Extraction Method of Fetal Phonocardiogram Based on Lifting wavelet analysis

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Abstract. Long-term monitoring of fetal health status is important for high-risk pregnancies. In order to extract the pure fetal phonocardiogram (fPCG) and increase the calculating accuracy of fetal heart rate (FHR), a combination of Empirical Mode Decomposition (EMD), Cepstrum, Lifting Wavelet (LWT) and Hilbert transform (HT) method was proposed. First, the heart sound signal was decomposed into finite intrinsic mode functions (IMF) by EMD, and then the signal de-noising was implemented by LWT. Second, the envelope of the signal was obtained by HHT. Finally, the fetal heart rate was obtained by cepstrum analysis. The simulation result shows that the fetal heart rate extracted by this integrated signal processing method is right, and it enhances the precision of fetal heart rate greatly. The wavelet de-noising technology can reduce the noise very well with small computation. It is concluded that this integrated signal method is capable of extracting feature from fPCG.

1. Introduction
Analysis of heart sound signals has been widely studied and has been reported to have the potential value to detect pathology accurately in clinical applications [1]. Monitoring the change of fetal heart rate is very important to improve the quality of birth. The routine clinical tool for recording the FHR is Doppler Ultrasonographic Cardiotocography (CTG), but high quality CTG devices are so expensive that this technology is not available for home care use [2]. So, the existing noninvasive methods for FHR monitoring are based on fetal magnetocardiogram (fMCG), fetal electrocardiogram (fEEG) and fPCG. However, the fPCG can be considered as an alternative for CTG, due to its cheapness and passiveness [3]. The fPCG contains noise. The following are the principal factors which distort it to a great degree [4]: foetal movement, maternal heart and respiratory sound, ambient noise.

The existing signal de-noising methods of fPCG are as follows: Autocorrelation de-noising, coherence average de-noising, filtering de-noising, wavelet de-noising, etc. However, the LWT is the best denoised method [5]. EMD is widely used in signal recognition and feature extraction. It is used to decompose signal into finite number of IMF. Therefore, considering the advantages of EMD and LWT, this paper proposed an analytical de-noising method of combining them, to extract the pure fPCG. The period of denoised fPCG still cannot be settled, due to its less smoothness. In order to smooth the signal, the envelop spectrum of fPCG was obtained by HT. The methods of FHR acquisition in [5] is Autocorrelation technique. However, the cepstrum analysis method has higher spectral resolution than Autocorrelation [6]. So, this paper proposed the method of obtaining FHR based on cepstrum analysis.
2. The fPCG data

The fPCG data in this paper is derived from PhysioNet database. A total number of 110 records have been recorded from different women who were between 30th and 40th weeks of gestation with the mean value of 37 weeks and the average of 25 years old [3]. The sampling length of the original fPCG data is 608160 and the sampling frequency is 16000Hz. The relationship between FHR and fetal health status is shown in table 1. Because the frequency of the major fPCG is under 1.5Hz, the signals were resampled to 3KHz. In order to accelerate operating speed, we chose $2^{14} (16384)$ sampling points to analyze, as shown in figure 1.

Table 1. The relationship between FHR and fetal health status

| FHR/bpm | States               | 100–119 | 120–160 | 161–180 | >180  |
|---------|----------------------|---------|---------|---------|-------|
|         |                      |         |         |         |       |
| <99     | bradycardia          |         |         |         |       |
| 100–119 | moderate bradycardia |         |         |         |       |
| 120–160 | normocardia          |         |         |         |       |
| 161–180 | moderate tachycardia |         |         |         |       |
| >180    | marked tachycardia   |         |         |         |       |

![Figure 1. Primary fPCG](image-url)

3. Method

The analysis of fPCG was divided into four steps. Firstly, EMD was performed on the fPCG signals to decompose it into finite number of IMFs. Secondly, we chose some IMFs to denoise by LWT. The selection rules of IMFs were introduced in Section 3.1. Then we reconstructed the signal using de-noising IMFs and the untreated low-frequency IMFs. Thirdly, the envelop spectrum of fPCG was obtained by HT. This is the step where we can get the smooth fPCG. Finally, in order to get FHR, the fPCG signal was analyzed by the cepstrum method. The analysis flow chart is shown in figure 2.

![Figure 2. Flow chart](image-url)

3.1. The basic theory of EMD

EMD was proposed by Huang et al. in 1998. It is mainly suitable for decomposition processing of non-stationary signals. The human signals are often characterized by non-stationary signals. EMD is that decomposing the original signal into several IMF components and one residual component. The different IMF components highlight the local characteristics of the signal. The residual component corresponds to the slowly changing components of the signal. In short, the signal features can be extracted and identified by analyzing these components. The decomposition process of EMD method for the fPCG signal $x(n)$ is as follows:

(1) All the extreme points of $x(n)$ are found.

(2) Interpolation is used to form a lower envelope $e_{min}(n)$ for the minimum points and an upper envelope $e_{max}(n)$ for the maximum values.

(3) The mean $m(n)$ is calculated as:

$$m(n) = \left( e_{max}(n) + e_{min}(n) \right) / 2$$  (1)
(4) The details are pulled away.
\[ d(n) = x(n) - m(n) \] (2)

(5) The appeal steps are repeated for the remaining \( m(n) \).
The signal form after decomposition is:
\[ x(n) = \sum_{n} d(n) + r(n) \] (3)

Where \( n \) is the number of IMFs decomposed; \( r(n) \) is the residual term obtained from the decomposition. In this case, EMD is equivalent to the function of a filter: The IMF component with the frequency from large to small can be obtained, and the frequency of the noise in fPCG is high. But deleting the first few is unreasonable, because they contain useful information. So, we selected 1~4 IMFs to denoise by LWT.

3.2. The basic theory of LWT

The basic process of LWT can be divided into three parts: splitting, predicting and updating.

(1) Split
The splitting process is also called the inert wavelet transform process. This process splits the original data (one-dimensional signal) into two disjoint subsets of data \( s_{j-1} \) and \( d_{j-1} \). Signals are generally divided into odd and even sequences. The equation is:
\[ F(s_j) = (s_{j-1}, d_{j-1}) \] (4)

(2) Predict
In the lifting structure, if we want to use \( s_{j-1} \) to predict \( d_{j-1} \), we need to predict \( d_{j-1} \) by using the prediction operator \( P(s_{j-1}) \). In practice, \( P(s_{j-1}) \) may be very close to \( d_{j-1} \). If the difference between the subset \( d_{j-1} \) and the predicted value \( P(s_{j-1}) \) is used to replace \( d_{j-1} \), this difference reflects the degree of approximation of the two. The resulting \( d_{j-1} \) contains less information than the original \( d_{j-1} \). Thus, equation is obtained.
\[ d_{j-1} = d_{j-1} - P(s_{j-1}) \] (5)

\( d_{j-1} \) can be regarded as a high-frequency component, also known as a wavelet coefficient. The smaller the wavelet coefficient, the better the prediction effect.

(3) Update
The update process is the original promotion process. Some of the overall properties of the subsets produced by splitting are not consistent with the original data. Therefore, a better sub-data set \( s_{j-1} \) is generated by using \( U \) operator, and some characteristics of the original data set \( s_j \) are kept. The updated expression is:
\[ s_{j-1} = s_{j-1} + U(d_{j-1}) \] (6)

When the operator \( U \) is fixed, this step is generally reversible, the equation is:
\[ s_{j-1} = s_{j-1} - U(d_{j-1}) \] (7)

The lifting scheme to achieve wavelet transform has the following advantages [7]:
• It is independent of Fourier transform.
• No extra memory is required.
• The inverse transformation is easily obtained from the positive transformation, which only changes the direction of the data flow and the sign.

The LWT method is very suitable for the time-varying stationary single-component signal obtained by EMD decomposition [2]. The methods we adopted:
• The corresponding lifting scheme is obtained by using the db6 wavelet base as;
• The IMF component was decomposed by three-layer wavelet;
• The threshold value of the high-frequency coefficient of each layer was set, and the semi-soft threshold function was used for de-noising; The hard threshold method can well retain the local characteristics such as the signal edge, but the signal will generate additional oscillations. It doesn't
have the smoothness of the original signal. Soft threshold processing is relatively smooth, but will cause edge blur distortion. The semi-soft threshold function can take advantage of both soft threshold and hard threshold methods [8].

- The wavelet reconstruction is carried out layer by layer to obtain the denoised signal.
- The processed IMF component was superimposed with the untreated low-frequency IMF component to reconstruct the enhanced fetal heart signal.

3.3. The basic theory of HT

HT is extensively used in the extraction of envelope spectrum. A variable measurement signal can be described as the result of different signal properties over time. These signal properties estimated is signal processing processes. The HT provides signal amplitude, instantaneous phase, and frequency information. HT definition is as follows:

\[ x(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(t-\tau)}{\tau} d\tau = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \]  

where \( x(t) \) is fPCG signal. The analytic signal of \( x(t) \) was obtained, as follows:

\[ w(t) = x(t) + j \tilde{x}(t) \]  

Module of \( w(t) \) is the envelope of \( x(n) \), as follows:

\[ A(t) = \sqrt{x^2(t) + \tilde{x}(t)} \]  

The Hilbert transform is equivalent to passing the original signal through a filter. In fact, the HT is the convolution of \( x(t) \) and \( h(t) \), \( h(t) \) is as follows:

\[ h(t) = \frac{1}{\pi t} \]  

3.4. The basic theory of Cepstrum

There are various definitions of cepstrum, the complex cepstrum, real cepstrum and correlation function cepstrum. Here we use real cepstrum, the definition is as follows:

\[ y(n) = \text{real} \left( \text{ifft} \left( \log \left( \text{abs} \left( \text{fft} \left( x(n) \right) \right) \right) \right) \right) \]  

where \( x(n) \) is fPCG signal; \( y(n) \) is real cepstrum of fPCG signal. The FHR signal can be approximate as a periodic signal, because the difference between two adjacent heart cycles is generally no more than 10% [9]. If the original signal cycle is \( \tau \) and their amplitude ratio is \( \alpha \), cepstrum function is:

\[ y(n) = \sum_{i=0}^{\infty} (-1)^{i-1} \frac{\alpha^i}{i} \delta(n-i\tau) = a\delta(n-\tau) - \frac{\alpha^2}{2} \delta(n-2\tau) + \frac{\alpha^3}{3} \delta(n-3\tau) + ... \]  

It can be known from equation (7), on the cepstrum of the function, a series of pulses will appear at \( n=\tau i \) (\( i=1,2,3,... \)). Evidently, we can recognize the frequency of the signal component on its cepstrum easily and extract the useful frequency component.

4. Experiments and results

Among all the fPCG signals in PhysioNet database, simulation analysis was carried out for the 20 fPCG data chosen randomly. With signal processing, the correct heart rate of them were obtained. Due to the space, one of them fPCG signal processing was shown.
4.1. Simulation results of fPCG de-noising

Figure 3. We decomposed the fPCG signal into IMFs by EMD. The right column shows the IMF components and left column shows the frequency of IMFs.

The noises in fPCG have high frequency, and from the left column we can see the frequency of 1~4 IMFs is high. So, the 1~4 IMFs were denoised by LWT respectively. After de-noising, all components reconstructed the blood pressure signal. Figure 4 (a) shows the original fPCG signal and denoised fPCG signal. Drawing of partial enlargement is shown in figure 4 (b).

Figure 4. The original and denoised fPCG signal

4.2. Simulation results of heart rate extraction

After fPCG signal preprocessing, the envelope of it was obtained by Lifting Wavelet transform, as shown in figure 5 (a). Figure 5 (b) shows the envelope separately.

Figure 5. The envelope of fPCG

Then fPCG was analyzed by the cepstrum method. The range of FHR is 99~180bpm, that is, 1.65~3Hz. After obtaining the cepstrum, we choose the signal from 0.2s to 1s to find the max value. The heart rate is the reciprocal of the time, as shown in figure 6.
In figure 6, the max value is 0.3863, so the FHR is the reciprocal of it, 2.59Hz. It is corresponding to 155.3 bmp. It can be seen from table 1 in Section 2, this FHR is normocardia.

5. Conclusions

The main innovation of this paper is the combined method of EMD, LWT, HT and cepstrum analysis for processing physiological signals.

The characteristics of fPCG signal in a certain frequency range have been emphasized in different IMFs. The 1~4 IMFs were selected for LWT denoising. It can reduce the computation. The processed IMF component was superimposed with the untreated low-frequency IMF component to reconstruct the de-noising fPCG. This de-noising method combines the adaptive filtering characteristics of EMD and small computation of LWT. The de-noising function of it is effective.

After lifting wavelet transformation, cepstrum analysis is carried on the fPCG to extract heart rate feature information. The FHR was obtained accurately in this way. And the simulation result shows that the cepstrum has higher localization accuracy and smaller computation.

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