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Classification of COPD and normal lung airways using feature extraction of electromyographic signals

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ABSTRACT

Airway obstruction is a common component in Chronic Obstructive Pulmonary Disease (COPD). Detection of obstruction and its grading is very essential. Obstruction in the airways, forces the accessory muscles like sternomastoid muscle (SMM) of respiration to work. Normally, only essential muscles of respiration work. In the said paper electromyographic (EMG) analysis of SMM is done for COPD and Normal subjects. We have developed improved slope based onset detection algorithm to detect the onset and offset timing of EMG. Time domain features are extracted for COPD and normal subject. The onset detection algorithm reduces the number of computations by 32.96% and increases accuracy of feature calculation by 40.19%. Dominant time domain features are selected and applied to Support Vector Machine Classifier. The SVM classification algorithm is compared with Threshold and Naïve Bayes classification algorithm. SVM gives the highest accuracy of 87.80%, sensitivity of 89.65% and specificity of 83.33%. Results are also compared with previously used FEV1/FEV6 and Forced Oscillation Technique. The activity of SMM has a significant role in the classification of Normal and COPD subject. Further analysis of SMM can be done to find different grades of COPD.

1. Introduction

Rising air pollution levels, tobacco consumption, biomass fuel, occupational exposures to organic or inorganic dusts and changing lifestyle are causing increases in respiratory diseases. COPD is becoming a major cause of mortality and morbidity. Hurd et al. (2017) says that; COPD kills more than 3 million peoples every year, making it fourth largest cause of death in the world. Common pathology in COPD is an obstruction in the airways secondary to their narrowing. Qi et al. (2013) has concluded that, these pathological changes lead to limitation of the flow of air to and from the lungs, causing shortness of breath. Various muscles participate during respiratory activity. Albert et al. (2008) observed that, the diaphragm and intercostal are the essential muscles of respiration while scalene and SMM are the accessory muscles of respiration. Normally, only essential muscles are active during inspiration and expiration is passive. While in obstructive lung diseases, due to increased workload of respiration, accessory muscles are recruited during quiet breathing. The proven and useful method to interpret the activity of muscle is electromyography. SMM is an easily accessible muscle of respiration and collecting its Surface EMG signal is easier. So, we have selected SMM muscle for the proposed method.

The brain generates nerve impulse. Motor neurons carry it to axon terminals. Axon terminals serve different muscle fibers. The characteristics of EMG signal depend on the physiology of muscle fiber. Muscle Fiber Conduction Velocity (MFCV) depends on an intramuscular milieu. The low value of pH decreases the MFCV. Therefore; during fatigue, conduction velocity decreases. Bell (1993) has observed linear relationship between muscle fiber diameter and MFCV. MFCV is also dependent on temperature, length of muscle fiber, age and force applied. Increase in activity

Abbreviations: COPD, Chronic Obstructive Pulmonary Disease; EMG, electromyographic; SMM, sternomastoid; MFCV, Muscle Fiber Conduction Velocity; MUAP, Motor Unit Action Potential; AIA, Average Instantaneous Amplitude; ARV, Average Rectified Value; FEV1, Force Expiratory Volume; FVC, Force Vital Capacity.

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of muscle fibers leads to the generation of Motor Unit Action Potential (MUAP). A motor unit has long axon twigs or equal length axon twigs. These variations generate complex MUAP. Equal length axon twigs results in a short duration and high amplitude MUAP. If there is demand of increased force, firing rate of MUAP increases and motor neurons get activated with greater frequency resulting in greater amplitude EMG. Oskoei and Hu (2007) concluded that the firing frequency of motor neurons decreases as muscle fatigue. Muscle fatigue is observed as a decrease in mean and median frequency. Amplitude alterations are observed depending on the level of muscle contraction. Increase in level of contraction increases the amplitude and firing frequency of the EMG.

Electromyographic signals are random in nature; local stationary nature can be achieved by dividing signals into different window size. Kamen and Gabriel (2010) suggested that; for processing and analysis of EMG, it has to be assumed that, EMG has zero mean random (stochastic) nature whose standard deviation is proportional to the number of motor units and firing rate. The inherent noise of electronic components, ambient noise, baseline wander and motion artifacts are common noise observed in EMG signals. Noise reduction is achieved by means of careful design of hardware and appropriate filters. Kumar et al. (2015) and Fatma et al. (2016) has designed filters to remove inherent noise. To improve accuracy of analysis, EMG signal should be analyzed in its active duration. Active duration is a region between onset and offset timing of muscle contraction. Feature value collected between onset and offset will be more accurate compared to traditional methods. Simone Pasinetti et al. (2015) compared multiple methods to find the active duration of muscle. In single threshold method, envelope of the waveform is detected by filtering the full wave rectified EMG signal. A threshold is selected by observation. The intersection of the envelope and threshold is detected as onset. Random nature of EMG makes onset detection sensitive for the single threshold method. In double threshold; two thresholds are calculated using mean and standard deviation, for no muscle contractions. EMG signal should pass through the first and second threshold to detect onset. The double threshold method minimizes false detection of onset. To overcome the limitations of single threshold and double threshold method, we have developed a novel slope based onset detection algorithm. Slope based onset detection algorithm is more accurate compared to single threshold and double threshold method with a slight increase in complexity.

Presently airway obstruction in the lungs is detected using spirometry. Hurd et al. (2017) (GOLD Guidelines 2017) and Kim et al. (2013) has recommended spirometry parameters (Force Expiratory Volume (FEV1) and Force Vital Capacity (FVC) for classification and detection of COPD. FEV1/FVC < 0.70 gives a diagnosis as lung airway obstruction and Post Bronchodilator FEV1 give a severity level of airway obstruction. Spirometry is effort dependent, difficult to perform on morbid patients, subjective, time consuming and require patient cooperation for specific respiratory maneuvers. A new technique, Impulse Oscillometry (IOS), gives information about resistive properties of the respiratory system during quiet breathing. Forced Oscillation Technique (FOT) employs small-amplitude pressure oscillations superimposed on the normal breathing. Amaral et al. (2015) found a significant correlation between spirometry and forced oscillation measurements with machine learning algorithms. Hellinckx et al. (2001) compared IOS with FOT and concluded that; similar but non-identical values of reactance are observed for IOS and forced oscillation. Tse et al. (2016) reported that forced oscillation is a good alternative; but reactance parameters are better than resistive parameters in correlation with air trapping. IOS and FOT are costly and upcoming technologies. Swanney et al. (2000) has reported that FEV6 is more reproducible, less physically demanding and accurate for COPD patients than FEV1/FVC parameter. Vandevoorde et al. (2006) has also done a COPD classification with fixed cutoff values of FEV6. FEV6 has limitations of over diagnosis of restrictive pattern in elderly persons. Besides of good result; FEV6 parameter is not recommended by GOLD 2017. Spirometry, IOS and FOT do not consider respiratory dynamics, which puts the respiratory system at a mechanical disadvantage and ultimately leads to progression of symptoms of COPD. SMM muscle analysis is non-invasive, considers respiratory dynamics and easy to perform technique for COPD diagnosis.

Researchers have demonstrated the presence of accessory muscles (SMM and scalene) activity in COPD. Mañanas et al. (2000) analysed the activity of SMM muscle in 7 COPD patients. They observed activity of SMM was increasing for incremental and maintained protocol, but the results were varied with spectral estimator. Stability analysis and onset detection were neglected. De Andrade et al. (2005) evaluated the activity of the diaphragm and the SMM muscle with a 30% Threshold load in 7 COPD patients. The RMS value is calculated and correlated with airway obstruction level, resulting the correlation coefficient of $r = -0.5370$. Myrrhaa et al. (2013) studied the activity of SMM for inspiratory loaded breathing in 13 male COPD patients. RMS value of EMG is calculated. RMS value has increased with the increased load on breathing. Kanwade and Bairagi (2016), we have analysed inspiratory muscle of respiration in 10 COPD Patients. Time and frequency domain features of EMG were calculated and correlated with FEV1/FVC; resulting a correlation coefficient of $r = -0.56226$.

These studies reported that; SMM becomes active during inspiration in COPD patients and activity of SMM muscle increases with increase in load on inspiration. The limitation of these studies was small sample size, the use of very few features, neglected non-stationary nature and lack of onset detection. Results can be improved by applying Averaging Instantaneous Amplitude (windowing), onset detection algorithm and increasing number of subjects.

2. Material and methods

Eighty-one (46 Male, 35 Female) subjects are selected for study. Out of them, fifty-three patients are COPD patients (30 Male, 23 Female) (age: 63 ± 6.7) with% FEV1/FVC < 0.70 and remaining twenty-eight are normal healthy subjects (16 male, 12 female) (age: 53.28 ± 10.47) without signs of medical illness such as cardiac, neurological, cervical, spine or respiratory disorder. Skin is prepared. Special abrasive and conductive pastes are applied. Surface EMG of SMM muscle is collected in a sitting posture during maximum voluntary ventilation using, the RMS SALUS (2/4 Channel Portable EMG, 480 Samples/Sec, band limited to 250 Hz, 12 bits A/D converter) EMG machine. A surface AgCl electrode was placed between the center of the muscle and reference was placed in the tendinous area of muscle. Interelectrode distance was 2 cm. Data was collected while the patient was breathing to its maximum voluntary ventilation. The room temperature was maintained constant at 24 °C to avoid the effect of temperature variations on EMG signal. The total time required to perform the test was less than 5 min.

Fig. 1 shows that normal subjects show lesser activity of SMM as compared to COPD subjects. Time domain analysis is preferred, as COPD shows larger amplitude compared to normal subjects. Time domain features like mean, variance, Average Rectified Value (ARV), number of peaks, Root Mean Square (RMS), entropy, kurtosis and skewness are extracted from EMG.

Comparison of the feature value shows that there is a less significant difference (refer Table 1: without onset detection algorithm) between Normal and COPD Subject. To get significant

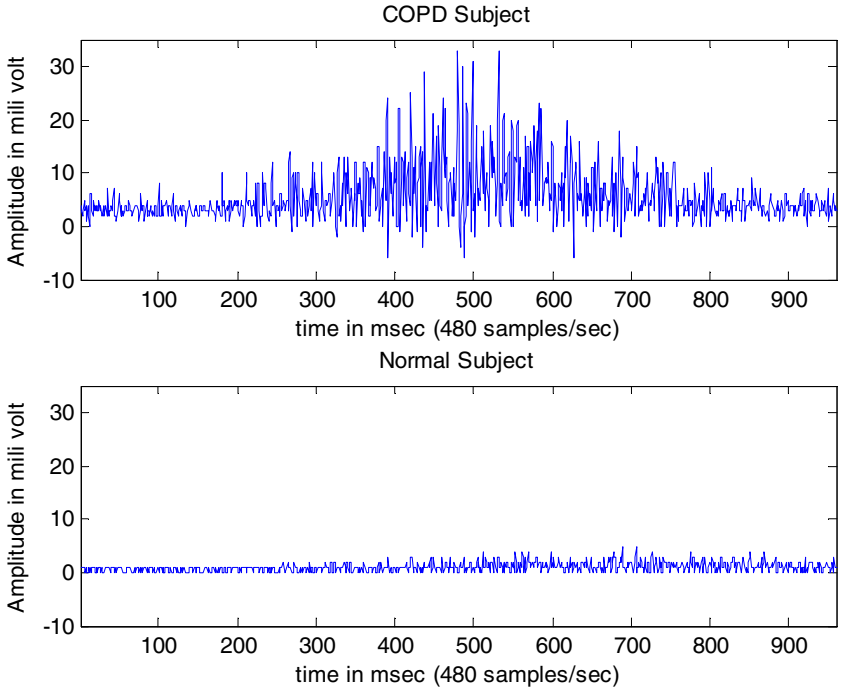

Fig. 1. Raw EMG acquired during Maximum Voluntary Ventilation for COPD and Normal Subject. COPD Subject shows larger amplitudes compared to Normal Subjects.

Table 1
Average of feature values for Normal and COPD subjects; before and after application of onset detection algorithm.

Category	Mean	ARV	Variance	Peak	RMS	Skewness	Entropy	Kurtosis	NFV
Without onset detection algorithm									
COPD	5.36	5.88	70.83	21	9.07	1.82	0.76	8.61	35.64
Normal	2	2.07	3.56	41.04	2.66	1.11	0.68	5.28	0.25
With slope based onset detection algorithm									
COPD	7.82	8.54	89.16	15.26	11.24	1.07	0.63	5.4	45.6
Normal	2.59	2.68	5.1	25.39	3.34	0.79	0.61	4.4	0.36
Using Improved slope based onset detection algorithm									
COPD	9.02	8.92	74.99	16.25	11.79	1.28	0.39	5.05	75.52
Normal	2.24	2.32	4.01	27.68	2.92	0.79	0.66	4.25	0.43

difference in the feature value, EMG analysis is performed in active duration. Active duration is the time between start of muscle activity (onset) and end of muscle activity (offset).

We have developed slope based onset detection algorithm to detect onset and offset. In this algorithm, the full wave rectified signal is divided into smaller windows. Full wave rectification of the EMG is done to include both positive and negative variations. The window size of 20 is selected to get 40 ms of segmentation. For each window the Average Instantaneous Amplitude (AIA) and slope is calculated. Please refer Eq. (1) for calculation of AIA. The change in slope is detected for each consecutive window. The maximum value of the slope gives onset timing and the minimum value of the slope gives offset timing.

$$AIA(n) = \frac{\sum_{i=1+n}^{i=20+n} \mathrm{EMG(i)}}{20} \tag{1}$$

where EMG(i) = Amplitude of the EMG for ith sample. n = Total number of samples.

The envelope is detected using AIA and considered for further analysis. AIA decreases the number of computations and improves local stationarity. The spurious change in slope is also observed at higher amplitude in between onset and offset. This may lead to incorrect results. Therefore, the single threshold detection algorithm is applied. The threshold coefficient of 0.393 is calculated by comparing rectified raw EMG signal with an amplitude threshold of mean power background noise. Refer equation number (2) for calculation of the threshold value.

$$Threshold = (0.393) \times max\ AIA \tag{2}$$

The slope values under the threshold are only considered for the detection of onset and offset. Fig. 2(a) shows that; the maximum value of the slope is detected as onset and the minimum value of the slope is detected as offset. Calculation of features is done only in between onset and offset duration. Please refer to Table 1 for the features calculated using onset detection algorithm. Onset and offset is detected with 86.41% of accuracy.

The results of onset detection algorithm were correct for the signals collected between two expirations (please refer Fig. 3(a)). For the signals captured between two inspirations (please refer Fig. 3(b)), the results were partially correct (sometimes onset and sometimes offset). To get improvement in onset and offset detection, improved slope based onset detection algorithm is developed.

In this algorithm; to detect the SMM activity which is immediately at the start and end of the waveform, zero padding is done at the start and end of the signal. Optimization with respect to accuracy in detecting onset and offset value is done to find the opti-

mum values for the threshold and the window size. To get an improvement in the onset detection, window length is reduced to 15 samples. The threshold value is increased to ((0.41) × max AIA EMG). A further increase in threshold value and decrease in window size is giving decrease in accuracy (incorrect onset and offset values). Improved onset detection algorithm has increased accuracy from 86.41% to 95.06%. Fig. 2 compares the AIA values for window size of 20 (threshold of 0.393) and a window size of 15 (threshold of 0.414). It is observed that the correct onset and offset is detected for –window size of 15 with a threshold of 0.414. Feature values are calculated and compared for three conditions: without onset detection algorithm, onset detection algorithm and improved onset detection algorithm. Results get improved for the improved onset detection algorithm. (Refer Table 1.)

Main features are calculated from the active muscle signal. These features are mean, variance, ARV, number of peaks, Root Mean Square (RMS), entropy, kurtosis and skewness. The mean is a weighted average of the signal; equal weightage is given to each observation. Mean provides a long run average of the variance of the variable. EMG is random in nature, therefore; it is required to find mean. ARV is a linear detector; it considers only the absolute value of EMG. ARV varies with motor unit recruitment, firing rate and muscle fiber conduction velocity; which depends on the effect of amplitude cancellation due to positive and negative phases. Refer equation (3) for calculation of ARV.

$$\mathrm{ARV} = 1/n\sum_{i=0}^{n}|\mathrm{EMG(i)}| \tag{3}$$

RMS voltage is the effective value of an alternating current; RMS measures instantaneous power output. RMS value varies with the number of active motor units, area, duration and the propagation velocity of motor units. Hibbs et al. (2011) gives information about the number of active motor units, on-off time and relative myoelectric activity over a time period. RMS is a non-linear detector (refer Eq. (4)). Rectification is not needed, as the square of EMG signal is considered.

$$RMS = \sqrt{1/n(\sum_{i=0}^{n} EMG^2(i)} \tag{4}$$

Numbers of peaks are calculated by counting number of positive and negative spikes. Peaks of low amplitude and high amplitude are given equal weightage; peaks having less than 2% change in amplitude is not considered. Number of peaks linearly increases with contraction force. Number of peaks is used to find muscle activity and its fatigue level.

The new feature is invented; it is based on Mean, Variance and Number of Peaks in the EMG signal. The formula for calculating new feature is given in Eq. (5).

$$\textit{New Feature Value } (NFV) = \frac{Mean * Variance}{No.\ of\ Peaks} \tag{5}$$

Asymmetry of data around a sample mean is measured by skewness. The negative skewness means the spread of the data towards the left and positive skewness means spread of data towards the right. The skewness of the normal distribution (or any perfectly symmetric distribution) is zero. Outlier-prone distribution is detected using Kurtosis. The kurtosis of the normal distribution is 3. More outlier prone distribution has kurtosis greater than 3; while less outlier-prone distribution have kurtosis less than 3. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input signal.

3. Results

Feature values of Mean, Variance, ARV, Number of Peaks, RMS, skewness, entropy and kurtosis are calculated for 81 subjects applying three algorithms. First is without application of onset detection algorithm. Second is by application of slope based onset detection algorithm. Third using improved slope based onset detection algorithm. The average of feature values for COPD (53 subjects) and Normal (28subjects) is shown in Table 1.

It is observed that feature values are improving after application of slope based onset detection and improved slope based onset

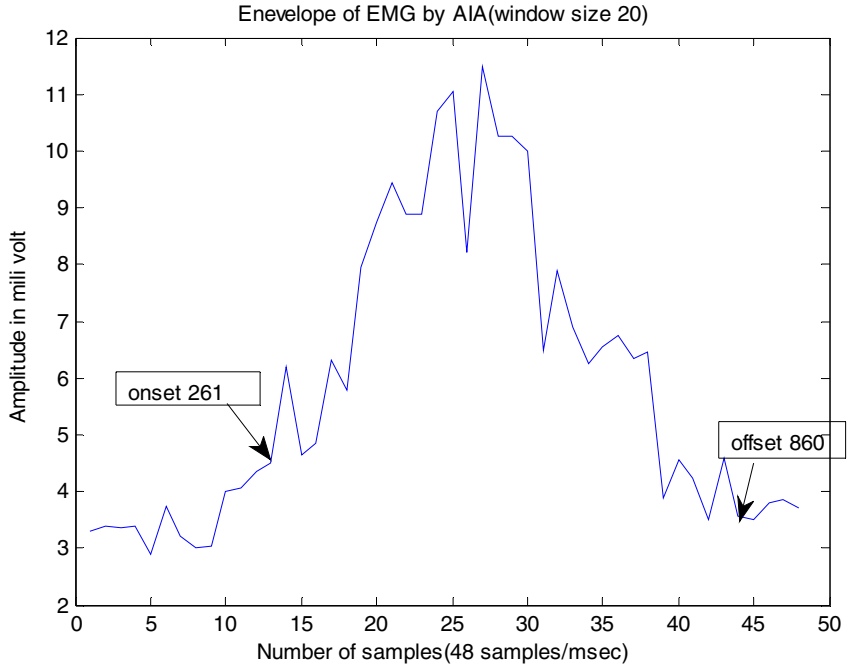

Fig. 2. Plot of AIA of EMG signals with onset and offset timings for the a) window size of 20 and b) window size of 15.

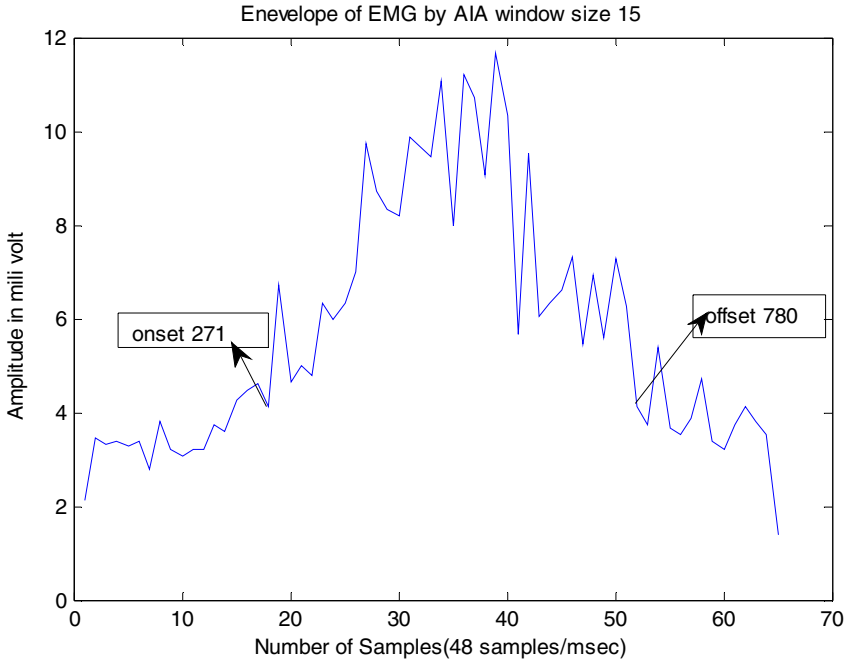

Fig. 2 (*continued*)

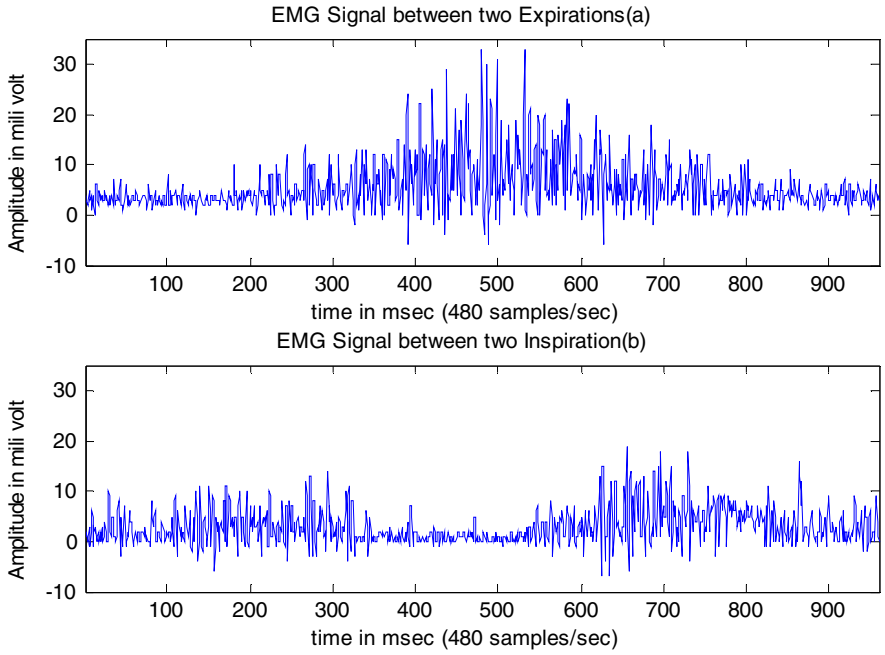

Fig. 3. Plot of SMM EMG signal (a) between two expiration (b) between two inspirations.

detection algorithm. The difference in the feature value is increasing for mean, ARV, Variance and RMS value. The difference in the feature value decreases for number of peaks. Because expiration activity peaks are now eliminated due to application of an improved onset detection algorithm. The feature value of the mean is improved by 27.166% after application of slope based onset detection algorithm and further improved by 13.03% after application of improved slope based onset detection algorithm. The same procedure is done for other features and improvement in the accuracy is found. A new feature (NFV) has the highest improvement in the accuracy (52.80%) with the application of the improved onset detection algorithm.

Fig. 4 shows the plots of mean, variance, Number of Peaks and NFV with%FEV1/FVC. It describes the distribution of feature for COPD and normal subjects. It is observed that variance and number of peaks and NFV shows greater spread compared to other features. NFV has two overlapping feature values for COPD and Normal Subjects.

For classification of COPD and Normal subjects "Support Vector Machine" (SVM) classifier is selected. SVM is a supervised machine learning algorithm used for classification. It has high accuracy, nice theoretical guarantees, regarding over fitting. Features, having the highest standard deviation (variance in amplitude and number of peaks) are selected as the input variables for classification. Data

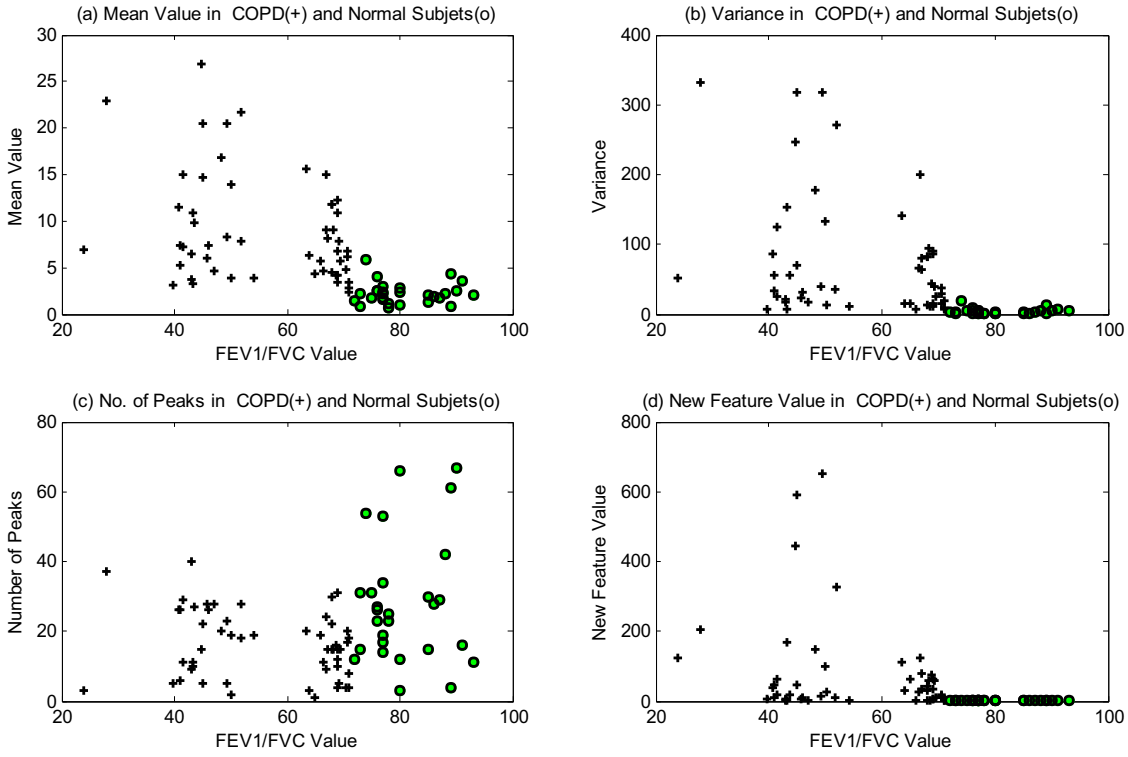

Fig. 4. Plot of (a) Mean Value (b) Variance (c) Number of Peaks (d) NFV against FEV1/FVC of EMG Signal with the application of improved slope based onset detection algorithm.

is plotted in 2 dimensional spaces and classification is done by finding support vectors. Randomly forty samples (25-COPD and 15-Normal) are considered for training and forty-one samples (28-COPD and 13-Normal) are considered for testing. Cross-Validation of the study is done by considering training samples as testing samples and vice versa. Linear kernel with α varying from -1.333 to 0.800 and bias is 0.9239 is used. Fig. 5 shows the support vectors and classification of COPD and Normal subject (1: COPD and 2: Normal subject).

Results of SVM classifier are compared with two binary classifiers (threshold based and Naïve Bayes). For threshold based method, the threshold is calculated using NFV. The minimum value of NFV for COPD subject and maximum value of NFV for normal subject is calculated. The average of these two values is considered as a threshold. Please refer Eq. (6) for calculation of the threshold value.

$$Threshold = \frac{\mathrm{Min}(NFV_{COPD}) + Max(NFV_{Normal})}{2} \quad (6)$$

For the proposed algorithm threshold value is calculated as 1.5779 from the training set. During testing, if NFV is greater than the threshold, subject is detected as a COPD else normal subject. The Cross Validation approach is applied for Threshold Based Classifier. Please refer to Table 2 for the results of threshold based classifier. Naïve Bayes classifier is a simple probabilistic classifier based on Bayes theorem with the strong independent assumption between features. Three independent features mean, variance and the number of peaks are selected for classification. The results of Naïve Bayes Classifier before and after cross validation are provided in Table 2. The results of three classification techniques are compared based on accuracy, sensitivity and specificity. SVM classifier is more accurate compared to Threshold based and Naïve Bayes classifier.

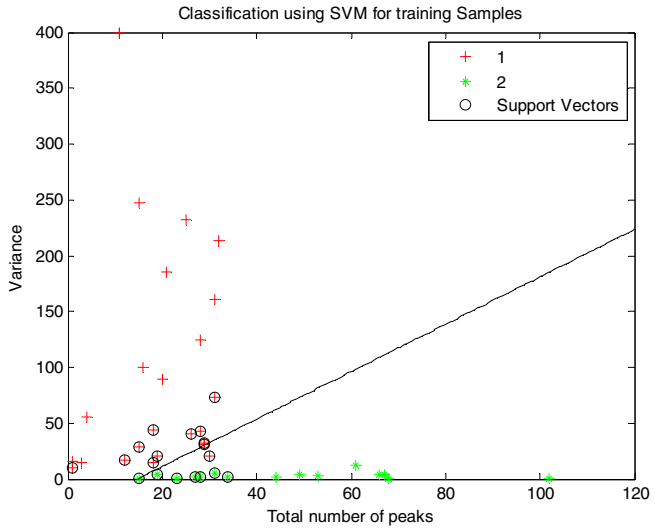

Fig. 5. Classification of COPD and Normal Subject using SVM Classifier for testing data with (o) support vectors and (+) COPD and (*) healthy subjects.

4. Discussion

COPD is detected by a diagnostic test called spirometry. It has many limitations; many researchers have proposed alternative methods for COPD diagnosis and classification. These are; FOT, FEV1/FEV6 parameter and EMG analysis. FOT, FEV1/FEV6 does not consider respiratory dynamics, costly and have large test duration. Surface EMG considers respiratory dynamics, duration of test is small. It can be performed with very less effort. Table 3 compares the results obtained by these methods. FEV1/FEV6 classifies the COPD in four grades (Grade- I, II, III, and IV) with higher accuracy,

Table 2
Performance of the proposed method for classification of COPD and Healthy Subject using accuracy, sensitivity and specificity.

Technique	Features used	With normal approach			With cross validation		
		Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Threshold based classifier	New feature value	85.36%	86.67%	81.81%	82.5%	80%	86.66%
SVM classifier	Variance, number of peaks	87.80%	89.65%	83.33%	85%	88%	80%
Naive Bayes classifier	Mean, variance, number of peaks	80.00%	84.00%	73.33%	77.50%	88.00%	62.50%

Table 3
Comparison of proposed methodology with earlier published results.

Author	Technique	Results	Limitation
Mañanas et al. (2000)	EMG, VMG	AR (40) is suitable model	Small sample size (7) Result varies with PSD Estimation Method
Swanney et al. (2000)	FEV1/FEV6	Sensitivity:84.40% Specificity:83.30%	Not suggested by GOLD Difficult to perform on morbid patients.
Hellinckx et al. (2001)	Comparison of IOS and FOT	Literature Survey	Different result for same pathophysiological event.
De Andrade et al. (2005)	EMG	Correlation Coeff. (−0.5370)	Small Sample size (7) Single feature-RMS
Vandevoorde et al. (2006)	FEV1/FEV6	Sensitivity:94.40% Specificity:93.30%	Over diagnosis in elderly persons, Difficult to perform on morbid patients
Myrrhaa et al. (2013)	EMG	SMM activity increased by 63.84% during IL	Small Sample size (13) Single feature-RMS.
Tse et al. (2016)	FOT	Sensitivity:76.00% Specificity:72.00%	Reactance parameters were better than resistance parameters
Proposed algorithm	EMG	Accuracy: 87.80% Sensitivity:89.65% Specificity: 83.33%	Small Sample size (81) Signal Classification Technique

sensitivity and specificity. FOT is providing accurate result with AUC $\geq$ 0.83 but resolved that reactance is better than resistive parameters.

FOT is a upcoming technology and limited by its availability. EMG analysis is non-invasive, easily available and considers physiology of the disease. Many researchers have done an EMG analysis (RMS) of SMM and showed activity of muscle for maximum inspiratory respiration. In the said paper, SMM signals are acquired and processed to identify onset duration. Activation interval (onset and offset) is detected using slope based onset detection algorithm. Slope based onset detection algorithm is a combination of slope detection using AIA and single threshold. Eminent features; Number of peaks, Variance and NFVs are applied to classifier. Classification is performed using three algorithms (Threshold, SVM, Naïve Bays). The results of the classification algorithm are compared and concluded that SVM is the most suitable algorithm for classification.

5. Conclusions

Classification of COPD and Normal Subjects is done using time domain analysis. Mean, ARV, Variance, Number of Peaks, RMS showed the significant difference in average value for COPD and Normal Subjects. Skewness exhibited the positively skewed distribution, as the majority of the signal was acquired after expiration. SMM was active during inspiration, minimal activity was observed during expiration; this results in a leptokurtic distribution in kurtosis. COPD is chronic; there is need of assistance of SMM recurrently. This frequent use of SMM in COPD leaded to muscle fatigue with reduction in number of peaks and increase in variance. Use of AIA is very beneficial as local stationarity was achieved and the numbers of computations had decreased by 26%. Use of improved onset detection algorithm had improved accuracy of onset and offset detection from 86.41% to 95.06% with the cost of increase in computational complexity by 12.04%. There is a trade-off between accuracy and computational complexity. Developed improved slope based onset detection algorithm is more efficient in terms of accuracy as well as the computational complexity. Features having greater deviations between COPD and Normal subjects were selected for classification. Greater deviations were observed for number of peaks, variance and NFV. SVM and Naïve Bayes classifier have used mean, variance and the number of peaks as input features for classification. The newly developed feature (NFV) had shown only two overlapping values between COPD and Normal Subjects. NFV was selected for the threshold based classifier. Classification results were compared for SVM, threshold and Naïve Bayes classification algorithm. SVM classified COPD and Normal subject with greater accuracy of 87.80% with sensitivity of 89.65% and specificity of 83.33%. Results of threshold based classifier vary with calculated threshold as threshold varies with the data set. The performance of the said paper is compared with FEV1/FEV6 and FOT. FEV1/FEV6 results with high sensitivity, but has spirometric test limitations. Proposed method of COPD and Normal subject classification provide accuracy of 87.80%. It is more advantageous compared with FOT and FEV1/FEV6 as it is non-invasive, easily available, short duration and considers physiology of the disease. Further classification of COPD into its four grades can be done as future work by increasing number of subjects, using improved EMG analysis techniques and neural network classification algorithms.

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