SEGMENTATION AND TIME-FREQUENCY ANALYSIS OF PATHOLOGICAL HEART SOUND SIGNALS USING THE EMD METHOD

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ABSTRACT

The Phonocardiogram (PCG) is the graphical representation of acoustic energy due to the mechanical cardiac activity. Sometimes cardiac diseases provide pathological murmurs mixed with the main components of the Heart Sound Signal (HSs). The Empirical Mode Decomposition (EMD) allows decomposing a multicomponent signal into a set of monocomponent signals, called Intrinsic Mode Functions (IMFs). Each IMF represents an oscillatory mode with one instantaneous frequency. The goal of this paper is to segment some pathological HSs by selecting the most appropriate IMFs using the correlation coefficient. Then we extract some time-frequency characteristics considered as useful parameters to distinguish different cases of heart diseases. The experimental results conducted on some real-life pathological HSs such as: Mitral Regurgitation (MR), Aortic Regurgitation (AR) and the Opening Snap (OS) case; revealed the performance of the proposed method.

Index Terms— Empirical mode decomposition, heart sound signal; pathological murmurs; correlation function.

1. INTRODUCTION

Heart sound segmentation is considered as a helpful operation for detection and partitioning in main component and especially pathological murmur in each cardiac cycle. The two main audible Heart Sounds (HS) in a normal cardiac cycle are the first (S1) and second (S2) HS. The first HS S1 consists of two major components M1 and T1, corresponding, respectively to the mitral and tricuspid valves. However the second HS S2 consists of two main components noted A2 and P2 corresponding respectively to the aortic and pulmonary valves. A heart murmur (systolic murmur (SM) or diastolic murmur (DM)) may be an important sign for the diagnosis of heart disease. The EMD method was first proposed by Huang et al. in 1998 [1]. The EMD technique is considered as a powerful tool for non stationary signals. It permits the decomposition of multi components signals on mono-components such as amplitude and frequency modulated (AM/FM) called the Intrinsic Mode Functions (IMFs). In particular, this technique expands the analyzed signal in terms of basic functions that are signal-dependent, and which can be estimated via an iterative procedure called sifting. An efficient algorithm for his implementation has been presented [2]. In Reference [3], the authors have used the EMD for study the characteristics of white noise. This method have been used also for denoising and detrending signals corrupted with noise [4],[5] and [6].The problem of HSs segmentation have been studied [7] using normalized average Shannon energy to compute the PCG envelope. Another paper present a successfully method for heart sound segmentation [8] based on Shannon energy. However, the method fails to segment heart pathological murmurs. The authors in [9] presents an algorithm based on the S-method for extracting individual components applied on the OS signal for the diagnosis of heart diseases. Segmentation method based on windowing the HS signal using the discrete wavelet transform and selecting the wavelet detail coefficients by an adaptive peak is proposed in [10]. Samjin Choi et al [11] used the normalized average Shannon energy and the envelope information of Hilbert transform using the characteristic waveform in order to extract the envelope for the cardiac sound signal segmentation. Boutana et al in [12] used the time frequency distribution in conjunction with Rényi entropy measure for identification and segmentation of some pathological HSs. Recently; the same authors proposed a new HS segmentation approach using the EMD in conjunction with the noise only model [13]. This paper is organized as follows. In Section 2, we present an overview of the EMD method. In Section 3, we present the proposed algorithm based on EMD in conjunction with the correlation coefficient. Section 4 presents various pathological cases and experimental results, and Section 5 concludes the paper.

2. BACKGROUND OF EMPIRICAL MODE DECOMPOSITION

The EMD is a signal decomposition method that allows the separation of the observed signal into a set of IMFs plus a residual function. Each IMF represents a monocomponent signal or an oscillatory mode with one instantaneous frequency. An IMF must satisfy the following two basic conditions [1]:

(a) the number of extrema and the number of zero crossings must be either equal or different by no more than one in the entire data set,

(b) the mean value of the envelope defined by the local maxima and the local minima is zero at the energy point. Thus, an IMF represents a simple oscillatory mode imbedded in the signal.

The EMD algorithm [1] allows extracting an IMF from a given signal following the step:

Step 1: It identify the extrema (local maxima and minima) of the observed signal *x(t)*.

Step 2: it make the interpolation of the local extrema using cubic spline obtaining the upper and the lower envelopes.

Step 3: it calculates the local mean value m_1 (t) of the upper and the lower envelopes.

Step 4: it gives the first component $h_1(t) = x(t) - m_1(t)$ by subtracting $m_1(t)$ from the original signal .

Step 5: if $h_1(t)$ satisfies the two basic properties mentioned in points (a) and (b) above, then, declare it as an IMF.

Step 6: if not, $h_1(t)$ is considered as a new original signal, and the above steps are repeated until we obtain an IMF, noted as C_1 (t). At this stage, we obtain the residual function r_1 (t) as:

$$r_1(t) = x(t) - C_1(t) \tag{1}$$

Now, $r_1(t)$ is considered as a new signal and the above steps are repeated again in order to obtain the next IMF. At the end of the algorithm, we obtain a set of IMFs and a residue. The first extracted IMF contains the highest frequency oscillation that exists in the signal. Each extracted IMF contains a lower frequency oscillation than the one extracted just before it. We observe that the residual function is constant function without frequency components. Finally, we can express the original signal *x (t)* as follows:

$$x(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \tag{2}$$

where $C_i(t)$ represents the extracted IMFs and $r_n(t)$ is the residual function.

3. METHODS OF HEART SOUND SEGMENTATION

This method is used for the first time in heart sound segmentation [13].

3.1. The proposed method via the correlation coefficient

The correlation coefficient ρ in this study is given by:

$$\rho = \frac{\sum_{i=1}^{N} x_i C_i}{\sqrt{\sum_{i=1}^{N} x_i^2 \sum_{i=1}^{N} C_i^2}} \tag{3}$$

where x_i and C_i are the i-th samples of the original signal and the extracted IMF respectively. The correlation coefficient is a good criterion to separate between IMFs containing components similar to the original signal and others representing the murmur signal. In most practical applications, EMD provide noise or like-noise such as murmur at the first IMFs (IMF1, IMF2 and IMF3). The coefficient is calculated between the original signal and the extracted IMF and allows saying that if the signal changes. The estimation of (3) between the original signal and an IMF provide two situations: (i) if the original signal and the i-th IMF are different, then the correlation coefficient ρ would be very weak and (ii) if the original signal and the i-th IMF are quasi-identical, then the coefficient ρ would be strong. So, the coefficient ρ between the IMFs containing some murmur and the original signal were weak and permits to select them as the IMFs of the murmur signal.

3.2 *The algorithm of the proposed method*

We present a novel segmentation algorithm of the HSs to obtain the main components (S1 and S2) and pathological murmur separately. The flowchart in Figure 1 graphically illustrates the steps of the algorithm. The algorithm consists for estimating the IMFs given by the EMD and characterizing the pathological murmur using the correlation coefficients such as criteria. They are estimated between the extracted IMFs and the signal in consideration. Any IMF that has correlation coefficients equal to the maximum presents best similarity with the signal without murmur. However, the IMFs having a correlation coefficient less than this maximum value is considered as murmur signals.We retained the index M of the IMF having the maximum value of the correlation coefficients. Then, the summation of the IMF with index less than the index M provides the separated murmur. However, the summation of all IMFs having index from M to the end IMF give the signal consisting by the main components. In order to characterize in time frequency domain the separated murmur obtained after the segmentation, we used the Spectrogram (SPEC) given by the squared magnitude of the short time Fourier transform:

$$\left|S(t,f)\right|^2 = \left|\int_{-\infty}^{+\infty} x(\tau)\, h(\tau - t) e^{-j2\pi f \tau}\, d\tau\right|^2 \tag{4}$$

The time-frequency resolution trade-off of the spectrogram is controlled by the size of the analysis window h(t). A large kernel provides a narrow-band spectrogram (good frequency resolution), whereas a small kernel provides a wide-band spectrogram (good time resolution).

4. RESULTS AND DISCUSSION

The segmentation study was conducted on abnormal real-life PCG signals collected from [14]. Each PCG signal was sampled at a frequency resumed by the Table 1.

4.1. Example 1: Case of the mitral regurgitation

In the first example, the method is applied on the PCG signal of a patient affected by the Mitral Regurgitation (MR). In this case, the valve does not close properly and causes blood to leak back into the left atrium when the left ventricle contracts. MR is mainly characterized by SM starting just after the sound S1 and the presence of the third HS noted S3 as can be seen in the top of the Figure 2.This figure showing the EMD analysis of the MR signal revealed ten IMFs and a residue. It observed that the second first IMFs contains the most part of the murmur and the maximum value of the correlation coefficient is obtained with the third IMF. According to the Figure 3, the summation of the second first IMFs has given the separated murmur obtained by the proposed method and illustrated in Figure 4(c). However the Figure 4(b) illustrates the separated signal formed by the main components.

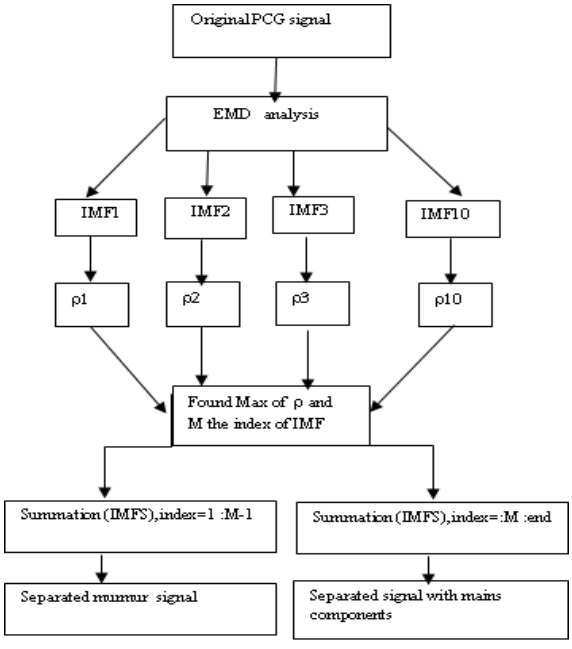

Fig. 1. Flowchart of the proposed algorithm.

The time frequency results obtained by the spectrogram are illustrated in Figure 5. It can be seen that the murmur of the MR is characterizing by a frequency range varying from 200 Hz to 500 Hz with complicated configuration. The dominant frequency component appears at frequency 200Hz and 400 Hz. We also observe the third signal S3 another characterization of the pathology.

PCG type	Notation	Sampling frequency, Hz
Mitral regurgitation	MR	8000
Aortic regurgitation	AR	8000
Opening snap	OS	16000

Table 1. The definition of the PCGs used signals.

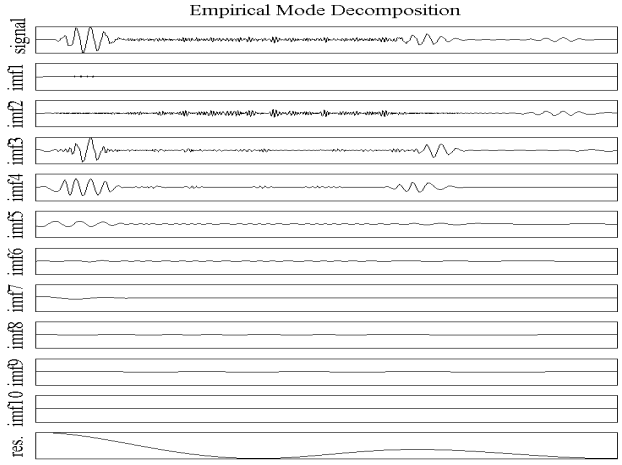

Fig. 2. EMD of the MR signal : from top to bottom the signal,ten IMFs and the residue.

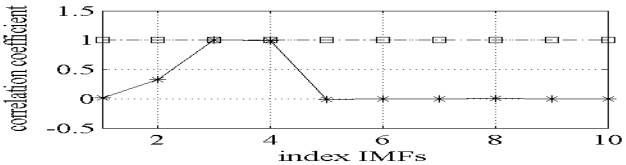

Fig.3. IMFs selection for MR signal by the proposed method.

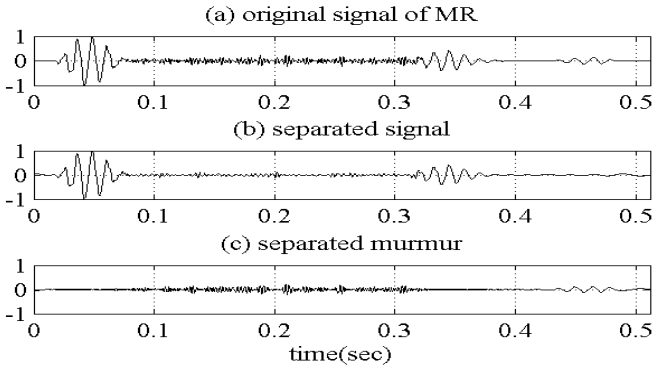

Fig.4. Segmentation results (a) MR signal, (b) separated signal and (c) separated murmur.

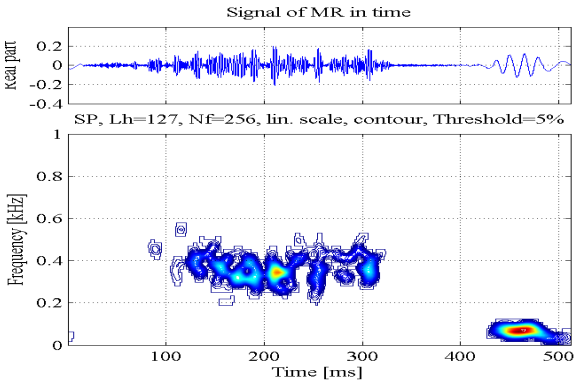

Fig. 5. (a) the extracted murmur of signal MR and (b) time frequency representation as contour plot (0-1KHz).

4.2. Case of the aortic regurgitation.

The second pathological HS signal studied in order to validate the method is the Aortic Regurgitation (AR).In AR a DM is close to the second HSs S2. It is caused by the backflow of blood across the aortic valve.EMD analysis of the AR signal has given 19 IMFs and a residue. We haven't introduced the figures of the EMD analysis because of the length limitation of the article. We can see that only the first four IMFs contain the murmurs signal. However, the fifth IMF presents the maximum value of the correlation coefficient and the start of the main components existing in the AR signal. The IMFs selection for HSs segmentation obtained by the proposed method is illustrated in the Figure 6. The separated signal is obtained by summing all IMFs from the fifth IMF to the end IMF (Figure 7 (b). However the murmurs signal is obtained by summing the IMFs from IMF1 to IMF4 such as showed in Figure 7 (c).The time frequency representation in the Figure 8 shows that the extracted murmur signal of AR lies from 200 Hz to 600 Hz and arrive after the second HSs S2.The peak of the dominant frequency of this DM is around 400 Hz with complicated configuration.

4.3. Case of the opening snap

The third pathological HS signal used is the Opening Snap (OS).The OS signal represented by a high–frequency sound associated with a stenotic mitral valve that can open only partially during the rapid filling phase of mid diastole. It is located after the second sound S2. EMD analysis of the OS signal has given 20 IMFs and a residue. We can see that only the first four IMFs contain the murmurs signal and the fifth IMF (IMF5) seems present the start of the main components existing in the original signal. The IMFs selection for segmentation of the OS signal is illustrated in the Figure 9. The separated signal is obtained by summing the IMFs from the fifth IMFs to the end IMFs (Figure 10 (b)). The murmur signal obtained by summing the IMFs from IMF1 to IMF4 is illustrated in Figure 10 (c).The time frequency analysis results are illustrated in Figure 11.The murmur signal of OS is located from 50Hz to 200 Hz with a peak value lies around 150 Hz, taken short time duration and arriving after the second HSs S2.

In table 2, the summary of some evaluated features that permit to distinguish between the pathological HSs used in this study is presented.

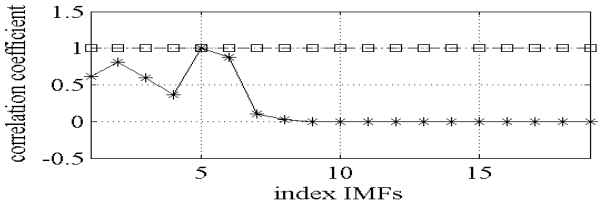

Fig.6. IMFs selection for AR signal by the proposed method.

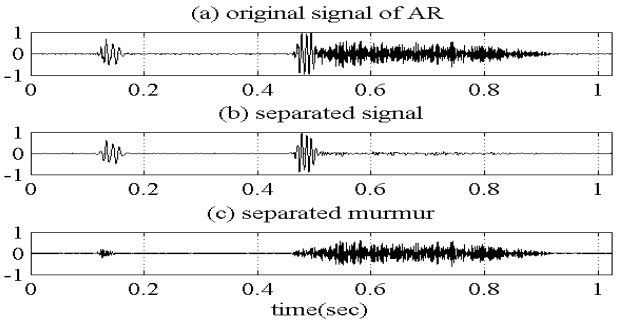

Fig. 7 Segmentation results (a) AR signal, (b) separated signal and (c) separated murmur.

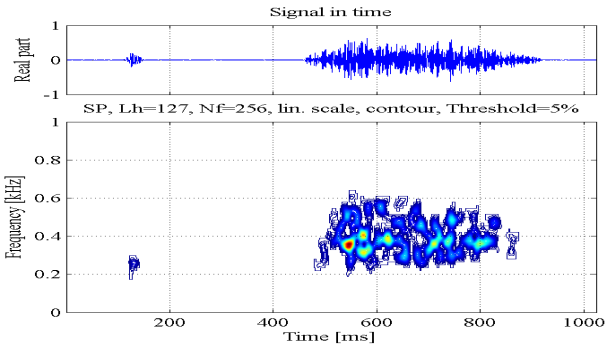

Fig. 8 . (a) the extrcated murmur of signal AR and (b) Time-frequency representation as contour plot (0-1KHz).

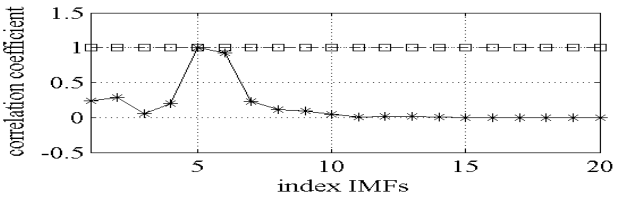

Fig.9. IMFs selection for OS signal by the proposed method.

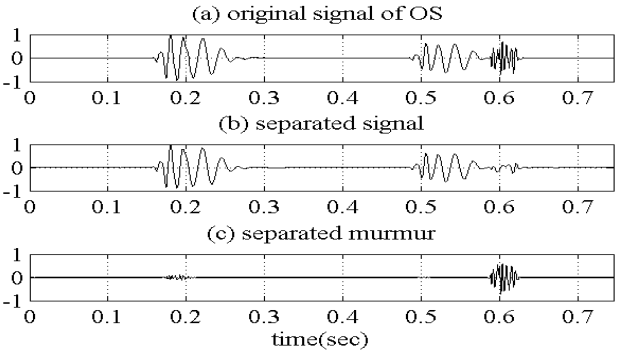

Fig. 10. Segmentation results (a) OS signal, (b) separated signal and (c) separated murmur .

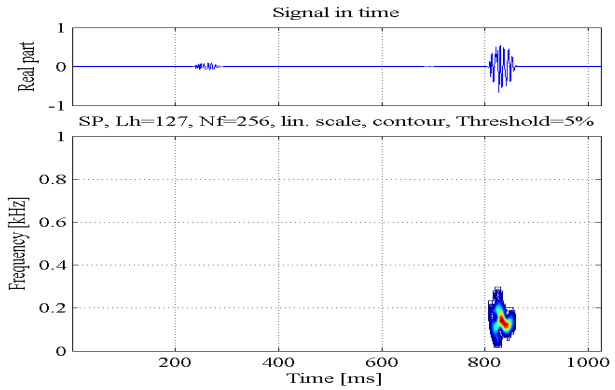

Fig.11 (a) the extracted murmur of signal OS and (b) Time frequency representation as contour plot (0-1KHz).

PCG signal	Band Frequency [Hz]	Peak of frequency [Hz]	location
MR	200-500	200 and 400	SM after S1
AR	200-600	400	DM after S2
OS	50-200	150	DM after S2

Table 2. Features and caracteristics for MR, AR and OS murmur signals.

5. CONCLUSION

In this paper a new approach of heart sound segmentation based on empirical mode decomposition in conjunction with the correlation coefficient is presented. The experimental results conducted on some real-life pathological heart sound signals revealed the performance of the proposed method. It may be used to discriminate between the IMFs giving the murmur signal and those providing the signal containing main components (S1 and S2). We have also extracted some features about the frequency characteristics of the studied cases of pathological murmurs. The proposed method is simple and gives good results for the studied pathological cases. It is expected that the results can be used to provide an aid in heart diagnosis systems. Work is underway for characterising and extracting some features and classifier several pathological HSs.

REFERENCES

[1] Norden E. Huang, Zheng Shen, Steven R. Long, Manli C.Wu, Hsing H. Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung and Henry H. Liu., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *In Proc. of the Royal Society of London,* 1998, vol. 454:903–995.

[2] G. Rilling, P. Flandrin and P. Goncalves, "On Empirical Mode Decomposition and its algorithms," *IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing NSIP-03, Grado (I)*, June 2003.

[3] Zhaohua Wu and Norden Huang, "A study of the characteristics of white noise using the empirical mode decomposition method," *In Proc. of the Royal Society of London,* Vol 460 pp.1597-1611, June 2004.

[4] P.Flandrin , P. Goncalves and G. Rilling, "Detrending and denoising with the empirical mode decomposition," *In proc. of Eusipco 2004,*pp.1582-1584.

[5] A. O. Boudraa and J. C. Cexus, "Denoising via empirical mode decomposition,"*In proc. of IEEE International symposium on control, communications and signal processing ISCCSP* 2006.

[6] Yanis Kopsisnis, Stefen McLauglin, "Empirical mode decomposition based soft thresholding," *In proc of the 16th European Signal Processing Conference* 2008, pp.43-47

[7] Liang H, Lukkarinen S, Hartimo I., "A heart sound segmentation algorithm using wavelet decomposition and reconstruction," *Proceedings of the IEEE EMBS, 19th Annual International Conf.* 1997; pp 1630-1633.

[8] D. Kumar, P. Carvalho, M. Antunes, J. Henriques, L. Eug´enio, R. Schmidt, J. Habetha, "Detection of S1 and S2 Heart Sounds by High Frequency Signatures," *Engineering in Medicine and Biology Society,EMBS '06. 28th Annual International Conference of the IEEE* Aug. 30 6-Sept. 2006,pp. 1410 – 1416.

[9] Ervin Sejdic, Predrag Rakovic, Milos Dakovic and LJubisa Stankovic , "An algorithm for decomposition of heart sounds based on S-method," *In proc. of the 15th European signal processing conference 2007,Sep. 3-7,*pp.2484-2488.

[10] Zümray Dokur and Tamer Ölmez, "Feature determination for heart sounds based on divergence analysis", *Digital Signal Processing* 19 (2009) 521–531.

[11] Samjin Choi, Youngkyun Shin , Hun-Kuk Park, "Selection of wavelet packet measures for insufficiency murmur identification", *Expert systems with Applications: An international journal* ,v.38 N°4,p.4664-4271,Avril,2011.

[12] Daoud Boutana, M. Benidir and B. Barkat, "Segmentation and identification of some pathological phonocardiogram signals using time-frequency analysis," *Signal Processing, IET* Volume: 5 , Issue: 6 , 2011 , Page(s): 527 -537.

[13] Daoud Boutana, B. Barkat and M. Benidir, "Segmentation of pathological heart sound signal using empirical mode decomposition", *International journal of computer and electrical Engineering,* Vol.5, N°1, February 2013.

[14] http://www.egeralmedical.com/