DENOISING OF HEART SOUND SIGNAL USING WAVELET TRANSFORM

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Abstract

This paper presents a novel wavelet-based denoising method using coefficient thresholding technique. The proposed method uses the adaptive thresholding which overcome the shortcomings of discontinuous function in hard-thresholding and also can eliminate the permanent bias in soft-thresholding. The qualitative evaluation of the denoising performance has shown that the proposed method cancels noises more effectively than the other examined techniques. The introduced method can be used as preprocessor stage in all fields of phonocardiography, including the recording of fetal heart sounds on the maternal abdominal surface.

Keywords *– PCG signal*, wavelets, signals to noise ratio (SNR), percentage of reconstruction (PR).

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1. INTRODUCTION

Phonocardiography is one of the best graphical representations of the heart sound and murmurs, which documents the timing and annotates their different relative intensities and provides valuable information concerning the heart valves and hemodynamics. Unfortunately the heart sound signal is very weak and can be easily subject to interference from various noise sources. These various noise components make the diagnostic evaluation of phono cardio graphic (PCG) records difficult or in some cases even impossible.

Cardiovascular diseases are the 21st century epidemic. Ageing, obesity, sedentary lifestyle and numerous other factors contribute to its growing numbers, with devastating causes, both economic and social. Heart sound provides clinicians with valuable diagnostic and prognostic information. Cardiac auscultation is one of the oldest methods for heart function assessment as it is a non invasive, low cost method which provides accurate information about heart mechanics and hemodynamics [1], [2], [7], [8].

Unfortunately, heart sound recordings are very often disturbed by various factors such as: respiration sounds (lung mechanics), patient movements, small movements of the stethoscope ("shear noises"), acoustic damping through the bones and tissues, and external noises from the environment etc. In case of fetal phonocardiography the most commons disturbances are: acoustic damping of forewaters and maternal tissues, acoustic noises produced by the fetal movements, noises of the maternal digestive system, and sounds of maternal heart.

Most of the existing phonocardiographic processing methods concern only with the diagnostic analysis of heart sounds without an adequate emphasis on the denoising of the PCG records. Existing methods usually apply digital band-pass filters (most commonly IIR-filters of FFT-based filtering) as a simple denoising method. The cut-off frequencies of the filters are determined by empirical observations, and commonly the pass band lies between 30 and 200 Hz [3], [4], [5], [6], [7].

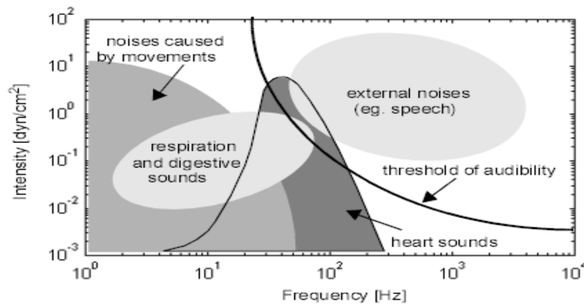

Fig. 1: Spectral intensity map of PCG records [8].

This paper presents a novel technique, which allows a more effective noise cancellation, also can be used as an advanced preprocessing stage in phonocardiographic diagnosis analyzer systems.

2. METHODS

In this proposed method Wavelet Transform is used for denoising of PCG signal, as wavelet allows to do multi-resolution analysis, which helps to achieve both time and frequency localization. Wavelet algorithms process the data at different scales or resolutions. In this proposed method we have studied the performance of different wavelets on PCG signal and an attempt is made to find the wavelet which gives the higher result for signal to noise ratio for all types of PCG signal and best level of reconstruction.

The coefficients of the Wavelet Transform (WT) of any signal contain important information whose amplitude is large, while wavelet coefficients of noise are small in amplitude. Selecting an appropriate threshold in different scale, the coefficients will be set to zero if it is below the threshold, while be retained if above the threshold, so that the noise in the signal is effectively suppressed. [9], [10]. Finally the reconstructed and filtered signals are obtained using wavelet inverse transform [11].

A wavelet is simply a small wave which has energy concentrated in very small time duration, of which the main lobe contains approximately the 98 % of the energy and the side lobes contains the rest 2 % of the energy given in equation (1) and depicted in figure 2. The wavelet basis's shifting and translation capability enables the wavelet to equip with flexible and variable time and frequency windows that narrow down at high frequencies and broaden at low frequencies, making it available to localize on any detail of the analytical object. Hence due to these enormous properties Wavelet Transform is suitable for analyzing such a highly unstable, transient, non-stationary signal like phonocardiogram (PCG). heart sound signals. As a result, the multi-resolution analysis of the wavelet has good characteristics and advantages in both the space domain and frequency domain [12].

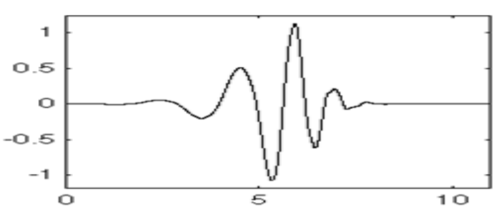

Fig: 2 db6 wavelet

$$CWT_{f(t)}^{\Psi} = \Psi_{f(t)}^{\Psi} = \frac{1}{\sqrt{|s|}} \int f(t)\Psi^{*}\left(\frac{t-\tau}{s}\right) dt \ldots (1)$$

A signal f (t) can be better analyzed and expressed as a linear decomposition of the sums or products of the coefficient and function of a wavelet function shown in Fig. 2. The set of coefficients are called the Wavelet Transform of f (t), which maps the function f (t) of a continuous variable into a sequence of coefficients having four properties. The representation of singularities, the representation of local basis functions to make the algorithms adaptive in-homogeneities of the functions, also having the unconditional basis property for a variety of function classes to provide a wide range of information.

A. THE BASIC ONE DIMENSIONAL MODEL

The noisy signal is obtained by generating and adding a white Gaussian noise to the original signal, mathematically given by

$$V_s(n) = V(n) + S(n) \ldots\ldots\ldots\ldots\ldots (2)$$

Where S (n) is the white Gaussian noise, V (n) noiseless PCG signal without noise and Vs (n) is the noisy PCG signal. Figure 3 depicts the plot of noiseless and noisy PCG signal.

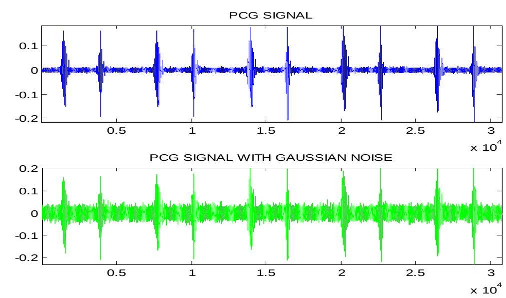

Fig. 3: PCG Signal without and with Noise

B. DENOISING PROCEDURES

The de-noising objective is to suppress the noise part of the signal S (n) and to recover V (n). From a statistical viewpoint, the model is a regression model over time and the method can be viewed as a nonparametric estimation of the function V (n) using orthogonal basis. The de-noising procedures are followed in three steps:

1. Decompose:

Choose a wavelet; choose a level L. Compute the wavelet decomposition of the signal s at level L.

2. Threshold detail coefficients:

Then this transforms (decomposed wavelet coefficients) are passed through a threshold, which removes the coefficients below a certain value For each level from 1 to L, select a threshold and apply the adaptive thresholding to the detail coefficients, given by

$$T = \sqrt{|M(n) + \sigma(n)|} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where M (n): mean of the n wavelet coefficients and σ (n): standard deviation of the n wavelet coefficient.

3. Choosing and applying threshold value:

This paper suggests an adaptive thresholding method which decides the different thresholding value at different level of decomposition for various Wavelets. For each level a threshold value is found through a loop, and it is applied for the detailed coefficients of the noisy and original signals. The optimum threshold is chosen by taking the minimum error between the detailed coefficients of noisy signal and those for original signal. A soft thresholding is used to shrinkage the wavelet detailed coefficients of the noisy signal such that:

$$C_o(s,\tau)\begin{cases} = C(s,\tau) & \text{if } C(s,\tau) \geq T \\ = 0 & \text{if } C(s,\tau) \leq T \end{cases}$$

Where C(s,τ): wavelet transform coefficients, Co(s,τ): is the output wavelet transform coefficients after thresholding, and T is the chosen threshold. Threshold determination using above method and the idea of not to threshold the approximation coefficients of PCG signal. The approximation coefficients contain the low frequency of the original signal where most energy exists.

4. Reconstruction:

The original signal is reconstructed using Inverse Wavelet Transform IDWR (Fig.4).Thresholding of wavelet coefficients affects greatly the quality of PCG morphology, thus, threshold determination is very essential issue in this case.

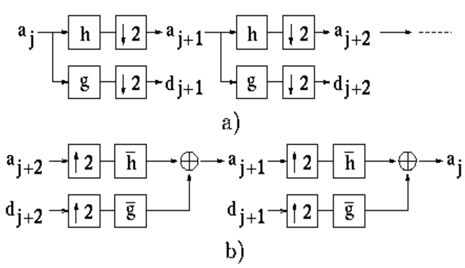

Fig 4 (a) decomposition, (b) reconstruction

Two parameters are used to ensure the qualitative studies of PCG denoising are:

1. Signal to Noise Ratio (SNR):

Signal-to-noise-ratio is a traditional method of measuring the amount of noise present in a signal. The standard definition of the SNR is the following, considering both signals V (n) and noise S (n) individually, during respective time periods L and N:

The SNR is given by:

$$(SNR = 10 * \log(Power_{signal} / Power_{noise})$$

$$= \frac{\frac{1}{L}\sum_{i=1}^{L} x_i^2}{\frac{1}{N}\sum_{i=1}^{N} n_i^2} \text{ (in dB)} \quad \ldots..(4.4)$$

2. Percentage of Signal Reconstruction:

The reconstruction level is analysed by the factor percentage of reconstruction given by

$$PR = (1 - \varepsilon) * 100$$

Error signal given by

$$\varepsilon = \frac{S(n) - S_R(n)}{S_R(n)}$$

Where S (n): original PCG signal and SR (n): reconstructed PCG signal.

3. RESULTS AND DISCUSSION

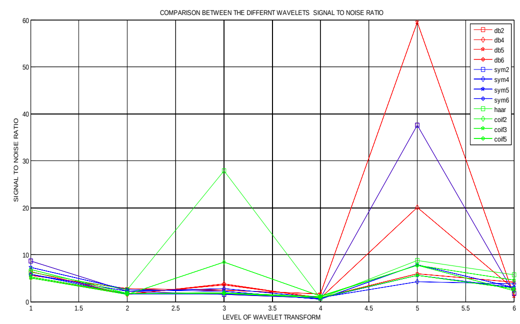

Fig 5: Plot of SNR at various level for different wavelet

The noisy PCG signal is tested with twelve different types of wavelet functions at six different levels. The result is depicted bellow in figure 5 which shows that, the wavelet function daubechies 5 (db5) gives maximum SNR at 5 level of decomposition giving the percentage of reconstruction moderate value. While, db5 at level 2 producing the maximum percentage of reconstruction given in table 1. The denoising results of denoising at the six different level of decomposition for db5 using the above relationship depicted in Fig. 6

Table 1 Percentage of Reconstruction

Wavelet Name / Level	1	2	3	4	5	6
db2	88.46	84.88	79.5	80.91	91.11	45.92
db4	93.67	92.73	91.42	75.57	65.89	66.69
db5	91.28	**98.19**	77.77	83.19	**92.06**	82.63
db6	88.06	91.83	83.31	73.23	89.9	57.02
sym2	88.46	84.88	79.5	80.91	91.11	45.92
sym4	89.4	89.44	81.29	79.11	66.56	56.19
sym5	87.84	91.05	91.19	89.64	70.15	77.57

sym6	89.21	93.51	91.21	90.13	67.79	87.12
haar	88.80	92.22	76.71	71.18	60.04	54.32
coif2	92.44	81.28	78.79	84.85	91.47	77.14
coif3	87.98	88.49	93.04	74.57	89.78	72.13
coif5	88.29	87.07	89.7	76.17	90.38	62.52

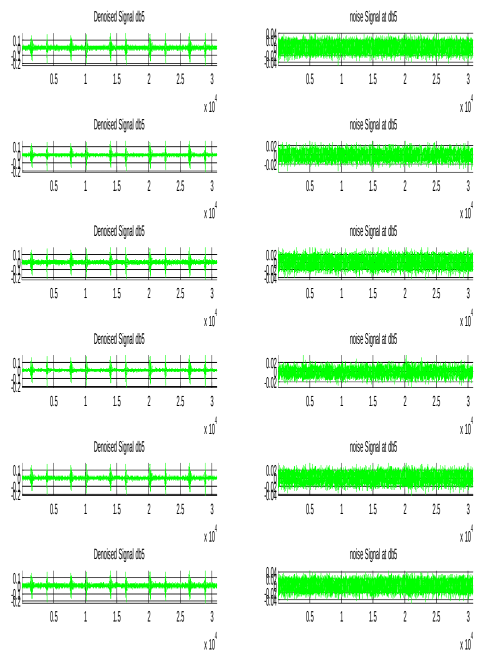

Fig 6: Denoising of PCG using db 5 for level 1 to 6

The presented method is based on choosing threshold value by finding minimum error of denoised and original signals. Therefore ensuring a high quality denoised signal and satisfied result.In this study a new relationship is suggested to find the threshold value for evaluation of PCG signal using various wavelet functions at different level. The results obtained are better than reported earlier in [10].

CONCLUSIONS

The main objective of the work described in this paper was to develop a robust denoising technique of the PCG signal. The introduced wavelet based signal analysis and adaptive coefficient thresholding methods produce a denoised heart sound signal which is more suitable for further diagnostic analysis. The threshold value is obtained experimentally after using a loop of calculating a minimum error between the denoised and original PCG signals.

For the future we design a wavelet which gives the much better result for the PCG signal. Also suggests some methods for denoising of PCG signals affected by different diseases. It is very much helpful for the physician to analysis the heart disease as easy and accurate.

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