A Comparative Phonocardiography Study: two Wavelet Based Methods for Fetal Heart Sound Detection

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Abstract

The Fetal Heart Rate (FHR) periodic monitoring is essential part during pregnancy. Auscultation is a noninvasive low cost technique for the heart sound examination. However, Fetal Phonocardiogram (fPCG) signals are correlated with high background noise due to the maternal breathing and heart sounds, fetal movement, etc. The aim of this study is to develop an automatic analysis technique to identify the location of the FHSs in fPCGs signals and calculate the FHR. In this paper two denoising methods are proposed and compared in real and simulated fPCGs signals. The signals were analyzed in the Wavelet domain and then two methods were proposed for the detection of the FHSs. The first approach combines the Wavelet Transform with the Fractal Dimension analysis (WT-FD) while the second approach combines the Wavelet Transform with Simplicity Filtering (WT-S), which is computed by the eigenvalue spectrum method. Both methods present good performance with the WT-FD presets 88% precision, 93% recall and WT-S 71% and 72% respectively in simulated signals from -4.4 to -26.7dB, while the WT-S method is more unstable in cases with robust noise than the WT-FD.

1. Introduction

In the early 1960s Electronic Fetal Monitoring (EFM) was presented as a new, developed tool for the fetal examination during pregnancy and childbirth [1]. Some common EFM devices are the doppler ultrasound, the cardiotocogram, the fetal electrocardiogram, the fetal phonocardiogram and the fetal cardiac MRI.

One of the most important parameters for fetal health examination during pregnancy is the Fetal Heart Rate (FHR) monitoring through which it is possible for the clinician to examine the fetal growth and physiology. Although, the doppler ultrasound is the typical device for examination of the FHR, this technique cannot be used for long-term monitoring mainly because of the cost of the monitoring device, the complexity of its use and the long-term exposure to ultrasound energy [2].

A passive alternative for long term monitoring of the fetus is the fetal heart auscultation. Auscultation is a low-cost and noninvasive method as it captures the acoustic signal of the Fetal Heart Sounds (fHSs) from the mothers' abdominal surface [3]. The acoustic signal produced by the fHSs can be visually depicted in the Fetal Phonocardiogram (fPCG).

Nevertheless, fetal auscultation has many challenges because the fPCG signals are contaminated with noise from various sources, such as maternal heart sounds, digestive sounds, maternal respiration movements, fetal movements, external noise and others [3].

In our previous studies, we have proposed the Wavelet Transform - Fractal Dimension (WT-FD) method for FHS detection in fPCG signals [4]. In this paper, the Wavelet Transform - Simplicity (WT-S) method is suggested and compared with the WT-FD in fPCG signals.

Through the years, many studies were proposing the Wavelet Transform combined with the Simplicity analysis for the heart sound segmentation. A Wavelet Transport and Simplicity based method was proposed by the D.Kumar et al. in [5] for heart murmur segmentation while an Energy based and Simplicity based segmentation method for features computed from multi-level Wavelet decomposition coefficients was proposed by J.Vepa et al in [6]. Moreover J.Korver presented a study about the comparison of Wavelet and Simplicity based heart sound and murmur segmentation methods in [7].

The aim of this study is to evaluate the performance of the two proposed methods in order to develop an automatic analysis technique to identify the location of the FHSs in fPCGs signals and calculate the FHR.

Figure 1 shows a flow chart for the two proposed methods. The normalized input signal $x(t)$, $t=1,...,N$ is decomposed into wavelet levels $WT_i(t)$, $i=1,...,M$ based on the signals' length and a level selection is applied. After that one of the preferred FD based and Simplicity based analysis is performed in the selected wavelet coefficients to create the estimated sequence. Then, the peak peeling algorithm is used to gathering only the peaks that represent heart sounds. A binary sequence segments the FHSs from the background noise and the reconstruction of the signal is achieved. The whole procedure is iteratively continues until the stopping criterion is satisfied.

The paper is structured in three main sections: the first section briefly describes the mathematical background of the proposed methods, in the second section the results of the research are addresses and finally the third section completes the paper with conclusion.

2. Mathematical Background

After preprocessing, where needed, the proposed iterative method includes multiple steps, as depicted in Figure 1. The steps are described in more detail in the following subsections.

2.1. Wavelet Transform

In this study, the fPCG signals were processed by means of stationary Wavelet Transform (WT), it is a time-frequency analysis method. Wavelets are families of functions generated from a single base wavelet called the 'mother wavelet', by dilations and translations [8]:

$$\psi_{\alpha,b}(t) = \frac{1}{\sqrt{\alpha}} \psi\left(\frac{t-b}{\alpha}\right), \alpha > 0, b \in R, \quad (1)$$

where α is the dilation parameter and b is the translation parameter.

The Daubechies family of wavelets was chosen to decompose the fPCG signals into levels. After the wavelet decomposition, an energy based selection is performed for the subtraction of the first noisy levels.

2.2. Fractal Dimension

The Fractal Dimension (FD) is a tool that reflects the signal complexity in the time domain. In this research FD was adopted as a means to detect the FHSs in the WT domain [8]. The Katz FD definition is estimated by:

$$FD = \frac{\log_{10}(n)}{\log_{10}\left(\frac{d}{L_C}\right) + \log_{10}(n)}, \quad (2)$$

where L_C is the total length of the curve, realized as the sum of distances between successive points, d is the distance between the first point of the sequence and the point of the sequence that provides the farthest distance and $n = L_C/a$ is the number of steps in the curve, where a denotes the average step, i.e., the average distance between successive points.

The FD technique is performed using a sliding window of $W=int(0.05Fs)$ samples length in each selected WT level, where $int(.)$ indicates the integer part of the argument, the constant is empirically set at 0.05 and Fs denotes the sampling frequency of the signal.

2.3. Simplicity

Simplicity and especially the eigenvalue spectrum is another mean to measure the complexity of a fPCG signal. The background noise and murmurs in PCG signals are characterized as high complex components while heart sounds as less complex components of the signals [5,7]. Low complexity implies high simplicity making the heart sounds separate from the background noise.

Let $x(t)$ be the input signal and the delay vector $x_i=[x(t),x(t-\tau),...,x(t-(m-t)\tau)]^T$ where T symbols the transpose. The embedding matrix is defined as:

$$X = \frac{1}{\sqrt{P}}[x_1, x_2, ..., x_P], \quad (3)$$

and τ is the embedding delay, m is the embedding dimension and $P=N-(m-1)$. The correlation matrix is the $C=X^TX$.

Let $D=\{\lambda_1, \lambda_2,..., \lambda_m\}$ be the singular spectrum of the embedding matrix X i.e. the diagonal matrix with the eigenvalues of C sorted in descending order. Let H be the entropy of the calculated normalized eigen values $\hat{\lambda}_k^i$:

$$H(i) = \sum_{k=1}^{m} \hat{\lambda}_k^i \log \hat{\lambda}_k^i, \quad (4)$$

The complexity can calculated by $\Omega^i=2^{H(i)}$ while the simplicity by $S^i=1/\Omega^i$.

2.4. Peak Pealing

Through a self-adjusted iterative procedure, the Peak Peeling Algorithm (PPA) iteratively 'peels' the estimated sequences in order to automatically detect the peaks resulting in the estimated FD or Simplicity sequence [8]. The iteration procedure starts with a threshold operation based on the mean and the standard deviation of the vectors as follows:

$$PPA_j = \begin{cases} FD_j^z, FD_j^z > \mu^z + \sigma^z \\ 1.0, elsewhere \end{cases}, \; j = 1,..., M \quad (5)$$

where μ^z denotes the mean value of the vector , σ^z is the standard deviation of the vector and z is the number of the self-adjusted iterations. The iterative procedure stops when the mean square error criterion is satisfied. A flow chart of the PPA procedure with details is available in [9].

The PPA method applied to the FD_j or S_j sequence leads to two binary sequences for each wavelet coefficient, one for the FHSs segmentation $SBTH_j(t)$ and one for the background noise extraction $NBTH_j(t)$. After the reconstruction of the two subsets the algorithm

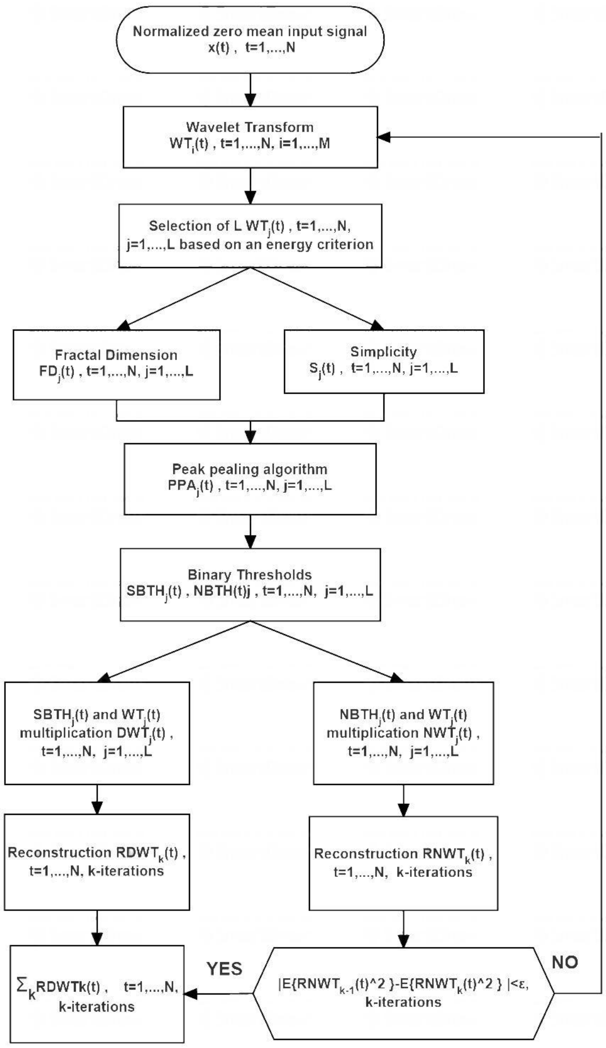

Figure 1. A shementic representation of the iterative procedure of the two methods.

decides based on the mean square error if the procedure stops or if there is more information in the background noise about the sounds and the whole procedure iterates.

3. Results

The analysis of this study was applied on a personal computer using Matlab R2015a and tested on simulated data and on three real signals. Every input signal was tested for 10sec for the simulated signals and for 4.5sec for the real signals considering Fs=1000Hz, i.e., 10000 and 4500 samples respectively.

A Simulated Web database from Physionet named simfpcgdb was used for the comparison of the two methods (https://physionet.org/pn3/simfpcgdb/). The database that was used is a fPCG simulated database created by Cesarelli et al. [3]. Simulated fPCG signals were generated including simulated S1 and S2 sounds, corrupted by noise. These signals are qualified by a range of SNR values which were computed in dB.

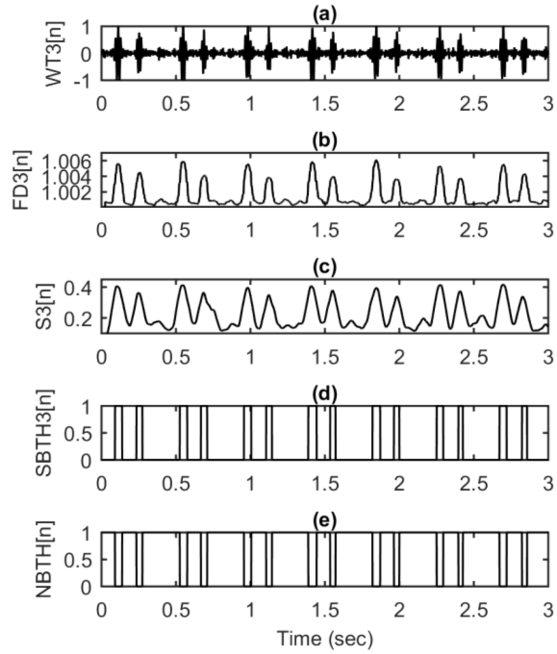

Figure 2. (a) Wavelet Transform third level coefficient, (b) Fractal Dimension sequence, (c) Simplicity sequence, (d) Binary thresholded components related to the heart sounds, (e) Binary thresholded background noise.

The two compared methods were also tested in Real fPCG signals from a small pilot study, involving recordings from three pregnant women. The fPCG signals were recorded using 4 vibration sensors [9].

For the evaluation of the two methods in the simulated signals the Recall (R), the Precision (P) and the geometric mean of the ratios of true positive to recorded sounds and true positive to the detected sounds (GM) are calculated. The simulated signals were divided in tree groups based on their Signal to Noise Ratio (SNR) and the mean results are shown in Table 1.

A second criterion for the evaluation of the methods was the fHR calculation. The location of the S1 heart sounds were identified by applying peak to peak time distance and amplitude criteria. The actual fHR of the simulated signals were 144bpm and the methods results are shown in Table 1.

In Both cases the methods successfully detects the location of the fHS with good performance in signals with high SNR while the WT-FD method presents better performance than the WT-S method in cases of low SNR. Based on the R index the WT-S method detects just over half of sounds in the last group of signals and based on

Table 1. Results of heart sound identification for the two compared methods WT-FD and WT-S.

SNR range	WT-FD				WT-S			
	R	P	GM%	fHR bpm	R	P	GM%	fHR bpm
[-4.4, -17.7]	0.98	0.93	94.30	144	0.87	0.82	82.76	144
[-19.1, -23.1]	0.93	0.92	91.39	144	0.70	0.72	68.88	141
[-23.3, -26.7]	0.88	0.79	81.79	141	0.61	0.60	57.83	136

the P index approximately half of the detected as sounds are false positive. However, examining the fHR in Table 1it appears that almost all of the correct predictive sounds in the last group of signals are S1 heart sounds because the calculated fHR is close to the actual rate. Hence, the method is not efficient in S2 heart sound detection in cases with low SNR.

In real fPCGs signals a preprocessing filter with the combination of the four different channels is a necessary additional step to remove the sounds of the mother to reveal and study the FHS. Table 2 shows the results of the fHR calculation based on the fHS detection of the two proposed methods. In real recordings neither method identifies all the sounds contained in every signal, but they detect a sufficient number to make a fHR approach. The WT-S method demonstrates a lower performance than the WT-FD while it is more sensitive in detecting of maternal heart sounds as shown in patient 3. Preliminary results indicate that it is worth analyzing the application of the two methods to real data in a more extensive study.

Table 2. Results of fHR calculation in real data for the two compared methods WT-FD and WT-S.

Patient	Calculated fHR bpm		Actual fHR bpm
	WT-FD	WT-S	
1	164	130	179
2	121	112	107
3	191	82	203

4. Conclusion

The aim of this study was to compare two methods applying in fPCG signals and test their performance relatively to the SNR intensity. The research indicate that both methods approach differently the heart sounds compared to the type of noise containing in the signals, adding a new perspective for better segmentation of fHS from the different types of maternal sounds.

Acknowledgements

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References

[1] Services eclecTA. Women's Health and Education Center (WHEC) - Obstetrics - Intrapartum Electronic Fetal Heart Rate Monitoring [Internet]. Women's Health and Education Center | WHEC |. [cited 2018Sep10]. Available from: http://womenshealthsection.com/content/obs/obs028.php3

[2] Abramowicz JS. Benefits and risks of ultrasound in pregnancy. Seminars in Perinatology. 2013;37(5):295–300.

[3] Cesarelli M, Ruffo M, Romano M, Bifulco P. Simulation of foetal phonocardiographic recordings for testing of FHR extraction algorithms. Computer Methods and Programs in Biomedicine. 2012;107(3):513–23.

[4] Koutsiana E, Hadjileontiadis LJ, Chouvarda I, Khandoker AH. Fetal Heart Sounds Detection Using Wavelet Transform and Fractal Dimension. Frontiers in Bioengineering and Biotechnology. 2017;5.

[5] Kumar D, Carvalho P, Antunes M, Henriques J, Maldonado M, Schmidt R, Habetha J. Wavelet transform and simplicity based heart murmur segmentation. Computers in Cardiology. 2006;13:173-6.

[6] Vepa J, Tolay P, Jain A. Segmentation of heart sounds using simplicity features and timing information. 2008 IEEE International Conference on Acoustics, Speech and Signal Processing. 2008;469-472.

[7] Korven J. A comparison of wavelet and simplicity-based heart sound and murmur segmentation methods. [thesis]. San Luis Obispo: Faculty of California Polytechnic State University; 2006.

[8] Hadjileontiadis L. Wavelet-Based Enhancement of Lung and Bowel Sounds Using Fractal Dimension Thresholding— Part I: Methodology. IEEE Transactions on Biomedical Engineering. 2005;52(6):1143–8.

[9] Ibrahim EA, Awar SA, Balayah ZH, Hadjileontiadis LJ, Khandoker AH. A Comparative Study on Fetal Heart Rates Estimated from Fetal Phonography and Cardiotocography. Frontiers in Physiology. 2017;8.