 3	0.3328	15000	-1.7581

The figure 4 shows the performance of the ICA algorithm

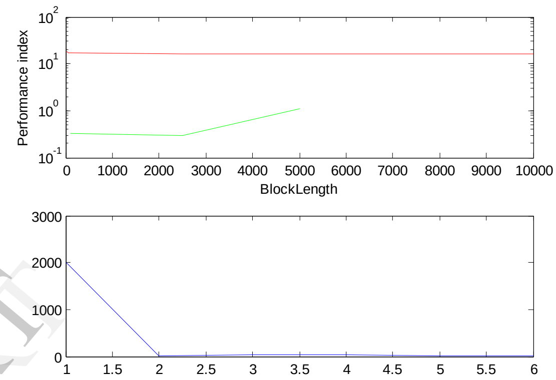

Fig 4: Performance of FAST ICA for various signals

The figure 5 shows the SNR of the noise signal separated from the original signal.

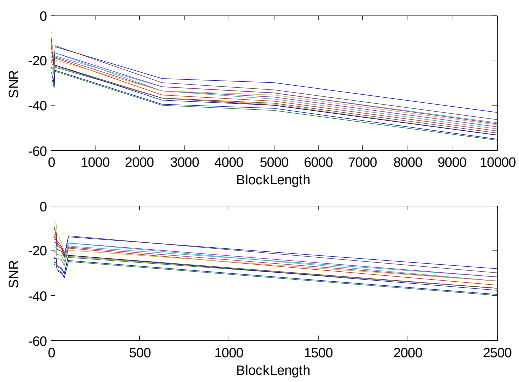

Fig 5: SNR separation of the signal

The figure 6 shows the of response of various algorithms of the ICA in terms of given parameters, after comparison it is found that the SIR response of FASTICA for source S and mixing matrix A is better than the other two. It can be concluded that the FASTICA out performs well and has the better ability to separate the noise and artifacts, it can be used to denoise the signal. The figure 6 also shows the response of the performance index and the separation of semi orthogonality, after comparison it is found that FASTICA can separate the signal in less time into independent components and its performance in removing the artifact is better than others.

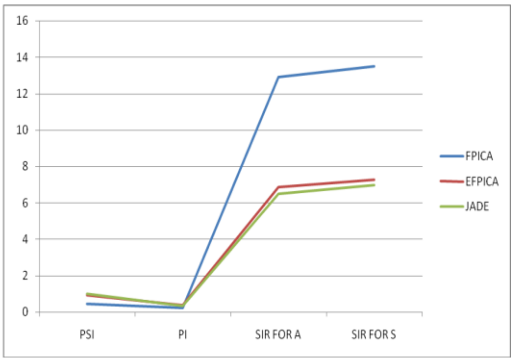

Fig 6: Different parameter comparisons for various algorithms

The table III shows the value of different parameters for various algorithms of ICA. After looking at the values it can be seen that FAST ICA is more efficient than the other two algorithms in removing artifacts from the signal. The performance of FAST ICA is also more effective.

TABLE III

PARAMETER COMPARISONS FOR VARIOUS ALGORITHMS

Parameters	FAST ICA	JADE	EFICA
Psi	0.44876	0.94977	0.9492
PI	0.23759	0.39519	0.4018
SIR FOR S (db)	13.4847	7.2668	6.8714
SIR FOR A (db)	12.8851	6.8412	7.277

V. CONCLUSION

ICA looks at the underlying distributions thus distinguishing each component. ICA gives high performance when datasets are large. It suffers from the tradeoff between a small data set and high performance. The results of different ICA algorithms like FastICA, EFICA& JADE are compared. A computationally very efficient method performing the actual estimation is given by the FastICA algorithm. The FastICA can also be effectively used for preprocessing the signal and we can get the centered and whitened signal. The time required to process the signal having large number blocks is more in FASTICA. It takes less time to give results for signal having samples less than or equal to 3000.

The SNR obtained is much better than the other filtering techniques. It can be concluded that ICA is amuch better filtering process for removing the noise and artifacts.JADE does not depend on gradient optimization techniques, neither on choice of unmixing matrix. This makes it moreattractive over others.The performance index, Signal to interference ratio, Global matrix could be analyzed. The mean and standard deviation obtained is much better than other algorithms.The advantages and limitations of various algorithms would be understood. It was concluded that FASTICA is the best method to separate the noise and artifacts .the signal to interference ratio for FASTICA is better than others.

REFERENCES

[1] AapoHyvärinen and ErkkiOja,"Independent Component Analysis: Algorithms and Applications" Neural Networks, 13(4-5):411-430, 2000

[2] Ganesh R. Naik, Dinesh K Kumar" An overview of Independent Component Analysis and its application", Informatica 35, 63–81,2011

[3] Tzyy-Ping Jung , Scott Makeig, Te-Won Lee , Martin J. McKeown,Glen Brown, Anthony J. Bell and Terrence J. Sejnowski "Independent Component Analysis Of Biomedical signals" from http://www.cnl.salk.edu/~jung/ica.html

[4] Taigang He, Gari Clifford and Lionel Tarassenko, "Application of ICA in Removing Artefacts from the ECG".Neural Computing & Applications Journal, vol: 15, issue 2, pp 105-116,April 2006

[5] Seong-Bin Yim, Steven E. Noel, and Harold H. Szu "Detecting electrocardiogram abnormalities with independent component analysis."Aerosence 2001

[6] AapoHyvärinen, E. Oja, JuhaKarhunen "Independent Component Analysis",Book, 2001 by John Wiley & Sons

[7] AapoHyvärinen "Fast and Robust Fixed-Point Algorithms for Independent Component Analysis"IEEE Trans. on Neural Networks, 10(3):626-634, 1999

[8] A.Hyvärinen, E. Oja, "A Fast Fixed-Point Algorithm for Independent Component Analysis," *Neural Computation*, 9(7), pp. 1483-1492, 1997

[9] Matic, W. Deburchgraeve, S. Van Huffel "Comparison Of Ica Algorithms For ECG Artifact Removal From EEG Signals" IEEE-EMBS Benelux Chapter Symposium , November 9-10, 2009

[10] Janett Walters-Williams & Yan Li "Performance Comparison of Known ICA Algorithms to a Wavelet-ICA Merger" Signal Processing: An International Journal, Volume (5) : Issue (3) : 2011

[11] Jarno M.A. Tanskanen and Jari J. Viik " Independent Component Analysis in ECG Signal Processing", Advances in Electrocardiograms – Methods and Analysis, www.intechopen.com

[12] H. P. Kasturiwale ,C.N.Deshmukh ,"Quality Assessment of ICA Algorithms for ECG Signal Analysis" Second International Conference on Emerging Trends in Engineering and Technology, ICETET 2009.

[13] Puneet Mishra , Sunil Kumar Singla, "Artifact Removal from Biosignal using Fixed Point ICA Algorithm for Pre-processing in Biometric Recognition" Measurement Science Review, Vol. 13,No.1, 2013

[14] Ganesh R.Naik, "A comparison of ICA algorithms in surface EMG signal processing"IJBET,Vol 6,No.4,2011.

[15] G. Thavasi Raja , P. Krishna Chaitanya and R. Malmathanraj, " Performance Analysis of Independent Component Analysis Algorithms for Multi-user Detection of DS-CDMA" International Journal of Computer Applications (0975 – 8887) Volume 39– No.11, February 2012