An Automatic Wavelet Selection Scheme for Heart Sounds Denoising

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Abstract. The phonocardiograms (PCGs), recording of heart sounds, have many advantages 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. One of the major problems with PCG is noise corruption. Many sources of noise may pollute a PCG signal including lung and breath sounds, environmental noise and blood flow noises which are known as murmurs. Murmurs contain many information on heart hemodynamic which can be used particularly in detecting heart valve diseases. Therefore such diseases can be automatically diagnosed using Murmurs. However, the first step before developing any automated system using Murmurs is the denoising and the segmentation of the PCG signal from which murmurs can be separated. Different algorithms have been developed in the literature for denoising and segmenting the PCG signal. A robust segmentation algorithm must have a robust denoising technique. The wavelet transform (WT) is among the ones which exhibits very high satisfactory results in such situations. However, the selection of level of decomposition and the mother wavelet are the major challenges. This paper proposes a novel approach for automatic wavelet selection for heart sounds denoising. The obtained results on real PCG signal embedded in different white noise intensity showed that the proposed approach can successfully and consistently extract the main PCG sound components (sound component S1 and sound component S2) from various types of murmurs with good precision.

Keywords: phonocardiogram, wavelet selection, denoising, decomposition level

1 Introduction

Generally, cardiologists do not consider the diagnostic by stethoscope as a principal tool to take a final decision about cardiac pathologies considering the limitations of human ear in diagnosing heart defects particularly in sound levels lower than the audibility threshold. To deal with this problem, new tool (digital stethoscope) has been developed. This has the capacity to record and replay the heart beat sound recordings covering all the frequencies issued from the heart activities. These recording are known as phonocardiograms (PCGs). Since, the PCG became a particularly useful diagnostic tool because it can show timings and relative intensities of heartbeat sounds in graphical recordings, also it may reveal information that the human ear cannot [1-2]. The PCG signal consists of four heart sound components, these are S1, S2, S3 and S4. The main components of heart sound are first heart sound (S1) and second heart sound (S2). S1 occurs during ventricular systole and it contributes to the lub of the lubdub characteristic that can be heard from each heartbeat. It is produced by the closure of atrio-ventricular valves (mitral and tricuspid). Meanwhile, S2 occurs during ventricular diastole and it contributes to the dub. It is caused by the closure of the sigmoid valves (aortic and pulmonary). A third and a fourth sound (S3 and S4) may also exist. S3 occurs just after S2 and has relatively lower energy. S4 occurs just before the S1 and has lower amplitude com-pared to the others heart sounds [3-4]. However, a variety of heart murmurs can be also present. The presence of murmur in PCG signal is often related to heart valve disease. The production of murmurs results from turbulent flow across valves. Three main factors have been attributed to cause a murmur: (1) high flow rate through normal or abnormal orifices, (2) forward flow through a con-stricted or irregular orifice or into a dilated vessel or chamber, and (3) backward or regurgi-tant flow through an incompetent valve. The evaluation of murmur is based mainly on respectively its timing, its shape, its location, its intensity, and its duration in the cardiac cycle. The murmurs can be divided on two categories: systolic and diastolic murmurs. The systolic murmurs are generated during heart contraction by a stenosis in aortic valve or regurgitation in mitral valve for left heart, or by a stenosis in pulmonary valve or regurgita-tion in tricuspid valve in right heart. The diastolic murmurs are generated during heart re-laxation by a stenosis in mitral valve or regurgitation in aortic valve in left heart, or by a stenosis in tricuspid valve or regurgitation in pulmonary valve in right heart. For each situa-tion the murmur takes a particular shape, for example: crescendo-decrescendo shape for aortic stenosis, decrescendo shape for aortic regurgitation, plat shape for mitral regurgita-tion or tricuspid regurgitation[5]. The PCG would be a much more useful diagnostic tool if these murmurs can be extract-ed and processed in order to find different parameters that can be used to identify their causes or to estimate their severity. However, to extract such parameters it is essential that the PCG signal has to be segmented into different components, i.e., S1, S2, and murmur. In the figure 1 below, an example of PCG signals is illustrated.

Many researchers have been carried out in order to develop heart sound segmentation (HSS) algorithms. However, most of these works take the energy of PCG signal as the main parameter to segment the different components of heart sounds. As for example the algo-rithms proposed by H Liang et al [6] and L. Hamza Cherif et al [7]. They developed a HSS algorithm, which is based on the normalized average Shannon energy of PCG signal. The algorithms showed

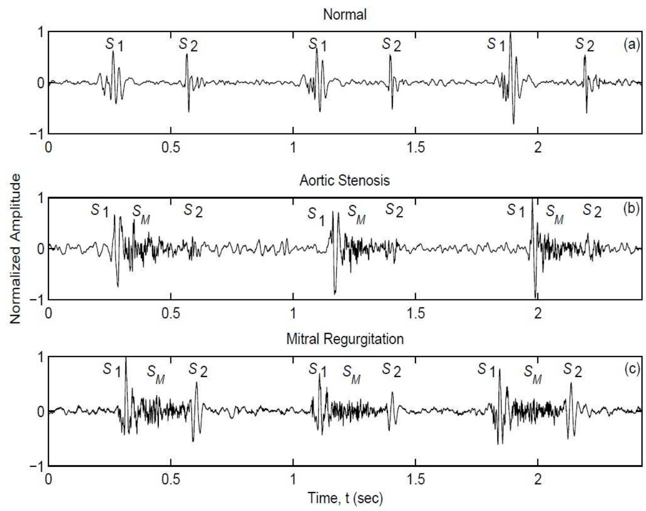

Fig. 1. Phonocardiogram of three heart sound sequences from: (a) normal heart sounds; (b) a case of medium aortic stenosis; (c) a case of severe mitral regurgitation. S1 and S2 represent the first and the second heart sound, respectively, while SM denotes the systolic murmur in aortic stenosis (b) and in mitral regurgitation (c). Adapted from [11].

good results particularly in the detection of S1 and S2. However, it was limited in cases where the heart sound was recorded with serious murmurs. Other researchers such as Malarvili et al. [8] proposed an approach to segment heart sound using the instantaneous energy of electrocardiogram (EKG) This technique showed a good result, however, it is not very appreciated because it needs two equipments simultane-ously an electronic stethoscope and an electrocardiogram. Also, this method fails to per-form properly due to the timing between electrical and mechanical activities. Other authors such as D.Kumar et al. [9] used a discrete wavelet transform and simplici-ty in the segmentation of PCG signal. In this article we can appreciate the powerful of sim-plicity measurement in envelope detection. However, the wavelet decomposition using DB6 as mother wavelet was unable to delete perfectly the murmurs. Their approach was not much better in the same difficult heart sound situations. The performance of this method degrades in severe murmurs. In such situation heart murmurs overlaps S1 and S2 sounds, leading to difficulty in identifying the boundaries of the sounds. Recently, A. Gavrovska et al. [10] and C. D. Papadaniil [11] proposed the application of empirical mode decomposition on HSS. This method seems to be important but it required long computation time. Also,this method is not tested on real PCG signals with various murmurs. The authors test the validity of their approach only by adding Gaussian noise with different levels. By analyzing the abovementioned methods, we can conclude that the HSS algorithms which lead to more successful segmentation results are based on DWT or EMD. However, as mentioned above the empirical mode decomposition process takes a long computation time compared with decomposition on wavelets transform. Also, we noticed that the DWT process is not perfectly studied in HSS. The majority of authors take the parameters found by [12] in the segmentation. However, these parameters are valuable only to remove Gaussian noise. This paper proposes an automatic scheme for mother wavelet selection in PCG signal denoising. The wavelets may be used to remove the murmurs and takeout only the basic sounds S1 and S2. The signal is decomposed by a discrete wavelet transform, the wavelet coefficients of S1 and S2 tend to be much larger than those due to murmurs. Thus, coeffi-cients below a certain level are regarded as noise and thresholded out. The signal is then reconstructed without significant loss of information. The question that this study attempts to answer is, which wavelet families, levels of decomposition, and thresholding techniques best remove the murmur in a PCG. In the proposed approach, the signal decomposition is performed at each level with all wavelet functions of a given library, followed by the calcu-lation of the proposed parameter (EXP). This method tends to concentrate the information of the main PCG components on the coefficients of greater relevance, providing a lower distortion of the signal. This part can be an extension of the work described by S. R. Messer et al. [12]. The paper is structured in three main sections: first section briefly explains the proposed method, in the second section achieved results are addressed, and finally in section 3 some main conclusions are drawn.

2 Methodology

The proposed methodology involves heart sound denoising using wavelet transform. Be-fore the description of the applied method, some generality on wavelet denoising are summarized in this section.

2.1 Denoising of heart murmurs

As stated above, the proposed method for denoising PCG signals is the DWT. Matlab routine provides built DWT by decomposing a signal into wavelet coefficients and then reconstructs it using the inverse discrete wavelet transform (IDWT). Many wavelet families are available in the toolbox. However, in the current study only orthogonal wavelets are examined since they allow perfect reconstruction of a signal. This operation is carried out by applying a series of highpass and lowpass filters in succession (quadrature mirror filters) and by downsampling to keep the original number of data-points. This procedure results in details, which are low scale, high frequency elements of the signal, and approximations, which are high scale, low frequency elements of the signal. This decomposition can be performed for many levels with the decomposition process being iterated for successive approximations [13]. In denoising operation all coefficients below a certain size are dis-carded with a specific threshold. In fact, some of the decomposed wavelet coefficients correspond to the main components (sound S1 & sound S2) of the PCG signal and others are associated with details on the original signal (murmurs). If the details are eliminated from signal decomposition, all characteristics of the main components can be extracted from the remaining coefficients since an orthogonal wavelet transform has the property of energy conservation [14].

2.2 Optimal parameter selection for wavelet denoising of PCG

When using wavelet to denoise PCGs, there are many factors that must be considered. Examples of such factors are respectively which mother wavelet to choose, which level of decomposition to fix, and which thresholding methods to use. In general, the more a wave-let resembles the signal, the better it denoises the signal. Various families of wavelets are provided in Matlab including the Morlet, Mexican hat, Meyer, Haar, Daubechies, Symplets, Coiflets and others [15]. In order to obtain perfect reconstruction after signal decomposition and a fast algorithm, only orthogonal wavelets will be considered. These wavelets are the Haar, Daubechies, Coifflets, and Symlets. In Matlab environment, the Daubechies family of wavelets consists of 45 wavelets, where Haar wavelet is the first and the most simple in this family. The Symlet family con-sists of 45 wavelets, and the Coiflet family of 5 wavelets. As mentioned previously, the signal attends a decomposition through quadrature filter banks resulting in approximations and details for each decomposition level. This process can be performed for many levels successively for each approximation obtained. To realize denoising operation, some threshold parameters must be chosen. The two common methods of thresholding a signal are soft and hard thresholding which are used in Matlab wavelet toolbox. The two methods can be defined as below where T represents the threshold and x denotes wavelet coefficient[16].

Hard Thresholding:

$$x_{ht} = \begin{cases} x & |x| \geq T \\ 0 & |x| < T \end{cases}$$

Soft Thresholding:

$$x_{st} = \begin{cases} sing(x)(x - |T|) & |x| \geq T \\ 0 & |x| < T \end{cases}$$

Although hard thresholding is a simplest method, soft thresholding can produce better results than hard thresholding. In fact, the hard thresholding may cause discontinuities at Ton reason that those values less than the threshold are set to zero. There are four principal rules to compute threshold T in wavelet toolbox :Sqtwolog, Rigrsure, Heursure and Minimaxi [16]. The first rule is a fixed threshold or global thresholding method and it is computed as the square root of two times the logarithm of the length of the signal. In the second method, the selection of threshold is based on Steins unbiased estimate of risk (SURE). This method estimates the risk for a certain threshold value T, and then by minimizing the risks in T, a selection of the threshold value is obtained. The third rule, Heursure, is a combination of first and second methods. If the signal-to-noise ratio of the signal is very small, then the SURE method estimation will have more amounts of noises. In this kind of estimation, the fixed form threshold is selected by means of global thresholding method. The fourth method also uses a fixed threshold which is chosen to yield minimax performance for mean square error (MSE). The minimax achieves the minimum of the maximum mean square error. It is generally used on statistics. These rules are resumed in the next table.

Table 1. Threshold selection rules

Rule name	Description
Rigrsure	Selection using the principle of Steins Unbiased Risk Estimate (SURE)
Sqtwlog	Fixed form threshold logarithm equal to the square root of two times the logarithm of the length of the signal
Heursure	Selection using a mixture of the first and the second rules
Minimaxi	Threshold selection using the minimax principle

In our work, the objective of the denoising process is to suppress the noisy part in the signal, murmurs, and recover S1 and S2 without noise. There are three methods available in Matlab wavelet toolbox which are one, sln, and mln define multiplicative threshold rescaling.The scheme one corresponds to no rescaling. The option sln performs threshold rescaling using a single estimation of level noise based on first-level coefficients. The mln method corresponds to the rescaling using level-dependent estimation of the noise at that decomposition level [16].

2.3 Auto-selection of Mother wavelet

Mother wavelet selection is one of the major tasks in wavelet-based Heart sounds de-noising. If the selected mother wavelet has high correlation with the real PCG signals, better denoising performance can be achieved. In the literature, some authors used fixed mother wavelets such as Daubechies 6, 11 and 20, Coiflet 4 and 5 and the symlet9, 11 and 14 [9,12,17]. However, heart sound signal is stochastic in nature and change from patient to other according to the pathological case. In [18], the author proposed to select mother wavelets based on simulative white noise added to PCG. However, since white noise may not match the real heart murmur, such approach may exhibit some limitations. On the other hand, other researches proposed several auto-selection schemes of mother wavelet, theses algorithms are used in denoising of Partial discharge signals [19-20]. Where, the highest energy in the approximation coefficientsis chosen as a principal parameter in the automatic mother wavelet selection[19]. More recently, in [20], the signal to noise ratio (SNR) is calculated in each level of decomposition, and the highest value of SNR is taken as reference to indicates the best level of decomposition with the best wavelet that can be used in the denoising operation.

In this paper, an automatic mother wavelet selection for heart sounds denoising is proposed. It is based on the determination of a coefficient EXP determined by the equation (1) given below.

$$EXP = cd_1 e^{ca_1} \tag{1}$$

Where cd_1 and ca_1 represents respectively the detail coefficients and the approximation coefficients, using a given mother wavelet for decomposition.

It is assumed that the main PCG signal component (S1 and S2) has higher energy than noises and they are only localized in the approximation coefficients. The determination of the exponential of these coefficients shows a high difference between the levels which have higher energy and those of lower energy. Then the multiplication of this exponential by the detail coefficient is used to increase the sensitivity in wavelet selection. The resulting coefficient is the EXP defined in the equation (1) above. The proposed algorithm is composed on the following steps:

1. Create a library of wavelet functions $\Psi_{(t,i)}$, for each type of wavelet family type : t=1,2,..,p and selected wavelet orders order: i=1,2,.,N.
2. For each wavelet of the library, perform the decomposition of the PCG signal in a single level, generating the approximation coefficients ca_1 and the detail coefficients cd_1.
3. Calculate EXP parameter in each wavelet, and select the one that produces the lower value as the best wavelet for that decomposition level.
4. Repeat steps 2) and 3) until the maximum number of levels is reached.
5. The higher value of EXP found in these levels indicates the most appropriate wavelet and the most appropriate level for the denoising operation.

The proposed algorithm will be compared with the algorithms described in [19] and [20]. The evaluation of each algorithm is carried out by calculating the correlation coefficient corr between the original PCG signal and the denoised one obtained by the selected mother wavelet in each level. In fact, more the correlation coefficient is near to 1 ($corr > 0,90$) , better is the denoising operation, if the coefficient of correlation is less than 0.90 the de-noising is jugged as poor. The others parameters used in denoising operation such as thresholding rule and rescaling method are arbitrarily fixed in sqtwolog and one. The maximum number of decomposition can be fixed using two methods. The first uses the lowest frequency component presents in the signal [21]. It is obtained by:

$$J = floor\left(log_2\left(\frac{F_s}{F_{min}}\right)\right) \tag{2}$$

Where, Floor is a Matlab routine which can round a number to the nearest integer towards minus infinity, Fmin is the frequency of the lowest frequency component whose power is greater than a certain percentage of the total signal power, and Fs is the sampling frequency of the signal. The second method uses the length of the signal [22].It is given by:

$$J = fix\left(log_2\left(length\left(signal\right)\right)\right) \tag{3}$$

Where, Fix is a Matlab routine which can round a number to the nearest integer towards zero. Our algorithm will be tested with a specific noisy signal. Unlike techniques that use only a various degree of white noise, we use a mixture between healthy PCG and a sinusoidal signal corrupted by a white noise as shown in figure 2. The broad range of heart murmur frequencies vary from 80 to 600 hz, and white noise cannot simulate these frequencies. Therefore, a sinusoidal signal is used with different amplitudes and frequencies to simulate various situations of murmurs. The mathematical model of our noisy signal can be expressed by nPCG.

$$nPCG(n) = PCG(n) + \sigma(n) \tag{4}$$

Where $PCG(n)$ is the useful signal and $\sigma(n)$ is the noise information , which includes a mixture of sinusoidal signal $sin_{(A,f)}$ and white noise $WN_{(I)}$ as presented by the following equation:

$$\sigma(n) = sin_{(A,f)} + WN_{(I)} \tag{5}$$

The noise σ depends of three variables A,f and I indicating the amplitude of sinusoidal signal, the frequency of sinusoidal signal and the intensity of white noise, respectively.

To evaluate the performance of our algorithm, three tests are carried out. The first test explores the effect of waveform frequency on auto-denoising operation, by varying the frequency of the sinusoidal signal from 80 to 500 hz, with a fixed value of amplitude at 0.2 and a fixed intensity of white noise at 2%. The second test explores the effect of waveform amplitude on auto-denoising operation, by fixing the sinusoidal signal to a specific frequency (i.e 200Hz) and to a specific intensity of white noise (2%), and varying the amplitude of the sinusoidal signal from 0.1 to 0.8.The third test explores the effect of white noise intensity on auto-denoising operation, by fixing the amplitude and the frequency of the sinusoidal signal at 0.2 and 200Hz, respectively, and varying the intensity of the white noise from 1% to 8%.

3 Results and Discussion

In the different tests carried out to evaluate the proposed algorithm, all Daubechies and Coiflet wavelet families are used. However, only the first 10 wavelets in the Symlet family are examined because their increasing complexity requires much more computation time. For example, on the same computer under similar conditions, the algorithm took about 6,5 s using only the first 10 Daubechies and 6,77 s using the first 10 Symlet. While using the last 10 Daubechies the algorithm took about 104 secs, however, the computation time increased to more than 10 mins (the algorithm has been cut) using the last 10 Symlet wave-lets. So, 60 wavelets (db1-45, sym1-10 and Coif1-5) are tested at each level.

In this paper, only third test which studies the effect of white noise intensity on auto-denoising operation is presented. Whither, 5 synthetic PCGs

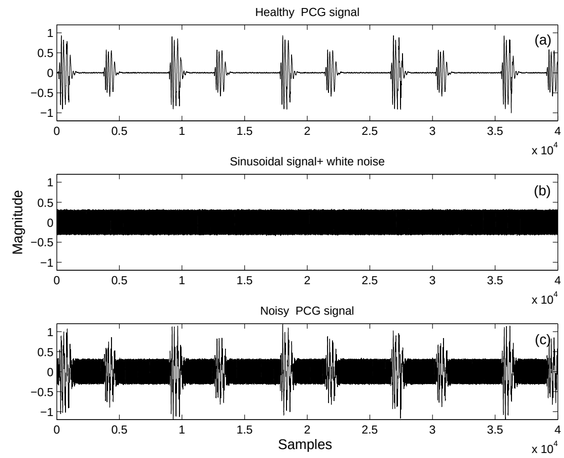

Fig. 2. The mixture used in the test. (a) clean PCG signal, (b) a sinusoidal signal (0.3sin(2.pi.100)) added with a white noise of 5%. (c) The resulting noisy PCG signal.

(nPCG1$\cdots$nPCG5) with various white noise intensity are used (see table2). For each signal, the performance of the methods (SNR[24], MAX[23] and EXP(the proposed method)) is compared. The processing of each method provides three informations (w, v and $corr$), indicating in each level the selected wavelet, the value found by the selected wavelet, and the correlation coefficient between the original signal and the denoised signal using the selected level and wavelet. Note that the maximum number of decomposition is fixed using equation (2). This last provides a number of 10 compositions for our test signal presented in figure 2.

In the case of nPCG1, where the intensity of noise is fixed at 1%, the highest value of SNR method indicates the wavelet $db43$ found at level 2 as the optimal. However the de-noising operation using these parameters provides a low correlation coefficient ($corr = 0.70$). Nevertheless, the highest correlation coefficient delivered by this method ($corr = 0, 94$) is found at level 6 via db17, but it cannot be detected. In the second method MAX, the highest value indicates the wavelet db43 at level 4 as the optimal. However the correlation coefficient found is too low ($corr = 0.70$). This method provides two high correlation coefficients at level 5 and 6 with a value of 0.93 and 0.96, respectively. Alike, these levels cannot be detected. In the proposed method (EXP), the highest value indicates the wavelet db32 found at level 5 as the optimal. Indeed, the correlation coefficient found by these parameters is the highest ($corr = 0.98$). This method provides another high value of correlation coefficient at level 6 ($corr = 0.97$). Also the value of EXP found in this level is great compared to the others.

The increasing of white noise intensity from 2% to 8% in the rest of test signal (see the cases nPCG2$\cdots$nPCG5 in table 2), the similar results can be observed. The proposed method provides better results than the others for most nPCG signals. The max(EXP) found coincides in most cases with the highest correlation coefficient used as reference method (*corr*). Also, it can be observed that the best denoising using EXP method is found in the middle levels of decomposition (5 and 6) and by using the same wavelet $db32$.

Figure 4 shows the evaluation of each method over decomposition levels for all test signals. From figure 4, the dark curves indicate the mean of correlation coefficient vectors found by each method. The colored curves indicate the evolution of the methods at each test signal.

Figure4.(a) presents the evolution of SNR method with its mean(*corr*) for all test signal. It can be observed that the curves evolve between two extreme values, max at level 2,3 and 4 and min at level 8. However, these points do not correspond to the highest value of correlation coefficient found in level 6. In figure4.(b), the same progression can be observed for Max method, the curve vary between two extreme values, max at level 4 and min at level 8. Also these points fail to meet the highest correlation coefficient value found in level 6. In figure4.(c) the evolution of the proposed method (EXP) is presented. It can be observed that this parameter takes a Gaussian form, where, its maximum coincides perfectly the highest correlation coefficient found in level 5.

Finally, it can be observed that the proposed algorithm presents the best performance in denoising of PCG signals, indicating that the idea of the exponential of approximation coefficients multiply by detail coefficients showed superior performance than those of other proposed methods.

4 Conclusion and future work

In this paper, we presented a novel automatic mother wavelet selection scheme, which selects the best mother wavelets and the best level of decomposition in PCG denoising operation. The proposed method based on the multiplication of detail coefficient by the exponential of approximation coefficient, referred as EXP, searches, at each level, for the mother wavelet that provide a smallest value, and then refers to the highest EXP value to select the wavelet and level of decomposition. The performance of the EXP scheme was compared to those of the SNR and MAX methods, previously proposed in the literature, for real PCG signal embedded in different white noise intensity. In order to evaluate the performance of the algorithm regarding murmurs extraction, the correlation coefficient was employed. .

The EXP method showed advantageous for most of the analyzed signals, indicating that the idea of searching the mother wavelet and the best level of decomposition using our method showed superior than maximizing the energy of approximation coefficients (MAX) or approximation coefficients to detail coefficients ratio (SNR). Future work will focus upon the improvement of computation time of this algorithm.

Table 2. Selected mother wavelets and decomposition level in different methods (SNR, MAX and EXP) by varying white noise intensity.

PCG Signal Sinus.Freq =200 Amp = 0.3			Decomposition Level 1	2	3	4	5	6	7	8	9	10
nPCG1 W.N = 1%	SNR	w	*db2*	***db43***	*db40*	*db27*	*coif1*	*db17*	*sym10*	*db12*	*db11*	*db8*
		v	17,03	**19,16**	18,08	13,08	5,262	5,719	1,83	-0,8	6,692	12,32
		corr	0,702	0,702	0,702	0,701	0,866	0,943	0,8	0,579	0,679	0,601
	MAX	w	*db42*	*db42*	*db43*	***db43***	*sym10*	*db14*	*coif4*	*coif4*	*coif4*	*coif4*
		v	2407	2415	2432	**2464**	1495	1204	670	382,8	745,4	1473
		corr	0,702	0,702	0,702	0,702	0,932	0,965	0,789	0,771	0,764	0,763
	EXP	w	*db1*	*db30*	*db19*	*db3*	***db32***	*db42*	*db34*	*db4*	*sym3*	*sym3*
		v	0,064	0,125	0,322	2,17	**52,24**	27,31	5,824	4,851	0,513	0,406
		corr	0,703	0,702	0,702	0,71	0,982	0,972	0,472	0,61	0,72	0,722
nPCG2 W.N = 2%	SNR	w	*db28*	*db23*	***db19***	*db33*	*coif1*	*db38*	*sym10*	*db12*	*db11*	*db8*
		v	14,22	15,85	**17,2**	13,28	5,355	5,692	1,821	-0,65	7,134	12,8
		corr	0,702	0,702	0,702	0,701	0,866	0,971	0,801	0,579	0,682	0,6
	MAX	w	*db42*	*db42*	*db43*	***db43***	*sym10*	*db14*	*coif4*	*coif4*	*coif4*	*coif4*
		v	2410	2416	2431	**2462**	1494	1204	668,9	382,1	745	1473
		corr	0,702	0,702	0,702	0,702	0,932	0,965	0,789	0,771	0,765	0,764
	EXP	w	*db40*	*db20*	*db33*	*db3*	***db32***	*db42*	*db34*	*db4*	*sym3*	*sym3*
		v	0,156	0,246	0,408	1,945	**54,37**	31,15	5,721	4,877	0,52	0,557
		corr	0,702	0,702	0,702	0,711	0,981	0,972	0,472	0,612	0,721	0,722
nPCG3 W.N = 4%	SNR	w	*db41*	*db26*	***db19***	*db33*	*db2*	*db17*	*sym10*	*db12*	*db11*	*db8*
		v	11,44	13,08	**14,48**	13,03	5,222	5,865	1,751	-0,95	6,325	11,7
		corr	0,699	0,701	0,702	0,701	0,862	0,943	0,801	0,577	0,675	0,597
	MAX	w	*db42*	*db42*	*db43*	***db43***	*sym10*	*db14*	*coif4*	*coif4*	*coif4*	*coif4*
		v	2428	2425	2435	**2463**	1495	1201	665	376	731,1	1445
		corr	0,699	0,701	0,702	0,701	0,932	0,965	0,79	0,771	0,764	0,763
	EXP	w	*db12*	*sym6*	*db5*	*db3*	***db32***	*db42*	*db34*	*db4*	*sym3*	*sym3*
		v	0,314	0,526	0,958	2,695	**55,55**	17,21	6,16	4,86	0,552	0,595
		corr	0,699	0,701	0,702	0,71	0,981	0,971	0,472	0,606	0,72	0,721
nPCG4 W.N = 6%	SNR	w	*db11*	*db26*	***db43***	*db27*	*coif1*	*db38*	*sym10*	*db12*	*db11*	*db8*
		v	9,341	11,09	**13,25**	13,11	5,236	5,756	1,713	-0,51	7,065	12,19
		corr	0,696	0,7	0,701	0,701	0,864	0,971	0,801	0,578	0,677	0,604
	MAX	w	*db42*	*db42*	*db42*	***db42***	*sym10*	*db14*	*coif4*	*coif4*	*coif4*	*coif4*
		v	2451	2435	2440	**2464**	1501	1213	675,9	400,1	780,6	1545
		corr	0,696	0,7	0,701	0,701	0,931	0,964	0,79	0,77	0,764	0,763
	EXP	w	*db38*	*db10*	*coif3*	*db3*	***db32***	*db42*	*db34*	*db4*	*sym3*	*sym3*
		v	0,502	0,715	1,294	2,202	**51,52**	25,79	5,665	4,954	0,522	0,671
		corr	0,696	0,7	0,701	0,711	0,981	0,971	0,47	0,611	0,72	0,721
nPCG5 W.N = 8%	SNR	w	*db20*	*db32*	*db44*	***db27***	*db2*	*db17*	*sym10*	*db12*	*db11*	*db8*
		v	8,586	10,1	11,5	**12,39**	5,402	6,236	1,951	-0,95	7,269	12,92
		corr	0,69	0,696	0,699	0,7	0,861	0,942	0,799	0,579	0,685	0,602
	MAX	w	*db43*	*db42*	*db43*	***db43***	*sym10*	*db14*	*db14*	*coif4*	*coif4*	*coif4*
		v	2486	2451	2445	**2464**	1496	1192	641,1	318,9	621,2	1229
		corr	0,69	0,696	0,699	0,7	0,93	0,964	0,62	0,769	0,765	0,764
	EXP	w	*db13*	*db20*	*db20*	*db39*	***db32***	*db42*	*db34*	*db34*	*sym5*	*sym5*
		v	0,662	1,066	1,566	3,842	**55,05**	23,38	5,633	4,755	0,356	0,26
		corr	0,69	0,696	0,699	0,7	0,98	0,971	0,472	0,328	0,705	0,699

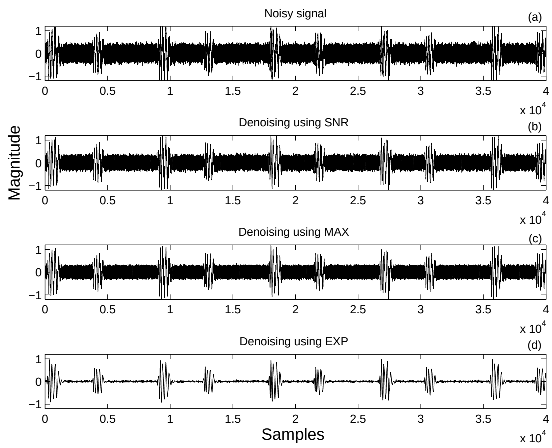

Fig. 3. Denoised signal found by each method. (a) Noisy PCG signal (case of PCG5-table4), (b) denoised signal from SNR, (c) denoised signal from MAX, (d) denoised signal from EXP.

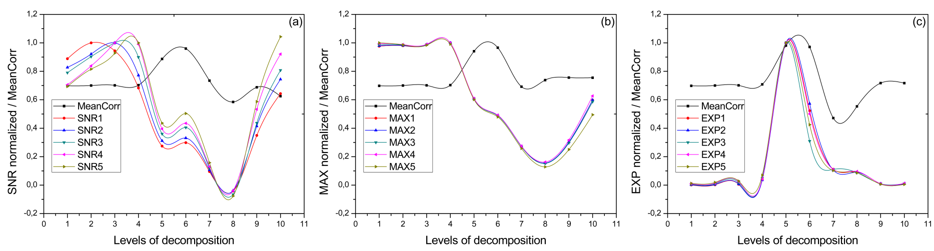

Fig. 4. The evolution of the methods over decomposition levels. (a): the evolution of SNR method, (b): the evolution of MAX method, (c): the evolution of EXP method (the proposed method).

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