

Smartphone Based Human Breath Analysis from Respiratory Sounds

Muhammad Awais Azam, Aeman Shahzadi, Asra Khalid, Syed M. Anwar, Usman Naeem

Abstract— Human breath analysis plays important role for diagnosis and management of pulmonary diseases to guarantee normal health. The critical task is to distinguish normal and abnormal lung sounds. This research work presents a scheme for breath analysis used to detect irregular patterns occurred in respiratory cycles due to respiratory diseases. After de-noising breath segments using wavelet de-noising method, intrinsic mode functions are extracted with complete ensemble empirical mode decomposition (CEEMD). Instantaneous frequency (IF) and instantaneous envelope are extracted to get robust features for classification. The study contains breath samples captured using smartphone under natural setting. The data set contains 255 breath cycles. For cycle classification, Bag-of-words was applied to group segments based features. The support vector machine (SVM) was applied on randomly partitioned data samples. Experiments resulted with performance accuracy of $(75.21\% \pm 2)$ for asthmatic inspiratory cycles and $(75.5\% \pm 3\%)$ for complete Respiratory Sounds (RS) cycle with diagnostic odds ratio (DOR) of 20.61% and 13.87% respectively.

I. INTRODUCTION

Normal breathing depends upon proper functioning of lungs. Respiratory disease due to smoking, infection, genetics and deficiency of oxygen causes airways obstruction that affects lung function. Respiratory diseases are among the leading causes of death worldwide. Among them, Chronic Obstructive Pulmonary Disease (COPD) has been reported as 4th leading cause of death [1]. So, absolute diagnosis and management of respiratory disease is required to assure proper health.

Breathing is a physical process that consists of inhalation of oxygen and exhalation of carbon dioxide used during respiration [2]. So, breath is a complex matrix where flow rate, temperature and humidity are diverse and time-dependent variables. Breathe consists of inspiration and expiration cycles. Air flow is turbulent in nature [3] that produces vibrations during breathe cycles. These vibrations can be used to classify breathe sounds into normal or abnormal sounds [4] which can be used to identify different lung diseases through analysis of breathe sound patterns.

Some portable solutions have been in practice since some time in order to assist patients to monitor breathing for health related issues [5] [6]. These portable solutions utilize

concepts of digital processing and characteristics of time and frequency domain features of acoustic signal. Although these solutions are in practice, their performance has limitations due to internal and external noise factors, inapt feature selection and calibration of sensors. Other than these issues, another significant and vital need is to have a feasible and unobtrusive system through which breathing signals can be recorded and analyzed in natural way.

Aim of this research work is to utilize the smartphone of a smartphone to capture breath signals and to detect adventitious sounds present in it due to various disorders. This is processed using efficient and robust signal analysis techniques that must perform well even under natural conditions. Therefore this work proposes a method that performs breath patterns classification between normal and abnormal patterns. Ultimately, it will help an individual to detect any abnormality in lungs, using a smart phone.

Rest of the paper is organized as follows: state of the art work is discussed in section-II, whereas details of methodology and results are discussed in section-III and IV respectively. Conclusion is presented in section-V.

II. STATE OF THE ART

Progression of ubiquitous technologies resulted into innovative portable devices equipped with a lot of sensors that can be used for health monitoring. If breath signal is considered, the traditional way of capturing and analyzing these signals is using a Stethoscope that helps Doctors listen these internal body sounds and perform diagnosis. However this process is extremely dependent and chances of error are also high. Different researchers have proposed solutions for these limitations, such as electronic nose [7], vortex whistle [8] and wireless stethoscope [9]. The problem with these solutions is complexity involved in their usage which is not always feasible for different patients.

Researchers have also proposed solutions that use smartphone's microphone for breathing signal detection [10] [11]. These recorded or real time breath samples are treated as acoustic signals. Researchers have started to use Machine Learning concepts for acoustic signal processing for last couple decades. It involves performing pre-processing, feature extraction and classification steps. During pre-processing phase, breath signal is recorded and saved in digital form for further processing. Noise from the captured signal is also removed at this stage by applying different filters [12][13][14][15]. The next step is features extraction which helps to get compact information and suitable representation of signal to feed in to the classifier for normal or abnormal pattern classification. For respiratory airflow signal, features are mostly extracted from instantaneous envelope (IE) and instantaneous frequency (IF) of signal.

*Research supported by University of Engineering & Technology Taxila, Pakistan.. M. Awais Azam Syed M. Anwar and Aeman Shahzadi are with the Department of Computer Engineering, University of Engineering and Technology, Taxila, Pakistan, (awais.azam@uettaxila.edu.pk, aemanfatima@yahoo.com,).

Asra Khalid is with COMSATS Institute of information Technology, WahCantt Pakistan (asra.khalid@ciitwah.edu.pk).

Usman Naeem is with University of East London, UK (u.naeem@uel.ac.uk)

Researchers have used Hilbert spectrum, audio spectral envelope, and power spectral density [16], [17], [18], [19] for IF and IE estimation. Third step is of classification where both supervised and unsupervised techniques have been used by researchers [17] [19]. Although above mentioned systems provide solutions, but performance of existing solutions limits due to sensor calibration, audible sensing of flow rate and external environmental noise. Our aim was to make use of only mobile phone's microphone to capture airflow signal and to detect adventitious sounds present in the breath signal due to various disorders.

Next section will discuss the proposed scheme of calculating IF and IE for each breath signal, feature extraction and details of the classification process.

III. METHODOLOGY

Figure-1 shows block diagram of methodology adopted in this research work. The dataset used in this work is of 50 participants which is sampled at the rate of 44.1 kHz. This dataset is collected in real-life hospital conditions under the guidance of pulmonologist and physician in Lung Function Testing Laboratory. Patients of different diseases were considered in this data collection, such as COPD, asthma, bronchitis and Pneumonia. Smartphone (Samsung galaxy S3) was used to record the airflow while placing it at a distance of 25 ± 5 cm from the patient's mouth. Due to presence of different types of noises in the recorded signals, segmentation into inspiratory and expiratory cycles is performed manually with the guidance of physicians. Each cycle is further labeled as normal or Adventitious Signal (AS). This labelling is used further in classification stage.

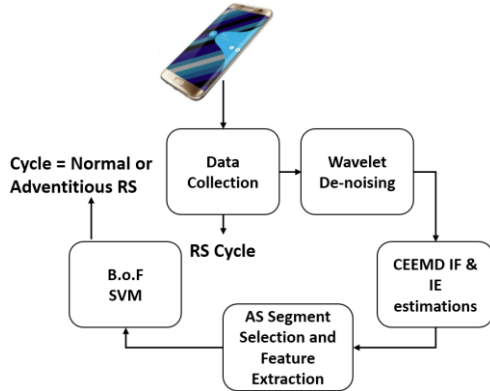


Figure-1: Block Diagram of Methodology

Next step is to perform de-noising in order to remove realistic background noises from the respiratory sounds (RS). We used wavelet de-noising technique to filter RS signals because it doesn't require any reference noise signal. Process involved, decomposing of noise signals using Discrete Wavelet Transform (DWT), soft thresholding in wavelet domain and then reconstruction of signal from these DWT coefficients.

After de-noising, next step is to estimate instantaneous frequency (IF) of RS signals which has multiple frequency components in it. We have used Complete Ensemble Empirical Mode Decomposition (CEEMD) [20] method to get Intrinsic Mode Function (IMF) of RS inspiratory cycles.

Eq.1 gives complete decomposition of signal $x[n]$ into K modes.

$$x[n] = \sum_{k=1}^K IMF_k + R[n] \quad (1)$$

Figure-2 shows the result of applying CEEMD to IMFs extract from an inspiratory cycle of RS having abnormality as wheeze. Only those IMFs are considered which covers AS frequency range of 100Hz.

Next step is to calculate IF and Instantaneous Envelop (IE). If a real signal is provided, analytical signal provides the best way to get phase of complex signal corresponding to that real signal. Eq.2 is used to calculate analytical signal $z_i[n]$ for each IMF $x_i[n]$, $y_i[n]$,

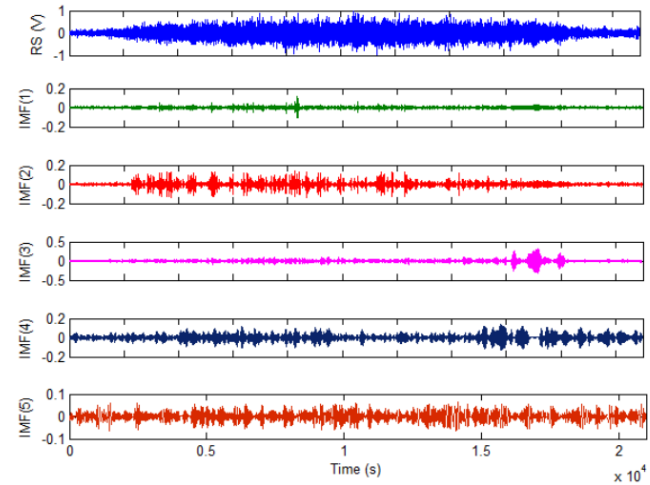


Figure-2: CEEMD applied to Inspiratory Cycle of RS containing wheeze. IMFs 1 to 5 cover frequency range of interest for AS detection

$$z_i[n] = x_i[n] + jy_i[n] = a_i[n]e^{j\theta[n]} \quad (2)$$

After having analytical signal, $IF_i[n]$ and $IE_i[n]$ for each IMF $x_i[n]$ needs to be calculated. Eq.3 and Eq.4 are used respectively for this purpose.

$$IF_i[n] = 1/2\pi \frac{d\theta_i[n]}{dn} \quad (3)$$

$$IE_i[n] = R_i[n] = \frac{1}{k_i[n]} \quad (4)$$

Next step is to classify the RS cycle by extracting the features of candidate adventitious segments. Following features were extracted to classify the cycle.

$$E1 = 100 * \frac{E_s}{E_m} \quad E2 = \frac{E_s}{E_T} \quad E3 = \frac{E_2}{D_T}$$

$$DR = \frac{t_2}{t_1} \quad Q = \frac{\delta_{IF_{i_v}}}{\delta_{IF_{i_v}} - 0.75\delta_{IF_{i_v}}} \frac{D_T}{D_T}$$

Where D_T is the mean standard deviation over the length of segment and E_s is the energy corresponding the segment location.

These candidate segments are then assigned identifiable labels and are grouped together using the Bag-of-Features (BoF) technique [21]. It provides solution to quantize features into histograms that used in classifier learning and testing stages.

Last step is to classify whole cycle into normal or adventitious sound through Support Vector Machine (SVM) classifier. Algorithm-1 shows details of classification process.

Algorithm-1

Input: IF_i shows Instantaneous Frequency calculated in Eq.3, 'W' is window of 40ms with 92% overlap, 'n' is number of segments, T1, T2, T3 are thresholds for segment categorization, t₁ duration of RS segment, 'L' shows the label to the candidate segment

Output: RS Cycle – Normal or AS

1. $\delta IF_i = \sqrt{\frac{\sum_{i=1}^n (IF_i - \overline{IF})^2}{n-1}}$
2. $T1 = \delta IF_i$
3. $T2 = \delta IF_i - 0.5 \delta \delta IF_i$
4. $T3 = \delta IF_i - 1.5 \delta \delta IF_i$
5. if ($\delta IF_i < T2$)
 switch (δIF_i)
 Case ($\min(\delta IF) \leq T3 \ \&\& \ t_1 \geq 100 \text{ ms}$)
 L=Type1
 Case ($\min(\delta IF) \geq T3 \ \&\& \ t_1 < 100 \text{ ms}$)
 L=Type2
 Case ($\min(\delta IF) > T3 \ \&\& \ t_1 \geq 100 \text{ ms}$)
 L=Type3
 Case ($\min(\delta IF) > T3 \ \&\& \ t_1 < 100 \text{ ms}$)
 L=Type4
 end switch
 end if
6. Energy based feature extraction
7. Bag of features
8. SVM classifier

IV. RESULTS AND DISCUSSION

Different sets of RS were used to evaluate the performance of the proposed algorithm against the IF estimation method presented by Lozano et. al. in [22] which is represented as Lozano K and Lozano 5 in Figure 3 and Figure 4. Different categories of RS cycle used for comparison are: Inspiratory Cycle (IC), expiratory cycle (EC), complete cycle (CC), IC and EC of Asthmatic patients, (IC-Asthma, EC-Asthma).

Table-I shows results of classifier performance. Figure-3 shows accuracy of all cycle categories from which it is cleared that as far as asthmatic ICs and ECs are considered, proposed algorithm shows better performance. Another comparison performed is based upon Diagnostic Odds Ratio (DOR) which shows in Figure-4 that for all RS cycles, DOR

for proposed scheme is maximum except for ICs. High value of DOR depicts good detection of adventitious sound.

TABLE-I: Classification of RS based on ICs, ECs and CCs

Cycles	Accuracy (%)	F1-Score	DOR
IC	67.77 ± 5.0	0.68 ± 0.35	10.84 ± 5.0
EC	84.31 ± 3.0	0.83 ± 0.14	47.93 ± 15
CC	75.21 ± 3.0	0.75 ± 0.21	20.61 ± 15
IC-Asthma	75.55 ± 2.0	0.70 ± 0.28	13.87 ± 5.0
EC-Asthma	76.47 ± 3.0	0.76 ± 0.2	15 ± 10

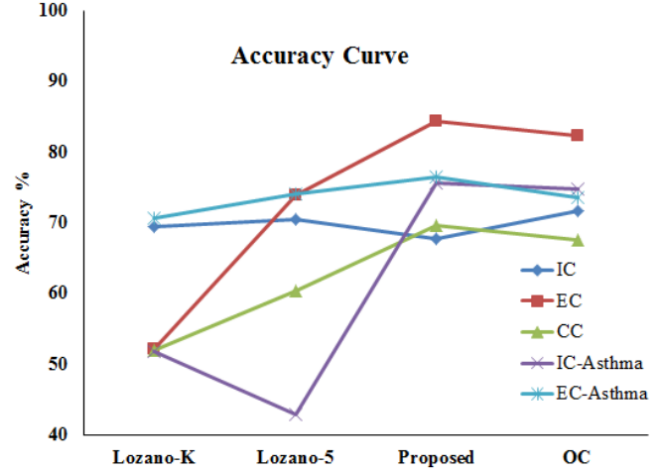


Figure-3 Accuracy graph for all cycles

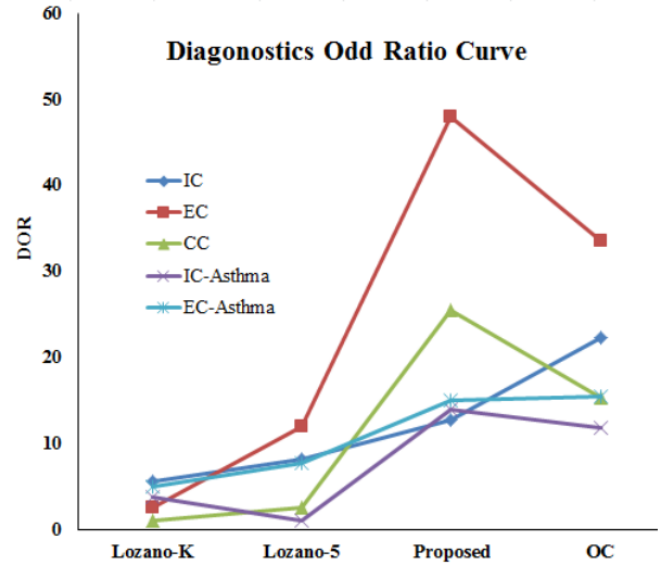


Figure-4 Comparison based on DOR

The advantage that our algorithm has on previous work is that it has the ability to classify RS cycle (IC, EC or CC) obtained from a variety of airflows from patients having different diseases such as Asthma, COPD and Bronchitis. Bottleneck of this technique is the manual segmentation of RS signal into cycle.

V. CONCLUSION

It is of an analytical importance to detect adventitious sounds for diagnosis and monitoring of respiratory diseases. This research work presented an algorithm for detection of AS and classification of RS cycle into normal or adventitious

sounds in real-life hospital situation. This system can be used confidently in other conditions as well. Detection is performed by doing wavelet de-noising and applying CEEMD to decompose RS signal into a set of IMF that contains RS segments. BoF and SVM classifier is further used to classify them into normal or Adventitious sounds. Our classifier is able to detect AS from inspiratory, expiratory or from complete cycle with accuracies of (67%), (84%) and (75%) having DOR of (10%), (47%) and (20%). In future, further refinements can be made in classification process to improve the accuracy and real-time implementation of the system to perform all processing on the mobile phone.

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