Automatic Cough Detection in Acoustic Signal using Spectral Features

Renard Xaviero Adhi Pramono, Syed Anas Imtiaz, and Esther Rodriguez-Villegas

Abstract—Cough is a common symptom that manifests in numerous respiratory diseases. In chronic respiratory diseases, such as asthma and COPD, monitoring of cough is an integral part in managing the disease. This paper presents an algorithm for automatic detection of cough events from acoustic signals. The algorithm uses only three spectral features with a logistic regression model to separate sound segments into cough and non-cough events. The spectral features were derived using simple calculation from two frequency bands of the sound spectrum. The frequency bands of interest were chosen based on its characteristics in the spectrum. The algorithm achieved high sensitivity of 90.31%, specificity of 98.14%, and F1-score of 88.70%. Its low-complexity and high detection performance demonstrate its potential for use in remote patient monitoring systems for real-time, automatic cough detection.

I. INTRODUCTION

Cough is a common symptom that manifests in numerous respiratory diseases [1]. In Chronic Respiratory Diseases (CRDs), such as asthma and Chronic Obstructive Pulmonary Disease (COPD), monitoring of cough is an integral part in managing the disease. In these cases, detecting the occurrence of cough and the onset of their spells, determining the cough frequency, and counting the number of cough events helps to understand the status of the disease progression [2], [3]. Understanding the pattern of cough occurrence over a longer period of time also helps to provide appropriate and timely care to patients.

Manual counting of cough events in recorded sounds, however, is a very laborious and error-prone task and suffers from inter-expert subjectivity in classification. To avoid these problems, there is a growing interest in developing algorithms to automate the process of detecting and counting cough events. A study in [4] used local Hu moment and k-Nearest Neighbour (KNN) and achieved 88.51% sensitivity (SE) with specificity (SP) of 99.72%. You *et al.* [5] employed Support Vector Machine (SVM) with Non-Negative Matrix Factorisation (NMF), and achieved an average performance were SE of 80.1% and SP of 83.1%. Mel-frequency Cepstral Coefficient (MFCC) has been used by different studies to detect cough sounds. MFCC as a feature for cough detection in [6] coupled with XGBoost algorithm, achieved average Area Under Curve of 0.916 in a Leave-One-Out Cross-Validation (LOOCV) scheme. Matos *et al* [7] used

MFCC with Hidden Markov Model (HMM) achieving 71% sensitivity. The study in [8] used Sequential Minimal Optimisation (SMO) with MFCC achieving 75.5% SE with 99.6% SP. Liu *et al* in [9] used Deep Neural Network (DNN) for classification with MFCC feature inputs and achieved performance of 90.1% SE and 85% SP. DNN was also used in [10], achieving 86.8% SE and 92.7% SP. Drugman *et al* [11] employed a large set of features including MFCC, spectral flatness, and spectral centroid. These were fed into two different ANNs. After feature selection based on mutual information, 50 features were used for each ANN resulting in classification performance of 89.7% SE and 89.85% SP. Another use of ANN was presented in [12], where MFCC, formant frequency, zero crossing rate, non-gaussianity score, and Shannon entropy were used as the input features. The average performance achieved was 92.8% SE and 97.5% SP. Our previous method in [13] used Logistic Regression Model (LRM) with MFCC and spectral features on a 50%-50% random data split, where the focus of the study was to diagnose pertussis. Part of the study was detecting coughs achieving a performance of 85.20% SE and 98.32% SP.

Most of the works mentioned above either require a large number of features or use complex machine learning methods. In contrast, the objective of this paper is to develop a simpler automatic cough detection method, using only a small number of useful features. This is particularly useful for use in long-term remote monitoring systems for patients with CRDs. This paper proposes a new method of automatic cough detection using only three spectral features, inspired by the observed characteristics of the cough sound spectrum in the frequency domain, and how it differs from other sounds typically recorded when monitoring cough. These characteristics include a wide spread spectrum, low tone prominence, and low harmonicity. To detect such sounds, two frequency bands of interest were extracted from the spectrum, from which the descriptive features were then calculated. Section II describes the database used, preprocessing steps, and the different features extracted from the signals for the algorithm proposed in this paper. Section III introduces the cough detection algorithm and reports its performance. Finally, Section IV discusses these results and compares its performance against those in other studies.

II. MATERIAL AND METHODS

A. Database

For this study, a total of 43 real-world environment recordings, with a length of over 32 minutes, from different patients were obtained from multiple repositories, as described in [13]. Based on the description provided at each source, the

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R. X. A. Pramono, S. A. Imtiaz, and E. Rodriguez-Villegas are with the Wearable Technologies Lab, Department of Electrical and Electronic Engineering, Imperial College London, SW7 2BT, United Kingdom. Email: {renard.pramono14, anas.imtiaz, e.rodriguez}@imperial.ac.uk

data collected contained cough sounds from various diseases including pertussis, croup, common cold, bronchitis, bronchiolitis, asthma, and COPD. As the recordings were collected from multiple public repositories, there were variations in the recording instruments, sampling frequencies, and noise level associated with each recording. In these recordings, cough sound locations were manually marked as reference to assess the performance of the proposed cough detection method. As a result, a total of 980 events were labelled as cough sounds whilst more than 1000 separate non-cough sound events were also identified. The non-cough sound events present included speech, laughter, sneeze, throat clearing, wheezing sound, whooping sound, machine noises, and other types of background noise.

B. Preprocessing

Before being used for analysis, all the recordings were first preprocessed to minimize the variations as a result of different recording conditions. Each recording was first filtered using a 5-th order Butterworth band-pass filter with 70 Hz and 3500 Hz as the low and high cut-off frequencies, respectively. All of the recordings were then resampled to 8000 Hz since cough-related information was observed to be contained below 4000 Hz. Subsequently, the amplitude of the recordings was scaled into a range between -1 and 1 without changing the distribution, so that important statistical parameters of the sounds were preserved. Signals were then segmented into frames of 256 ms width with 50% overlap between consecutive segments.

Prior to the detection of cough sounds, it is helpful to remove silent parts of the recordings to ensure that all further processing is performed only on parts of the signals containing a sound event. This also helps in reducing the processing load downstream if the silence removal approach is much simpler than the further processing stages. In this study, silence and low noise frames of the recordings were detected using a simple threshold, based on the standard deviation of the previous samples. Thus, further processing was performed only when the average energy of a frame was above this threshold. Fourier transform was then performed on each detected frame to obtain the frequency spectrum of the signal. Blackman window was used to minimize spectral leakage on the Fourier transform. Each signal frame $x[n]$ was represented by 1025 frequency points between 0 to 4000 Hz in the spectrum $X(f)$.

C. Features extraction

An example of cough and non-cough segment spectrum $X(f)$ is shown in Fig. 1. It can be observed that the spectrum of the cough segment is spread wide, has low tone prominence, and low harmonicity; as mentioned previously. Based on these characteristics, two different frequency bands of interest were extracted. The first frequency band was obtained by taking the frequency contents between the fundamental frequency $F0$ and its next harmonic $F1$, called $B-01$. This band was used to represent the low tone prominence and harmonicity of the spectrum. $F0$ was assumed to be

the frequency with the highest spectral content, while $F1$ was found by finding a peak at frequency near twice $F0$. The second frequency band edges, called $B-HF$, and used to represent the high frequency component of the spectrum, were 2.5 to 3 kHz. An example of these frequency bands for both cough and non-cough segment is shown in Fig. 1. A total of three features were then derived from these frequency bands to detect cough sound as follows.

Fig. 1. Example of spectrum of 256 ms cough and non-cough segment taken from one recording with their respective frequency bands of interest $B-01$ and $B-HF$.

1) *High-frequency content in $B-HF$ ratio*: The first feature was calculated using Eq. 1 as the ratio of the median of the high frequency content in $B-HF$ and the spectrum maximum amplitude.

$$HFMax_{ratio} = \frac{\text{median}(X(f)_{f \in B-HF})}{\text{max}(X(f)_{f \in B-01})} \quad (1)$$

2) *Min-max ratio in $B-01$* : The second feature was derived as the ratio between the minimum and maximum value within frequency band $B-01$, as shown in Eq. 2.

$$MinMax_{ratio} = \frac{\min(X(f)_{f \in B-01})}{\max(X(f)_{f \in B-01})} \quad (2)$$

3) *Low quantile ratio in $B-01$* : The third feature was calculated using Eq. 3. This is the ratio between the median value of the lower quantile and the maximum value in frequency band $B-01$. The lower quantile was defined as in Eq. 4, where the distribution limit is 0.25.

$$LQMax_{ratio} = \frac{\text{median}(LQ(X(f)_{f \in B-01}))}{\max(X(f)_{f \in B-01})} \quad (3)$$

$$LQ(Y) = Y(Y < y), \text{ where } Pr[Y < y] \leq 0.25 \quad (4)$$

Fig. 2. Overview of the automatic cough detection algorithm.

III. COUGH SOUND DETECTION ALGORITHM

A. Overview

Fig. 2 shows an overview of the proposed cough detection algorithm. The first step was preprocessing, to filter and normalize the sound recordings, as well as to remove silent segments from them. STFT was then used to obtain the spectrum of segments not removed by the pre-processing step. Frequency bands of interest, *B-HF* and *B-O1*, were extracted. The spectral features, $HFMax_{ratio}$, $MinMax_{ratio}$, and $LQMAX_{ratio}$, were calculated based on these frequency bands. The features extracted were then scaled into range between -1 and 1 prior to the detection. The segments were then assessed for the presence of cough based on the extracted features using LRM.

To evaluate the detection performance of the algorithm, the recordings were separated into training and test set using LOOCV scheme. The data split was performed at the recording level, such that the training and test set contained different recordings and that the test set consisted of entirely unseen data. Thus, a total of 43 train-test sets were obtained, where the average of the detection performance was reported.

B. Performance metrics

The performance of the cough detection algorithm was evaluated by counting the number of correctly detected cough events as True Positives (TP), incorrectly missed cough events as False Negatives (FN), correctly rejected non-cough frames as True Negatives (TN), and incorrectly labeled non-cough frames as False Positives (FP). From these, the Sensitivity (SE), Specificity (SP), Positive Predictive Value (PPV), Negative Predictive Value (NPV), F1-score (F1), and Matthews Correlation Coefficient (MCC) were calculated, as in Eq. 5.

$$\begin{aligned}
 SE &= \frac{TP}{TP+FN}, \quad SP = \frac{TN}{TN+FP}, \\
 PPV &= \frac{TP}{TP+FP}, \quad NPV = \frac{TN}{TN+FN}, \\
 F1 &= \frac{2(SE)(PPV)}{SE+PPV}, \\
 MCC &= \frac{(TP)(TN) - (FP)(FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (5)
 \end{aligned}$$

TABLE I
AVERAGE DETECTION PERFORMANCE

Metric	Average (%)	Metric	Average (%)
SE	90.31	PPV	88.47
SP	98.14	NPV	98.54
F1	88.70	MCC	87.46

Fig. 3. Performance of the cough detection algorithm.

C. Results

In each repetition, the training set consisted of 42 recordings which were used to train the LRM while the one recording left was used as the test set to evaluate the model. The evaluation performance in terms of TP, TN, FP, and FN of each repetition was obtained, from which SE, SP, PPV, NPV, F1, and MCC were calculated. Table I shows the cough detection algorithm LOOCV average performance, using the proposed features. The standard deviation of each metric is shown in Fig. 3. It can be observed, from Table I, that the average SE achieved was 90.31% while the average PPV, F1, and MCC was 88.47%, 88.70%, and 87.46% respectively. The high sensitivity shows that most cough events were detected, while the low false positive detection resulted in a high PPV, F1, and MCC. The specificity and NPV values are also high, showing the ability of the algorithm to reject most non-cough segments correctly.

TABLE II
DETECTION PERFORMANCE COMPARISON

Ref.	SE (%)	SP (%)	PPV (%)	NPV (%)	F1 (%)	MCC (%)	Features Type	# Features	Method
[4]	88.51	99.72	87.51	99.78	88.02	86.85	Cepstral	13	kNN
[5]	80.10	83.10	83.50	-	81.76	-	Spectral	60	SVM
[6]	AUC 91.60		-	-	-	-	Cepstral	12	XGBoost
[7]	71.00	FAR 13/h	-	-	-	-	Cepstral	39	HMM
[8]	75.50	99.60	-	-	-	-	Cepstral	39	SMO
[9]	90.10	85.50	-	-	40.00	-	Cepstral	39	DNN
[10]	86.80	92.70	-	-	-	-	Spectral	64	CNN
[11]	89.70	89.85	-	-	-	-	Cepstral, Spectral, Time	50	ANN
[12]	92.80	97.50	-	-	-	-	Cepstral, Spectral, Time	22	TDNN
[13]	85.20	98.32	84.62	98.37	84.91	83.16	Cepstral, Spectral, Time	26	LRM
This work	90.31	98.14	88.47	98.54	88.70	87.46	Spectral	3	LRM

IV. DISCUSSION

In this paper, a new method for automatic detection of cough events is presented. The method uses only three spectral features with a logistic regression model for classification of acoustic sound segments as cough or non-cough events. The performance of the algorithm was evaluated on a database that consisted of 980 cough sounds and more than 1000 non-cough events, from 43 different recordings. Using LOOCV as validation scheme, consistent results were obtained with high average sensitivity of 90.31% and PPV of 88.47%. Performance of the algorithm is also reported as F1-score to show the low rate of false positives and MCC where a more balanced ratio of the positive and negative classes can be obtained. The algorithm proposed achieved F1-score and MCC of 88.70% and 87.46%, respectively. The small range of performance variation in each iteration demonstrates the capability of the proposed algorithm to work well with unseen data. It also shows that the small number of features used in this work compared to previous studies provide enough information that can be used for a reliable detection of cough sounds.

Table II shows the comparison of the cough detection performance between the proposed algorithm and those in other studies. It can be seen that, of the ten other listed studies, only [12] have reported SE higher than what is achieved in this paper. However, the proposed algorithm still achieves higher SP while using less features when compared to this study. Additionally, the methods presented in the other studies in Table II are more complex than the algorithm in this paper. For example [4], uses kNN classification with local Hu moment as the main feature which, as reported by the authors, is very time-consuming to compute. The algorithm in [9] uses a deep neural network for classification with 13 MFCC features, while [12] also uses a neural network with MFCC, with additional time and frequency features. In contrast, the algorithm proposed in this paper uses a simple classifier with only three features and achieves a comparable detection performance. It should be noted though that the data used to report performances of the different algorithms is not the same. The differences in signal acquisition methods, recording conditions, and types of non-cough signals present in different data would have an impact on the achieved performance. However, since the data used by most studies is not publicly available, it is not possible to

make a direct comparison between all the different methods. Nevertheless, the results reported in this study demonstrate the potential for the proposed low-complexity algorithm to be used in remote patient monitoring systems for real-time, automatic cough detection.

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