AN ALGORITHM FOR DECOMPOSITION OF HEART SOUNDS BASED ON S-METHOD

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ABSTRACT

Clinical experience has shown that heart sounds can be an effective tool to noninvasively diagnose some forms of heart disease. In this paper, an algorithm based on time-frequency analysis is used for the decomposition of the heart sounds. The decomposition algorithm is based on the S-method. The S-method is a time-frequency representation that can produce a distribution equal or close to the sum of the Wigner distributions of individual signal components. The decomposition algorithm is used for segmentation of the heart sound recordings that contain either of the two sounds: opening snap or third heart sound, which indicate distinct heart diseases. The results show that the algorithm effectively decomposes each heart beat into the corresponding components. Hence, they may be used in conjunction with a classification algorithm, allowing automatic decomposition and classification of the heart diseases associated with the opening snap and the third heart sound.

1. INTRODUCTION

Noninvasive diagnosis based on a stethoscope serves as a critical diagnostic tool in cardiovascular evaluation since it offers useful information about the functioning heart. Therefore, by using auscultation physicians attempt to analyze the heart sound components separately and then synthesize the heart features. They are particularly interested in irregular sounds, which suggest the presence of an abnormal cardiac pathology and also provide diagnostic information. For example, an important task in cardiovascular diagnostics is the distinct detection of two heart sounds known as an opening snap (OS) and a third heart heart sound (S3), since they indicate two different diseases [1] [2].

Along with other signal processing techniques, time-frequency analysis has already been used for the analysis and decomposition of the heart sounds. In particular, the OS and S3 have been studied in more details in [3] [4], where linear time-frequency techniques such as short-time Fourier transform, continuous wavelet transform and S-transform have been used for analysis. Recently, in [5] it has been shown that the bilinear time-frequency transform, known as S-method, provides higher resolution for the OS and the S3 than the linear time-frequency transforms, and hence, it is more suitable for analysis. There have been also contributions which dealt with the decomposition of the heart sounds based on the time-frequency tools [6]-[8]. However, these algorithms rely heavily on optimization of some of parameters introduced by authors.

In this paper we show that a recently proposed decomposition technique based on the S-method [9] [10] can be used for the automatic decomposition of the heart sounds. The technique is applied to heart sound recordings that contain either the OS or the S3. The aim of this investigation is to examine whether the technique is applicable to the heart sounds and whether the technique can extract the OS/S3 from the recordings.

The main contribution of the paper is the fact that by applying this time-frequency analysis based decomposition method, the heart sounds can be successfully separated into individual components. The benefit of these results lies in the fact that an automatic extraction and classification procedure can be developed for the diseases associated with the OS and S3.

This paper is organized as follows: An introduction to the heart sounds and the diseases associated with them is given in Section 2. In Section 3, the concepts behind the S-method and the decomposition technique are given. The results of the heart sounds decomposition are covered in Section 4. Finally, conclusions are drawn in Section 5 followed by a list of references.

2. HEART SOUNDS AND DISEASES

Despite numerous advances and decades of declining death rates, cardiovascular disease (CVD) remains the leading cause of death worldwide, contributing to more than 17 million deaths or one-third of all deaths each year. CVD is becoming increasingly prevalent in developing countries and, by 2010, CVD is expected to kill more people in developing countries than infectious diseases according to the World Health Organization [11]. Fortunately, clinical experience has shown that heart sounds can be an effective tool to noninvasively diagnose some of the diseases [1] [2], as they provide clinicians with valuable diagnostic and prognostic information concerning the heart valves and hemodynamics. Hence, heart auscultation is an important technique allowing the detection of abnormal heart behaviour before it can be detected using other techniques such as the ECG [12] [13] [14].

Heart sounds are the result of sudden closure of the heart valves during different phases of cardiac contraction. They are nonstationary, non-deterministic signals that carry information about the anatomical and physiological state of the heart. Heart sounds are a result of the interplay of dynamic events associated with the contraction and relaxation of atria and ventricles, valve movements and blood flow [2] [12]. Each heart beat consists of at least the first heart sound (S1) and second heart sound (S2). S1 occurs at the onset of ventricular contraction during closure of the mitral and the tricuspid valves. It indicates the beginning of ventricular systole. The intensity of S1 is closely related to that event. S1 consists of 4 components with frequency range 70-110 Hz. It starts with a low-frequency component (M1); synchronous with the first myocardial contraction after the onset of rise in the ventricular pressure. The second component (T1) has a higher frequency and is caused by tension of the left ventricular structures, contraction of the myocardium and deceleration of the blood flow. The third component, occurring at the time of the opening of the aortic valve, is related to a sudden acceleration of the blood into the ventricular walls. The fourth component is due to turbulence in blood flowing through the ascending aorta. The intensity of S1 varies depending on the following factors: position of auscultation, the anatomy of the patient's chest, the vigor of ventricular contraction, valve position at the onset of ventricular contraction, and pathological alternation of the valve structure [13] [15] . The S2 marks the end of ventricular systole and the beginning of ventricular relaxation following the closure of the aortic (A2) and pulmonary valves (P2). Therefore, S2 can be further decomposed into the subcomponents, A2 and P2. They are produced from vibrations initiated by the closure of the aortic and pulmonary semilunar valves and by sudden cessation of the backflow of blood [1] [2].

A heart problem, known as mitral stenosis, is caused by a rheumatic heart disease in the majority of cases, which leads to a narrowing of the mitral valve. As a result, it slows down the free flow of blood from the left atrium to the left ventricle. Blood returning from the lungs backs up in the left atrium and in the lungs. As a consequence, there is a gradual increase of pressure in the left atrium and pulmonary (lung) circulation. This condition will eventually lead to an enlargement of the left atrium and weakened atrium walls; gradually resulting in more serious conditions due to a reduced ability to propel blood efficiently [15]. Mitral stenosis is very often manifested through the heart sound known as opening snap (OS), which is a short, sharp sound occurring in early diastole, caused by abrupt halting at its maximal opening of an abnormal atrioventricular valve and the OS usually occurs 0.08-0.10 s after S2 [2] [13]. However, the difficulty lies in the fact that the OS sounds very similar to the third hear sound (S3), which is often heard in normal children or young adults but when heard in individuals over the age of 40 it usually reflects cardiac disease characterized by ventricular dilatation, decreased systolic function, and elevated ventricular diastolic filling pressure. It is generally difficult to distinguish them by hearing the sounds without sufficient training [1] [2] [13].

3. DECOMPOSITION BY S-METHOD

The methodology behind the decomposition algorithm is described in this section. Only the essential details are presented here. For further information about the algorithm, the reader should refer to [9] [10].

Let us assume a multicomponent signal of length N:

$$f(n) = \sum_{i=1}^{M} f_i(n) \tag{1}$$

consisting of M monocomponent signals, $f_i(n)$. Given a definition of the STFT for some signal, $f(n)$, as [16][17]:

$$STFT(n,k) = \sum_{m=-N/2}^{+N/2} f(n+m)w(m)e^{-j\frac{2\pi}{N+1}mk} \tag{2}$$

where $w(n)$ is a window function, then the S-method is defined as [18]:

$$SM(n,k) = \frac{1}{N+1}\sum_{l=-L}^{L} P_d(l) \times STFT(n,k+l)STFT^*(n,k-l) \tag{3}$$

where $2L+1$ is the width of a discrete window $P_d(l)$. In this paper, a rectangular window will be used in the computation of the transform. A basic property of the S-method is that it can produce a time-frequency representation of a multicomponent signal equal to the sum of the Wigner distributions of each component, avoiding cross-terms. Note that the spectrogram can be obtained for $L = 0$ and the Wigner distribution for $L = N/2$ [18].

Assume that the STFT of each component lies inside the region $D_i(n,k)$, $i = 1,2,...,M$, Denote the length of i^{th} region along k, for a given n, by $2B_i(n)$, and its central frequency by $k_{0_i}(n)$. The S-method of $f(n)$ is equal to the sum of the Wigner distributions, $WD_i(n,k)$, $i = 1,2,...,M$, of each signal's component separately [9][10]:

$$SM(n,k) = \sum_{i=1}^{M} WD_i(n,k). \tag{4}$$

if the regions $D_i(n,k)$, $i = 1,2,...,M$, do not overlap, $D_i(n,k) \cap D_j(n,k) = \emptyset$ for $i \neq j$, and the number of terms L in (3), for a point (n,k), is defined by:

$$L(n,k) = \begin{cases} B_i(n) - \|k - k_{0_i}(n)\| & \text{for } (n,k) \in D_i(n,k) \\ 0 & \text{elsewhere.} \end{cases} \tag{5}$$

Proof is very similar to the one provided for the continuous S-method case in [19].

This is the S-method with a constant value of L, as it was originally introduced in [18], and it will be used in this paper. The signal dependent method would be more accurate, but also more complex. A constant number of terms are used here in numerical implementation since it simplifies the implementation, producing satisfactory and robust results.

Given (4), let us introduce the notation

$$R_{SM} = \frac{1}{N+1}\sum_{k=-N/2}^{N/2} SM\left(\frac{n_1+n_2}{2},k\right) e^{j\frac{2\pi}{N+1}k(n_1-n_2)} \tag{6}$$

Using eigenvalue decomposition of the matrix R_{SM}, whose elements are $R_{SM}(n_1,n_2)$, we get

$$R_{SM} = \sum_{i=1}^{N+1} \lambda_i u(n)u^*(n) \tag{7}$$

The eigenvectors, $u_i(n)$, will be equal to the signal components $f_i(n)$, up to the phase and amplitude constants. Amplitude constants are contained in the eigenvalues λ_i. Phase constants can be determined by multiplying each reconstructed component by $\exp(j\phi_o)$, where $0 \le \phi_o < 2\pi$, and by subtracting the product from the original signal. The phase value, ϕ_o, that minimizes the energy of the remainder is chosen as the phase constant of the component. Note that it is assumed that signal components do not overlap in the time-frequency plane which implies their orthogonality.

Originally, the decomposition algorithm is proposed for the multicomponent signals, whose components are separated in frequency bands [9] [10]. The decomposition is also valid for the multicomponent signals whose components are separated in time, however, a slight modification is required. Instead of the time-domain version of the signal, its Fourier transform, $F(k)$, should be used in (2). Therefore, the calculation procedure is given as follows:

- Choose appropriate time window $w(n)$.
- Calculate the Fourier transform of the signal, i.e., $F(k) = \mathscr{F}\{f(n)\}$.
- Calculate the STFT of the zero-padded $F(k)$, which is also oversampled by factor 2. Oversampling is necessary in order to avoid noninteger indices in (6).
- Choose value of L such that (4) is satisfied.
- Calculate the S-method of the signal according to (3) for a given L.
- Calculate the matrix R_{SM} according to (6).
- Decompose R_{SM} into eigenvectors and eigenvalues.

The first M eigenvectors, with corresponding eigenvalues are the separated signal components. The entire signal can be reconstructed by summing extracted components.

4. HEART SOUNDS DECOMPOSITION

The purpose of this experiment is to demonstrate the behaviour of the decomposition algorithm, presented in the previous section, when applied to heart sounds. The main goal is to examine whether the algorithm is capable of segmenting heart beats into individual components.

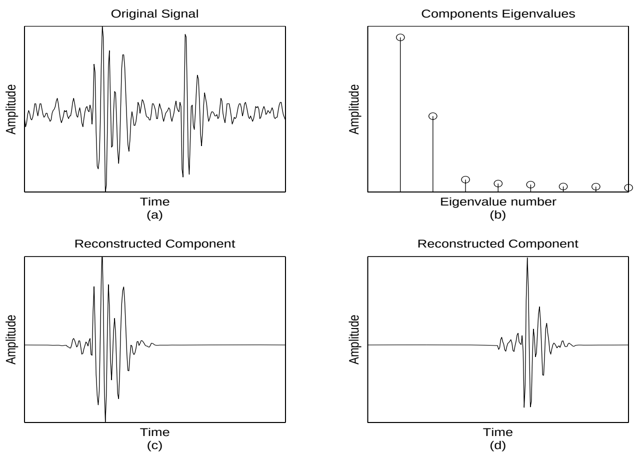

Figure 1: Heart beat with the OS: (a) Time-domain representation; (b) eigenvalues of the signal's S-method; (c) reconstructed S2; (d) reconstructed OS.

The phonocardiograph recordings of actual heart sounds were obtained from patients at St. Joseph's Hospital in Toronto, Canada during clinical examinations which also included heart auscultation. The data acquisition system consists of an analog recorder/player (Cambridge AVR-I which was specially designed for heart sounds) and a personal computer fitted with a 16-bit acquisition board [3]. The heart sounds are sampled at 4000 Hz for 4096 samples (1.024 seconds in length). The sampling rate is high enough since the maximum frequency content of heart sounds is usually below 600 Hz [2]. The recordings contain the S1, the S2 and one of the two sound which signify a disease: the OS or the S3. They have been carefully studied by the chief cardiologist to validate the presence of the opening snap or the third heart sound.

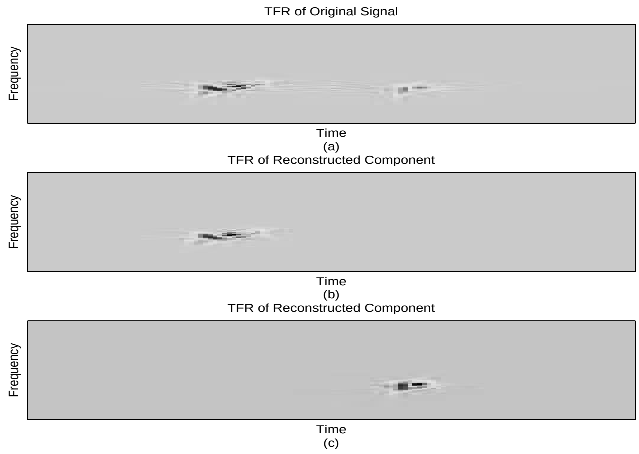

Figure 2: Heart beat with the OS: (a) time-frequency representation of the original signal; (b) time-frequency representation of the reconstructed S2; (c) time-frequency representation of the reconstructed OS.

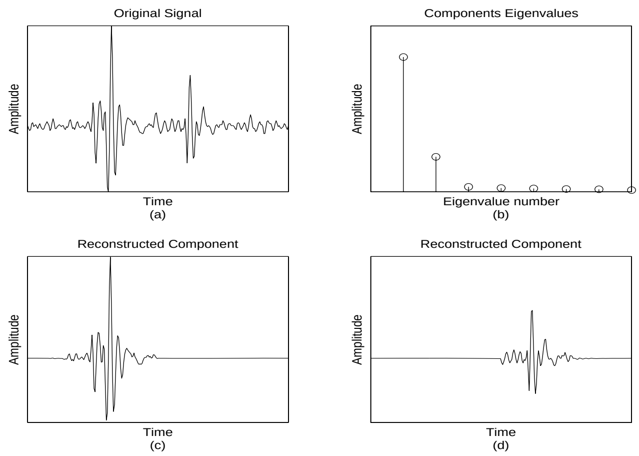

Figure 3: Heart beat with the OS: (a) time-domain representation; (b) eigenvalues of the signal's S-method; (c) reconstructed S2; (d) reconstructed OS.

The results of the decomposition are depicted in Figures 1-7, with Figures 1-4 representing the decomposition of the heart beats with the OS present, and Figures 5-7 representing the decomposition of the heart beats with the S3 present. In practice, physicians usually observe heart anomalies in the time domain. Therefore, in order to emphasize the applicability of the proposed algorithm in real life situations, the results are only considered in the time domain. For comparison purpose, the time-frequency representation of the signal, considered in Figure 1, is shown in Figure 2. It depicts the results of implementation of the proposed algorithm in the time-frequency domain. Hence, the algorithm is an automatic signal decomposition method that can produce results in either the time domain or the time-frequency domain. However, due to previously stated reasons, the rest of results, depicted in Figures 3-7, are only considered in the time domain.

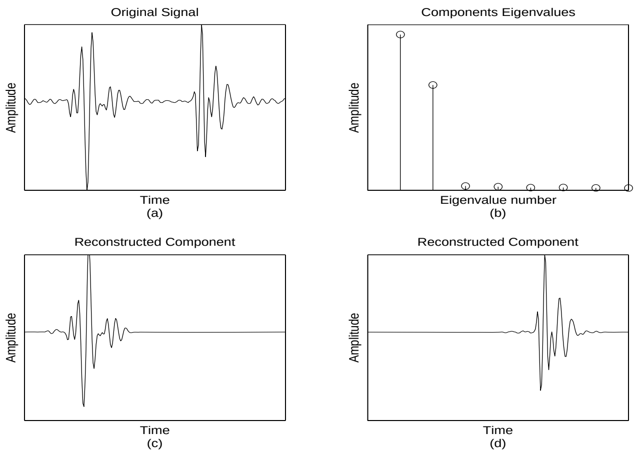

Figure 4: Heart beat with the OS: (a) time-domain representation; (b) eigenvalues of the signal's S-method; (c) reconstructed S2; (d) reconstructed OS.

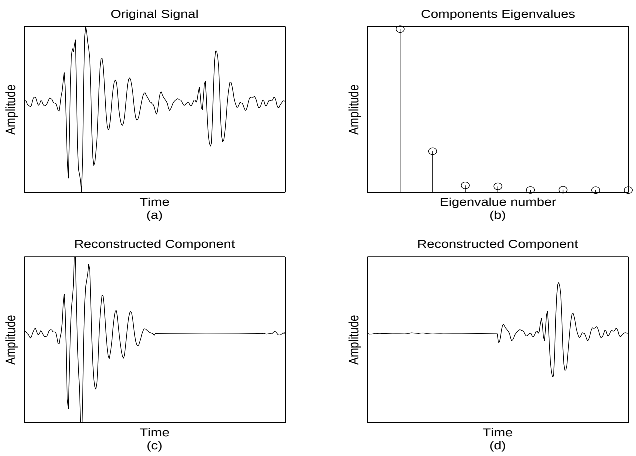

Figure 5: Heart beat with the S3: (a) time-domain representation; (b) eigenvalues of the signal's S-method; (c) reconstructed S2; (d) reconstructed S3.

In these decompositions, only the first eight eigenvectors are used in analysis. In order to diminish the computation cost, the decomposition is performed only for the S2 and the OS/S3, since the S1 can be automatically extracted using the QRS peak of the electrocardiogram [8].

The values of L, used for the decomposition of the heart sounds depicted in Figures 1-7, are given by $L = \{31, 31, 41, 39, 53, 63, 55\}$, respectively. This is in accordance with [18], where it is noted that in some cases it is also possible to obtain time-frequency distribution equivalent to the Wigner distribution with small L (i.e. $L \ll N/2$), which further reduces a computation cost associated with the Wigner distribution.

The results of the decomposition of the recording with the OS present show that the technique is quite useful in heart sound analysis. The technique is capable of separating both the S2 and the OS, and it yields distinct eigenvalues for both.

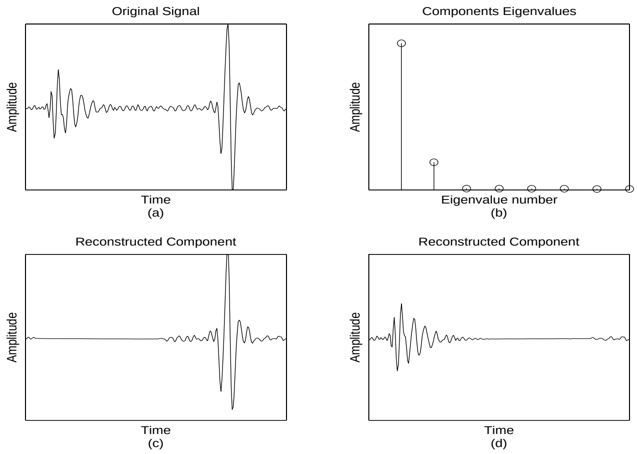

Figure 6: Heart beat with the S3: (a) time-domain representation; (b) eigenvalues of the signal's S-method; (c) reconstructed S3; (d) reconstructed S2.

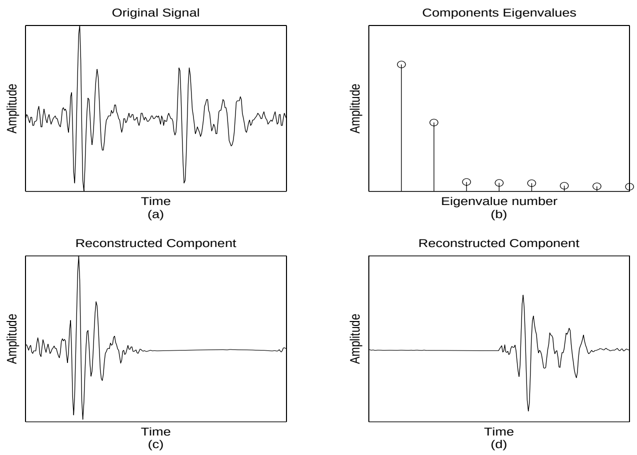

Figure 7: Heart beat with the S3: (a) time-domain representation; (b) eigenvalues of the signal's S-method; (c) reconstructed S2; (d) reconstructed S3.

Similarly, the decomposition technique presented here is capable of separating the S2 and the S3. As in the case of the S2 and the OS, the technique produces distinct eigenvalues and eigenvectors for these components as well. Figure 6 represents some interesting results. The recording used contains the S3 with stronger energy than the S2. Therefore, the first eigenvalue is associated with the S3, rather with the S2 as shown in other figures.

The practical value of these results lies in the fact that the applied algorithm can *automatically* decompose heart sounds into individual components. This is an extremely important fact, especially when it is known that other techniques, such as windowing or time-varying filtering, require constant tuning due to non-stationary nature of heart sounds. For example, the algorithm presented here automatically determines the duration of each component, while the technique presented in [6] requires additional computational steps to determine the components' duration. Also, the results of the decomposition can be further used in conjunction with the classification algorithm proposed in [20] for automatic decomposition and classification of the heart diseases associated with the OS and the S3.

5. CONCLUSIONS

In this paper, a recently proposed decomposition technique based on the S-method is applied to heart sounds in order to examine the suitability of such analysis for the diagnosis of heart diseases. The results have shown that the technique is suitable for the decomposition of the heart sounds, and it is capable of automatic extraction of individual components from the recordings of heart sounds.

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