A Robust Framework for Noninvasive Extraction of Fetal Electrocardiogram Signals

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Abstract

In this paper, a robust framework is presented for fECG extraction from maternal abdomen recordings. The idea is based on extracting the fECG from contaminated signals using a multistage interference and noise cancelation method, designed specifically according to the time, space and frequency characteristics of the fECG and its interferences. The suitable combination of different denoising methods has both the advantages of multichannel and single channel denoising schemes. The proposed framework has also exploited the benefits of both temporal and statistical properties of ECG signals. Moreover, the ranking property of the algorithm, in comparison to permutation ambiguity of the independent component analysis (ICA) methods, helps reliable automatic detection of fECG signal in long recordings. The results have shown that the proposed framework outperforms conventional ICA and has effectively detected the fetal QRS in presence of full-rank maternal interference.

1. Introduction

The noninvasive extraction of fetal electrocardiogram (fECG) from multichannel maternal abdomen recordings is an emerging technology used for fetal cardiac diagnosis. Blind Source Separation (BSS) and Independent Component Analysis (ICA) are among the well-known techniques for the extraction of fECG, which have been shown to be more robust and accurate than most conventional methods [1]. However, ICA-based methods, despite their vast and effective applications have some intrinsic ambiguities according to their simplified assumptions. Typically, it is assumed that sources are independent and equal to the number of sensors [2], the number of sources is fixed, sources are stationary and the mixture is time invariant [3]. As a result, the performance of ICA degrades in presence of full-rank Gaussian noise [2], correlated and/or distributed sources. The permutation and sign ambiguities in consecutive blocks also limit the automatic fECG extraction in long recordings.

In this paper, a robust framework is presented that can deal with fECG extraction problems even in the cases that ICA assumptions are not satisfied. This method consists of a set of algorithms for signal subspace extraction, iterative multichannel subspace decomposition based denoising and Bayesian filtering. The suitable combination of these effective methods, introduced in recent literatures, combines the advantages of multichannel and single channel filtering and exploits the information of temporal and statistical properties of the data.

2. Method

Electrical signals recorded from the abdomen of a pregnant woman consist of mixtures of various signals including the mECG, fECG, fetal electroencephalogram (fEEG), baseline wanders and muscle contractions considered as noise. The following linear instantaneous data model has been shown to be rather realistic for modeling multichannel maternal abdominal signals [4]:

$$\begin{aligned}\mathbf{x}(t) &= \mathbf{H}_m(t)\mathbf{s}_m(t) + \mathbf{H}_f(t)\mathbf{s}_f(t) + \mathbf{H}_\eta(t)\mathbf{v}(t) + \mathbf{n}(t)\\ &\triangleq \mathbf{x}_m(t) + \mathbf{x}_f(t) + \boldsymbol{\eta}(t) + \mathbf{n}(t)\end{aligned} \tag{1}$$

where $\mathbf{s}_m(t)$, $\mathbf{s}_f(t)$ and $\mathbf{v}(t)$ are, respectively, the maternal signal source, fetal signal source and structured noises (such as electrode movements, muscle contractions and fEEG). $\mathbf{n}(t)$ is full-rank measurement noise and $\mathbf{H}_m(t), \mathbf{H}_f(t)$ and $\mathbf{H}_\eta(t)$ are the transfer functions that model the propagation media [5]. In a realistic model, the cardium (of the mother and fetus) should be considered as a distributed signal source. Therefore, $\mathbf{s}_m(t)$ and $\mathbf{s}_f(t)$ are generally full-rank signals [6]; but the effective number of dimensions can be less depending on the sensor positioning and SNR.

The main purpose of conventional BSS methods is to find a separating matrix $\mathbf{B}(t)$ such that $\hat{\mathbf{s}}(t) = \mathbf{B}(t)\mathbf{x}(t)$ is an acceptable estimation of $\mathbf{s}_f(t)$ [7]. In the hereby proposed method, the objective is to extract $\mathbf{x}_f(t)$ from its

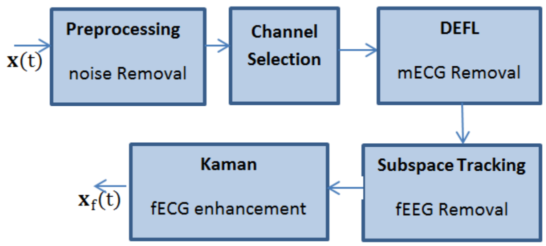


Figure 1. General scheme of the Multistage Interference and Noise Cancelation (MINC)

mixture through successive noise and interference cancelation methods, designed specifically according to their time, space and frequency characteristics. The general scheme of the proposed method is shown in Fig.1. The different parts of the scheme are explained in more details in the following sections.

2.1. Maternal ECG removal

One of the most challenging interference is the maternal cardiac source (mECG) that can be up to two orders of magnitude stronger than the fECG [8]. After conventional preprocessing to remove other noises and artifacts, a deflation subspace decomposition procedure, which we call *denoising by deflation* (DEFL), was used to remove the mECG interference [4, 6] .

The DEFL consists of a sequence of *linear decomposition*, *denoising* and *linear re-composition* as shown in Fig. 2. The data is first transformed to the new subspace using πCA, such that the data is ranked from most to least resemblance to the maternal reference signal in sense of periodicity [9]. Next, the first L components (in the transform domain) are passed through a denoising stage, which separates the mECG contents. Finally, the residual signals and the $N-L$ unchanged channels are back-projected to the original subspace. The procedure is repeated in multiple iterations until all the maternal components within the data are eliminated.

2.2. Background noise cancellation

At this stage, the mECG is considered to be removed. However, the background noise has an amplitude close to the fECG. Therefore, the output still has a low SNR and should be denoised prior to fetal QRS detection.

At this stage, we benefit from a subspace decomposition scheme. To separate the signal and noise subspaces, the signal model at this stage can be stated as follows:

$$\hat{\mathbf{x}}(t) = \mathbf{H_f s_f(t)} + \mathbf{w(t)} \tag{2}$$

where $\hat{\mathbf{x}}(t) \in \mathbf{R^n}$ is the remaining observation vector after previous denoising processes and $\boldsymbol{w}(t) \in \mathbf{R^n}$ consists of

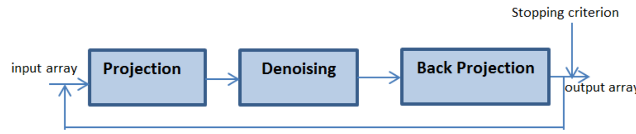


Figure 2. General iterative projection and back projection denoising scheme

all the non-cardiac noises that have not yet been removed. $\boldsymbol{w}(t)$ is assumed as full-rank white Gaussian noise with a covariance matrix equal to $\sigma^2\mathbf{I}$. With the assumption of independence of signal and noise, the signal and noise subspaces can be considered as orthogonal complements. Therefore, the data covariance matrix can be modeled as follows [10]:

$$\mathbf{R} = \mathbf{AQA^T} + \sigma^2\mathbf{I} \tag{3}$$

where $\mathbf{R} = \mathbf{E}\left\{\mathbf{x(t)x^T(t)}\right\}$ and $\mathbf{Q} = \mathbf{E}\left\{\mathbf{s(t)s^T(t)}\right\}$ are covariance matrices of $\mathbf{x}$ and $\mathbf{s}$, respectively. By eigenvalue decomposition (EVD) of $\mathbf{R}$, we have:

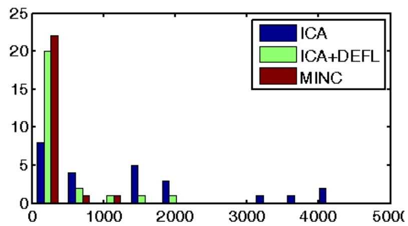
$$\begin{aligned} \mathbf{R} &= [\mathbf{U_s} \quad \mathbf{U_w}] \begin{bmatrix} \boldsymbol{\Lambda}_s & 0 \\ 0 & \boldsymbol{\Lambda}_w \end{bmatrix} [\mathbf{U_s} \quad \mathbf{U_w}]^{\mathbf{T}} \\ &= \mathbf{U_s \Lambda_s U_s^T} + \mathbf{U_w \Lambda_w U_w^T} \end{aligned} \tag{4}$$

where $\mathbf{U_s}$ contains the eigenvectors of the signal subspace corresponding to the m largest eigenvalues of $\boldsymbol{\Lambda}_s = \mathrm{diag}(\lambda_1, \cdots, \lambda_m)$ in descending order and $\mathbf{U_w}$ contains the eigenvectors of the noise subspace corresponding to the $N-m$ smallest eigenvalues of $\boldsymbol{\Lambda}_w = \mathrm{diag}(\lambda_{m+1}, \cdots, \lambda_{N-m})$. This means that using EVD of observation covariance matrix, the observations can be divided into *signal subspace* and *noise subspace*, providing the source dimension m be known [10]. The effective number of dimensions (m) can be estimated using related methods for estimating the signal/noise dimensionality [11, 12].

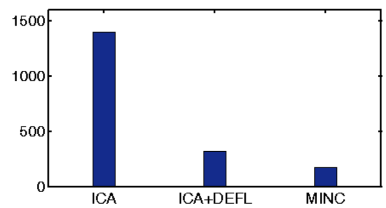
In this work, the idea of signal subspace extraction is utilized in an iterative projection and back projection denoising procedure, as shown in Fig. 2. For this, the data is projected using the transformation matrix $\mathbf{W} = [\mathbf{U_s} \quad \mathbf{U_w}]$. The first M channels in the transformated domain, corresponding to the signal subspace, are denoised through wavelet denoising. The last $N-M$ channels, corresponding to the noise subspace, are set to zero. The data is then back projected and the process is repeated in multiple iterations. As a result, the full-rank background noise is effectively removed.

2.3. fECG signal enhancement

After removing the mECG and other background noise, the fetal QRS (fQRS) is the dominant signal that should



(a)The histogram of error score



(b)The mean value of error scores

Figure 3. The error score in three different methods

be extractable. However, considering the fact that noises and interferences in the previous stages may not have been completely removed, the fECG can be still contaminated by some background noises. At this stage, the quality of the fECG signal is enhanced using a single channel denoiser based on Kalman filtering, introduced in [6, 13, 14].

3. Results

To evaluate the performance of the proposed method, the accuracy of the fQRS detection is computed using the PhysioNet challenge dataset [15]. The dataset consists of four channels one minute signals with high level of noise and full-rank maternal ECG interference and somehow correlated channels. The evaluation is based on the WFDB TACH scoring function that calculates the mean square error between the reference and the estimated fQRS points [15]. The proposed framework, which we call Multistage Interference and Noise Cancelation (MINC) is compared with the two other methods: ICA and ICA plus DEFL. Both of these methods consists of preprocessing, post processing and channel selection stages similar to the proposed framework. The histogram and the average value of the error in the dataset are shown in Fig. 3. As we can see, the average value of the error in ICA is 1390 and its distribution is wide. So according to the quality of the data the score error can be up to 4150. Adding the DEFL method to the ICA, as a preprocessing for eliminating the mECG, decreased the average error score to 319 and the histogram is also narrower. The best result is obtained for the proposed method, MINC, with the average error of 170. As we can see from Fig. 3, the amount of error is concentrated on the average except for two signals that have 655 and 1090 . Based on this result, MINC has had the most reliable and robust performance as compared with the other benchmark methods. This outperformance can be due to the limitations and assumptions that are imposed in conventional ICA methods, which restrict their application in general scenarios.

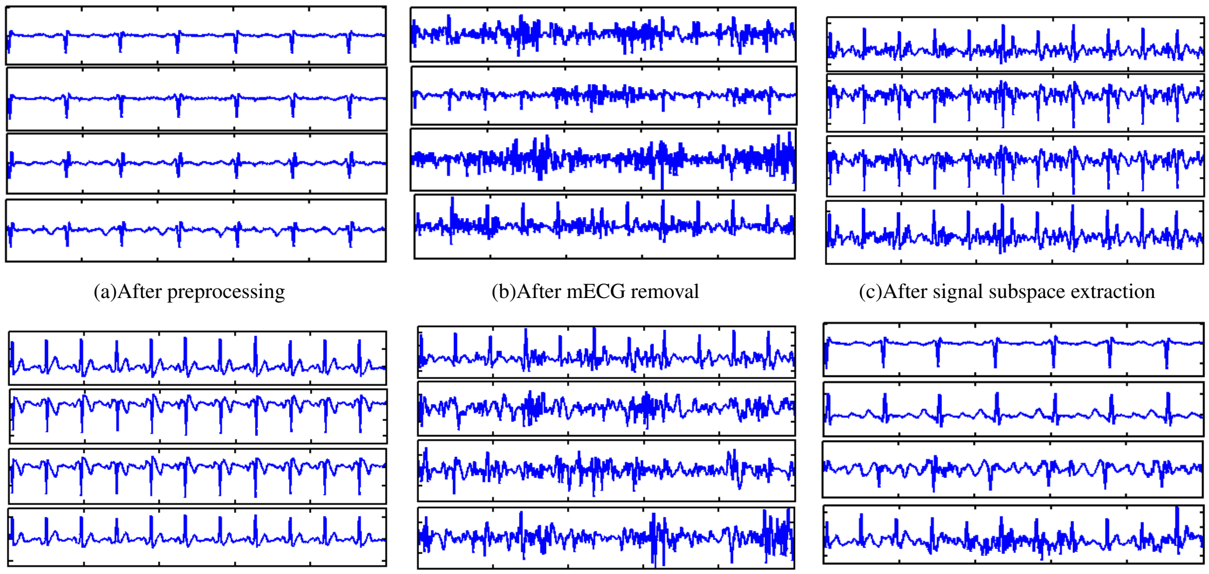
An example of the fECG extracted algorithms applied on the Physionet data set is also shown in Fig.4. The selected input signal is a rather clean sample and we expect all the three methods to at least extract the fQRS complexes. Figs. 4(a), 4(b) and 4(c) show the results at the outputs of preprocessing, mECG removal and background noise cancellation stages, respectively. Figs. 4(d), 4(e) and 4(f) indicate the fECG extracted by MINC, DEFL plus ICA and ICA methods. We can see that in ICA, the mECG signal appears in three of the channels and a noisy fECG signal is appeared in the forth channel. Adding the DEFL method to ICA, has removed the effect of the mECG and leads to better fECG in other channels. The best result is obtained for the proposed method, in which the clear fECG containing the main fQRS complexes is visible in the output. Besides, due to the fact that in this method the actual contribution of the fECG signal projected on the leads is detected, it is somehow easier to interpret for physicians.

4. Conclusion

In this paper, a method was proposed for extracting the fECG signal from maternal abdomen recordings. The idea is based on separating the contribution of the fECG signal in each of the channels from the other contaminating signals and noises, through a multistage interference and noise cancelation scheme. Using this method, while preserving the original dimensions of the data, the contribution of the fECG in each of the channels can be extracted distinctly. Estimating the projected fECG in each of the leads is also more interpretative for the physicians, as compared to linear decomposition of different channels. Besides, due to the multichannel nature of the extracted fECG, better improvement can be obtained on the estimated fQRS complexes and RR intervals, depending on the quality of different channels. The results have shown that the proposed method has significant performance in comparison to conventional ICA methods, due to the fact that it can deal with the situations that conventional ICA assumptions are not satisfied. In future studies, the hereby developed technique can be extended to online processing scenarios.

References

[1] Zarzoso V, Nandi A. Noninvasive fetal electrocardiogram extraction: blind separation versus adaptive noise cancella-



(a)After preprocessing (b)After mECG removal (c)After signal subspace extraction

(d)The fECG extracted by MINC (e)The fECG extracted by DEFL+ICA (f)The fECG extracted by ICA

Figure 4. Different stages and the output of three method on a template signal

tion. Biomedical Engineering IEEE Transactions on January 2001;48(1):12–18. ISSN 0018-9294.

[2] Graupe D, Zhong Y, Graupe MH. Extracting fetal from maternal ecg for early diagnosis: theoretical problems and solutions - baf and ica. In Proceedings of the fifth IASTED International Conference: biomedical engineering, BIEN '07. Anaheim, CA, USA: ACTA Press, 2007; 352–356. URL `http://dl.acm.org/citation.cfm?id=1295494.1295558`.

[3] Enescu M, Koivunen V. Tracking time-varying mixing system in blind separation. In Sensor Array and Multichannel Signal Processing Workshop. 2000. Proceedings of the 2000 IEEE. 2000; 291–295.

[4] Sameni R, Jutten C, Shamsollahi MB. A Deflation Procedure for Subspace Decomposition. IEEE Transactions on Signal Processing April 2010;58(4):2363–2374.

[5] Sameni R, Clifford GD, Jutten C, Shamsollahi MB. Multichannel ECG and Noise Modeling: Application to Maternal and Fetal ECG Signals. EURASIP Journal on Advances in Signal Processing 2007;2007:Article ID 43407, 14 pages. URL `http://www.hindawi.com/GetArticle.aspx?doi=10.1155/2007/43407`. ISSN 1687-6172, doi:10.1155/2007/43407.

[6] Sameni R. Extraction of Fetal Cardiac Signals from an Array of Maternal Abdominal Recordings. Ph.D. thesis, Sharif University of Technology – Institut National Polytechnique de Grenoble, July 2008.

[7] Cardoso JF. Blind signal separation: statistical principles. Proceedings of the IEEE 1998;86(10):2009–2025. ISSN 0018-9219.

[8] Sameni R, Clifford GD. A Review of Fetal ECG Signal Processing; Issues and Promising Directions. The Open Pacing Electrophysiology Therapy Journal TOPETJ November 2010;3:4–20.

[9] Sameni R, Jutten C, Shamsollahi MB. Multichannel Electrocardiogram Decomposition Using Periodic Component Analysis. IEEE Trans Biomed Eng August 2008; 55(8):1935–1940. ISSN 0018-9294.

[10] Cichocki A, Amari S (eds.). Adaptive Blind Signal and Image Processing. John Wiley & Sons Inc., 2003.

[11] Nadakuditi R, Edelman A. Sample eigenvalue based detection of high-dimensional signals in white noise using relatively few samples. Signal Processing IEEE Transactions on July 2008;56(7):2625 –2638. ISSN 1053-587X.

[12] Lee JA, Verleysen M. Nonlinear Dimensionality Reduction. Springer Science, 2007.

[13] Sameni R, Shamsollahi MB, Jutten C, Clifford GD. A Nonlinear Bayesian Filtering Framework for ECG Denoising. IEEE Trans Biomed Eng December 2007;54(12):2172–2185.

[14] Sameni R, Shamsollahi MB, Jutten C. Model-based Bayesian filtering of cardiac contaminants from biomedical recordings. Physiological Measurement May 2008; 29(5):595–613.

[15] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation 2000 (June 13);101(23):e215–e220. Circulation Electronic Pages: http://circ.ahajournals.org/cgi/content/full/101/23/e215 PMID:1085218; doi: 10.1161/01.CIR.101.23.e215.

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