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Performance of Various ICA Algorithms for an Electrocardiogram Signal

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Abstract: ***De-noising of electrocardiogram signals is of utmost importance to diagnose the cardiovascular diseases. Many techniques have been utilized for filtering and removing noise from the raw electrocardiogram signal, such as traditional Wiener methods, neural networks and wavelet decomposition methods. These methods may lead to reduction in the amplitude of the QRS complex. The recorded multichannel electrocardiogram signal is correlated and is difficult for analysis. A suitable technique to overcome these problems is the appropriate use of Independent Component Analysis to maximize the required statistical parameters to make the output to be correlated. This work relates the performance of three of the Independent Component Analysis Algorithms such as JADE (Joint Approximate Diagonalisation of Eigen Matrices), Fixed Point ICA (Fast ICA) and AMUSE (Algorithm for Multiple Unknown signals Extraction) by which the three channel signal was made uncorrelated so that the best signal among the three different channels can be identified for further processing based on the values of the Signal to Interference Ratio(SIR) obtained in each of the algorithm .***

Keywords : ***Electrocardiogram, signal to noise ratio, noises in electrocardiogram , independent component analysis***

I. INTRODUCTION

The electrocardiogram(ECG) is the recording of the bio-potential of the human heart with respect to time . Due to its ease of use and non-invasiveness, electrocardiogram has a vital role in patient monitoring and diagnosis .Electrocardiogram and heart rate are vital physiological signals that have received increasing attention to diagnose cardiac diseases in recent years. The increase in the percentage of elderly people leads to the subsequent increase in the need for long term monitoring of electrocardiogram to prevent the cardiovascular diseases. The various methods to diagnose heart disease are ECG, ultrasound, Magnetic Resonance Imaging (MRI) and Computer Tomography (CT). Among all these techniques, electrocardiogram is more convenient and low cost[20]. However, certain arrhythmia sometimes occur only during stress conditions. Such arrhythmia are very difficult to be recorded tracing as its recorded only for a few minutes[20].

The electrocardiogram recorded during stress conditions may sometimes corrupt the signal by noise that may originate from other organs in the human body. The various noises which contaminate the electrocardiogram are powerline noise, baseline noise, motion artifact, electrode contact noise and noise generated by the electronic devices. Hence, de noising is a vital step in electrocardiogram signal processing to obtain accurate diagnosis. Powerline noise that is made up of 50Hz or 60 Hz and its harmonics can be modeled as sinusoids. Electrode contact noise is a caused by loss of contact between the electrode and the skin of the subject. The baseline drift can be modeled as a sinusoidal component at the frequency of respiration added to the ECG signal. The baseline wander has frequency below 1 Hz and its a low-frequency noise and is used as a parameter to detect myocardial infarction.Motion artifacts happen due to the variation in the electrode-skin impedance with to the motion of electrodes or the subjects. This type of interference is represented as an abrupt shift in the ECG base line.Therefore, there is a need to remove artifacts by the preprocessing of the ECG , so that only the vital information in ECG may be used for analysis and clinical diagnosis.Hence, this work on the use of ICA algorithms is carried out to find the most suitable channel from multi channel ECG to study about the health of the patient.

2.0 RELATED WORKS

The various interferences in electrocardiogram recordings such as baseline drift, power-line interference, electromyogram (EMG) and motion artifacts were mentioned by Friesen et al (1990). Various methods have been proposed to cancel the noise signal such as subtraction of an averaged pattern, adaptive filters (S. Haykin, 1991) etc., but in the above mentioned filtering systems, the stability is not so good in the case of Infinite Impulse Response filter because the impulse response length is coupled from the number of filter parameters of the Finite Impulse Response (FIR) filter. These filters have symmetric coefficients to obtain linear phase response with respect to pass band But these symmetric coefficients lead to enhanced group delays. In 1992, Comon P [4] proposed independent component analysis (ICA) of a random vector that reduces the statistical dependence between its components. Hence, to find the necessary information in the composite signal, a suitable criteria is used to segregate the composite mixed signal. ICA is actually an extenstion of PCA and is suitable to find out the second order statistical derivatives that are orthogonal to each other. Tzyy-Ping Jung *etal* studied few applications of ICA that were done to a variety of biomedical signals such as electroencephalogram recorded from the biopotentials of the brain. In 1997, Adel Belouchrani etal [1] used a new source technique that separated the source signals based on their time coherence. This approach can be

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used only on pairs of co variance matrices that have stationary second-order statistics based on a joint diagonalization . In 2000, Aapo Hyvärinen and Erkki Oja [2] derived a solution to find a better representation of multivariate data that may consist of random vectors that represent a linear combination of the original variable so that the components are statistically independent that helps in signal separation and in feature extraction steps of signal/image processing.

In 2005,V.Krishnaveni , S.Jayaraman *etal* compared the various parameters that were obtained from various ICA algorithms along with Mutual Information Estimator that were calculated on the basis of k-neighbor statistics which does not use the probability density functions. This work shows out that the RADICAL algorithm separates the EEG signals in a best manner from the ocular noise present in the acquired EEG. [9].

In 2009, V. Matic, W. Deburchgraeve, S. Van Huffel proposed Independent Component Analysis (ICA) to remove electrocardiogram (ECG) artifacts from electroencephalogram signals from neonatal EEG. They studied the effectiveness of the various ICA algorithms to remove noise in the above application.In 2012, Balaiah Paulchamy *etal* [3] used ICA based algorithms to remove the artifacts from the EEG signals and studied the performance of various ICA algorithms based on suitable metrics .

3.0 CONVENTIONAL METHODS

3.1 WEINER FILTERING

Wiener filtering is a non causal lossy transformation in the Fourier domain that works with the use of Fourier co-efficients. While applying the Wiener filter to Electrocardiogram (ECG) filtering, it is more better to use an approximate model of the ECG to estimate the power spectrum of the signal.

3.2 PRINCIPAL COMPONENT ANALYSIS

PCA[15] is an algorithm which converts the data into principal components that are uncorrelated by the use of an orthogonal conversion of variables that are correlated observations. The count of these principal components has to be less than or equal to the total number of original variables. Here, first principal component contains the largest possible variance and each following component is orthogonal to the previous components. These principal components will be independent only if the data set is normally distributed. PCA is accomplished by eigen value decomposition done on the correlation matrix or by the singular value decomposition of a data matrix.

4.0 MATERIALS AND METHODS

ICA computes the matrix projection of one set of principal components onto another set of independent components so as to create the output variables that have maximized statistical independence on each others. In ICA, both the original sources and the mixture matrix are not known and therefore, this method is named as the Blind Separation of Sources (BSS) and is discussed in[6] [7][11-19] .This can be done by calvulating the higher order statistical parameters of the signal by the use of various optimization techniques.

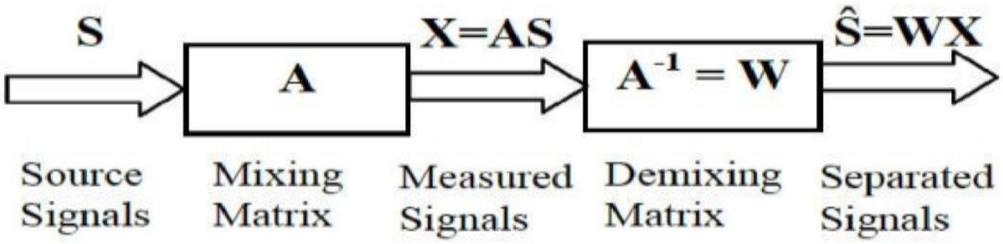

Fig.4.1: Schematic Illustration Of The Mathematical Model Used To Perform Independent Component Analysis Decomposition

The input vector S has M rows and N columns and the mixing square matrix **A** has M number of rows and columns. Here, M represents the count of statistical independent sources and N is the represents the count of samples in each source .The output of this process is the demixing matrix **W** which is used to find the estimated statistical independent sources, Ŝ from the mixtures. A illustration of the mathematical model in shown in Figure 4.1.

$$X = AS \qquad \hat{S} = WS \tag{1}$$

4.1 PRE-PROCESSING FOR ICA

Pre-processing for independent component analysis is done by Centering and Whitening.

4.1.1 Centering

Next, pre-processing is done by finding the “centering” of the observation vector *x* .The observation vector, X_c is given by the equation

$$X_c = x - m \tag{2}$$

This helps in simplification of ICA by assuming a zero unmixing matrix based on the estimation of the centered data,
from which the actual estimates of the independent components is calculated from the following equation

$$(t)=A^{-1}(x_C+m)$$
(3)

All observation vectors are assumed to be centered. The mixing matrix remains the same after this pre-processing step, so this is done without affecting the estimation of the mixing matrix.

4.1.2 Whitening

Another step which is very useful in practice is to prewhiten the observation vector *x*. Whitening involves linearly transforming the observation vector such that its components are uncorrelated and have unit variance. Let x_w denote the whitened vector, and then it satisfies the following Covariance matrix is calculated by the equation given by

$$E\{X_w\}=I \tag{4}$$

where $E\{X_W\}$ is the covariance matrix of X_W. Also, since the ICA is insensitive to the variances of the independent components, i.e. $E\{SS_T\} = I$.

The whitening transformation is done by the calculation of Eigen vectors of *x* and the decomposition of the covariance matrix of *x* is given as

$$E\{XX_T\} =VDV_T \tag{5}$$

where *V* is the Eigen vector matrix of $E\{xx_T\}$, and *D* represents the diagonal matrix of eigen values, i.e. D $=diag\{\lambda1,\lambda2, ...,\lambda n\}$. The whitening of the observation vector is done by the equation as

$$X_W=VD_{-1/2}V_T X \tag{6}$$

where the matrix $D^{-1/2}$ =diag{ ,....... }. Whitening converts the mixing matrix into a new orthogonal matrix as

$$X_w =VD^{-1/2}V^T As = A_w s \tag{7}$$

Hence,

$$\begin{aligned} E\{X_w\} &= A_w E\{ss^T\} \\ &= A_w A^T \\ &= I \end{aligned} \tag{8}$$

Whitening reduces the number of parameters to be calculated . Instead of using the n^2 elements of the original matrix A, the new orthogonal mixing matrix needs only $n(n-1)/2$ degrees of freedom. This process is more efficient as it reduces the complexity of computations of ICA.

4.2 ICA ALGORITHMS

The algorithms which are considered in this work are JADE, FAST ICA and AMUSE Algorithms. A brief description of JADE algorithm is given below.

4.2.1 JADE Algorithm

Joint Approximation Diagonalisation of Eigen matrices (JADE) algorithm uses the fourth order statistical moments for separating the source signals from the composite mixed signals. The working of JADE is as given below:

I. **P** is the whitening matriz and the matrix **Z** = **PX** are estimated.

II. The fourth cumulants of the whitened mixtures are computed. Their *m* most significant eigen values λ_i and their respective eigen matrices V_i are found. The estimation of the unitary matrix R can be calculated by the maximization of the parameter $\lambda_i V_i$ by the use of joint diagonalisation procedure. If $\lambda_i V_i$ cannot be jointly diagonalised exactly , then a joint approximate diagonalisation can be maximized.

III. The rotation matrix **R** to optimize the orthogonal contrast is calculated by the equation

$$R = \underset{\bar{X}}{argmin} \; \textstyle\sum_i off\left(R^T T \hat{Q}^z\right) \tag{9}$$

IV. The estimated matrix $\hat{A} = \mathbf{RP}^{-1}$ and the components are found by the use of the equation

$$\hat{\mathbf{S}} = \hat{\mathbf{A}}^{-1}X \tag{10}$$

4.2.2 Fast ICA OR Fixed Point ICA Algorithm:

In this Negantrophy,(i.e , Negantrophy means things becoming more in order) is used for the maximization of Non-Gaussianity by the use of Fast – ICA algorithm as discussed in[5][8].

4.2.2.1 Fast ICA for n units

Estimation of the various independent component is called as the weights associated with components of **x** . i.e.W_1, W_2...W_N, as independent sources. The algorithm given below is used iteratively. is done as follows:

(a) Take an initial row vector W_i

(b) Apply Newton phase:

$$Wi = E\{\hat{x}g(W_i^T\hat{x})\} - E\{g'(W_i^T\hat{x})\}Wi \tag{11}$$

Whereas

$$g_1(y)=\tanh(a_1y);g_2(y)=y^* e^{(-1/2y)};\ g_3(y)=4y^3 \tag{12}$$

(c) Normalization:

Normalize total matrix obtained after the above iterations

$$W_i = (W_i - \text{mean}) / \text{std. deviation} \tag{13}$$

(d) Decorrelation:

$$W_i =W_i -\Sigma \quad W_j W_j \tag{14}$$

(e) Normalization again {Repeat step (c)}

(f) If $W^T(i) *W(i-1)$ is not be equal to 1, then

$i+1, W$ and go back to step (b), (15)

4.2.3 Amuse Algorithm

AMUSE uses the second order statistical parameters of a process s (t). The estimation of higher order moments shows a larger variance that affects the approximate calculation of the matrix A_0 and source vector S_0.

4.2.3.1 Working of AMUSE Algorithm

(i) The data is collected and the covariance matrix is estimated

$$R_x = E\,(XX^t) \tag{16}$$

(ii)Singular value decomposition is calculated for the matrix R_x and the noise variance σ is estimated along with the estimation of singular values Ψ, Ψ_{12m}, Ψ

(iii) Data is transformed by $g_3(y)= 4y^3$

Y: = C_x (17)

(iv) τ is selected and the estimation of $R_Y(\tau)$ is computed as

$$R_Y(\tau) = E(y(t)\, y(t-\tau)^t) \quad (18)$$

(v) The eigen values, eigen vectors and the singular vectors (V) are calculated.

(vi) The source signals are found by

$$= V^t C^x \quad (19)$$

(vii) Finally, A_0 is estimated as

$$= U_s \; diag\,(\psi_1, \psi_2, \psi_3, \ldots\ldots \psi_m) V \quad (20)$$

5.0 RESULTS AND DISCUSSION

This work compares the performance of the different Independent Component Analysis Algorithms and the Signal to Interference Ratio is computed to estimate the most efficient algorithm for source separation. The simulation was carried out with pre-processing and without pre-processing for the input multi-channel ECG signal. Pre-processing was done using low pass filters and Average filter and the results were analysed. To calculate the efficiency of the proposed technique, several real world datasets were downloaded from the MIT-BIH database.

Table 5.1: Signal to Interference ratio for 100.mat, 103.mat, 113.mat, 114.mat, d7.mat are tabulated

Record No	No pre-processing (in dB)	Low pass filter (in dB)	Average filter (in dB)
100	22.601	22.6034	7.8995
103	25.054	25.1237	15.924
113	15.0818	15.147	19.5253
114	17.0736	17.0814	17.1108
121	13.742	13.6976	14.4128

The values in the above table show that performance of average filter performs better for JADE algorithm

5.2 PERFORMANCE ANALYSIS OF FAST ICA ALORITHM

Table 5.2: Signal to Interference ratio for 100.mat, 103.mat, 113.mat, 114.mat, d7.mat are tabulated

Record no	No pre-processing (in dB)	Low pass filter(in dB)	Average Filter (in dB)
100	24.9292	25.1713	10.6394
103	23.6936	27.2811	17.0776
113	14.8303	13.7964	7.806
114	17.0934	17.0825	17.0248
121	11.0737	15.1833	12.7454

The above table 5.2 show that low pass filter pre-processing is better suited for fast ICA algorithm.

The signal to interference ratio in each case was determined and tabulated in table 5.3

5.3. PERFORMANCE ANALYSIS OF AMUSE

Table 5.3: Signal To Interference Ratio For 100.Mat, 103.Mat, 113.Mat, 114.Mat, D7.Mat Are Tabulated

Record no	No pre- processing (in dB)	Low pass filter(in dB)	Average Filter (in dB)
100	24.3242	24.2355	8.8065
103	21.435	21.436	20.6819
113	10.697	10.6928	14.3947
114	10.2862	10.2834	10.2718
121	11.0737	11.0379	12.5245

The table 5.3 show that the AMUSE algorithm performs equally in terms of Signal to Interference ratio for no pre-processing and low pass filter

5.4. INFERENCES FROM THE PERFORMANCE COMPARISON OF JADE, FAST ICA AND AMUSE ALGORITHM

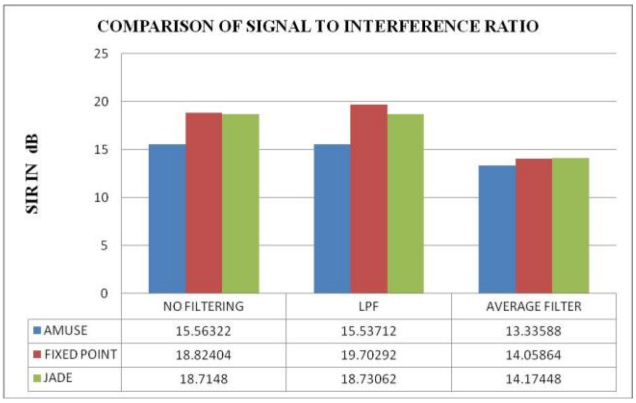

Figure 5. 1 Comparison of JADE (Joint Approximate Diagonalization Of Eigen Matrices) Algorithm),

The average of the signal to interference ratio is taken and the graph is plotted in figure 5.1 to determine the algorithm with the maximum signal to interference ratio.

Fixed-Point Algorithm/Fast ICA Algorithm and the AMUSE (Algorithm for Multiple Unknown Signals Extraction) algorithms

The fixed-point algorithm has a number of desirable properties when compared with existing methods for independent component analysis such as

•The convergence is cubic (or at least qusadratic), under the assumption of the independent component analysis data model. This is in contrast to 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.

• Contrary to gradient-based algorithms, there are no step size parameters to choose (in the original fixed-point algorithm). This means that the algorithm is easy to use. Even in the stabilized version, reasonable values for the step size parameter are very easy to choose.

• Using any optimized non linearity g , the algorithm is used to find the independent components directly for any non-Gaussian distribution which is just opposite to most other algorithms, that find the estimate of the probability distribution function.

• A suitable nonlinearity is used to find algorithms that are robust and/or of minimum variance.

• The independent components has to be computed one by one

• The fixed-point algorithm is parallel and works in distributed manner. It is simple in computation, therefore occupying very little memory.

6.0 CONCLUSION

The need for the improved health care stresses the need to diagnose the cardio vascular diseases among the human beings to improve the mortality rate. Hence the need to denoise electrocardiogram is utmost of importance. In this work, the electrocardiogram input considered is multi channel and the independent component analysis is carried out to separate the individual signals from the various electrodes used to record the electrocardiogram. The three channel Electrocardiogram signal was made un-correlated using the JADE Algorithm, Fast ICA Algorithm and Amuse Algorithm and their Signal to Interference (SIR) were compared with no pre-processing and with pre processing such as low pass filter and average filter. The SIR value of the un-correlated signal of the Fast ICA with low pass filter as pre-processing technique shows a 26.81% increase over the performance of JADE Algorithm with the same. Similarly there is a 5.19% increase in Fast ICA with low pass filter as pre-processing technique over the performance of Amuse Algorithm with the same in terms of signal to interference ratio (SIR). The SIR values of Fast ICA are higher than the JADE and AMUSE methods

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