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Adaptive overlapping-group sparse denoising for heart sound signals

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ABSTRACT

The heart sound (HS) is an important physiological signal of the human body and can provide valuable diagnostic information in the clinical auscultation. The HS signal, however, is often contaminated by noise and the noisy HS signal will cause adverse influence of making the diagnosis. In this paper, we proposed an adaptive denoising algorithm, named adaOGS denoising, based on the overlapping-group sparsity (OGS) of the first-order difference of the HS signal. Under the Bayesian framework, the adaOGS algorithm is derived and solved as an optimization problem with OGS regularization based on the majorization–minimization (MM) algorithm. Compared with the conventional wavelet method, the proposed algorithm has the advantage that it does not need the predefined base functions and can also be performed in an adaptive way according to the noise level. Moreover, the experimental results show that the proposed algorithm outperforms the conventional wavelet methods such as 'db10', 'db5', and 'bior5.5', for denoising the noisy HS signals in lower noise level.

1. Introduction

As an important physiological signal of the human body, the heart sound (HS) signal can provide valuable diagnostic information about the heart by the auscultation with a stethoscope in a conventional way. Nowadays, the auscultation can be performed by acquiring the HS signals with a digital stethoscope and then analyzing or recognizing with modern techniques emerging in the field of digital signal processing and machine learning. [1–4], without the limitations of the human ear and the great experiences required by users. The HS signal, however, is a kind of weak signal of the human body and is easy to be contaminated by the external noise, which can cause great influence of the diagnosis of heart disease [5]. Therefore, the HS signal denoising is a significant problem before the HS signal is used for further processes such as analysis, segmentation, and classification.

A normal HS signal contains four sound components: the first heart sound (S1), the second heart sound (S2), the third heart sound (S3), and the fourth heart sound (S4). In addition to these components, the abnormal HS signal also contains some murmurs in the systole (systolic murmurs) or diastole (diastolic murmurs). A good denoising method should be able to retain the available information of these sound components and murmurs, but effectively and adaptively suppress the noise interference.

The most commonly used method for HS signal denoising is wavelet transform (WT) with different base functions such as 'db10' [6–8], 'db5' [5], and 'bior5.5' [6,5,9]. The WT-based method is carried out by decomposing the noisy HS signal into several levels, removing the noisy components according to thresholding techniques, and then reconstructing the denoised HS signal. As a well-studied denoising method in the signal processing, the WT-based method can be adaptively performed without manually tuning the parameters of the algorithms according to the noise levels, as done in [10]. Considering different wavelet bases have different time-frequency characteristics and have different denoising performance, Xiefeng et al. [5] proposed the self-construct HS wavelet based on the characteristics of the HS signal. Although their experimental results show that their method achieves a better denoising performance than the 'db' or 'bior' wavelet, they do not provide any information of adaptively selecting the thresholds in their algorithm. In general, all these wavelet methods are required to predefine the wavelet bases which should be able to reserve the characteristics of signals as much as possible. However, one of the limitations of the wavelet approach is that the fixed wavelet base functions do not necessarily match all the HS signals, which come from a wide range of individuals with different age, gender, and health conditions.

Recently, the denoising method based on the total variation (TV) regularization (or TV norm) has emerged as a powerful and gen-

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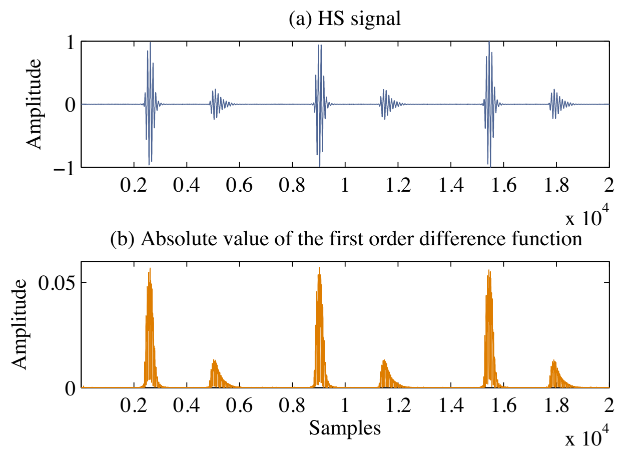

Fig. 1. Example of first-order difference function of HS signal. (a) HS signal; (b) Absolute value of the first-order difference function.

eral technique for biomedical signals such as Electrocardiogram (ECG) and HS signal [11–14]. Given a signal (or vector) $\mathbf{x} = [x(0), \ldots, x(N-1)]$ of length N, the TV regularization of $\mathbf{x}$ is defined by

$$\mathrm{TV}(\mathbf{x}) = \sum_{i=1}^{N-1} |x(i-1) - x(i)|$$

where $|\cdot|$ denotes the absolute value function. The TV regularization can impose constraints on the sparsity of the first-order difference function of $\mathbf{x}$. The assumption behind the TV regularization is that the first-order difference function of $\mathbf{x}$ only contains a few large values. For the HS signal, however, its first-order difference function is not only sparse, but also that these large values in the first-order difference function rarely occur in isolation. As an example, Fig. 1(b) shows that the large values of the first-order difference function of the HS signal in Fig. 1(a) usually arise near other large values. Therefore, instead of using TV regularization, the first-order difference function of the HS signal is more suitable characterized by using the overlapping-group sparse (OGS) regularization [15–17]. By using the absolute value function in the OGS regularization, Chen et al. [17] proposed the overlapping-group shrinkage algorithm and further extended their work to the case of non-convex regularization [18]. However, these methods did not provide an efficient way to select the regularization parameter in their algorithms, which limits the application of the algorithm in an adaptive way.

In this paper, an adaptive algorithm for HS signal denoising is proposed by solving the problem of the OGS regularization optimization, in which the regularization parameter is adaptively estimated based on the Bayesian framework. The OGS regularization characterizes the overlapping-group sparsity of the first-order difference of the HS signal and is viewed as the prior knowledge about the denoised HS signal. The proposed algorithm needs to iteratively solve two optimization subproblems: estimating the regularization parameter and solving the problem of the OGS regularization optimization with the estimated parameter. For the first subproblem, by assuming that the variance of the noise is known, the regularization parameter can be estimated with the Gamma prior of the parameter under the Bayesian inference by using the majorization–minimization (MM) algorithm [19]. For the second subproblem, with the estimated regularization parameter, the optimal solution of the OGS regularization optimization can be obtained by solving the proximity operator based on the MM algorithm, as done in [15]. Compared with the conventional wavelet method, the proposed algorithm has the advantage that it does not need the predefined base function and can be performed in an adaptive way according to the noise level and group size. Also, our experiments are performed on the Michigan HS database [26], and the results show that the proposed algorithm outperforms the conventional wavelet methods for the problem of HS signal denoising in lower noise level.

The paper is organized as follows. In Section 2, we give some basic concepts, properties of the OGS regularization, and the proximity operator for the OGS regularization optimization with fixed regularization parameter. A methodology is described in Section 3. The proposed method is derived based on the Bayesian framework and MM algorithm, which can adaptively denoising the noisy HS signals according to noise levels by using an adaptive scheme to update the regularization parameter and a pre-stop condition. Compared with the wavelet methods, the experimental results and discussion are given in Section 4. Finally, we concluded this paper in Section 5.

2. Background

2.1. Overlapping-group sparse regularization

The noisy HS signal $\mathbf{y}$ of length N, denoted as $\mathbf{y} = [y(0), \ldots, y(N-1)]^T$ in $\mathbb{R}^N$, can be modeled as

$$\mathbf{y} = \mathbf{x} + \mathbf{n} \tag{1}$$

where $\mathbf{x}(\in \mathbb{R}^N)$ and $\mathbf{n}(\in \mathbb{R}^N)$ denote the clean HS signal and the added noise, respectively. Besides the prior knowledge regarding the noise $\mathbf{n}$, it also requires some prior knowledge about the clean HS signal $\mathbf{x}$, such as the sparsity used in basis pursuit denoising (BPDN) [20], to better suppress the noise $\mathbf{n}$ and estimate the clean HS signal $\mathbf{x}$ from the noisy signal $\mathbf{y}$. As shown in Fig. 1(b), the first-order difference of $\mathbf{x}$ exhibits the group sparsity, i.e., the large values of the difference are not isolated. To characterize the prior knowledge of the first-order difference of $\mathbf{x}$, the TV with overlapping-group sparsity is used as the regularization term (penalty function) for estimating the clean HS signal $\mathbf{x}$. The regularization term is referred to as overlapping-group sparse (OGS) regularization [15], just like the sparse regularization used in BPDN [20].

Let us briefly introduce several notations and definitions, which will be used throughout the paper. To introduce the OGS regularization for the first-order difference, we need to define the first-order difference matrix and the group over a vector. The first-order difference matrix $\mathbf{D} \in \mathbb{R}^{(N-1)\times N}$ for the signal $\mathbf{x} \in \mathbb{R}^N$ is defined by

$$\mathbf{D} \triangleq \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & \ddots & \ddots & \\ & & & -1 & 1 \end{bmatrix}$$

Then, the first-order difference of the clean HS signal $\mathbf{x}$ is obtained by $\mathbf{Dx}$, which is also a vector of length $N-1$. The group of $\mathbf{x} \in \mathbb{R}^N$ at the n-th element $x(n)$ with the group size K, $\mathbf{x}_{n,K} \in \mathbb{R}^K$, is defined by

$$\mathbf{x}_{n,K} \triangleq [x(n), \ldots, x(n+K-1)]$$

which is a block consisting of K contiguous elements of $\mathbf{x}$ starting at its index n.

The OGS regularization term is defined by

$$\varphi(\mathbf{x}) \triangleq \sum_{n=0}^{N-K+1} \phi(\|\mathbf{x}_{n,K}\|_2) \tag{2}$$

where the sparse penalty function $\phi(\cdot)$ can be absolute value function $|\cdot|$ or other concave functions such as *logarithmic*, *arctangent*,