Heart Sound Localization in Chest Sound Using Convex-Hull Algorithm

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Abstract

This paper presents a technique to estimate heart sound localization in chest sound. In the proposed technique, chest sound is divided into frames and for each frame various types of acoustic features are extracted. The acoustic features used in this work are energy, log-energy and entropy with their smoothed versions. The heartbeat locations are detected by an algorithm known as convex-hull algorithm. It uses the features extracted from chest sound and pre-defined threshold in heartbeat detection process. The experimental results show that the proposed algorithm achieves 98-100% correct rate for detection of heartbeat locations.

1. Introduction

Examining the lung sound signal is one of the most important noninvasive methods for diagnosing various types of lung diseases. Since most of the lung sound energy below 200 Hz, it overlaps with the main frequency component of heart sound. That is, heartbeats are considered as interference for lung sound analysis [1]. Therefore, numerous methods in the literature are proposed to reduce or eliminate the effect of heart sound in lung sound recordings. Among them [2, 3] use adaptive filtering. Other methods given in the literature are wavelet denoising [4, 5] and two-dimensional interpolation of lung sound in the time-frequency domain [6].

One of the main problems in heart sound elimination in chest sound is to find location of the heartbeats [7]. For this purpose, we propose an algorithm to find heartbeat locations. The proposed algorithm have two main stages; detection of the segments which contain heartbeat and boundary enhancement to improve heartbeat locations [8].This work only examines the detection part of the algorithm, which is based on convex-hull algorithm [9,10,11]. The convex-hull algorithm is used in speech segmentation applications. In this study, we modify the algorithm to find heart beat locations. The experimental results show that the proposed algorithm detects heartbeat locations with the performance of 98-100% correction.

The rest of the paper is organized as follows: Section 2 gives a summary of the proposed algorithm stages: feature extraction method and the convex-hull algorithm. Section 3 examines experimental conditions and results. Conclusions and discussion are given in Section 4.

2. The Proposed Method

The main stages of the proposed algorithm are the feature extraction and the convex-hull algorithm are explained as follows.

2.1. Feature Extraction

To find heart sound locations, the chest sound signal is separated into frames. For each frame, three types of acoustic features (i.e., energy, logarithm of energy and entropy) are calculated. In this section we explain these features in detail. This wok also uses the smoothed version of acoustic features as explained below.

Energy: The first type of acousticic feature used in this work is the energy of the frame. The energy of each frame is calculated using following equation.

$$E = \frac{1}{N}\sum_{n=1}^{N}|s[n]|^2$$

where, E is the energy of the corresponding frame, $s[n]$ is the chest sound in the frame and N is the length of the frame.

Log-Energy: Log-Energy is calculated by taking logarithm of the energy as follows.

$$E_{log} = \log_{10} E$$

Entropy: Entropy is related to uncertainty of the process. The probability of density function (pdf) of each frame is calculated by using kernel density estimation procedure explained in [1, 7]. After calculation of pdf, the entropy of the frame is estimated as follows.

$$H = -\sum_{n=1}^{M} p[n]\log_2 p[n]$$

where, H and $p[n]$ are the entropy and estimated pdf of the corresponding frame respectively, and M is the length of the pdf.

Smoothing: In order to increase the robustness of the features mentioned above, we also calculate smoothed version of the acoustic features. The smoothing process is done by Kalman smoother, which is explained in [11, 12]. As an example, Figure 1 shows calculated features and their smoothed version for a given chest sound.

2.2. Convex-Hull Algorithm

The Convex-Hull algorithm is initially used for speech segmentation and described in [9,10,11]. For the sake of completeness, we describe it in here briefly. A small log-energy segment (from 30 to 100 frames in Fig.1.c) is selected for analysis, which can be seen in Fig.2. The convex hull of the selected log-energy segment is the minimal-magnitude function such that it is monotonically non-decreasing from the start of the segment to its point of maximum point, and is monotonically non-increasing thereafter. The convex-hull of the log-energy segment can be seen in Fig.2 with black line (dotted line), which called h1(t).

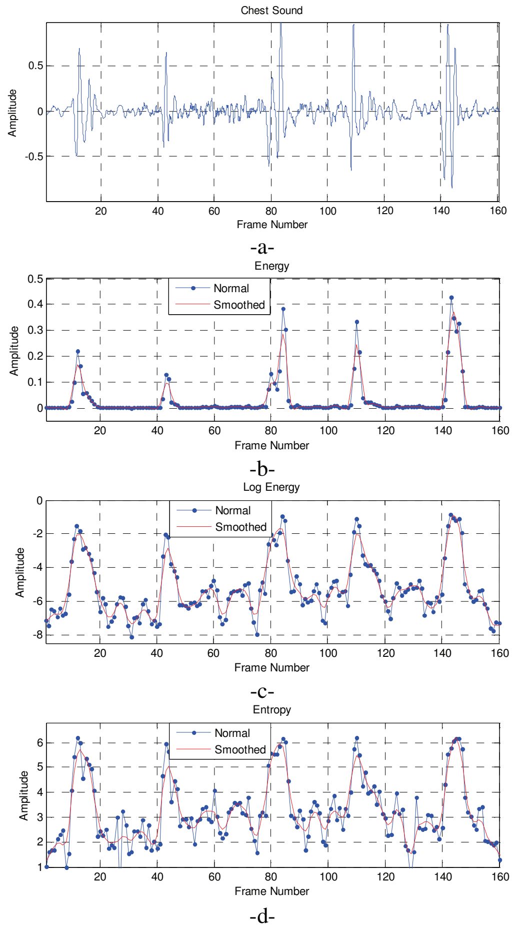

Figure 1. An example for features: Chest Sound (-a-), Energy (-b-), Log-Energy (-c-), Entropy (-d-) and their smoothed versions.

Within the segment, the maximal difference point between the convex-hull and the log-energy function is a potential boundary. If the difference exceeds the threshold, the segment is divided into two sub-segments. Assuming that maximum difference d1 at point c' exceeds the threshold, then, the algorithm divides segment (a-c) in to two sub-segments (a-c') and (c'-c). Then convex-hull is performed for each new segment. If d2 and d3 are smaller than the threshold, there will be no further segmentation. Segmentation is carried out recursively until the difference within the segment is below the threshold. That is, no further segmentation of that segment is possible.

3. Experiments

3.1. Database

In this work we used chest sound taken from single subject. This data is publicly available in [13]. The length of the data is about 80 s and it contains 222 heartbeats. The recording of this data is done under four levels of respiration: low, medium, high and no respiration (the subject holds their breath). The experimental results are given for each of levels separately. To measure performance of the proposed algorithm, the database is segmented by hand. That is, the true heartbeat locations are available for performance measure.

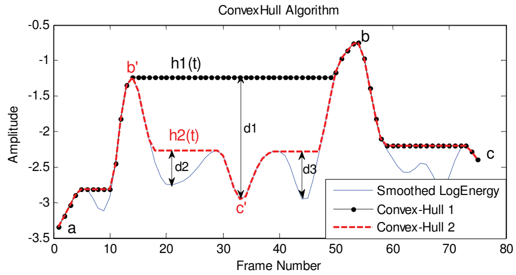

Figure 2. Convex-Hull Algorithm for sound segment

3.2. Threshold Types

The convex-hull algorithm uses pre-defined threshold for finding heartbeat locations. According to feature type, two different thresholds are used in this study; mean (μ) and mean plus standard deviation ($\mu + \sigma$) of the corresponding acoustic feature.

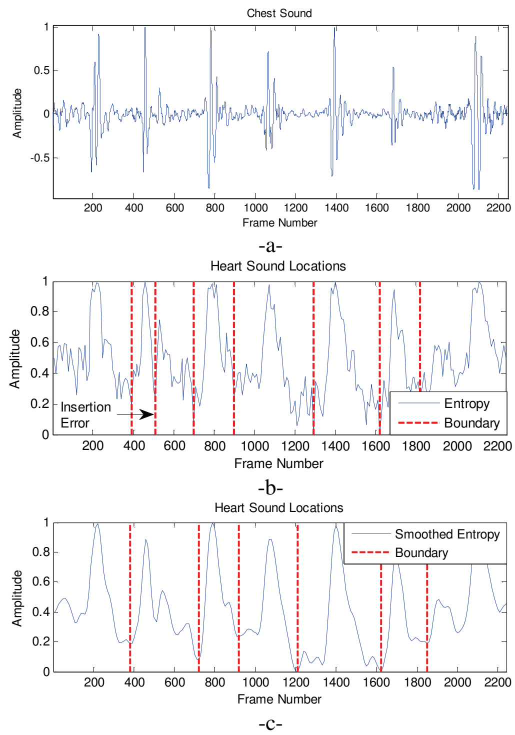

Figure 3. An example: The output of proposed algorithm for a given chest sound: Chest Sound (-a-), Entropy of the chest sound with heart sound boundaries (-b-), the smoothed entropy with heart sound boundaries (-c-)

3.2. Performance Measures

In this study three performance measures are used. First one is related to the number of correctly detected heartbeat locations. Other two performance measures are related to error measures which are called deletion and insertion error. Deletion error is related to the number of heartbeat which is missed by the proposed algorithm. The insertion error, on the other hand, is related to the detected heartbeat locations which are not true indeed. The formulae of the performance measures are defined as follows.

$$C = 100x\frac{N_C}{N_T}$$
$$D = 100x\frac{N_M}{N_T}$$
$$I = 100x\frac{(N_E - N_T)}{N_T}$$

where, C is correct rate. D and I are deletion and insertion error respectively. N_C , N_M , N_E and N_T are the number of correct, missed, estimated and total heartbeat locations.

3.3. Experimental Results

An example for the output of the proposed algorithm can be seen in Fig.3. In this figure, some parts of the chest sound Fig.3.a is examined by the proposed algorithm using entropy and smoothed entropy features. It can be seen from the figure that the proposed algorithm finds heartbeat boundaries successfully. Moreover, the algorithm give one insertion error about 450'th frame in Fig.3.b when using entropy features. On the other hand when we use smoothed entropy features, all the heartbeat boundaries are found correctly.

Table 1 shows the experimental results related to low-level inspiration rate. This part of the database contains 58 heartbeats cycle. When we examine the table, we can see that the proposed algorithm find all heartbeat location correctly (100% correct) for all feature types including smoothed ones. Moreover the log-energy feature does not give any insertion or deletion error. However, proposed algorithm detect two extra heartbeats with energy feature and one extra heartbeat with entropy feature in normal features (not smoothed features). That is, insertion error is about 3.3% and 1.7% for energy and entropy features respectively.

Table 1. Performance results of heart sound localization for low-level lung sound

	Normal Features				Smoothed Features			
	Correct	Delete Error	Insert Error	Threshold Type	Correct	Delete Error	Insert Error	Threshold Type
Energy	58 (100%)	0 (0%)	2 (3.3%)	μ+σ	58 (100%)	0 (0%)	0 (0%)	μ+σ
Log-Energy	58 (100%)	0 (0%)	0 (0%)	μ	58 (100%)	0 (0%)	0 (0%)	μ
Entropy	58 (100%)	0 (0%)	1 (1.7%)	μ+σ	58 (100%)	0 (0%)	0 (0%)	μ+σ

Table 2. Performance results of heart sound localization for medium -level lung sound

	Normal Features				Smoothed Features			
	Correct	Delete Error	Insert Error	Threshold Type	Correct	Delete Error	Insert Error	Threshold Type
Energy	71 (100%)	0 (0%)	2 (2.7%)	μ+σ	71 (100%)	0 (0%)	0 (0%)	μ+σ
Log-Energy	71 (100%)	0 (0%)	0 (0%)	μ	71 (100%)	0 (0%)	0 (0%)	μ
Entropy	71 (100%)	0 (0%)	1 (1.4%)	μ+σ	71 (100%)	0 (0%)	0 (0%)	μ+σ

Table 3. Performance results of heart sound localization for high -level lung sound

	Normal Features				Smoothed Features			
	Correct	Delete Error	Insert Error	Threshold Type	Correct	Delete Error	Insert Error	Threshold Type
Energy	76 (98%)	2 (2.6%)	11 (12.6%)	μ	77 (98.7%)	1 (1.3%)	1 (1.3%)	μ
Log-Energy	76 (98%)	2 (2.6%)	2 (2.6%)	μ	77 (98.7%)	1 (1.3%)	0 (0%)	μ
Entropy	77 (98.7%)	1 (1.3%)	3 (3.75%)	μ	77 (98.7%)	1 (1.3%)	0 (0%)	μ

Table 4. Performance results of heart sound localization for only heart sound

	Normal Features				Smoothed Features			
	Correct	Delete Error	Insert Error	Threshold Type	Correct	Delete Error	Insert Error	Threshold Type
Energy	15 (100%)	0 (0%)	0 (0%)	μ	15 (100%)	0 (0%)	0 (0%)	μ
Log-Energy	15 (100%)	0 (0%)	0 (0%)	μ	15 (100%)	0 (0%)	0 (0%)	μ
Entropy	15 (100%)	0 (0%)	0 (0%)	μ	15 (100%)	0 (0%)	0 (0%)	μ

On the other hand, when smoothed features are used, no feature type produces extra heartbeat (That is, the percentages of the both error types are zero). Also, the similar results are observed for medium-level inspiration rate, which can be seen in Table-2.

Table 3 shows the experimental results related to high-level inspiration rate and this part of the database contains 78 heartbeats. The highest correct rate is about 99.7% for non-smoothed entropy features and for all smoothed features. For this inspiration rate, the proposed algorithm gives best result for smoothed log-energy and entropy features with correct rate 99.7%, delete error: 1.3% and no insertion error. In addition to these, Table 4 denotes that the proposed algorithm find all heartbeat correctly with error-free when there is no inspiration.

4. Conclusions and Future Work

This study examines effectiveness of convex-hull algorithm in detection of heartbeat locations in chest sound. For this purpose three types of acoustic feature are extracted from chest sound, which are energy, log-energy and entropy. Under four-level respiration rate, the proposed algorithm finds heartbeat locations with 98-100% correct rate. It is observed that among the three features log-energy gives the best performance. In the future, we will test our algorithm with multiple subjects with different type of features. Moreover, as we mention introduction section the proposed algorithm in this work, which detects the segments containing heartbeats in chest sound, is the first part of our heart sound localization algorithm. In the second part of the algorithm, we will use some boundary correction algorithms to find precise locations of onset and offset of heartbeats.

5. References

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