I J C T A, 8(5), 2015, pp. 1997-2003

FCOMBI Algorithm for Fetal ECG Extraction

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Abstract: Fetal ECG extraction has an important role in the medical diagnosis during pregnancy. This problem can be modeled from the approach of blind source extraction. The mathematical modeling of fetal ECG extraction using ICA algorithm is described in this paper. It also proposes an efficient BSS method (FCOMBI) for the extraction of fetal ECG. This algorithm combines the strengths of non-Gaussianity based blind source separation and cross-correlation based BSS. This is done by combining the separation abilities of two BSS algorithms such as EFICA and WASOBI algorithms. The Simulation results show the clear winner as FCOMBI which makes it especially acceptable method for the extraction of fetal ECG from abdominal ECG signal.

Key words: Blind Source Separation, ICA, EFICA, WASOBI, FCOMBI

1. INTRODUCTION

The fetal ECG extraction is a very important for the early diagnostics stage of fetal health. In the clinical point of view it is the only information source for the physician to know the health status of the fetus before delivery. Acquisition of fetal ECG is done by placing electrodes on mother's abdomen. Unfortunately the desired fetal heart beat signals will contains additive mixture of disturbances appears at the output of electrode. The different disturbances such as high amplitude mother's heart beat signal, noise produced by mother's respiration and electronic equipment. A proper signal processing technique is needed to recover the wanted signal from the corrupted recordings. Many approaches have been developed to get the FECG from the mixtures. These approaches needs to remove the artifacts and then to upgrade the FECG for the monitoring of FHR. Some of the commonly used extraction methods are SVD [1], Adaptive noise cancellation [2], ICA, etc… The main intension of this paper is first to model the fetal ECG extraction using ICA algorithm from the database created using MATLAB programming and the extraction of fetal ECG using FCOMBI algorithm from the database collected from physionet ATM bank[1] scrutinized in depth to implement in real-time applications.

Cocktail party problem (one separate voice is taken from voices of many persons) is solved by a popular method called Independent Component Analysis (ICA). Cocktail problem shows a scenario of loud party full of people. During the conversation between two people human ear engaged with different sources like music instruments, people talking around, some external noises etc… Though human hear mixed signal in order to concentrate a sole signal. The hand machines like microphone gets confused. Such problem indicates the need to develop a system that required finding out the source signal. This is the key motivating factor for blind source separation. It deals with the problems that are closely linked with cocktail party problem. This paper mainly explains about the extraction of fetal ECG using BSS technique.

2. ICA (INDEPENDENT COMPONENT ANALYSIS)

BSS problem is solved by a very important signal processing technique named as Independent component analysis. The ultimate goal of this method is to state a set of random variables as linear combinations, that are statistically independent component variables.

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2.1 Problem formulation

The ICA based BSS problem recover the unknown source signal from the mixture of signal by making a simple assumption of 'n' independent signals which are denoted as

$$s(t) = s_1(t), S_2(t), S_3(t), \ldots \ldots \ldots S_n(t) \tag{1}$$

The observed signals are denoted as

$$x(t) = x_1(t), x_2(t), x_3(t), \ldots \ldots \ldots x_n(t) \tag{2}$$

For the set of random variables,

$$x(t) = As(t) \tag{3}$$

Where 'A' is unknown mixing matrix and 't' denotes time instance.

The procedure used for the transformation of source signal into mixed signal is unknown which shows the "blindness" property of the problem [3].The ultimate aim of ICA is to determine the unmixing matrix. This unmixing matrix W is used to find out the unknown input (source) signals.

$$y(t) = Wx(t) \tag{4}$$

Where W is the separation matrix.

The mixing matrix is taken as the abdominal ECG signal which is the mixture of unwanted noises with mother and fetal ECG signals.

2.2. ICA ambiguities

The different ambiguities in the ICA model are

(i) Variances of the independent components cannot be determined.

(ii) Order of the independent component cannot be determined.

2.3. Preprocessing of ICA

The preprocessing steps for ICA are used to reduce the noises in the multidimensional dataset and also to avoid the performance degradation in ICA.

The preprocessing steps are

(i) Centering

(ii) Whitening

Centering: The independent components are determined by removing the mean variables. This process is called centering.

$$x_c = x - m \tag{5}$$

Where x_c the centered observation vector and 'm' is the mean vector.

Centering process allows specifying ICA algorithm and unmixing matrix can be estimated by centered data.

Whitening: Whitening is the process by which the observation vector is linearly transformed [4]. The correlation in the data is removed by this process. It is also used to minimize the number of parameters to be estimated.

Let x_w indicates the whitened vector, it should satisfies the equation

$$E\left\{X_w X_W^T\right\} = I \tag{6}$$

Where $E\left\{X_w X_W^T\right\}$ is the co variance matrix of x_w

The whitening transformation is done by an easy simple method called Eigen value decomposition (EVD) [5]. This method decomposes the covariance matrix of 'x'.

$$\varepsilon = \operatorname{cov}(x) = E[xx^T]$$

$$\varepsilon = E[ASAS^T]$$

$$\varepsilon = AA^T \tag{7}$$

Using Eigen value decomposition,

$$\varepsilon = VDV^T \tag{8}$$

Where V denotes the Eigen vector of $E[xx^T]$

D denotes the diagonal matrix of Eigen values.

The transformation used to whiten the observation vector as,

$$X_w = VD^{-1/2}V^{T_x} \tag{9}$$

The mixing matrix is transformed into a whitening matrix by whitening process, which is orthogonal.

$$X_w = VD^{-1/2}V^{T_x}$$

$$X_w = A_w S \tag{10}$$

Hence

$$E\{X_w X_w^T\} = A_w[E\{SS^T\}]A_w^T$$

$$= A_w A_w^T$$

$$= I$$

The number of parameters to be estimated can minimized by Whitening process. For example the matrix A with n^2 elements, we required to estimate the matrix with $n(n-1)/2$ degrees of freedom. From this we can indicate that half of the ICA problem was solved by whitening problem.

2.4 Illustration of ICA

To clarify the above discussed section, one simple illustration is presented here for the dissociation of mother and fetal ECG signal from the mixture of signal.

Separation of two signals

For these illustration two independent signals $S1$ and $S2$ are generated. $S1$ is taken as mother's ECG signal and $S2$ is taken as fetal ECG signal. The mixing matrix A is obtained by mixing the two independent signals as shown in the figure 1.

The mixing matrix A (abdominal matrix) is given by

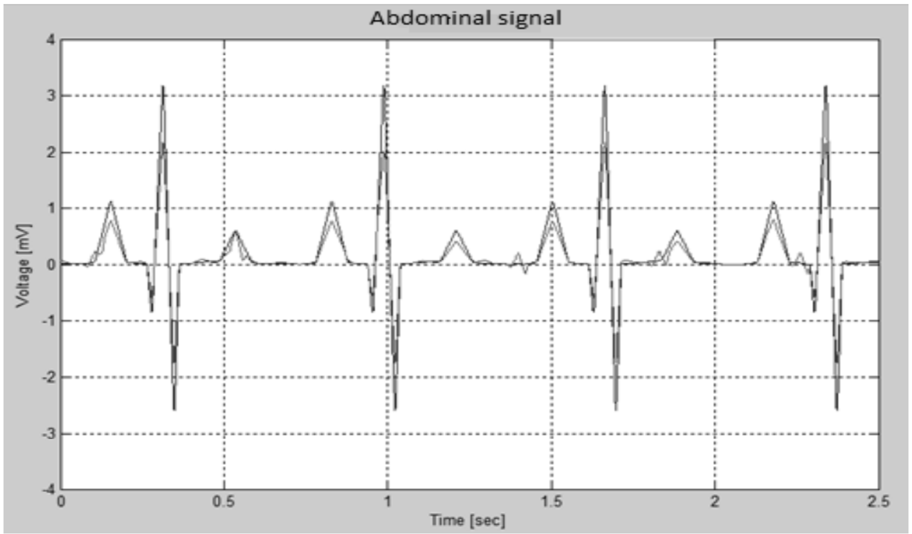


Figure 1: Mixed abdominal signal

$$A = \begin{pmatrix} 0.0934 & 0.4561 \\ 0.3074 & 0.1017 \end{pmatrix}$$

Centering: The observation matrix X is subtracted by its mean value to zero for center the matrix X. From this point we can assume that all the observation vectors to be centered. Using the centered data we can estimate the unmixing matrix.

Whitening: The co variance matrix of 'X' is given by

$$\varepsilon = cow(X) = AA^T$$

$$= \begin{pmatrix} 0.2181 & 0.0751 \\ 0.0751 & 0.1048 \end{pmatrix}$$

Using EVD and Jacobian rotation we can calculate the unmixing matrix W as,

$$w = \begin{pmatrix} 0.1539 & 0.2039 \\ 0.0904 & 0.1873 \end{pmatrix}$$

The estimated output is given by

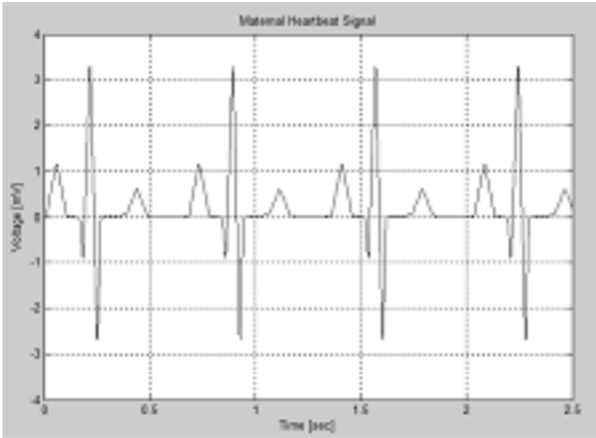
$$Y_{est} = WX$$

$$Y_{est} = \begin{pmatrix} 0.0703 & 0.0332 \\ 0.0521 & 0.0231 \end{pmatrix}$$

The separated signals are shown in figure 2.

4. EXTRACTION OF FETAL ECG USING BSS ALGORITHM

The main target of ICA method is to appraise the source signal from the mixture of signal. The ICA method has the ability to extract the reference signal from the mixture of signal. The obtained signals are viewed as non-Gaussian and statistically independent of one another.



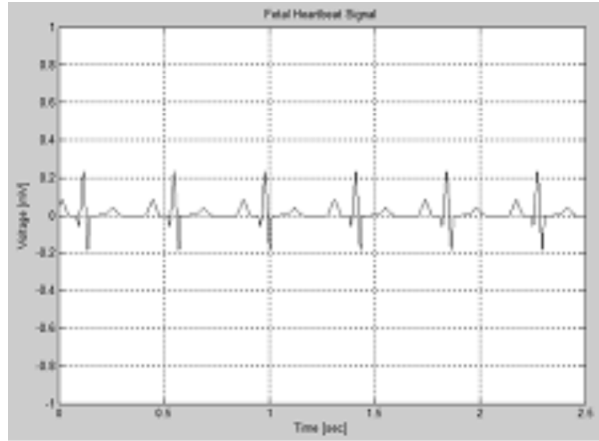


Figure 2: Separated fetal and mother ECG signals

But in the case of real world signals are both Gaussian and non-Gaussian components. In that case the BSS algorithms are developed to extract the reference signals. This paper described the FCOMBI algorithm to be applied in the task of extracting the FECG from the mixture of abdominal ECG signal.

4.1. Proposed Algorithm (FCOMBI)

FCOMBI BSS algorithm is used to obtain the fetal ECG signal from mixture of abdominal signal. This method is the modified method of MULTI-COMBI. The FCOMBI method gives better PSNR and SIR values compared to MULTI-COMBI method. FCOMBI method incorporates the strengths of EFICA and WASOBI.

EFICA: EFICA is a revised method of fast ICA algorithm [6]. It utilizes non-gaussianity of sources distributions [ignoring any time structure]. In general, to extract each of'd' sources, a user-defined choice of set of non-linear functions $g_k(.)$ [k = 1, 2, ... d] is required for fast ICA. EFICA enhance fast ICA by giving a detailed data-adaptive choice of non-linearities followed by a refinement step.

"S" contains "N" independent realizations of non-Gaussian random variables ε_k [7] using the assumption that each row $S_k(k = 1, 2, ... d)$. The ISR matrix contains the elements

$$ISR_{ki} = \frac{1}{N}\frac{\gamma_k(\gamma_l + \tau_l^2)}{\tau_l^2\gamma_k + \tau_k^2(\gamma_l + \tau_l^2)} \tag{11}$$

Where

$$\gamma_k = \beta_k - \mu_k^2 \qquad \mu_k = E\left[\varepsilon_k g_k(\varepsilon_k)\right]$$

$$\tau_k = |\mu_k - \rho_k| \qquad \rho_k = E\left[g_k'(\varepsilon_k)\right]$$

$$\beta_k = E\left[g_k^2(\varepsilon_k)\right]$$

Where E [.] gives the expectation operator

$g_k'(.)$ gives the derivative of $g_k(.)$

For the best possible case, the equation (11) equals to Cramer-Rao Lower Bound (CRLB) [8].

WASOBI: The weighted version of SOBI [9] algorithm is called WASOBI. This algorithm is the member to a family of second order statistics based ICA algorithms. This algorithm mainly depends on time structures in the sources.

Both SOBI and WASOBI are depends on Approximate Joint Diagonalization (AJD) of several time-lagged determined correlation matrices, which is represented by

$$\tilde{R}_x(\tau) = \frac{1}{N-\tau}\sum_{n=1}^{N-\tau} x[n]x^T[n+\tau]\tau = 0,1,2,...M-1 \tag{12}$$

Where $x[n]$ denotes the n^{th} column of x.

Under asymptotic conditions, if all sources are Gaussian AR of order M-1, the ISR matrix obtained by WASOBI is equal to respective CRIB [10]. The ISR matrix is stated as,

$$ISR_{kl} = \frac{1}{N}\frac{\varphi_{kl}}{\varphi_{kl}\varphi_{lk} - 1\sigma_l^2 R_k[0]} \tag{13}$$

Where

σ_k^2 represents the variance of the innovation sequence of the k^{th} source.

$$\varphi_{kl} = \frac{1}{\sigma_k^2}\sum_{i,j=0}^{M-1} a_{il}a_{jl}R_k[i-j]$$

Where

$\{a_{il}\}_{i=0}^{M-1}$ are the AR co-efficient of the l^{th} source with $a_{ol} = 1$ for $k = 1, 2, \dots d$.

$R_k[m]$ is the auto-correlation of the k^{th} source at time lag m.

Steps in FCOMBI:

Step 1: Apply WASOBI on the input data.

Step 2: EFICA is applied on the output of WASOBI.

Step 3: Run WASOBI on the cluster of unresolved components in the output of

EFICA

5. RESULTS AND DISCUSSION

The database signals are taken from MIT physionet ATM bank. The obtained signal consists of both AECG signal and FECG signal. FCOMBI algorithm is applied to the database. The mother's ECG signal, fetal ECG signal and noise signals are separated as shown in the figure 3.

The performance parameters like PSNR and SIR values are calculated. These values show the effectiveness of the algorithm. FCOMBI gives the PSNR value as 7.92 and the SIR value as 6.54. These SIR and PSNR values of FCOMBI are better when compared to other extraction techniques like MULTICOMBI, MICA, etc…

6. CONCLUSION

This paper presented the mathematical modeling of ICA algorithm using synthetic database and the fetal ECG is extracted using FCOMBI BSS algorithm. This method is a simple, fast method and implemented using real time data. It is obvious that the real time abdominal signal recorded from mother's abdomen carries of mother's ECG signal, Fetal ECG signal and different types of noises. Some of the noises are

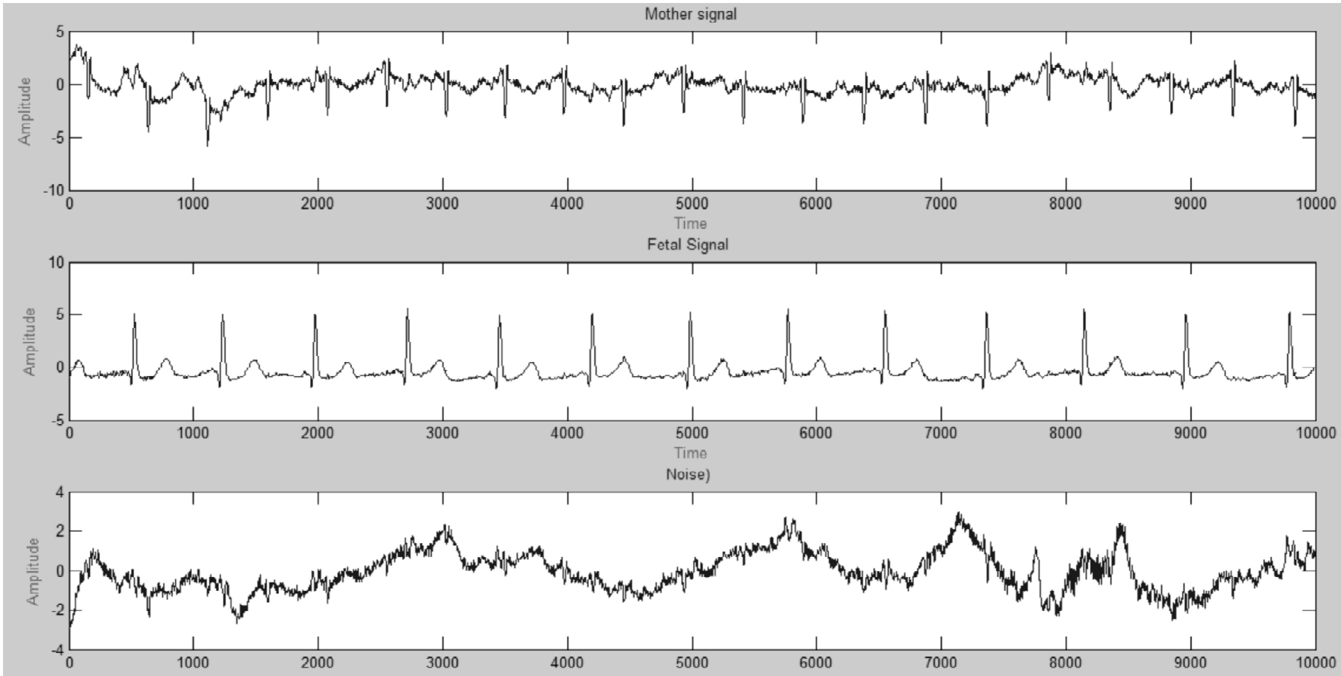


Figure 3: Output of FCOMBI algorithm

eliminated using filtering techniques followed by FCOMBI algorithm separates the FECG signal from high amplitude MECG and unwanted noises. It gives better values of PSNR and SIR. These values show the potency of the algorithm.

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