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Research paper

An innovative multi-level singular value decomposition and compressed sensing based framework for noise removal from heart sounds

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ABSTRACT

Heart sounds have attracted increasing attentions resulting from the correlation with cardiac mechanical activity. Nevertheless, the interferences caused by broadband noise have an influence on the further processing and analyzing of heart sounds. This paper presents an innovative denoising framework based on a joint combination of modified singular value decomposition (SVD) and compressed sensing (CS) in order to solve this problem. Firstly, the modified SVD is proposed to process the raw heart sounds, and it aims to separate the heart sound components from the noise components as many as possible by multi-level decomposition and reconstruction, named multi-level SVD. Then, the CS based denoising is applied to further elimination of the noise remaining after the multi-level SVD operation through sparse reconstruction. The performance of proposed framework is evaluated qualitatively and quantitatively, including the test and verification in terms of several standard metrics, and the comparison with the widely used denoising methods such as wavelet transform (WT) and empirical mode decomposition (EMD) using the heart sound databases in different noise levels. The results show that the denoising framework not only improves the signal quality but also preserves the original morphological characteristics of heart sounds, which corresponds to a higher signal-to-noise ratio (*SNR*), a smaller mean square error (*MSE*) and a higher correlation coefficient between the denoised signal and original signal. It indicates that the denoising framework can remove the noise and maintain the original physiological and pathological information of heart sounds effectively. This suggests that the denoising framework has potentially theoretical and applied value in heart sounds denoising as well as the future applications of other biomedical signals denoising.

1. Introduction

Heart sounds, as a type of important physiological signal, contain the information of cardiac mechanical activity, which can be utilized to evaluate cardiac function and screen cardiovascular diseases noninvasively [1–3]. Nevertheless, heart sounds are so weak as to be polluted easily in the process of collection. The noise interferes with heart sounds in not only the time domain but also the spectral content. This could have an impact on the feature extraction of heart sounds for the further analysis, which lead to the serious disturbance in their applications to the noninvasive diagnosis of cardiovascular diseases [3]. As a result, an efficient denoising technology is essentially necessary before the further processing and analyzing of heart sound signal as well as the other biomedical signals.

Since a variety of interferences may be introduced during heart sounds acquisition, such as frictional noise caused by the placing of sensor, environmental acoustic noise, instrument noise and electrical noise [4], numerous approaches, which perform in time domain [5], frequency domain [6] and transform domain [4,7,8], have been applied to heart sounds denoising. The adaptive filter has the limitation of the synchronous reference signal recording, which increases the complexity in the signal collection. The wavelet transform (WT) and empirical mode decomposition (EMD) based denoising methods need to set the algorithm parameters and estimate the noise threshold value based on the priori knowledge of noise [4,7]. If the

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noise and signal overlap in both time and frequency domains or their respective frequency ranges are unknown, then it is ineffective to use these methods for noise removel. The cyclostationary based denoising method isolates the heart sounds from the noise in the cycle frequency-time-frequency domains that can obtain satisfied result, but it relies heavily on more cardiac cycles, and the short period electrocardiogram need to be recorded synchronously [8].

In addition, for the denoised heart sound signals, the morphological characteristics of original signals should be preserved as many as possible to obtain the unbroken physiological and pathological information relating to the diagnosis of cardiovascular diseases. There are mainly two normal heart sounds that occur in turn during each heartbeat such as the first heart sound (S1) and second heart sound (S2), relating to the opening and closing of the atrioventricular valves and semilunar valves [9]. Except for these normal sounds, the other sounds including the gallop rhythms (the third and fourth heart sound (S3) and (S4)) and heart murmurs are known as the extra heart sounds, whose appearance may imply the change of cardiac condition. However, the traditional denoising methods could lead to the morphological distortion in the denoised heart sound signals, which is caused by the fact that the principal components of extra heart sounds are filtered out together with the noise, because of the overlap of their contents in both time and frequency domains [10]. Since the extra heart sounds could provide clues for noninvasive cardiac valve disorders screening and cardiac function evaluation [3,11–13], it is meaningful to maintain and preserve the original shapes and characteristics of heart sound signals after noise removel. Nevertheless, for all we know, there are only few studies referring to this topic except for the researches proposed by Tang and Zeng [14,15].

In this paper, we propose an efficient denoising framework by employing the combination of multi-level singular value decomposition (SVD) and compressed sensing (CS) in order to achieve better denoising performance, including enhancing the signal quality as well as preserving the original morphological characteristics of heart sounds after denosing as many as possible. In the first stage, multi-level SVD is proposed to process the raw heart sound signals, and it aims to separate heart sound components from the noise components as many as possible by multi-level decomposition and reconstruction. In the second stage, the CS based denoising is applied to the processed signal obtained by multi-level SVD operation for further noise removal through sparse reconstruction. The performance of the denoising framework is evaluated by several qualitative analyses and quantitative comparisons with the other two widely used denoising methods using the heart sound databases in different noise levels. Then, the state-of-the-art studies on heart sounds denoising have been summarized and reviewed, and the innovation points of our denoising framework have been stated. The experimental results indicate that the denoising framework can both remove the noise and maintain the original physiological and pathological information of heart sounds effectively. It has been proven that the denoising framework has potentially theoretical and applied value in heart sound signal denoising, with the advantage of preferable denoising performance and algorithm parameter selection without need for knowing the priori knowledge of noise, in comparison to the recent relevant studies on heart sounds denoising.

The outline of this paper is organized as follows. Section 2 provides the methodology including the fundamental theory of SVD and CS, the detail presentation of denoising framework and the description of performance evaluation. Section 3 represents the experiment results of qualitative and quantitative analyses. The corresponding discussions including the innovation points and comparison with the relevant studies are given in Section 4. The conclusion and future work of the paper are stated in Section 5.

2. Methodology

2.1. Principle of singular value decomposition

Singular value decomposition (SVD) is an efficient matrix decomposition technique which is used to decompose a certain signal into a series of eigenvalues ordered by their contribution to the reconstruction of signal. With the superiority of unrestricted condition for arbitrary matrix, it has been generally applied to varieties of fields [16,17]. For a matrix $\mathbf{H} \in \mathbf{R}^{M \times N}$ with $rank\,(\mathbf{H}) = r$, there exists matrices $\mathbf{U} \in \mathbf{R}^{M \times M}$ and $\mathbf{V} \in \mathbf{R}^{N \times N}$ such that

$$\mathbf{H} = \mathbf{U}\boldsymbol{\Sigma}V^T \tag{1}$$

where the matrices $\mathbf{U}$ and $\mathbf{V}$ are both orthogonal. $\boldsymbol{\Sigma}$ is a $r \times r$ square diagonal matrix which can be expressed as:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \sigma_r \end{bmatrix} \tag{2}$$

The diagonal elements of matrix $\boldsymbol{\Sigma}$, that are $\Sigma_{ii} = \sigma_i$, can be arranged in descending sequence. The nonnegative ones are named the singular values of the matrix $\mathbf{H}$.

The another form of SVD can be described as:

$$\mathbf{H} = \sum_{i=1}^{r} \sigma_i \boldsymbol{u}_i \boldsymbol{v}_i^T \tag{3}$$

where $\boldsymbol{u_i}$ and $\boldsymbol{v_i}$ denote each column of the matrices $\mathbf{U}$ an $\mathbf{V}$, respectively.

2.2. Compressed sensing theory

Compressed sensing (CS) is an emerging technology that has gained extensive attention in many research fields [18]. It breaks through the sampling constraint of the conventional Nyquist theorem and offers solutions for compressible signal reconstruction at a sub-Nyquist sampling rate (below Nyquist sampling). The CS scheme mainly consists of three elements such as sparse representation of signal, establishment of measurement matrix and the design of reconstruction algorithm. Sparsity is the necessary condition for a signal to be reconstructed in the application of CS. Assume that an N dimension vector $\mathbf{X}$ is sampled by M dimension vector $\mathbf{Y}$, and this acquisition can be described as:

$$\boldsymbol{Y} = \boldsymbol{\Phi X} \tag{4}$$

where $\boldsymbol{\Phi} \in \mathbf{R}^{M \times N}$ is the measurement matrix. It models the process of the linear encoding with the sampling rate M. The principle of CS presents that $\mathbf{X}$ can be retrieved from the measurement matrix $\boldsymbol{\Phi}$ and sampled vector $\mathbf{Y}$, if $\mathbf{X}$ is sparse in a certain domain. Although actual signals are always not sparse, they can be sparse in their some transform domains. Therefore, under some sparse orthogonal basis $\boldsymbol{\Psi} \in \mathbf{R}^{N \times N}$, the signal $\mathbf{X}$ can be expressed as:

$$\mathbf{X} = \boldsymbol{\Psi\theta} \tag{5}$$

where $\boldsymbol{\Psi}$ is the sparse basis matrix and $\boldsymbol{\theta} \in \mathbf{R}^{N}$ is the sparse projection coefficient vector with a few non-zero elements. According to the Eqs. (4) and (5), the CS model can be described as:

$$\mathbf{Y} = \boldsymbol{\Phi\Psi\theta} = \boldsymbol{\Xi\theta} \tag{6}$$