



Extraction of fetal ECG signal from abdominal and thoracic ECG signal using periodic component analysis

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ABSTRACT

In this paper, Periodic Component Analysis is used to extract the fetal electrocardiogram (ECG) from the abdominal and thoracic maternal electrocardiogram. The thoracic ECG (TECG) is assumed to be almost completely maternal while the abdominal ECG (AECG) is considered to be composite as it contains both the maternal and fetal ECG signals. Three channels of signal, from chest leads and five from abdominal leads from DaISy data set are used. Extracted signals consist of mixture of components including maternal ECG, fetal ECG and random noise. Periodic Component Analysis (π CA) is used to isolate the fetal ECG from maternal ECG signal. Generalized Eigen Value Decomposition is used to decompose the ECG record. It uses phase-wrapping of the R-R interval, for extracting the most periodic linear mixtures of a recorded dataset. Comparison with Independent Component Analysis (ICA) demonstrates the quality of this method. This method is therefore of special interest for the decomposition of ECG and the extraction fetal ECG from maternal ECG signal. The average sensitivity and accuracy of this method is 99.04% and 94.56% respectively. By using one thoracic signal and three abdominal signals this method is able to achieve 100% sensitivity and accuracy.

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Introduction

Electrocardiography (ECG) is a trans thoracic interpretation of the electrical activity of the heart over time captured and externally recorded by skin electrodes. It is a noninvasive recording produced by an electrocardiographic device. ECG has become the most common diagnostic tool for monitoring the patients believed to suffer from cardiac disease. The recorded ECG signal consists of contaminated noise and artifacts. Among all the noises, baseline wandering is the most significant one and can affect the ECG signal strongly. To remove baseline wandering noise, discrete wavelet transform is used. The signal is then processed to remove the maternal artifact that is to extract the fetal ECG from the maternal ECG signal. The fetal ECG (FECG) is the electrical activity of the fetal heart. Early diagnosis of fetal ECG before delivery increases the effectiveness of the treatment. The main noise contribution is the maternal electrical activity since its amplitude is much higher than the fetal. By eliminating the maternal ECG component from the composite signal, the reasonable fetal ECG signal is obtained. The fetal ECG extraction is a typical Blind Source Separation (BSS) problem [1]. Blind Source Separation deals with the separation of signals without the aid of information about the source signals.

Independent Component Analysis (ICA) is a computational method used for separating multivariate signal into active subcomponents. ICA has been extensively used for solving BSS problems and hence its application gets increased in case of biomedical signals. For pseudo periodic signals such as electrocardiogram (ECG), the temporal structure of the signal is rich in information and hence a measure of periodicity of the extracted signal is more appropriate than independence. The

temporal periodicity of ECG signal has been exploited in source separation algorithms [1].

In this paper, an extension of source separation method is customized. This method is based on the notion of periodic component analysis (π CA) proposed in [2] and generalized eigen value decomposition [3]. Periodic Component Analysis is a recently developed technique, which decomposes a set of multichannel recordings in terms of pseudo-periodic components ranked in order of periodicity. It uses constructive interference to enhance periodic components of the frequency spectrum and destructive interference to cancel noise. It is able to extract the most periodic components to a desired signal from a set of multichannel recordings. Periodic Component Analysis along with Generalized Eigen Value Decomposition (GEVD) [4] is used to measure the periodicity of the ECG signal, in order to extract the fetal ECG. It also uses an eigenvalue principle to combine periodicity cues from different parts of the frequency spectrum. The relationship between Periodic Component Analysis and well-known Independent Component Analysis Method (ICA)-Joint Approximate Diagonalization of Eigen-Matrices are also discussed. This method has several benefits over conventional ICA and is applicable to both maternal and fetal ECG embedded in noise.

This paper is organized as follows: Methods and materials in section II. Quantitative and qualitative results obtained using this method and comparison of the ability of this method in section III. Finally conclude with some remarks in section IV.

Methods And Materials

Independent Component Analysis

In the context of ICA, a finite number of samples of an n dimensional observation vector $x(t) = [x_1(t), \dots, x_n(t)]^T$, has been

taken. Each column of x is a sample from n sensors and seeks for a linear mixture of these observations that maximizes some measure of independence, or namely a *contrast function*. $x(t)$ is the linear combination of original independent signals. The entire system of n -measured signals can be expressed as $x(t)=A*s(t)$, where A is the $n*n$ mixing matrix that generates X from S and each row of s is the extracted independence signal. Under some general assumptions the estimated components are solutions of a BSS problem with a linear latent variable model. The ICA estimation consists of two phases: the learning phase and the processing phase. During the learning phase, the ICA algorithm finds a whitening matrix W , which minimizes the mutual information between variables. The whitening transformation converts the covariance matrix of z into the identity matrix I . This effectively creates new random variables that are uncorrelated. The processing phase is the actual source separation. The amplitude of separated signals is completely rescaled. This is because any scalar multiplier does not affect its statistical dependency. In this approach, JADE (Joint Approximate Diagonalization of Eigen matrices) [5]-[8] algorithm is used.

JADE algorithm, which is based on the joint diagonalization of cumulant matrices, has been successfully applied to the processing of biomedical signals. It is very efficient for separation when there is a small number of an observation. It has four steps:

Step 1: The sample covariance matrix is determined and a whitening matrix (W) is computed.

$$Z(t) = W^* x(t) \quad (1)$$

Step2: The fourth-order cumulant matrix $Q_z(M)$ is estimated by

$$Q_z(M) = E(z^* M z z z^*) - R_z M R_z - R_z \text{Trace}(M R_z)$$

Step3: The rotation matrix V is determined such that the cumulant matrix is as diagonal as possible.

Step4: The separated component vector and the mixing matrix is estimated by

$$S(t) = V^* Z(t), A = W^{-1} * V \quad (2)$$

The components extracted using Independent Component Analysis consists no order and identifying the signals becomes difficult. Therefore for indexing the signals in clinical applications it shows poor result. To overcome the limitation, Periodic Component Analysis along with Generalized Eigen Value Decomposition (GEVD) is proposed

Generalized Eigen Value Decomposition

For $n \times n$ symmetric matrices A and B , the problem of generalized eigen value decomposition (GEVD) [7], of the matrix pair (A,B) , consists of finding the matrices U and D , such that

$$U^T A U = D, U^T B U = I \quad (3)$$

where D is the diagonal generalized eigen value matrix corresponding to the eigen matrix U , with real eigen values sorted in ascending order on its diagonal. As it is seen from eqn.(1), U is a transformation that simultaneously diagonalizes A and B .

Periodic Component Analysis

ECG signals have a pseudo periodic structure that is repeated cycle of ECG beat. For such signals, a time varying period that is updated on a beat to beat basis is proposed [8]. Given an n -dimensional vector $x(t)=[x_1(t) \dots x_n(t)]^T$, where n resembles the number of sensors. Each row of $x(t)$ constitutes the ECG signals. The step involved in Periodic Component Analysis is given in fig.1. The R-peak of the ECG signal is

detected by threshold method. Phase signal $\phi(t)$ ranging from $(-\pi, \pi)$ is determined from the detected R-peaks.

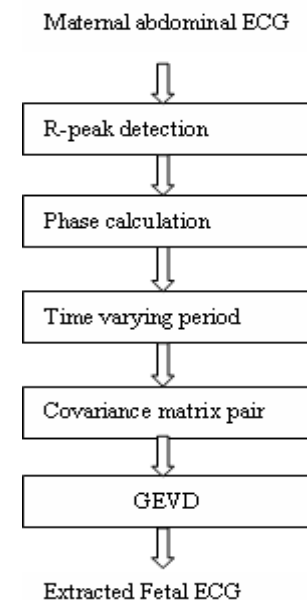


Fig. 1. Steps involved in periodic component analysis for fetal extraction

With the phase signal $\phi(t)$, the time varying period τ_t may be mathematically defined as follows:

$$\tau_t = \min \{ \tau | \phi(t + \tau) = \phi(t), \tau > 0 \} \quad (4)$$

Using this definition, the covariance matrix is defined as:

$$C_x(\tau_t) = E\{x(t + \tau_t)x(t)^T\} \quad (5)$$

with zero time lag the covariance matrix is defined as:

$$C_x(0) = E\{x(t)x(t)^T\} \quad (6)$$

To assure the symmetry of $C_x(\tau_t)$ and $C_x(0)$ and the realness of its eigen values, the following step is considered.

$$C_x = (C_x(\tau_t) + C_x(\tau_t)^T) / 2 \quad (7)$$

$$C_x(0) = (C_x(0) + C_x(0)^T) / 2 \quad (8)$$

C_x is the matrix which contains the measure of periodicity extracted from the ECG R-peak information. With the covariance pair $(C_x(\tau_t), C_x(0))$, the GEVD solution is determined. The eigenvectors ranked in descending order of their corresponding generalized eigen values are determined as U . The desired signal vector $y(t) = [y_1(t), \dots, y_n(t)]^T$, is then found from

$$y(t) = U^T * x(t) \quad (9)$$

The components of $y(t)$ are sorted according to the amount of their periodicity, relative to the heart beat. In other words, $y_1(t)$ is the most periodic component and $y_n(t)$ is the least periodic, with respect to the R-peaks of the ECG signal. For instance, for the problem of fetal ECG extraction, if $\Phi_m(t)$ and $\Phi_f(t)$ are defined as the maternal and fetal ECG phases found from the maternal and fetal R-peaks, C_{mx} and C_{fx} are the covariance matrices of the maternal and fetus, are found by averaging using eqn.(5) over the maternal and fetal periods, respectively. Then the matrix C_x used in the GEVD may be set to any of the following matrices

$$C_x = C_{mx} \quad (10a)$$

$$C_x = C_{fx} \quad (10b)$$

$$C_x = C_{mx} - C_{fx} \quad (10c)$$

The matrices defined in equs.(10) is respectively equivalent to finding (10a) the most periodic components with respect to the maternal ECG, (10b) the most periodic components with respect to the fetal ECG, and (10c) the most periodic components with respect to the maternal ECG while being the least periodic components with respect to the fetal ECG. In this latter case the extracted components should gradually change from the maternal ECG to the fetal ECG, from the first to the last component.

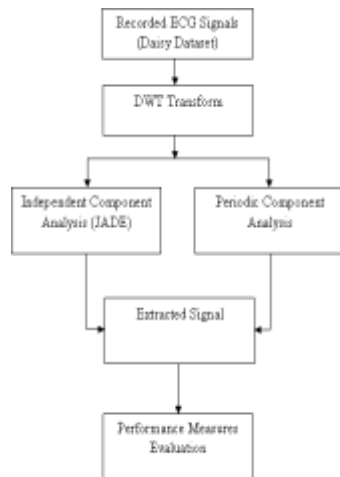


Fig.2. Block diagram for the proposed method

Here Daisy dataset is used as input. It has five abdominal and three thoracic ECG signals as one set. The recorded ECG signals consists of noise artifacts such as power line interference, electrode pop or contact noise, baseline wander noise and electromyography noise such as maternal ECG. The ECG acquisition hardware removes power line interference. Baseline wandering usually comes from respiration at frequencies wandering between 0.15 and 0.3 Hz, it is suppressed by a high pass digital filter. The wavelet transform is used here to remove baseline wandering by eliminating the trend of the ECG signal. The Daubechies6 (db06) wavelet is used. Independent Component Analysis and Periodic Component Analysis are performed on the preprocessed signal. Basis of Periodic Component Analysis is same as that of Independent Component Analysis and it differs due to the property of the temporal pseudo periodicity of the ECG, i.e., the extracted signals were ranked according to their degree of synchronization (periodicity) with the R-peaks. The extracted signal is then evaluated using performance measures such as accuracy and sensitivity [11-17]. The block diagram of the proposed method is given in Fig.2.

Performance measures

Sensitivity and Accuracy are used as performance measures. The sensitivity is the fraction of peaks that are correctly detected. Accuracy is the overall correctness of the method. These two parameters are calculated using the following equations

$$\text{Sensitivity} = TP / (TP + FN) \quad (11)$$

$$\text{Accuracy} = TP / (TP + FP + FN) \quad (12)$$

where TP (True Positive) is the number of correctly detected R-peaks, FN (False Negative) is the number of missed R-peaks,

and FP (False Positive) is the number of wrong R-peak detections.

Results and Discussion

The well-known DaISy fetal ECG database is used to evaluate the performance of this method. The database consists of five abdominal and three thoracic channels recorded from the abdomen and chest of a pregnant woman with a sampling rate of 250Hz [9]. The eight channels of the dataset is shown in Fig. 3. One of the maternal ECG signal is taken and its R-peaks are detected. A linear phase $\Phi(t)$ ranging from $-\pi$ to π is assigned to each sample, with the R-peak fixed at $\Phi(t)=0$ and is shown in Fig.4. The linear phase provides the means of phase-wrapping the R-R interval onto the $[-\pi, \pi]$ interval. Then the ECG signal is converted to a polar representation in which the ECG and components in different beats are aligned especially over the QRS segment and is given in Fig.5.

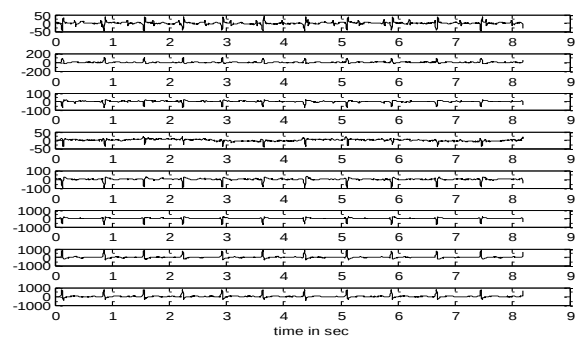


Fig. 3. The DaISy dataset consisting of five maternal abdominal and three thoracic channels

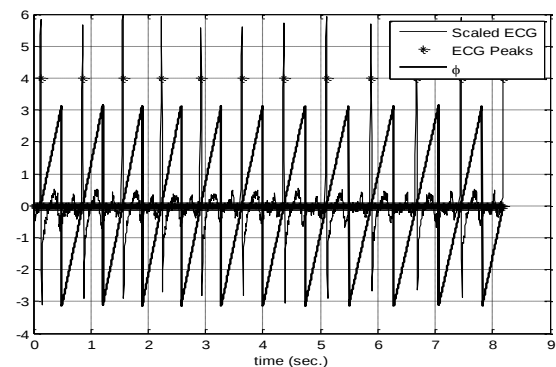


Fig.4. Illustration of the phase assignment procedure used for calculating time lag in each ECG beat.

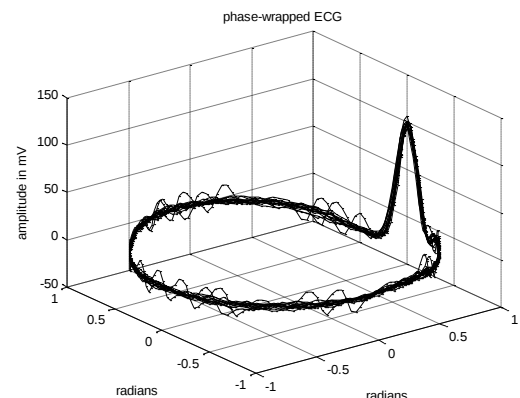


Fig.5. Polar representation of a noisy ECG using the ECG phase $\Phi(t)$

By using JADE algorithm, the separated signals are distinguished into three independent components: (i) random noise, (ii) maternal ECG and (iii) fetal ECG. It is found that the

random noise is estimated as the first independent component while the desired FECG is estimated as the third component and is shown in fig.6. The extracted signal from JADE has no order of resemblance and hence acts as a limitation in clinical applications.

R-peak is detected by using one of the maternal thoracic channels, the maternal ECG phase $\Phi_m(t)$ is determined from that the time-varying maternal ECG period τ_{mt} is calculated using eqn.(4) from which the matrix C_x and the generalized eigen matrix U of the $(C_x, C_x(0))$ pair are found and sorted in descending order of the eigen values. The resultant periodic components derived using eqn.(10a) are given in Fig. 7. The first component corresponding to largest eigen value has the most resemblance of maternal ECG and as the eigen value decreases its resemblance also gets decreased. The maternal ECG contribution reduces from top to bottom. This is explained by considering that Periodic Component Analysis is ranking the extracted components according to their resemblance with the maternal ECG period, while the fetal components do not resemble the maternal ECG, when averaged synchronously with respect to the maternal R-peaks. The fetal components are therefore extracted among the last components.

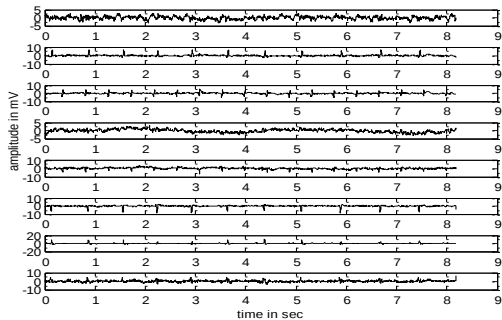


Fig. 6. Independent components extracted from the DaISy dataset, using JADE ICA

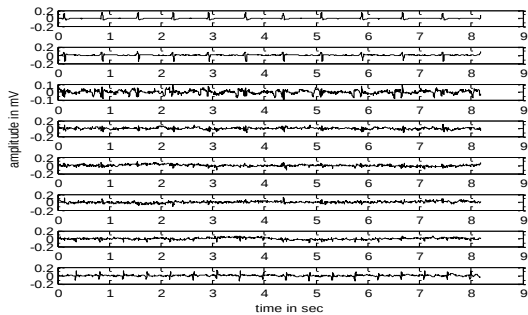


Fig. 7. Periodic components extracted from the dataset with maternal ECG beat synchronization

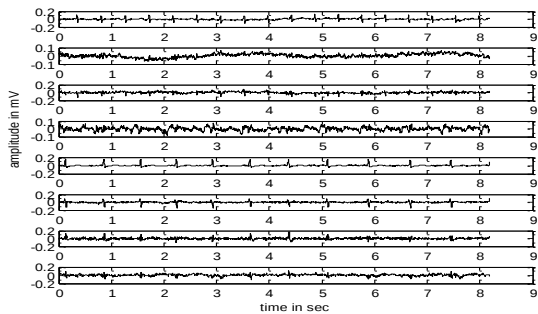


Fig. 8. Periodic components extracted from the dataset with fetal ECG beat synchronization

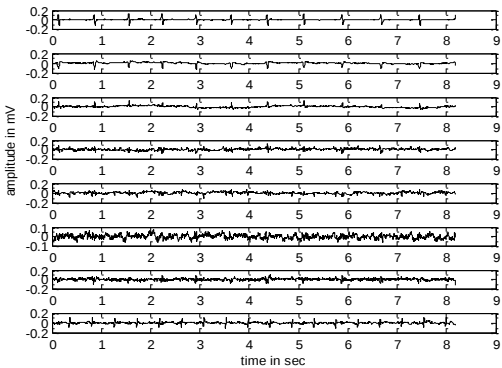


Fig. 9. Periodic components extracted from the dataset with maternal & fetal ECG beat synchronization

Table.1. Performance measures for Periodic Component Analysis using maternal and fetal synchronization

No. of abdominal signals	No. of thoracic signals	Sensitivity Se (%)	Accuracy Acc (%)
1	1	100	94.12
2	1	100	94
3	1	100	100
2	2	93.3	73.68
3	2	100	100
4	3	100	100
5	3	100	100
Average		99.04	94.56

It is also possible to consider the fetal ECG periodicity in the matrix C_x , which requires the fetal R-peaks for extracting the time-varying fetal period τ_{ft} . For this, the fetal ECG component extracted by JADE ICA in the third channel of Fig. 6 is used for fetal R-peak detection and phase calculation. Having calculated the fetal ECG phase $\Phi_f(t)$, the previously explained procedures are repeated to extract the periodic components of the fetal ECG. The resultant periodic components are given in Fig. 8. Now, the extracted components are ranked according to their resemblance with the fetal ECG. Fig.9 corresponds to the last type of covariance matrix defined in eqn.(10c). The first component has the most resemblance with the maternal ECG, while the last component mostly resembles the fetal ECG and the intermediate components are mixtures of maternal and fetal components and noise. The last component is the extracted fetal ECG signal and is given in Fig.10.

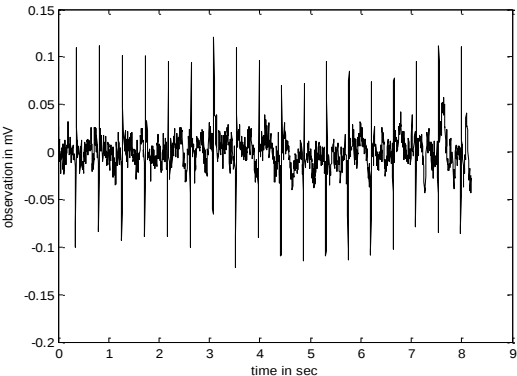


Fig. 10. Extracted fetal ECG Signal

The R-peaks of the extracted fetal ECG are detected and the R-R interval, i.e. the successive difference between the R-peaks is determined and correspondingly the Fetal Heart Rate (FHR) is calculated using the formula

$$FHR = \frac{60}{R - R_{interval}} \text{beats per minute} \quad (13)$$

The normal FHR varies from 110 to 180 beats per minute. Table 1 gives the number of abdominal and thoracic signals combination used to extract fetal ECG signal with the corresponding performance measures such as sensitivity and accuracy. These two parameters are calculated using the equation (11) & (12) respectively. Thoracic signal mainly consists of maternal ECG signal and the abdomen signal consists of the combination of maternal and fetal ECG signals. If the number of abdominal and thoracic signals is equal then the percentage accuracy obtained is lower when compared to the other combinations. Higher accuracies are obtained when three thoracic signals are used and if the number of abdominal signal is greater than the number of thoracic signals. By using one thoracic signal and three abdominal signals this method is able to achieve 100% sensitivity and accuracy.

Conclusion

In this paper, Periodic Component Analysis method is used to extract the most periodic components corresponding to a desired ECG signal from a set of recordings by forming covariance matrix. The independence criterion of Independent Component Analysis is replaced with a periodic temporal structure criterion. The temporal information of the ECG is included in the covariance matrix (C_x). The extracted components are ranked according to their degree of synchronization with the R-peaks while in ICA, it is not possible to predict the order of the extracted components. Since the components are ranked according to their resemblance with the ECG, The first component has the most resemblance with the maternal ECG, while the last component mostly resembles the fetal ECG and the intermediate components are mixtures of maternal and fetal components and noise. This feature is very helpful for automating the removal of the maternal ECG from fetal ECG recordings, or generally for removing cardiac interference from multichannel bio-signals. The last component is the extracted fetal ECG signal. The fetal R-peaks are detected and RR interval and Heart Rate (FHR) are calculated from the extracted fetal ECG. Number of abdominal and thoracic signals combination used to extract fetal ECG signal with the corresponding performance measures such as sensitivity and accuracy are calculated. If the number of abdominal and thoracic signals is equal then the percentage accuracy obtained is lower. Higher accuracies are obtained when three thoracic signals are used and if the number of abdominal signal is greater than the number of thoracic signals. By using one thoracic signal and three abdominal signals this method is able to achieve 100% sensitivity and accuracy.

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