Fetal Electrocardiogram Extraction and Performance Analysis

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***Abstract*—In biomedical engineering, to extract the fetal electrocardiogram (FECG) exactly is a significant and challenging research topic, and so it has been a hot field in biomedical research. Now, a variety of different methods have been proposed to address this problem. From the perspective of blind signal processing, FECG extraction can be modeled as Blind source separation (BSS). In this paper, we present a novel approach, which apply the technique of independent component analysis (ICA) and the theory of wavelet transform, to obtain FECG from the real-life sampled recordings. And in this system diagram, we firstly adopt wavelet de-trending and wavelet de-noising as preprocessing stages to eliminate various kinds of noise, then for these ECG signals processed, in the view of BSS, FastICA algorithm as an ICA method was used to estimate the fetal electrocardiogram signals. Moreover, two different de-trending algorithms are presented to remove the baseline noise. The last but not the least, Performance analysis was provided on the results of the experiment.**

***Index Terms*—blind source separation, independent component analysis, wavelet detrending, wavelet denoising, fastICA,fetal electrocardiogram extraction**

I. Introduction

The fetal electrocardiogram is an objective indicator to reflect the fetus' heart condition and its health, as well as being a diagnostic tool which can monitor conditions such as arrhythmia, and assess the fetal acidosis, and may be of vital importance to both mother and child when risk factors are present during pregnancy [1]. By analyzing the fetal ECG obtained, we can diagnose possible diseases and take some appropriate treatments earlier and timely before delivery. The best way to acquire accurate fetal electrocardiogram signals is to place an electrode directly on the fetal scalp during delivery. However, this way is only achievable during delivery, and clearly cannot be used to monitor the state of the fetus throughout pregnancy, or for an early diagnosis [2][3]. Therefore, one should look for noninvasive techniques. Generally, the extraction of the antepartum fetal ECG can be carried out through skin electrodes, known as leads, attached to the mother's abdominal and thoracic region. Unfortunately, the desired fetal heartbeat signals appear at the electrode output buried in an additive mixture of undesired disturbances[4], broadly speaking, mainly contain the maternal electrocardiogram (MECG) contributions, of considerably higher amplitude than the fetal components, electromyography noise, power line interference, baseline wandering and so on. These contaminated signals affect the extraction of the FECG to a great degree, and further reduce diagnostic accuracy.

In order to extract useful information from the noisy ECG records, we need to preprocess the raw ECG signals necessarily. And before we get ready to do something with the raw signals, we without no doubt need to analyze the components of the signal sampled by electrode. Broadly, ECG contaminants can be classified into the following categories [2][5]:

(1). Maternal ECG contributions.

(2). Electromyography noise.

(3). Baseline wandering, including respiration signals.

(4). Noise generated by electronic equipment, mainly contains power line interference, electrode contact noise.

As mentioned above, in all cases where the FECG is observed, the MECG is higher in amplitude, so eliminating the MECG from the recorded signal is very important [6]. In [7], it said that the maternal ECG can be 5-1000 times higher in its intensity and ability to induce surface potentials. As the frequency spectrum of both ECG signals overlapped, it is a difficult task to remove the maternal ECG contributions from the sampled ECG records directly.

Besides, among these noises, the power line interference and baseline wandering are the most significant and can strongly affect FECG signal extraction. The power line interference is narrow-band noise centered at 60Hz (or 50Hz) with a bandwidth of less than 1Hz. Usually it can be suppressed by applying a

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notch filter, or adopt the subtraction procedure to cope better with this problem. The subtraction procedure has largely prove advantageous over other methods for power line interference cancellation in ECG signals [8]. Baseline wandering (or drift) mainly comes from respiration at frequencies wandering between 0.1Hz and 2Hz. Thus, most of baseline wandering can be discarded by applying a linear phase high-pass filter with a cut-off frequency about at 2Hz. Except for these two types of noise, other noise may be wideband and usually a complex stochastic process which also distorts the ECG signals.

The BSS approach provides a general versatile framework for extracting the signal of interest whereby each of the recorded signals, so-called observations, may contain the desired and the interfering contributions. Furthermore, the source signals may contain overlapping time-frequency spectra with possibly non-repetitive irregular waveforms. In its basic formulation, BSS assumes that each of the observations is an unknown instantaneous linear mixture of the sources, and aims at inverting the mixture in order to recover the sources. The FECG extraction was originally formulated as a BSS problem [9]. In view of BSS problem, A variety of approaches have been proposed to address this problem, techniques such as principle component analysis (PCA), independent component analysis (ICA) and so on. FastICA algorithm, a fast fixed-point algorithm using negentropy, which uses an approximation of the Newton method that is tailored to the ICA problem and provides fast convergence with little computation per iteration, was proved to cope better with BSS problem, and have been extended to a variety of problems in biomedical signal processing and other domains, like fetal ECG extraction and the analysis of atrial fibrillation.

In this article, it has put forward the corresponding solutions to solve problems of eliminating noise and extracting fetal ECG in the view of above. Wavelet de-trending and wavelet de-noising were used as preprocessing stages before to derive relatively stationary ECG signals.

II. METHODOLOGY

A. System Diagram

According to these analyses above, we propose an approach that can realize the cancellation of noise and interference as well as fetal electrocardiogram extraction. The system diagram can be depicted in Fig.1. It mainly contains two processed stages: preprocessing stage and BSS stage.

Before we are ready to present the experimental results at length, it is necessary for us to analyze each module in details.

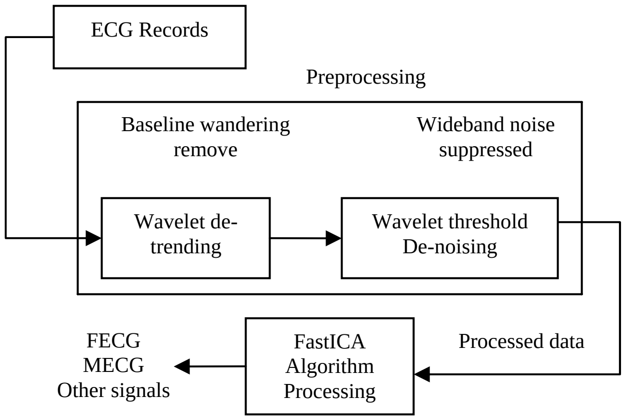

Fig.1 system diagram for fetal electrocardiogram extraction, where concrete practicable methods will be introduced next.

B. Preprocessing Stages

B1. Wavelet Transform Theory

As illustrated in Fig.1, it contains two steps in preprocessing module, mainly including baseline wandering remove and wideband noise suppressed. In term of the characteristics of these types of noise and interference in the recorded electrocardiogram signals, in theory, wavelet transform is an appropriate analytic tool to this application.

The wavelet transform ,mapping a signal from the time domain to the time-scale domain [2], is a useful tool for analyzing non-stationary and multi-component signals. Mathematically speaking, the wavelet transform of a signal s is the family $C(a,b)$,which depends on two indices a and b , and also can be expressed as follow:

$$C(a,b)=\int_R s(t)\frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})dt \quad (a>0, b\in R) \qquad (1)$$

Where $\psi(a,b)$ is the wavelet function or mother wavelet.

Generally, formula (1) is called Continuous Wavelet Transform (CWT). If we discretize the parameters a and b like this: $a=2^j, b=k2^j, (j,k)\in Z^2$, we can obtain the formula for Discrete Wavelet Transform (DWT). Form an intuitive point of view, the wavelet decomposition consists of calculating a “resemblance index” between the signal and the wavelet located at position at b and of scale of a. The indexes $C(a,b)$ are called coefficients.

In wavelet analysis, we often speak of approximations and details. The approximations are the high-scale, low-frequency components of the signal; the details are the low-scale, high-frequency components. In the general case, we can acquire the approximations by using a low-pass filter, and correspondingly, obtain the details through a high-pass filter. In the view of wavelet decomposition, we prefer to call approximation coefficients (cA) and detail coefficients (cD) rather than go by the name of approximations and details in a great degree. Due to lack of space, not all the aspects can be covered in detail. Here we just talk about partial theory of discrete wavelet transform for one-dimensional signals.

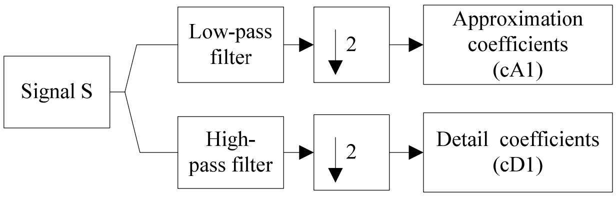

Fig.2 The first step for DWT decomposition

Given a signal s of length N, the DWT consists of $\log_2 N$ stages at most. Starting from s, the first step produces two sets of coefficients: cA_1 and cD_1. These vectors are obtained by convolving s with low-pass filter for approximation, and with the high-pass filter for detail. The process is described precisely in Fig.2. the next step splits the cA_1 into two parts using the same scheme, replacing s by cA_1 and producing cA_2 and cD_2. Therefore, the wavelet decomposition for one-dimensional signal s at level j has the structure: $\lfloor cA_j, cD_j, cD_{j-1}, \cdots, cD_1 \rfloor$, which can be vividly depicted as a tree in Fig.3.

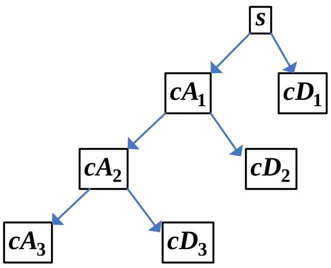

Fig.3 Tree for the structure of decomposition coefficients of one-dimensional signal s, where $j=3$.

Through wavelet transform or wavelet decomposition, signal s is split into approximation part which contains the low-frequency components of the signal and detail part containing the high-frequency components. As the level j grows, we can obtain more information about the signal s. For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. Take human voice for example, If you remove the high-frequency components, the voice sounds different, but you still tell what's being said. However, if you remove enough of the low-frequency components, you hear gibberish [10]. Thus we can firstly distill coefficients at each level, and then process these coefficients obtained and finally realize removing various types of noise form the signal and signal compression, and so on.

B2. Wavelet Selection

As for ECG signals, in [11], The series of Daubechies wavelet are similar in shape to heart beat wave (QRS complex) and their energy spectrum are concentrated around low frequencies. Notably particularly, The wavelet filter with scaling function more closely to the shape of the ECG signal can achieve better performance in various kinds of processes, and also in [12], and also in [13], it shows that Daubechies 8 is optimal wavelet basis functions for ECG signal processing, with theoretical and experimental explanation. And in [2], it also selected the db8 as the target wavelet. For these, in this article, we choose the wavelet db8 as the wavelet basis function.

B3. Baseline Remove

As mentioned above, baseline wandering usually distribute at frequencies between 0.1 and 2Hz. Generally, we can suppress it by a linear phase high-pass digital filter, such as a high-pass FIR digital filter based on Kaiser window whose stop band edge frequency is about 0.2Hz and pass band edge frequency 2Hz. In this paper, we apply wavelet de-trending to cancel baseline wandering by eliminating the trend of recorded ECG signal. Theoretically, the trend of signal s represents the slowest part of signal s, in other words, the lowest-frequency components display the trend of signal s. In wavelet analysis terms, this corresponds to the greatest scale value. Therefore, in order to remove baseline wandering, firstly the observation ECG signal is processed by wavelet decomposition at level j, and then set coefficients of cA_j to zeros, finally reconstructed based on all the detail coefficients. Through these steps, without no doubt, we can reduce the influence of baseline drift. Now, we focus on the accuracy value of level j to yield the best performance of de-trending.

In the [14], Kwang Eun Jang, Sungho Tak and Jaeduck Jang have proposed a wavelet minimum description length (Wavelet-MDL) de-trending algorithm to address the global-drift issues. And the authors have demonstrated and discussed advantages of the approach over traditional methods both theoretically and practically.

In the Wavelet-MDL de-trending algorithm, it deduces that the maximum level of decomposition j can be given by :

$$j_{\max} = \left\lfloor \log_2 \frac{N}{M-1} \right\rfloor \tag{2}$$

Where M denotes the support length of the wavelet, and N is the length or number of sampling points of a column vector, which stands for the signal. Also need to note is that $\lfloor X \rfloor$ denotes an operator that truncates X to the nearest integers toward zero. Optimal performance can be yielded only if level j is equal to $j_{\max}$.

In the article [5], the author also have proposed a good de-trending algorithm. In [5], the trend level can be computed by the following equation:

$$trend\ level: tl = \frac{\log_2 2t}{\log_2 N} \tag{3}$$

Where t is the sampling duration and N is the number of sampling points. And it deduces that the trend level

tl must be between 0 and 1. The optimal decomposition level can be computed as follows:

$$j_o = \lceil (1 - tl) \times \log_2 N \rceil \tag{4}$$

While $\lceil X \rceil$ means that an operator rounds the value X to the nearest integer greater than or equal to X.

Theoretically speeking, the larger the decomposition level, the closer the estimated trend matches the input signal. And now we can draw a parallel between the two detrending algorithms. Fig.4 shows curves of function y_1 and y_2, respectively. Where

$$y_1 = \log_2 \frac{N}{M-1}$$

$$y_2 = \left(1 - \frac{\log_2 2t}{\log_2 N}\right) \times \log_2 N$$

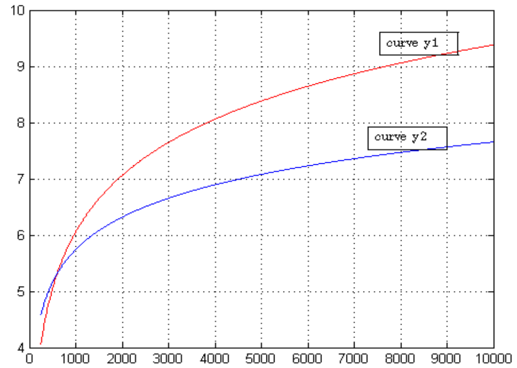

Fig.4 Two Curves for y_1 and y_2, respectively. The red curve represents the y_1, and the blue one corresponding to the y_2.

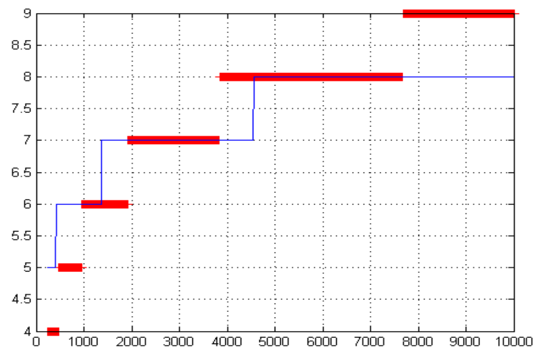

Fig.5 Curves for $j_{\max}$ and j_o, boldline for $j_{\max}$ and another for j_o.

Decomposition level is an integer value, According the theory above, we can get that :

$$j_{\max} = \lfloor y_1 \rfloor \quad j_o = \lceil y_2 \rceil$$

And Fig.5 shows curves for $j_{\max}$ and j_o. From Fig.4 and Fig.5, we can get that too some extent, the Wavelet-MDL de-trending algorithm is better than the algorithm proposed in [5] to remove the very low-frequency component.

B4. Wideband Noise Suppressed

As discussed in the preceding section, after baseline drift cancellation, the resulting ECG signals are still contaminated by other types of noise and interference. These noises affect the effectiveness of Fetal ECG extraction, so it is necessary to suppress them. While these types of noise may be complex stochastic process with a wideband that is to say that we cannot remove them by using traditional digital filters.

Wavelet threshold de-noising method may be especially adapted to remove these noises with wideband, and there are various algorithms for wavelet threshold de-noising. In its broadest sense, wavelet threshold de-noising just apply a certain algorithm to deal with detail coefficients for each level from 1 to N of signal s, which has been decomposed at level N .and reconstruct the signal based on the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N. More information can refer to [15][16][17]. Of course, the so-called certain algorithm is related to the soft threshold selection. Threshold selection rules are based on the underlying model:

$$y = f + \sigma\varepsilon \tag{5}$$

Where y represents input signal, f is an unknown deterministic signal, and ε is a while noise $N(0,1)$, σ denotes the noise level. There are several universal rules for soft threshold selection until now. For example, In [18], David L. Donoho proposed a universal threshold selection method. And in [19], David L. Donoho and Iain M. Johnstone put forward minimax threshold selection rule in wavelet domain. Also introduced a procedure, SureShrink that suppressed noise by thresholding the empirical wavelet coefficients in [20]. Another well-known threshold selection procedure is base on Stein's unbiased risk estimator (SURE)[21]. In this paper, we adopt minimax rule to get the soft threshold value. Minimax threshold selection rule uses a fixed threshold chosen to yield minimax performance for mean square error (MSE) against an ideal procedure. The minimax principle is used in statistical decision theory in order to design estimators. Since the de-noised signal can be assimilated to the estimator of the unknown regression function, the minimax estimator is the one that realizes the minimum of the maximum MSE obtained for the worst function in a given set

C. Independent Component Analysis and FastICA

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie set of random variable, measurements, or signals [22]. In the literature, BSS with an instantaneous linear mixture has been formulated as an independent component analysis problem. Mathematically, ICA assumes that n source signals $s = [s_1, s_2 \cdots, s_n]^T$ are statistically and mutually independent with no more than one Gaussian source signal. The sources are instantaneously and linearly mixed by an unknown $n \times n$ matrix A .The relationship between sources and observations is demonstrated as follow:

$$x = As + n \tag{6}$$

Where $A_{n\times n}$ is the mixing matrix, and columns of that are linearly independent; $x = [x_1, x_2, \cdots, x_n]^T$ is referred to as the observation signals; $n = [n_1, n_2, \cdots, n_n]^T$ represents additive noise, which is statistically independent from the sources. ICA now consists of estimating both the matrix A and the source s_i ($i = 1,2,\cdots,n$), when we only observe the x_i ($i = 1,2,\cdots,n$).Note that we assumed here that the number of independent components s_i is equal to the number of observed variables; this is a simplifying assumption that is not completely necessary. ICA aims to recover source signals s from observation x . The estimated signals can be referred as $y = [y_1, y_2, \cdots, y_n]^T$, and obtained by formula (7).

$$y = W^T x \tag{7}$$

Where W denotes the demixing matrix. Thus, all kinds of ICA methods' focus is how to acquire the demixing matrix..

FastICA is a fast fixed-point algorithm using negentropy. It uses negentropy combines the superior algorithmic properties resulting from the fixed-point iteration with the preferable statistical properties due to negentropy [22].Because BSS algorithms in general assume that each component of sources is a extraneous variable with zero mean, and the components of the signals s are mutually uncorrelated, hence, the centering and whiteness are necessary as preprocessing steps in BSS model. Further more, as a matter of fact, they are highly useful and widely used in independent component analysis, partly due to that the speed of convergence can be accelerated. The whole process of FastICA can be illustrated in Fig.6. For detailed information about FastICA algorithm, please refer to [22].

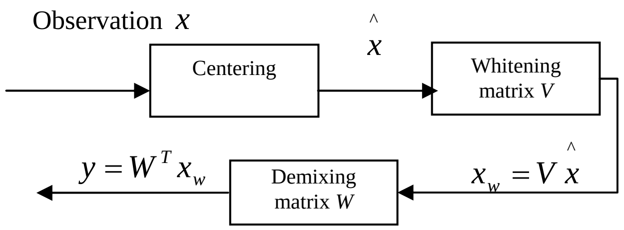

Fig.6 FastICA model, and the whole process of the FastICA algorithm. Where centering is just to remove the mean of each component of X , that is, after centering step, Components of Observation X are all rand vector with zero mean

III. Experiment And Result

Fig.7 shows the cutaneous potential recordings used in this experiment, which are obtained from [23]. The signals in Fig.7 were recorded from eight skin electrodes located on different points of a pregnant woman's body. The sampling frequency is 250Hz,and the sampling time 10 seconds, so each signal is composed of $N = 2500$ samples. The horizontal axis displays the sample number n ,with respect to the vertical axes the relative amplitude. For details about data acquisition, please refer to [23].

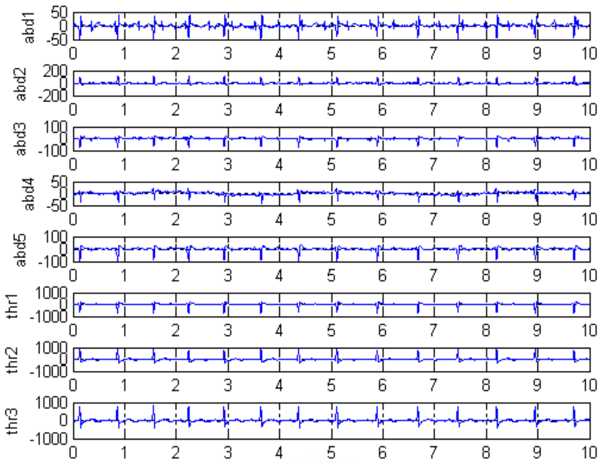

Fig.7 Eight-channels set of cutaneous data recordings.

According to information about the sampled recordings, the value of M is equal to 16, N is 2500, and the sampling duration t is 10. Based on Formulate (2), $j_{\max}$ gets the value 7. while according to the equation (3), the trend level tl is equal to 0.3829, and the optimal decomposition level j_o gets the value of 7 according to the formulation (4). It is interesting and a coincidence that these two different detrending algorithms get the same result.

In Fig.7, the first five recordings correspond to electrodes located on the mother's abdomen. In them a mixture of maternal ECG ,fetal ECG and other types of noise are visible. For channels 6-8 electrodes have been placed on the thorax. Due to large amplitudes of the Maternal ECG in thoracic region, the Fetal ECG is less visible. Moreover, the abd4 lead presents an relatively clear baseline wandering.

Fig.8 shows the ECG recordings after wavelet de-trending. Via wavelet de-trending, The trend of each channel ECG is cancelled from recorded ECG, also illustrated in Fig.9. And in Fig.10, it shows the frequency spectrum of baseline respectively. From Fig.10, we can see that the baseline, mainly contains respiration, is a low-frequency signal indeed. Also in Fig.8, each channel ECG signal is more stationary and explicit than that in Fig.7.

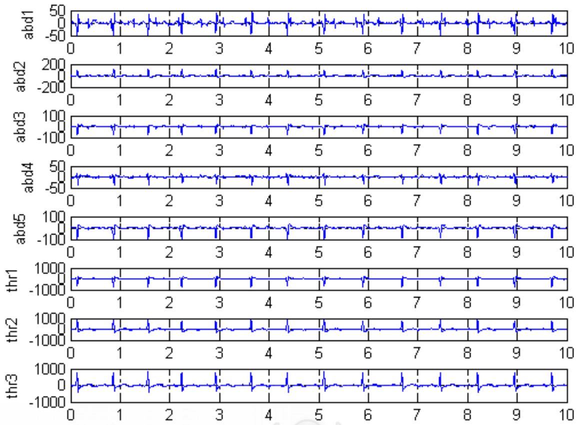

Fig.8 The ECG recordings after wavelet de-trending, that is, the baseline wandering was removed.

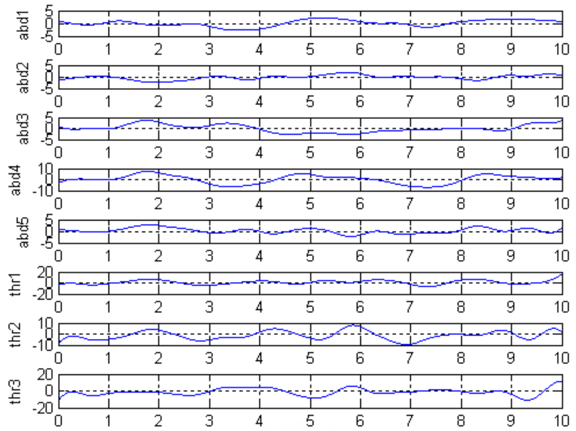

Fig.9 The trend of recorded ECG signal from each electrode, obtains by wavelet de-trending method.

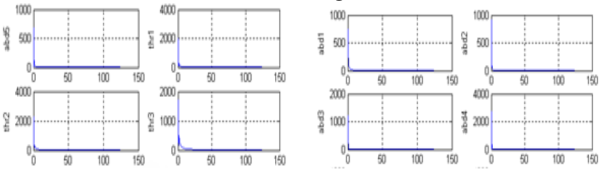

Fig.10 The frequency-spectrum of the trend corresponding to Fig.7, where the horizontal axis displays the value of frequency (Hz), with respect to the vertical axes, which represents the amplitude.

Fig.11 demonstrates the signals after wavelet threshold de-noising . From Fig.11, we can say that the wideband noise is suppressed to a great degree, while most of the details of the ECG signals are kept invariant. The estimated ECG signals through FastICA algorithm are displayed in Fig.12. As is reported in [2][24], the bioelectric activity of the maternal heart can be represented by a three-dimensional dipole current. In another words, Maternal ECG signals can be expressed as the linear combination of three statistically independent vectors, which form the MECG-subspace. The FECG-subspace, on the other hand, which describes electric activity of fetus' heart, doesn't consist of three vectors, but subject to changes during the period of pregnancy. As depicted in Fig.9, channels 1, 3 and 4 describe the MECG-subspace; The Maternal ECG also appears in channel 6. Estimated Fetal ECG can be clearly seen in channel 2, and also appears in channel 5, in spite of not clear. Channels 7 and 8 mainly show noise contributions.

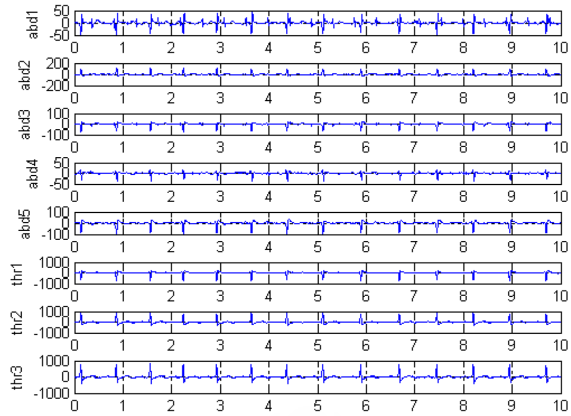

Fig.11 The ECG recordings after processed by wavelet de-noising .

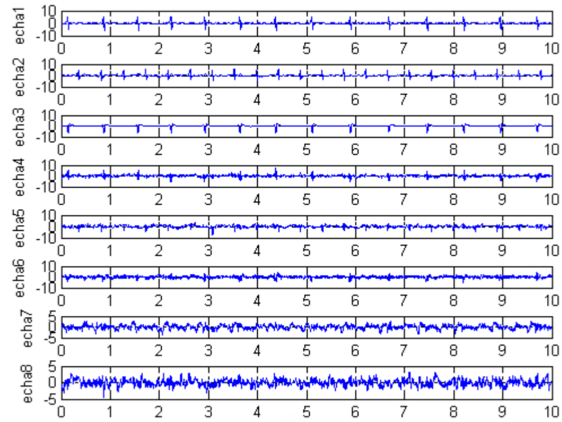

Fig.12 Source estimates obtained by means of preprocessing module and FastICA algorithm.

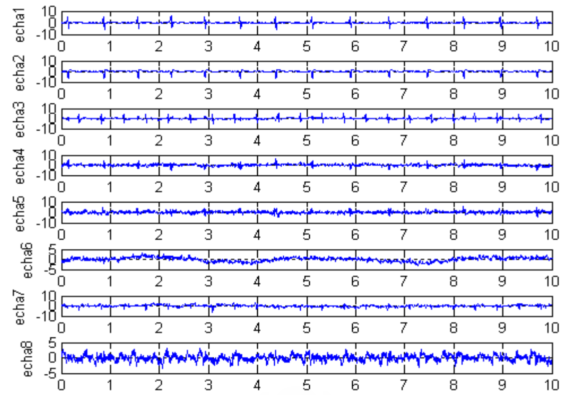

Fig.13 Source estimates obtained directly by means of FastICA.

Fig.13 demonstrates the estimated signals through BSS by using FastICA algorithm. While a big difference is that the result recordings were directly throng FastICA processed, not processed by preprocessing module. That is to say, wavelet de-trending and wavelet de-noising were not used.

Now, the key issue is how to evaluate their performance according to Fig.12 and Fig.13. In general case, Performance Index (PI) is very useful for performance evaluation purpose. However, it provided that the mixing matrix A is known. In terms of engineering application, the sources s and the mixing matrix A are both unknown, in such a case; it seems PI has significant restriction. To be exact, PI cannot be a evaluating indicator in engineering field, like the biomedical application in this paper. Hence, in this article, As far as effectiveness of BSS be concerned, Firstly, From the visual point, it is somewhat better in Fig.12 than that in Fig.13. Further more, we consider value of kurtosis as evaluation criterions to illustrate the performance of both methods. Kurtosis is a classical measure of non-Gaussianity of a signal. Signals with negative kurtosis are called sub-Gaussian, while those with positive kurtosis are referred to as super-Gaussian [2]. For a Gaussian signal, kurtosis is zero. Generally, the greater the absolute value of kurtosis value, the better convergence of the signal for ICA methods [25]. That is to say, the strong non-Gaussianity of signals will be useful in convergence behavior of ICA approaches. And it can reduce the time of extracting fetal ECG by ICA methods.

TABLE.1
KURTOSIS VALUES OF SAMPLED RECORDINGS

	Recordings	W-de-trending	**W-de-noising**
Abd1	8.3341	8.6911	8.8702
Abd2	13.8271	13.9177	13.9476
Abd3	15.0838	15.8044	15.8342
Abd4	6.8025	15.0176	15.6673
Adb5	15.8416	15.9907	15.9389
Thr1	20.8363	20.8530	20.8664
Thr2	16.4521	16.4630	16.4792
Thr3	16.8044	16.8373	16.8887

As can be observed in Table.1, the kurtosis value of each ECG signal, processed by wavelet transform, from sampled ECG recordings is greater than that of corresponding column in the ECG recordings. In this respect, the proposed method can improve the performance of BSS-ICA for extracting Fetal ECG. Where ‘Recordings’ stands for the kurtosis of the observation ECG signals, ‘W-de-trending’ means the kurtosis of the ECG signals before wavelet de-trending step, and ‘W-de-noising’ shows the kurtosis of the ECG signals before wavelet de-noising step.

III. CONCLUSION

A variety of different approaches have been proposed to cancel artifacts and enhance signals of interest in the ECG until now. In this paper, we provide a novel approach based on the characteristics of recorded ECG signals, obtained by sampling through skin electrodes attached to the mother’s body, in terms of theory to extract Fetal ECG. During the entire process, Wavelet detrending and wavelet threshold de-noising are adopt as preprocessing stages, and FastICA algorithm as a BSS method to derive fetal ECG. The experiments presented and discussed show this method is feasible and successful to the noninvasive fetal ECG extraction problem. Moreover, Compare with the method that is lack of preprocessing stage, directly adopts FastICA algorithm, we find that this approach is more robust and can get better performance for extracting fetal ECG, although the superior performance is attained at the expense of an increase operational complexity. Yet the achieved FECG extraction quality offers promising prospects for the use of this technique in prenatal medical diagnosis, and what’s more, it may provide a new insight into how to tackle the fetal ECG extraction problem effectively.

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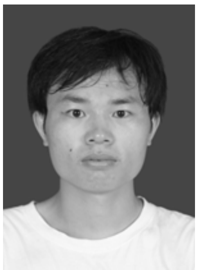

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