

LETTER

Detection of S1/S2 Components with Extraction of Murmurs from Phonocardiogram

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SUMMARY The simplicity is a type of measurement that represents visual simplicity of a signal, regardless of its amplitude and frequency variation. We propose an algorithm that can detect major components of heart sound using Gaussian regression to the smoothed simplicity profile of a heart sound signal. The weight and spread of the Gaussians are used as features to discriminate cardiac murmurs from major components of a heart sound signal. Experimental results show that the proposed method is very promising for robust and accurate detection of major heart sound components as well as cardiac murmurs.

key words: heart sound, simplicity, Gaussian regression

1. Introduction

Detection of **S1** and **S2** components from a heart sound signal, i.e., a phonocardiogram (PCG), is generally the first step in heart sound analysis for the automated diagnosis of heart disorders. Many algorithms have been reported so far, and most of them are based on the energy or time-frequency characterization of the signal [1]–[3]. But they are mostly affected by amplitude and frequency variations of the heart sounds. Recently, simplicity that shows a large value in the regions where the major components of the PCG occur has been proposed as a new measure [4], [5]. The advantage of simplicity measure is that it is robust to amplitude and frequency variation of a heart sound signal.

This letter presents a heart sound segmentation algorithm that can detect **S1**, **S2** effectively from the pathological heart sound signals containing various types of cardiac murmurs. It employs Gaussian regression to the smoothed simplicity profile of a heart sound signal, and discriminate cardiac murmurs from **S1** and **S2** components by examining the weight and spread of the Gaussians.

2. Simplicity Profile of a Heart Sound Signal

The simplicity is calculated on the frame basis. First take the N data samples as an analysis frame. Then construct a subframe whose length is m . Here m is called an embedding dimension. We can construct $p = N - m + 1$

subframes within the analysis frame by shifting sample-by-sample. Then these subframes construct a data matrix $X(m \times p)$ to compute the simplicity. The procedure to get the simplicity profile can be summarized as follows.

- Construct a data matrix X for a given PCG.
- Generate a covariance matrix C , where X^T denotes the transpose of X and p is for normalization.

$$C = X^T X / p \quad (1)$$

- Obtain a diagonal matrix D whose elements are eigenvalues of C sorted in descending order. Then get the normalized eigenvalue $\hat{\lambda}_j$ with Eq. (3).

$$D = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_m), \lambda_1 > \lambda_2 > \dots > \lambda_m \quad (2)$$

$$\hat{\lambda}_j = \frac{\lambda_j}{\sum_{k=1}^m \lambda_k}, \quad j = 1, 2, \dots, m \quad (3)$$

- Calculate the entropy and complexity defined as Eqs. (4) and (5).

$$H = \sum_{j=1}^m \hat{\lambda}_j \log_2 \hat{\lambda}_j \quad (4)$$

$$\Omega = 2^H \quad (5)$$

- The simplicity is then obtained by Eq. (6).

$$\text{simplicity} = 1/\Omega \quad (6)$$

- Shift the analysis frame by one sample, and repeat the steps for the given PCG.

Figure 1 shows both an energy contour and a smoothed simplicity profile of a PCG, which contains a systolic murmur of aortic stenosis. The sampling frequency of the signal is 8 kHz. For simplicity computation, we set $N = 50$, $m = 10$, and a moving average with length 100 is used to get the smoothed simplicity profile. The zero mean unit variance white Gaussian noise with scale factor of 0.02 is also added to the amplitude normalized PCG to improve discriminating capability of the simplicity profile between its major components and background noise [6]. From the Fig. 1, we can see the robustness of the simplicity against energy measure with respect to amplitude and frequency variation.

3. Extraction of Major Components of the PCG Using Gaussian Regression

The proposed simplicity-based heart sound analysis method

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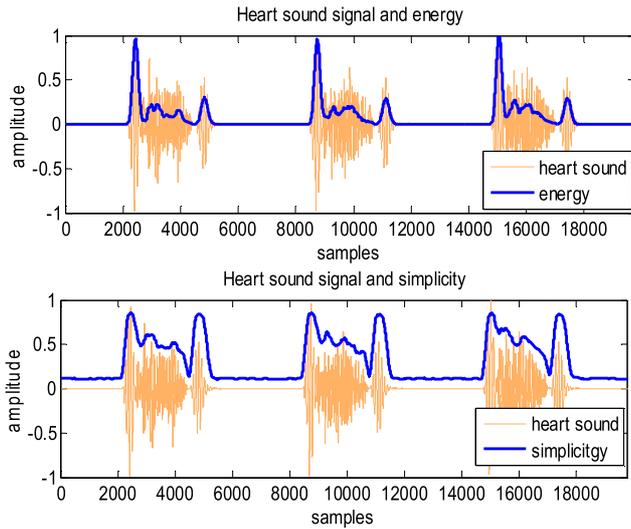


Fig. 1 Comparison of energy contour with simplicity profile for a pathological PCG.

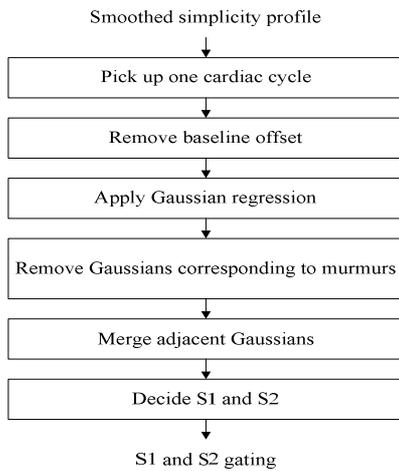


Fig. 2 Block diagram of the proposed method.

to detect **S1**, **S2** and cardiac murmurs is shown in Fig. 2. First, we pick up one cardiac cycle of the smoothed simplicity profile using its autocorrelation. Then it is necessary to remove the baseline offset of the simplicity profile to fit Gaussians well to the major components and cardiac murmurs separately. After removing the baseline offset, the simplicity profile is fitted using Gaussian regression given by Eq. (7).

$$f(x) = \sum_{i=1}^l a_i \exp \left[- \left(\frac{x - b_i}{c_i} \right)^2 \right] \quad (7)$$

where a_i is a weighting factor, l denotes the number of Gaussians, b_i and c_i correspond to mean and spread, respectively. The values of a_i , b_i , and c_i are obtained using nonlinear least square method. Considering **S1**, **S2**, and cardiac murmurs, the number of Gaussians should be at least equal to or greater than three, and we set $l = 5$, empirically.

Figure 3 shows the result of **S1**, **S2** detection using the

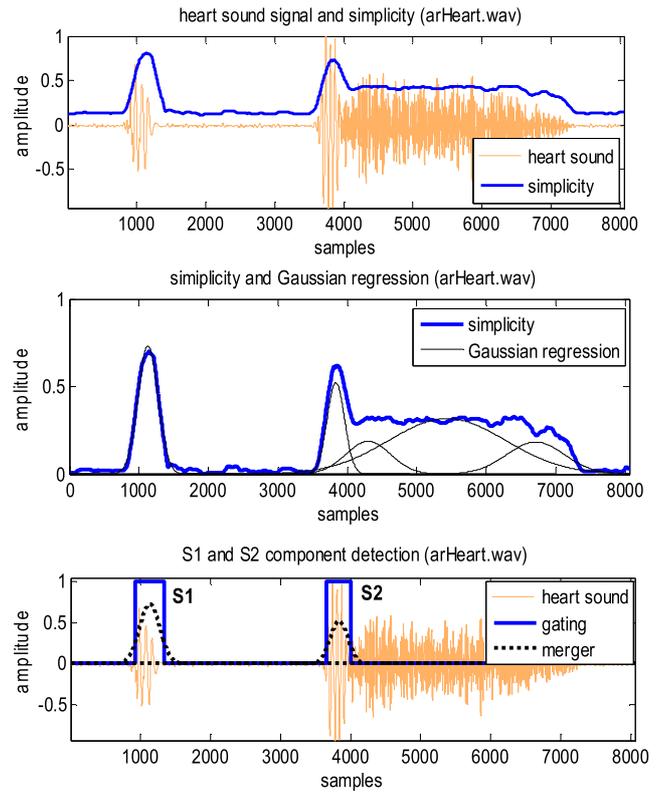


Fig. 3 Results of **S1**, **S2** detection using the proposed method.

Table 1 Gaussian regression parameters for the PCG in Fig. 3.

Gaussians	a	b	c	r
G1(S1)	0.73	1125	201	3.63
G2(S2)	0.52	3834	181	2.87
G3(murmur)	0.18	4289	473	0.38
G4(murmur)	0.32	5414	1280	0.25
G5(murmur)	0.18	6695	600	0.30

proposed Gaussian regression method. We can see that very accurate time gating is obtained after removing Gaussians correspond to cardiac murmurs. In Table 1, typical values of Gaussian regression parameters for a pathological PCG shown in Fig. 3 are given. Here G1 ~G5 represent fitted Gaussians to the simplicity profile, and (\cdot) stands for the heart sound component corresponds to each Gaussian. In the Table 1, we can find that the ratio of a_i and c_i , i.e., r_i as given in Eq. (8) shows a big difference between **S1**, **S2** components and murmurs. It can be used to discriminate them and extract Gaussians corresponding to cardiac murmur components using an appropriate threshold. To determine appropriate threshold value, we used the histogram of r_i of all Gaussians for **S1**, **S2** components and murmurs. Figure 4 shows the distribution of r_i value using histogram analysis. It is obvious that **S1/S2** components and murmurs occupy different regions in Fig. 4. Using the histogram, we set the threshold value to 1.6.

$$r_i = (a_i/c_i) \times 1000 \quad (8)$$

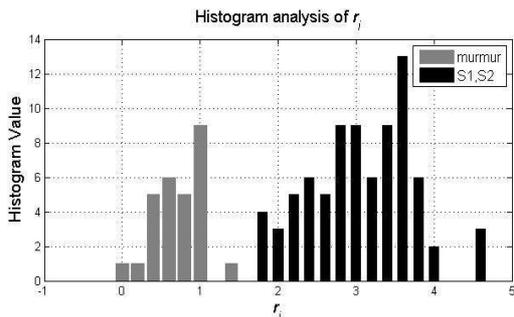


Fig. 4 Histogram value for r_i .

Table 2 Experimental result of S1 and S2 detection.

	Fuzzy c-means [5]	Proposed
Success rate	59%	82%

If we remove Gaussians corresponding to cardiac murmurs, the remaining Gaussians belong to **S1** and **S2** components. In order to get accurate gating for **S1** and **S2** separately, adjacent overlapped Gaussians are merged if they are located very near. The criterion for merging adjacent Gaussians is whether one is within two times of standard deviation ($\sqrt{2}c$) of the other. Finally decision of **S1** and **S2** from two Gaussians is made based on the general medical domain feature that the duration of systole period is less than the diastole period.

4. Experimental Results

The heart sound signals used in this work were obtained from [7], and the sampling rate was converted from 44.1 kHz to 8 kHz. We selected 22 files of normal heart sounds and 21 pathological ones containing various types of cardiac murmurs. In case of normal sounds, it is not difficult to detect **S1/S2** components. Even with a simple energy, we can easily discriminate **S1/S2** components from the normal sounds.

Figure 5 shows some detection results for various pathological PCGs and their Gaussian regression. We can see that the proposed method works quite well for various types of systolic and diastolic murmurs. Once **S1** and **S2** are detected from the PCG we can identify the location and characteristics of cardiac murmurs, which can help the diagnosis of heart valve abnormalities. Table 2 shows the success rate of correct time gating of **S1** and **S2**. It is shown that the proposed method outperforms the simplicity-based fuzzy-c means clustering method [5].

5. Conclusion

This letter presented a simplicity-based heart sound segmentation method. It uses the weight and spread of multiple Gaussians as feature parameters to discriminate **S1**, **S2** of the PCG from cardiac murmurs. Experimental results have

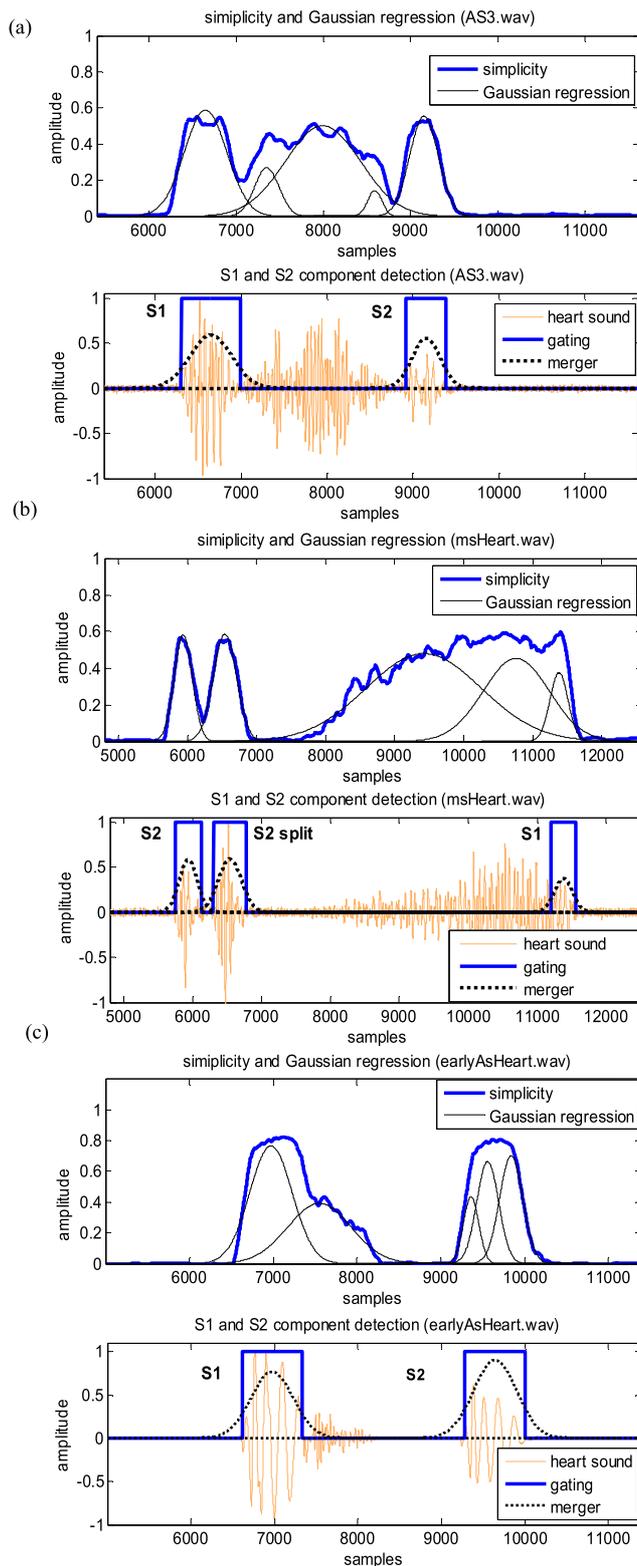


Fig. 5 Examples of some heart sound detection results. (a) AS (Aortic Stenosis heart sound), (b) MS (Mitral Stenosis), (c) early AS (early Aortic Stenosis).

shown that the proposed is very promising for robust detection of major components of the PCG and extraction of cardiac murmurs.

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