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Heart Sound Localization in Chest Sound Using Temporal Fuzzy C-Means Classification

Hamed Shamsi and I. Yucel Ozbek *Member, IEEE*

Abstract— **Most of heart sound cancellation algorithms to improve the quality of lung sound use information about heart sound locations. Therefore, a reliable estimation of heart sound localizations within chest sound is a key issue to enhance the performance of heart sound cancellation algorithms. In this paper, we present a new technique to estimate locations of heart sound segments in chest sound using the temporal fuzzy c-means (TFCM) algorithm. In applying the method, chest sound is first divided into frames and then for each frame, the entropy feature is calculated. Next, by means of these features, the TFCM algorithm is applied to classify a chest sound into two classes: heart sound (heart sound containing lung sound) and non-heart sound (only lung sound). The proposed method was tested on the database used in the liteature and experimetal results are compared with the baseline which is a well-known method in the literature. The experimental results show that the proposed method outperforms the baseline method interms of false negative rate (FNR), false positive rate (FPR) and accuracy (ACC).**

I. Introduction

Auscultation of chest sound is an essential and noninvasive procedure for detection of both heart and pulmonary diseases. For examining heart diseases, it may be necessary to concentrate on one of the heart cycle regions such as S1, S2, systole or diastole. Therefore, it may be necessary to estimate these heart cycle regions, which can be considered as heart sound segmentation and localization task [1, 2]. On the other hand, in the detection of lung diseases by monitoring a chest sound, a heart sound is considered as an interference sound which prevents the examination of lung sound correctly. In such a case, it is crucial to cancel negative effects of a heart sound from a lung sound. Some cancellation algorithm needs to be estimated boundaries of a heart sound in advance, and the performance of these types of cancellation algorithms is dependent upon how accurately heart sound boundaries are estimated. To determine accurate heart sound boundaries in a chest sound, there are several methods proposed in the literature such as multi-resolution methods [3-5], the variance fractal dimension method [6], adaptive filtering methods [7-8] and the non-linear prediction method [9].

Recently, Yadollahi *et al.* [4] have proposed a heart sound localization scheme based on entropy-thresholding technique. It gives more accurate and robust results than those of the methods in [3, 6]. The authors of the singular spectrum method [5] state that their methods give only slightly better test results than the entropy-thresholding method with a lower computational cost.

In this work, we propose a new method, where the heart sound localization problem is converted into classification problem. Classification task is done by fuzzy c-means (FCM) and the temporal fuzzy c-means (TFCM) algorithms such that chest sound is divided into two classes: heart sound (HS) and non-heart sound (non-HS). The TFCM algorithm is originally devised from the SFCM [10] algorithm which is generally used in image segmentation task by considering spatial features information. We modified the SFCM algorithm and call it TFCM algorithm. The TFCM algorithm has similar idea with SFCM algorithm, but it uses temporal feature information instead of spatial ones. The results of the proposed method are compared with the baseline method on the test database used in [4]. The results show that the proposed method outperforms the baseline method in terms of false negative rate (FNR), false positive rate (FPR), detection error rate (DER), and accuracy (ACC).

The organization of the paper is as follows. Section II gives description of the proposed algorithm stages: feature extraction method, FCM and the TFCM algorithms. The experimental comparisons are given in section III. Finally, in section IV, we present discussion and conclusion.

II. The Proposed Method

A. Feature Extraction

Yadollahi *et al.* [4] show that entropy features extracted from a chest sound is useful for heart sound localization process since entropy of the segments with a heart sound will be much greater than that of the segments without a heart sound. Therefore, we decided to use entropy of the chest sound as a feature value. Following the procedure in [4], a chest sound is first divided into frames with 20 ms window length (205 samples) and with 50% overlap. Then, the probability density function (pdf) is estimated by the nonparametric normal kernel estimation method. After this estimation, the entropy of a frame is calculated as follows:

$$H(p) = -\sum_{i=1}^{N} p_i \log_2\left(p_i\right) \tag{1}$$

where p_i is the probability density at index i and N is the number of observation samples in the frame.

B. Classification Methods

In this work, we use the FCM and the TFCM classification algorithms to classify a chest sound into HS and non-HS.

H. Shamsi and I. Yucel Ozbek are with the Department of Electrical and Electronics Engineering, Ataturk University, Turkey (e-mail: hamed.shamsi@atauni.edu.tr, iyucelozbek@gmail.com).

Each algorithm is briefly introduced in following subsections.

Fuzzy c-means algorithm:

The FCM is a clustering algorithm proposed by Bezdek as an improved version of the k-means algorithm [11]. It first assigns frame samples to each class by using fuzzy memberships, and then, in an iterative manner, minimizes the cost function defined as follows:

$$J_{FCM} = \sum_{j=1}^{n}\left[\sum_{i=1}^{c} u_{ij}^{m}\left\|x_j - v_i\right\|^2\right], \quad (2)$$

where $X = \{x_1, x_2, ..., x_n\} \subseteq R$ is the entropy data. The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification, c is the number of clusters with $2 \le c \le n-1$ (in this work c=2; HS and non-HS), $V = \{v_1, v_2, ..., v_n\}$ is the c centers of the clusters, and v_i is the center of the cluster i. The partition matrix U is defined as:

$$U = \left\{ u_{ij},\ u_{ij} \in [0,1]\ ,\ \sum_{i=1}^{c} u_{ij} = 1\ ,\ 1 \le i \le c \right\}, \quad (3)$$

where u_{ij} is the fuzzy membership degree of the entropy data point x_j to the ith cluster. The objective function J_{FCM} can be minimized under the constraint U and V. Specifically, taking of the derivative J_{FCM} with respect to u_{ij} and v_i, and then equating to zero, two necessary but not sufficient conditions for J_{FCM} to be at its local extreme will be as the following:

$$U_{ij} = \sum_{k=1}^{c}\left[\frac{\left\|x_j - v_i\right\|}{\left\|x_j - v_k\right\|}\right]^{\frac{-2}{m-1}}, \qquad V_i = \frac{\sum_{j=1}^{n}(u_{ij})^m x_j}{\sum_{j=1}^{n}(u_{ij})^m}, \quad (4)$$

where $1 \le i \le c$ and $1 \le j \le n$. Although the FCM algorithm is a very useful clustering method, the classification results are given without considering temporal information about data used in classification purpose. Chest sound data carries important clues in temporal domain: therefore, we also use the TFCM, where temporal information is used in classification task.

Temporal Fuzzy c-means algorithm:

To overcome the problem of the FCM algorithm, Chuang *et al.* [10] introduced a spatial constraint term derived from the image into the objective function of the FCM (SFCM). We modified the spatial information in the time domain for the chest sound and called Temporal Fuzzy C-means (TFCM). To exploit the temporal information, a temporal function is defined as:

$$T_{ij} = \sum_k U_{ik}, \quad k \in NB(x_j). \quad (5)$$

where $NB(x_j)$ represents a window centered on frame sample in the temporal domain. The temporal function is the weighted summation of the membership function in the neighborhood of each frame sample under consideration. The nine-frame length window was used throughout this work. Just like the membership function, the temporal function T_{ij} represents the probability that a frame sample x_j belongs to *i*th clustering. The value of temporal function is the largest if all of its neighborhood frame samples belong to ith clustering, and is smallest if none of its neighborhood frame samples belong to *i*th clustering. The temporal function is incorporated into membership function as follows:

$$U_{ij}^{*} = \left(U_{ij}^{p} T_{ij}^{q}\right) \Big/ \left[\sum_{k=1}^{c} U_{kj}^{p} T_{kj}^{q}\right], \quad 1 \le i \le c\ ,\ 1 \le j \le n, \quad (6)$$

where, p and q are two parameters to control the relative importance of both functions. In a homogenous region (heart sound or lung sound), the temporal functions simply fortify the original membership, and the clustering result remains unchanged. However, for a frame on the boundary between HS and non-HS or vice versa, this formula reduces the weighting of cluster by the labels of its neighboring frame samples. For each clustering iteration, there are two steps. In the first step membership function calculate based on entropy data and cluster center and in the second step the temporal function is calculated based on the membership function for each frame.

After clustering process, for a decision rule for hard segmentation, we use a certain threshold value, which is defined as $\mu_{fm}+\sigma_{fm}/2$. Here μ_{fm} and σ_{fm} denotes mean and standard deviation of fuzzy membership degree respectively. HS and non-HS decisions are given according to this threshold value such that if fuzzy membership degree exceeds the threshold value, decide HS, otherwise decide non-HS. The summary of the proposed algorithm can be seen Table I.

III. EXPERIMENTAL STUDIES

The experimental studies carried out in this work are explained in this section as follows.

A. Database

The database used in this work includes five persons with 3 females. Originally, this database used in [4] contains six persons. However, five of them are provided by authors of [4] to us to use in our experimental studies. In this work, the experimental results are tested under three flow rates: low, medium and high. To measure performance of the proposed algorithm, the localization of the heart sound is determined by hand. Hand labeling of the database is performed by two trained persons with careful examination of data. The labeling is performed by using the WaveSurfer toolkit [12], and decisions for boundaries of heart sound are made by examining time waveform, spectrogram, and listening of the chest sound.

B. Performance Measures

To measure the performance of the methods, we calculated four quantitative results: 1) true-positive (TP) when a HS

TABLE I. THE PROPOSED HEART SOUND LOCALIZATION ALGORITHM

Step-1. Take 2 sec chest sound segment and, then divided it into frames
Step-2. Estimate the pdf and calculate related entropy for each frame
Step-3. Calculate the mean (μ) and standard deviation (σ) of entropy for the segment.
Step-4. Set the threshold value as $\lambda_1=\mu+\sigma$ (or $\lambda_2=\mu+\sigma/2$)
Step-5. Initialize the cluster centers of the TFCM algorithm using the threshold. HS cluster center is initialized if entropy feature exceed the threshold λ_1 (or λ_2) and non-HS cluster center is initialized otherwise.
Step-6. Set m =2, c=2, window length =9 frames, p=1, q=2
Step-7. Compute Uij and Vi by using Eq. (4)
Step-8. Compute temporal function Tij by Eq. (5)
Step-9. Update the membership by Eq. (6) and the centroids by Eq. (4)
Step-10. If $\| V_{i+1} - V_i \| < \varepsilon$ Stop the iteration otherwise, go to Step-8.
Step-11. Decide HS if fuzzy membership degree exceeds the threshold ($\mu_{fm}+\sigma_{fm}/2$) and decide non-HS otherwise.
Step-12. Go to Step-1 if there is reaming data to be classified

sound is correctly detected by the algorithms; 2) true-negative (TN) when a non-HS sound is correctly detected by the algorithms; 3) false-negative (FN) when a HS sound is missed; and 4) false-positive (FP) when non-HS are detected as HS sound. To evaluate the performance of the proposed localization algorithm, the FN rate (FNR) and the FP rate (FPR) are calculated. Also, the overall performance of the methods is measured by the detection error rate (DER) and accuracy (ACC). The calculation rules of the metrics can be seen as follows:

$$FNR \triangleq \frac{FN}{TP+FN}\times 100, \quad FPR \triangleq \frac{FP}{TN+FP}\times 100, \tag{7}$$

$$DER \triangleq \frac{FN+FP}{TD}\times 100, \quad ACC \triangleq \frac{TP+TN}{TD}\times 100, \tag{8}$$

where, $TD \triangleq TP+TN+FN+FP$. Note that the standard deviation of each measure is calculated by averaging the results for all five persons in the database.

C. Baseline Method

Azadeh *et al.* [4] shows that HS localization with entropy based method gives better results than many methods [3,6]. Therefore, we decide to use this method as a baseline method in this work and compare our results with this method. The adaptive threshold used in [4] is described as the mean plus standard deviation ($\lambda_1=\mu+\sigma$) of the data. Hence, we use this threshold value and call the baseline method as Baseline-1. On the other hand, our experimental results show that using $\lambda_2=\mu+\sigma/2$ value of the data as a threshold gives better results than λ_1. So we use this threshold value and call it as Baseline-2. The summary of the baseline methods used in this work can be seen in first five steps of the algorithm given in Table I. In Baseline algorithm, Step-5 gives final decision of classification results: HS and non-HS according to threshold values given in Step-4 instead of initialization procedure for the TFCM algorithm given in Table I.

D. Experimental Results

In order to validate and compare the results of the proposed methods, the FCM and the TFCM, with the baseline methods in heart sound localization task, we evaluate all the methods on same database described above. The experimental results are given in Tables II-IV for three respiratory flow rates: low, medium and high respectively. Note that the values are given in these tables are averaged for five subjects and standard deviations are calculated in that averaging step. The first observation from these tables can be explained as follows. Although Baseline-1 method has lowest FPR than Baseline-2 method (and other methods), its FNR is higher than all methods. Therefore, considering overall performance, it can be stated that Baseline-2 method is better than Baseline-1 method. As a second observation, it is seen from these tables that the Baseline-2 method is slightly better than one of the proposed methods FCM in terms of DER and ACC. However, FCM produces lower FNR than Baseline-2 method. Since, in heart sound localization tasks, it is more important not to miss any segment including the heart sound than to detect the segment containing the lung sound, the FCM method may be preferable to Baseline-2 method due to its lower FNR value. The last observation from these tables is that the second proposed method, the TFCM gives better result than any other methods in this work in term of FNR, DER, and ACC. Moreover, it produces lowest standard deviation; hence it can be considered more robust than any other methods. Fig. 1 illustrates an example for chest sound segment waveform, the related spectrogram, and entropy feature with the decision given by the algorithm used in this work. The hand labeled ground truth locations of HS boundaries are superimposed on the all three sub-figures. The related entropy of the chest sound segment and the threshold values (λ_1 and λ_2) for baseline algorithms are demonstrated in Fig. 1(c). While the solid horizontal line with cyan color denotes

TABLE II. MEAN AND STANDARD DEVIATION RESULTS (%) OF DIFFERENT HS LOCALIZATION METHODS AT LOW FLOW RATE

Method	FNR (%)	FPR (%)	DER (%)	ACC (%)
Baseline-1	35.6 ± 12.3	0.6 ± 0.3	11.2 ± 6.0	88.8 ± 6.0
Baseline-2	16.1 ± 11.1	5.5 ±1 .8	9.0 ± 4.7	91.0 ± 4.7
FCM	11.3 ± 6.6	8.7 ± 2.9	9.6 ± 3.7	90.4 ± 3.7
TFCM	9.9 ± 6.5	4.5 ± 1.9	6.1 ± 2.2	93.9 ± 2.2

TABLE III. MEAN AND STANDARD DEVIATION RESULTS (%) OF DIFFERENT HS LOCALIZATION METHODS AT MID FLOW RATE

Method	FNR (%)	FPR (%)	DER (%)	ACC (%)
Baseline-1	38.8 ± 7.8	0.7 ± 0.6	12.2 ± 3.6	87.8 ± 3.6
Baseline-2	17.8 ± 5.3	5.6 ± 3.1	9.4 ± 2.2	90.6 ± 2.2
FCM	12.3 ± 3.6	10.4 ± 5.3	11.2 ± 3.9	88.8 ± 3.9
TFCM	11.1 ± 3.8	4.2 ± 1.2	6.3 ± 0.9	93.7 ± 0.9

TABLE IV. MEAN AND STANDARD DEVIATION RESULTS (%) OF DIFFERENT HS LOCALIZATION METHODS AT HIGH FLOW RATE

Method	FNR (%)	FPR (%)	DER (%)	ACC (%)
Baseline-1	45.2 ± 4.7	0.8 ± 0.6	14.5 ± 1.5	85.5 ± 1.5
Baseline-2	23.6 ± 6.0	6.3 ± 2.8	11.6 ± 3.3	88.4 ± 3.3
FCM	15.5 ± 4.3	12.5 ± 6.3	13.6 ± 4.9	86.4 ± 4.9
TFCM	16.2 ± 4.4	6.0 ± 2.2	9.1 ± 2.7	90.9 ± 2.7

λ_1, the dashed horizontal line with green color designates λ_2. According to these threshold values, the decision results can be seen in Figs. 1(d) and 1(e) in which solid red lines show the estimated HS regions for each threshold value. Evaluating these decisions, it can be deduced that the λ_1 threshold estimates only some part of correct HS segment (Fig. 1(d)) yielding a high FNR as discussed for the results in Tables II-IV. Besides, using the λ_2 threshold gives much better results than λ_1, and its estimation covers almost all segments of correct HS regions as can be seen from Fig. 1(e). However, there are some HS segments in Fig. 1(e) which are not correctly estimated by the λ_2 threshold. For example, only some of the first and fourth (from left) HS segments are correctly estimated by this threshold. On the other hand, we note from Fig. 1(f) that the proposed TFCM algorithm is superior to both baseline methods and accurately estimates the correct HS segments.

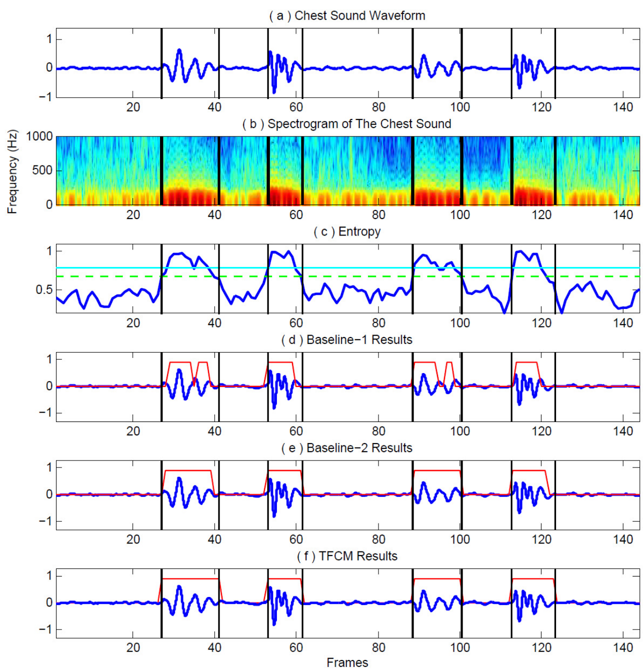

Figure 1. (a) An example of chest sound signal with superimposed on the hand labeled heart sound boundaries (vertical black lines). (b) Related spectrogram of the chest sound. (c) Corresponding entropies of the chest sound with two types of thresholds: $\lambda_1=\mu+\sigma$ (horizontal solid cyan line) and $\lambda_2 = \mu+\sigma/2$ (horizontal dashed green line). (d)- (f) The decisions (solid red lines) made by Baseline-1, Baseline-2 and the TFCM superimposed on chest sound respectively.

IV. Discussion and Conclusion

In this study, we proposed new heart sound localization methods, where localization problem is considered as classification problem such that heart sound localization task is achieved, when chest sound signal is classified into two classes: heart sound (HS) and non-heart sound (non-HS). Classifications task is performed by the FCM and the TFCM algorithms. The performance of the proposed method is compared with the baseline method (which is entropy-thresholding method used in the literature [4]). The experimental results show that the proposed algorithm better estimate heart sound locations than baseline method in terms of correct detection, false detections and accuracy. Moreover, the proposed algorithm produces lower standard deviation than baseline method when quantitative performance measures are averaged between individuals. That means, it has more robust than the baseline algorithm.

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