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Automatic crackle detection algorithm based on fractal dimension and box filtering

Cátia Pinho[a,b]; Ana Oliveira[a]; Cristina Jácome[a,c]; João Rodrigues[d]; Alda Marques[a,e]*

[a] Lab 3R – Respiratory Research and Rehabilitation Laboratory, School of Health Sciences (ESSUA), University of Aveiro, 3810-193 Aveiro, Portugal

[b] IT – Aveiro, Instituto de Telecomunicações, University of Aveiro, Aveiro, 3810-193, Portugal

[c]Research Centre in Physical Activity, Health and Leisure (CIAFEL), Faculty of Sports, University of Porto, Porto, 4200-450, Portugal

[d]Institute of Electronics and Telematic Engineering of Aveiro (IEETA), Aveiro 3810-193, Portugal

[e]Center for Health Technology and Services Research (CINTESIS), ESSUA, Aveiro 3810-193, Portugal

Abstract

Crackles are adventitious respiratory sounds that provide valuable information on different respiratory conditions. Crackles automatic detection in a respiratory sound file is challenging, and thus different signal processing methodologies have been proposed. However, limited testing of such methodologies, namely in respiratory sound files collected in clinical settings, has been conducted. This study aimed to develop an algorithm for automatic crackle detection and characterisation and to evaluate its performance and accuracy against a multi-annotator gold standard. The algorithm is based on three main procedures: i) extraction of a window of interest of a potential crackle (based on fractal dimension and box filtering techniques); ii) verification of the validity of the potential crackle considering computerised respiratory sound analysis established criteria; and iii) characterisation and extraction of crackle parameters. Twenty four 10-second files, acquired in clinical settings, were selected from 10 patients with pneumonia and cystic fibrosis. The algorithm performance was assessed by comparing its results with gold standard annotations (obtained by the agreement among three experts). A set of 7 parameters was optimised. High levels of sensitivity (SE=89%), positive predictive value (PPV=95%) and overall performance (F index=92%) were achieved. This promising result highlights the potential of the algorithm for automatic crackle's detection/characterisation in respiratory sounds acquired in clinical settings.

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Keywords: Adventitious respiratory sounds; Crackles; Automatic detection/classification algorithms; Fractal dimension; Box filtering.

* Corresponding author. Tel.: +351 234 372 462; fax: +351 234 401 597.
*E-mail address:*amarques@ua.pt

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1. Introduction

Respiratory diseases are a major health and economic burden worldwide[1]. Therefore, during the last decade, research efforts have been dedicated to improve the diagnosis and monitoring of patients with respiratory diseases[2].

The stethoscope has been used for 200 years to perform lung auscultation during clinical examinations as it is simple, non-invasive, economic, practical and applicable to all populations and settings[3]. However, it is known that auscultation is subjective, i.e., respiratory sound interpretation depends on the stethoscope properties, hearing ability and clinical experience of users and their capacity to memorise sound patterns[4]. To overcome the associated subjectivity, research efforts have been devoted to develop computerised respiratory sound analysis (CORSA), which consists of recording respiratory sounds with an electronic device and objectively analysing/classifying them based on advanced digital signal processing techniques. Through CORSA, respiratory sounds were found to be a more sensitive indicator, detecting and characterising the severity of respiratory diseases before any other measure[5]. Since then, special attention has been given to the automatic detection and characterisation of respiratory sounds, such as crackles, as changes in their properties can early inform the presence of several respiratory conditions[6].

Crackles are acoustically defined as explosive and discontinuous sounds with a duration of less than 20 ms[6]. The most studied crackle's parameters are the initial deflection width (IDW), the largest deflection width (LDW) and the two cycle deflection (2CD)[6,7] (Fig. 1).

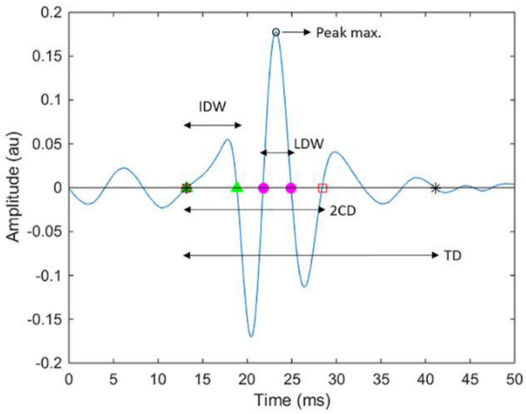

Figure 1. Crackle time-domain parameters: initial deflection width (IDW), largest deflection width (LDW), two-cycle duration (2CD), total duration (TD) and maximum peak (peak max.).

Despite crackles' great value to contribute for the diagnosis and monitoring of respiratory diseases, their automatic detection and characterisation is still challenging namely, in respiratory sound files recorded in clinical settings, as these sounds often present associated artefacts (e.g., environmental noise and movement artefacts), which affect the recognition accuracy of algorithms[8]. Several signal processing techniques have been proposed, including digital filters[9], spectrogram analysis[10], time-domain analysis[10], auto-regressive models[11] and wavelet-packet transform methods[12], fuzzy filters[13] and fractal dimension filtering[14]. Despite the high values of sensitivity and specificity associated with these techniques, limited testing[12,14] have been performed with respiratory sound files recorded in clinical settings and validated against a multi-annotator gold standard[15]. Taking these factors into consideration, it may be hypothesised that, when tested in such conditions, the proposed signal processing techniques will have lower performances than originally reported. Therefore, a robust algorithm to detect and characterise crackles in respiratory sound files acquired in clinical settings is needed.

This study aimed to develop an algorithm for automatic crackle's detection and characterisation and to evaluate its performance and accuracy against a multi-annotator gold standard. Accordingly, this paper is organised as follows: section 2 describes the methodologies underlying the development and validation of the proposed algorithm; section 3 presents the results of the algorithm's validation in terms of sensitivity (SE); positive predictive value (PPV) and F-index; section 4 discusses the results and highlights possible improvements; and section 5 concludes the paper and presents future work.

2. Methods

Twenty-four respiratory sound files of adult patients with pneumonia acquired in the community (15 sound files from 6 patients; 46±14.6yrs) and cystic fibrosis (9 sound files from 4 patients; 32.3±18.1yrs) were obtained from 2 academic repositories. Respiratory sounds of patients with pneumonia belong to a repository built at University of Aveiro in the scope of a research project (PTDC/SAU–BEB/101943/2008). Respiratory sounds of patients with cystic fibrosis were collected during a PhD project at University of Southampton (SFRH/BD/21375/2005).

All respiratory sounds were acquired following CORSA short-term sound acquisition guidelines[16] for 25 seconds with a Thinklabs® digital stethoscope (Thinklabs® Rhythm: ds32a, Colorado, US) in patients with pneumonia and with a WelchAllyn digital stethoscope (WelchAllyn Meditron, 5079-402) in patients with cystic fibrosis. Recordings were performed at a sampling rate (fs) of 44.1 kHz. Ethical approvals and written informed consents were obtained before any data collection.

2.1. Crackles manual annotation

Manual annotation of crackles was performed in all respiratory sound files. Firstly, the files duration was reduced to 10-seconds, as manual annotation is a time-consuming process[2,17]. Then, three respiratory researchers, with experience in visual-auditory crackle recognition, independently annotated the beginning and the end of each crackle in each respiratory sound file. Respiratory Sound Annotation Software V1.1 was used to perform the annotation[2].

For each respiratory sound, a gold standard annotation was obtained by combining the annotations from the three researchers. An event was flagged as a crackle if at least two researchers had identified it (i.e., agreement by majority)[18]. The agreement between researchers was set considering the maximum absolute peak within each crackle annotation[15] and was assessed by dividing the number of crackles in which the researchers agreed by the total number of crackles annotated. An agreement of 86% was achieved.

2.2. Automatic crackle detection

The proposed algorithm can be summarised in three main steps: i) extraction of a window of interest of a potential crackle (based on fractal dimension and box filtering techniques)[14,19-21]; ii) verification of the validity of the potential crackle considering CORSA established criteria[7,22]; and iii) characterisation and extraction of crackle’s parameters.

The signal was downsampled to 11025Hz (fs) after appropriate anti-aliasing filtering, to reduce computation requirements. The signal filtering consisted in the application of a passband filter of [100 – 2000] Hz (finite impulse response, designed with a 83ms Blackman window), to eliminate high frequency noise, ensuring that the main features of the crackles were still preserved[6,23].

2.2.1. Extraction of a window of interest

The extraction of a window of interest involved different signal processing steps: i) Savitzky-Golay (polynomial) finite impulse response (FIR) smoothing[24]; ii) fractal dimension estimation[12,14,19]; iii) box filtering[21,25]; and iv) application of a threshold to extract the beginning and the end of a window of interest. A diagram summarising these steps is presented in figure 2.

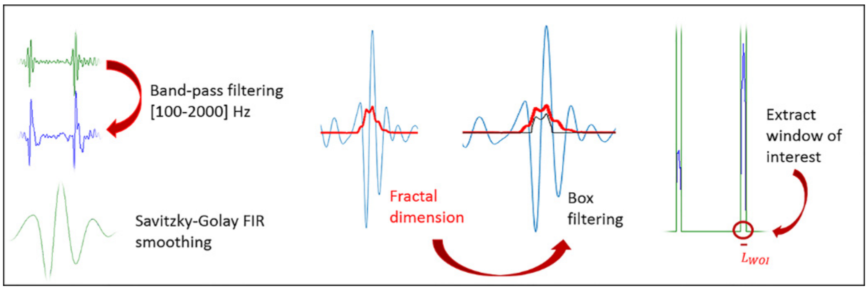

Figure 2. Main steps performed by the algorithm to extract a window of interest of length (L_{WOI}), i.e., identifying a potential crackle.

Firstly, a smoothing in the signal was performed to extract the remaining high frequency peaks of noise. Secondly, the fractal dimension of the signal was estimated using a sliding window of length L_{FD}. Fractal dimension is a statistical measure that indicates an object's complexity in fractal geometry and it is used to evaluate the complexity of a waveform. The method proposed by Sevcik (2010)[20] was used, as it is more sensitive to waveform changes and faster than other commonly used methods, such as the signals envelop method[20]. Fractal dimension is defined by:

$$FD = 1 + \frac{\ln(L)}{\ln(2N')} \tag{1}$$

where N' is the number of steps in the waveform ($N' = L_{FD} \times fs - 1$) and L represents the total length of the waveform, i.e., the sum of the Euclidean distance between successive data points:

$$L = \sum_{i=1}^{N'} dist(i, i+1) \tag{2}$$

Thirdly, an additional smoothing to estimate the trend of the fractal dimension signal in each time instance was applied. The estimation of the trend was based on box filtering, also known as average or mean filtering, with a sliding window of length L_{BF}. This is a commonly used technique to reduce noise, accomplished by replacing each amplitude value with the average value of the surrounding neighbours, including itself. Therefore, the large amplitude variations between samples was removed and a much smoother signal was produced (i.e., the trend). This will enhance the identification of crackles in noisy signals, such as sounds acquired in a clinical settings or sounds containing other adventitious respiratory sounds, e.g., wheezes.

In the fourth step, the fractal dimension signal was compared to an adaptive threshold to identify the window of interest of a potential crackle by $FD > X \times trend$, where X is a free parameter for optimisation (Fig. 3). The final length of the window of interest was defined as the variable L_{WOI}.

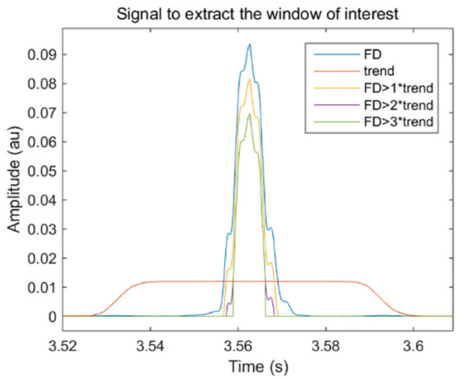

Figure 3. Adaptive threshold applied to the fractal dimension (FD) signal to identify the window of interest of a potential crackle by $FD > X \times trend$, where $X = 1, 2, 3$.

2.2.2. Verification of crackle

A function was developed to evaluate the validity of the potential crackle by verifying if the window of interest met CORSA established criteria for crackles[10]. Also, additional considerations empirically established by the analysis of noisy signals were implemented to correct errors in the detection. Therefore, the following set of conditions were established:

i) the amplitude of the different peaks of the crackles had to be progressively lower than the LDW;
ii) peaks had to be progressively wider after the IDW (variable defined as W_{peaks});
iii) crackle zero-crossings were verified: minimum of 5 zero-crossings, to guarantee the calculation of 2CD, and maximum of 16 zero-crossings;
iv) the mean absolute amplitude of the crackle had to be higher than F times the mean absolute amplitude of the background noise estimated from a segment of length L_{bckg} preceding the crackle (considering the CORSA criteria, that suggests that crackle amplitude had to be higher than 2*background noise)

v) crackle's IDW had to be higher than 1/8 of the LDW.

2.2.3. Optimization of algorithm parameters

Seven threshold parameters were established to improve the performance of the automatic crackle's detection algorithm. Three different values were tested for each parameter, resulting in a total of 2187 (3^7) combinations. The best combination was defined as the one presenting the highest F-index similarity with the gold standard annotation.

The threshold parameters and corresponding values evaluated were:

1) width of the fractal window of approximately half the length of the crackle[12] ($L_{FD} = 4, 6, 8\ ms$);
2) width of the box filtering window ($L_{BF} = 40, 60, 80\ ms$);
3) parameter X ($= 1, 2, 3$) applied in the adaptive threshold to identify the window of interest;
4) minimal length of the window of interest of each crackle ($L_{WOI} = 0.5, 1, 2\ ms$);
5) error factor range ($= 1/5, 1/4, 1/3$), associated with the width of the peaks following IDW ($W_{peaks} \pm error\ factor \times W_{peaks}$);
6) length of the background sound before the crackle ($L_{bckg} = 20, 40, all^{*}\ ms$) **considering all background length before the crackle*;
7) factor multiplied by the amplitude of the background sound ($F = 1.6, 1.8, 2$).

Parameters 6 and 7 were established to evaluate the amplitude of the crackle when compared with the background noise (condition 'iv' defined in the section 2.3.2). Only the background length before the crackle window was evaluated. This strategy allowed the extraction of previous crackles detected in that signal, ensuring that only background sound was considered. Figure 4 provides a flow diagram of the proposed algorithm to detect crackles.

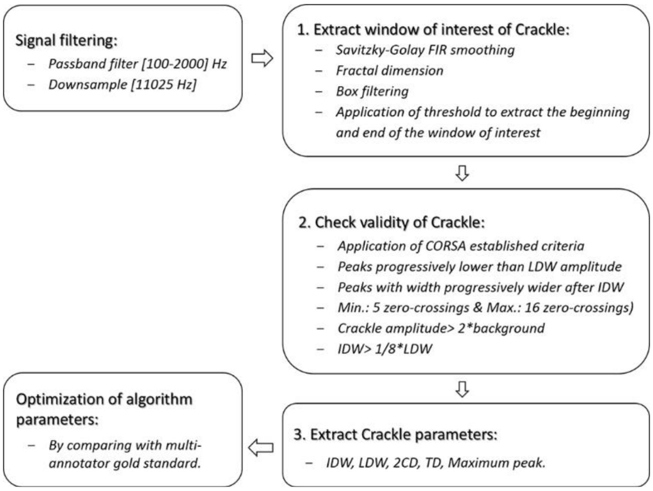

Figure 4. Flow diagram of the proposed algorithm to detect crackles.

2.3. Classification measures to validate the algorithm

The validation of the performance and accuracy of the automatic crackle's detection algorithm was obtained by comparing the results against the multi-annotator gold standard (see section 2.2).

Classifier performance[26] is typically based on four well-known parameters, namely true positive (TP), true negative (TN), false positive (FP) and false negative (FN) counts. These parameters are the basis of many common classification metrics, for example sensitivity (SE) and positive predictive value (PPV), both usually expressed as percentages. These metrics imply a comparison between the automatic detection results and a gold standard, which for respiratory sounds is the judgment of respiratory experts[15]. Thus, the algorithm performance was assessed by comparing the maximum absolute peak within each identified crackle with the results of the multi-annotator gold standard. Then, SE, PPV and the algorithm's F-index were calculated.

SE is defined as the ratio between crackles correctly detected (TP) and the sum of TP with the number of crackles not detected by the algorithm (FN).

$$SE = \frac{TP}{TP + FN} \tag{3}$$

PPV is the ratio between TP and the total number of crackles detected by the algorithm, i.e., correctly (TP) and incorrectly detected (FP).

$$PPV = \frac{TP}{TP + FP} \tag{4}$$

The total performance (F index) is an additional and more robust measure of an algorithm's performance and is given by the combination of both SE and PPV values[21].

$$F = 2 \times \frac{SE \times PPV}{SE + PPV} \tag{5}$$

All respiratory sound files were processed using algorithms written in Matlab®R2009a (Mathworks, Natick, MA, USA).

3. Results

The performance of the automatic crackle's detection algorithm was optimised with the following set of parameters: $L_{FD} = 6\ ms$; $L_{BF} = 60\ ms$; $X = 3$; $L_{WOI} = 2ms$; $error\ factor =\ 1/4$; $L_{bckg} = 20\ ms$; and $F = 2$. Using this algorithm, the number of crackles identified (range: 1-108) was similar to the obtained by the multi-annotator gold standard (range: 2-129). Results per respiratory sound file are shown in figure 5.

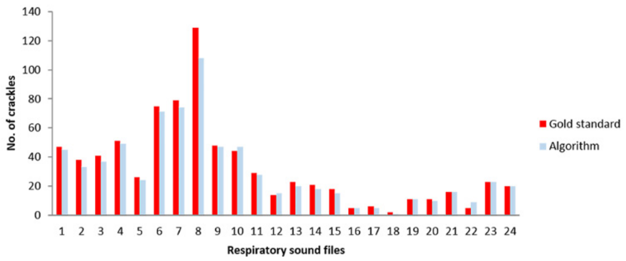

Figure 5. Crackles detected by manual annotation (gold standard) and by the proposed algorithm for each respiratory sound file.

Figure 6 presents the SE, PPV and F index of the algorithm for each respiratory sound file. Files 18 and 22 (from patients with pneumonia) were those in which the algorithm presented the lowest performance (F index of 57 and 67%). Considering the 24 respiratory sound files, the average of SE, PPV and F index of the proposed algorithm were 89±10%, 95±11% and 92±10%, respectively.

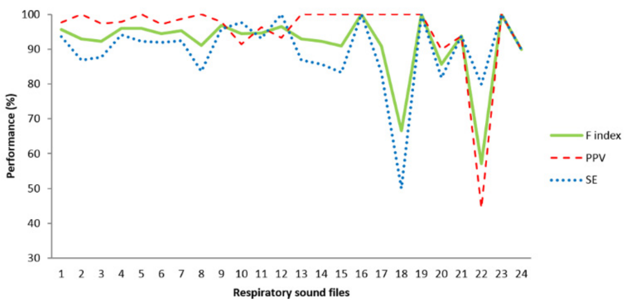

Figure 6. Sensitivity (SE), positive predictive value (PPV) and F index of the proposed algorithm for each respiratory sound.

4. Discussion

A set of seven parameters were used to optimise the proposed algorithm in a sample of 24 sound files. The results demonstrated that this was an efficient and robust method for crackle's detection/classification and highlights its potential to be used in respiratory sound files acquired in clinical settings.

The conditions initially implemented in the algorithm strictly followed the ones proposed by the CORSA criteria. However, during the iterative assessment of the algorithm, a sharp divergence between the results obtained with the algorithm and those from the gold standard was verified. Thus, some refinements of the standard rules were implemented, e.g., in the criteria stating that the width of the peaks should be progressively wider after IDW, a deviation of 25% was allowed. It should be noted, that despite the high subjectivity associated with human detection of crackles, this is still considered the only valid method for its detection[4], as health professionals are the ones who use it routinely to establish diagnosis and monitoring patients. Therefore, algorithms should be developed to match the gold standard annotation and not the opposite.

The SE (89%), PPV (95%) and F index (92%) of the proposed algorithm are comparable or even higher than those of other methods (SE 80–91%; PPV 83–88%; F index 86.7%)[15,24]. However, it should be noted that, contrarily to other algorithms, the presented one was tested with respiratory sound files clinically recorded, which further increase its potential to be used by health professionals during their clinical practice. Only in two respiratory sound files from patients with pneumonia, the performance of the algorithm did not reach these high standard values (F index of 57% and 67%). Such findings are related with the low number of crackles presented (TP) in these two respiratory sound files (1−9 crackles in the sound file), causing the few FP and FN to have a negative impact in the F-index. Nevertheless, this error might not have relevance for clinical practice as it has been reported that healthy people present approximately 4 crackles per breathing cycle[27]. Hence errors of this magnitude might not be clinically significant for diagnosis and monitoring of respiratory diseases.

This study has some limitations that need to be acknowledged. The proposed algorithm was developed by comparing the results against a multi-annotator gold standard obtained from the annotations of three respiratory researchers. Despite the high agreement achieved (86%), it is well-known that human annotation is associated with high levels of subjectivity, thus future studies should consider creating a repository of respiratory sounds annotated by an additional number of experts to minimise bias. Also, a small sample of respiratory sounds files was included from adult patients with pneumonia and cystic fibrosis. Therefore, it would be of great asset to validate the proposed algorithm in large sets of data from patients with other respiratory diseases and different age ranges (young children and infants). Finally, although the proposed algorithm is currently processing in real-time, making it suitable to be used in the clinical practice, it would also benefit from being included in Clinical Decision Support System, e.g., by allowing patterns comparison of samples and providing info/pre-diagnosis to the caregiver[28], not yet addressed in the current version of the algorithm.

5. Conclusion and Future Work

The proposed algorithm achieved a high performance (F index 92%). This promising result highlights the potential of this new approach for automatic crackle's detection and classification in respiratory sounds acquired in clinical settings.

Future research should focus in developing a portable technology including a sound acquisition device plus an open source software integrating the developed algorithm. This would allow health professionals to have instant feedback on their lung sounds recordings. Additionally, international collaborations are being established to acquire a large database of normal and adventitious respiratory sounds (including crackles, wheezes, rhonchi, stridor, etc) that could be used to find unsuspected relationships, summarise respiratory data into patterns and thus be used in Clinical Decision Support System.

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