Cardiac Sound Separation

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Abstract

The phonocardiogram (PCG) is a mixture of sounds produced by several cardiac structures and hemodynamic activities. Methods such as time segmentation of the heart sound into, for example, the S1 and S2 sounds, or spectral segmentation into frequency bands do not result in sounds produced by individual cardiac structures. Without any prior knowledge of PCG properties, we give a method to separate the PCG into sounds produced by individual parts of the heart. The Cardiac Sound Separator(TM), which is intended be used like an electronic stethoscope, gives, in real-time, the individual sounds that contribute to the composite heart sound. This enables localizing cardiac abnormalities, and makes it possible to hear cardiac murmurs without the interference from sounds produced by other cardiac structures.

1. Introduction

Many pathological conditions that occur in the cardiovascular system surface as murmurs and aberrations in a phonocardiogram much before they are reflected in other symptoms, such as changes in the Electrocardiogram signal (Liang et al, 1997)[1]. Furthermore, modern analytical methods provide new insights into heart sounds and murmurs and the precise timings of valve movements, firmly establishing auscultation as a cornerstone of the detection and evaluation of valvular disease and other cardiac disorders (Hadjileontiadis, 1997)[2].

Auscultation has its demerits as well, as it is a highly subjective task and depends largely on the experience and training of the observer. Therefore, extensive training is required for a person to associate a particular heart sound with a particular diagnosis as well as classifying heart sounds into pathological or innocent sounds. Non-optimal listening conditions (such as a busy hospital ward), the co-existence of other sounds or murmurs, rapid heart rate, or the presence of non-cardiac sounds such as chest wheeze, lung sounds can make auscultation of little help in contributing to a diagnosis (Asir et al, 1996) [3].

A cost-effective method and device that can assist a physician to localize and classify heart sounds and murmurs is presented in this paper. Cardiac sounds have been the subject of many kinds of analyses. Frequency analysis of the heart sounds includes applying the Fourier Transform, Short-time Fourier Transform and the S-Transform (Livanos et al, 2000)[4]. The sounds have also been analyzed using parametric and non-parametric methods (Haghighi-Mood and Torry, 1995)[5], as well as energy-based (Sharif et al, 2000; Liang et al, 1997a) methods [6].

Most of the current and past research focused on time segmenting the heart sound or finding features. Heart sound segmenting (Groch et al, 1992) [7] is useful to find the traditional heart sounds, the major sounds S1 and S2 and the intervals in between – the systole and diastole, but does not give any idea about the cause of the sounds. In the case of other advanced techniques like artificial neural networks and wavelet neural networks and wavelet transforms, features are extracted from the heart sound, and then these features are used to train a neural network in order to differentiate between pathological and physiological sounds.

In this paper we present the *Cardiac Sound Separator*™ to separate sounds caused by the opening and closing of valves from the composite heart sound and also isolate heart murmurs from the composite sound. Sounds produced by other cardiac structures and cardiac activities are also separated. These separate components of the heart sound are useful to diagnose particular heart dysfunctions by providing visual and auditory input to the physician as well as to further diagnostic algorithms.

The *Cardiac Sound Separator*™ makes it possible to analyze abnormalities occurring in specific source sites. By separating the composite heart sound into sound components due to individual cardiac structures and cardiac activities, the *Cardiac Sound Separator*™ is useful to find the actual number and kinds of sources, the role that they play in producing the heart sound and at the same time also pinpoint the location of an abnormality.

To separate different components from the composite heart sound, we assume that the valves, other cardiac structures and cardiac activities produce sounds that are independent of each other over time. Based on this assumption, we consider the application of blind source separation (BSS) techniques to separate the individual components from the PCG.

2. Method

Blind source separation (BSS) [8] denotes observing mixtures of independent sources, and by making use of these mixture signals only and nothing else, recover the original signals. The basic BSS problem assumes instantaneous mixing of sources, and this is modeled by a linear relation between the observations **x** and sources **s** given by

$$\mathbf{x} = \mathbf{A}\mathbf{s}, \quad \mathbf{x} \in R^{n}, \quad \mathbf{s} \in R^{m}, \quad \mathbf{A} \in R^{n \times m}$$

We assume that the components of **s** are statistically independent and have probability distributions that are not Gaussian except for at most one component. To obtain a unique separation of sources given a set of mixtures, we assume that m, the number of sources, is less than or equal to n, the number of observations. The goal of BSS is to estimate a separation matrix **W** that satisfies

$$\mathbf{WA} = \mathbf{PD}, \mathbf{W} \in R^{m \times n}, \mathbf{P} \in R^{m \times m}, \mathbf{D} \in R^{m \times m}$$

where **P** is a permutation matrix that has one large entry in each of its rows and columns and **D** is a diagonal matrix. With the separation matrix, we can reconstruct the sources with

$$\mathbf{y} = \mathbf{Wx}$$

Learning W by observing x only requires making use of higher order statistics. Typically, the separating matrix W is calculated iteratively by optimizing some cost function of the output y. Presently reported approaches to this problem can be divided into two categories. One category makes use of higher order statistics explicitly, and the other category makes use of these statistics implicitly through the non-linearity of neurons in a neural network. Bell and Sejnowski showed that another criterion for BSS can be the mutual information among the output y components. In the current work we use mutual information between outputs as the cost function to achieve our objective.

3. Results

The separation of m independent sources requires the simultaneous recordings of at least m composite mixtures that are each made up of these independent sources. We assume that one cycle of a PCG, defined as the time interval between two successive S1 sounds is made up of the following major independent sources

1) Mitral Valve Sound
2) Tricuspid Valve Sound
3) Aortic Valve Sound
4) Pulmonary Valve Sound
5) S3
6) S4
7) Background Noise

Figure 1 shows a normal PCG. The components were downloaded, and have a sampling frequency of 22.05 KHz. With these 7 independent sources we simulated 7 mixtures to find the 7 measurements in the observation vector ***x(t)***.

Figure 2 shows the separated components of the composite PCG that were obtained by processing the 7 simulated measurements.

Next we simulated an instance of a pathological PCG that is affected by the VSD murmur. The data corresponding to the VSD murmur was also downloaded. Thus we now have 8 independent sources. A pathological PCG including a VSD murmur is shown in Figure 3. The result of separation is shown in Figure 4.

Here, we successfully separated the different independent heart sounds from a composite PCG. We were also able to isolate the VSD murmur from other normal heart sounds. However the separated sources were obtained in a random order due to the permutation ambiguity inherent in BSS algorithm, as described in Section 2. However, desired ordering of separated components is possible if some prior information about the separated independent components is applied. In the case of heart sounds we do have such

We know that cardiac murmurs have significant energy at higher frequencies as compared to other heart sounds whose energy is mostly concentrated at relatively lower frequencies. This information was used to steer the isolated murmur into a fixed channel through permutation of the weight matrix of the separating network. Once the murmur has been steered into a predefined channel, the outputs of all the remaining channels were combined to obtain a composite sound. This was essential to detect the occurrence of the composite S1 and S2 sounds. Once the S1 and S2 were detected, the localization of the murmur (already separated in a different channel) was accomplished. Figure 5 shows the steering of the permutation. Note how the murmur is steered to the first channel.

4. Discussion and conclusions

We developed the *Cardiac Sound Separator*™ that utilizes a novel algorithm to non-invasively separate independent components of the heart sound through BSS techniques. The particular design of the *Cardiac Sound Separator*™ makes it especially suited for near real-time separation of cardiac sounds, making quick analysis and diagnosis possible. Successful separation of the VSD murmur from the other heart sounds was also demonstrated. Currently we are working to take propagation delays of different heart sounds into consideration.

Acknowledgements

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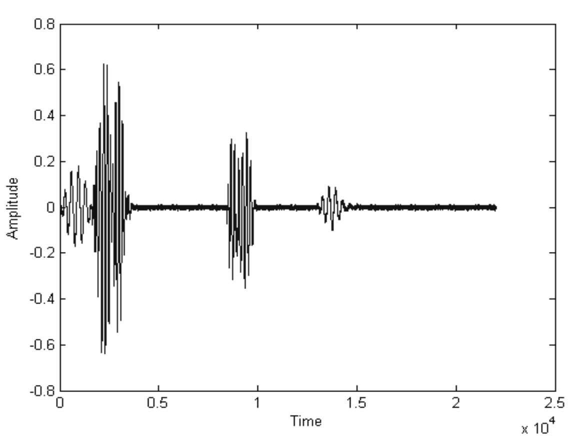

Figure 1. A composite PCG signal.

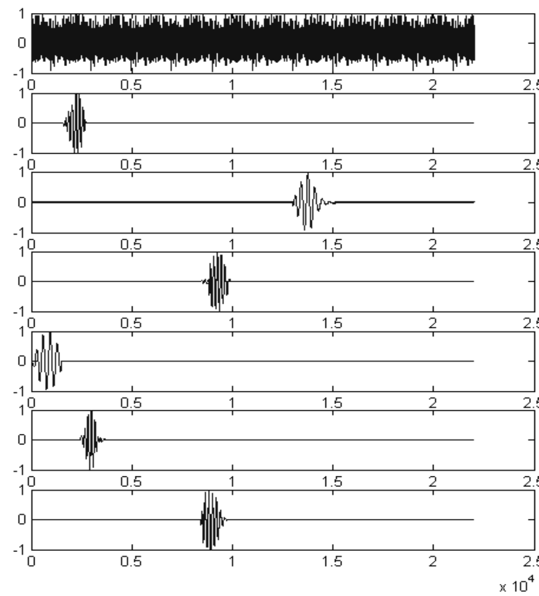

Figure 2. Separated components of the composite PCG in Fig. 1. The separated components from the top are: 1) Background Noise, 2) Mitral, 3) S3, 4) Aortic, 5) S4, 6) Tricuspid, 7) Pulmonary.

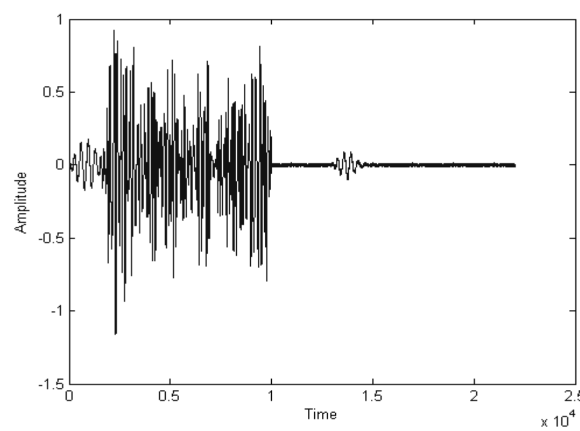

Figure 3. A pathological PCG with a VSD murmur.

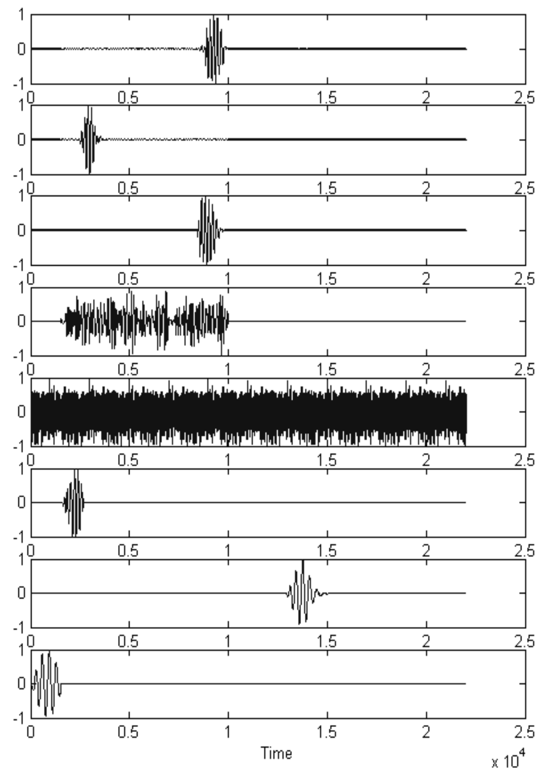

Figure 4. Separated components of the pathological PCG in Fig. 3. The separated components from the top are: 1) Aortic, 2) Tricuspid, 3) Pulmonary, 4) VSD Murmur, 5) Background Noise, 6) Mitral, 7) S3, 8) S4.

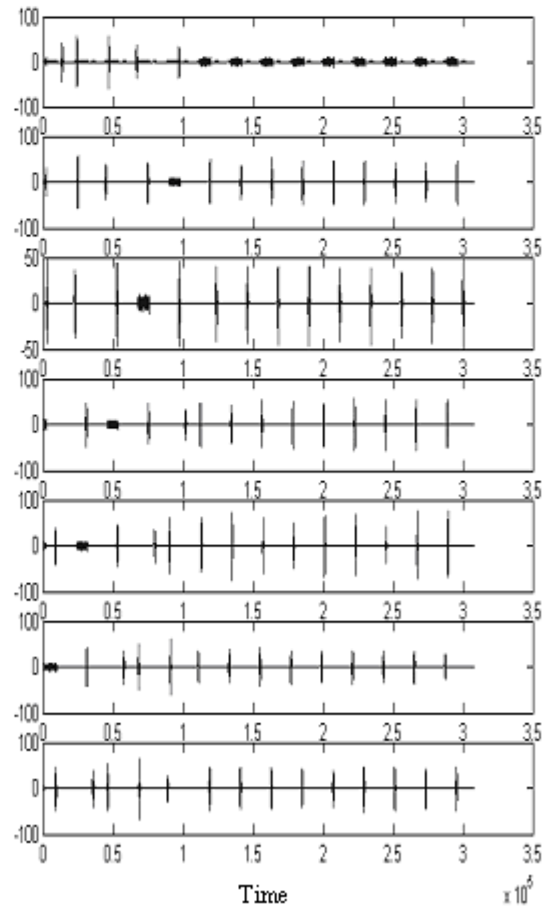

Figure 5. Steering of permutation. Note how the murmur is steered to the first channel. The other channels contain the other separated heart sound components.

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