Fetal Phonocardiogram Denoising by Wavelet Transformation: Robustness to Noise

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Abstract

Fetal phonocardiography (fPCG) is a clinical test to assess fetal wellbeing during pregnancy, labor and delivery. Still, its interpretation may be jeopardized by the presence of noise. Specifically, fPCG is typically corrupted by maternal heart and body organs sounds, fetal movements noise and surrounding environment noise. Thus, appropriate filtering procedures have to be applied in order to make fPCG clinically usable. Wavelet transformation (WT) has been proposed to filter fPCG; however, WT robustness to noise remains unknown. Thus, aim of the present work is to evaluate WT ability and robustness to denoise fPCG characterized by varying signal-to-noise ratios (SNR). To this aim a filtering procedure based on Coiflets mother wavelet (4^{th} order, 7 levels of decomposition) was applied to 37 fPCG simulated tracings, all available in the Simulated Fetal PCGs database by Physionet. Original SNR values ranged from -1.38 dB to 4.54 dB; after application of WT-filtering procedure to fPCG, SNR increased significantly, ranging from 12.95 dB to 17.94 dB ($P<10^{-14}$). Moreover, SNR values before and after filtering were associated by a low correlation ($\rho=0.4$; $P=0.01$). Eventually, WT filtering introduced no fPCG signal delay and left heart rate unaltered. Thus, WT filtering is a suitable and robust technique to denoise fPCG signals.

1. Introduction

Continuous and long-term fetal monitoring is essential for better accuracy in diagnosis [1]. Traditional non-invasive monitoring techniques (cardiotocography, fetal electrocardiography and ultrasound scan) allow a visual analysis of the fetal status, but appear sophisticated, expensive and operator-dependent [2-5]. An alternative approach is found in the fetal PhonoCardioGraphy (fPCG), which consists in the non-invasive recording of the acoustic sounds occurring during the fetal cardiac cycle through the abdomen of the mother [6]. Typically, there are two fetal heart sounds: the first heart sound (S1), that represents the closure of atrio-ventricular valves; and the second heart sound (S2), that represents the closure of semilunar valves. Considering its physiological meaning and its suitability, fPCG is potential clinically useful test to evaluate fetal heart rate (fHR) during pregnancy and to assess fetal wellbeing during pregnancy, labor and delivery [7,8].

Clinical fPCG interpretation may be jeopardized by the presence of various types of noise typically affecting it. Indeed, fPCG is a linear summation of fetal heart sounds, internal noise and external noise. The internal noise is a random signal caused by fetal movement, fetal breathing, maternal respiratory sounds, maternal digestive sound, maternal heart sound, placental blood turbulence. These noises are of low amplitude with main frequency components from 0 to 25 Hz [9]. Similarly, the external noise is a combination of shear noise from movement of the sensor during recording and environmental noise such as sound produced by fan, air conditioner, hue and cry of the nearby people, additional components result from powerline interference, reverberation noise and background noise [9]. It is comparatively of high amplitude and frequency. As it is heavily contaminated by noise, fPCG processing implies mandatory filtration of these noise components. Thus, appropriate filtering procedures have to be applied in order to make fPCG clinically usable and to extract important diagnostic information, such as fHR.

Wavelet transformation (WT) has been proposed to denoise fPCG. WT is an advanced signal processing technique that maps a time domain waveform into frequency-time domain waveform by providing a good localization in both time and frequency domains [7]. In this way, WT is an effective method to analyze the information of non-stationary signals providing a time-frequency localization which is useful to detect various signal information in both normal and pathological conditions [10]. In literature, WT is a well-known de-noising technique in the fPCG signal processing [7]; however, WT robustness to noise remains unknown.
Thus, aim of the present work is to evaluate WT ability and robustness to denoise fPCG affected by varying level of noise in order to correctly extract fHR.

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2. Material and Methods

2.1 Simulated Data

Clinical data consisted of 37 fPCG simulated tracings corrupted by different levels of noise (i.e. characterized by different signal-to-noise ratios; SNR), as in real recordings. Simulated PCG were generated (sampling frequency: 1kHz) as sequences of simulated S1 and S2 heart sounds to which corrupting noise was added. Noise is a sum of different contributions: maternal heart sounds, maternal body organs sounds, fetal movements, surrounding environment and additive white Gaussian noise. All fPCG are 8 min long, characterized by a fHR of 140 bpm and belong to the "Simulated Fetal PCGs database" [6,11] of PhysioNet [12] freely accessible on the web under the ODC Public Domain Dedication and License v1.0.

2.2 Wavelet Transformation Filtering

All fPCG signals were processed by means of continuous Wavelet Transform (WT).

WT is a time-frequency analysis method that quantifies temporal changes of the frequency content of non-stationary signals without losing resolution in time or frequency [13]. WT of the input signal x(t) is defined as the inner product (Eq. 1):

$$WT_{x(a,b)} = \int x(t)\Psi^{*}_{a,b}(t)dt \quad a \neq 0 \qquad (1)$$

where the basis function $\Psi_{a,b}(t)$ is the mother wavelet, featured by scale and shift parameters, a and b respectively. $\Psi_{a,b}(t)$ can be expressed as (Eq. 2):

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \qquad (2)$$

where a represents the scale parameter, b represents the translation parameter (time shifting), and $\Psi_{a,b}(t)$ is obtained by the mother wavelet function $\Psi(t)$ at time b and scale a. In terms of frequency, the multiresolution analysis provides global information of the signal corresponding to low frequencies and detailed information associated to high frequencies [14].

WT decomposes a signal into several multiresolution components (coefficients), and performs a series of high- and low-pass filter operations followed by down-sampling. Thus, the signals were decomposed into its frequency content form and then were reconstructed.

The fPCG signal is interfered by various noises with unknown spectral and temporal characteristics. Thus, a filtering procedure based on WT was applied to decompose the corrupted signal into several levels. The decomposition processing allows to remove the corrupting decomposed level to improve SNR.

In this work, mother wavelet Coiflets of 4th order with 7 levels of decomposition was used, since a preliminary still unpublished work indicated that this is the wavelet which provided best results for fPCG denoising. The flow chart of the denoising algorithm is reported in Figure 1.

2.3 Statistics

SNR values characterizing each fPCG were computed according to the following definition (Eq. 3):

$$SNR = 20 \cdot Log\left(\frac{PeaktoPeak\,fPCG}{4 \cdot std(fPCG)}\right) \qquad (3)$$

where PeakToPeakfPCG is a signal-measure representing maximum-minus minimum amplitudes of the S1 and std(fPCG) is a noise-measure representing the fPCG standard deviation. SNR values were computed before (SNRbefore) and after (SNRafter) WT filtering.

In order to evaluate association between two fPCG characterizing variables, the Pearson correlation coefficient (ρ) and the regression line where computed. Non-normal variable distributions were described in terms of 50th [25th; 75th] percentiles and comparted using the Wilcoxon Rank-Sum test for equal medians. Statistical significance was set at 0.05 in all cases.

3. Results

A qualitative example of raw and denoised fPCG signal is reported in Figure 2 that displays row fPCG signals with different levels of noise (left column of panels) and corresponding denoised fPCG signals after WT filtering (right column of panels), respectively.

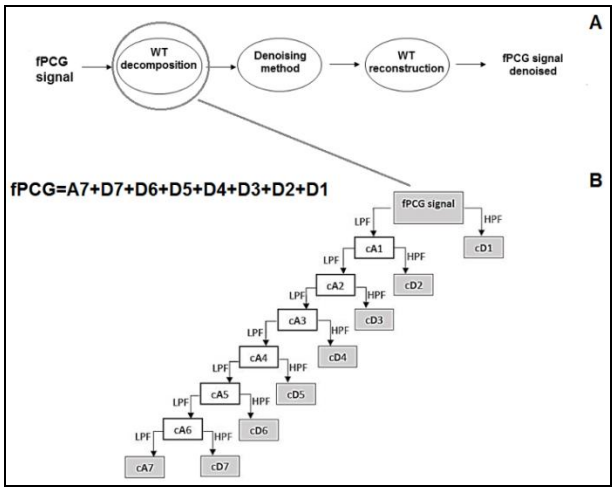

Figure 1. Panel A: WT-filtering block diagram; panel B: WT decomposition of fPCG signal.

SNRbefore values ranged from -1.38 dB to 4.54 dB and its distribution (0.15 dB [-0.60; 1.91]) was found to be characterized by a significantly lower value than SNRafter (15.86 dB [15.21; 16.27]; $P<10^{-14}$), which ranged from 12.95 dB to 17.94 dB. In addition, fPCG signals before WT denoising were perfectly aligned to those obtained after filtering and fHR remained unaltered (140 bpm). Eventually, SNRbefore and SNRafter were associated by a low correlation ($\rho=0.4$) but significant ($P=0.01$) correlation. Regression line was SNRafter=0.55·SNRbefore+14.95 (Figure 3).

4. Discussion

Aim of this study was to evaluate WT ability to denoise fPCG, varying SNR. To this aim, "Simulated Fetal PCGs database" [6,11] of PhysioNet [12] containing 37 simulated fPCG affected by different levels of noise. According to Physionet characterization of fPCG signals, SNR ranged from -26.7 dB and -4.4 dB. However, since original simulated fPCG signals and noise amplitudes were not available to reproduce such SNR values, these were recomputed as in Eq. 3.

Original and recomputed SNR values did not match

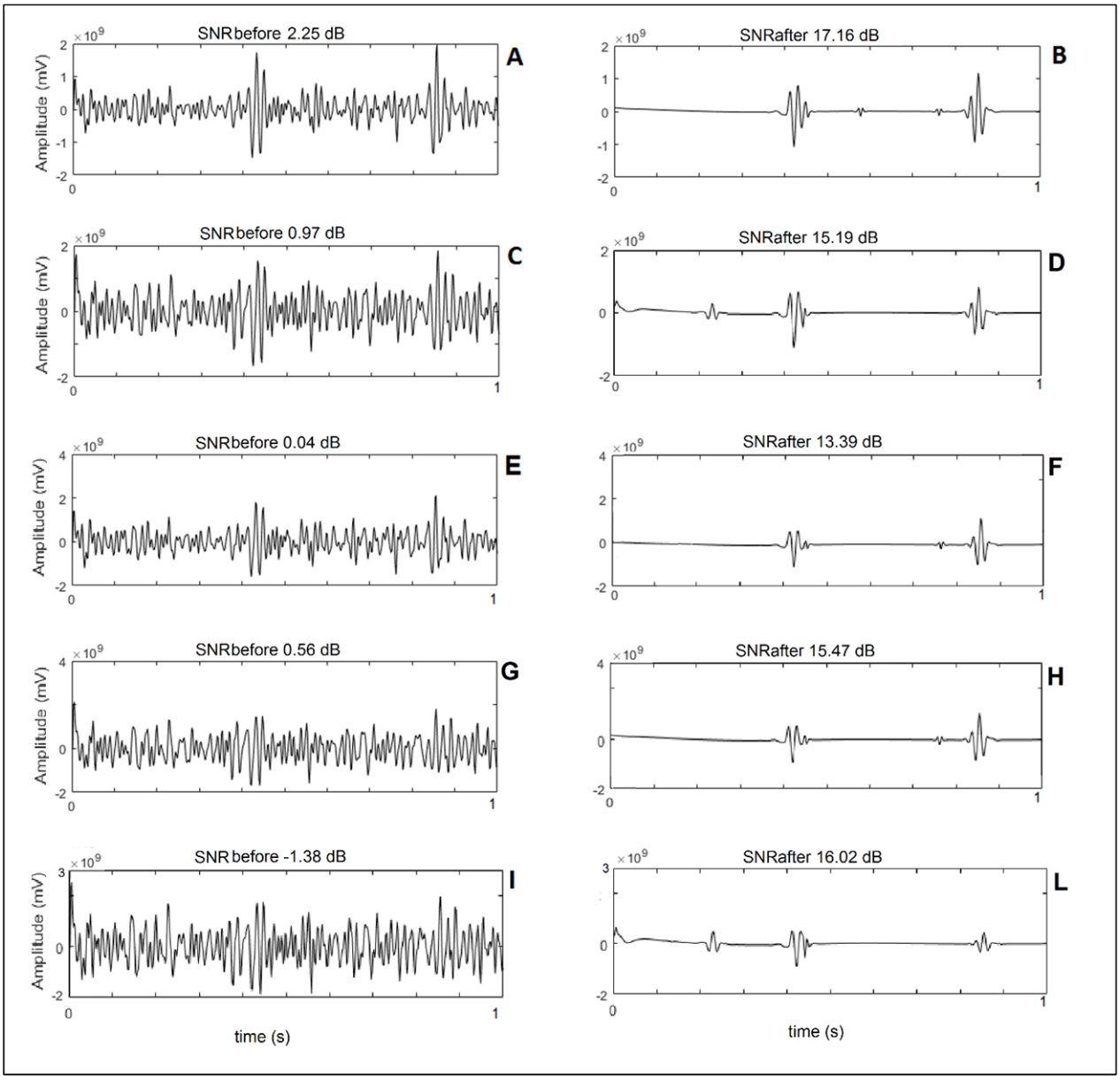

Figure 2. Raw fPCG signals affected by different levels of noise (right columns of panel) and corresponding denoised fPCG signals (right column of panels) after WT filtering.

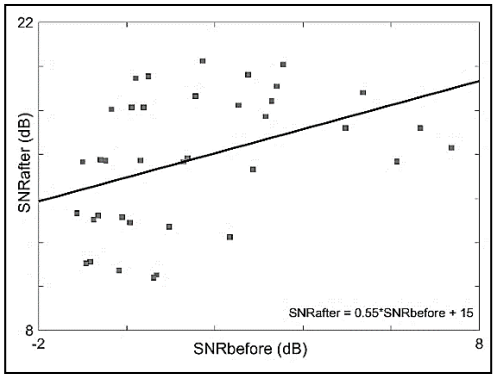

Figure 3. Association between SNR values before and after WT filtering.

numerically but were perfectly correlated (ρ=1.0; $P<10^{-200}$), indicating that they provide the same amount of information.

To denoise fPCG signals, WT with Coiflets mother wavelet (4th order, 7 levels of decomposition) was used. As shown in Figure 2, which qualitatively depicts denoised fPCG signals for several SNR, noise level was drastically reduced and S1 becomes always visible; still, some noise survived to filtration, especially in signals initially characterized by very low SNR. Denoised fPCG were perfectly aligned (same S1 location) and fHR values were unaltered, valid sign of how WT filtering introduces no signal delay and thus maintains unaltered fPCG clinical characteristics based on fHR. Eventually, WT filtering significantly increased SNR values ($P<10^{-14}$). Moreover, SNR values before and after WT filtering were associated by a low correlation coefficient, indicating that WT filtering is very robust to noise (low slope, Figure 3).

Future studies will have the aim to test the proposed WT-filtering procedure on real fPCG in order to confirm its clinical utility. Moreover, different mother wavelets and/or different decomposition levels will be tested in order to further confirm which is the optimal filtering configuration method for denoising fPCG signals.

5. Conclusion

Filtering based on WT with mother wavelet Coiflets of 4th order with 7 levels of decomposition is a suitable and robust technique to denoise fPCG signals since maintains unaltered fundamental fPCG features, like fHR and S1 time-location.

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