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Automatic detection of obstructive and restrictive lung disease from features extracted from ECG and ECG derived respiration signals

Surita Sarkar [a], Parthasarathi Bhattacharyya [b], Madhuchhanda Mitra [a], Saurabh Pal [a,*]

[a] Department of Applied Physics, University of Calcutta, Kolkata, India
[b] Institute of Pulmocare & Research, Kolkata, India

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ABSTRACT

Early detection of both obstructive and restrictive lung diseases is essential for maintaining proper lung function, which plays a pivotal role in decreasing the escalating number of deaths worldwide. Even though conventional methods are vastly used for diagnosing these two diseases, their use is often associated with high cost, low comfort, high patient-effort dependency, and interference with natural breathing. Consequently, the development of a non-invasive, inexpensive, reliable, and comfortable technique for detecting these respiratory diseases has become an important area of research. Therefore, unobtrusive and automatic identification of these two pulmonary diseases based on ECG and ECG derived respiration (EDR) has been presented in this study. Temporal information was extracted from the morphological variations observed in both ECG and EDR signals to derive distinctive features. Finally, supervised classifiers were used for differentiating the subjects into normal, obstructive, and restrictive categories. Performance of the classifiers evaluated on 90 subjects (both normal and diseased) demonstrated classification accuracy of more than 98 %. Results indicate that the proposed method can be effectively utilized for primary identification of obstructive and restrictive lung diseases.

1. Introduction

In today's world, respiratory disease becomes a serious matter of concern as it causes millions of deaths and disabilities. The growing number of affected patients constitutes huge economic burden to the society [1]. Pulmonary diseases can be broadly categorized as obstruction in airflow, restriction in lung volume, or a combination of both the defects [2]. Obstructive lung disease is generally characterized by airflow limitation followed by airway inflammation and broncho constriction [3]. As a result of this, air gets entrapped inside the hyper inflated lungs and patients struggle to exhale air through constricted air passages. On the other hand, reduced lung function in restrictive lung disease makes it tough for patients to entirely fill their lungs with oxygen [4]. This leads to gradual decrement of total lung volume which is caused either due to stiffness of lungs or problem associated with chest-wall expansion during inspiration. Primary identification of both obstructive lung disease (OLD) and restrictive lung disease (RLD) is utterly essential for timely supervision and effective control to preserve proper lung function. However, limited availability of detection modality and sheer ignorance about the detrimental impacts of these diseases often lead to deterioration of quality of life and even premature death [5].

Extensive researches have been performed so far for detecting obstructive and restrictive lung disorders with a limited technique capable to diagnose both of them. Clinicians vastly use spirometry for diagnosing and detecting pulmonary abnormalities that affects the lung function. An airway obstruction can be identified by the reduction in the forced expiratory volume in 1st second (FEV1) to the forced vital capacity (FVC) of lungs (FEV1/FVC) ratio [6]. Spirometry is also used for predicting lung volume restriction when a decreased FVC value has been observed [7]. However, it is not fully accurate in sorting out restrictive defects as lower FVC also can be observed if the patients have severe obstruction with air stuck in lungs [7]. Besides, reliable and successful completion of spirometry requires supervision of trained technician and significant amount of patient-effort. Restrictive disorder can be confirmed by a decreased total lung capacity (TLC) measuring through diffusion capacity of the lungs for carbon monoxide (DLCO) or body-plethysmography [2]. Though the methods can identify both restrictive disorder and combination of restrictive-obstructive defect, but the tests require longer execution time and are costly [2]. In addition, elderly patients and those with serious medical issues find it arduous to perform pulmonary function testing (PFT) that involves

* Corresponding author.
E-mail address: spaphy@caluniv.ac.in (S. Pal).

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forced inhalation and exhalation of air [8]. Pulmonary imaging techniques like X-ray, computed tomography (CT) and high-resolution CT (HRCT) are occasionally used to detect the existence of obstruction or restriction in lungs [9,10]. However, the methods often lack proper evidence which can indicate the presence of that specific disease in lungs and also suffers from risk of radiation exposure. In this situation, the necessity to develop an unobtrusive, cost-effective, reliable and comfortable technique for diagnosing OLD and RLD is in high demand.

Prior research works on these two pulmonary diseases revealed structural changes in breathing pattern amongst them [11,12]. Cough and breathing patterns were also analysed for patients with idiopathic pulmonary fibrosis (IDF) [13]. The observation results revealed a significant increment in respiration and heart rate with presence of cough during wakefulness of IDF patients. Substantial decrement in inspiration time, expiration time and tidal volume have also been found in RLD patients compared to healthy normal subjects [14]. Electrocardiogram (ECG) is a reliable diagnostic technique for measuring electrical activity of heart and the process of extracting respiration signal from it is well-recognized [15]. Earlier studies found significant variation in electrocardiographs of patients with obstructive and restrictive diseases [16,17]. Researches depicted that respiration information can be measured from ECG signal in the form of ECG derived respiration (EDR) signal [18,19]. EDR has been effectively applied in diagnosis of various respiratory diseases [20,21].

In this work, an automatic identification technique has been proposed to classify patients with obstructive and restrictive lung diseases from normal subjects using features derived from ECG and EDR signal. Use of single-lead ECG for data acquisition not only made the proposed method unobtrusive and cost-effective but also minimized the number of leads, enhanced patient comfort, and monitored respiration signal without using any extra device. The characteristics of both the signals for OLD, RLD and normal subjects were observed and distinctive temporal features were extracted from the morphological differences found in the signals. Derived features were fed into three supervised classifiers- Naïve Bayes, Support Vector Machine, and K-Nearest Neighbor and their classification results were compared to determine the optimum classifier. The detailed block diagram for the proposed work has been shown in Fig. 1.

Aiming towards a single lead ECG based pulmonary disease detection and monitoring technique, the main contribution of this work are as follows:

i) Characterization of ECG derived respiration for restrictive and obstructive lung disease.
ii) Extraction of temporal feature set form ECG and EDR signal that captured useful information from the morphological variations found in OLD and RLD.
iii) Developing an automatic detection method for categorizing OLD, RLD and normal subjects.

2. Materials and methods

2.1. Database used

Participants, included in this study, has been categorized into three separate groups- normal, obstructive and restrictive. The study protocol, based on Helsinki Declaration [22], was sanctioned by the Institutional Ethics Committee Board of Institute of Pulmocare and Research, Kolkata. After submitting the written informed consent before being included in this study, each subject underwent a physical examination followed by medical history taking done by expert physicians. Patients with obstructive defects were diagnosed with pulmonary function testing, whereas, restrictive defects were confirmed only after DLCO test. Healthy individuals who had normal spirometry and had not diagnosed with any major illness during the previous six months of the recruitment, were included in the Normal subject group. Spirometry was done as per the guideline of American Thoracic Society (ATS) guideline [23] by trained technicians of Institute of Pulmocare and Research. Subjects having severe cardiovascular disease, pulmonary disease other than restrictive and obstructive disorder, any systemic disease, malignancy, sepsis, pregnancy or any chronic disease, recent history of hospital admission or illness were excluded from the study.

2.2. ECG signal acquisition

During signal recording, subjects were instructed to rest in supine position and to take regular paced breaths for noise minimization in acquired signals. ECG signal was collected using a data acquisition device MP45 by Biopac Systems Inc. [24]. ECG was recorded from each subject for 300 s duration at a sampling frequency of 1000 Hz. Three disposable body surface type electrodes, positioned on the medial surface of both legs and on the anterior forearm at the right wrist, established lead II configuration.

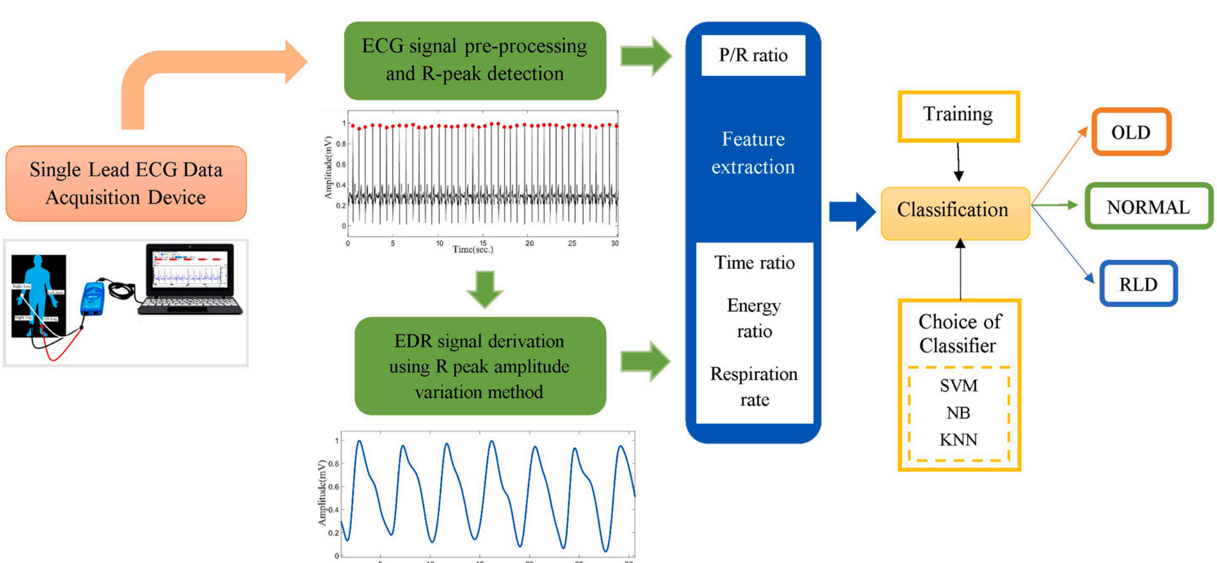

Fig. 1. Framework of the proposed study for OLD and RLD discrimination from Normal subject. The grey boxes describe the function of the corresponding blocks.

2.3. Signal pre-processing

In this study, recorded ECG signals were mainly influenced by baseline wandering and 50 Hz powerline interference. The artifacts may cause signal alteration and thus required serious consideration for eliminating those noises. Since the adopted technique needed respiration signal to be extracted from ECG, filter was selected with utmost care to keep the respiratory information intact. For eliminating both low frequency and high frequency noises a 2nd order Bandpass Butterworth filter with a passband of 1–47 Hz [20] was applied. The choice of this frequency range effectively removed the noises and maintained the essential bandwidth of ECG signal as shown in Fig. 2.

2.4. Extraction of ECG derived respiration signal

The effects of respiration on cardiovascular activity have been observed by many previous researchers [25,26]. The respiratory sinus arrhythmia (RSA) is the modulation of the heart rate during the respiratory procedure, whereas, QRS amplitude modulation produces due to superficial variation of the cardiac axis during respiration [27]. In this study, QRS amplitude variation technique was used to extract EDR signal as this method depends on the cardio-mechanical activity and is unaffected by the autonomic nervous system (ANS) which reduces with age [25]. Before EDR extraction, ECG signal has been normalized between zero to unity and R peaks were detected using a peak-detection algorithm. To sort out all local maxima, sliding window technique was implemented initially with window length of 2 s. and a threshold value of 60 % of the maximum amplitude was applied then. Another window with 0.2 s. (0.1 s. each side of probable peak) duration was applied thereafter to identify the potential R peaks. The process is shown in Fig. 3.

Finally, the peak having the maximum co-ordinate value within the range was selected as actual R-peak. If $A_{rb}(k)$ is the amplitude of detected R-wave against baseline, then it can be represented as,

$$A_{rbi}(k) = \sum_{i=1}^{N} X_{ri}(k) A_r \tag{1}$$

Where, N = total number of heart beat within a selected segment, A_r = actual value of R-wave amplitude in the middle of a resting tidal volume breath i.e., constant, and $X_r(k)$ = variation in R wave amplitude as a result of respiratory movement. The variable amplitude differences were plotted against the baseline and the EDR signal was constructed (Fig. 4).

Considering the fact that respiration signal has generally a low frequency range (0.2–0.7 Hz), cubic-spline interpolation was selected here to generate a derived respiration signal similar to original respiration signal [18]. Signals were interpolated with the same sampling frequency of ECG signal i.e. 1 KHz. Therefore, for the range $t_{i-1} \le t \le t_i$ with an interval of $T_i = t_i - t_{i-1}$, the cubic-spline polynomial can be written as,

$$d(\tau) = A_{rb}(i)_0 + A_{rb}(i)_1\tau + A_{rb}(i)_2\tau^2 + A_{rb}(i)_3\tau^3 \tag{2}$$

Where, $\tau = t - t_{i-1}$ is a local co-ordinate within the interval.

In previous researches [28,29], similarities between derived and original respiration signal have been observed. Hence, in this study only ECG signal was acquired for extracting respiration signal from it.

2.5. Identification and extraction of features

As a result of physiological changes in lungs, breathing patterns changed in different subject groups [11]. Morphological alterations were also identified in EDR signals of different subjects (Fig. 5).

The feature selection procedure requires minute detection of the discriminating variables so that the parameters can produce optimum classification. Based on the most prominent morphological pattern variances amongst the three subject groups, four features were extracted from both ECG and EDR signals as discussed below. After noise elimination the signals has been normalized between zero to unity and each feature has been calculated for a set of ten cycles. The cycles were selected randomly from the total duration of signal, and their mean value was taken. Using peak-detection algorithm the co-ordinates of onset, peak, and trough point locations were identified for each cycle (Fig. 6).

2.5.1. EDR time ratio (TR)

The time duration of inspiration portion was identified as inspiration time (T_I), and the duration between peak to trough denoted the expiration time (T_E). The time ratio (TR) has been calculated as shown in Eq. 3.

$$TR = \frac{1}{k}\sum_{j=1}^{k}\frac{T_{Ej}}{T_{Ij}} \tag{3}$$

Where, j = 1,2, 3, …, k is the jth number of randomly selected cycles.

2.5.2. EDR Energy Ratio (ER)

Signal energy (E_T) of the signal y(t) was calculated as, $E_T = \int_{-\infty}^{\infty} |y(t)|^2 dt$, where $0 < E_T < \infty$. Prior calculating the energy ratio of EDR signal, the signal was parted into inspiration and expiration portion. The energy of inspiration (E_I) and expiration (E_E) were measured individually and their ratio (ER) was derived as,

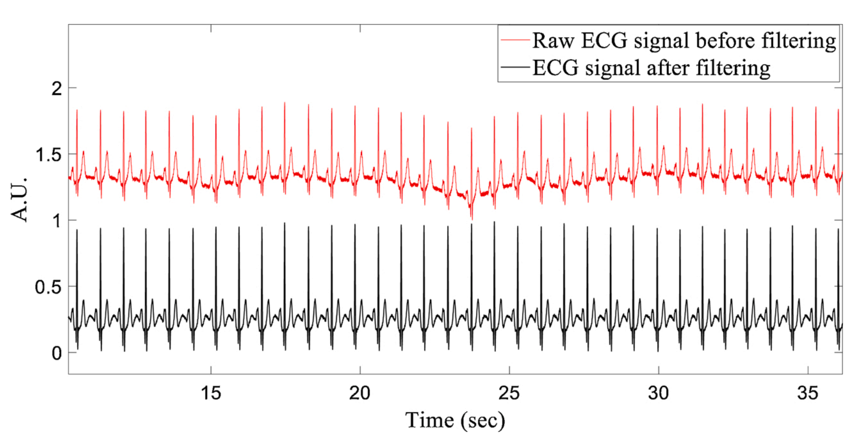

Fig. 2. The waveforms show the ECG signal before and after filtering.

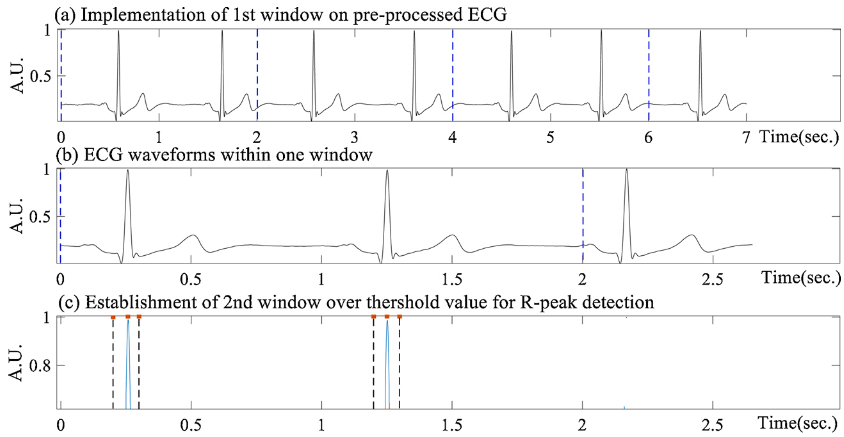

Fig. 3. Steps of R-peak detection in ECG signal- (a) Implementation of 1st window (dotted line) on pre-processed ECG, (b) ECG waveforms within one window span, (c) Application of 2nd window (dotted line) over threshold value of maximum amplitude.

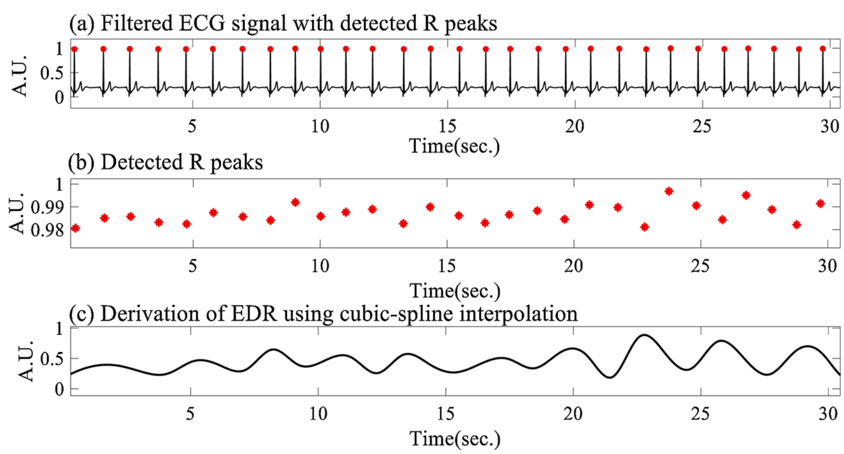

Fig. 4. From top- (a) Filtered ECG with detected R peaks, (b) detected R-peaks plotted against baseline, and (c) ECG derived respiration signal.

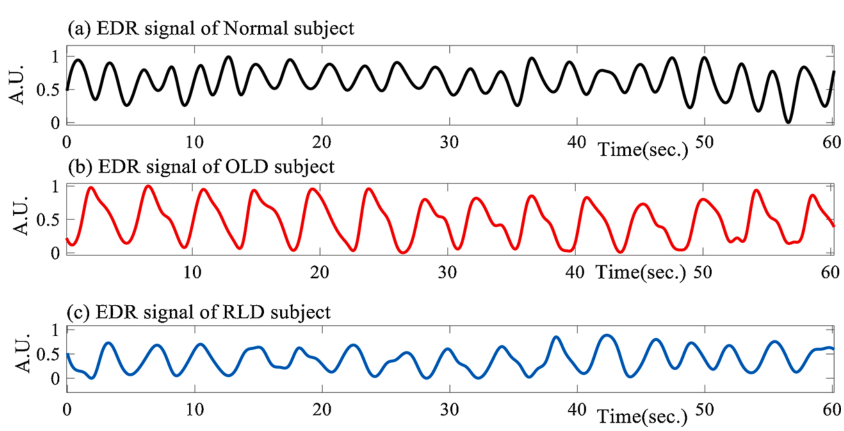

Fig. 5. Typical EDR signals of (a) Normal subject, (b) OLD subject, and (c) RLD subject.

$$ER = \frac{1}{k}\sum_{j=1}^{k}\frac{E_{Ej}}{E_{Ij}} \tag{4}$$

2.5.3. EDR respiration rate (RR)

The respiration rate (*RR*) was calculated from the occurrence of two consecutive peaks (D_j,D_{j+1}), as shown in Eq. 5.

$$RR = \frac{1}{k}\left(\sum_{j=1}^{k}\frac{60}{D_{j+1} - D_j}\right) \tag{5}$$

2.5.4. P/R ratio (PR)

Earlier researchers [30,31] found significant changes in P and R wave in obstructive and restrictive disorders. P wave verticalization was

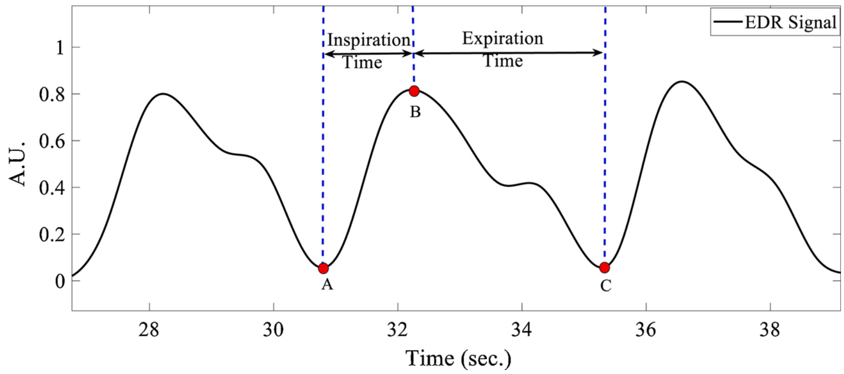

Fig. 6. Onset (A), Peak (B), and Trough (C) points of an EDR signal has been identified and inspiration and expiration duration have been calculated from these points.

found to be predominant in OLD patients [31]. Based on this finding, P/R ratio was taken as a feature in this study. After identifying R peaks, a window of 0.2 s. length was applied leftward and the maximum point within the range was selected as P peak. The amplitude of P-peak (A_p) and R-peak (A_r) of each ECG cycle against the baseline were calculated then as shown in Fig. 7.

The ratio (*PR*) between P peak amplitude and R peak amplitude was measured as,

$$PR = \frac{1}{k}\sum_{j=1}^{k}\frac{A_{pj}}{A_{rj}} \tag{6}$$

2.6. Statistical analysis

Majority of the demographic and all other feature values were represented in terms of mean ± standard deviation (SD). One-way Analysis of Variance (ANOVA) method has been used to find out if the extracted parameters were statistically significant or not before classification process [32].

2.7. Classifiers

Classification involves the design of classifier algorithm that can separate different classes by examining the extracted feature sets. In this study, Support Vector Machine (SVM), Naïve Bayes (NB), and K- Nearest Neighbor (KNN) classifiers were implemented to categorize three subject groups. These classifiers are often used in classifying obstructive and restrictive diseases [33,34].

2.7.1. Support vector machine

It is a supervised binary classifier that transforms the input data into a higher dimensional feature space. Though support vector machine generally behaves as a linear classifier, it becomes non-linear during the non-linear mapping of the input space to higher dimension space using kernel trick [35]. The selection of kernel function for this study was attained by using radial basis function (RBF).

2.7.2. Naïve Bayes

NB is a probabilistic classifier that follows the Bayes rule. It is based on the assumption that the occurrence of an individual feature in a given class is conditionally independent from other features. The outcome is generated in such a way as if all the features provide contribution separately [36]. In this study, Gaussian Naïve Bayes model was used for classification purpose.

2.7.3. K-Nearest Neighbor

KNN is a basic instance-based classifier that assumes the feature value of a given class by determining the *k* closest training observations in the n-dimensional feature space [37]. For better assessment of class, the values of *k* and the probability density function should be higher. In our study, the nearest neighbors of a feature were calculated using Euclidean distance metric.

For classifying multiple classes, several binary class classifiers have to fuse together within a multiclass classifier to discriminate three subject groups- normal, obstructive, and restrictive. The classifiers followed one-to-all approach where each of those was used to classify one group from the two others. The final output was calculated by combining the three classifier-outputs. Since the dataset is small, stratified 10-fold cross validation was used to assess the performance of classification model [33,38]. The total dataset was randomly divided into equal 10 subset with each subset consisted of training and testing data in a 9:1 ratio. For each iteration a new model was trained and

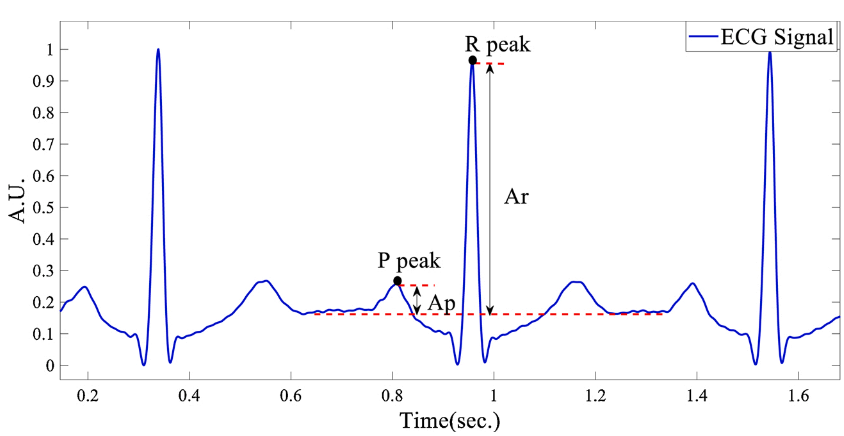

Fig. 7. Amplitudes of P peak and R peak have been calculated against baseline of ECG.

validated on the remaining test data. Hence, each subset was utilized once for training and testing during the entire process. The stratification approach maintained equal distribution of each class throughout all subset and ensured unbiased evaluation of the population proportion [39].

2.8. Performance evaluation

Classification performance has been analysed by calculating following metrics: sensitivity, specificity, accuracy and AUC. The performance of each classification depends on its capability to identify true positive conditions while discarding the false positive conditions [40]. For measurement of the metrics the number of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) occurrences were required (Table 1).

True positive case happens when the classifier correctly detects a diseased case, whereas, a true negative case occurs when the classifier correctly identifies a case without any disease.

3. Results and discussion

This section illustrates the results of various steps carried out using the proposed method. Comparative analysis of the extracted features and the performance assessment of different classifiers are also described.

3.1. Demographic and spirometric details

The study has been done on a total of ninety subjects from three groups. Each group consisted of 30 subjects aged between 21–70 years. The demographic details of the subject group are given in Table 2.

The cut-off value of FVC is <80 % for restrictive pattern and FEV1/FVC < 0.70 for obstructive pattern [41]. The number of smokers was predominant in the obstructive disease group with 83.33 % patient with a history of smoking, whereas, only 23.33 % from the restrictive disease group were smokers. Other than smoking, patients with obstruction have either asthma or exposure to pollution.

3.2. Statistical analysis of features

The mean $\pm$ standard deviation values of the features extracted for each group are shown in Table 3. Individual feature for each subject has been calculated by taking the average of feature values extracted from ten randomly selected waveforms and mean of 30 such feature values for each group has been enlisted.

The statistically significant p values (<0.00001) between features of different classes indicate that there is significant difference between the feature values. The data distribution of each class for each extracted feature has been shown through the boxplot representation (Fig. 8).

The median values of each feature for three classes have been attained as: TR (1.692), ER (1.639), RR (23) and PR (0.175) for OLD group; TR (0.882), ER (0.932), RR (26) and PR (0.245) for RLD group; and TR (0.873), ER (0.934), RR (16.5) and PR (0.05) for Normal group. Based on the median values, it has been observed that most of the features extracted for OLD and RLD groups varies largely from Normal group.

Table 1
Evaluation matrix.

Parameter	Formula
Sensitivity	TP/(TP + FN)
Specificity	TN/(TN + FP)
Accuracy	(TP + TN)/(TP + TN + FP + FN)

3.3. Evaluation of classification performance

The extracted features were fed to SVM, NB, and KNN classifiers separately. Fig. 9 shows a scatter plot for multiclass classification using KNN classifier.

Classification performance metrices have been summarized in Table 4.

The result showed that both SVM and KNN achieved the best accuracy result amongst the three. Moreover, the number of false positive and false negative subjects during classification were found to be very less which increased the level of specificity and sensitivity. Performance of the classifiers were assessed by plotting the receiver operating curve (ROC). The plot portrayed the complete area under the ROC curve (AUC) ranging consisted of all possible pairs of sensitivities and specificities for that specific classifier (Fig. 10).

The higher value of AUC ($\geq$0.99) for all three classifiers clearly demonstrates the validity of this test for discriminating different classes correctly [42].

3.4. Performance comparison

The presence of obstruction or restriction in lungs not only changes the pulmonary physiology, but also affects the normal breathing pattern [11]. The respiratory system is affected in such a way that lung compliance varies in both disorders and as a result alteration has been observed in inspiration and expiration [43]. The main observation of this study is that both OLD and RLD subjects have exhibited morphological changes and classifiable features can be extracted from ECG and EDR signal for discriminating the three groups.

Though the number of patients affected by respiratory diseases is increasing at an alarming rate, it is very unfortunate that most of them cannot avail proper diagnosis due to lack of awareness and unavailability of diagnostic tools. Hence, the necessity for developing easily available and reliable technique turns out to be essential for detecting both obstructive and restrictive lung diseases in their early stages. From this point of view, the proposed work using ECG and EDR signal can be beneficial. Table 5 gives the detailed comparison of the proposed method with other reported methods.

Other studies [6,44,45] mainly involved spirometry data for feature extraction that needs proper supervision to achieve accurately. Moreover, spirometric features used for identifying obstructive and restrictive disorders require forced breathing which is often difficult for this type of patients to perform. Nield et al. [44] implemented breathing pattern parameters like flow, volume and timing for extracting features, but their work mainly focused on detecting obstructive and restrictive ventilatory anomalies during exercise and dyspnea. However, the proposed method used a smaller number of feature set compared to that study [44]. The current study also provided better classification performance than other techniques. Therefore, ECG and EDR signal can be used for classification and primary screening of pulmonary obstruction and restriction, thus, reducing the need of unnecessary lung function testing.

3.5. Strengths and shortcomings of the study

Several researches on ECG [16,46] and EDR [21,47] characteristics for chronic obstructive pulmonary disease detection has been conducted, however, not much work is reported to use these signals for differentiating OLD and RLD patients. Also, till date no previous study has been reported on the EDR characteristics of patients with restrictive lung disease as per the authors' knowledge. In addition to this, the exclusive use of temporal features for simultaneous discrimination of OLD, RLD and normal subject enhances the utility of the proposed method.

The study confronted few shortcomings as well. The number of subjects in this approach was much lesser compared to other studies [6,45]. Besides, subjects only having pure obstructive or restrictive lung

Table 2
Demographic and spirometric details of subject groups.

Group (n = 30)	Age (mean ± SD)	Height (mean ± SD)	Weight (mean ± SD)	BMI (mean ± SD)	Male:Female	FVC	FEV1/FVC
Normal	56.4 ± 13.2	161.5 ± 8.3	61.8 ± 13.2	24.2 ± 3.1	3:2	0.88 ± 0.05	0.84 ± 0.02
Obstructive	64.4 ± 5.4	163.5 ± 5.7	63.4 ± 11	23.2 ± 5.3	4:1	0.84 ± 0.06	0.65 ± 0.17
Restrictive	55.33 ± 12.8	159.5 ± 10.9	65.6 ± 13	25.8 ± 4.5	1:1	0.55 ± 0.14	0.82 ± 0.06

Table 3
Statistical assessment of features.

Extracted features (mean ± SD)	Subject group			p value
	Normal	Obstructive	Restrictive	
EDR time ratio	0.84 ± 0.15	1.72 ± 0.37	0.87 ± 0.16	<0.00001
EDR energy ratio	0.92 ± 0.16	2.13 ± 1.34	0.93 ± 0.11	<0.00001
EDR respiration rate	16.5 ± 1.38	23.53 ± 3.12	25.3 ± 2.9	<0.00001
P/R ratio	0.06 ± 0.04	0.26 ± 0.23	0.14 ± 0.06	<0.00001

disease were recruited in the work. Study comprised of a large number of data in each class and inclusion of subjects with combination of pulmonary restriction and obstruction will lead to a more generalized approach.

Table 4
Classification performance attained by different classifiers.

Classifier	Sensitivity	Specificity	Accuracy	AUC
Naïve Bayes	98.87 %	97.78 %	97.81 %	0.99
Support Vector Machine	98.89 %	98.89 %	98.92 %	1
K-Nearest Neighbor	98.89 %	98.89 %	98.92 %	1

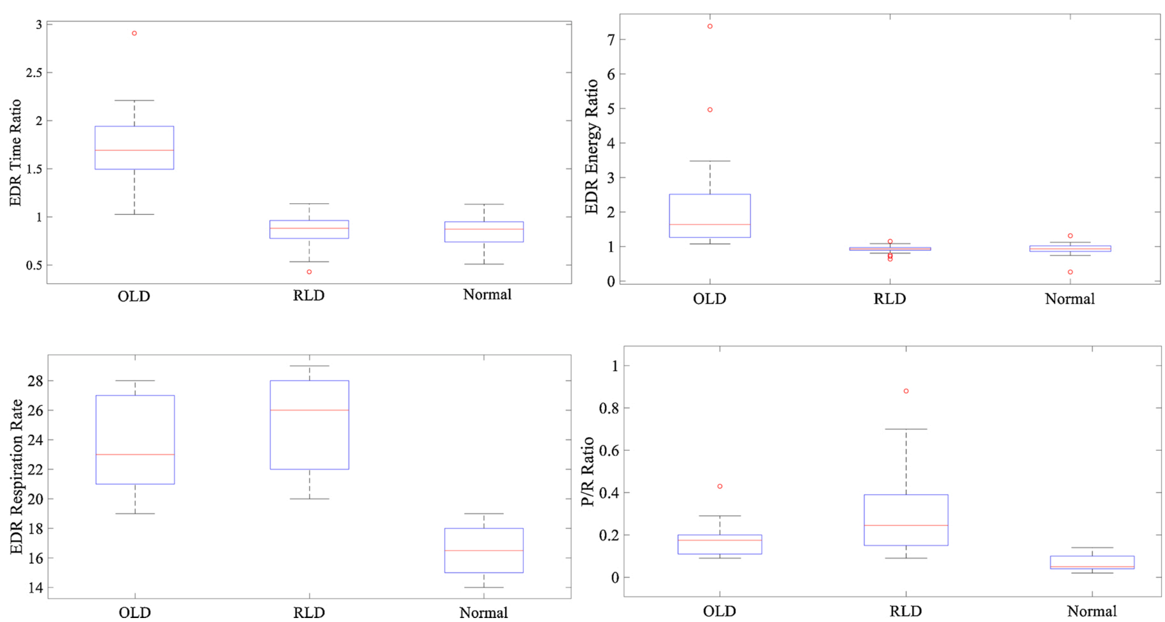

Fig. 8. Box-whisker plot of each feature for corresponding three classes. The red horizontal line inside the box indicates the median value, the box denotes the interquartile ranges, the whiskers indicate the extreme value, while the red circles are the outliers.

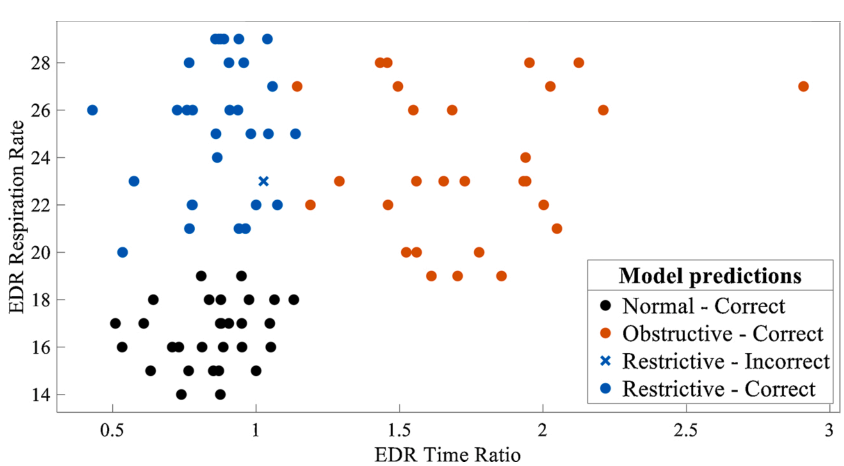

Fig. 9. Scatter diagram of multiclass classification using KNN classifier. The blue cross mark which actually belongs to obstructive group, misclassifies as restricted.

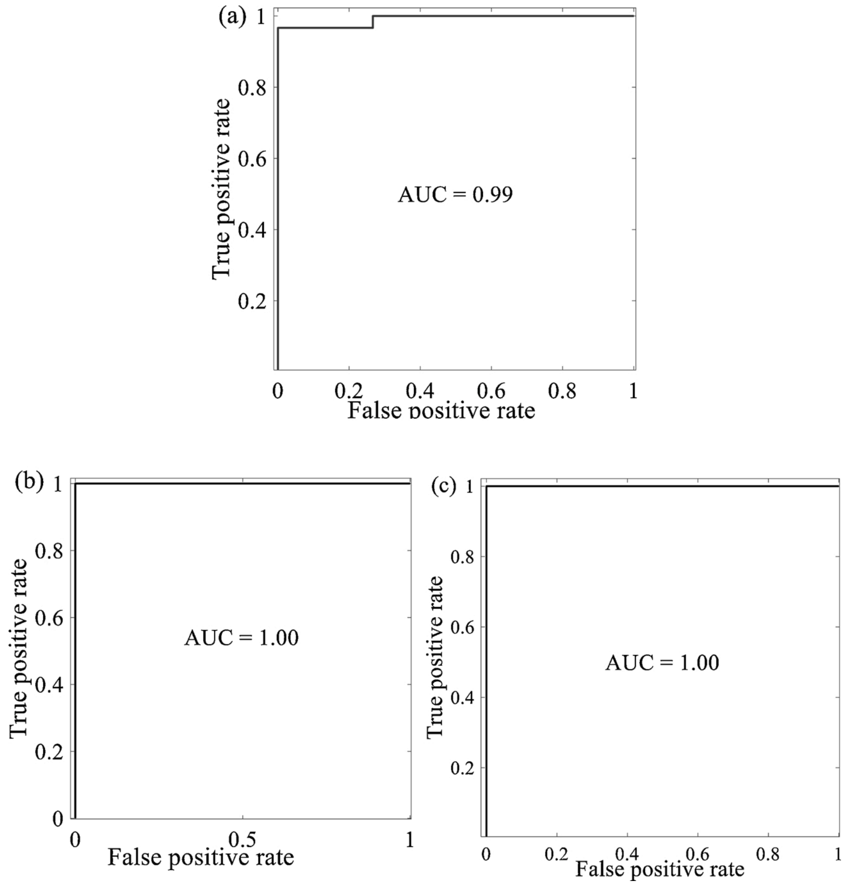

Fig. 10. ROC curves using (a) Naïve Bayes, (b) SVM and (c) KNN classifier.

Table 5
Comparative study of some previous literatures on classifying obstructive from restrictive with the proposed work.

Sl	Refs.	Subject group	Dataset	Signal analyzed for experiment	Features used	Technique used	Classification performance		
							Accuracy %	Specificity %	Sensitivity %
1	Sahin et al. [6]	Normal, obstructive, restrictive	499	Spirometry	FEV1, FEV1/FVC, FVC	Multiclass SVM	97.32 %	97.97 %	94.44 % (for Restrictive), 94.29 % (for obstructive)
2	Nield et al. [44]	Obstructive, restrictive	20	Spirometry and maximal voluntary ventilation	Breathing frequency, high minute ventilation, tidal volu me, inspiratory and expiratory time (T_E), inspiratory to expiratory ratio (T_I/T_E), total breath time, inspiratory time to total time (T_I/T_{TOT}), mean inspiratory flow, mean expiratory flow, inspiratory to expiratory flow ratio (V_I/V_E)	ANOVA	$p < 0.008$ for T_I/T_E and V_I/V_E at all exercise intensity levels. $p < 0.008$ for T_E and T_I/T_{TOT} at baseline and maximum exercise.		
3	Vandevoorde et al. [45]	Obstructive, restrictive	11,676	Spirometry	FEV6, FVC, FEV1/FEV6, FEV1/FVC	SPSS	97.4 % PPV, 96.9 % NPV	93.1 % (for obstructive), 99.6 % (for restrictive)	94 % (for obstructive), 83.2 % (for restrictive
4	Proposed method	Normal, obstructive, restrictive	90	Single lead ECG	Time ratio, energy ratio, respiration rate, P/R ratio	NB, SVM, KNN	97.81 %, 98.92 %, 98.92 %	97.78 %, 98.89 %, 98.89 %	98.87 %, 98.89 %, 98.89 %

4. Conclusion

In today's world, respiratory diseases are spreading like an epidemic due to increased air pollution and lifestyle changes. Even cumulative incidents of hospital admission and morbidity due to these diseases impose a huge burden over both governments and society. The prevention, management and cure of these diseases lies in early detection and proper treatment. In view of this, a fast indicator of respiratory ailments is a need of the day.

Structural variations can be found in the disease-affected breathing patterns even if they are extracted from ECG signal. However, the use of EDR remains unexplored till date for detection of OLD and RLD from normal subjects. This proposed method may have some shortcomings compared to the earlier reported studies, but provides noteworthy advantages like enhanced patient comfort, easy availability, simple operability, and cost effectiveness for detection of obstructive and restrictive diseases. Moreover, the employment of single-lead ECG secure lead-minimization and unobtrusive monitoring of ECG and respiration simultaneously.

Features like time ratio, energy ratio, respiration rate, and P/R ratio were extracted from EDR and ECG signal were used for classification of restrictive and obstructive lung diseases to normal ones. Fairly high classification accuracy demonstrated the superiority of this work over the existing techniques. Hence, the proposed method can be projected as a reliable alternative for detection of obstructive and restrictive lung diseases. The current work may be extended further for developing a portable healthcare device for automated detection of these respiratory diseases.

CRediT authorship contribution statement

Surita Sarkar: Conceptualization, Investigation, Formal analysis, Software, Visualization, Writing - original draft. **Parthasarathi Bhattacharyya:** Resources, Investigation, Validation. **Madhuchhanda Mitra:** Resources, Methodology, Supervision. **Saurabh Pal:** Conceptualization, Methodology, Supervision, Writing - review & editing.

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Declaration of Competing Interest

The authors report no declarations of interest.

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