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52 - 59

Modified Fast ICA for Blind Signal separation

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***Abstract*--**The Fast ICA or fixed-point algorithm is one of the most widely known algorithm for Blind Signal Separation (BSS) in terms of accuracy speed and computational complexity. Two versions of the algorithm are made available in literature: a one unit (deflation) algorithm and a symmetric algorithm. Both algorithms provide four standard contrast functions namely Skew, Pow3, Gauss and Tanh for selection to have better performance. In general, the selection of the contrast function depends on the data and the application. In Biomedical applications Electro Cardio Graph (ECG) data is problematic due to heart rate variation and several interferences such as muscle activity, respiration , thermal/electronic noise and noise from electrode-skin contact that corrupt the signal. We propose modified Fast ICA algorithm employing different data-adaptive contrast functions that are obtained from the underlying pdf of source signal distribution. We test the performance of modified Fast ICA algorithm for ECG application ECG data set is simulated and then added with four different types of noise distributions, white Gaussian, Flicker, Impulse and Rayleigh. We compare performance across the standard contrast functions in Fast ICA and modified Fast ICA using Signal Mean Square Error (SMSE) and Signal Noise Ratio (SNR) of estimated sources.. We show that the performance of modified Fast ICA is superior to standard contrasts in case of noisy ECG data .

Keywords*--FastICA, ECG, Contrast functions,*

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I. INTRODUCTION

Blind source separation (BSS) is the method of extracting underlying source signals from a set of observed signal mixtures with little or no information as to the nature of these source signals. Independent component analysis (ICA) is used for finding factors or components from multivariate statistical data and is one of the many solutions to the BSS problem [1]-[2]. ICA looks for the components that are both statistically independent and nongaussian. The various ICA algorithms extract source signals based on the principle of information maximization, mutual information minimization, maximum likelihood estimation and maximizing nongaussianity.ICA is widely used in signal processing, seismic data processing in Geophysics , Biomedical engineering medical image processing, economic analysis and telecommunication applications.

One of the most widely used ICA algorithms for the linear mixing model is FastICA, a fixed point algorithm first proposed by Hyv¨arinen and Oja [3], [4]. It is based on the optimization of a nonlinear contrast function measuring the nongaussianity of the sources. A widely used contrast function both in FastICA and in many other ICA algorithms is the kurtosis [5].

There are two varieties of the FastICA algorithm: the deflation or one-unit algorithm and the symmetric algorithm. The deflation approach, which is common for many other ICA algorithms [5], estimates the components successively under orthogonality conditions. The symmetric algorithm estimates the components in parallel. This consists of parallel computation of the one-unit updates for each component, followed by subsequent symmetric orthogonalization of the estimated demixing matrix after each iteration.

Fast ICA provides four standard contrast functions for selection by the user for better performance of signal separation. However, the best performances of these methods are obtained for the ideal noise free data and their effectiveness is definitely decreased with observations corrupted by noise. We have constructed four kinds of stochastic models 1) The pure white Gaussian noise model 2) Flicker or Pink color noise model 3) Impulse noise model and 4) Rayleigh noise model. In order to improve the effectiveness of fast ICA algorithm for noisy ECG data data adaptive contrast functions are proposed.

The purpose of the present paper is to look at the performance of the FastICA algorithm, for one-unit version for standard contrast functions and compare with newly modified data adaptive contrast alternatives in the context of Noisy ECG data. This paper is organized as follows: In section 2 , we introduce different types of noise sources in ECG . Then in section 3, we explain the ICA method and contrast functions, FastICA algorithm. In section 4 Modified FastICA algorithm is explained. Finally, in section 5 we apply new modified FastICA for signal separation of noisy mixtures and short summary concludes this paper.

II. NOISE TYPES

By definition, Noise is the part of the observation that masks the underlying signal we wish to analyze by lowering its Signal to Noise Ratio (SNR), and in itself adds no information to the analysis. However , for a noise signal to carry no information, it must be WHITE with flat spectrum and an autocorrelation function equal to an impulse. Most real noise is not really white, but colored in some respect. The following Color or spectrum noises and Spatial noises and their effect on separation of signals are investigated.

a) COLOUR NOISE:

The color of a noise signal (a signal produced by a stochastic process) is generally understood to be some broad characteristic of its power spectrum. Different colors of noise have significantly different properties: for example, as audio signals they will sound differently to human ears, and as images they will have a visibly different texture. Therefore, each application typically requires noise of a specific color. The practice of naming kinds of noise after colors started with white noise, a signal whose spectrum has equal power within any equal interval of frequencies. That name was given by analogy with white light, which was (incorrectly) assumed to have such a flat power spectrum over the visible range. Other color names, like pink, red, blue and violet were then given to noise with other spectral profiles.

b) SPATIAL DISTRIBUTED NOISES:

Often the signals are corrupted by **spatial distributed noises** during transmission due to interference in the channel **.:** Impulse noise and Rayleigh noise or fading is a statistical model for the effect of a propagation environment on a radio signal, such as that used by wireless devices. Rayleigh fading models assume that the magnitude of a signal that has passed through such a transmission medium will vary randomly, or fade, according to a Impulse or Rayleigh distribution — the radial component of the sum of two uncorrelated Gaussian random variables.

c).FOUR NOISE MODELS

Model 1) White Gaussian Noise (WGN) Model:

WGN is basic and general model for thermal noise in communication channels. It is the set of assumptions that the noise is additive, i.e., the received signal equals the transmit signal plus some noise, where the noise is statistically independent of the signal, the noise is white, i.e, the power spectral density is flat, so the autocorrelation of the noise in time domain is zero for any non-zero time offset and the noise samples have a Gaussian distribution.

Pdf of Gaussian distribution is

$$p(z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(z-\mu)^2/2\sigma^2} \quad \text{.................. (1)}$$

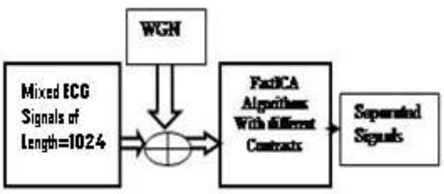

Figure 1 White Gaussian Noise model

In this model, ECG Signals of length 1024 are generated and mixed .The mixtures are then added WG Noise with mean=0 and sigma =1.0 is added to the signal. Noise is varied in 2dB steps from -4dB to +8dB. Noisy mixtures are then separated using FastICA algorithm and modified FastICA algorithm using different contrast functions and results are compared for performance using SMSE and SNR metric criterion.

Model 2) Flicker Noise or Pink color noise Model:

The flicker noise is sometimes used to refer to pink noise, although this is more properly applied only to its occurrence in electronic devices. Pink noise or 1⁄f noise is a signal or process with a frequency spectrum such that the power spectral density (energy or power per Hz) is inversely proportional to the frequency of the signal. In pink noise, each octave (halving/doubling in frequency) carries an equal amount of noise power. The name arises from the pink appearance of visible light with this power spectrum.

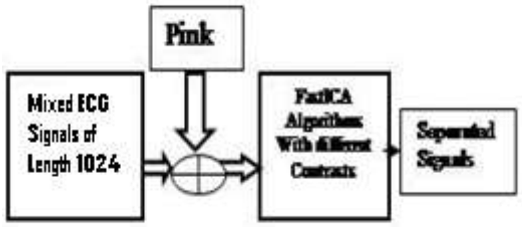

Figure 2 Ficker or pink noise model

In this model, ECG Signals of length 1024 are generated and mixed .The mixtures are then added Pink Noise with mean=0 and sigma =1.0 is added to the signal. Noise is varied in 2dB steps from -4dB to +8dB. Noisy mixtures are then separated using FastICA algorithm and modified FastICA algorithm using different contrast functions and results are compared for performance using SMSE and SNR metric criterion.

Model 3) Impulse Noise Model:

Impulse noise or spike noise also called salt-and pepper noise is usually caused by timing errors in the process of digitization, faulty memory locations, malfunctioning of pixel elements in Camera sensors. Impulse noise of equal height impulses is called salt-and pepper noise and there are only two possible values exist that is a and b the probability of each is less than 0.2.Impulse noise of un equal height impulses is called random values impulse noise is used in this model. The probability density function of impulse noise is

$$p(z) = \begin{cases} P_a & for\ z = a \\ P_b & for\ z = b \\ 0 & otherwise \end{cases} \quad \text{............. (2)}$$

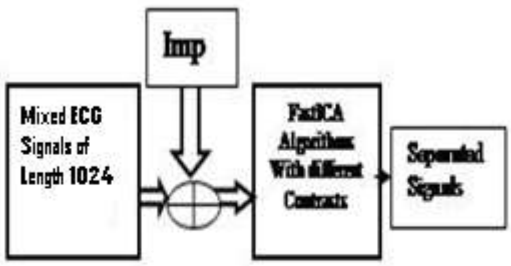

Figure 3 Impulse noise model

In this model, ECG Signals of length 1024 are generated and mixed .The mixtures are then added Impulse Noise with mean=0 and sigma =1.0 is added to the signal. Noise is varied in 2dB steps from -4dB to +8dB. Noisy mixtures are then separated using FastICA algorithm and modified FastICA algorithm using different contrast functions and results are compared for performance using SMSE and SNR metric criterion.

Model 4) Rayleigh Noise Model:

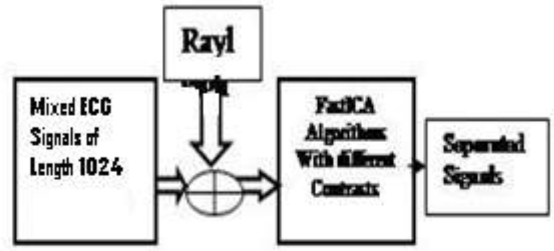

Figure 4 Rayleigh noise model

Rayleigh fading is viewed as a reasonable model for troposphere and ionosphere signal propagation as well as the effect of heavily built-up urban environments on radio signals. Rayleigh fading is most applicable when there is no dominant propagation along a line of sight between the transmitter and receiver. How rapidly the channel fades will be affected by how fast the receiver and/or transmitter are moving. The probability density function of the Rayleigh distribution is

$$p(z) = \begin{cases} \frac{2}{b(z-a)e}^{-\frac{(z-a)2}{b}} & for\ z \geq a \\ 0 & for\ z < a \end{cases}$$

$$\sigma^2 = b(4-\pi)/4, \ \ \mu = a + \sqrt{\pi b/4} \ldots\ldots\ldots\ldots (3)$$

In this model, ECG Signals of length 1024 are generated and mixed .The mixtures are then added Rayleigh Noise with mean=0 and sigma =1.0 is added to the signal. Noise is varied in 2dB steps from -4dB to +8dB. Noisy mixtures are then separated using FastICA algorithm and modified FastICA algorithm using different contrast functions and results are compared for performance using SMSE and SNR metric criterion.

III. INDEPENDENT COMPONENT ANALYSIS

Let us mention the famous cocktail party problem to understand ICA. Imagine where two people are speaking simultaneously using two microphones in two different locations. The microphones give you two recorded signals, which we could denote by $x_1(t)$ and $x_2(t)$ with x_1 and x_2 the amplitudes of signals and 't' the corresponding time index. Each of these recorded signals is a mixture (weighted sum) of the speech signals emitted by two speakers which is denoted by $s_1(t)$ and $s_2(t)$. BSS assumes linear combination and is expressed as linear equation.

$$x_1(t)=a_{11}s_1+a_{12}s_2 \ldots\ldots (4)$$
$$x_2(t)=a_{21}s_1+a_{22}s_2 \ldots\ldots (5)$$

The parameters a_{11}, a_{12}, a_{21} and a_{22} depend on distance of microphones from speakers and room response. BSS is to estimate the two speech signals $s_1(t)$ and $s_2(t)$ using only the $x_1(t)$ and $x_2(t)$ recordings (mixtures) or observations. Without loss of generality we can write equation as ,

$$x(t)=As(t) \ldots\ldots (6)$$

A blind source separation method, ICA (Independent Component Analysis) uses the assumption of statistical independence among source signals to estimate the source signals and the mixing matrix coefficients. In our setup, the sources include ECG signals and also various noise components such as white Gaussian noise, impulse, flicker and Rayleigh noise . In ICA, it is assumed that the observed signals are at least as many as the sources .

ICA methods try to determine the de-mixing matrix **W** ,which is the inverse of **A** , so that the rows of $\hat{\mathbf{s}}(t) = \mathbf{W}\,\mathbf{x}(t)$ becomes statistically independent . There are various measures of statistical independence in literature such as mutual information and non-gaussianity [6]. In this experiment, we focus on ICA algorithms using maximization of nongaussianity. The relation between non-gaussianity and independence could be explained easily using the central limit theorem (CLT) [7]. According to the CLT, the distribution of a sum of independent random variables tends to a Gaussian distribution under certain assumptions. This indicates that the sum tends to be "more" Gaussian than the original random variables. Notice that multiplication with **W** (inverse of mixing matrix **A)** is also a linear operation. Consider a single row of $\hat{\mathbf{s}}(t) = \mathbf{W}\mathbf{x}(t)$, e.g.

$$\hat{s}_i(t) = \mathbf{w}^T\mathbf{x}(t) = \mathbf{w}^T\mathbf{A}\mathbf{s}(t) = \mathbf{z}^T\mathbf{s}(t); \ldots\ldots (7)$$

where **w** is the i^{th} row of **W**, and $\mathbf{z} = \mathbf{w}^T\mathbf{A}$. Eqn.7 tells that each source estimate can be represented as linear combination of the original sources. Since original sources are assumed to be independent, if we find a **w** so that $\hat{s}_i(t)$ is "least" Gaussian, then our estimate is closest to the original source. Hence, in the ICA context, independence is equivalent to non-gaussianity. In the literature, two different measures of non-gaussianity are used namely kurtosis and negentropy [8]. The kurtosis of a random variable *y* is defined as

$$K(y) = E\{y4\} - 3(E\{y2\})^2 \ldots\ldots (8)$$

For a zero-mean Gaussian random variable, the kurtosis is known to be zero. If the kurtosis is away from zero, the random variable could be considered to be non-Gaussian. In theory, kurtosis is the optimized criterion for ICA, however, in practice since the value is estimated from the measured samples (since underlying a probability density function (pdf), is unknown), ICA based on kurtosis could be sensitive

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52 - 59

to outliers [8,9].On the other hand, the negentropy for a random variable y is defined as

$J(y) = H(y\ gauss) - H(y)$…………………..(9)

where $H(y) = \int f(y) \log f(y)\, dy$ denotes the information theoretic differential entropy, and $ygauss$ is a Gaussian random variable with the same covariance as y. Since a Gaussian random variable has the largest entropy among all the random variables with the same variance, the negentropy is always nonnegative. The larger the negentropy, the closer the random variable gets to be non-Gaussian. Similar to kurtosis, the main issue with negentropy calculations is the fact that the distribution of the random variable y is needed in the calculation. Instead, we can use approximation of negentropy [8]. The classical method of approximating negentropy using higher-order moments [8] will give

$J(y) \approx 1/12E\{y3\}^2 + 1/48\, K(y)^2$ …… (10)

Similar to kurtosis, this form of approximation is not a robust measure for nongaussianity. Instead, we can use another approximation of negentropy [8], Eqn. 9,

$J(y) \approx [E\{G(y)\} - E\{G(\nu)\}]^2$ ………(11)

for a non-quadratic function G, and zero-mean, unit variance Gaussian random variable ν. The nonlinear function G is known as *contrast function*. Ideally, if the source distribution $f(y)$ is known, then $G(y) = -\log f(y) = \int f(y) / f(y)\, dy$ would be the optimal choice for the contrast function.

The separation ability of a contrast function and there by algorithm is characterized by the relative presence of the k^{th} source signal in the estimated i^{th} source signal. It is possible, if the source signals are known. This was shown in [10] that the asymptotic interference-to-signal ratio (ISR) of separated signals for one unit deflation FastICA is ,

$$ISR = \frac{1}{N}\frac{\gamma}{r^2} \quad …………………….(12)$$

Where $\gamma = \beta - \mu^2$ and $r = |\mu - \rho|$ and

$\mu = \int y g(y) f(y) dy$, $\rho = \int g'(y) f(y) dy$, $\beta = \int g^2(y) f(y) dy$

Thus ISR is function of source probability distribution and nonlinear function g(.). Given the distribution and nonlinearity these expressions can be evaluated.

A) Fast-ICA Algorithm

Fast-ICA is a fixed point algorithm that maximizes an approximation of negentropy for non-gaussianity. The details of the fast-ICA algorithm are shown below.

1. Make the data zero-mean (centering)
2. Whiten the data
3. Choose and initial random vector **w**. The vector **w** **d**enotes one column of the estimated inverse matrix **W**.
4. Fixed-point iteration:

$$\mathbf{w} \leftarrow E\{\mathbf{z} g(\mathbf{w}T\,\mathbf{z})\} - E\{g'(\mathbf{w}T\,\mathbf{z})\}\mathbf{w}$$

where **z** is the whitened & centered data, and $g()$ is the derivative of the contrast function $G()$, and $g'()$ is its second derivative.

5. Normalization: $\mathbf{w} \leftarrow \mathbf{w} = \|\mathbf{w}\|$
6. Check convergence, if not go to step-4.

The main iteration step in the algorithm is

$$\mathbf{w} \longleftarrow E\{\mathbf{z} g(\mathbf{w}T\,\mathbf{z})\} - E\{g(\mathbf{w}T\,\mathbf{z})\}\mathbf{w}:$$

Here the vector **w** denotes one column of the estimated Inverse matrix **W** (inverse of the mixing matrix **A**) . The Vector **z** is the whitened & centered data, $g()$ is the derivative of the contrast function $G()$, and $g'()$ is its second derivative. Commonly used contrast functions with Fast-ICA algorithm are below listed as:

Skew: $g(y) = y^2$
Pow3: $g(y) = y^3$
Gauss: $g(y) = y\ exp(-y^2/2)$
Tanh: $g(y) = tanh\ (y)$

Main advantages of the fast-ICA algorithm are its speed (superior to gradient-based schemes), user-friendliness (does not require the probability distribution or selection of certain parameters), and its flexibility for performance optimization (done via choice of the contrast function $G(y)$ or equivalently $g(y) = G'(y)$).

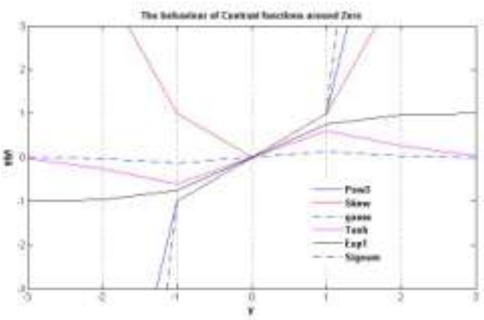

Figure 5 . The behavior of contrast functions around zero, a1=a2=1, a3=2 and a4= 5.

B) Practical Contrast Functions

Practically any non-quadratic contrast function G , the negentropy approximation in Eqn. 11 is valid and ICA will separate the sources. However, if one needs to optimize the performance, choice of contrast function becomes important. In general, the selection of the contrast function depends on the data and the application. For example, if the data seems to have outliers, one should choose contrast functions that are more robust. On the other hand, speed / complexity of algorithm could be another concern .If we choose $G(y) = y^4$ in Eqn. 11, we obtain the kurtosis-based approximation, Eqn. 10 which also might suffer from robustness. In particular, by choosing G that does not grow too fast, one can obtain more robust estimators. The following choices of *G* have proved to be useful and robust contrast functions [8]:

$G(y) = 1/a1 \log \cosh a1y$, (*Tanh*)

$G(y) = -\exp(-a2y^2/2)$, (*Gauss*)

$G(y) = \exp(-a3|y|^2)$ (*Exp1*)

$G(y) = \text{Sign}(y) = \text{sign}(y)\,|y|^{a4}$ (Signum)

where a1 ,a2 a3 and a4 are suitable constants.

In the next section, we describe new modified FatICA algorithm that uses certain characteristics of the ECG signal to derive data-driven contrast functions.

IV. Modified FastICA.

In this subsection, previous analysis is used to derive a modified FastICA algorithm which combines advantages of previous discussions and is called modified FastICA or simply mFastICA. Step by step explanation is as follows.

1) In this algorithm, for each post estimated source signal the pdf distribution is evaluated by finding its fourth moment (Kurtosis).

2) If the Kurtosis of source signal is greater than 3, then its distribution is known as Super Gaussion. The contrast functions that perform one unit algorithm efficiently to estimate unmixing matrix W such as Exp1 is selected.
- Similarly if the Kurtosis of source signal is less than 3, the source signal Pdf distribution is known as Sub Gaussian .
This sub Gaussian distribution further classified as Extremely sub Gaussian for Kurtosis values 0 to 2.For kurtosis values from 2 to 3, the source distribution said to Sub Gaussian or Gaussian.
Extremely Sub Gaussian distributions Score function contrasts signum(x) is used.

For Sub Gaussian or Gaussian distributions, Tanh contrast of FastICA is used

3) The parameters μ, ρ and β are computed as sample estimates and ISR is evaluated. If the obtained ISR is better than the former ISR estimate , the one unit algorithm is performed, taking advantage of a more suitable nonlinearity g for each of particular cases as detailed in step 2.

4) Then , μ, ρ and β and ISR are computed again. If new ISR is better than the previous one and if , at the same time , the scalar product between the former separating vector and the new one is higher in absolute value than a constant (we have used 0.95), then one unit refinement is accepted in favor of the former vector.

5) Steps 3 and 4 are continued until set number of iterations are completed or the scalar product (step 4) test is a failure. This optimized de-mixing vector w is better one.

The following is the flowchart of the modified Fast ICA algorithm.

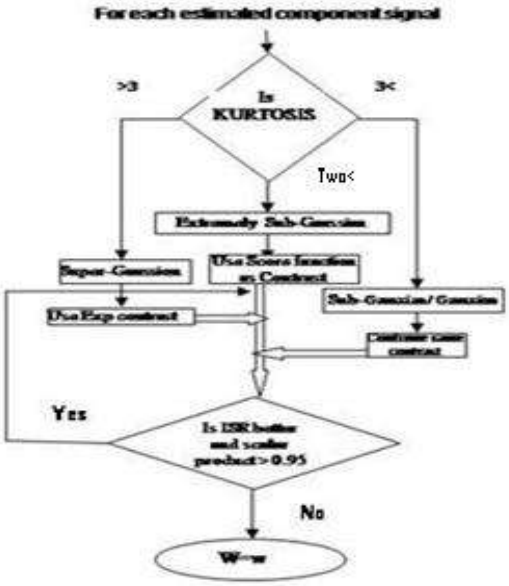

Figure 2 . Flowchart of Modified part of FastICA

V. EXPERIMENTAL RESULTS

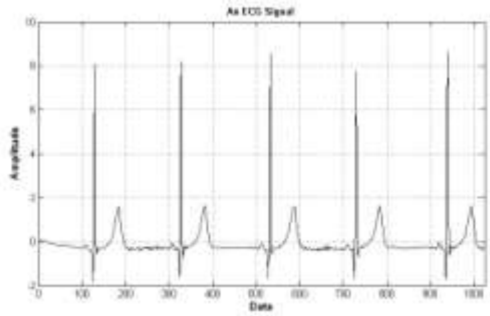

Figure 3 The ECG signal

The simulation experiment we ran on the ECG dataset that had 1024 samples as shown in Figure 3

The experimental analysis of this section aims at objectively evaluating the FastICA algorithm's performance with four standard contrast functions Gauss, Pow3,Tanh and Skew and performance mFastICA. In order to precisely describe the performance of the FastICA algorithm with different contrasts, we employ **Signal Mean Square Error** (SMSE), a contrast-independent criterion defined as

$$SMSE = 1/N \sum_{j=1}^{N} E\{|x_j - Xj|^2\} \quad \ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where x_j is the source signal or the noise free signal, Xj is estimated signal, and N is sample number of the signal. The performance is better when the value of SMSE is smaller

The **Second criterion** of performance measure is **Signal to Noise Ratio (SNR)** of estimated sources**:** It is a measure of signal strength relative to noise in the separated outputs. This measures the level of signal to the level of noise present in the signal. This measure gives clarity of separated outputs. The equation describing the SNR is:

$$\mathbf{SNR} = 10 log_{10}\left(\frac{\sum|s(t)^2|}{\sum|n(t)^2|}\right) \text{ ....(14)}$$

Where s(t) is the desired signal and n(t)=y(t)-s(t) is the noise indicating the undesired signal. y(t) is the estimated independent component.

First we tested the ECG data separation by FastICA with standard contrast functions and modified FastICA contrast functions for Four noise distribution models. FastICA algorithm performance is measured in terms of SMSE, SNR at noise levels from -4dB to 8dB. The results of the experiment are shown in figures 4 to 11 and corresponding data is shown in Tables 1-8.

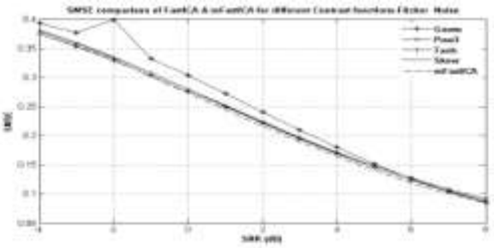

Figure 4: SMSE Comparison of contrasts – Flicker noise

From figure 4, we first notice clustering in the performance of Skew, Pow3,Tanh and mFastICA contrast functions with Gauss contrast performing poor in the range -4dB to 5dB and becomes normal in the range 5dB to 8db.This shows that newly proposed mFastICA algorithm perform better than standard contrast functions.

Table-1 : SMSE for different Contrasts -Flicker Noise

Contrasts	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	0.3925	0.3762	0.3987	0.3319	0.3033	0.2724	0.2408	0.2094	0.1795	0.1516	0.1262	0.1038	0.0845
Pow3	0.3788	0.3570	0.3330	0.3071	0.2799	0.2520	0.2242	0.1973	0.1717	0.1481	0.1268	0.1079	0.0914
Tanh	0.3747	0.3528	0.3288	0.3031	0.2761	0.2486	0.2210	0.1942	0.1687	0.1451	0.1237	0.1047	0.0881
Skew	0.3817	0.3592	0.3344	0.3076	0.2796	0.2510	0.2225	0.1949	0.1689	0.1450	0.1234	0.1043	0.0877
mFICA	0.3746	0.3533	0.3302	0.3006	0.2729	0.2446	0.2166	0.1895	0.1638	0.1402	0.1190	0.1003	0.0841

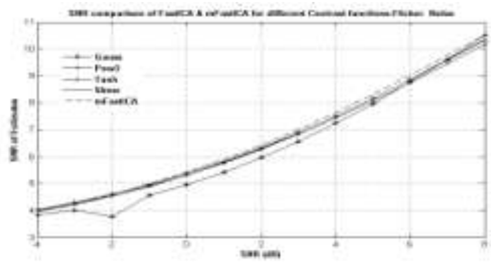

Figure 5: SNR Comparison of contrasts – Flicker noise

From Figure 5,the SNR performance of estimated signals for contrast functions are clustered with Gauss performing poor in -4dB to 6dB range. Once again the mFastICA is performing better when SNR is high compared to standard contrasts.

Table-2: SNR Comparison of contrasts – Flicker noise

Contrasts	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	3.8412	4.0252	3.7738	4.5705	4.9608	5.4274	5.9631	6.5694	7.2390	7.9734	8.7688	9.6160	10.5090
Pow3	3.9961	4.2534	4.5559	4.9072	5.3100	5.7653	6.2726	6.8298	7.4323	8.0749	8.7505	9.4513	10.1687
Tanh	4.0429	4.3050	4.6108	4.9644	5.3686	5.8256	6.3356	6.8976	7.5082	8.1633	8.8562	9.5818	10.3301
Skew	3.9632	4.2269	4.5378	4.8995	5.3147	5.7839	6.3068	6.8811	7.5031	8.1676	8.8685	9.5987	10.3506
mF ICA	4.0447	4.2986	4.5924	5.0008	5.4201	5.8948	6.4234	7.0042	7.6376	8.3112	9.0248	9.7681	10.5345

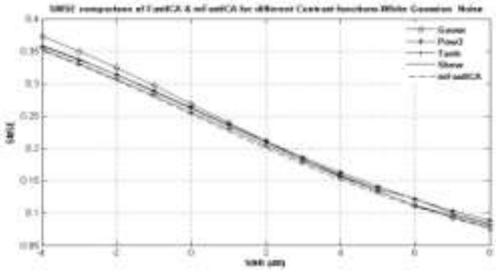

Figure 6: SMSE Comparison of contrasts – White Gaussian noise

In the presence of White Gaussian noise in Figure 6 on can observe that almost all contrast functions perform equally with Gauss performing little poor in the range -4dB to –2dB.Thus the newly proposed mFastICA performed on-par with the standard contrast functions and some times better than standard contrast functions.

Table 3:SMSE comparison of Contrasts-White Gaussian Noise

Contt	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	0.3728	0.3492	0.3238	0.2965	0.2681	0.2393	0.2108	0.1832	0.1574	0.1335	0.1120	0.0930	0.0766
Pow3	0.3577	0.3362	0.3129	0.2882	0.2625	0.2365	0.2108	0.1859	0.1624	0.1407	0.1211	0.1037	0.0885
Tanh	0.3523	0.3304	0.3067	0.2817	0.2559	0.2298	0.2040	0.1791	0.1556	0.1339	0.1116	0.0970	0.0818
Skew	0.3588	0.3368	0.3129	0.2876	0.2613	0.2346	0.2083	0.1829	0.1590	0.1370	0.1219	0.0995	0.0841
mFICA	0.3511	0.3286	0.3043	0.2788	0.2525	0.2259	0.1998	0.1747	0.1512	0.1296	0.1103	0.0932	0.0784

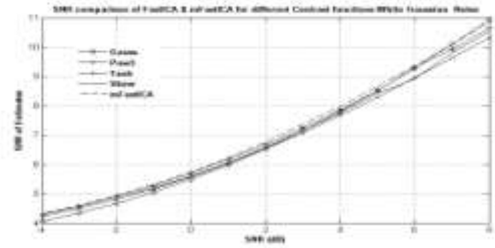

Figure 7: SNR Comparison of contrasts – White Gaussian noise

The SNR of estimated signals from Figure 7 is clustered with Gauss performing poorly -4dB to 2 dB. Once again the performance of mFastICA is onpar sometimes better when compared to standard contrasts of FastICA.

Table 4: SNR Comparison of contrasts -WG Noise

Contt	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	4.0657	4.3492	4.6777	5.0597	5.4973	5.9909	6.5419	7.1497	7.8113	8.5256	9.2884	10.0971	10.9395
Pow3	4.2448	4.5140	4.8258	5.1831	5.5879	6.0408	6.5412	7.0866	7.6730	8.2955	8.9482	9.6226	10.3121
Tanh	4.3111	4.5902	4.9128	5.2817	5.6997	6.1673	6.6845	7.2502	7.8607	8.5121	9.3042	9.9135	10.6515
Skew	4.2314	4.5064	4.8258	5.1928	5.6094	6.0763	6.5929	7.1572	7.7656	8.4135	8.9190	9.8037	10.5322
mFICA	4.3260	4.6135	4.9463	5.3268	5.7580	6.2408	6.7749	7.3574	7.9852	8.6533	9.3539	10.0855	10.8355

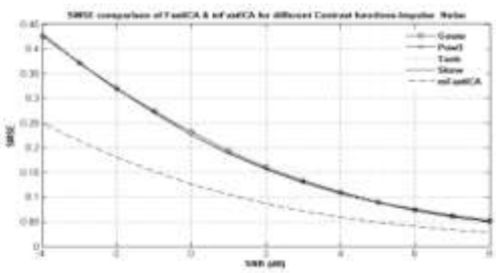

Figure 8: SMSE Comparison of contrasts – Impulse noise

For impulse noise in Figure 8, we can observe close clustering in the performance of almost all standard contrast functions and mFastICA totally away from the cluster. The performances of mFastICA is far superior to standard contrasts of FastICA .

Table 5: SMSE Comparison of contrasts – Impulse noise

Contt	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	0.4248	0.3721	0.3217	0.2739	0.2319	0.1937	0.1612	0.1335	0.1105	0.0911	0.0749	0.0615	0.0507
Pow3	0.4288	0.3711	0.3175	0.2734	0.2263	0.1893	0.1577	0.1311	0.1090	0.0908	0.0758	0.0637	0.0538
Tanh	0.4312	0.3730	0.3188	0.2697	0.2321	0.1884	0.1561	0.1288	0.1061	0.0873	0.0750	0.0618	0.0492
Skew	0.4311	0.3730	0.3188	0.2697	0.2262	0.1884	0.1562	0.1291	0.1065	0.0878	0.0726	0.0601	0.0500
mICA	0.2502	0.2138	0.1809	0.1519	0.1267	0.1051	0.0869	0.0718	0.0593	0.0490	0.0407	0.0340	0.0285

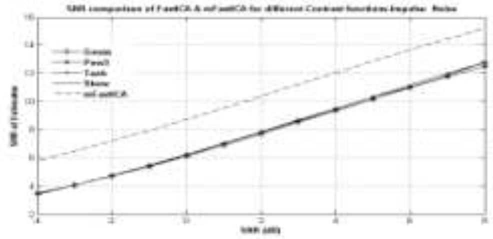

Figure 9: SNR Comparison of contrasts – Impulse noise

The SNR of estimates in the case of mFastICA is much superior to standard contrasts performance. Thus there is 2dB SNR improvement by mFastICA in the case of impulse noise.

Table 6:SNR Comparison of contrasts – Impulse noise

Contt	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	3.4981	4.0729	4.7050	5.4037	6.1273	6.9076	7.7054	8.5239	9.3468	10.1852	11.0324	11.8901	12.7269
Pow3	3.4573	4.0852	4.7624	5.4121	6.2324	7.0086	7.8012	8.6023	9.4042	10.1994	10.9808	11.7412	12.4739
Tanh	3.4332	4.0633	4.7450	5.4715	6.1233	7.0296	7.8467	8.6799	9.5223	10.3677	11.0297	11.8704	12.8587
Skew	3.4346	4.0634	4.7449	5.4716	6.2356	7.0288	7.8435	8.6721	9.5075	10.3433	11.1724	11.9888	12.7861
mFICA	5.797	6.480	7.205	7.963	8.752	9.562	10.387	11.219	12.051	12.875	13.683	14.468	15.226

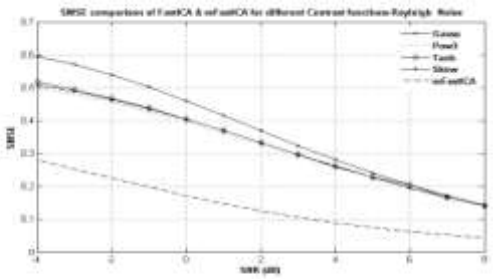

Figure 10: SMSE Comparison of contrasts –Rayleigh noise

Once again incase of Rayleigh noise ,we observe mFastICA performing better and clustering is seen in performance of all other contrasts with Gauss performing poor in the range of 6dB to -4dB.We can relate the performance of contrasts is similar to impulse noise case.

Out of Four noise models , the contrast functions performed better in Flicker and White Gaussian noise models. Fixed contrasts like Gauss and Tanh do not use data in their estimation but seem to perform on-par with data driven contrasts.

Table 7: SMSE Comparison of contrasts –Rayleigh noise

Contt	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	0.5942	0.5703	0.5389	0.5021	0.4598	0.4151	0.3695	0.3239	0.2807	0.2403	0.2038	0.1713	0.1431
Pow3	0.4988	0.4790	0.4548	0.4268	0.3955	0.3618	0.3268	0.2915	0.2570	0.2407	0.1936	0.1731	0.1414
Tanh	0.5176	0.4944	0.4675	0.4374	0.4045	0.3695	0.3333	0.2968	0.2612	0.2271	0.2038	0.1666	0.1409
Skew	0.5082	0.4883	0.4638	0.4351	0.4031	0.3685	0.3324	0.2960	0.2604	0.2265	0.1949	0.1663	0.1409
Poly3	0.2808	0.2530	0.2250	0.1977	0.1715	0.1475	0.1257	0.1064	0.0895	0.0750	0.0625	0.0523	0.0438

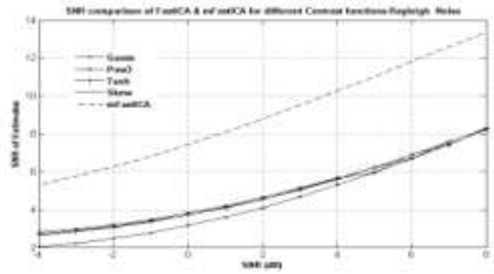

Figure 11 : SNR Comparison of contrasts –Rayleigh noise

This observation is similar to impulse noise and SNR of estimated components in the case of mFastICA out perform all other standard contrast functions.

Table 8: SNR Comparison of contrasts –Rayleigh noise

Contrast	-4dB	-3dB	-2dB	-1dB	0dB	1dB	2dB	3dB	4dB	5dB	6dB	7dB	8dB
Gauss	2.0410	2.2193	2.4650	2.7718	3.1547	3.5986	4.1034	4.6758	5.2972	5.9726	6.6874	7.4424	8.2229
Pow3	2.8009	2.9770	3.2016	3.4779	3.8085	4.1947	4.6367	5.1329	5.6804	5.9656	6.9099	7.3960	8.2760
Tanh	2.6397	2.8395	3.0823	3.3714	3.7110	4.1039	4.5518	5.0546	5.6110	6.2183	6.6879	7.5639	8.2904
Skew	2.7195	2.8930	3.1169	3.3936	3.7262	4.1161	4.5632	5.0665	5.6234	6.2299	6.8808	7.5702	8.2910
mFICA	5.2959	5.7487	6.2585	6.8189	7.4373	8.0913	8.7859	9.5096	10.262	11.029	11.822	12.594	13.369

VI. CONCLUSIONS

In this simulation study, we experimented FastICA algorithm to extract simulated ECG signals under different noise distributions, White Gaussian, Flicker, Impulse and Rayleigh distributions. We have explored use of four standard contrast functions and modified FastICA algorithm with different contrast functions in this experiment to study their performance. The performance of modified FastICA algorithm is shown to improve through the use of data-adaptive contrast functions that are selected based on pdf distributions of sources. This modified algorithm performed extremely well for Impulse and Rayleigh noise distributed sources resulting better SMSE and improved SNR of estimated signals

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