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DENOISING OF PCG SIGNAL BY USING WAVELET TRANSFORMS

ABHISHEK MISAL[1*] AND SINHA G.R.[2]

[1]Department of Electronics & Telecoomunication, Chhattrapati Shivaji Institute of Technology, Durg, CG, India
[2]Department of Engineering & Tech., Shri Shankaracharya Technical Campus, Bhilai, India
*Corresponding Author: Email- abhishekmisal@csitdurg.in, drgrsinha@ieee.org

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Abstract- In this paper, we present a method for single channel noise reduction of heart sound recordings. Multiple noise sources, such as lung sounds, muscle contraction and background noise can contaminate the heart sound collection making subsequent analysis difficult. This method uses a “decision-directed” approach to estimate the noise without the need for a separate reference signal. The wavelet denoising method based on three thresholding functions is used for heart sound signals de-noising; soft-thresholding and hard-thresholding functions are traditional and an improved novel thresholding function with double variables parameters is novel. The critical point of the wavelet based de-nosing of signals is the choice of the wavelet and thresholds. The change of wavelet can give different results. It can overcome the shortcoming discontinuous function in hard-thresholding and also can eliminate the permanent bias in soft-thresholding. We have developed the function this denoises the PCG signal by different wavelets and results the selection of suitable wavelet that is best for a complex signal .
Keywords- Normalized root mean square error (NMRSE), Peak signal to noise ratio (PSNR), PCG signal, Wavelet transform.

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Introduction

Heart sound signals can reflect the physiological and pathological characteristics of the heart. Each heart beat is very complex and short and the main frequency of heart sound signals is in the range of 10Hz to 250Hz. Phonocardiogram can record heart sounds, noise and the additional sounds. So it is an important complement to make up the heart auscultation examination. Heart sounds are very weak acoustic signals. In the process to collect heart sound signals it is vulnerable to external acoustic signals and electrical noise interference, in particular, the friction caused by subjects breathing or body movement [1]. The sounds produced by friction in the phonocardiogram could give rise to a big interfering signal. Thus, it's important to analyze heart sound signals accurately and eliminate the interfering signal successfully during pre-processing [2] .With the development of the wavelet theory it has become a hot topic, so it also has been applied to the heart sound signal de-noising. Usually the methods include the de-noising to the details of the weight scales of the wavelet multi-resolution decomposition, the thresholding processing in wavelet domain, the modulus maxima method of the wavelet transform. These methods can effectively remove noise in heart sound signals, but there are some shortcomings that every wavelet is design for different for processing different type of signals. So in practical applications it needs some measures to improve denoising performance [1-2].

Related Research

There are several research papers reported in the literature on denoising using wavelet transform but few of them only could address the denoising of phonocardiogram signals. S. Messer et al. (2001) proposed the advantages of PCG over traditional auscultation in that they may be replayed and analyzed for spectral and frequency information. PCG is not a widely used diagnostic tool as it could be. This paper also discussed possible applications of the Hilbert transform to heart sound analysis are discussed [1]. L. Durand et al. (1995) provided a detailed review of the most recent developments in instrumentation and signal processing of digital phonocardiography and heart auscultation and described about a multidegree of freedom theory on the origin of the heart sounds and murmurs [2]. Zhao Xiu-min et al. (2009) proposed a novel de-noising method for heart sound signal using improved thresholding function in wavelet domain. The novel thresholding function can give different results only by changing the values of variable parameters [3]. H. Sava et al. (1997) demonstrate the feasibility of an adaptive time-frequency analysis, the matching pursuit method, to detect each cardiac cycle of the phonocardiogram (PCG). The method combines a global search of the PCG in terms of energy distribution of the most important components with a local search according to the specific events found within a cardiac cycle [4]. Vikhe et al. (2009) concerned with the analysis of the first (S1) and second (S2) heart sound of the Phonocardiogram signal (PCG) using Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT). Denoising and finding split between A2 and P2 is carried out using DWT. The frequency components of S1 and S2 of PCG are determined using CWT. Also split between A2 and P2 have been measured using CWT [5]. L. Durand et al. (1995) provide a detailed review of the most recent developments in instrumentation and signal processing of digital phonocardiography and heart auscultation. They discuss about a multidegree of freedom theory on the origin of the heart sounds and murmurs [6-7] F. Jin et al. (2008) considered problem of heart sounds (HS) localization from single channel respiratory sounds (RS) recordings by applying wavelet-based localization scheme. After a wavelet-based multi scale decomposition of the noisy signal, HS contaminated segments are localized in the noisy RS signal based on the cumulative sums of likelihood ratios capturing the dynamic behavior of the signal [8]. Djebbari et al. (2000) presented results of the PCG (phonocardiogram) signal analysis using the STFT (Short-Time Fourier Transform). Because of the nonstationarity of the PCG signal, it is important to maintain an analyzing time window as short as possible to guaranty the stationary hypothesis over small analyzed segments. This will reduce the frequency resolution of the resulting spectrogram [9]. Y Song et al. (2006) developed a passive acoustic apparatus for maternal abdominal fetal heart rate (FHR) monitoring. The fetal heart sound signals are detected, de-noised and reconstructed by utilizing wavelet transform based signal processing approach. The proposed approach improves the signal to noise ratio which allows reliable fetal heart rate variation to be estimated under very weak signal environment [10]. Bai. fang-fang et al. (2010) proposed a generalized mathematical morphology in handling the signal which contains noise, high-frequency and low-frequency noise could be eliminated by a combination of opening-closing and closing-opening generalized mathematical morphological filter, opening-closing and closing-opening generated through cascade of the structural elements of different sizes, based on mathematical morphology we combine threshold and removing interference peaks methods to improve the method of denoising, designing a method of removing noise which algorithm is simple [11]. Micheal Unser et al (1996) emphasized the statistical properties of the wavelet transform (WT) and discuss some examples of applications in medicine and biology. The CWT, in particular, can be interpreted as a pre whitening multi-scale matched filter. Redundant wavelet decompositions are also very useful for the characterization of singularities, as well as for the time-frequency analysis of non-stationary signals. Wavelets, present certain advantages because they can improve the signal-to-noise ratio, while retaining a certain degree of localization in the time (or space) domain [12]. Jalel Chebil et al. (2007) developed a fundamental tool in the diagnosis of heart disease. It is the most commonly used technique for screening and diagnosis in primary health care. The efficiency of this diagnosis can be improved considerably by using modern digital signal processing techniques [13 -14]. Sreeraman Raj et al (1998) presented a methodology for detecting all the components of the phonocardiogram (PCG) signal based on a time-scale map obtained from a proposed wavelet based bank of co-realtors, without the aid of any additional reference signal to provide cardiac phase information[15]. Anindya S. Paul et al. (2006) developed method for single channel noise reduction of heart sound recordings. Multiple noise sources, such as lung sounds, muscle contraction, and background noise can contaminate the heart sound collection making subsequent analysis difficult. Our approach is based on spectral domain minimum-mean squared error (MMSE) estimation, originally introduced by Ephraim and Malah in the context of speech enhancement [16]. O. Rioul et al. (1991) analysis of non-stationary signals, because it provides an alternative to the classical Short-Time Fourier Transform [STFT) or Gabor transform [GAB46, ALL77, POR80][17]. Jung Jun Lee et al. (1999) proposed the wavelet transform analysis method to the phonocardiogram (PCG) signal. Heart sound is a highly nonstationary signal. So in the analysis of heart sound it is important to study the frequency and time information. To investigate the exact features of heart sound we adopt Short-Time Fourier Transform (STFT) and Wavelet Transform (WT) as a time-frequency representation. As a result, it is found that the first sound in the PCG signal and the two components of the second sound are inaccurately detected. On the other hand, it is found that the wavelet transform is capable of detecting the two components [18]. Obaidat et al. (1993) presented Wigner distribution and wavelet transform analysis methods to the phonocardiogram (PCG) signals. A comparison between these three methods has shown the resolution differences between them [19].

Methods

Wavelet coefficients of the 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. [5-6] .Finally the reconstructed and filtered signals are obtained using wavelet inverse transform [7].

Wavelet Transform

A wavelet allows one to do multi-resolution analysis, which helps to achieve both time and frequency localization. Wavelet algorithms process data at different scales or resolutions [11]. If we look at a signal with a large window, we would notice gross (or averaged) features [10]. Similarly, if we look at a signal with a small window, we would notice detailed features.

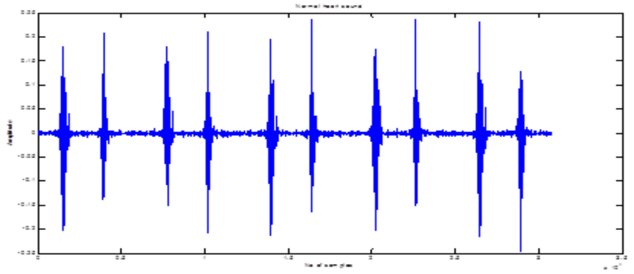

Fig. 1- Standard Normal Heart Sound Signal

Thus, by using varying resolution, the method not only inherits the excellent characteristics of the Fourier transformation but makes up for its disadvantages [11]. The wavelet basis's translation and companding capability enables the wavelet to possess flexible and variable time frequency windows that narrow down at high frequencies and broaden at low frequencies, making it available to focalize on any detail of the analytical object and perfectly suitable to analyze unstable 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]. Nowadays, wavelet analysis has successful applications in biomedical engineering, intelligent signal processing, image processing, voice and image coding, speech recognition and synthesis, multi-scale edge detection and reconstruction, fractal and digital television, and other fields [11]. In this paper we take four types of heart sound signal [13] which are: normal heart sound, aortic insufficiency, atrial septal defect and patent ductus arteriosus.

Signal Decomposition Using Wavelet Transform

The scaling function and wavelet functions can be implemented using pair of simple low pass and high pass filters. If the filters are interpreted with their impulse responses as {H(n),nЄN} for a low pass filter and {G(n),nЄN} for a high pass filter, then the decomposition of a signal using DWT will be as shown in Fig (2). This decomposition is also called as dyadic decomposition. First stage divides the frequency spectrum into two equal parts (low pass and high pass). The second stage then divides the low pass band into another low pass and high pass band .The second stage divides the lower half into quarter and so on[9],[7].

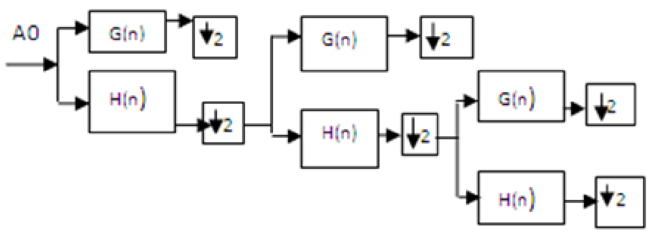

Fig. 2- Signal decomposition using DWT

where H (n) = impulse response of low pass filter, A-approximate coefficient s, G (n) =impulse response of high –pass filter, D-Detail coefficients, 2-down sampling by factor 2.

Six level wavelet decomposition

The heart sound signal is interfered by various noises with unknown spectral and temporal characteristics. The wavelet decomposition is applied to decompose the corrupted signal into several levels. The purpose of the decomposition processing is to remove the decomposed level which seriously corrupted by noise so as to improve the signal-to-noise-ratio. The six level wavelet decomposition is used in the processing. [5] The figure shows the graph of de-noised standard normal heart sound by db (2) wavelet from one to six levels.

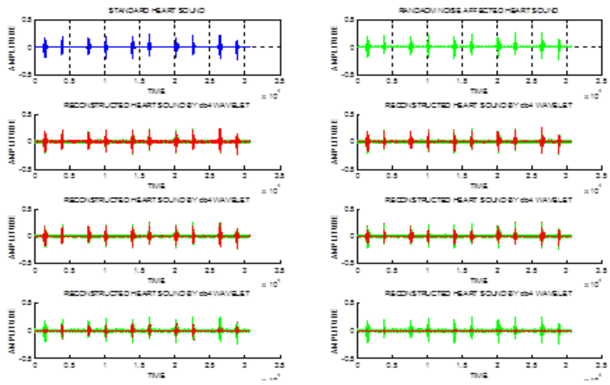

Fig. 3- The graph of the db (2) wavelet which contains ideal heart sound, noisy heart sound and different level of wavelet

Results

In order to illustrate performance of the new thresholding function, a section of the standard signal in the standard PCG phonocardiogram shown in Fig.(1) is chosen to be tested twice[14]. Firstly, adding low-intensity Gaussian noise to the standard signal as the first signal .Secondly, adding comparatively high-intensity Gaussian noise as the second signal. For objectively comparing the de-noising effect of the three methods, signal to noise ratio (SNR), the greater the value the better the de-noising is induced. SNR is defined as: [15].

$$SNR = \frac{\textit{power of signal}}{\textit{power of noise}} \quad (1)$$

The peak signal to noise ratio is other method of measuring the amount of noise present in a signal. PSNR is defined as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

$$PSNR= 10*\log10(N*(X^2))/Ediff). \quad (2)$$

It is the methods which find the error in the denoising process. NRMSE is defined as differences between values predicted by a model or an estimator and the values actually observed from the thing being modeled or estimated. NRMSD is a good measure of precision[11 -16] these individual differences are also called residuals, and the root mean square difference serves to aggregate them into a single measure of predictive power

$$NRMSE= \sqrt[2]{(M_{den}/M_{scal}} \quad (3)$$

According to the following parameters we calculate all the parameters for four types of heart sound in 6 level of decomposition. We show the maximum SNR, PSNR and minimum NRMSE in best level. In this table the maximum value is shown by red colour. For better analysis of wavelets transforms we plot the graph of all wavelets SNR which is shown below. Similarly other parameters graph is also plotted and evaluated their performance. The heart sound is denoised by all the wavelets which are available in mat lab. [17-18-19] .The table shows value of SNR for all four sounds at their best level. In the table after the name of heart sound we mention the best level.

Table 1- Signal to noise ratio for random noises and white Gaussian noise

Level / wavelets	Normal heart sound (4)	Artial spectral defect (3)	Aortic insufficiency (3)	Patent ductus arteriosus (3)
db2	7.6556	4.8666	4.8666	-0.7916
db4	2.7819	7.5093	7.5093	6.8996
db6	2.0935	7.7634	7.7634	7.0625
haar	1.4554	4.4016	4.4016	4.1862
sym2	7.6556	5.9662	5.9662	5.5263
sym4	1.9861	7.6371	7.6371	7.0030
sym6	2.1060	7.8216	7.8216	7.1171
coif1	1.8529	5.9338	5.9338	5.5439
coif3	3.0965	8.0052	8.0052	7.2541
coif5	2.7233	7.9299	7.9299	7.2315
dmey	2.8423	8.0673	8.0673	7.1981
bior 1.1	1.4554	4.3780	4.3780	4.1917
boir 2.4	1.4554	7.3297	7.3297	6.6775
boir 3.3	2.6899	7.3857	7.3857	6.4271
rbio1.1	1.4554	4.3990	4.3990	4.2175
rbio2.4	1.2344	6.8179	6.8179	6.2909
rbio3.3	-0.6504	2.9131	2.9131	2.6758
rbio4.4	1.4781	7.2433	7.2433	6.6128

After calculating SNR we plot the graph between SNR calculated by different wavelets and their decomposition level.

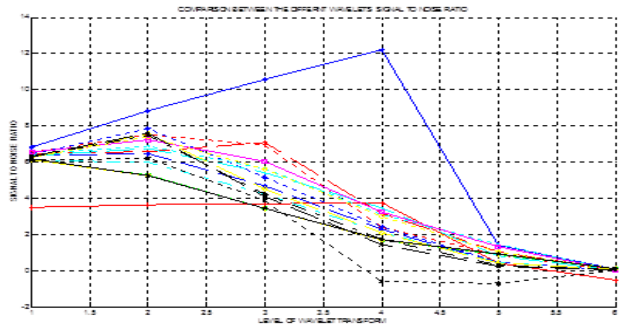

Fig. 4- Comparisons between different wavelets signal to noise for random noise

Conclusions

We have implemented the 'wavelet transform' method to PCG signal analysis and application. A comparison of the different wavelets has been shown. As we know that the performance of wavelet varies according to the different types signal. PCG signals are high frequency and low amplitude which are similar to the noise property so it is very important to find the suitability of wavelet giving the best performance. It has been found that for more than 0.2 volt and less noisy signal the *sym6* gives the best result and for less than 0.2 volt amplitude and noisier signal the *coif5* gives the best result. It means that if we recorded the heart sound of young and healthy people we can use the *sym6* wavelet for denoising and for children, aged person and weak person we can use the *coif5* wavelet for denoising the PCG signals. For persons sufferening with disease we can use coif5 wavelet for analysis of the heart condition and for any other person like athletes and young person we use the sym 6 wavelet. From the tables it is concluded that the symlet wavelets are the wavelets which depend on the signal amplitude if the signal amplitude is high the symlet wavelet gives best result.

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