IIIT-S CSSD: A Cough Speech Sounds Database

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***Abstract*—Paralinguistic sounds such as laughter, cry and cough etc. communicate different messages as well, apart from the linguistic content in speech. These non-verbal speech sounds may possibly communicate some emotion, gesture or physiological condition of a human being. Cough sounds mostly indicate symptoms of a disease and are used sometimes as a gesture to draw attention. Analysing cough sounds using speech signal processing methods can be useful for assisting the medical experts in ailment diagnosis, and also for making machines more intelligent and human-like. This paper describes a database collected for cough speech sounds, named as IIIT-S CSSD. The database consists of three categories, namely, *ailment cough*, *simulated cough* and *normal speech*. Normal speech is recorded for each speaker, as a reference. Spectrograms are used as ground truth reference for preliminary analysis. This database can be helpful in analysing further the differences in cough sounds of different categories such as dry and wet cough, involuntary and voluntary cough, *ailment* and *simulated* cough, or *age-wise differences* in cough sounds etc. Few signal processing methods and initial analysis results indicating the differences in characteristics of different cough sounds are also discussed.**

***Index Terms*—Cough Speech Sound Database, dry and wet cough, ailment and simulated cough, involuntary and voluntary cough, spectrograms**

I. Introduction

Cough is a powerful reflex mechanism of the human body that clears the central airways from foreign objects, mucus and secretions. It does not occur frequently in healthy speakers. But it is an important symptom in many respiratory diseases. Production of cough sounds involves air turbulence, vibration of tissues, movement of fluid through airways, and opening and closure of glottis in the human speech production system. These sounds provide us the information required to distinguish between *wet* and *dry* cough and between *ailment* cough and *voluntary* (or simulated) cough. Furthermore, cough sounds can also indicate differences in cough related to *long term ailments* such as asthma or bronchitis, and those related to *short term ailments* such as throat infection, cold cough etc. Thus the ability to characterize the cough sounds of unhealthy speaker should be immensely helpful in medical diagnostics as well as in the domain of artificial intelligence and robotics.

The temporal pattern of *cough sound production* starts with an explosive burst, opening of glottis, followed by a period of noisy sound and slow decay of the noise, as the air flow reduces due to transient glottal closure [1]. Acoustic analysis of *dry* and *wet* cough sounds was attempted for medical purposes in [2]. Automated recognition of cough sounds with the detection of cough signals using Hidden Markov Models (HMM) was explored in [3]. Mean frequency, standard deviation and other statistical measures of asthmatic cough sounds were used for a quantitative description of asthmatic cough sounds in [4]. High frequency analysis of cough sounds of paediatric patients was carried out to study the respiratory diseases and check the presence of any important information in the higher frequency regions (up to 9 kHz) in [5].

Different speech features have been explored in different studies on cough sounds. The number of peaks in the signal energy envelope and energy ratio in various frequency-bands were used for feature extraction and analysis of dry and wet cough sounds [2]. Zero crossing rate, amplitude, duration, peak frequency and highest frequency components were used to characterize the various cough sounds in the acoustic analysis carried out in [1]. Spectrographic analysis was exploited for the quantitative description of asthmatic cough sounds [4]. Signal to noise ratio and formant frequencies were exploited for the modelling of cough sounds in the autoregressive acoustical modelling of cough sounds [6].

The instantaneous fundamental frequency (F0) is an important feature in the study of speech signals. The F0 is computed using the autocorrelation of preprocessed signal, while carrying out the high frequency analysis of cough sounds in paediatric patients [5]. The energy envelope is determined from the input signal by computing $S^2(t)$. It is passed through a second order Butterworth Low-pass filter, with a cut-off frequency of 10 Hz, in order to determine its energy envelope $E(t)$ [2]. Energy in various frequency bands is determined, which is used further to compare the signal content in various frequency bands. A quantitative description of asthmatic cough sounds is also attempted using phase detection, based on the amplitude and root mean square of amplitude for each frame [4]. Though few studies have been carried out to analyse cough sounds, there has not been any detailed study carried out so far, to the best of our knowledge, that explains the production characteristics of different cough sounds. Such a study would also require, necessarily, the collection of natural and semi-natural database of cough sounds, along with reference speech sounds.

In this paper, we describe a database of cough speech sounds collected for their analysis, from the production point of view. The database is named as 'IIIT-Sri City: Cough Speech Sounds Database', i.e., *IIIT-S CSSD*. Cough sounds of

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speakers suffering from various ailments are recorded along with simulated cough sounds produced by healthy persons. The objective is the identification and classification of different cough sounds, such as *ailment cough* vs *healthy cough*, *dry cough* vs *wet cough*, etc. In the preliminary analysis, the spectrograms and the fundamental frequency are observed. Spectrograms are used as ground truth reference, that indicate significant difference in the fundamental frequency and their harmonics for different types of cough sounds. A few ideas towards cough signal analysis, for possible diagnosis of the type of ailment, are also discussed. Possible applications of this cough speech sound database may range from disease prediction and estimation, to finally diagnosis and cure of ailment. Also, for the machine recognition of speech sounds, identifying the cough sounds and cough regions in human speech would be immensely useful for multiple purposes.

This paper is organised as follows. A categorisation of the cough speech sounds is discussed in Section II. Section III discusses the details about the collection of cough sounds database. Section IV describes the organization of the database collected. Section V discusses the preliminary analysis of cough sounds carried out using spectrograms. Few observations are noted in Section VI. Features for the analysis of cough sounds signal, are discussed in Section VII. A summary is given in Section VIII, along with scope of further work.

II. Categorisation of Cough Sounds

Production of cough sounds involves explosive bursts of air, causing air turbulence in the vocal tract, rapid opening of glottis, and noise related to the gushing air passing through the vocal tract during transient closure of the glottis [1]. Cough sounds can be produced as *voluntary* or *involuntary*. *Voluntary cough* sounds are produced mostly for simulating the cough sounds during medical diagnostics, or as a gesture to indicate one's presence or draw attention. *Involuntary cough* is produced by the human speech production mechanism due to some medical condition. It is often indicative of some ailment or disease, the human body is suffering from. The nature and type of disease or ailment is often estimated or predicted by medical experts, based upon the cough sounds that may be associated with mucus or phlegm produced.

Depending upon the nature, density and colour of phlegm produced, the nature of disease or ailment can possibly be predicted. The presence or absence of phlegm gives indication of *wet cough* or *dry cough*, respectively, and that can indicate the intensity or extent of the disease, or its different phases such as initial, growth or terminal stage. The sounds of cough while deep breathing are carefully used by medical experts, to estimate the duration of ailment as well, apart from other indicators that help in diagnosis of the ailment. The cough duration may indicate *short-term ailment* (short burst of cough sounds) or *long-term ailment* (several long bursts of cough sounds). Cough sounds also vary, as per the age of the human patient. Hence, cough sounds can possibly be used for also estimating the age of a human being.

The cough sounds can be categorised in different ways, such as mentioned below:

(i) *Involuntary (i.e., natural)* cough vs. *voluntary (or simulated)* cough

(ii) *Wet* vs. *dry* cough

(iii) *Short-term ailment* cough vs. *long-term ailment* cough

(iv) *Age-wise* differences in cough sounds, for example, cough-sounds of a Baby vs. Young vs. Old person.

The IIIT-S CSSD is collected to possibly study all these different categories of cough sounds. The primary focus in this paper is to distinguish first between the *ailment cough* and *simulated cough*, that would be corresponding to *involuntary cough* and *voluntary cough*, respectively. Hence, the (i) *ailment cough* sounds and (ii) *simulated cough* sounds are recorded, along with (iii) *normal speech* of each speaker, as a reference speech sound.

III. Collection of data

Databases of emotion and paralinguistic sounds have the limitation of being branded as *artificial*, and that is different from *natural* data which is difficult to collect. Hence, in this study, an attempt is made to collect the *natural* data of cough sounds. For comparison purposes, *simulated (i.e. artificial)* cough sounds by a healthy person or by the patient after getting cured, are recorded. *Normal speech* of each speaker acts as a ground truth (base) reference, for comparisons etc.

In order to study the differences among different ailment coughs, the cough sound data was was collected from various people, who were suffering from different ailments such as throat infection, asthma, pulmonary infection, etc. Data was also collected from healthy people, for the purpose of comparison with the base reference. Collected data includes a sentence spoken by the person along with his/her cough sounds. The speakers were asked to speak the sentence and then cough three to four times.

Details recorded along with the Data

Along with the speech sounds data collected, the following details were also recorded:

(a) Speaker name

(b) Age

(c) Sex

(d) Mother tongue

(e) Place

(f) Health condition (name of disease if any)

These details may prove to be useful while classifying the ailments into different demographics and categories, using speech signal processing methods.

Equipment and Environment Details

Cough sounds were recorded using smart phones, for convenience. *Asus Zenfone 5, Samsung galaxy S5312* and *Samsung Galaxy S duos* were the different smart phone models, that were used with a sampling frequency of 44100 Hz. The data was stored under different categories, using the bit-encoding-rate of 16 bits per sample. It is understandable that using some professional recording device such as Edirol or Zoom Inc.'s

Table I: Nomenclature

S01_M_Sn01_AilCh1	
S01_M_Sn01_Nml voice1	
S01_M_Sn01_SimCh1	
Abbreviation	**Interpretation**
S#	Number of the Speaker
M/F	Sex of the Speaker (male in this case)
Sn#	Numeral correspond to session number (in this case session #01)
AilCh/SimCh#	Type of *Cough* Sound (Ailment or Simulated)
Nml Voice#	It corresponds to *Normal* voice of the Speaker

device would have been better. But convenience and recording by multiple people were the constraints behind the current choice of smartphones. Data was recorded in a silent room and efforts were made to have very low or no background noise. While multiple measures were taken to keep the recorded data noise-free, there could possibly be some noise present along with the signal, due to fan-sound in the background for some samples and cross-talk for others. Hence, some pre-processing of the signal may be needed, but not much is carried out in this study due to the possibility of inadvertently disturbing some significant features present in the signal.

IV. Organization of the Database

The data collected in the IIIT-S CSSD has been organized meticulously, for gaining the in-depth understanding of cough sounds signal and their effective analysis. Data was collected from 30 speakers. *Normal* voice along with the cough sounds was recorded for most speakers. Each such occurrence, consisting of single cough or cough bursts, is termed as a *session*. Each session has sub parts for better analysis. For some speakers, data was collected in 2 sessions with a gap of 10 -15 minutes in between. Table I elaborates the template of the nomenclature used for saving the files of cough sound and normal speech signal data. For each speaker, an attempt is made to record (i) *ailment cough* sound, when the person was suffering from an ailment, (ii) *simulated cough*, when the person was cured, and (iii) *normal speech*, after cure, as a reference.

The study was undertaken in a two stage process. The first stage was the collection of data, which was carried out at multiple locations. The second stage comprised of pre-processing and preliminary analysis of cough sounds. The raw data collected for each speaker was then segmented into different files. Each speaker was asked to cough 3-4 times in a session. The cough sounds collected from various speakers were categorized based on the (known) ailment they were suffering from. The database consists of *natural* cough sound samples collected from speakers suffering from different ailments such as asthma, common cold, throat infection, as well as *simulated* cough sounds from healthy speakers. Details of the database are summarised in Table II. The IIIT-S CSSD consists of 34 sound files for 30 speakers. The cough/normal speech sound recordings were carried out in 2 sessions for most speakers. Thus, the database has 110 cough sounds signals, along with 20 normal speech sounds signals recorded. The *MATLAB* and *‘Wave-Surfer Tool’* are used to analyse the cough sound signal data at a preliminary level. Preliminary analysis and observations are discussed in next sections, in some detail.

Table II: Cough Database Summary

Attributes	**Values**
Total # of files	34
Total # of speakers	30
Total # session subparts	34
Total # of cough in subparts	110
Total # of Normal voice corresponding to cough	20
Average # of Sessions of Cough Sounds per speaker	3.66

V. Preliminary Analysis of Cough Sounds

Spectrogram is the visual representation of the spectrum of the speech signal. Short-time Fourier Transform (STFT) is used to determine the sinusoidal frequency and phase content of a segment of the cough signal, by processing it in the frequency domain [7]. The STFT is computed frame-wise and is different for each time-frame taken. The process of computing STFTs involves segmenting a longer duration audio signal in time-domain, into shorter segments of equal time-lengths and then computing the Fourier transform separately for each shorter segment, i.e., frame. This gives the Fourier spectrum for each shorter segment, i.e., frame of signal. One can then plot the changing spectra as a function of time. The data to be transformed is first divided into frames, which generally tends to overlap with each other. The Fourier transform is calculated for each frame and the complex result is stored in a matrix, capturing the magnitude and phase for each signal-frame taken in time domain, and the corresponding point in frequency-domain, using the equation:

$$X(m,w) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-jwn} \qquad (1)$$

where, *x[n]* is the signal and *w[n]* is the applied window, i.e., frame. Here *m* is descrete and *w* is continuous [7]. The magnitude squared of the STFT yields the spectrograms of the function: $|X(m,w)|^2$

The spectrogram provides essential information about the instantaneous fundamental frequency and energy in various frequency ranges. In 3D plot of spectrogram, the X axis denotes time, Y axis denotes frequency, and the Z axis denotes the log magnitude of the sinusoidal frequency components. But in the 2D plot of spectrogram, X axis denotes time, Y axis denotes frequency, and the log magnitude of the sinusoidal frequency components is represented by intensity of the spectrogram [8]. In the study performed, spectrogram is analysed only up to 1 kHz, i.e, Y axis is limited to 1 kHz.

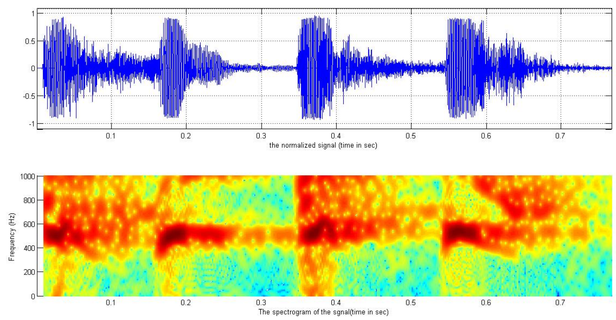

Figure 1: The *Cough* Sound of 8 years old Speaker.

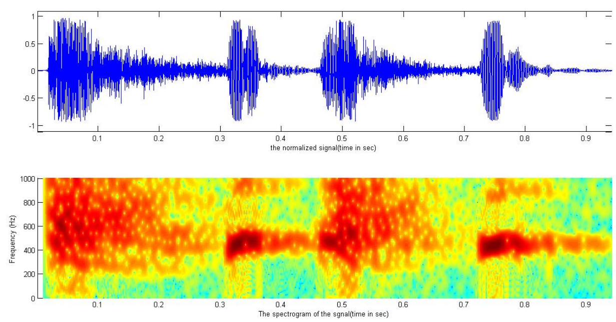

Figure 2: The *Cough* Sound of 14 years old Speaker.

In the preliminary analysis carried out, the sampling frequency is 16 kHz with 8-bit quantification. In this paper, each cough sample is divided into 20 ms frames, with a frame shift of 2 ms. The instantaneous fundamental frequency (F0) along with its harmonics is observed using the spectrogram. Short time signal energy is computed for each frame, using $\sum_n x^2$(n). Next, energy threshold-based unvoiced/silence frame removal is performed on each cough sample. Auto correlation and Linear Prediction analysis of the cough sample are being carried out for further analysis of the healthy and ailment cough sounds.

VI. Observations

Spectrograms are used for this study as the the ground truth reference. Spectrograms are computed by dividing the signal into 20 ms frames, with a frame shift of 2 ms. Pattern of changes in the contours of fundamental frequency, harmonics structure and energy in various frequency bands are observed from the spectrograms of the cough sounds studied.

Various cases have been chosen for the analysis and the following cases have been found to have significant observations. There were two major parts of the study: First was analyzing the *cough* of speakers in different *age-groups* but each suffering from common *cold*. Second was analyzing the differences in voice and cough of both *healthy* and *unhealthy* speakers.

The spectrograms of coughs of speakers suffering from cold cough have been observed for speakers of different age-groups.

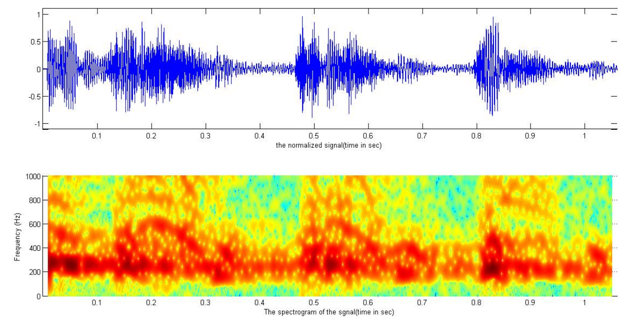

Figure 3: The *Cough* Sound of 20 years old Speaker.

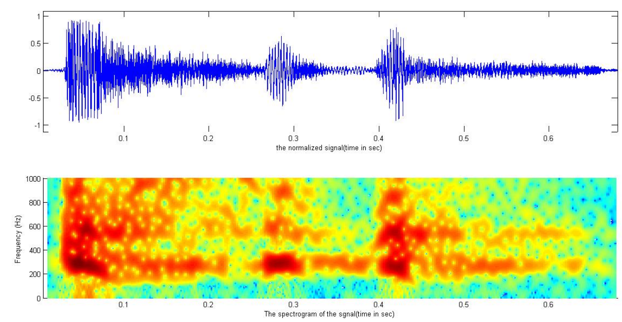

Figure 4: The *Cough* Sound of 42 years old Speaker.

There were marked differences in the spectrograms depending on the age of speakers. The instantaneous *fundamental frequency (F0) of cough sounds appears to decrease as the age of speakers increases*. Harmonics appear as all flat bands. Energy in frequencies below 400 Hz is very less in the coughs of kids, whereas there is relatively more energy in the 400-600 Hz band as can be observed in Fig 1. In the case of speakers aged around '20 years', the 200-400 Hz band has relatively more energy whereas the energy levels are relatively low in the bands in frequencies below 200 Hz, as can be observed in Fig 3. For speakers aged above 40 years, more energy is present even below the frequency range of 200 Hz, however the energy level observations of the 0-400 Hz band remain the same as in the previous case. This difference can be observed in Fig 4.

The second part of the study is to analyse the differences between the spectrograms of normal speech and cough sound of both *healthy* as well as *unhealthy* speakers. First, in the spectrogram of normal speech signal of both *healthy* and *unhealthy* speakers, a clear harmonic structure is visible and 5-7 harmonics are visible in the frequency below 1 kHz, as can be observed in Fig 6 and Fig 8, respectively. Second, in the cough of *healthy* speakers, where the cough sounds may be *voluntary* or *simulated*, the signal energy is distributed in all the frequencies and in 2-3 harmonics are visible. Third, for the *wet cough* there is no clear pattern in the harmonics structure or sometimes 2-3 harmonics present below 1 kHz,

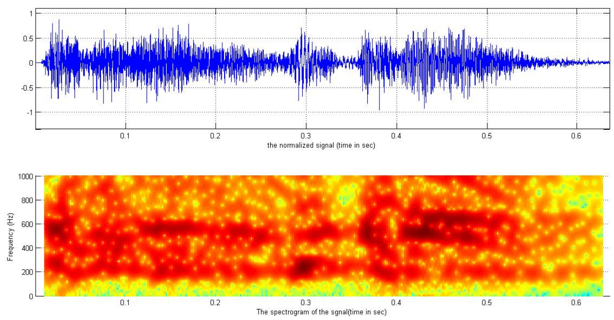

Figure 5: The *Cough Sound* of *Healthy* Speaker.

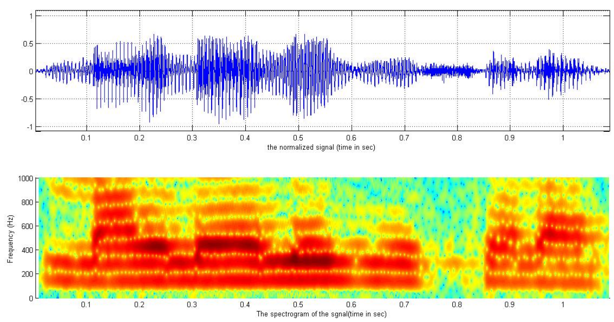

Figure 6: The *Normal Speech* of *Healthy* Speaker.

as can be observed in Fig 5 and Fig 7, respectively.

VII. Features Planned For The Analysis

The instantaneous fundamental frequency (F0) can be used for further study of the cough sounds. For the quantitative analysis of the cough sounds, work is in progress towards carrying out autocorrelation based analysis and Linear Prediction (LP) analysis, of the short segment of cough sounds signal. Objective here is to find out the instantaneous fundamental frequency, by developing a new peak detection algorithm in near future. However, a brief discussion is presented in this section on the features being explored by the authors for analysing the cough sounds signals. Methods for deriving these features are also discussed briefly, in order to help the readers who may be interested in these details.

A. Autocorrelation Analysis of Cough Signal

Autocorrelation is the measure of similarity between a random sequence and its time lapse. If the random sequence is stationary and periodic with time period T0, then the auto correlation will also be stationary and periodic with the same time period [7]. For the speech signal x(n), whose correlation function is defined as follows:

$$r_x(m) = E[x(n)x(n+m)]$$

$$= \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x[n]x[n+m] \qquad (2)$$

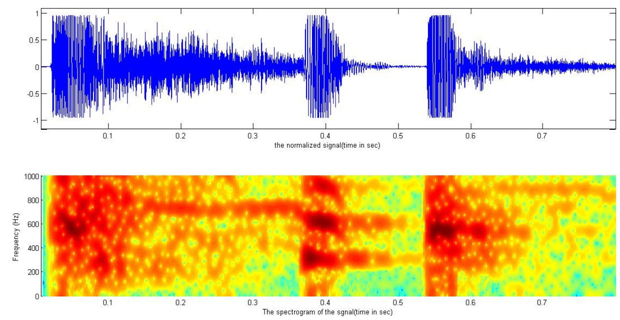

Figure 7: The *Cough Sound* of *Unhealthy* Speaker.

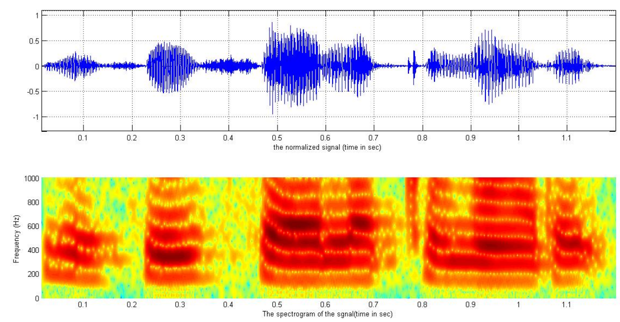

Figure 8: The *Normal Speech* of *Unhealthy* Speaker.

E[.] represents *statistical expectation*, which is equal to the progressive average when the signal is infinite or length of the data is large enough.

Speech signal is non-stationary for long durations, but for short durations it can be considered to be stationary. The autocorrelation function can now be rewritten for short duration of speech signal as follows:

$$r_x^{'}(m) = \frac{1}{2N+1} \sum_{n=-N}^{N} x[n]x[n+m] \qquad (3)$$

When m = 0, then equation (3) represents short term energy of the signal [7]. The pitch period is more pronounced in the auto correlation sequence as compared to speech.

B. LP Analysis of cough signal

The speech signal can be modelled as the convolution of the excitation signal and the impulse response of the vocal tract system. It is time varying in nature, but for short duration (10-40) ms, it is considered as a stationary system [9]. The basic idea behind LP analysis model is that a given speech sample at time n can be approximated as a linear combination of past p speech samples [10]. The predicted signal $s(n)$ can be represented as follows:

$$\hat{s}(n) = -\sum_{k=1}^{p} a_k s(n-k) \qquad (4)$$

where *p* is the order of prediction and prediction coefficients $a_k s$ are assumed to be constant over the speech analysis frame. The windowed speech sequence $s(n)$ is obtained by multiplying the window function $w(n)$ by the speech sequence $x(n)$ which is given by:

$$s(n) = x(n)w(n) \tag{5}$$

The prediction error *e(n)* can be computed by the difference between the actual sample *s(n)* and the predicted sample $\hat{s}(n)$, which is given by:

$$\begin{aligned} e(n) &= s(n) - \hat{s}(n) \\ &= s(n) + \sum_{k=1}^{k=p} a_K s(n-k) \end{aligned} \tag{6}$$

$a_k s$ can be computed using minimization of prediction error *e(n)*. The popular method for computing the LP coefficients is the *'least squares autocorrelation'* method. This is achieved by minimizing the total prediction error [10].

Prediction error $e(n)$ is called LP residual of the signal. In the z domain, the equation (6) can be represented as:

$$E(z) = S(z) + \sum_{k=1}^{p} a_k S(z) z^{-k} \tag{7}$$

i.e,

$$A(z) = \frac{E(z)}{S(z)} = 1 + \sum_{k=1}^{p} a_k z^{-k} \tag{8}$$

Therefore LP residual can be obtained by filtering the speech signal with A(z), while the LP spectrum H(z) can be obtained from the following equation,

$$H(z) = \frac{1}{1 + \sum_{k=1}^{p} a_k z^{-k}} = \frac{1}{A(z)} \tag{9}$$

As A(z) is the reciprocal of H(z), LP residual is obtained by the inverse filtering of speech. *Formants* can be obtained using the spectrum of the LP residual H(z), and first peak in LP spectrum corresponds to first formant of the speech signal [9]. The auto correlation of LP residual can also give information about the pitch period.

VIII. Summary and Conclusions

Cough is an important symptom in various respiratory diseases. Few research studies are carried out on the cough sounds to analyse and characterize the various types of coughs. These studies though are aimed at extraction of features from the cough sounds in order to classify dry and wet coughs and automated recognition, but no single study focuses on characterising the differences from production point of view, of cough sounds.

This paper describes a database of cough sounds collected from speakers, healthy as well as unhealthy. This IIIT-S CSSD is especially collected for analysing the cough sounds in four different categories, as discussed in this paper. During the process of data collection, diseases or infections that the speaker is suffering from, have also been noted. Preliminary analysis of the cough sounds has been carried out, using spectrograms. An attempt is made to extract the instantaneous fundamental frequency, and analyse the differences in *ailment* cough and *healthy* cough. The collection and organisation of the database is described in detail. The pattern of ailments has been observed to be similar to that reflected in the spectrograms of the cough sounds of speakers suffering from the respective ailments. These patterns can be useful for the diagnosis and preliminary identification of the ailment, by medical experts.

The main goal of the study is to finally classify the *ailment cough* and *healthy cough* sound signals, and compare these with *normal speech signals* of speakers. This can be helpful to figure out the medical condition of central airways. In future, possibly, the patients unable to explain the type of cough they are suffering from, can record their cough sound at home, which the doctors can process remotely, in order to find out the details of the cause of cough or ailment the patient is suffering from.

Further work on the quantitative analysis of this database is in progress. The cough sound signal characteristics observed in the paper are being studied further, in detail. Further analysis of the cough sounds of different categories is being carried out using several signal processing methods, that include *autocorrelation* and *linear predictive analysis*. The aim is to investigate the different characteristics of cough sound signals and to possibly classify them automatically. Efficient and more quantitative approaches are also being explored for better analysis in future.

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