An Automatic Tool for Pediatric Heart Sounds Segmentation

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Abstract

In this paper, we present a novel algorithm for pediatric heart sound segmentation, incorporated into a graphical user interface. The algorithm employs both the Electrocardiogram (ECG) and Phonocardiogram (PCG) signals for an efficient segmentation under pathological circumstances. First, the ECG signal is invoked in order to determine the beginning and end points of each cardiac cycle by using wavelet transform technique. Then, first and second heart sounds within the cycles are identified over the PCG signal by paying attention to the spectral properties of the sounds. The algorithm is applied on 120 recordings of normal and pathological children, totally containing 1976 cardiac cycles. The accuracy of the segmentation algorithm is 97% for S_1 and 94% for S_2 identification while all the cardiac cycles are correctly determined.

1. Introduction

Several studies showed that developing a screening tool for pediatric heart disease through digital processing of heart sound signal is feasible [1] [2] [3]. This is of special importance for pediatric heart disease screening in which such a noninvasive and inexpensive approach is a priority [4]. However, one important obstacle in developing the all-automatic tool is end-pointing of cardiac cycles as well as localization of first heart sounds (S_1) and second heart sounds (S_2), termed by heart sound segmentation. Inaccurate segmentation can put a negative impact on the screening results relying on the fact that most of the algorithms are applied on a particular segment of a cardiac cycle [1] [5]. It is possible to develop an automatic segmentation algorithm using a synchronous 12-lead ECG. However, using a 12-lead ECG along with an electronic stethoscope is inconvenient for pediatric cases and a single lead ECG by itself is insufficient for the segmentation in certain cases. There are a large number of the algorithms in which only PCG signal is used for the segmentation [6] [7]. However, developing an accurate algorithm for segmentation using PCG only in sever pathological cases of children is still problematic. Earlier researchers studied short-time energy and sub-band energy techniques to obtain an envelop over the PCG by which the the heart sounds are localized [8] [9]. In later studies, Neural networks were employed for either cardiac cycle end-pointing or S_1 and S_2 detection on the PCG signal [10] [11]. Recently, statistical classifiers (e.g. HMM) have been used for the segmentation [12] [13]. Nevertheless, the harsh murmurs caused by sever pathologies in children might decline efficiency of the algorithms particularly when the classifiers with high structural risk (e.g. neural networks) are invoked. The other risk factor for such algorithms is the presence of forth heart sound (S_4). In this case, the beginning of the cardiac cycles might be misinterpreted specially for children with a high heart rate.

In this study, we present a robust algorithm for heart sound segmentation using joint ECG and PCG signals. In our automatic algorithm, ECG signal is employed in order to determine beginning and end points of cardiac cycles. Then, S_1 and S_2 are identified using the PCG signal recorded synchronously with ECG. The automatic algorithm is incorporated into a graphical user interface in which manual and semi-automatic segmentation are possible. The graphical user interface together with the automatic algorithm serves as a segmentation tool which can be used both for medical and biomedical engineering purposes. Results showed that the automatic algorithm efficiently improves the applicability of the tool in which replaying the segmented signals makes it profitable for medical assessments or even for pedagogical purposes.

2. Materials

2.1. Segmentation tool

The segmentation tool is constituted of an automatic algorithm and a graphical user interface in which manual and semi-automatic possibilities are also embedded. In manual segmentation mode, all the cardiac cycles as well as S_1 and S_2 sounds are manually annotated by the user using zoom facility while in semi-automatic segmentation mode,

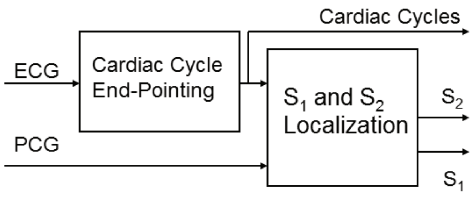

Figure 1. Flowchart of the automatic segmentation algorithm

the cardiac cycles are automatically determined and represented using the automatic algorithm and the S_1 and S_2 sounds are annotated within the extracted cycle. Clearly, in the automatic mode, cardiac cycles along with S_1 and S_2 sounds are identified by the algorithm. The tool is developed under the MATLAB platform where further signal processing routines could be easily augmented.

2.2. Data collection

We have recorded 120 samples, each containing 10 seconds of synchronous PCG and ECG signals taken from 120 normal and pathological children, referred to the Children Heart Center of Tehran, Iran. Pathological samples (80 samples) contains valvular and septal heart diseases in which the following pathological sounds are found: low to medium grades of systolic murmurs, wide splitting of second heart sound and third heart sound. Various types of ECG abnormalities (e.g. baseline drift, long T-wave, and long P-wave) are seen in the recordings. All samples were recorded under the supervision of a pediatric cardiologist, using a commercial electronic stethoscope, a laptop computer with a 16-bit sound card and sampling rate of 44.1 KHz.

3. Methods

The proposed tool incorporates two distinct phases:
a. Cardiac cycle end-pointing.
b. S_1 and S_2 localization.

Figure 1 shows the flowchart of the algorithm. In the first phase, beginning and end points of each cardiac cycle are determined using the ECG signal. Several studies have already been done in order to use only PCG for cardiac cycle extraction [6] [12] [13]. However, we use ECG signal since it gives much less complexity to the end-pointing algorithm and the accuracy of the segmentation process is highly linked to the end-pointing phase. In the second phase, S_1 and S_2 are localized within the end-pointed cardiac cycles over the PCG signal. It is sometimes difficult to develop an algorithm for a complete segmentation using a single lead ECG, because T-wave is too weak to be identified in some patients.

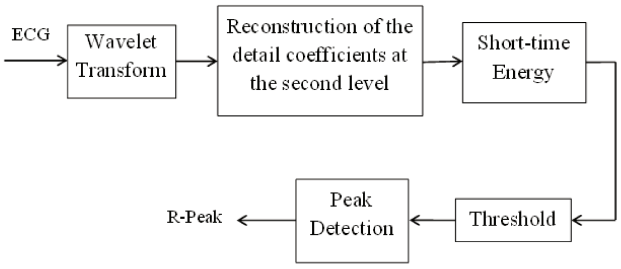

Figure 2. The flowchart of cardiac cycle end-pointing

3.1. Cardiac cycle end-pointing

Our end-pointing algorithm is based on R-Peak detection using wavelet transform relying on the fact that each cardiac cycle is proceeded by a R-peak. Figure 2 depicts the flowchart of the algorithm.

We used quadratic spline wavelet with compact support and one vanishing moment as an efficient matched filter for QRS complex [14]. It is a first derivative of a smooth function [15] whose Fourier transforms is:

$$\hat{\Psi}(\omega) = i\omega \left(\frac{sin\frac{\omega}{4}}{\frac{\omega}{4}} \right)^4 \quad (1)$$

where $\hat{}$ represents the discrete Fourier transform [14]. Based on this definition, the high-pass filter $G(\omega)$ and low-pass filter $H(\omega)$ for the detail and approximate coefficients are as follow [14]:

$$H(\omega) = e^{j\frac{\omega}{2}} \left(cos\frac{\omega}{2} \right)^3 \quad (2)$$

$$G(\omega) = 4je^{j\frac{\omega}{2}} \left(sin\frac{\omega}{2} \right) \quad (3)$$

The wavelet transform of the input signal at the second level is reconstructed for R-Peak detection. Computing short time energies over 100 ms windows provides a curve which better discriminates the QRS complexes. An average of the energies is assumed as the discriminative threshold for the QRS intervals in which the peak point corresponds to R-Peak. Figure 3 represents a typical ECG signal with high T-wave, the reconstructed signal at the second level and the short time energy graphs.

It is easily seen in the graphs that the algorithm effectively boosts the QRS interval against T-Wave.

3.2. S_1 and S_2 localization

Several studies showed that the power spectral distribution of PCG is substantially changed in the presence

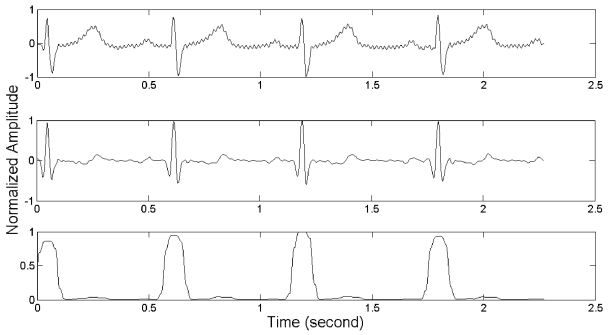

Figure 3. An ECG signal (top) along with the reconstructed signal at the second level (middle) and the upsampled short time energies (bottom).

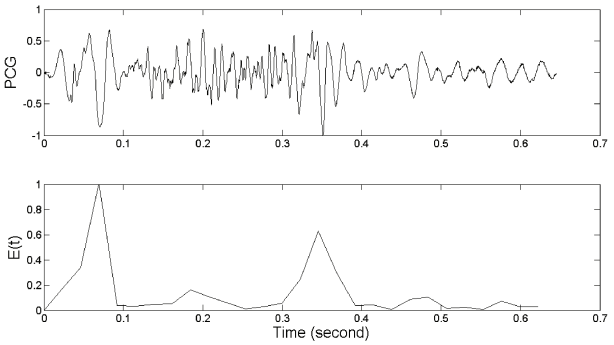

Figure 4. A cardiac cycle of PCG signal (bottom) and E (bottom).

of heart murmurs [1] [16] [17]. On the other hand, the main frequency contents of the S_1 and S_2 are below 200 Hz, while it can be extended up to 600 Hz for heart murmurs [6] [16]. Our localization algorithm is based on windowing a cardiac cycle into K temporal frames and computing the cross-spectrum of each frame t_k ($k = 1, ..., K$) with the first frame t_k as follow:

$$P(\omega, t_k) = \sum_{m=1}^{K} R_{t_k,t_1}(m) e^{-j\omega m} \quad (4)$$

where R_{t_k,t_1} is the cross-correlation of the two temporal frames. The cross-spectral energy is computed for each frame as:

$$E(t_k) = \sum_{\omega=W_1}^{W_2} P(\omega, t_k) \quad (5)$$

where W_1 and W_2 are the lower and upper frequency limits for the basic heart sounds (S_1 and S_2), respectively. It is clear that the first frame contains a segment of S_1 since the cardiac cycles are commenced by S_1. Therefore, $E(t_k)$ is the spectral correlation of the frame t_k with S_1 and represents high values for the frames associated with S_1 or S_2. We used $W_1 = 30$ and $W_2 = 150$ taking the frequency contents of the S_1 and S_2 into account [6]. The number of the temporal frames K and the overlap percentage are empirically obtained as 30 and 20%, respectively. Figure 4 depicts a cardiac cycle and the corresponding $E(t_k)$ under a harsh systolic murmur.

As seen in figure 4, S_1 and S_2 are clearly discriminated using $E(t_k)$. The tentative discriminating threshold is:

$$T = 0.9E_{Min} + 0.1E_{Max} \quad (6)$$

where E_{Min} and E_{Max} are the maximum and minimum of $E(t_k)$, respectively. It is worth noting that the frequency limits ($W_1 = 30$ and $W_2 = 150$) attenuates those sounds with frequency contents out of the S_1 and S_2 e.g. third heart sounds [6]. It is clear that the first peak above the threshold corresponds to S_1. End point of S_1 is determined as the first point after the peak and below the threshold on which the first derivative of $E(t_k)$ exceeds to its local maximum. In order to identify S_2, we apply the statistical mode operator on the peaks, discriminated by the threshold. The peak, corresponds to the largest mode is selected as S_2. The beginning and end points of S_2 are determined in the same way as S_1 end-pointing.

4. Results

The algorithm is applied on the data described in section 2.2. The signals are manually annotated after several rehearings. For the first step, the detected end-points are visually compared with the R-peaks of the ECG. An error is assumed when the detected point is out of range of QRS complex. Results showed that all the cardiac cycles available in our dataset (totally 1976 cycles) are correctly identified by the algorithm.

The evaluation of the second step is based on the accuracy of the identified sounds comparing with the annotated sounds. 20% of the temporal duration of each sound is assumed as its error margin for the beginning and end points of the sound. Based on this definition, the results obtained for S_1 and S_2 localization are tabulated in table 1.

Table 1. Results of S_1 and S_2 localizations.

Sound Type	Number of the sound	Number of Errors	Accuracy (%)
S_1	1976	53	97
S_2	1976	113	94

5. Discussion and conclusions

This paper presents an automatic tool for segmentation of heart sound signals. The tool constituts of a graphical user interface along with an automatic algorithm for heart sound segmentation, developed under a MATLAB platform. The automatic algorithm for PCG segmentation was tested with pathological cases in which robustness of the algorithm plays an important role. Results showed that the algorithm efficiently identifies the beginning and end points of the cardiac cycles as well as S_1 and S_2. A semi-automatic facility is added to the tool in order to correct possible errors in S_1 and S_2 identification within a cardiac cycle.

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