

Diagnosing lung status using PPG-derived respiratory signals

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Abstract: The measurement of human respiratory signals is crucial in field of medicine. A disordered breathing pattern can be the first symptom of different mechanical or psycho-logical dysfunctions. Therefore, a real-time monitoring of the respiration pattern is a critical need in medical applications. In clinical settings, respiration measurement methods are used a large number of sensors to the patient's body for recording vital signals, which might interfere with natural breathing of the patients and also cause discomfort if used for longer durations. This paper presents a novel algorithm for diagnosing lung status using photoplethysmographic (PPG) derived respiratory signals. The algorithm contains two steps. First one is the Respiratory cycle extraction process and second one is the Classification of respiratory activity. The pulse oximeter's PPG signals can be well utilized for extracting respiratory activity, avoiding the usage of additional sensor for recording respiratory signal. Modified Multiscale Principal Component Analysis (MMSPCA) is used for extraction of respiratory activity embedded in the PPG signals. Functioning of the proposed algorithm is tested on the dataset consists of different PPG patterns i.e., normal, hypoventilations, hyperventilation's and kussmaul recordings available with MIMIC database of Physio net archive. The second part is the evaluation of lung status according to the respiratory signal which is extracted from the PPG signal in the first part. Multiclass support vector machine (MSVM) classifier or Kernel Nearest-Neighbour (knn) classifier are used to classify the respiratory signals according to the features extracted from respiratory signal. This paper presents a comparative study of the classification of respiratory cycle using MSVM and k-nn classifier.

Keywords: Modified MSPCA (MMSPCA), principal component analysis (PCA), Pulse oximeter's Photoplethysmographic (PPG) signal, respiratory signal, wavelets, Multiclass Support Vector Machine (MSVM), K-nn classifier.

I. INTRODUCTION

Respiration signals are one of the Vital signs are used to measure the body's functions. Without adequate respiratory activity, human life is under threat. Respiration signals are monitored by physicians, in many situations like ambulatory monitoring, operation theatres, post-operative recovery units, intensive care units, during stress tests, and in sleep disorder investigations. Monitoring a patient's respiratory status usually takes place in a hospital setting for providing timely information regarding pulmonary function of that patient. These measurements are taken to help assess the general physical health of a person, give clues to possible diseases, and show progress toward recovery. The normal ranges for a person's vital signs vary with age, weight, gender, and overall health. In general, respiration signals are recorded making use of cumbersome devices like spirometers, pneumotachometers, nasal thermistors, abdomen/chest belts or whole body plethysmograph, impedance plethysmography, and inductive plethysmography, which might interfere with natural breathing of the patients and also cause discomfort if used for longer durations as demanded in many situations [1]. So In this paper, introduce a robust algorithm called modified multi scale principal component analysis (MMSPCA), for extraction of respiratory activity embedded in the PPG signals.

A. Extraction of Respiratory activity from PPG Signals

The pulse oximeter's photoplethysmographic (PPG) signals can be well utilized for extracting the vital respiratory activity, in addition to saturation and heart rate

estimations, avoiding the usage of additional sensor for recording respiratory signal, in turn reducing the number of sensors connected to the patient's body for recording vital signals. Pulse oximetry is a procedure used to measure the oxygen level (or oxygen saturation) in the blood. It is considered to be a non-invasive, painless, general indicator of oxygen delivery to the peripheral tissues (such as the finger, earlobe, or nose).

Pulse oximetry, a non-invasive technique developed by Hertzman [2], uses photoplethysmographic (PPG) signals, obtained by opto-electronic recording of the volumetric changes in the arterial blood at a specific point of interest in the body, usually the body extremities like index finger or ear lobe. In fact, two PPG signals are recorded in pulse oximeter's at different wavelengths viz., red (660 nm) and infrared (940 nm) for estimation of the accurate oxygen saturation level in the arterial blood. The recorded PPG signals inherently contain respiratory information as the blood flow to the various body extremities get affected by the movement of thoracic cavity while breathing. Thus, the PPG signals modulated by the respiratory activity can be used for deriving the respiratory signals and become an alternative or indirect method for recording respiratory information [3].

B. Evaluation of lung status

This proposed system is designed particularly for patients with breathing problems. Four types of respiratory activities like normal ,hypoventilation ,hyperventilation ,and Kussmaul

breathing are classified based on MSVM and k-nn classifiers with six different features[4]. In this paper evaluated the performance of the proposed classifications and the simulation results shown that the k-nn classifier effectively diagnoses the lung status than MSVM classifier[5].

II. PROPOSED METHOD

The method has two parts. First part is the extraction of respiratory cycle. MMSPCA algorithm used for extraction of respiratory activity embedded in the PPG signals. Second part is the evaluation of lung status [6]. It is the implementation of automatic classifier which classifies the respiratory signals to normal [7] respiration or hypoventilation, hyperventilation or kussmaul respiration according to the features extracted from the respiration signal. A comparative study of multiclass support vector machine (MSVM) classifier or Kernel Nearest-Neighbour (k-nn) are used in this paper.

In the presented algorithm, the kurtosis and energy contribution levels (ECLs) of approximate and detail coefficients are calculated for each wavelet sub-band matrix, generating a modified wavelet sub-band matrix. This makes the presented algorithm based on MMSPCA more robust in the sense that it is preserving the morphological features of the extracted respiratory signal to a large extent. The following algorithm gives the implementation steps of MMSPCA, wherein the wavelet sub-band matrix is suitably modified based on kurtosis and ECL of approximate and detail coefficients.

Step 1: For each column in data matrix of PPG, perform wavelet decomposition considering the input as multivariate data set, form 'N' column data matrix, where each column is with univariate data. For each column matrix, wavelet decomposition is performed to a level of frequency below which no considerable signal component of interest is present. Any suitable mother wavelet can be used in wavelet decomposition [17]. In general, shape of the mother wavelet best matching with signal shape is normally considered.

Let $A_{L1}; D_{11}; D_{21}; \dots; D_{L1}; A_{L2}; D_{12}; D_{22}; \dots; D_{L2}$ and $A_{LN}; D_{1N}; D_{2N}; \dots; D_{LN}$ are the approximate and detailed coefficients, computed during decomposition, on each column matrix.

Step 2: For each scale, form the wavelet sub-band matrix with corresponding approximate and detailed coefficients. At each level, sub-band matrix is formed with corresponding detailed and approximate coefficients of each column matrix

$$\begin{aligned} D1 &= [D_{11}; D_{12}; D_{13}; \dots; D_{1N}] \\ D2 &= [D_{21}; D_{22}; D_{23}; \dots; D_{2N}] \\ &\dots \text{upto} \dots \\ DL &= [D_{L1}; D_{L2}; D_{L3}; \dots; D_{LN}] \\ AL &= [A_{L1}; A_{L2}; A_{L3}; \dots; A_{LN}] \end{aligned}$$

Step 3: Compute kurtosis for each wavelet sub-band matrix formed in Step 2

$$C = \mu_4 / \sigma_4 \quad (1)$$

Where μ_4 is the fourth-order central moment and σ_4 is the standard deviation. Kurtosis is a measure of whether the data is flat relative to normal distribution i.e., data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather a sharp peak.

Step 4: Compute ECL of approximate and detail coefficient for each wavelet sub-band matrix

$$ECL_{AL} = [C_{AL}] / \left[T[C_{AL}] + \sum_{j=1}^L T[C_{Dj}] \right] \quad (2)$$

$$ECL_{Dj} = T[C_{Dj}] / \left[T[C_{AL}] + \sum_{j=1}^L T[C_{Dj}] \right] \quad (3)$$

Where 'T' denotes the trace (sum of all diagonal elements) of the matrix indicated in the braces. The matrices are the covariance matrices (C) of approximate and detail coefficients. C_{AL} is the covariance matrix of A_L sub-band matrix. Similarly C_{Dj} is the covariance matrix of D_j , where j is 1, 2, 3, ..., L. The ECL is used here to estimate the energy contribution of each wavelet sub-band components, so that we can estimate, which frequency sub-band is contributing more toward the total energy of the overall signal, and thereby identifying strong periodic component in the given signal.

Step 5: Modify the wavelet sub-band matrix based on the above parameter mentioned in equations (3.1)-(3.3). The modification in this process may consist of retention of some of the frequency sub-bands and omission of others, based on the requirement. For example, if $D4$ corresponds to highest ECL producing wavelet sub-band then all the lower sub-bands, i.e., from $D4$ to $D1$ are forced to zero, leaving others unchanged. Or else, if $D5$ corresponds to the low kurtosis producing wavelet sub-band matrix, then all the low level detailed sub-band matrices starting from $D5$ to $D1$ are forced to zero, leaving others to remain unchanged. This process ensures the removal of higher periodic components starting from a specific band, from the wavelet sub-band matrices.

Step 6: For all scales, reconstruct the signal using modified detail and approximate coefficients. From the modified wavelet sub-band matrices, separate the corresponding approximate and detailed coefficients of different column data matrices and form the signals by wavelet reconstruction.

Step 7: Compute PCA for wavelet reconstructed signal. By applying PCA on the wavelet reconstructed signal, obtain 'N' number of PCs.

Step 8: The lowest kurtosis producing PC identified as the required periodic signal. A strong periodic component is then selected on the basis of the lower kurtosis producing PC

Step 9: Calculate the features from extracted respiratory signal. Four types of respiratory signals, Normal, hypoventilation, hyper ventilation, Kussmaul's breathing are classified with six different features. Number of peaks, Time duration between the peaks, rise time duration of peaks mean, standard deviation, energy index are the features that used for classification of the respiratory

signals.

Step 10: Classify the respiratory signals according to the features that fed to the MSVM or K-nn classifier. Diagnose lung status according to the result from the classifier.

Above steps are illustrated in the form of a block diagram as shown in Fig. 1.

III. EXPERIMENTAL RESULTS AND DATASETS

A. Respiratory cycle extraction process (MMSPCA)

The recorded PPG and respiratory data were processed and analysed using signal processing toolbox of MATLAB R2010a software.

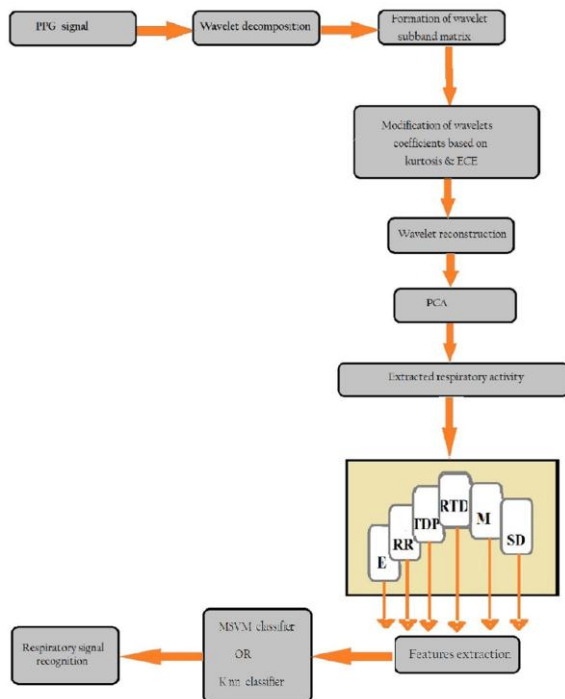


Fig. 1. Block diagram

1) Extraction of Respiratory signal from PPG signals:

As every frame of 60 seconds duration of the down sampled signal was used for processing by the proposed algorithm. It processed 7500 points (samples) in each frame, on which the proposed MMSPCA algorithm was applied. The Daubechies10 (db10) mother wavelet was considered here for decomposition, as it was found [8] to be more advantageous in restoring the useful respiratory information from PPG. The detailed and approximate coefficients were obtained by decomposing the signals using db10 wavelet, to an 11th level (well below 0.1 Hz).

Fig.2 represents normal respiration. In human beings, the normal respiratory rate is 12-25 bpm; any deviation from this span is an indication of respiratory distress. Wavelet decomposition applied to these PPG signals and then calculate the approximate and detailed wavelet coefficients of that signal. The obtained wavelet coefficients are modified in such a way that high-frequency noises are eliminated. Thus, it preserves all the morphological features of the respiratory signal. For the

modification of these wavelet coefficients, a novel method based on two important parameters viz. percent ECL and kurtosis is proposed.

- After formation of wavelet sub-band matrices, kurtosis and ECL were computed on the wavelet sub-band of Approximate and detail coefficients.
- A graph drawn with the obtained ECL values against the corresponding wavelet coefficients, shown in Figure 5.5, indicates ECL of respiratory activity for each individual coefficient. It clearly shows D6 coefficient is contributing highest energy level for normal respirations.

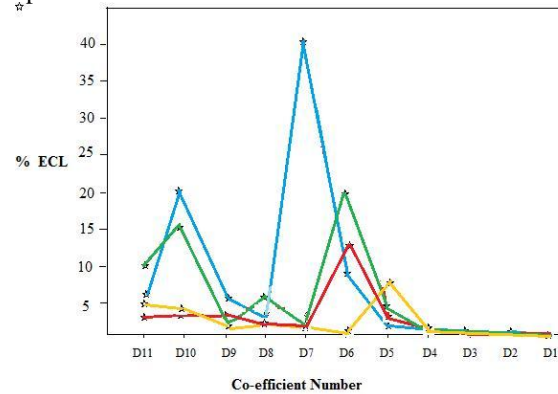


Fig. 3. ECL plot of approximate and detail coefficients of normal signal (Red), hypoventilation signal (Blue), hyperventilation signal (Yellow), kussmaul respirations (Green).

- Starting from the highest energy contributing wavelet coefficient, which represents highest periodic component of the signal (related to heart beat), all the higher detail coefficients are made equal to zero.
- This is done since no other useful components will be present after the heart beat frequency, and most of these coefficients represents high frequency noise. Also, we are interested retaining respiration whose frequency is less than that of heart beat frequency. As shown in Table I, normal respiration case contributes coefficient D6 as highest ECL and lowest kurtosis value. Therefore, all the detail coefficients from D6 to D1 are forced to zero, retaining all the frequencies less than heart rate, which includes respiratory signal.

Coeff	ECL	Kurtosis
D11	0.0325	8.2206
D10	0.0575	13.0778
D9	0.0412	2.6332
D8	0.0116	3.6456
D7	0.0080	11.2077
D6	0.1263	1.7688
D5	0.0461	2.0784
D4	0.0065	2.2944
D3	0.0001	11.6102
D2	0.0000	17.8692
D1	0.0000	12.7071

TABLE I: ECL AND KURTOSIS OF DETAIL COEFFICIENTS FOR NORMAL SIGNAL

- Wavelet reconstructed signal is obtained by, using the remaining coefficients representing the lower frequency

- bands.
- PCA was applied on the wavelet reconstructed signal.
 - Finally, the respiratory signal was extracted by retaining PC with lowest kurtosis, shown in Fig 2. It can be clearly seen that the extracted respiratory signal, Fig 2(c), closely resembles the original respiratory signal, Fig 2(b).

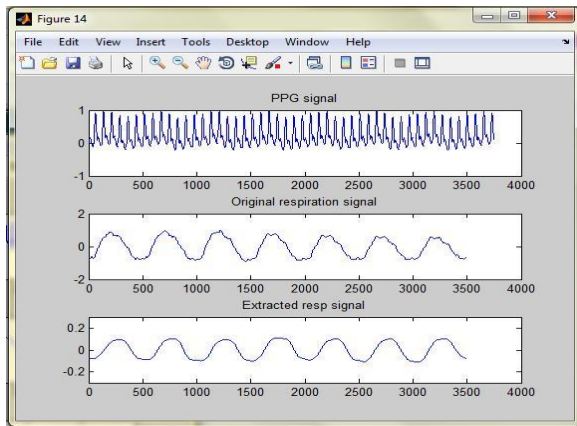


Fig. 2. (a) PPG signal from MIMIC database (b) Recorded respiratory signal from MIMIC database and (c) the derived respiratory signal using modified MSPCA.

TABLE III: RESULTS OF CORRELATION COEFFICIENT EVALUATED FOR DIFFERENT SUBJECTS

A wide range of diverse respiration patterns exists in human subjects. However, the decision boundary to distinguish the irregular patterns from diverse respirations is proposed in this paper. Three types of irregular breathing signals i.e., hypoventilation, hyperventilation or kussmaul respiration are particularly used in this method. Irregular respiration means which involves episodes of overly shallow breathing or an abnormally low respiratory rate or high respiration rate. In human beings, the normal respiratory rate is 12-25 bpm; any deviation from this span is an indication of respiratory distress.

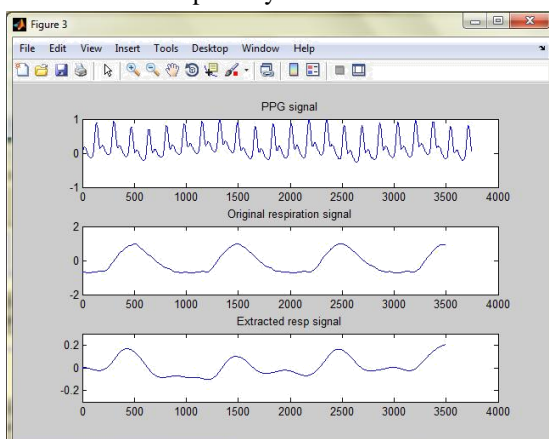


Fig. 4. (a) PPG signal from MIMIC database (b) Recorded respiratory signal from MIMIC database and (c) the derived respiratory signal using modified MSPCA.

Hypoventilation: Hypoventilation is a rare disorder in which a person does not take enough breaths per minute. Normally, when the oxygen level in the blood is low or the

carbon dioxide level is high, there is a signal from the brain to breathe more deeply or quickly. The breathing rate is below 12 bpm.

Kussmaul Respiration: Kussmaul breathing is a type of abnormal respiration, characterized by a consistently deep and rapid respiratory pattern. Kussmaul breathing occurs only in advanced stages of acidosis (Acidosis is an increased acidity in the blood and other body tissue), and is fairly rarely reached. Kussmaul breathing is a kind of very deep, gasping, desperate breathing. The respiration rate is between 12-25 bpm. Most commonly, this condition is observed in people with diabetic ketoacidosis leading to coma. It is a serious clinical sign and an indicator of the need for immediate medical treatment if it is not already being offered. When patients go into metabolic acidosis, their blood becomes very acidic. The body uses a number of measures to compensate, including respiratory compensation. Patients in the early stages may breathe quickly and shallowly. As the acidosis progresses, Kussmaul breathing can develop. In Kussmaul breathing, patients breathe at a normal or slightly slower rate, but their breaths are much deeper than usual.

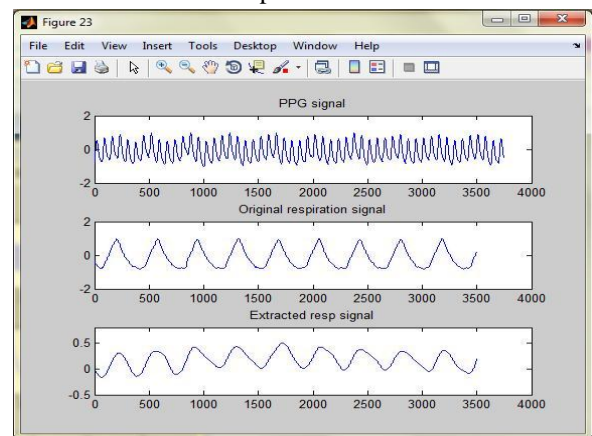


Fig. 5. (a) PPG signal from MIMIC database (b) Recorded respiratory signal from MIMIC database and (c) the derived respiratory signal using modified MSPCA.

Hyperventilation: Hyperventilation is a rare disorder in which a person does not take rapid or deep breathing. Shorter inspiration and longer expiration with rates over 20-30 breaths per minute. Often caused by anxiety or panic, seen distance runners at end of run. The breathing rate is above 20 bpm.

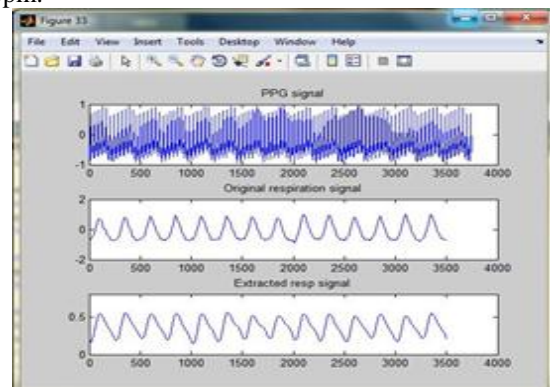


Fig. 6. (a) PPG signal from MIMIC database (b) Recorded respiratory signal from MIMIC database and (c) the

derived respiratory signal using modified MSPCA. As shown in Table II, The detail coefficient which contribute highest ECL and lowest kurtosis values are different in the irregular respirations. The coefficient D7, D6, D5 con-tributed highest ECL and lowest kurtosis values in hypoventilation, kussmaul respiration and hyperventilation respectively. Therefore, all the detail coefficients from that particular coefficient to D1 are forced to zero, retaining all the frequencies less than heart rate, which includes that corresponding respiratory signal.

Coeff	Hypoventilation		kussmaul signal		Hyperventilation	
	ECL	Kurtosis	ECL	Kurtosis	ECL	Kurtosis
D11	0.0705	7.1878	0.0905	4.9879	0.0589	3.9235
D10	0.0208	9.6270	0.1423	8.3987	0.0468	3.5313
D9	0.0538	3.2527	0.0182	5.8461	0.0056	4.4645
D8	0.0225	8.3862	0.0613	2.4634	0.0167	2.6147
D7	0.4012	1.8074	0.1583	12.3354	0.0071	3.2984
D6	0.1187	2.0299	0.2178	1.7928	0.0018	2.0247
D5	0.0154	2.1757	0.0564	2.1375	0.0808	1.6538
D4	0.0076	4.0927	0.0030	2.8686	0.0334	2.0853
D3	0.0001	17.9312	0.0001	23.4994	0.0047	2.2172
D2	0.0000	35.2816	0.0000	19.2267	0.0000	4.0403
D1	0.0000	18.9961	0.0000	18.5281	0.0000	7.6479

TABLE II: ECL AND KURTOSIS OF DETAIL COEFFICIENTS FOR IRREGULAR BREATHING SIGNALS

IV. STUDY OF ROBUSTNESS OF THE PROPOSED METHOD

Though the visual inspection of the derived respiratory signals indicates a close match with that of reference respiratory signals, a degree of similarity in time domain was quantified in terms of correlation coefficient (CC) defined as

$$CC = COV(x, y) / (\sigma x * \sigma y) \quad (4)$$

Where COV means covariance; x and y are the standard deviations.

Signal	correlation value
Normal respiration	.89
Hypo-ventilation	.83
kussmaul respiration	.81
Hyperventilation	.86

TABLE III: RESULTS OF CORRELATION COEFFICIENT EVALUATED FOR DIFFERENT SUBJECTS

From this TABLE III, it clear that the MMSPCA method provides high correlation between the original and extracted respiratory activities. Higher values of calculated similarity parameter (CC) clearly indicates that this method can be used for monitoring patients breathing activity.

V. EVALUATION OF LUNG STATUS

It is the second stage of the proposed method. It provides an implementation of automatic classification of extracted respiratory signals using a MSVM classifier and k-nn classifier. In this paper four different types of respiration disorders either are considered and remotely classified based on the best extracted features from the

extracted respiratory data. SVM classifier and K-nn classifier are evaluated on four different breathing disorders, and finally compare the accuracy, sensitivity, specificity of both classifiers.

A. Feature Extraction

Features can be thought of as statistically unique elements of the sensor data, which are used to differentiate diverse classes or states. The feature extraction plays a vital role since the classification is completely based on the values of the extracted features. The fundamental features of respiratory signal provide the numerical value which is compared with the threshold values and the classification results will be produced. In the proposed system, classify the respiration patterns according to the features such as energy, mean, standard deviation, time duration between peaks, rise time duration, respiration rate.

1) Energy (E): If the total energy of a signal is a finite non-zero value, then that signal is classified as an energy signal. Typically the signals which are not periodic turn out to be energy signals. The equation for computing Energy index is,

$$E = 1/N \sum_{n=0}^{N-1} |X_n|^2 \quad (5)$$

2) Respiration rate (RR): A common requirement in scientific data processing is to detect peaks in a signal and to measure their positions, heights, and widths. Counting peaks is a method used to estimate the fundamental frequency of signal. The interval between peak values gives a good estimation of its frequency. Peak detection algorithm is used to find out the peak values of each signal. The respiration rate of a signal is equal to the number of peaks of that particular signal.

3) Time Duration between Peaks (TDP): The time duration between peaks value measured.

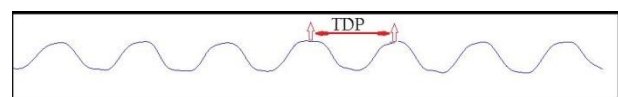


Fig. 7. Time Duration between Peaks

4) Rise Time Duration (RTD): It is a time domain feature, the value measured between rising point to the peak value.

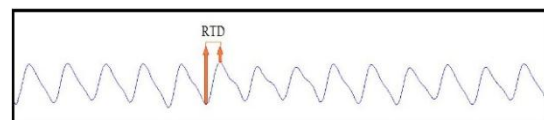


Fig. 8. Rise Time Duration

5) Mean (M): Mean of each signal calculated.

$$M = 1/N \sum_{n=0}^{N-1} X_n \quad (6)$$

Where X_n corresponds to the samples
 $n = 1; 2; 3:::N$

6) Standard Deviation (SD):

Standard deviation of each signal calculated.

$$SD = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} (X_n - M)^2} \quad (7)$$

Where X_n corresponds to the samples $n = 1; 2; 3:::N$

B. MSVM Classification

A support vector machine (SVM) is based on constructing one or a set of hyperplane in a high dimensional space, which can be used for classification purposes. Support vector machines were originally designed for binary classification. SVM is not used for more than binary classification. So MSVM used in this paper. MSVM constructs classification from a set of labelled training dataset. It classifies the respiratory signals according to the features extracted from respiratory signal.

C. k-nn Classification

K nearest neighbours is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions).The K-nn Classifier is a simple classifier that works well on basic recognition problems. It has been used in statistical estimation and pattern recognition already in the beginning of 1970s as a non-parametric technique. In pattern recognition, the k-Nearest Neighbours algorithm is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space.

D. Performance evaluation of classifiers

Sensitivity and specificity are statistical measures of the performance of a classification

- Accuracy: The classification test performance of the classifier can be determined by computation of accuracy (Acc).

$$Acc = (\text{correctly classified/total}) * 100$$

Classifier	Correctly classified	Total	Accuracy
MSVM	14	20	.7
K-nn	16	20	.8

TABLE V: PERFORMANCE EVALUATION OF MSVM K-NN CLASSIFIERS

Table V shown the Performance evaluation of classifiers. It indicate that the k-nn classifier give high accuracy than MSVM classifier. Therefore this proposed method can be used as a diagnostic tool for detecting lung status from PPG signals.

It is clear from the TABLE V that the proposed method can be used as a diagnostic tool for detecting lung status. In order to evaluate the performance of the proposed method for classification of different respiratory signals. The proposed method with k-nn classifier provides higher classification accuracy for classification respiratory signals.

VI. CONCLUSION

In this paper, implemented an algorithm for diagnosing of lung status by using PPG signal .The MMSPCA method used for extraction of respiratory activity from PPG signals. Results exhibited higher degree of correlation of the extracted respiratory signal with the originally recorded signal .Higher values of calculated similarity parameter (CC) as well as a measure of signal deviation clearly indicated that the PPG-derived respiratory signal can be used for monitoring patients breathing activity. Functioning of the proposed algorithm is tested on the dataset consists of different PPG patterns i.e., nor-mal, hypoventilation, hyperventilation, kussmaul recordings available with MIMIC database of Physio net archive. Then evaluate of lung status according to the respiratory signal which is extracted from the PPG signal in the first part. Multiclass support vector machine (MSVM) classifier or Kernel Nearest-Neighbour (knn) classifier are used to Classified the respiratory signals according to the features extracted from respiratory signal. This paper presents a comparative study of the classification of respiratory cycle using MSVM and k-nn classifier. Simulation results shown that the k-nn classifier gives better classification of respiratory signals than MSVM classifier.

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