# EFFECTIVE PERFORMANCE EVALUATION OF DIFFERENT ABDOMINAL ECG SEPERATION TECHNIQUES

SHAHANA BARVIN M Dept. of Electronics and communication engineering LBS Institute of Technology for Women Poojappura Trivandrum, India shahanazahra93@gmail.com HEMA S

Dept. of Electronics and communication engineering LBS Institute of Technology for Women Poojappura Trivandrum, India hemarajen@gmail.com

Abstract— In the biomedical field, fetal electrocardiogram (FECG) extraction is very challenging task, so it has been a significant field in biomedical research. Diagnosis of maternal and fetal heart beat is very important during pregnancy. Hence use fetal electrocardiogram (FECG) extraction for the same. The signal contains important information that can help doctors during pregnancy and labor. In order to access the fetus health and potentially detect heart disease, these signals are used. In order to choose appropriate treatment and prevent further damage and complications early diagnosis is essential. Here the signals contain maternal ECG which is taken from abdomen and fetal ECG along with noise. Several methods can be used for fetal ECG extraction. This paper aims to compare the performance parameters like Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) numerical values for three different techniques such as Principal Component Analysis, Independent Component Analysis And Weight Adjust Second Order Blind Identification for separating these source signals.

Index Terms — Fetal ECG, Abdominal ECG, Maternal ECG, Principal component analysis, Independent component analysis, WASOBI, BSS

#### I. INTRODUCTION

An Electrocardiogram (ECG) is a simple painless test which measures electrical activity of heart that controls heart rhythm also measures how electrical impulses move through heart muscles as it contracts and relaxes [1]. It is also known as ECG or EKG which is a periodic signal that represents recorded electric potentials that produce from the tissues of heart.

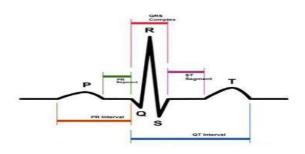


Fig 1.This figure shows one period of a typical clean ECG signal

The ECG translates the electrical activity of heart in to the line tracing on paper. The spikes and dips in the line tracings are called waves. ECG waveform is also called PQRST wave. The above figure 1 shows a typical ECG waveform. The first waveform in the ECG is P-wave is due to the atrial contraction that is a record of electrical activity through upper heart chambers. The next waveform is QRS complex due to ventricle contraction which is a record of the movement of electrical activity through lower heart chambers. The ST segment occurs when the lower heart chambers is contracting but no electricity is flowing through it and usually appears as a straight level line between the QRS complex and T wave. The final waveform is the T wave occurs when the ventricles (lower heart chamber) are resetting electrically and preparing for their next muscle contraction [1].

All Heart related problems are usually affecting the electrical activity of heart. Doctors may recommend to taking an ECG if you are experiencing symptoms that may cause a heart problem such as pain in chest, trouble breathing, feeling tired or weak, pounding, racing or fluttering of your heart, irregular heart beating and detection of unusual sounds. An ECG will help the doctor to determine the causes of symptoms along with what type of treatment might be necessary.

Heart rate is the number of beats (rhythmic contractions) per minute of heart. It is a measure of cardiac activity. Heart rate is one of the vital signs like body temperature, pulse, breathing rate and blood pressure provides information about person's heart state. Any abnormality of these signs gives diagnostic information [1].

Principles of ECG analysis can also be used to evaluate the heart performance and development from a fetus in the womb during the different stage of pregnancy as well as

delivery [3]. Fetal electrocardiogram is a test similar to an ultra sound. This test allows doctor to better see the structure and function of your unborn child's heart. It's typically done in the second trimester, between weeks 18 to 24 [2]. This test uses sound waves that "echo" off of the structures of the fetus' heart. A machine analyzes these sound waves and creates a picture, or echocardiogram, of their heart's interior. This image provides information on how your baby's heart has formed and whether it's working properly [2].

It also allows the doctor to see the blood flow through their heart. This in-depth look allows the doctor to find any defects or abnormalities in the baby's blood flow or heartbeat. In order to access the fetus health and potentially detect heart diseases [2]. An early diagnosis is essential in order to choose appropriate treatment and prevent further damage and complications. Accurate and non invasive FECG extraction is still the biggest challenge in this area. The most suitable method to extract a fetal ECG is to take measurement from mother's abdomen. This particular signal is heavily mixed with maternal ECG abdominal muscles and various noises [3]. The peaks of QRS complex give the information about the heart rate of the abdominal ECG signal. Since the Abdomen ECG is mixture of noises with Maternal ECG signal and Fetal ECG, it is very difficult to calculate the heart rate from raw ECG signal. Hence the fetal ECG is extracted from the raw signal to get the proper heart rate of the fetal ECG signal. This paper aims to separate the Abdominal ECG signal using three different methods such as Principal Component Analysis, Independent Component Analysis and Weight Adjust Second Order Blind Identification. Also compare their performance parameters in terms of Mean Square Error and Peak Signal to Noise Ratio.

This paper is organized as follows: The second section describes literature survey of fetal ECG extraction methods. The third section describes the performance comparison of PCA, ICA and WASOBI. The fourth section describes the Experimental results and the fifth section describes the conclusion.

# **II. EXISTING METHODS**

#### A. Principal Component Analysis

PCA is a multivariate analysis method, which can be used for the pre processing of the abdominal signal. The dimensionality of the data representation can be reduces by using this method [3]. Actually PCA can be considered as a blind source separation method. PCA is like a version of ICA, i.e. the source signals are assumed to be Gaussian. Pre processing using the Principal Component Analysis helps to speed up the estimation process by reducing the number of input data under consideration. Co variance matrix is used in pre processing using PCA.

PCA de-correlates the data by performing an orthogonal projection of the data, which reduces the dimension of the data from N to P (P < N) to remove unwanted components in the signal. PCA

representation is an optimal linear dimension reduction technique in the mean-square sense. One important application of this technique is to noise reduction, where the data contained in the last N - P components is assumed to be mostly due to noise. Another benefit of this technique is that a projection into a subspace of a very low dimension, for example two or three, is useful for visualizing multidimensional or higher order data. The computation of the Eigen vectors (Vi) is accomplished by using the sample covariance matrix (C) is  $C=X^{T}X$ . The Vi are the eigenvectors of C (an  $M \times M$  matrix) that corresponds to the N Eigen values of C [3]. The method for determining the Eigen values in this manner is known as Singular Value Decomposition (SVD) [11]. To determine the principal components of a multidimensional signal, PCA uses the method of Singular Value Decomposition [11].

## B. Independent Component Analysis

Independent Component Analysis (ICA) chooses a measure of independence other than variance which leads to a more effective method for separating signals. ICA has proven to be a very powerful machine learning algorithm to perform signal separation [4][5]. Essentially, this method tries to find a weighted linear combination function that best represents the multivariate (mixed) data. Given that we observe several different mixed signals, we can write formulate the following equation.

$$\mathbf{x}_{j} = \mathbf{w}_{j1}\mathbf{s}_{1} + \mathbf{w}_{j2}\mathbf{s}_{2} + \dots + \mathbf{w}_{jn}\mathbf{s}_{n}$$

Where  $x_j$  represents each mixed signal observed,  $s_n$  represents each independent component and  $w_{jn}$  as their respective weight [7].

Essentially, when performing blind source separation via ICA, the only parameter we know is  $x_j$ . Therefore, the algorithm tries to estimate the values of  $s_j$  and  $w_{jn}$  using only the multivariate signal. More practical for is given by:

### x=Ws

Where x is a vector containing every mixed value, s a vector contains each independent elements and W, also called the mixing matrix, containing the values of each weight [5].

After performing ICA to estimate the mixing matrix W [8][9], one can easily calculate the independent components by taking the inverse of W and setting the following equation:

 $s = W^{-1} x$ 

In order to carry a successful use of ICA a couple of important guidelines and restrictions should be noted:

1) Each signal  $x_j$  and  $s_n$  are treated as random variables rather than actual time signals.

2) We assume each  $s_n$  is independent from each other.

3) We must make sure that the input mixed signals  $x_j$  do not possess Gaussian distributions.

One of the key methods for performing BSS is known as Independent Component Analysis (ICA), where it

takes the advantage of (an assumed) linear independence between the sources.

#### C. Weight Adjust Second Order Blind Identification

The term WASOBI refers Weight Adjust Second Order Blind Identification. It is a member in family of second order statistics based ICA algorithms [6]. Seperation of sources consist of recovering a set of signals of which only instantaneous linear mixtures are observed. In many situations, no a priori information on the mixing matrix is available. This linear mixture of signals should be blindly processed. This is one of the BSS algorithms [11]. It exploits the time coherence of the source signals. Second order statistics that are based on a joint diagonalization of a set of covariance matrices [10].

BSS consists in identifying a mixing matrix and retrieving the source signals without resorting to any a priori information about the mixing matrix. For that it exploits only the observed signals hence the term blind. The lack of information on mixing matrix must be compensated by some additional assumptions on source signals. For non- Gaussian independent sources, this algorithm exploits marginal distribution of the observation otherwise based on temporal correlation. Since these are second order statistics they are expected to be more robust in adverse SNR. For stationary sources with different spectral contents; Blind Identification is feasible based on spatial covariance matrices. These matrices that allow Blind Identification procedure based on Eigen value decomposition (ICA). A Blind Identification technique based on joint diagonalization of several covariance matrices. A second order seperation algorithm includes two parts. First, after whitening the data, it can remove the correlation from the data but cannot achieve independence at this time. Then take EVD on the whitened covariance to achieve unitary diagonalization to minimize the elements beyond the diagonal. The processing of the Unitary matrix and whitening are strong enough to estimate the mixing matrix and separate mixtures.

#### **III. COMPARISON OF EXISTING METHODS**

First procedure is the data acquisition. Abdominal ECG can be taken by placing electrodes on the different position on the mother's Abdomen. Here the abdominal ECG dataset is taken from the PHYSIONET which is medical website. Abdomen ECG contains a mixture of unwanted noise with maternal ECG and Fetal ECG. This mixture of signal is given to above described signal seperation techniques. These methods are useful for both preprocessing and signal seperation. After separating abdominal signals by using PCA, ICA and WASOBI, compare the performance parameters of each method. ICA basically looks for statistical independence whereas PCA looks for orthogonal components which are uncorrelated. ICA maximizes non gaussianity whereas PCA maximizes

variance in the components. ICA is actually a generalization of PCA because the constraints of orthogonality are not present in ICA. PCA only looks at second order statistics that is variance but ICA usually looks at higher order statistics. The objective of ICA is to determine a transformation which assures that the output signals are statistically independent as possible. Second order methods (WASOBI) assume that sources have some temporal structures while the higher order methods assume their mutual independence. PCA take the orthogonal matrix which is a matrix where the product of the matrix and its transpose is the identity matrix where as WASOBI takes unitary matrices is a matrix where the product of the matrix with its complex conjugate transpose is the identity matrix. These three methods are used for noise reduction or compression and seperation.

## IV. EXPERIMENTAL RESULTS

Here the datasets consist of a mixed signal which contains both maternal ECG and fetal ECG signal along with noise which is given in the figure 2. Different signal seperation techniques such as PCA, ICA and WASOBI were applied on these mixed signals which perform both preprocessing and signal seperation. Resultant Seperated signals by using PCA is given in the figure 3, using ICA is given in figure 4 and using WASOBI is given in the figure 5. Results show improved extraction performance and successful removal of noises. Numerical results on mean square error and peak signal to noise ratio for PCA, ICA and WASOBI were calculated and tabulated which is shown in the table 1.

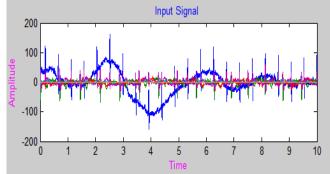


Figure 2: Input Abdominal Signal.

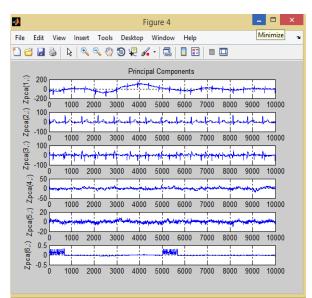


Figure 3: Signal Seperation using Principal Component Analysis.

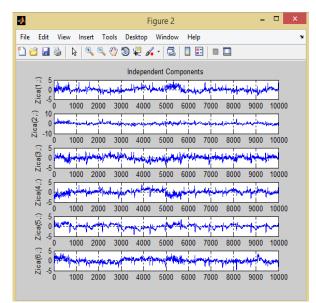


Figure 4: Signal Seperation using Independent Component Analysis.

(c' 1)//	10 0 -10	1000	yo - the o	4 million a	الإسمام	~~~p i~~ q~	a the state	-+	****		<b>h</b> 4
	0	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000
W(2,:)	0	**frankrad	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	not be	FRagen J.		dress of p			*1-4-+	-
	<u> </u>	1000	2000			5000	6000	7000	8000	9000	10000
N(3,:)	0	-1	le superior de la constante de	- 4	hone h	•	-		ento	44-4	
_	-10	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000
W(4,:)	0	e His Marthad	an		YC4129A		New America	mour		ويعتر وأوجعهم	19 Y 14
VV(4,:)	0 -5 0		2000	3000	4000	5000	6000	7000	8000	9000	10000
ĺ	-5 -5 -5		2000	3000		5000		7000	8000	(بیر او بر بر بر 9000 مربع بر بر بر	10000
ĺ	-5 -5 -5	1000	2000	3000	4000	5000		7000	8000	9000 9000	10000
ĺ	-50 5 -50 10	1000	2000 2000	3000 3000 3000	4000	5000 	6000	7000	9-4-4-4-4-4-4-4-4-4-4-4-4-4-4-4-4-4-4-4	9000	10000

Figure 5: Signal Seperation using WASOBI

TABLE 1- Performance Parameters of techniques like PCA, ICA and WASOBI based on MSE and PSNR were tabulated and calculated below:

Method	ICA	WASOBI	PCA
MSE	0.0371	0.0375	0.1411
PSNR	66.0018	71.4309	120.5336

It has been noted that PCA gives better PSNR value when other two techniques ICA and WASOBI. i.e. Signal content is more in PCA. Signal content is low in WASOBI and ICA. Also clear that ICA and WASOBI gives good MSE values when compared to PCA.

### V.CONCLUSION

Accurate and non-invasive fetal ECG extraction is still a challenging task; there is a lot more work and research to be done. To access fetus health status, Fetal ECG extraction is necessary. Here the mixed signals are separated using different techniques like PCA, ICA and WASOBI. Their performance parameters were calculated in terms of MSE and PSNR. The use of PCA gives better results which yields good PSNR. ICA and WASOBI gives better MSE value means better noise reduction. PCA contains more signal content when compared to other two methods. Among the separated signal we can be detect the fetal ECG and extract the clean fetal ECG signal.

# REFERENCES

[1] www.healthline.com/health/electrocardiogram.

[2] http://www.healthline.com/health/fetal-echocardiography.

[3] Savitha R V, S.R.Breesha and X.Felix Joseph, "Pre Processing the Abdominal ECG signal using combination of FIR filter and Principal Component Analysis," International Conference on Circuit, Power and Computing Technologies [ICCPCT] 2015 IEEE.

[4] "Fetal ECG Extraction Using Independent Component Analysis "German Borda Department of Electrical Engineering, George Mason University, Fairfax, VA, 2003.

[5] A Hyvarinen, E. Oja, "Independent Component Analysis: Algorithm and Applications," Neural Networks, 13(4-5), pg. 411-30, 2000.

[6] "A Least-Squares Approach to Joint Diagonalization" Mati Wax, Fellow, IEEE, and Jacob Sheinvald, IEEE Signal Processing Letters, Vol. 4, No. 2, February 1997.

[7] Burghoff, M., Van Leeuwen, P., "Separation of fetal and maternal magnetocardiographic signals in twin pregnancy using independent component analysis (ICA)," Neurology, Neurophysiology and Neuroscience, 2004. Parkhurst, "Cisco Multicast Routing and Switching",MCGraw Hill, 1999.

[8] W. Chen, T. Nemoto, et al., "Fetal ECG Extraction from Maternal Body Surface Measurement using Independent Component Analysis", Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual

International Conference of the IEEE, vol. 2, 2001,pp 1990-1993,.

[9] Aapo Hyvärinen, "Fast and Robust Fixed-Point algorithms for Independent Component Analysis", IEEE Transactions on Neural Networks, 10(3):626-634, 1999.

[10] Ananthanag, K., and Sahambi, L., "Investigation of blind source separation methods for extraction of fetal ECG", In Canadian Conference on Electrical and Computer Engineering. May 2003.

[11] P.P. Kanjilal, S. Palit, G.Saha, "Fetal ECG extraction from single channel maternal ECG using singular value decomposition", IEEE Trans. Biomed. Eng. 44(1)(1997)51-59.

[12] A. Belouchrani, K. Abed-Meraim, J.-F. Cardoso, and E Moulines, "A blind source separation technique using second order statistics," IEEE Trans. Signal Processing, vol. 45, pp. 434-444, Feb. 1997.

[13] E. Doron, A. Yeredor and P. Tichavsk'y, "Cram'er-Rao-Induced Bound for Blind Separation of Stationary Parametric Gaussian Sources", IEEE Signal Processing Letters, vol. 14, no. 6, pp. 417-420, June 2007.