Automated Severity Detection Of Chronic Obstructive Pulmonary Disease Using Lung Sounds

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Content

Introduction to lung sound

- Produced due to tubulan air flow in trachea-bronchial tree
- Can be heard at the course of chest auscultation
- Linked to structural faults occurred in lungs due to disease condition

Table 1: Description of different lung sounds

Lung sound	Frequency range	Inspiratory/ expiratory	Associated disease
Normal	bellow 1000Hz	Both	Heathy
Wheeze	200-2500Hz	expiration or both in severe condition	COPD, bronchial asthma
Crackle	100-500Hz	Inspiratory	Pneumonia. pulmonary edema
Pleural rub	200-4000Hz	Inspiratory	Lung tumor, infection in inner linings

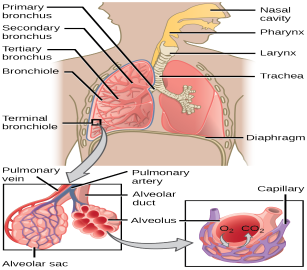


Figure 1: Human respiratory system

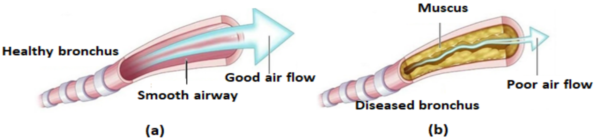


Figure 2: Cross sectional view of (a) healthy bronchous and (b) COPD diseased bronchous

Chronic obstructive pulmonary disease (COPD)

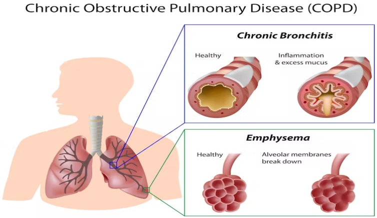
COPD is associated two airway obstruction defect:

- **Emphysema:** destruction of the elastic fibers of the alveoli.
- **Chronic bronchitis:** bronchial tubes become inflamed and narrowed.

Cause: Cigarette smoking, secondhand smoke, pipe smoke, α1-antitrypsin deficiency.

Alarming statistics:

- According to WHO, COPD is the world's third leading cause of mortality[1]
- COPD accounted for 75.6 percent of all chronic respiratory illness in India in 2016 [2].



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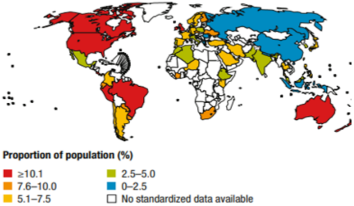

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Figure 3: (a) Airway obstructions in COPD, (b) World map of the prevalence of clinical COPD [1]

Motivation for lung sound based diagnostic modality

Gold standard modality: Spirometry or lung function test based parameters (FEV1, FVC measure).

Disadvantage of spirometry:

- Highly dependent on patient efforts, cooperation with the technician.
- Laborious procedure, especially for younger and the elderly
- Costly

Why intervention of lung sounds:

- Observable wheezing sounds during auscultation.
- Low-cost non-invasive modality.

Table 2: Different COPD severity levels described by GOLD [3]

COPD severity	qualitative severity level	Gold standard measures (FEVR)	Physiological effect
COPD0	Under Risk	>85%	non-chronic symptoms, persistent cough
COPD1	Mild Level	>80%	Light wheezing
COPD2	Moderate level	50% - 80%	chronic symptoms, wheezing
COPD3	Severe Level	30% - 50%	all chronic symptoms, pulmonary infections
COPD4	Very severe level	<30%	bedridden case with respiratory machine

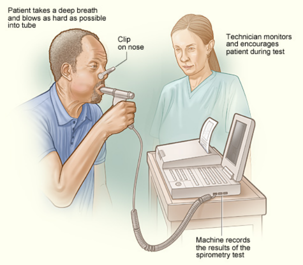

Figure 4: Spirometric measurement apparatus

Database

Database used: RespiratoryDatabase@TR [3]

Table 3: Description of RespiratoryDatabase@TR[3]

Recording device	Littmann3200 digital stethoscope
Sampling rate	4000 Hz
Acquisition sites	4 anterior, 8 posterior (Fig.5)
Recording length	Uneven, atleast 17 sec
Distribution of classes	COPD0: 5, COPD1: 7, COPD2:7, COPD3:7, COPD4: 10

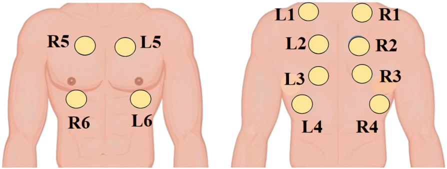

Figure 5: Lung auscultation positions on the anterior and posterior side of body.

Proposed framework for automated severity detection of COPD using lung sounds

Objective: To develop an automated COPD severity detection system using the lung sound signal based on signal processing and machine learning technique.

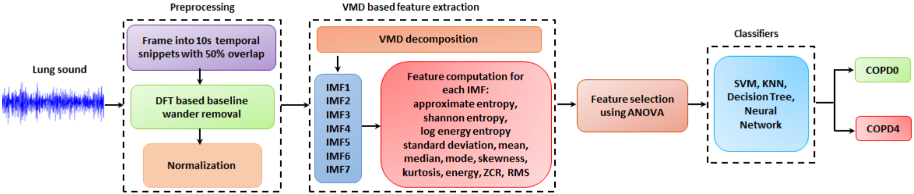

Figure 6: Block diagram of the proposed COPD severity classification framework

Preprocessing

- **Temporal snippet generation:**
  Let, $s[n]$ be the raw lung sound signal, being segmented into 10 sec. snippets ($s_t[n]$) keeping 50% overlap with adjacent frame.
- **DFT based baseline wander (BW) component removal [4]:**
  DFT of the t^{th} temporal snippet ($s_t(n)$) is calculated as:

$$S_t(K) = \sum_{n=0}^{N-1} s_t(n) e^{\frac{-j2\pi nK}{N}} \tag{1}$$

  Frequency range of BW component is 0-1 Hz. Thereby, remove DFT coefficients which are smaller than 1 Hz. DFT coefficient index for the f Hz: $K = \lceil \frac{fN}{f_s} \rceil$ where, f_s denotes the sampling rate of lung sound. Threshold the DFT coefficient:
  $\tilde{S}_t(K) = [0, ..., 0, S_t[K+1], ...S_t[N-K-1], 0, ..., 0]$
  Baseline wander removed signal:

$$LS^t_{bwf}(n) = \frac{1}{N} \sum_{K=0}^{N-1} \tilde{S}_t(K) e^{\frac{j2\pi nK}{N}} \tag{2}$$

- **Normalization:**

$$LS^t_{norm}(n) = \frac{LS^t_{bwf}(n)}{max|(LS^t_{bwf}(n))|} \tag{3}$$

Preprocessing (Contd.)

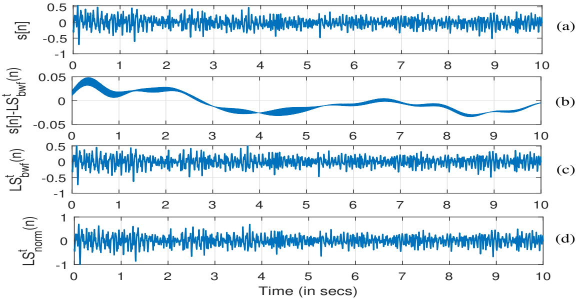

Figure 7: (a) Lung sound snippet, (b) BW component, (c) BW removed signal, (d) Normalised lung sound snippet.

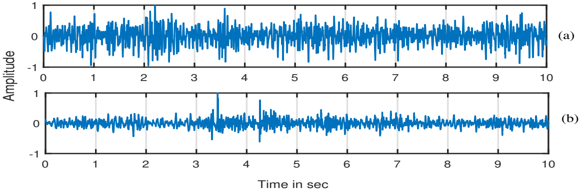

Figure 8: Preprocessed lung sound signals of (a) COPD-0 and (b) COPD-4 subject

Variational mode decomposition (VMD) [5]

VMD [5] decomposes a 1-D signal: $v(t)$, into K number of modes $\{h_k\}$, each with a different center frequency $\{\omega_k\}$ with compact bandwidth. The IMF extraction process is described as:

- calculate analytic version of each mode $\{h_k\}$ to get unilateral frequency spectrum
- shift the frequency component to base-band
- compute the bandwidth by considering L^2 norm of the gradient resulting in the following equality constrained variational problem:

$$\min_{h_k,\omega_k} \left\{ \sum_k \left\| \partial_t \left[(\delta(t) + j/\pi t) * h_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad \text{s.t.} \ \sum_k h_k(t) = v(t) \tag{4}$$

Unconstrained optimization is formulated by adding augmented Lagrangian function:

$$\begin{aligned} \mathscr{L}\left(h_k, \omega_k \lambda\right) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * h_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ + \left\| v(t) - \sum_k h_k(t) \right\|_2^2 + \left\langle \lambda(t), v(t) - \sum_k h_k(t) \right\rangle \end{aligned} \tag{5}$$

VMD (Contd.)

The minimization problem is solved by using ADMM optimization which results in the following update equations for modes and center frequencies:

$$\hat{h}_k^{q+1}(\omega) \leftarrow \frac{\hat{v}(\omega) - \sum_{i<k} \hat{h}_i^{q+1}(\omega) - \sum_{i>k} \hat{h}_i^{q}(\omega) + \frac{\hat{\lambda}^q(\omega)}{2}}{1 + 2\alpha\left(\omega - \omega_k^q\right)^2} \tag{6}$$

$$\omega_k^{q+1} \leftarrow \frac{\int_0^\infty \omega \left|\hat{h}_k^{q+1}(\omega)\right|^2}{\int_0^\infty \left|\hat{h}_k^{q}(\omega)\right|^2} \tag{7}$$

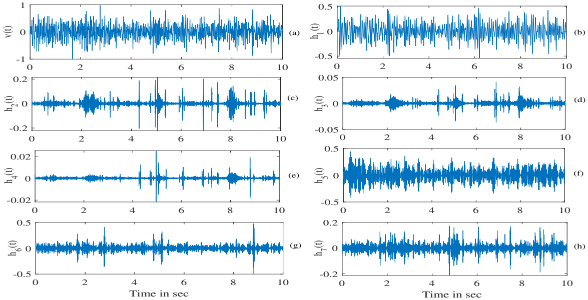

Figure 9: (a) Lung signal of COPD-0 subject, (b-h) IMFs extracted using VMD

VMD based feature extraction

Mean$=\frac{1}{N}\sum_{n=1}^{N} h[n]$ [9]

St. dev$=\sqrt{\frac{1}{N}\sum_{n=1}^{N}(h[n]-\bar{h})^2}$ [9]

skewness $\frac{1}{N}\sum_{n=1}^{N}\frac{(h[n]-\bar{h})}{\sigma}^3$ [9]

Kurtosis$=\frac{1}{N\sigma^4}\sum_{n=1}^{N}(h[n]-\bar{h})^4$ [9]

RMS$=\sqrt{\frac{1}{N}\sum_{n=1}^{N} h[n]^2}$ [9]

Energy$=\sum_{n=1}^{N} h[n]^2$ [9]

Shannon entropy$=-\sum_i h(i)log(h(i))$ [9]

Log energy entropy$=\sum_i log(h^2(i))$ [9]

ZCR$=\frac{1}{2N}\sum_{n=1}^{N}|sgn(h[n])-sgn(h[n-1])|$ [9]

Approximate entropy(M,R)$=\lim_{n\to+\infty}\Psi^M(R)-\Psi^{M+1}(R)$

where, $\Psi^M(R)=\frac{1}{N-M-1}\sum_{i=1}^{N-m+1} logC_i^M(R)$, and $C_i^M(R)$ provides count in resolution R, M is embedded dimension, R denotes a threshold value.

Feature Selection using analysis of variance (ANOVA) test

- Analysis of variance (ANOVA) test-based feature selection
- Considered the features which have $p - value < 0.05$

Table 4: Selected Features By Employing ANOVA Test

IMF No.	**Selected features with** $p - value < 0.05$
IMF1	ShEn, RMS, st. dev, energy, ZCR, ApEn, LogEn
IMF2	ZCR, ApEn, LogEn
IMF3	ZCR, ApEn, LogEn
IMF4	Kurtosis, ApEn, LogEn, ZCR
IMF5	ApEn, ZCR, LogEn
IMF6	Mode, ZCR, ApEn
IMF7	St. dev, ShEn, RMS, energy, mode, ApEn, LogEn

- Total 30 features have been selected by ANOVA test.

Box plot visualization of the selected features

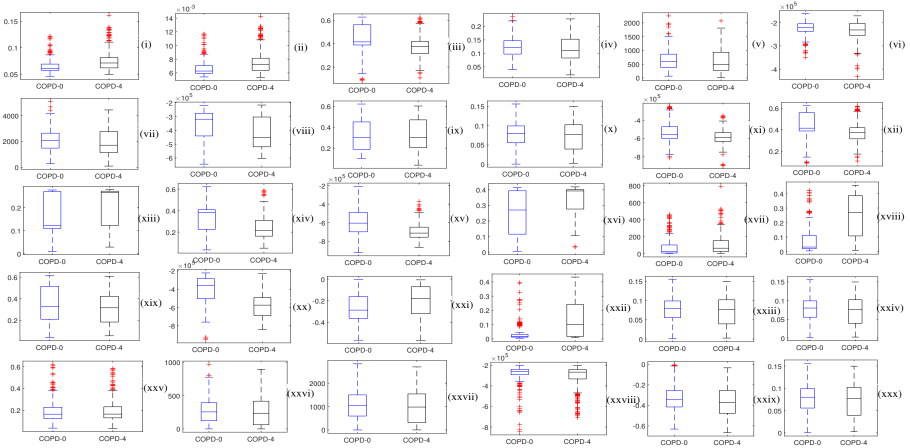

Figure 10: Illustrate box plots of different features: (i) IMF1 ApEn, (ii) IMF1 ZCR,(iii) IMF1 st. dev,(iv) IMF1 RMS,(v) IMF1 Energy,(vi) IMF1 LogEn,(vii) IMF1 ShEn,(viii) IMF2 LogEn,(ix) IMF2 ApEn,(x) IMF2 ZCR,(xi) IMF3 LogEn,(xii) IMF3 ApEn,(xiii) IMF3 ZCR,(xiv) IMF4 ApEn,(xv) IMF4 LogEn,(xvi) IMF4 ZCR,(xvii) IMF4 Kurtosis,(xviii) IMF5 ZCR,(xix) IMF5 ApEn,(xx) IMF5 LogEn,(xxi) IMF6 mode,(xxii) IMF6 ZCR,(xxiii) IMF6 ApEn,(xxiv) IMF7 RMS,(xxv) IMF7 ApEn,(xxvi) IMF7 energy,(xxvii) IMF7 ShEn,(xxviii) IMF7 LogEn,(xxix) IMF7 mode,(xxx) IMF7 st dev, from COPD-0 and COPD-4 class

Classification using machine learning (ML) classifier

- **ML classifiers**: **support vector machine (SVM)**, **K- nearest neighbor (KNN)**, **decision trees (DT)**, **shallow neural network** (2 hidden layers having 20, 15 neurons)
- **Performance metrics**: classification accuracy (C_a), sensitivity (S_e), specificity (S_p). Where $S_e = \frac{t_p}{t_p+f_n}$ $\quad S_p = \frac{t_n}{t_n+f_p}$ $\quad C_a = \frac{t_p+t_n}{t_p+t_n+f_p+f_n}$

Table 5: Performance of Different Classifiers Evaluated on Test Set

Classification Scheme	Classifiers	S_e	S_p	C_a
COPD-0 versus COPD-4	KNN [10]	0.9375	1	0.9743
	SVM [8]	0.9538	0.9607	0.9615
	DT [7]	0.8518	0.96	0.923
	Shallow NN	0.9259	0.9572	0.949

Sensitivity with respect to processing length and performance comparison

- Tested the algorithm with respect to varying processing lengths: 5 sec, 10 sec, and 15 sec

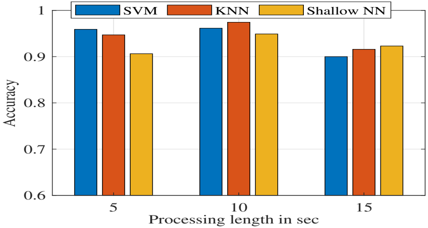

Figure 11: Effect of processing length with respect to accuracy

Table 6: Performance Comparison with Other Existing Works

Sl. No.	Work reference	Data used	Proposed technique	C_a (%)	S_e (%)	S_p (%)
1	Altan et al. [6]	Lung sound	3D-SODP based features, DBN	95.84	93.65	93.34
2	**Proposed**	**Lung Sound**	**VMD based feature extraction and ML classifier**	**97.43**	**93.75**	**100**

3D-SODP: 3-dimensional second-order difference plot, DBN: deep belief networks

Conclusion

- Establishes the fact that lung sounds play an important role in COPD severity detection
- This shows importance towards the early detection of COPD due to the incorpopration of COPD0 class
- This work highlights the feasibility of automatic COPD severity detection using machine learning while emanating complex deep learning

References I

A. A. Cruz, "Global surveillance, prevention and control of chronic respiratory diseases: a comprehensive approach", *World Health Organization*,2007.

Salvi, Sundeep, et al. "The burden of chronic respiratory diseases and their heterogeneity across the states of India: the Global Burden of Disease Study 1990–2016." *The Lancet Global Health* 6.12 (2018): e1363-e1374.

ALTAN, Gökhan, Yakup Kutlu, Yusuf Garbi, Adnan Özhan Pekmezci, and Serkan Nural. "Multimedia respiratory database (RespiratoryDatabase@ TR): Auscultation sounds and chest X-rays." *Natural and Engineering Sciences* 2, no. 3 (2017): 59-72.

Satija, U., Ramkumar, B. and Manikandan, M.S., 2017. Real-time signal quality-aware ECG telemetry system for IoT-based health care monitoring. IEEE Internet of Things Journal, 4(3), pp.815-823.

K. Dragomiretskiy and D. Zosso, "Variational Mode Decomposition," in IEEE Transactions on Signal Processing, vol. 62, no. 3, pp. 531-544, Feb.1, 2014.

Altan G, Kutlu Y, Pekmezci AÖ, Nural S, "Deep learning with 3D-second order difference plot on respiratory sounds." *Biomedical Signal Processing and Control* 45 (2018): 58-69.

S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," in IEEE Transactions on Systems, Man, and Cybernetics, vol. 21, no. 3, pp. 660-674, May-June 1991.

Kamruzzaman, Joarder Begg, Rezaul. (2007). "Support Vector Machines and Other Pattern Recognition Approaches to the Diagnosis of Cerebral Palsy Gait." IEEE Transactions on Biomedical Engineering, 53. 2479 - 2490.

G. Sahu and K. C. Ray, "An Efficient Method for Detection and Localization of Myocardial Infarction," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-12, 2022.

Cunningham, P., Delany, S. J.. "K-nearest neighbor classifiers-a tutorial" *ACM Computing Surveys (CSUR)*.

Thank You