31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Fetal R-wave detection from multichannel abdominal ECG recordings in Low SNR

Shahrzad Kharabian[1], Mohammad B. Shamsollahi[1], Reza Sameni[2]
[1]Biomedical Signal and Image Processing Laboratory (BiSIPL), School of Electrical Engineering, Sharif University of Technology, Tehran, Iran
[2]School of Electrical & Computer Engineering, Shiraz University, Shiraz, Iran

Abstract— **Abdominal recordings of fetal ECG (fECG) have lower signal-to-noise ratio (SNR) as compared with invasive procedures. In this paper we have combined two previously proposed methods, one for extracting fECG, called πCA and the other, a transformation based on Hilbert transform to enhance the R-peaks. The combination of these methods seems to work well in situations of noisy data and fetal repositioning. Also a comparison is done by using ICA in order to extract the fetal signals. Performance of both methods is studied separately. Results show that applying the transformation on the components extracted with the use of πCA (after maternal ECG cancellation), had a very good performance. Also, as πCA ranks the components according to their resemblance to maternal ECG, it could be used in automatic fetal ECG extraction algorithms.**

Keywords— **Multichannel fetal ECG, R-wave detection, Periodic Component Analysis, Hilbert transform.**

I. Introduction

Fetal heart monitoring is an important part of prenatal care. Sonography and Doppler ultrasound, although being the most available means of fetal monitoring, contain only anatomical and mechanical information about the fetal heart. On the other hand, electrical and magnetic signals generated by the electrochemical activity of the heart are believed to reveal much more information. Moreover, cord compression, fetal heart block, fetal malposition, fetal hypoxia and some other abnormal situations can also be detected by the fetal heart monitoring.

Electrical signals of the fetal heart, known as fetal electrocardiogram (fECG), can be recorded invasively using electrodes attached to the fetal scalp, or non-invasively from the surface electrodes placed on the maternal abdomen. Invasive recordings have better quality but the procedure is rather inconvenient and is limited to during labor [3].

Fetal magnetography (fMCG) is another technique for measuring the magnetic fields of the heart using extremely sensitive device such as the Super Conducting Quantum Interference Device (SQUID). Using the current SQUID technology for magnetic recordings, the SNR of the fetal MCG is usually higher than the ECG. However, ECG recording apparatus are much simpler and currently more affordable as compared with MCG systems.

Commonly, the first step in cardiac signal processing is the QRS complex detection. In previous works, many single channel RR-interval extraction algorithms have been developed for adult ECGs [1, 2]. Most of these algorithms follow a two-step procedure; first, the ECG signal is passed through a digital filter or pre-processing step designed to enhance the QRS complex with respect to the P and T-waves or simply to enhance the ECG quality. In the second step, a template detection method is used to identify the R-wave positions. For fetal ECG signals, since one of the most considerable interferences found in maternal abdominal recordings is the maternal ECG itself, an additional preprocessing step for removing the maternal ECG interferences is also required.

In this work, the blind source separation (BSS) technique proposed in [3, 4] is used to extract the fetal cardiac components from abdominal recordings, followed by the Hilbert transform for R-wave enhancement [2, 5]. Then, using the multichannel properties of our recordings and enhancing the fiducial points of the ECG, the detection of the QRS complex is rather straightforward.

The proposed method is carried out on the realistic synthetic ECG proposed in [10, 3].

The rest of the article is organized as follows. In section II, there is a brief description of the simulated data and then *independent component analysis* (ICA), *periodic component analysis* (πCA), and the Hilbert methods are reviewed. A simple description of the proposed algorithm and the peak detection procedure is presented at the end of this section. In section III, the results and a brief discussion are presented.

II. Methodology

A. Simulated Data

In this work we have used the multichannel ECG and the noise generator proposed in [3, 10], for generating simulated ECGs. The model is as follows:

$$\begin{aligned} X(t) &= X_m(t)+X_f(t)+\alpha(t)+n(t) \\ &= H_m.R_m.\beta_m.S_m(t)+H_fR_f\beta_fS_f(t)+\alpha(t)+n(t) \end{aligned} \quad (1)$$

where $S(t)=[x(t),y(t),z(t)]$ Contains the 3 components of the dipole vector of heart, $H\epsilon\mathcal{R}^{Nx3}$ (with $N=8$ in this work) corresponds to the body volume conductor model, $\alpha=diag(\lambda_x,\lambda_y,\lambda_z)\epsilon\mathcal{R}^{3x3}$ is a diagonal matrix corresponding to the scaling of the dipole in each of the x, y, z directions. $R\epsilon\mathcal{R}^{3x3}$ is the rotation matrix for the dipole vector, with the subscripts *m* and *f* referring to the mother and fetus, respectively. $\alpha(t)$ is low-rank noise, representing other biological sources that contaminate the ECG, and $n(t)$ is full-rank observation noise that always exist in physiological measure-

ments. Using this equation, we simulate eight channels of abdominal recordings sampled at 500Hz.

Baseline wander removal was done as the only preprocessing step on the dataset using the OSET tools [6].

B. Independent Component Analysis (ICA)

Assuming an *N*-dimensional vector x signals generated by a mixture of *N* independent sources *s*, we can formulate the mixture as:

$$x=A\,s \tag{2}$$

ICA uses the observed signals (x) to estimate *A* and *s* with the assumption of independence and a non-Gaussian distribution for the sources [7]. These assumptions are believed to be fulfilled in fECG recordings because the signal subspaces corresponding to the maternal and fetal heart are generated by different sources that act independently of each other (at least from the signal processing perspective). Once the matrix *A* has been estimated by ICA, the matrix $W=A^{-1}$ can be computed to obtain the independent components as follows:

$$s=W\,x \tag{3}$$

C. Periodic Component Analysis (πCA)

Here we describe the problem of πCA from [3, 4]. Given an *N*-dimensional observation vector $x(t)$, we seek for the linear mixture $y(t)=W^T x(t)$ with a maximal periodic structure that minimizes the following measure of periodicity:

$$\epsilon(W,\tau)=\frac{\sum_t |y(t+\tau)-y(t)|^2}{\sum_t |y(t)|^2} \tag{4}$$

where $W=[w_1,\ldots,w_N]$ and τ is the period of interest.

It is known that for symmetric matrices $A, B\epsilon\,\mathcal{R}^{NxN}$, the problem of *generalized eigenvalue decomposition* (GEVD) of the matrix pair (A, B), consists of finding the matrices *W* and *D* such that

$$W^TAW=D \quad \text{and} \quad W^TBW=I \tag{5}$$

where D is the generalized eigenvalue matrix corresponding to the eigenmatrix W, with real eigenvalues sorted in ascending order on its diagonal. Therefore, W is a transform that simultaneously diagonalizes A and B. Moreover, the first eigenvector w_1 corresponding to the largest generalized eigenvalue, also maximizes the following ratio known as the Rayleigh quotient [8]:

$$j(W)=\frac{W^TAW}{W^TBW} \tag{6}$$

ECG signals have a pseudo-periodic structure that is repeated in every cycle. However, normal ECG can have RR-interval deviations up to 20% [3], which means that we should define a time-varying period updated on a beat-to-beat basis. For this, by detecting the R-peaks of the ECG, a linear phase $\varphi(t)$ ranging from $-\pi$ to π is assigned to each ECG sample, with the R-peaks being fixed at $\varphi(t)=0$. Now we can replace the time-lag τ in (4) with a variable τ_t that is calculated from $\varphi(t)$ from beat-to-beat as follows:

$$\tau_t=\min\{\tau|\varphi(t+\tau)=\varphi(t),\tau>0\} \tag{7}$$

And the covariance matrix is defined as

$$\widetilde{C_x}=E_t\{x(t+\tau_t)x(t)^T\} \tag{8}$$

$$\widetilde{C_x}\leftarrow\frac{\widetilde{C_x}+\widetilde{C_x}^T}{2} \tag{9}$$

where $E_t\{.\}$ indicates averaging over *t*, and (9) assures the symmetry of $\widetilde{C_x}$ and the realness of its eigenvalues. With these definitions, $\widetilde{C_x}$ is the matrix containing a measure of ECG periodicity extracted from the ECG R-peak information.

Equation (4) can be rearranged as follows

$$\varepsilon(W,\tau)=\frac{W^TA_x(\tau_t)W}{W^TC_x(0)W}=2\left[1-\frac{W^T\widetilde{C_x}(\tau_t)W}{W^TC_x(0)W}\right] \tag{10}$$

where

$$\begin{aligned}A_x(\tau_t)&=E_t\{[X(t+\tau_t)-X(t)]\ \ [X(t+\tau_t)-X(t)]^T\}\\&=2C_x(0)-2\widetilde{C_x}(\tau_t)\end{aligned} \tag{11}$$

Next, we find W, the GEVD solution of the $(\widetilde{C_x},C_x(0))$ pair with the eigenvectors ranked in descending order of their corresponding eigenvalues and calculate the desired sources as $y(t)=W^Tx(t)$. Hence, the components of y(t) are sorted according to the amount of their periodicity relative to the heart beat.

D. Rate of change of Hilbert Amplitude (RHA)

For a real function x(t), the Hilbert transform is defined as:

$$\hat{x}(t)=\frac{1}{\pi}\text{P.V.}\int_{-\infty}^{+\infty}x(\tau)\frac{1}{t-\tau}d\tau \tag{12}$$

where P.V. denotes the Cauchy principal value [12]. Analytic signal or pre-envelope of a real signal x[n], $x_a[n]$ is defined as follows:

$$x_a[n]=x[n]+i\hat{x}[n] \tag{13}$$

Next, as stated in [5], the distance R[n] between successive points in the $x_a[n]$ time series is computed by

$$R[n]=\sqrt{(x[n+1]-x[n])^2+(\hat{x}[n+1]-\hat{x}[n])^2} \tag{14}$$

The R[n] time series which shows the rate of change of the Hilbert amplitude contain R-wave like features. As, it can be seen, R[n] is always positive. Therefore, the polarity of QRS complexes in different channels is not important and a typical bipolar R-wave has a unipolar response with only one peak. This property solves the problem of QRS location detection, since for bipolar waveforms one could choose any of the positive or negative peaks or the zero crossing point as the R location. After applying the method on all fetal channels (components) and supposing that the cardiac signal of the fetus reaches all abdominal electrodes approximately at the same time (resulting in an instantaneous mixture), one can average all the RHAs to improve the signal quality and to enhance the R-peaks.

E. Proposed Algorithm

In abdominal recordings, the fetal ECG is buried in noise and interferences. At first we need to cancel the maternal ECG, as the most important interference in time and frequency domain, using methods such as JADE [11] or πCA [3]. Having 8 channels of abdominal recordings (with 0dB SNR) in the input, both methods extract 8 components in which 3 are related to the maternal signal (due to the 3 dimensions assumed for the cardiac dipoles in [1]). In πCA the maternal components can be simply removed, since they are the first 3 extracted components, whereas in the results obtained from JADE they should be found and removed by visual inspection.

Now we have two choices: converting the 5 remaining components to the channel space, which results in 8 noisy fetal ECG recordings but without maternal interference, or simply compute the RHA of the five fetal and noise components, add the results and find the R-peaks on the resulting signal.

In order to find the QRS complexes we suggest a simple peak detector which uses a constant moving window and finds the local maximum in each window [6]. Next, the vector of possible QRS complexes is searched for refractory peaks. Any peak occurring within a refractory period *p* (0.2s by default) of a previous peak is disregarded, since the refractory period represents the interval immediately following a QRS complex during which no further excitation of the cardiac tissue can initiate another QRS complex [9]. Thus, detection of false peaks can be minimized. Fig.1 shows the block diagram of the algorithm.

III. Results and Descusion

As mentioned earlier, eight channels of abdominal recordings are simulated and used (with their baseline wander removed). Next, maternal components were removed with both methods, as described in section II, and the RHA was calculated for each method.

Table I compares the quantitative results of the proposed methods by calculating sensitivity (se), positive predictive value (+P) and detection error rate. As we have simulated the data, the exact locations of the fetal R peaks are readily known. Therefore, average time error of the peak detection is calculated as follows:

$$\text{Average time error(ms)} = \frac{\sum_{i=0}^{TP} |\text{located QRS-actual QRS}|}{TP}$$

TP is the overall percentage of QRS correctly located by the detector and FP represents the false ones.

Fig. 2. shows a segment of fetal and noise mixture signal, the signal after maternal ECG removal and the RHA signal. The R-peaks are located using the πCA method in component space.

TABLE I
EVALUATION OF THE PERFORMANCE OF THE PROPOSED TECHNIQUE

	ICA		*πCA*	
	Component space	Channel space	Component space	Channel space
Total R	*2347*	*2347*	*2347*	*2347*
TP	*2346*	*2146*	*2347*	*2200*
FP	*0*	*45*	*0*	*24*
FN	*1*	*231*	*0*	*171*
Se (%)	*99.96*	*90.29*	*100*	*92.78*
+P (%)	*100*	*97.95*	*100*	*98.92*
Error rate (%)	*0.043*	*11.76*	*0*	*8.31*
Time error(ms)	*0.8*	*33.6*	*0.6*	*25.6*

As Table I shows, better results could be obtained by applying the transformation on the extracted components.

ICA techniques are usually based on the maximization of some measure of component independence. However, for ECG as a pseudo-periodic signal, the temporal structure of the signal is rich in information and a measure of periodicity of the extracted signals, both clinically and mathematically, is a more appropriate criterion as compared to independence.

From the sparsity viewpoint, the ECG signals are rather sparse in time and the second or higher-order statistics estimated in conventional ICA techniques can be susceptible to noise. The measure of periodicity in the πCA method is a way of using *a priory* information to have better estimates of the required statistics. Also ranking the components is a helpful feature, spatially for automating the maternal ECG removal. While in conventional ICA it is not possible to predict the order of the extracted components [3].

Mentioned features are some reasons that make πCA as a great choice in the fetal ECG source separation problems.

Also as noted in [5], the RHA method deals with the dynamical changes in the polarity of the fECG waveform and fetal repositioning.

Since the magnitude of the analytic function is always positive, and thus independent of signal polarity, and to a large extent independent of QRS waveform morphology this measure, calculated over multiple sensors, can be averaged to improve the signal-to-noise ratio, to eliminate transient

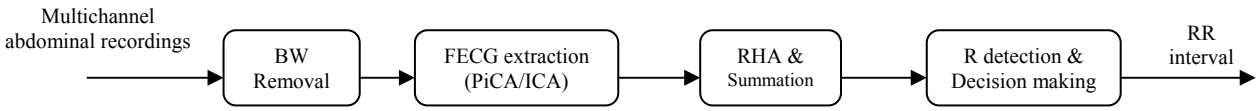

Fig. 1. Block diagram of the proposed algorithm

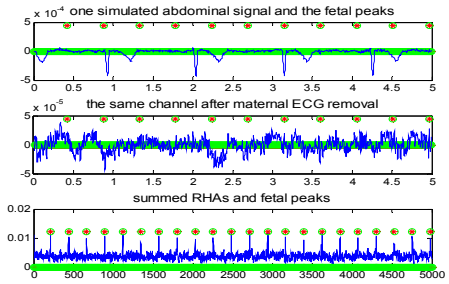

Fig. 2. Five seconds of simulated fECG signal before and after maternal ECG removal. The last signal is the summed R[n] series. The fetal peaks are located using πCA in the component space (stars), compared with the real fetal peaks (circles).

signals, and also to retain the fECG amplitude rather constant during the entire recording [5].

REFERENCES

[1] P. S. Hamilton and W. J. Tompkins, "Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database," *IEEE Trans.Biomed. Eng.*, vol. BME-22, no. 12, pp. 1157–1165, Dec. 1986.

[2] S. Benitez, P. A. Gaydecki, A. Zaidi, and A. P. Fitzpatrick, "The use of the Hilbert transform in ECG signal analysis," Comput. Biol. Med., vol. 31,pp. 399–406, 2001.

[3] R. Sameni, "Extraction of Fetal Cardiac Signals from an Array of Maternal Abdominal Recordings," Ph.D. dissertation, Sharif University of Technology – Institut National Polytechnique de Grenoble, July 2008. [Online]. Available: http://www.sameni.info/Publications/Thesis/PhDThesis.pdf

[4] L. K. Saul and J. B. Allen, "Periodic component analysis: An eigenvalue method for representing periodic structure in speech." in NIPS, 2000, pp. 807–813. [Online]. Available: http://www.cs.cmu.edu/Groups/NIPS/00papers-pub-on-web/SaulAllen.pdf

[5] James D. Wilson, R. B. Govindan, Jeff O. Hatton, Curtis L. Lowery, and Hubert Preissl,, "Integrated Approach for Fetal QRS Detection",*IEEE Trans.Biomed. Eng.*, vol. 55, no. 9, September 2008

[6] R. Sameni, Open Source ECG Toolbox (OSET), 2006. [Online]. Available: http://ecg.sharif.ir/

[7] P. Comon, "Independent component analysis—A new concept?," *Signal Process.*, vol. 36, pp. 287–314, 1994.

[8] G. Strang, Linear Algebra and Its Applications, 3rd ed. Brooks/Cole, 1988.

[9] Shubha Kadambe, , Robin Murray, and G. Faye Boudreaux-Bartels," Wavelet Transform-Based QRS Complex Detector", *IEEE Trans.Biomed. Eng.*, vol. 46, no. 7, July 1999.

[10] R Sameni, G. D. Clifford, C. Jutten, and M. B. Shamsollahi. Multichannel ECG and Noise Modeling: Application to Maternal and Fetal ECG Signals. EURASIP Journal on Advances in Signal Processing, 2007:Article ID 43407, 14 pages, 2007. ISSN 1687-6172, doi:10.1155/2007/43407.

[11] J.-F. Cardoso, Blind Source Separation and Independent Component Analysis, 2005. [Online]. Available: http://www.tsi.enst.fr/˜cardoso/guidesepsou.html

[12] R.N. Bracewell, The Fourier Transform and its Applications, McGraw-Hill, New York, 1978, pp. 267–274.