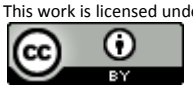
Available online at: https://ijact.in

Date of Submission	21/10/2018
Date of Acceptance	12/11/2018
Date of Publication	30/11/2018
Page numbers	2852-2861 (10 Pages)



ISSN:2320-0790

An International Journal of Advanced Computer Technology

DETECTION OF SLEEP APNEA IN ECG SIGNAL USING PAN-TOMPKINS ALGORITHM AND ANN CLASSIFIERS

Jyoti Bali[1], Anilkumar Nandi[2], P.S. Hiremath[3], Poornima .G. Patil[4]

[1,2,3]KLE Technological University, Hubballi-580031, Karnataka, India
[4]Visvesvaraya Technological University, Belagavi-590018, Karnataka, India

[1]jyoti_bali@kletech.ac.in , [2]anilnandy@bvb.edu , [3]hiremathps53@yahoo.com ,[4]poornima_g_patil@yahoo.com

Abstract: In this paper, a novel methodology for Sleep apnea detection is proposed using ECG signal analysis. It involves the following sequential procedure: Pre-processing using digital filters, Peak or QRS complex detection using Pan-Tompkins algorithm, Feature extraction from detected QRS complex, Reduction of features using Principal Component Analysis (PCA) and finally the Classification using Artificial Neural Networks (ANNs). The result of classification of the input ECG signal record is as either belonging to apnea or normal category. For experimentation, the ECG-Apnea database from MIT's Physionet.org is used. The performance measures of Peak or QRS complex detection are Accuracy(Acc)=94%, Sensitivity(Se)=95%, Specificity(Sp)= 93% and Precision (Pr) = 92%. The PCA is applied on the set of time and frequency features of ECG signal to achieve dimensionality reduction and thus reduce the computational time cost, both in training and testing phase of classification by 43% and 33% respectively. The performance of ANN clasifier trained using Scaled Conjugate Gradient (ANN_SCG) has marginally improved values of Acc, Se, Sp, Pr and F-measure , where as the execution time is significantly reduced by 66% as compared to that of ANN classifier trained with Levenberg-Marquardt algorithm (ANN_LM). The experimental results demonstrate the effectiveness of the proposed method in terms of significantly reduced time cost even as compared with two of the published results.

Keywords: ECG-Apnea database; Pan-Tompkins algorithm; Principal Component Analysis; Artificial Neural Networks; Levenberg–Marquardt algorithm; Scaled Conjugate Gradient algorithm.

I. INTRODUCTION

Sleep apnea is a disorder that occurs during night sleep as a result of cessations in breathing causing interruptions of sleep. In the global scenario, sleep apnea disorder is highly prevalent among adults by about 4% in males and 2% in females as per survey [1, 2]. There are three types of Sleep Apnea namely, Obstructive Sleep apnea (OSA), Central Sleep Apnea (CSA) and Mixed sleep Apnea (MSA). OSA is the most prevalent of all and is caused by complete closure or partial closure of upper airway gap, which is the passage for supply of oxygen to the heart. This is because of the relaxation caused by muscles around the airway gap during sleeping. CSA is caused because of the absence of respiratory effort initiated by brain. MSA may occur because of the mixed occurrences of OSA and CSA. In all

these cases, intermittent cessation of breathing causes the insufficient supply of oxygen to heart, which leads to problems in its functioning. Initially, the effect of cessation causes the developing of low heart rate, i.e. bradycardia condition and lowered oxygen level in the blood. This condition is sensed by brain and it then commands the arteries to pump blood at a higher rate, which in turn increases the heart rate, i.e. tachycardia condition. The episodes of bradycardia and tachycardia that result due to apnea effect are harmful. In the aggravated conditions, there can be continuous episodes of tachycardia even during daytime causing adverse cardiac related ailments [3].

Polysomnography (PSG) is a gold standard used for the study of sleep disorders in a sophisticated lab setup under supervision of expert personnel. PSG study includes the parameters like breath air-flow, respiratory movement, blood de-saturation oxygen, body position, Electrocardiogram (ECG), Electroencephalogram (EEG) etc. The ECG signal gets modulated in amplitude and frequency due to breathing cessations caused in sleep apnea condition resulting in insufficient supply of oxygen to the heart. Hence, ECG signal can be relied upon for the study of sleep apnea which causes variations in the ECG signal parameters by deviating from their ideal values [1-4]. Measure of these deviations is of interest for the proposed study of sleep apnea detection. Hence, a well tested and validated system for early detection, classification and estimation of sleep apnea, based on analysis of ECG signal, could prove to be useful as a non-invasive sleep apnea screening method. The ECG signal in each of its beat cycle consists of wave components, namely, P wave, QRS complex, S wave and T wave caused by atrial depolarization, ventricular polarization and ventricular repolarization respectively, as shown in the Figure 1. The ECG parameters are represented in terms of its wave amplitudes, time intervals namely, PQ, QRS and TU intervals, as well PR segment, ST segment and TP segments as indicated in the Figure 1 and Table I [4,5].

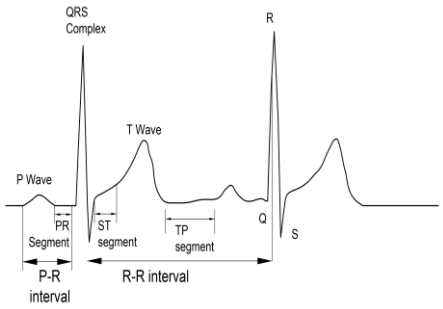


Figure 1. Ideal or the Normal ECG waveform

Table I. Time values and Amplitudes of components of ideal (normal) ECG waveform

ECG component	Time (sec)	ECG wave	Amplitude (mV)
PR Interval	0.12 - 0.20	P wave	0.25
QT Interval	0.35 -0.44	Q wave	0.4
ST Segment	0.05 - 0.15	R wave	1.6
QRS complex	0.09	T wave	0.5

II. RELATED WORK

Piotr Figoń et al.[6] described a simplified auto-adaptation filter algorithm for improving the quality of the real time ECG records of patients by removing noise. Pan Jiapu and Tompkins [7] proposed an algorithm for QRS complex detection of ECG signals by analyzing the slope, amplitude and width of the QRS complex followed by the adaptive dual threshold technique, wherein the detection accuracy of 99.3% with improved sensitivity is attained by testing the algorithm using the MIT/BIH ECG arrhythmia database records. Ahlstrom M. L. et al. [8] proposed implementation of a set of real-time digital filters for ECG signal like an adaptive 60-Hz interference filter, two low-pass filters, and a high-pass filter in the form of subroutines, which is tested on a microprocessor based platform. Mihaela Lascu et al.[9] proposed a method of filtering artifact noise and interference from ECG signal effectively using time domain filtering and signal averaging method implemented in LabVIEW. Its performance is reported to be better than linear filters. Mohamed Elgendi et al. [10] proposed a QRS detector based on adaptive quantized threshold and the secondary dynamic threshold, while working with ECG signals of lower SNR, lower QRS amplitude and non-stationary characteristics. The testing was done on CSE and MIT-BIH database, achieving sensitivity and positive prediction rate as 97.55% and 99.55%, respectively. Mohammad Pooyana et al. [11] combined two algorithms, namely, Pan Tompkins algorithm and state logic machine, to find QRS complexes of ECG signals belonging to the category of normal sinus and arrhythmia gathered from MIT-SCD database. An accuracy value of 95% has been attained using morphological features of QRS complex. Balambigai Subramanian et al. [12] used the wavelet transform based QRS detection process along with Pan Tompkins algorithm and Derivative based method, and attained accuracy and specificity of 93.4% and 90%, respectively. Francisco Castells et al. [13] proposed the use of PCA while addressing problems related to noise reduction, beat classification along with clinically oriented issues related to characterization and diagnosis of arrhythmia. Thomas Penzel et al.[14] proposed a Bi-variate Auto-regressive model to analyze beat by beat power spectral density of Heart Rate Variabilty (HRV) and R peak area. K-Nearest Neighbor (KNN) supervised learning classifier is later employed using minute by minute analysis and distinguish between apnea events from normal events with an accuracy of 100%. Sebastian Canisius et al. [15] proposed a simpler method for detection of sleep disorder

based on ECG signal analysis using a combination of signal processing algorithms and experimented with ECG-Apnea database [16,17] by monitoring cyclical variations in heart rate. Training of the algorithm is done with 35 annotated bio-signals, which is then tested on 35 pre-scored recordings X01-X35. Laiali Almazaydeh et al. [18] discusses on the use of an automatic classification method based on Support Vector Machine (SVM) for sleep apnea detection by the analysis of set of basic and derived features from 15 sec epochs of ECG signal records from MIT's ECG Apnea database, attaining an accuracy of 96.5%.

III. PROPOSED METHODOLOGY

The proposed methodology comprises the following steps: i) Preprocessing the input ECG signal for noise removal, ii) QRS detection process using Pan Tompkins algorithm to locate QRS complexes in ECG signal, iii) Feature extraction to gather ECG parameters, keeping QRS complex as the reference, iv) Feature reduction using Principal Component Analysis (PCA), and v) classification using ANN to classify the input ECG signal record as either belonging to Apnea category or normal category [15, 16]. The block diagram of the proposed methodology is shown in the Figure 2.

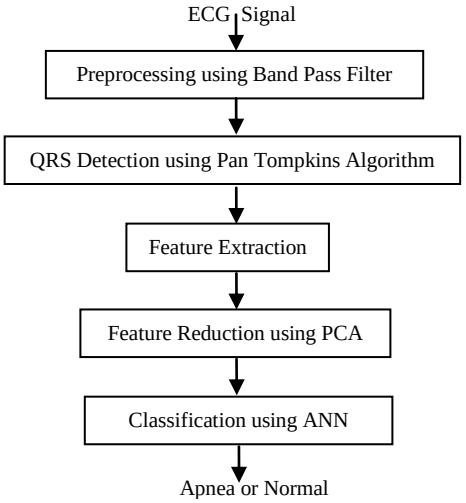


Figure 2. Proposed Methodology

3.1 Pre-processing and QRS Complex Detection

The methodology followed under Pan Tompkins algorithm [7] is as depicted in the Figure 3.

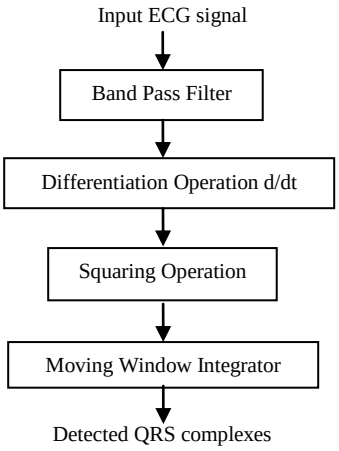


Figure 3. PT algorithm to locate QRS complexes in ECG signal

It is a real time algorithm that uses slope, amplitude and width of the QRS complex for its detection. Its implementation is done in following four stages.

Stage I: The Band-Pass Filter (BPF) is used to remove different types of noise affecting the ECG signal quality, measured with Signal to Noise Ratio (SNR). Power-line interference is the noise at 50/60Hz due to power sources in the vicinity of ECG signal acquisition system and can be filtered using Notch filter. Base line wander noise is of low-frequency caused by the respiration activity or body movement of the patient and can be filtered out by a Low Pass filter (LPF). Motion artifacts are resulted due to improper contact between the electrode and the skin resulting in large artifacts and can be filtered out using High Pass filter (HPF). Firstly, the ECG signal is brought to frequency domain using Fast Fourier Transform (FFT) and then applied with a digital BPF, 5-15 Hz. BPF is implemented using a LPF followed by HPF. The Transfer Function (TF) of LPF is as given in Eq.(1)[7].

$$H_{lp}(z) = \frac{(1 - z^{6})^{2}}{(1 - z^{-1})^{2}} \tag{1}$$

The difference equation of LPF is given in Eq.(2) [7].

$$y(nT) = 2y(nT - T) - y(nT - 2T) + 1/32(x(nT) - 2x\,(nT - 6T) + 2x\,(nT - 12T) \tag{2}$$

where y is the output of discrete filter , x is the discrete input signal, T is the sample period and n is an integer. Here, the cut off frequency is about 11Hz with filter processing delay of 6 samples. HPF is resulted as an All-pass filter minus a LPF and its TF is represented in Eq.(3) [7].

$$H_{hp}(z) = \frac{= -1 + 32\,z^{-16} + z^{-32}}{(1 - z^{-1})} \tag{3}$$

and difference equation is as shown in Eq.(4) [7].

$$y(nT) = 32x(nT - 16T) - [y(nT - T)\ +\ x(nT) - x(nT - 32T)] \tag{4}$$

.

HPF uses the cut off frequency f_c = 5 Hz and processing delay of 16 samples i.e. 80 milliseconds. Thus the BPF is used to filter out the noise and retain only the signal information keeping QRS complex, P wave peak and T wave peak. The goal here is to improve SNR and the overall detection sensitivity. A sample raw ECG signal, X05, and the corresponding preprocessed signal after BPF are shown in Figures 4(i) and (ii), respectively.

Stage II: Derivative operation is used to detect the QRS complex with largest slope suppressing P and T waves. Derivative TF and the difference equation are shown in Eq.(5) and Eq.(6), respectively [7].

$$H(z) = \left(\frac{1}{8}T\right)(-z^{-2} - 2z^{-1} + 2z^{1} + z^{2}) \tag{5}$$

$$y(nT) = \left(\frac{1}{8}T\right)[-x(nT-2T) - 2x(nT-T) + 2x(nT+T) + x(nT+2T)] \tag{6}$$

The derivative output of the pre-processed signal is shown in Figure 4(iii).

Stage III: The slope information got from differentiator in Stage II is enhanced by squaring process as shown in Eq.(7) [7]. It provides selective amplification of large differences arising from QRS peaks and attenuation of small differences resulting from P and T waves.

$$y(nT) = [x(nT)^2] \tag{7}$$

Output of the squaring operation Stage III is shown in Figure 4(iv).

Stage IV: Squared output of Stage III is passed through Moving-Window Integrator (MWI) that produces a large amplitude pulse for every QRS, lower amplitude pulses for noise spikes. The smoothened output from the moving window integration filter is as shown in Eq.(8) [7].

$$y(nT) = \left(\frac{1}{N}\right)[x(nT-(N-1)T + x(nT-(N-2)T + \cdots \ldots + x(nT)] \tag{8}$$

N, the window width, is taken as 30 which is adequate for sampling frequency fs=100Hz. The output of MWI Stage IV indicates the position and amplitude of all the detected peaks.

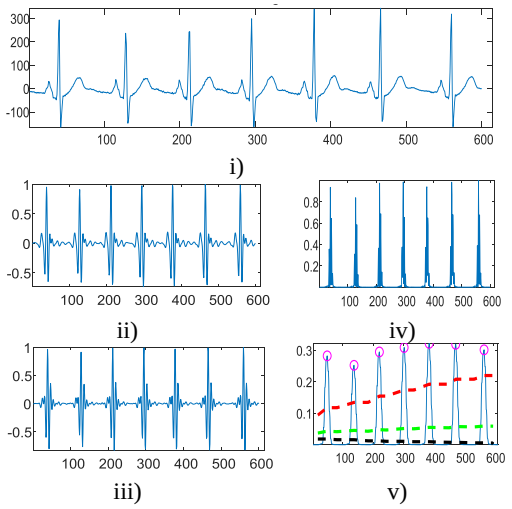


Figure 4. Stages of Pan Tompkins algorithm (i) Raw ECG signal , X05 (ii) BPF output (iii) Differentiator Output (iv) Squared output v) Output of MWI and application of adaptive threshold

After MWI, the decision making of detection process uses the intelligence for peak detection with adaptive threshold technique. It consists of three stages namely Learning Phase I, Learning Phase II and Detection. In learning phase, it requires about 2sec of time to initialize the thresholds for detection based on signal and noise peaks. Learning Phase II uses two heart beats to compute RR interval average and its limiting values producing a pulse for QRS complex detected as shown in Figure 4(v). Thresholds and other parameters of the algorithm are adjusted based on the changing characteristics of the signal. The two thresholds that are applied during the QRS complex detection are: the first threshold aplied for the filtered ECG in Stage I and the second threshold for resultant signal produced after MWI in Stage IV. These thresholds help in reducing the number of false positives caused by noise. The two threshold levels in each of the two sets of thresholds are such that one is half of the other. If the algorithm does not find a QRS complex in the time interval, corresponding to 166% of the current average RR interval, the maximum peak detected in the time interval that lies between these two thresholds is considered to be a possible QRS complex and the lower of the two thresholds is applied. After the identification of one QRS complex, there is a 200 msec refractory period before the occurence of next QRS complex , as two QRS complexes cannot occur closer than this period physiologically. Thus the refractory period eliminates the possibility of a false detections and multiple triggering for the same QRS complex within the considered time interval [5, 7, 8].

3.2 Feature Extraction

Feature extraction is the process of gathering thirty ECG parameters keeping the detected QRS complex in each beat cycle as reference as discussed in the section 3.1. Once the QRS complex or R-peak is located, RR interval, the time interval between consecutive QRS complexes, Heart rate, number of QRS complexes detected per minute, PR interval, time difference of onset of P wave and onset of QRS complex etc. can be computed in time domain and their statistical distribution of parameters are obtained for minute-wise duration. Similarly, the spectral features of variability characteristics of each of these intervals are considered for analysis in frequency domain [19-23].

Among the HRV based parameters in time domain, first one being RR interval variability that can be estimated in terms of (1) Number of Beats detected, (2) Inter-Quartile Range (IQR), (3) Standard Deviation (SD), (4) Mean Absolute Deviation (MAD) from its Mean, (5) Mean epoch, (6) $pNN50_1$, (7) $pNN50_2$, (8) SDSD measure, (9) Root Mean Square of Standard Differences (RMSSD). The second one is the Heart rate value expressed in terms of (10) Mean, (11) Median, (12) SD, (13) QRS complex Area. The third one is the PR interval value expressed in

terms of (14) Mean, (15) Median, (16) SD. Lastly, the QT interval is expressed in terms of (17) Mean, (18) Median, (19) IQR. Abbreviations of some of statistical features based on RR interval variability are defined as under:

i. The NN50 measure (Variant1) and NN50(Variant2) are computed as the number of pairs of adjacent RR intervals, where the first interval exceeds the second interval by more than 50 ms, or vice versa, respectively.
ii. $pNN50_1$ and $pNN50_2$ are the measures divided by the total number of RR intervals.
iii. The SDSD measure is the measure of deviation between adjacent RR intervals.
iv. The RMSSD is the root mean square value of differences between the adjacent RR intervals.
v. IQR is the difference between 75^{th} and 25^{th} percentile of RR value distribution.
vi. MAD is the mean of absolute values obtained by the subtraction of the mean RR interval values from all the RR interval values in an epoch.

The frequency domain based HRV parameters used for the study are listed as under:

(20) Low-Frequency (LF) power, (21) High-Frequency (HF) power, (22) (LF power / HF power) ratio, (23) Spectrogram of S wave amplitude, (24) Spectrogram of QRS complex, (25) Pulse energy, (26) Power of Spectrogram of HRV, (27) Spectrogram of Heart Rate, (28) Power spectral density (PSD) of RR intervals, (29) PSD of R wave maximum. Lastly, the feature (30) Apnea-Hypopnea Index (AHI) is the number of Apnea-hypopnea events per hour. The AHI is computed by counting the number of apnea episode occurrences in the form as described below:

a. Repeated episodes of Bradycardia followed by episode of tachycardia or continuous episodes of tachycardia or Bradycardia episode followed by abrupt tachycardia is tracked by analyzing the heart rate variability pattern and RR interval variability in time domain.
b. Spectrogram of Heart rate showing a pattern of growing amplitude and decreasing frequency is tracked by analyzing the RR interval variability in frequency domain.
c. Patterns with increased Low Frequency (LF) band spectral power around 0.02Hz and decreased HF band spectral power is observed in spectral characteristics.

3.3 Feature Reduction using PCA

Features extracted from ECG signal may have inherent redundancy. But the need is to retain the features that are statistically significant, having discriminatory characteristics. Hence, the PCA is employed for dimensionality reduction of feature set, which reduces the overall computation cost effectively [24-26]. The input and output of PCA stage are described as following:

1. PCA function in Matlab software takes the input as the feature data matrix of size n X p, where n is number of observations for each record= 420(7 hours*60 minutes) and p is number of features = 30
2. The output of PCA is the p X *p* matrix, where p number of principal components arranged in the order of decreasing variance. Hence, the size of output matrix from PCA stage is 30 X 30, from which the dominant principal components are chosen for computation of the performance measures of the proposed method.
3. Then, the optimal number of PCA components required to achieve the maximum accuracy is determined. Thus, the method is optimized to yield improved accuracy and reduced execution time or the computation cost.

3.4 Classification using Artificial Neural Networks

The artificial neural network (ANN) has an input layer having number of neurons equal to the number of principal components received from PCA stage. ANN has its second layer called as hidden layer comprising of thirty neurons, followed by an output layer having only one neuron. The classification process of any ANN uses two stages, namely, the training stage and the testing stage. In the training stage, neural network is trained with minute-wise data from each of the ECG record of the training dataset and the train labels taken from respective expert annotations. Training of ANN is done with Back Propagation (BP) algorithms, namely, LM algorithm or SCG algorithm [27,28].

3.4.1 ANN trained with LM algorithm (ANN_LM)

The training of ANN is done with LM optimization algorithm [28], which uses Jacobian for calculations. The performance of the network is estimated in terms of Mean of Sum of squared Errors (MSE). The generalization ability of the network is tested with test vectors. Training of the network is stopped for conditions like maximum number of epochs being reached, the network performance failing to improve or remains the same for max_fail epochs in a row. Hessian matrix H and the gradient G are computed as shown in Eq. (9) and Eq. (10) given below:

$$H = J^T J \tag{9}$$

$$G = J^T e \tag{10}$$

where the Jacobian matrix J contains first derivatives of the network errors with respect to weights and biases, e is a network of errors. LM algorithm uses this approximation to a Newton-like update and converges earlier and accurately near an error minimum as shown in Eq.(11) [27-29].

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{11}$$

where I is the identity matrix and μ is the combination coefficient. When the scalar μ is zero, the approximate Hessian matrix reduces as Newton's method, which converges faster at an error minimum. When μ is large, this becomes gradient descent with a small step size. Thus μ is

decreased after every successful iteration and increased only when the performance function increases temporarily. In this way, the performance function is reduced at each iteration of the algorithm.

3.4.2 ANN trained with SCG (ANN_SCG) algorithm

The principal components generated from PCA stage are applied with K means clustering, an unsupervised learning technique. Here the objective is to group the data with similar features under same cluster. The number of clusters is defined by variable K set to 10 to produce 10 clusters under each of the two classes namely Apnea and Normal. Clustering process uses K means++ algorithm to produce these clusters in 100 iterations. It returns the cluster indices of each observation along with cluster centroid locations. Each centroid of the cluster is the representative value of the feature values that belong to that cluster. This clustering method uses the squared Euclidean distance measure and the cluster centers are initialized using *k*-means++ algorithm. Thus a well defined set of ten clusters under each of Apnea and Normal classes are fed to Scaled Conjugate Gradient (SCG) method to train the ANN. This helps in faster convergence towards minimizing the MSE through step size scaling mechanism based on error magnitude. It thus avoids a time consuming line search. The outputs of the network are recognition rate of training data, the recognition rate of test data, the produced class labels of training data, the root mean square error of training data [29-31].

IV. Results and Discussion

The implementation of the proposed method is done using Matlab2017a on a personal computer with configuration, Intel(R) Core(TM), i3CPU, 2.4.GHz, 4GB RAM and 64bit Operating system.

Database:

The ECG signal night time recordings are gathered from the publicly available benchmark dataset, namely, ECG-Apnea database of MIT's Physionet.org. It consists of 70 night time ECG recordings of length from 8 to 10 hours, sampled at 100Hz and the expert annotations on occurrences of QRS beats and apnea events. The database has ECG recordings of apnea patients (a01-a20), borderline case patients (b01-b05) and control patients (c01-c10). This forms a set of 35 minute-wise annotated recordings used for training of ANN classifier. The expert annotations contain labels as either 'A' or 'N', indicating the presence of apnea or normal condition, respectively, for each minute. Every one minute of ECG record is categorized as either a apnea minute or normal minute. There is a collection of other 35 ECG recordings X01-X35 of both apnea patients and normal beings, which are used as test datasets [16, 17].

4.1 Results of Preprocessing and QRS detection

The digital filtering used in preprocessing of ECG signal has improved the SNR by 12%, approximately. The summary of the results of Pan-Tompkins algorithm based QRS detection tested with X01-X35 records of the database is given in Table II. The average performance measures are estimated in terms of Accuracy(Acc), Sensitivity(Se), Specificity(Sp) and Precision (Pr), using the detected True positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN), and are found to be 94%, 95%, 93% and 92%, respectively. Table II compares the performance measures of QRS complex detection performed using the proposed PT method with that of HT method proposed by Bali, J. et al.[35]. The performance measures Acc, Se, Sp and Pr are considerably low, whereas the execution time of PT method is quite lower for proposed PT method as compared with those of HT method [35]. Hence QRS complex detection using PT method proves to be highly computational efficient. The F-measure, which is the harmonic mean of precision and sensitivity, is found to be 0.92 for the proposed method as compared to 0.93 value computed for HT method [35]. The Receiver Operating Characteristics (ROC) curve of QRS detection is shown in Figure 5 as a plot of False Rejection Rate (FRR) versus False Acceptance Rate (FAR), where FRR=1-Sensitivity and FAR=1-Specificity for both the methods [35]. The Equal Error Rate (EER), the desired operating point on ROC curve with equal values of FRR and FAR is found to be 0.176 and 0.11 for PT method and HT method [35] respectively. For HT method [35], EER is reduced by 37% as compared with proposed method of QRS detection, which has the advantage of reduced computation cost by 65% as compared with its counterpart [32-35].

Table II. QRS Detection Performance Measures

Performance Measures	Average values for Proposed PT Method	Average values for HT Method [35]
Accuracy (%)	94	98.7
Sensitivity (%)	95	94
Specificity (%)	93	94
Precision (%)	92	92
F-measure	0.92	0.93
Execution time(sec)	0.5	1.42
Equal Error Rate	0.176	0.11

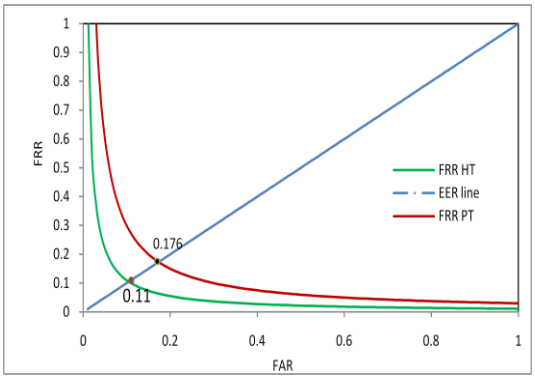


Figure 5. ROC curve plot of FRR vs. FAR for QRS detection using proposed PT method and HT method in Bali, J. et al.[35]

4.2 Results of Feature Extraction

Feature extraction is carried out on all the 35 training ECG records, namely, a01-a20, b01-b05 and c01-c10 records and the thirty features are computed minute-wise from each of these records. Thus, totally, 14,700 feature vectors of dimension 30 are obtained (35 records * 7 hours * 60 minutes), i.e., one feature vector per minute, which are fed to PCA stage to select the dominant set of features to be used for training of ANN with LM and SCG algorithms. Later, during the test phase, for every test record, the feature extraction process yields 420 feature vectors (1 record * 7 hours * 60 minutes) that are fed to PCA stage.

4.3 Results of Feature Reduction & Classification

The experimentation has been done on test ECG records with different number of PCA components in order to determine the number of dominant principal components sufficient enough to attain the desired accuracy of classification. The classification accuracy and execution time for different number of PCA components in case of both the classifiers under proposed method is summarized in the Table III. The same tabulated data is shown as graphs in Figure 6 and Figure 7 respectively. There is no significant improvement in accuracy and execution time observed with further increase in number of PCA components after 20. Hence the first 20 dominant features are used with both the classifiers during train and test stage. The accuracy is found to be 95% for ANN_SCG classifier, a smaller improvement over 92% found for ANN_LM classifier. But the execution time of ANN_SCG classifier is lesser, i.e., 1.2 sec against 3.5 sec for ANN_LM thus reducing the execution time, hence the computation cost by 66%. This has resulted due to the reduced feature set size achieved through PCA by 43% during training and by 33% during testing, along with the saving of time achieved by using fast converging SCG training algorithm.

Further the results are compared with results of classifier using HT based Feature Extraction proposed by Bali, J.et al.[35], which use 25 and 20 principal components for ANN_LM and ANN_SCG methods respectively. As both the classifiers use same training algorithms LM and SCG, the results can be compared in a justifying manner. The proposed classifiers both ANN_LM and ANN_SCG require 20 principal components for classification, achieving lower performance measures, but with improved computation cost efficiency as compared with HT based ANN classifiers proposed by method Bali, J. et al.[35]. It is observed that the ANN_SCG classifier performs better as compared with ANN_LM classier for both PT and HT methods, in terms of each of the performance measures as well the computation time. This is due to the support of K-means clustering used with SCG method along with its inherent fast convergence nature. While considering the final classification, HT method [35] performs better in terms of its accuracy measure, whereas PT method performs well in terms of significant computation efficiency (Table III).

Table III. Classification Accuracy and Execution Time (secs.) v/s number of PCA components for ANN_SCG & ANN_LM algorithms

No. of PC components	Proposed ANN Classifier with PT method				ANN Classifier with HT method in Bali J. et al.[35]			
	Accuracy		Execution time (secs)		Accuracy		Execution time (secs)	
	LM	SCG	LM	SCG	LM	SCG	LM	SCG
5	82	85	0.8	0.5	94.5	95.2	12	3.9
10	88	91	1.9	0.83	97.4	98.3	15	3.7
15	89	94	2.3	0.95	98.1	99	16	5.2
20	**92**	**95**	**3.5**	**1.2**	98.2	**99.2**	15.2	**6.5**
25	92	95	4.5	1.6	**98.5**	99.2	**15.5**	6.9
30	92	95	6	2.1	98.5	99	20	7.8

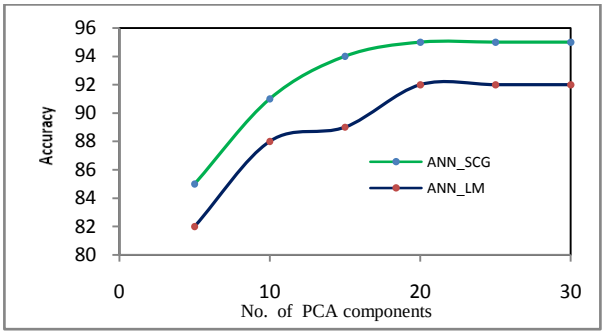


Figure 6. Accuracy vs. No. of PCA components for ANN –SCG & ANN_LM algorithms of proposed method

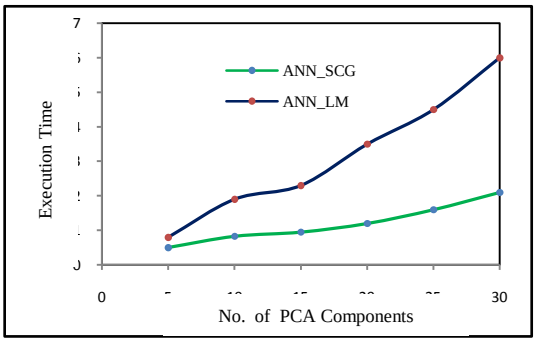


Figure 7. Execution Time (secs.) vs. No. of PCA components for ANN_SCG & ANN_LM algorithms of proposed method

4.5 Results of Classification using ANN Algorithms

As per the experimentation results got in PCA stage (section 4.4), the proposed method uses 20 principal components for classification of test records. The proposed algorithm uses the train data and train labels for training the ANN classifier utilizing twenty dominant PCA components that represent the features ECG signal and is tested with X01-X35 records of the database. The tabulation of results of detection of apnea minutes (in percentage) for each record is done in Table IV based on total recording time of ECG signal, for both ANN_LM and

ANN_SCG classifiers. Expert annotations are available as number of apnea minutes (in percentage) and also the decision of a record belonging to Apnea category as 'Yes' and the one belonging to normal category as 'No'. Comparison of results of ANN_SCG and ANN_LM algorithms is done with the expert annotations to estimate the number of TP, FN, TN and FP values, needed to compute the performance measures of classification summarized in Table V. The test input ECG signal record is decided to be of Apnea category, if the percentage of detected apnea minutes is more than 10%, otherwise it is decided to be of Normal category. [15,35].
Summary of the results of table IV is shown in Table V for comparison of the performance of proposed method with Bali, J. et al.[35] and Sebastian[15].

Table IV. Results of Sleep apnea detection for X01-X35 records using ANN_LM and ANN-SCG algorithms

ECG Record	Expert Annotation		ANN-LM		ANN-SCG	
	% Apnea minutes	Decision	% Apnea minutes	Decision	% Apnea minutes	Decision
X01	71.70	Yes	43	Yes	65	Yes
X02	44.25	Yes	65	Yes	52	Yes
X03	2.58	No	5	No	4	No
X04	0.00	No	2	No	12	Yes
X05	63.61	Yes	80	Yes	50	Yes
X06	0.00	No	2	No	2.3	No
X07	47.30	Yes	8	No	52	Yes
X08	62.84	Yes	73	Yes	60	Yes
X09	32.87	Yes	18	Yes	45	Yes
X10	18.84	Yes	3	No	15	Yes
X11	3.07	No	1	No	8	No
X12	10.80	Yes	15	Yes	13	Yes
X13	57.44	Yes	29	Yes	62	Yes
X14	88.21	Yes	42	Yes	75	Yes
X15	38.64	Yes	25	Yes	22	Yes
X16	13.59	Yes	37	Yes	15	Yes
X17	0.25	No	4	No	1	No
X18	0.65	No	7	No	3	No
X19	82.92	Yes	87	Yes	79	Yes
X20	52.10	Yes	64	Yes	45	Yes
X21	23.74	Yes	48	Yes	30	Yes
X22	0.83	No	5	No	3	No
X23	22.33	Yes	41	Yes	34	Yes
X24	0.23	No	4	No	2	No
X25	57.59	Yes	65	Yes	61	Yes
X26	66.15	Yes	55	Yes	9	No
X27	97.99	Yes	85	Yes	92	Yes
X28	87.24	Yes	76	Yes	90	Yes
X29	0.00	No	2	No	6	No
X30	61.22	Yes	50	Yes	65	Yes
X31	92.61	Yes	80	Yes	86	Yes
X32	78.97	Yes	55	Yes	62	Yes
X33	1.06	No	23	Yes	5	No
X34	0.84	No	6	No	2	No
X35	0.00	No	2	No	4	No

The classification measures for the proposed ANN_LM classifier are Acc=91%, Se=91%, Sp=92%, Pr=95%, F-measure=0.93 and MSE=0.4 and an improvement is observed in these measures for the proposed ANN_SCG classifier yielding Acc=95%, Se=94%, Sp=91% and Pr=96%, F-measure=0.95 and MSE = 0.32. The performance measures of both the ANN_LM and ANN_SCG classifiers are better than Sebastian method [15]. But in comparison with ANN Classifier using HT based Feature Extraction method proposed by Bali, J. et al. [35], the performance measures for the proposed classifiers are quite low. But, the execution time taken by proposed classifiers is quite low, making it computationally efficient as compared with HT method [35]. Accuracy values obtained by proposed PT based method reduce by 6.5% and 4.2% for LM and SCG based ANN classifiers as compared with that obtained by HT based method [35]. However, the total execution timings of proposed PT based method reduce by 77.4% and 81.5% for LM and SCG based classifiers, respectively, as compared with that for HT based method [35]. The computation time incurred by proposed PT based method is significantly lesser than that for HT based method [35], but at the cost marginal decrease in accuracy.

Table V. Comparison of performance measures of proposed method with methods in Bali, J. et al.[35] and Sebastian et al.[15].

Average Performance Measures	Proposed classifier		HT based Classifier Bali J.et al.[35]		Sebastian et al.[15]
	ANN-LM	ANN-SCG	ANN-LM	ANN-SCG	
Accuracy (Acc) (%)	91	95	98.5	99.2	83
Sensitivity (Se) (%)	91	94	95	97	92
Specificity (Sp) (%)	92	91	94	98	60
Precision (Pr) (%)	95	96	95.2	96	85
F-measure	0.93	0.95	0.95	0.97	0.88
Execution Time (sec)	3.5	1.2	15.5	6.5	-

Table VI. Comparison of proposed methods with state of art literature

Method	Features	Classifier	Performance Measures (%)
Proposed Method	PT based QRS complex detection, 30 features & AHI	ANN_ LM	Acc: 91, Se: 91
		ANN_ SCG + K-means Clustering	Acc: 95, Se: 94
Bali, J. et al. [35]	HT based QRS detection, 30 features & AHI	ANN_LM	Acc:98.5, Se:95
		ANN _SCG + K-means clustering	Acc:99.2, Se:97
A.F. Quiceno et al. [37]	Dynamic Time & frequency features	K-NN classifier	Acc. :92.67
Khandoker et al. [38]	Wavelet features	SVM	Acc: 93
C. Varon et al. [39]	Time domain features	Least Squares SVM	Acc>90
Bsoul et al.[40]	Time and Spectral features	SVM	Se: 96
Oussama et al. [41]	11 time domain features	ANN	Acc: 96

The performance measures of the proposed method is compared with other methods reported in literature [36] as shown in Table VI and it proves to be quite competitive.

Test of Significance

The Chi-Square test is performed at 5% significance level to validate the agreement between the expert annotations and the test results for both the PT and HT based methods. The classification result using HT method proves to be in

better agreement with the expert annotations as compared to that of classification using proposed PT based method [42,43].

V. CONCLUSION

In the proposed work, the Pan-Tompkins algorithm based feature extraction of preprocessed ECG signal is carried out followed by classification of ECG signal as the one belonging to sleep apnea patient or a normal person. Testing was done using X01-X35 records of the database. Preprocessing has improved the SNR of the input ECG signal by 12%. The performance measures of QRS complex detection are Acc=94%, Se=95%,Sp= 93% and Pr=92%. PCA reduces the extracted feature set size by 43% in training phase and by 33% in test phase of classification. contributing to a considerable reduction of execution time. ANN_SCG classifier has improved performance over ANN_LM classifier in terms of Acc, Se, Sp, Pr , F-measure and MSE by a smaller margin. But the speed of execution of ANN_SCG classifier has increased compared to ANN_LM classifier by around 66%, due to its fast converging behaviour, K-means clustering , along with the saving of time acheived through PCA stage. ANN_SCG classifier has outperformed ANN_LM classifier as well the reference classifier [15]. The merit of the proposed PT based method is in the form of significantly reduced computational time cost as compared with HT based method [35].

Acknowledgement

This research is supported by Management of KLE Technological University, BVBCET Campus, Hubballi-580031, Karnataka, India, under Capacity Building Project Grant Scheme. I am thankful to Dr. Shrikanth Hiremath, Pulmonologist, S.D.M College of Medical & Health Sciences, for providing domain knowledge and guidance on study of sleep apnea, while carrying out the proposed work.

VI. REFERENCES

[1] Nathaniel S. Marshall, Keith K. H. Wong, Peter Y. Liu, Stewart R. J. Cullen, Matthew W. Knuiman, Ronald R. Grunstein, "Sleep Apnea as an Independent Risk Factor for All-Cause Mortality: The Busselton Health Study", SLEEP, Vol. 31, No. 8, 2008

[2] Jonathan C. Jun, Swati Chopra, Alan R. Schwartz, "Sleep apnoea" , Eur Respir Rev. 25(139) 2016, 12–18.

[3] Robert Joseph Thomas, Chol Shin, Matt Travis Bianchi, Clete Kushida and Chang- Ho Yun, "Distinct polysomnographic and ECG spectograpic phenotypes embedded within Obstructive Sleep Apnea" Sleep Science and practice, 2017,1:1.

[4] Rangayyan, Rangaraj M. "Biomedical signal analysis : a case-study approach" . c2002, IEEE Press ,New York, Wiley-Interscience.

[5] Valtino Afonso, "Biomedical Digital Signal Processing" 1993, Pages 236-264, Prentice-Hall, Inc. , ISBN:0-13-067216-5

[6] Piotr Figoń, Paweł Irzmański, Adam Jóśko , "ECG signal quality improvement techniques", PRZEGLĄD ELEKTROTECHNICZNY, ISSN 0033-2097, R. 89 NR 4/2013

[7] Pan, Jiapu; Tompkins, Willis J. "A Real-Time QRS Detection Algorithm" , IEEE Transactions On Biomedical Engineering, Vol. BME-32, No. 3, 1985.

[8] Ahlstrom, M. L ,Tompkins, W. J. (1985). "Digital Filters for Real-Time ECG Signal Processing Using Microprocessors", IEEE Transaction on Biomedical Engineering, Vol.32, No.9, 2007,pp. 708-713.

[9] Mihaela Lascu,Dan Lascu , "Labview Based Event Detection using Pan Tompkins Algorithm ", Proceedings of 7th WSEAS International Conference on Signal Processing, computational Geometry and Artificial Vision, Athens Greece, 2007.

[10] Mohamed Elgendi, Mirjam Jonkma, Friso De Boer , "Improved QRS Detection Algorithm using Dynamic Thresholds", International Journal of Hybrid Information Technology,Vol.2, No.1, 2009.

[11] Mohammad Pooyan and Fateme Akhoondi, "Providing An Efficient Algorithm For Finding R Peaks In ECG Signals And Detecting Ventricular Abnormalities With Morphological Features" , Journal of Medical Signals & Sensors , 6(4): 218–223, 2016.

[12] Philip De Chazal, Richard B Reilly, "A Patient Adapting Heart Beat Classifier Using ECG morphology and Heart Beat Interval Features" , IEEE Transactions on Biomedical Engineering, VOL.53, No.12, 2006.

[13] Francisco Castells, Pablo Laguna, Leif Sornmo, Andreas Bollmann, and Jose Millet Roig, "Principal Component Analysis in ECG Signal Processing" , Hindawi Publishing Corporation EURASIP Journal on Advances in Signal Processing Volume 2007, Article ID 74580, 2007, 21 pages.

[14] Penzel and A. Bianchi "Detection of Sleep Apnea from Surface ECG Based on Features Extracted by an Autoregressive Model, Proceedings of the IEEE International Conference on Engineering in Medicine and Biology Society, 2007, pp. 6105-6108.

[15] Sebastian Canisius, Thomas Ploch, Volker Gross, Andreas Jerrentrup, Thomas Penzel, Karl Kesper, "Detection of Sleep Disordered Breathing by automated ECG analysis", 30th Annual International IEEE EMBS Conference, Vancouver, British Columbia, Canada, 2008, 978-1-4244-1815-2/08/$25.00 ©2008 IEEE.

[16] T. Penzel, G. B. Moody, R. G. Mark, A. L. Goldberger, and J. H. Peter, "The apnea-ECG database". Computers in Cardiology, 2000, pp. 255-258.

[17] L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdor, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet : Components of a new research resource for complex physiologic signals", Circulation, 2000.

[18] Laiali Almazaydeh, Khaled Elleithy, Miad Faezipour , " Detection of Obstructive Sleep Apnea Through ECG Signal Features" 978-1-4673-0818-2/12/$31.00 ©2012 Crown.

[19] Valtino Afonso, Biomedical Digital Signal Processing, Pages 236-264 ,Prentice-Hall, Inc. Upper Saddle River, NJ, USA ©1993.

[20] B.U.Kohler , C. Hennig and R. Orglmeister,"The principles of software QRS detection", *IEEE Engineering in Medicine and Biology Magazine*, vol. 21, no. 1, 2002, pp. 42-57.

[21] Udit Satija, Barathram. Ramkumar, and M. Sabarimalai Manikandan, "A Review of Signal Processing Techniques for Electrocardiogram Signal Quality Assessment", IEEE Reviews in Biomedical Engineering, 2018.

[22] Fatin A. Elhaj, Naomie Salim, Arief R. Harris, Tan Tian Swee, Taqwa Ahmed, "Arrhythmia Recognition and Classification using combined linear and nonlinear features of ECG signals", Computer Methods and Programs in Biomedicine, 127, 2016, 52-63.

[23] Yeldos A. Altay and Artem S. Kremlev, "Comparative analysis of ECG signal processing methods in the time-frequency domain ",IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), 2018, 1058-1062.

[24] Sridhar Krishnan, Yashodhan Athavale," Trends In Biomedical Signal Feature Extraction", Biomedical Signal Processing and Control journal, 43, 2018, 41-63.

[25] Harjeet Kaur, Rajni Rajni, "Electrocardiogram Signal Analysis for R-Peak Detection and Denoising with Hybrid Linearization and Principal Component Analysis" ,Turkish Journal of Electrical Engineering & Computer Sciences, 25, 2017, 2163-2175.

[26] Roshan Joy Martis , U. Rajendra Acharya , K.M. Mandana , A.K. Ray, Chandan Chakraborty, "Application Of Principal Component Analysis To ECG Signals For Automated Diagnosis Of Cardiac Health", Expert Systems with Applications Volume 39, Issue 14, 2012 , 11792-11800.

[27] R.Rodrígueza, A. Mexicanob, J. Bilac, S. Cervantesd, R. Ponceb, "Feature Extraction of Electrocardiogram Signals by applying Adaptive Threshold and Principal Component Analysis", Journal of Applied Research and Technology 13 , 2015, 261-269.

[28] M. F. Moller, "A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning", Neural Networks, 6, 1993, pp. 525–533.

[29] S. Ali and K. A. Smith, "On learning algorithm selection for classification", Applied Soft Computing, (6), 2006, pp.119–138.

[30] W.W. Hager and H. Zhang, "A survey of nonlinear Conjugate Gradient methods", Pacific of Journal Optimization, 2:35, 2006, pp. 35–58

[31] M. K. S. Alsmadi, K. B. Omar, S. A. Noah, "Back propagation algorithm: The best algorithm among the Multi-layer Perceptron algorithm", International Journal of Computer Science and Network Security, vol., 9(4), 2009, pp. 378–383.

[32] Powers, D.M.W. "Evaluation: From Precision, and F-Measure To ROC, Informedness, Markedness & Correlation" Journal of Machine Learning Technologies, , Volume 2, Issue 1, 2011, pp-37-63.

[33] Krzysztof Gajowniczek, Tomasz Ząbkowski, Ryszard Szupiluk " Estimating the ROC Curve and its significance for Classification Models", Assessment Quantitative Methods In Economics, Vol. Xv, No. 2, 2014, Pp. 382 – 391,

[34] Philip de Chazal, Thomas Penzel, Conor Heneghan, "Automated detection of Obstructive Sleep Apnoea at different time scales using the Electrocardiogram", IOP Publishing Ltd, Physiological Measurement, Volume 25, Number 4 , 2004.

[35] Bali, J., Nandi, A., Hiremath, P, "Performance Comparison of ANN Classifiers For Sleep Apnea Detection Based on ECG Signal Analysis Using Hilbert Transform", International Journal Of Computers & Technology, 17(2), 2018, 7312-7325. https://doi.org/10.24297/ijct.v17i2.7616.

[36] FAUST, Oliver, ACHARYA, U. Rajendra, NG, E. Y. K. and FUJITA, Hamido (2016). "A review of ECG-based diagnosis support systems for obstructive sleep apnea", Journal of Mechanics in Medicine and Biology, 16 (01), 2016, p. 1640004.

[37] A.F. Quiceno-Manrique, J.B. Alonso-Hernandez, C.M. Travieso-Gonz´alez, M.A. Ferrer-Ballester, G. Castellanos-Dom´ınguez, "Detection of obstructive sleep apnea in ECG recordings using time-frequency distributions and dynamic features", 31st Annual International Conference of the IEEE EMBS Minneapolis 2009.

[38] A. Khandoker, C. K. Karmakar, M. Palaniswami, "Automated recognition of patients with Obstructive Sleep Apnoea using wavelet-based features of Electrocardiogram recordings", Computers in Biology and Medicine 39 (1),2009, 88–96

[39] C. Varon, D. Testelmans, B. Buyse, J. A. K. Suykens and S. Van Huffel, "Sleep apnea classification using least-squares support vector machines on single lead ECG," *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Osaka, 2013, pp. 5029-5032.

[40] M. Bsoul, H. Minn, L. Tamil, "Apnea medassist: Real-time sleep apnea monitor using single-lead ECG", IEEE Transactions on Information Technology in Biomedicine 15 (3) (2011) 416–427.

[41] B. M. Oussama, B. M. Saadi, H. S. Zine-Eddine, "Extracting features from ECG and respiratory signals for automatic supervised classification of heartbeat using Neural Networks", Asian Journal of Information Technology 15 (1) ,2016 , 5–11.

[42] S.C. Gupta, V.K. Kapoor, "Fundamentals of Mathematical Statistics a Modern Approach", 10th Edition 2000.

[43] Priscilla E. Greenwood , Michael S. Nikulin, "A Guide to Chi-Squared Testing" (Wiley Series in Probability and Statistics), 1st Edition.