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Blind Source Separation (BSS) of Mixed Maternal and Fetal Electrocardiogram (ECG) Signal: A comparative Study

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Abstract

Electrocardiogram (ECG) test is very important for fetus condition inspection so as to avoid stillbirth and neonatal death during pregnancy. It is well known and widely used as a medical tool as it is convenient and non-invasive. Nevertheless, analysing fetal ECG (FECG) signal by using naked eye is tedious as the observed signal is a mixed signal which consists of weak FECG, maternal ECG (MECG) and also other signals including mother's respiratory noise. Hence, in this paper, Blind Source Separation (BSS) is used to extract the estimated desired signal i.e. FECG from the mixed signal. BSS is a well-known separation method that is able to extract desired signal without knowing any information of the source signal. The aim of this study is to elucidate the performance of BSS algorithms i.e. Fast Fixed-Point for Independent Component Analysis (FastICA), Joint Approximate Diagonalization of Eigenmatrix (JADE) and Principal Component Analysis (PCA) for FECG extraction. We integrate R-peak detection algorithm as a post-separation process to the BSS system in order to distinguish the estimated FECG and MECG for easier analysis process. Estimated signals are evaluated based on waveform characteristics observation and Signal-to Interference Ratio (SIR) parameter. We can conclude that JADE performance performs better in term of accuracy while FastICA is good in term of the computational time. However, FastICA manages to get comparable result as JADE after many fine-tuning steps and it is more flexible compared to JADE as it is not sensitive to low quality input signal.

Keywords: Electrocardiogram (ECG); Fetal ECG (FECG); Maternal ECG (MECG); Blind Source Separation (BSS), Fetus.

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1. Introduction

Electrocardiogram (ECG) test is a non-invasive test used by physician for identifying irregularities in human heart activity to determine one's medical condition [1]. It has also become a useful test for fetal heart activity so as to prevent neonatal morbidity and mortality during pregnancy period [2][3]. Typically, the test is conducted by ECG machine where the electrode is placed on the mother's thorax and abdomen which allows a long term monitoring. This procedure will transmit high frequency ultrasonic sound through maternal abdomen surface and the reflected sound wave produced by this process will be collected and recorded for further diagnosis. ECG test is a well-known medical tool because it is convenient where the test can be carried out without any complicated procedures [2]. Nevertheless, analysing fetal ECG (FECG) signal by using the naked eye is tedious as the observed signal is a mixed signal which consists of FECG, maternal ECG (MECG) and also other signals including mother's respiratory noise. FECG is weak signal with small amplitude which easily get obstructed by the high amplitude MECG signal. Due to this, direct analysis on the raw FECG signal is inaccurate thus effective FECG extraction process is significant and in demand [4].

Previous researches on the FECG extraction was reported in Sugumar et al (2014). This study evaluated the impact of Joint BSS (JBSS) algorithm on separating the mixed maternal and fetal signal. Various JBSS algorithms like MCCA, SOBI, JBSS-SOS and JBSS-CUM4 were evaluated and this study reported that JBSS-CUM4 shows good performance in extracting FECG [2]. In another research by Ghaffari et al. (2015), a new method on selecting the best channel which carries strongest FECG was proposed to detect the fetal QRS complexes from FECG signal. A combination of geometric features and wavelet based technique was adopted as reported in this study [5]. Subsequently, Nikam & Deosarkar (2016) studied the use of FastICA algorithm with maternal R-peak suppression approach to extract the FECG signal [6]. An Improved FastICA method for fetal ECG extraction was reported by Yuan et al. (2018). In this research the over relaxation factor was incorporated into Newton's iterative algorithm to process the initial weight vector randomly. The improved FastICA was able to separate the source component by selecting the best MECG and removed it by singular value decomposition (SVD) [4]. Then, a comparative study based on artificial neural network (ANN), BSS and adaptive filtering in separating FECG and MECG was reported in Zhongliang et al. (2019). From the experimental result observed from this study, BSS performances based on empirical mode decomposition (EMD) give relatively better extraction [7]. Another research based on BSS technique was also reported in Ramli (2019). In this study, Degenerate Unmixing Estimation Technique (DUET) algorithm was evaluated in extracting the FECG extraction. This study focussed on BSS underdetermined case where the number of sources is more than the number of mixture i.e. for the case of twins or triplets' pregnancy [8].

This paper is outlined as follows. In Section 2, the theory of BSS and its algorithm is presented. The methodology in performing the BSS experiments using FastICA with Kurtosis, FastICA with Negentropy, JADE and PCA is explained in Section 3. The experimental results are presented in Section 4 and finally, Section 5 provides the conclusion of the research finding.

2. Blind Source Separation (BSS) Theory and Algorithm

2.1. Blind Source Separation (BSS)

Blind Source Separation (BSS) can be described by the cocktail party problem where M voices (original signals) that are perceived in the cocktail party are recorded by microphones (sensors). Each of the recorded sound is a weighted linear mixture of M voices [9][10]. So as to recover the original voice namely as estimated signal from the observed mixture, the BSS algorithm can be performed. The word blind is referred to the condition where the separation process is done without any information about the nature of the original signals and the mixing process. The BSS relies on the assumption that the original voice (source signal) are non-redundant i.e. the signals are statistically independent or de-correlated [9][10]. The theory of BSS in recovering unknown source signals from the mixture signals can be described as follows:

Let $s(t) = [s_1, s_2, \dots, s_m]^T$ is unknown source signal vector whose exact distribution function is unknown, t is discrete time variable and $i = 1,2, \dots, m$ is the sequence of m source signals. Suppose that the numbers of sensors to provide the observed signals (recorded signals) is n then the observed signals is given as $x_j(t) = [x_1, x_2, \dots, x_n]^T$

where $j = 1,2,\ldots,n$ is the sequence of n observed signals. Consequently, in general it can be expressed as

$$X = AS \tag{1}$$

where A is unknown n x m linear matrix that represent the mixing system. In this system, X is the information that is available, while A and S are unknowns. In BSS, the objective is to recover all source signals, S.

In most cases, to simplify BSS, the number of source signals are assumed to be equal to the number of observed signals, $n = m$. Hence, the mixing system A becomes a square matrix. Then, a simple linear separating system is executed in order to recover the original source signal from the observed mixture,

$$Y = WX \tag{2}$$

where $W \approx A^{-1}$. Note that $y_i(t) = [y_1, y_2, \ldots, y_n]^T$ is an estimate $s(t)$ and W is a n x m (assume $n = m$) separating linear matrix.

In this study, we focus on 4 algorithms used in BSS i.e. Principle Component Analysis (PCA), FastICA with Kurtosis, FastICA with Negentropy and JADE to perform fetal ECG extraction from the mixed ECG signal. All techniques employ statistical domain for data representation in which the data are projected onto a new axes and assume that there are from sets of independent sources.

2.2. Principle Component Analysis (PCA)

The aim of PCA is to decorrelate the observed signal X using variance as a measure by projecting the data onto orthogonal axis [11]. Here, the idea of PCA is to decompose $X = AS$ into

$$X = UZV \tag{3}$$

where Z is a diagonal matrix of singular values (zeros except the leading diagonal) with elements z_i is arranged in descending order of magnitude. Each z_i is equal to $\sqrt{\lambda_i}$, the square root of Eigenvalues, λ_i of the covariance matrix, $C = X^T X$. The columns of V are the Eigenvectors of $C = X^T X$ which correspond with the obtained Eigenvalues in orthogonal subspace. U is projection matrix of X onto the Eigenvectors which is the source estimate.

To perform Singular Value Decomposition (SVD) filtering, the first p eigenvectors is used hence the filtered observation is given as below:

$$X_{fit} = UZ_pV \tag{4}$$

Now, U is the estimated source space which can be found using X_{fit}, Z_p and V [9].

2.3. Independent Component Analysis (ICA)

ICA is a computational method for separating a multivariable signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signal. From the Central Limit Theorem, adding enough independent signal together yields a Gaussian. Hence, in order to find independent sources, the data components must be made non-Gaussian. The essential different between ICA and PCA is that PCA uses variance (a second order moment) rather than higher order statistics as a measure for signal separation. The second order measure works fine if the signal has a Gaussian probability density function (PDF) but many real-life signal are the non-Gaussian. Non-Gaussianity can be measured by Kurtosis or approximation of Entropy [9][10]. The basic idea of ICA is to apply operation to the observed data X and the demixing matrix, W by measuring the independence between the output signal, Y in order to derive the source estimate.

Kurtosis

The fourth order moment of a distribution is known as Kurtosis [9]. It measures the relative peaked-ness of flatness of a distribution with respect to a Gaussian distribution. Kurtosis of a Gaussian is equal to 3 (mesokurtic). A distribution with positive Kurtosis is called as super-Gaussian (leptokurtic) while negative Kurtosis is called as sub-Gaussian (platykurtic). From the standard definition of the mean of a vector, x with N values (dimensions), $x = [x_1, x_2, \dots, x_N]$, the empirical estimate of Kurtosis is defined by:

$$\widetilde{K} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{x_i - \hat{\mu}_x}{\hat{\sigma}}\right] \tag{5}$$

Negentropy

Nevertheless, Kurtosis is highly sensitive to small changes in distribution tails. A more robust measure of Gaussianity is based on differential Entropy. Negentropy is one of the non-Gaussianity that is a modified version from differential Entropy definition. It is used to obtain zero Gaussian variable and being non-negative all the time [9]. Randomization of variable determines the size of the Entropy. Entropy, H is defined such that

$$H(x) = -\int f(x)\log\big(f(x)\big)\ dx \tag{6}$$

where $f(x)$ is probability density function and x is random variables. Negentropy J is defined as follows:

$$J(x) = H(x_{gauss}) - H(x) \tag{7}$$

where x_{gauss} is Gaussian random variable that has the same covariance matrix as x. Due to the complexity in equation [7], then equation below has been introduced

$$J(x) = k[E\big(G(x)\big) - E(G(v))]^2 \tag{8}$$

where v is Gaussian random variable that is always positive i.e. $v \geq 0$ with zero mean and unit variance; G is non-quadratic function that is used to avoid outlier problem that happens in Kurtosis.

Algorithm for ICA includes infomax, FastICA and JADE. In this study, we focus on two ICA algorithms i.e. FastICA and JADE.

2.3.1 Fast Fixed-Point for Independent Component Analysis (FastICA)

In practice, iterative methods are used to maximize or minimize a given cost function to update each element of W so as to measure Kurtosis or Entropy for the non-Gaussinity. FastICA is fixed point ICA algorithms originally proposed by Bingham & Hyvärinen *et al* (2000) [12]. FastICA transforms Neural Network learning rule, gradient decent into fixed point iteration. The advantage of this algorithm is no user-defined parameters are needed and it is fast to converge finding non-Gaussian independent components. In FastICA, given the cost function, ϵ, each element of weight, w_{ij} at each step, τ is updated to recalculate the cost function until the computation converges.

2.3.2 Joint Approximate Diagonalization of Eigenmatrix (JADE)

JADE is one of the ICA algorithms which was originally developed by Jean-François Cardoso *et al* in year 1993 [13]. It is based on orthogonal approximate joint diagonalization approach which employs the fourth order cumulants matrix (Kurtosis) with assumption relies to independence by assuming non-Gaussian source signals. JADE formulation can be described by assuming the covariance matrix of Y is the identity matrix i.e. $COV(Y) = I$ and $\epsilon = COV(X) = AA^T$ denote the covariance matrix, X. Then, for standardized random variable

$$X_{st} = (X - \mu)C^{-\frac{1}{2}} \tag{9}$$

we have

$$Y = X_{st}U \tag{10}$$

For some orthogonal matrix U, the search of the ummixing matrix, W can be found

$$W = U\epsilon^{-\frac{1}{2}} \tag{11}$$

The whitening step is performed using covariance matrix while rotation matrix U is found via joint diagonalization by first solving the Eigenvalues and Eigenvector problem. As BSS is not the case of finite data, thus approximate joint diagonalization is performed by trying to make the cumulant matrix as diagonal as possible. Here, the rotation of matrix U is based on the measure of diagonality using sum of squares of off diagonal elements (cross-cumulant) [13][14]. JADE does not require any gradient descent which means it has no parameter to tune in order to get better performance as in FastICA [15]. A disadvantage with this algorithm as mentioned in *Yan Li et al* (2000) is that it requires storage when estimating complete set of fourth order cumulant matrix.

3. Methodology

3.1. Experimental data

We use ECG data provided by Physionet Database for our experimental data [16]. There are many types of ECG database available in Physionet with different specifications, formats and releases. The recorded ECG data used in this work is from the Non-Invasive Fetal ECG Database. It contains ECG signals recorded from subjects between 21 to 40 weeks of pregnancy by multiple electrodes and position with sampling rate of 1 kHz and bandwidth of 0.01 Hz to 100 Hz, respectively. The mixed MECG and FECG signals are obtained from thoracic region, (X_{mother}) and abdominal region of the mother, (X_{fetus}), respectively by placing electrodes on near the mother heart and fetus (i.e. mother abdominal region). Here, X_{mother} and X_{fetus} are the mixed signals (observed signals) where X_{mother} is more dominant to mother ECG sound while X_{fetus} is more dominant to fetus ECG sound. There are five or six signals from one single release of recording which consist of two thoracic signals and three or four abdominal signals. For this study, only a pair of ECG data is selected i.e. one thoracic signal and one abdominal signal. Five sets of recorded data are taken for our BSS experiment i.e. ecgca102.edf, ecgca127.edf, ecgca192.edf, ecgca244.edf and ecgca22.edf with 60 seconds of recording duration.

3.2. PCA implementation

PCA requires pre-processing of centered data and performs singular-value decomposition (SVD) to obtain parameter of U, Z and V. The parameters are used for estimation of principal component.

The main steps in developing PCA are shown below:

1. Apply centered and whitened data that contains zero mean and unit variance, to remove noises in covariance matrix.
2. Calculate the Eigenvalues, λ_i of the matrix $C = X^TX$.
3. Form a non-square diagonal matrix, Z by placing $z_i = \sqrt{\lambda_i}$ in descending order of magnitude on the leading diagonal and setting all other elements of Z to zero.
4. Find the orthogonal Eigenvector of matrix $C = X^TX$ corresponding to the obtained Eigenvalues and this gives the matrix, V.
5. Determine the first p eigenvalues for principle component, find filtered observed signal, X_{fit}
6. Find the estimated source signal, U given that $X_{fit} = UZ_pV^T$.

3.3. FastICA implementation

FastICA requires to take in centered and whitened data, x initially. Then, FastICA initialize and randomize an initial weight, w_{ij} and estimate demixing matrix, W based on the observed mixture signal, X. By iteratively updating W, Kurtosis and Entropy will be measured for non-gaussianity of Y.
FastICA is implemented as below:

1. Takes in centered and whitened data that contains zero mean and unit variance, to remove noises in covariance matrix.
2. Initialize matrix w_{ij}. $W = A^{-1}$.
3. Given a cost function, ϑ, update each elements of w_{ij} at each step, τ.
$$w_{ij}^{\tau+1} = w_{ij}^{\tau} - \gamma \frac{\partial \vartheta}{\partial w_{ij}}$$
4. Recalculate cost function, ϑ based on learning rate, γ
5. Iteratively update w_{ij} and measure the Kurtosis or Negentropy for the measure of non-Gaussianity.
6. Loop back to iteration until converge and find the estimated source signal, $Y = WX$.

3.4. JADE implementation

JADE algorithm starts by taking the centered and whitened data and estimates forth order of cumulant matrix and compute the rotation matrix such that the cumulant matrix are as diagonal as possible. If it does not exceeds the threshold then computation of JADE is considered completed.
The main steps in developing JADE are shown below:

1. Assuming zero mean from input signal.
2. Apply whitening on the input signal to generate whitening transformation and form a fourth-order cumulant matrix from the whitened input signal.
3. Estimate maximal of cumulant matrix.
4. Computing and reshaping the most significant Eigenmatrix.
5. Compute the rotation U such that cumulant matrix Q is as diagonal as possible.
6. Estimate mixing matrix W and consequently estimate Y .

3.5. R-Peak detection

ECG signal has its characteristic on its waveform. It contains three distinct waveforms which are P-wave, QRS-wave, and T-wave as shown in Fig. 1. P-wave indicates atrial depolarization or atrial contraction, whereas QRS-wave contains three peak points at centre of a signal and named accordingly to their position. Q is first negative peak right after P point, R is first positive peak point right after Q, whereas S is first negative peak point right after R point. QRS-wave is sometimes called as QRS complex represents ventricular depolarization. Meanwhile, T-wave represents ventricular polarization.

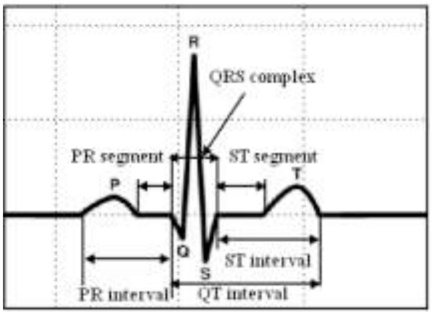

Fig. 1. P-wave, QRS-wave, and T-wave pointed on a ECG signal [1]

Therefore, by using the characteristic of ECG signal, the R-peak amplitude is the most significant point to recognise whether the point belongs to fetus ECG signal or maternal ECG signal. Hence, in this study, the R-peak detection algorithm is developed to recognize estimated maternal and estimated fetal ECG signals. The objective of this algorithm is to solve BSS permutation ambiguities of BSS which often leads to invalid peak detection.

ICA consists of permutation ambiguity for estimated maternal and fetal ECG signals which causes difficulty in determining estimated fetal ECG after separation. R-peak detection is used as a post separation tool for calculating the number of peaks that helps to determine frequency of the both estimated signals. As data taken from PhysioNet database is captured in real case scenario that has baseline shifting problem, hence, ECG detrending step is applied on the input signal. R-peak detection is implemented in performance evaluation stage to determine number of R-peak on each estimated signal based on four developed steps i.e. detrending, finding minimum peak height, finding peaks and determining signal.

The steps of developing R-peak detection tool is shown below:

1. Detrending the estimated signals to solve amplitude or phase shifted problem.
2. Implementing *MinPeakHeight function* so that R-peak detection tool identify those peaks that are higher than the value set only.
3. Implementing *findpeaks* function to identify R-peak and obtain number of R-peak.
4. Based on the number of R-peak result, determine estimated fetal ECG and estimated maternal ECG.

3.6. Performance Evaluation

Objective evaluation for fetal and maternal ECG separation is normally done by using Signal-to-Interference Ratio (SIR), Signal-to-Noise Ratio (SNR), and Signal-to-Distortion Ratio (SDR). However, these measurement requires the source signal, S (fetus's ECG signal and mother's ECG signal) for computation. As database is collected from actual environment (only observed mixed signal, X) there is no source signals to be used as reference. Hence, a modified version of SIR measurement is proposed by D. Sugamar et al. (2014) as given below:

$$SIR = 10\,log10\,\frac{\sum_{k=0}^{T} E_k^2}{\sum_{k=0}^{T}(M_k - E_k)^2} \tag{12}$$

where M_k is mixed abdominal or thorax signal, E_k is estimated source signal of length T.

Here, the numerator indicates estimated signal of maternal or fetal, whereas denominator is the noise interference (the difference between mixed signal and estimated signal). High SIR value indicates less noise interference, hence good separation has been performed.

4. Results and Discussions

In the experiment, four different algorithms which are FastICA with Kurtosis, FastICA with Negentropy, JADE and PCA have been employed to evaluate five datasets of ECG signals from PhysioNet database. The separation performances are measured based on subjective evaluation and objective evaluation (SIR).

For subjective evaluation, the outputs from the separation process for each dataset are displayed into four types of waveforms i.e. Mixed Signal, Separated and Overlapped of Maternal and Fetal Signal, Maternal Signal, and Fetal Signal. Mixed Signal is the raw mixed ECG data which is from the ECG machine. Meanwhile, Separated and Overlapped of Maternal and Fetal Signal indicates the signals that have already been separated, and they are plotted into the same subplot for better observation on the overlapping of amplitude, frequency and number of R-peaks. Besides, Maternal Signal and Fetal Signal are the estimated signals which is presented in different subplot, respectively. However, due to the limited space, output from dataset 2 is chosen for discussion in this paper as shown in Fig. 2, Fig. 3, Fig. 4 and Fig. 5. Two requirements need to be fulfilled for subjective evaluation i.e. 1) magnitude of estimated maternal signal must be higher compared to magnitude of fetal signal and 2) frequency of fetal signal must be twice (or more) compared to frequency of maternal signal.

From the observed experimental output shown, FastICA with Kurtosis, FastICA Negentropy and JADE apparently manage to extract fetal signal from the raw mixed ECG signal. It is observed that estimated fetal signal has lower magnitude compared to the estimated maternal ECG signal and the estimated fetal signal has twice frequency compared to the estimated maternal signal. Nevertheless, JADE performs better compared to FastICA with Kurtosis and FastICA with Negentropy in term of the intense magnitude of its fetal signal. Hence, this shows less interference in fetus ECG extraction. On the other hand, it is observed that PCA algorithm has the lowest performance among the other algorithms in fetal ECG separation. Some of the estimated fetal signal has higher amplitude compared to the estimated maternal signal. However, the estimated fetal signal has twice frequency compared to the estimated maternal signal. Although PCA algorithm has met one of the two requirements but it cannot be considered as good separation as it is theoretically wrong when estimated fetal signal has higher magnitude. The defect shows that PCA algorithm is not capable in estimating fetal signal.

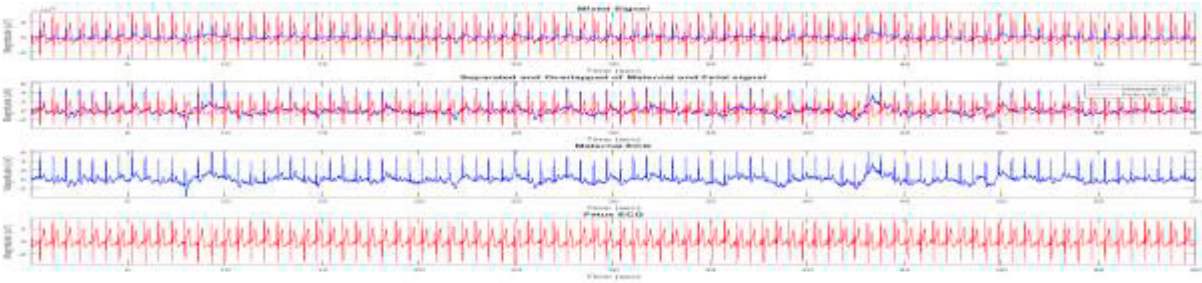

Fig. 2. Normalized estimation of maternal and fetal signal by using FastICA with Kurtosis for dataset 2.

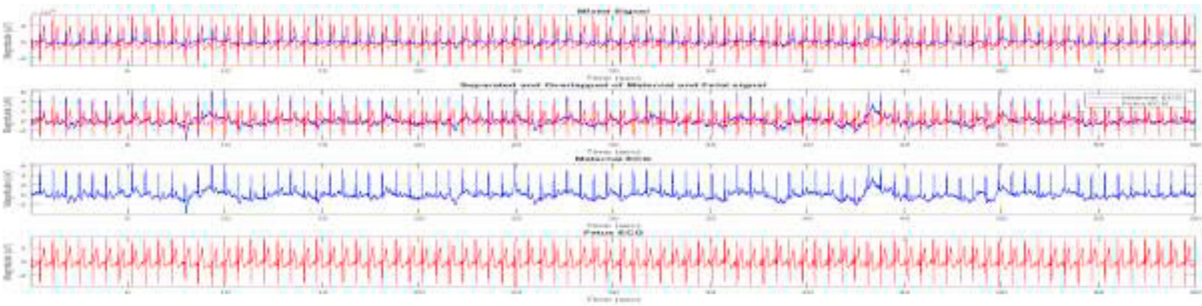

Fig. 3. Normalized estimation of maternal and fetal signal by using FastICA with Negentropy for dataset 2.

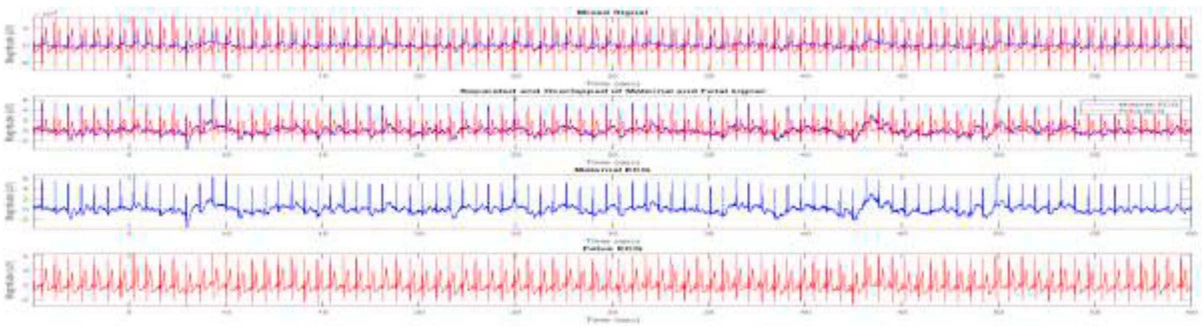

Fig. 4. Normalized estimation of maternal and fetal signal by using JADE for dataset 2.

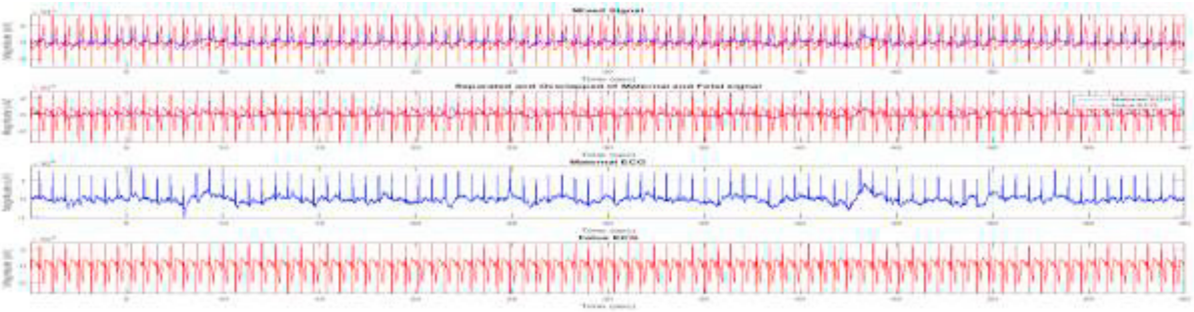

Fig. 5. Normalized estimation of maternal and fetal signal by using PCA for dataset 2.

Subjective evaluation evaluates the separated signal quality based on the two requirements above. Table 1 below shows the objective evaluation based on SIR performance for the 5 datasets for FastICA with Kurtosis, FastICA with Negentropy, JADE and PCA algorithms.

Table 1 : Table shows result of SIR for each algorithm on every ECG dataset.

SIR (dB)	FastICA Kurtosis		FastICA Negentropy		PCA		JADE	
	Maternal	Fetal	Maternal	Fetal	Maternal	Fetal	Maternal	Fetal
Dataset 1	5.188	0.260	7.355	0.653	13.105	-3.873	5.603	0.054
Dataset 2	14.268	-2.082	21.465	-2.627	4.491	-4.967	3.786	1.101
Dataset 3	25.027	-2.760	9.780	-1.335	8.345	-4.395	7.811	-0.804
Dataset 4	15.260	-2.191	2.384	2.262	8.443	-4.382	4.495	0.644
Dataset 5	11.382	-1.660	23.080	-2.695	7.656	-4.488	4.328	0.741

Based on Table 1, SIR results for FastICA with Kurtosis and FastICA with Negentropy is comparable. But in average, Negentropy shows better performance compared to Kurtosis. The advantage of Negentropy over Kurtosis can be also found in [9] as it reported that Negentropy is more robust on the measure of non-Gaussianity and faster to be computed compared to Kurtosis. This is because, Kurtosis is more sensitive to outliers when its performance is decided by few values that are extremely large or small, hence it is not robust enough for non-Gaussianity measure. Nevertheless, Negentropy uses non-quadratic function to avoid this outlier problem [6][17][19].

In comparison between JADE and FastICA, JADE shows better performance than FastICA which has less interference in fetal ECG extraction. However, the weakness of JADE is no fine tuning process compared to FastICA which has some parameters that can be used for fine tuning [15][19]. Furthermore, computational load of JADE grows faster compared to FastICA when the numbers of components increase as experimented in Nicola Falco et al (2014) [19]. Consequently, the performance of PCA is the worst compared to the other algorithms. It is clearly shown that fetal signals is severely affected by interference as referred to the SIR values and this is also confirmed from the subjective evaluation.

5. Conclusion

Based on our experimental results and reported literature reviews, we conclude that JADE has better performance. However, FastICA manages to obtain comparable results as JADE after fine-tuning process and FastICA is more computational effective for large number of components. For future study, the effect of fetal ECG extraction based on BSS can be investigated in terms of noisy mixed ECG with higher number of components using various types of BSS algorithms.

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