Pulmonary Crackle Detection using the Hilbert Energy Envelope

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Abstract. This paper presents a method for automatic pulmonary crackle detection based on the Hilbert energy envelope (HEE). Automatic detection of crackles in lung sounds offers a non-invasive way of monitoring or diagnosing cardiopulmonary diseases. The algorithm is divided into four main steps: (a) preprocessing, (b) estimation of HEE, (c) thresholding, and (d) applying time width conditions based on crackle two-cycle deflection and initial deflection width. Its performance is tested using a publicly available lung sound dataset of fine and coarse crackles and evaluated by the sensitivity (95.7%), positive predictive value (89.5%), and F-score (91.7%) for crackle detection. The good detection performance indicates the potential of the HEE-based algorithm as an automatic method for crackle detection in lung sound recordings.

Keywords: Pulmonary crackle, Automatic pulmonary crackle detection, Hilbert energy envelope (HEE) algorithm.

1 Introduction

In this paper we present, a method for automatic pulmonary crackle detection based on the Hilbert energy envelope (HEE).

Pulmonary crackles are short-lived, explosive lung sounds which are superimposed on normal breath sounds in some pathological lung conditions [1]. Crackles can provide valuable diagnostic information regarding different cardiopulmonary diseases including cystic fibrosis, pneumonia, fibrosing alveolitis, bronchiectasis, sarcoidosis, congestive heart failure, and asbestosis [2].

A traditional stethoscope offers a non-invasive way of examining the lung condition by listening to lung sounds through the chest wall, however the interpretation of the sound is highly subjective and depends on the expertise and hearing ability of the physician [3]. Visual detection of crackle sounds through analysis of a recording of the acoustic lung sound signal made with an electronic stethoscope [4], can also be very dependent on the expertise of the analyst. Computerized detection of crackles can, however, overcome these limitations and providing an objective way to detect crackle sounds [5].

In recent years, several automatic methods have been proposed for detecting crackles in lung sounds: time-varying autoregressive algorithm [3], fractal dimension and box filtering algorithm [5], first derivative absolute value (FDAV) based time domain analysis [6], and fractal dimension detector (FDD) [7]. These methods show good crackle detection ability for high quality sound recordings, but as mentioned in [5] have not been widely tested with recordings made in clinical settings where movement artefacts and environmental noise are commonplace. A crackle detector for a clinical setting needs high crackle detection accuracy and robustness to noise, further, low computational complexity can be advantageous for rapid processing to support clinical decision-making.

Fig. 1 displays the waveform of a typical crackle. Crackles can be characterized in the time domain by their initial deflection width (IDW) and their two-cycle deflection width (2CD) and may be divided into fine crackles (mean IDW = 0.7 ms; mean 2CD = 5 ms) and coarse crackles (mean IDW = 1.5 ms; mean 2CD = 10 ms) [8].

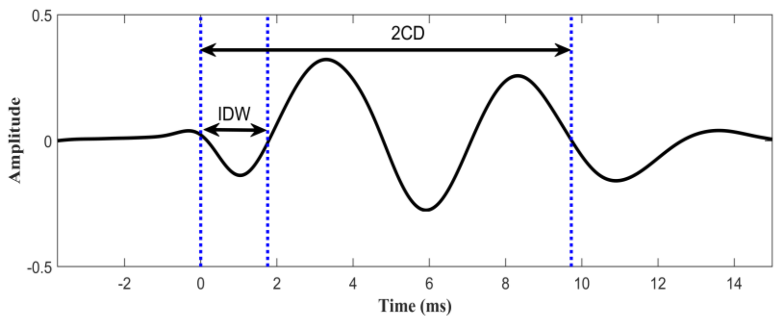

Fig. 1. The waveform of a typical crackle showing the characteristic time domain features: initial deflection width (IDW) and two-cycle deflection width (2CD).

The next section of this paper presents the HEE algorithm for crackle detection. Test data and the quantitative evaluators used for performance analysis are discussed in Section 3. Section 4 contains the results and discussion with conclusions presented in Section 5.

2 Hilbert energy envelope algorithm

The Hilbert energy envelope (HEE) constructs an energy envelope for a signal using the Hilbert transform to determine its instantaneous characteristics. Sharma et al. [9] presented an algorithm based on the HEE for heart rate extraction from acoustic recordings at the neck. Here the concept is adapted for automatic crackle detection. The process is shown schematically in Fig. 2. The HEE algorithm was developed using Matlab (R2019a) programming language.

Fig. 3 shows a worked example for a 0.137 s section of a lung sound signal recorded from a patient with idiopathic pulmonary fibrosis (Fig. 3(a)). The location of each crackle has been audio-visually identified by an experienced pulmonary acoustics researcher and marked with an arrowhead.

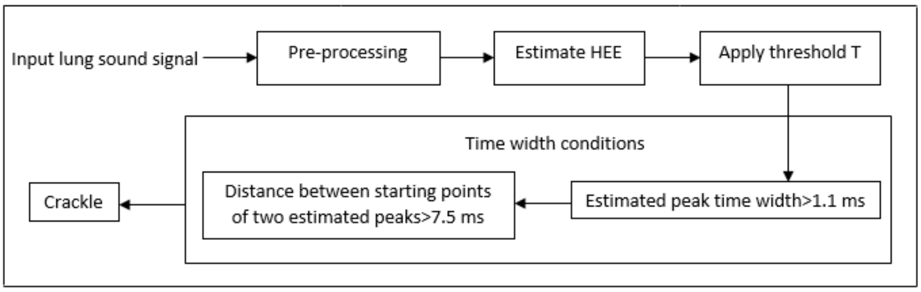

Fig. 2. Block diagram of the HEE algorithm for crackle detection.

The steps of the algorithm are as follows:

2.1 Pre-processing

The lung sound signal ($y[n]$) is pre-processed using a 6th order Butterworth high pass filter with cut off frequency 75 Hz, (Fig. 3(b)).

2.2 Estimation of Hilbert energy envelope

The instantaneous characteristics of the preprocessed signal ($y_q[n]$) are calculated using the analytical function $z[n]$[9].

$$z[n] = y_q[n] + ix[n] \tag{1}$$

Where, $y_q[n]$ is the preprocessed input signal, $x[n]$ is the Hilbert transform of the preprocessed input signal and $i = \sqrt{-1}$.

Using the analytical function in (1), the instantaneous amplitude ($a[n]$) and the instantaneous frequency ($\omega[n]$) are estimated.

$$a[n] = \sqrt{(y_q[n])^2 + (x[n])^2} \tag{2}$$

$$\omega[\mathrm{n}] = \tan^{-1}\left(\frac{x[n]}{y_q[n]}\right) \tag{3}$$

The energy envelope $H(y_q[n])$ is then calculated using (4) and is illustrated in Fig. 3(c):

$$H\big(y_q[n]\big) = |a[n]|^2 = (y_q[n])^2 + (x[n])^2,\ 1 \leq \mathrm{n} \leq \mathrm{N} \tag{4}$$

where N is the total number of samples in the input signal.

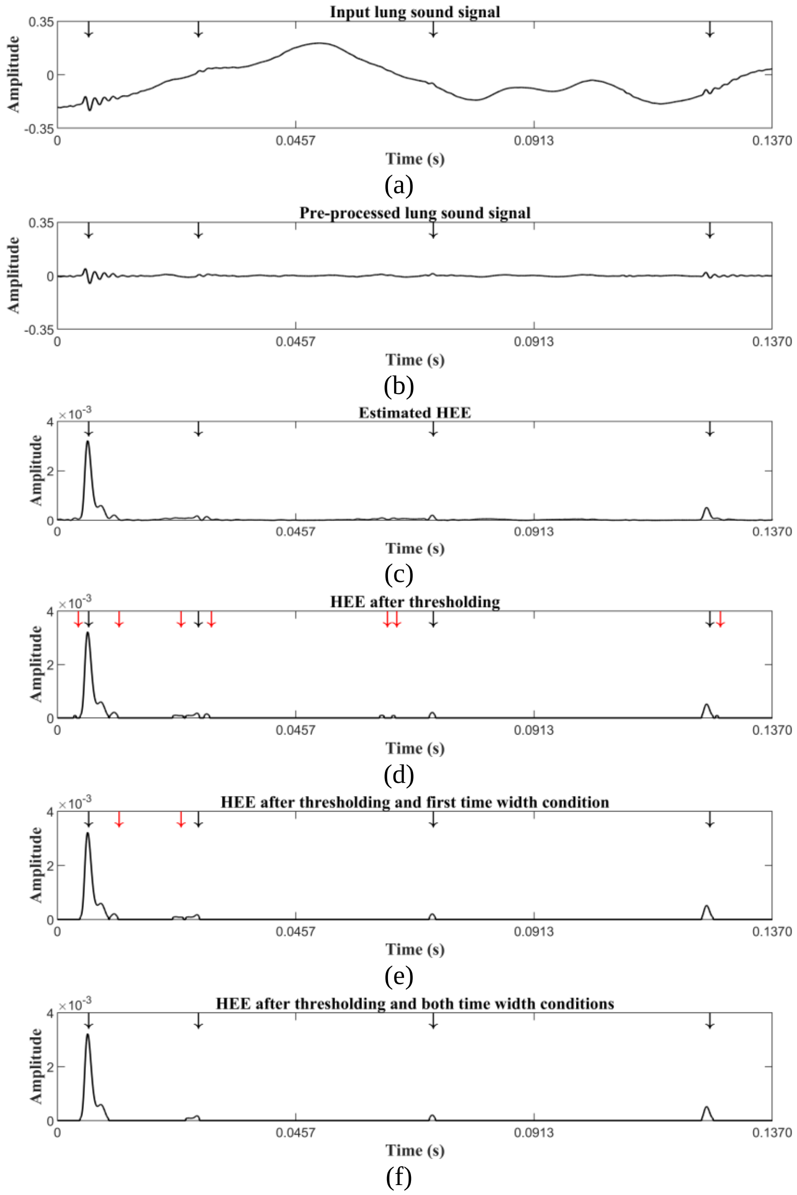

Fig. 3. Worked example of the HEE algorithm based on crackles time domain features. (a) A time section of 0.137 s lung sound data recorded from a patient with idiopathic pulmonary fibrosis (location of the crackles is marked with black arrowheads); (b) Pre-processed signal; (c) Estimated Hilbert energy envelope of the pre-processed signal; (d) Output after thresholding; (e) Removal of unwanted envelope peaks using first time width condition; (f) Eliminating remaining unwanted peaks using the second time width condition.

2.3 Thresholding:

An energy threshold T is calculated using the estimated energy envelope $H(y_q[n])$:

$$T = m_f \times max\{ H(y_q[n])\}, \qquad 1\leq n \leq N \tag{5}$$

where m_f is a multiplication factor We have selected the value of the multiplication factor to be m_f = 0.025. This choice is justified in Section (3.4). Threshold T is applied to the energy envelope $(H(y_q[n])$ and only values greater than T are kept. The estimated envelope signal after thresholding is displayed in Fig. 3(d) where the peaks related to crackles are shown using the black arrowheads and the peaks not related to crackles are marked using red arrowheads.

2.4 Time width conditions:

To reduce the number of false crackle detections, two conditions are empirically selected based on typical values for the crackle time domain features: IDW and 2CD [8]:

(1) HEE peaks with time width less than 1.1 ms (i.e. the average of the mean IDW for fine and coarse crackles respectively) are discarded, (Fig. 3(e)).

(2) To prevent multiple detections of the same crackle and to eliminate any remaining false peaks after applying the first time width condition, the distance between the starting points of two envelope peaks is considered. If the distance between those starting points is greater than 7.5 ms (i.e. the average of the mean 2CD for fine and coarse crackles respectively), both peaks are considered to be crackles; otherwise only the peak with longer duration is considered to be a crackle and the other is discarded. The output, after applying this condition, is shown in Fig. 3 (f), where it can be seen that all false peaks have been eliminated.

3 Dataset and performance evaluators

3.1 Dataset

The HEE algorithm was tested using a publicly available data set [10] of simulated and real fine and coarse crackles which can be embedded in two types of background noise: breath noise, and Gaussian white noise. The dataset also contains a sample of a real lung sound with fine crackles recorded from a patient with idiopathic pulmonary fibrosis and a sample of a real lung sound with coarse crackles recorded from a patient with bronchiectasis. The real lung sound files were recorded using an electronic stethoscope and all files in the dataset are sampled at 44100 Hz. Table 1 shows the cases selected from the dataset for performance analysis, SNRs tested ranged from 0 to 10 dB because for SNR levels less than 0 dB either a large number of false crackles were detected or estimated peaks, which may correspond to crackles, started to combine with each other due to background noise. Note that although the data set also provides the option of embedding the crackles in Gaussian white noise, performance in that condition was not tested in this study.

Table 1. Cases generated from the test dataset [10].

Cases	IDW & 2CD (ms)	N_C	D_g	BN	SNR
	0.7 & 5 [8]	10	NA	BR_N	
Simulated fine crackles	0.5 & 3.3 [11]	10	NA	BR_N	
	0.9 & 6 [12]	10	NA	BR_N	0
	1.5 & 10 [8]	10	NA	BR_N	to
Simulated coarse crackles	1 & 5.1 [11]	10	NA	BR_N	10
	1.25 & 9.5 [12]	10	NA	BR_N	dB
Real fine crackles	ND	10	IPF	BR_N	
Real coarse crackles	ND	10	B_r	BR_N	
Real breath sound with fine crackles	ND	ND	IPF	NBS	ND
Real breath sound with coarse crackles	ND	ND	B_r	NBS	ND

N_C: Number of crackles; Dg: Diagnosis; ND: Not defined; NA=Not applicable; IPF: Idiopathic pulmonary fibrosis; Br: Bronchiectasis; BN: Background noise; BR_N: Breath noise; NBS: Normal breath sound; SNR: Signal to noise ratio.

3.2 Performance evaluators

Three parameters were used to evaluate the crackle detection performance of the algorithm: sensitivity (SE), positive predictive value (PPV), and F-score (F_1) [13] where:

$$F_1 = 2 \times \frac{SE \times PPV}{SE + PPV} \tag{6}$$

For each SNR tested, 501 test samples were generated (see section 3.3). The SE, PPV and F_1 were calculated for each sample and the average over all test samples was generated. Note that the case of temporally overlapped crackles was not considered and if more than one crackle lay under a single HEE peak, or if, due to background noise, two or more peaks were connected with each other, then they were considered as one crackle.

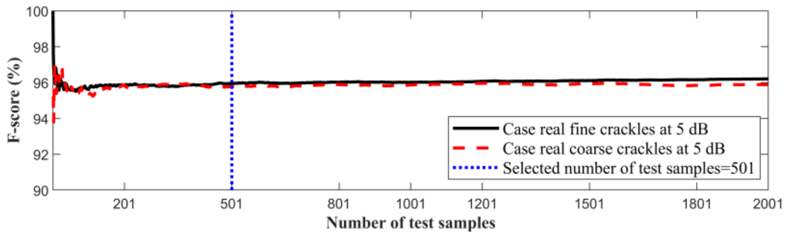

Fig. 4. Selection of number of test samples to eliminate random variation in the HEE algorithm crackle detection performance using real fine crackles case and real coarse crackles case at an SNR of 5 dB.

3.3 Selection of the number of test samples

Fig. 4, shows the average F_1 of the HEE algorithm in the cases of real fine crackles (RFC) and real coarse crackles (RCC) at 5 dB SNR as the number of test samples is increased from 1 to 2001 in steps of 1. We note that average F-score is approximately independent of the number of samples when the number of samples exceeds 500. The blue vertical dotted line indicates the selected number of samples for all tests reported here.

3.4 Selection of multiplication factor (m_f)

As mentioned in Section 2.3, those HEE peaks, which are likely to correspond to crackles, are selected using a threshold, T. The threshold value is calculated (equation (5)) using a multiplication factor m_f .

Fig. 5 shows the performance of the HEE algorithm in terms of SE and PPV in the case of real fine crackles and real coarse crackles at an SNR of 5 dB as the multiplication factor ranges from 0.01 to 0.03, in steps of 0.001. We observe that, for $m_f > 0.025$ the SE drastically decreases and for $m_f < 0.025$ the PPV gradually starts to decrease. The selected multiplication factor $m_f = 0.025$ is marked on Fig. 5 and is chosen to avoid both these regions.

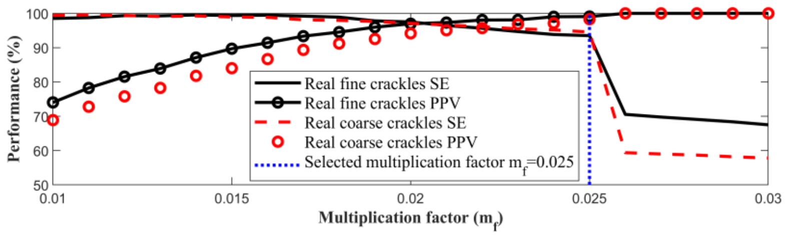

Fig. 5. Selection of multiplication factor m_f using real fine and coarse crackles cases (Table 1) at 5 dB SNR.

4 Results and Discussion

Figs. 6(a) and (b) show the F-score plots for the HEE algorithm for fine (real and simulated) and coarse (real and simulated) crackles, respectively in the SNR range of 0 to 10 dB. It can be observed that for SNR > 5 dB the F-score plots start to converge to 100% in both cases, with generally faster convergence fine crackles. The performance of the HEE algorithm in terms of SE, PPV and F_1 on the whole test data with SNR = 5dB, is shown in Table 2.

The overall performance of the HEE algorithm in terms of SE (95.7%), PPV (89.5%), and F_1 (91.7%) is equivalent to or better than that reported for other detection methods reported in the literature (e.g. [5], [6], [14]). Moreover, the average detection time (D_T) for the algorithm to finish is less than 1 sec. The main advantage of

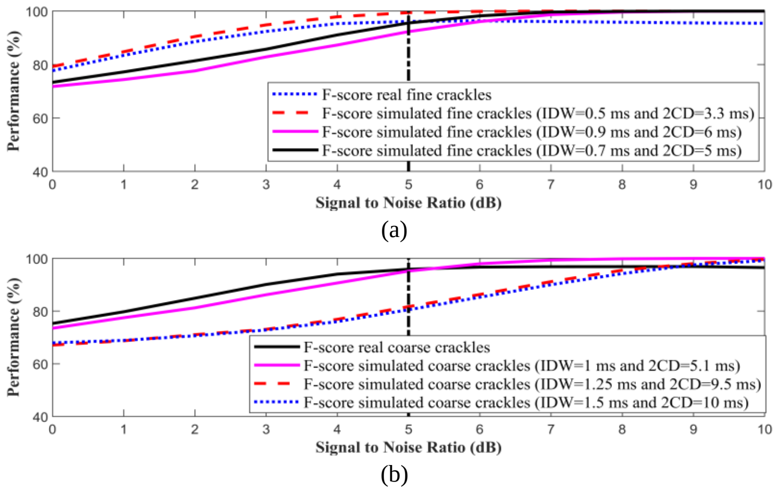

Fig. 6. The HEE algorithm F-score (F_1) plots for breath noise cases with a signal to noise ratio in the range of 0 to 10 dB (Table 1). (a) Real fine crackles and simulated fine crackles cases; (b) Real coarse crackles and simulated coarse crackles cases.

Table 2. Crackle detection performance.

Cases		**N$_c$**	**SNR**	**NS**	**HEE**			
					$\overline{SE}(SD)$	$\overline{PPV}(SD)$	$\overline{F}_1(SD)$	$\overline{D}_T(SD)$ s
	A$_F$	10	5 dB	501	99.4 (2.2)	91.6 (7.3)	95.2 (4.3)	0.72 (0.03)
SFC	H$_F$	10	5 dB	501	99.9 (0.9)	99.1 (2.8)	99.5 (1.7)	0.75 (0.04)
	C$_F$	10	5 dB	501	99.7 (1.7)	87.3 (7.9)	92.9 (4.7)	0.79 (0.04)
	A$_C$	10	5 dB	501	99.7 (1.6)	67.6 (9.2)	80.2 (6.5)	0.78 (0.04)
SCC	H$_C$	10	5 dB	501	99.8 (1.4)	91.1 (7.2)	95.1 (4.1)	0.72 (0.04)
	C$_C$	10	5 dB	501	99.9 (1.1)	69.5 (8.6)	81.7 (5.9)	0.77 (0.04)
RFC		10	5 dB	501	93.9 (4.2)	99.0 (3.1)	96.3 (2.7)	0.75 (0.05)
RCC		10	5 dB	501	93.9 (5.9)	98.0 (4.1)	95.8 (3.6)	0.72 (0.02)
RBFC		32	ND	1	71.1	91.4	80.0	0.24
RBCC		6	ND	1	100	100	100	0.25
Overall performance					95.7 (9.0)	89.5 (11.8)	91.7 (7.9)	0.65 (0.21)

SFC: Simulated fine crackles; A$_F$: IDW=0.7 ms & 2CD=5 ms [8]; H$_F$: IDW= 0.5 ms & 2CD= 3.3 ms [11]; C$_F$: IDW=0.9 ms & 2CD=6 ms [12]; SCC: Simulated coarse crackles; A$_C$: IDW= 1.5 ms & 2CD=10 ms [8]; H$_C$: IDW=1 ms & 2CD= 5.1 ms [11]; C$_C$: IDW=1.25 ms & 2CD=9.5 ms [12]; RFC: Real fine crackles; RCC: Real coarse crackles; RBFC: Real breath sound with fine crackles; RBCC: Real breath sound with coarse crackles; N$_C$: Number of crackles; SNR: Signal to noise ratio; NS: Number of test samples; $\overline{SE}$: Mean of sensitivity; $\overline{\text{PPV}}$: Mean of positive predictive value; $\overline{F}_1$: Mean of F-score; $\overline{\text{D}}_\text{T}$: Average detection time; s: Second; ND: Not defined; SD: Standard deviation; In all cases number of samples (N)=*32,768*.

the proposed HEE algorithm is its structural simplicity, lower computational cost (detection time) and the ability to perform in low SNRs for both fine and coarse crackles.

Although the favorable results show the potential of the HEE algorithm for automatic crackle detection, this study has some limitations. First, the overall performance of the algorithm is dependent on a suitable choice of the non-adaptive multiplication factor for calculating the threshold, *T*. Second, though the method works well to determine the location of the start of the crackle, its ability to extract the full duration of each crackle signal has not been examined, so it remains to be determined whether the method can be recommended where characterization of the temporal morphology of crackles is important.

5 Conclusion

In this paper a new HEE algorithm for automatic crackle detection based on crackle time domain features (IDW and 2CD) has been presented. The results suggest that the proposed method is fast ($D_T < 1$ s) and offers high detection performance (SE 95.7%, PPV 89.5%, and F_1 91.7%) even when signal to noise ratio is low.

Future research will focus on evaluating performance on a larger dataset recorded from a range of cardio pulmonary patients with different diagnoses.

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Conflict of Interest

The authors declare no conflict of interest.

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