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Auto-regressive Time Frequency Analysis (ARTFA) of Electrocardiogram (ECG) signal

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Abstract
The combination of P-wave, QRS-complex and T-wave is known as one cardiac cycle of Electrocardiogram (ECG) signal. It shows the electrical activity of the heart during polarization and depolarization activity. It is acquired by standard lead arrangement through electrodes pasted on specified locations on the body during ECG test. It is plotted on chart paper and stored in computer for analyzing in the future. Any change in the standard ECG signal leads to heart disease (abnormal). During the acquisition of the ECG datasets different noises involve. These noises hide the important characteristic of the ECG signal that misleads the signal analysis. Therefore, morphological technique is not sufficient for analyzing such types of ECG datasets. Moreover, cost of ECG test is very high. It requires automated ECG signal analysis technique using computerized classification that gives accurate, fast and reliable detection of the disease. Time domain techniques work well in the cleaned signal analysis and Frequency domain techniques are prone to spectral leakage problems. For analyzing ECG signals, Time-frequency analysis (TFA) methods offer simultaneous interpretation of the signal in both time and frequency domain. Among existing TFA techniques, Auto-regressive Time Frequency Analysis (ARTFA) offers good time-frequency resolution. ARTFA were used for finding the coefficients in first step and time-frequency, description in the second step. Coefficients clearly states about the status of the patient heart. Time-Frequency Analysis depicts the existing R-peak of the patient ECG dataset. On the final stage, KNN were used. It gave sensitivity(R_{SE}) of 99.79% and detection rate(R_{DR}) of 99.9%. KNN has been improved detection rate about 3.7%.

Keywords: Electrocardiogram(ECG) signal, standard lead arrangement, heart disease, ECG datasets, computerized classification, Frequency domain techniques, Time-frequency analysis (TFA) methods, Auto-regressive Time Frequency Analysis (ARTFA).

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Introduction
The cardiovascular system is the combination of the heart, blood and blood vessels [1]. Cardiovascular diseases (CVD) are the key factor of death worldwide (World Health Organization (WHO), Alwan 2011) in both women and men [2-3]. About the Heart, Electrocardiography (ECG) is the authorized tool among researchers and clinical practitioners in the assessment of cardiac function [2]. Further, it requires verification from an expert cardiologist [2]. Electrocardiogram (ECG) is a non-invasive tool for analyzing the heart status of the patient by visualizing pattern of the ECG signal [4]. It classifies the patterns of P-wave, QRS-complex, T-wave and after P-wave repeats. These waves show potential differences between the excited and non-excited parts of the heart generated by action potentials of myocardial cells [5] and patterns of these waves classify the existing arrhythmia in the ECG dataset [6] and also give pathological information. The combination of P-wave, QRS-complex and T-wave is known as one cardiac cycle of Electrocardiogram (ECG) signal. It shows the electrical activity of the heart during polarization and depolarization activity [7]. The contraction of the atria is represented by P-wave, contraction of the ventricles is represented by the QRS complex and the return of the ventricular mass to a rest state depolarization represents the T wave. It is acquired by standard lead arrangement through electrodes pasted on specified locations on the body [8] during ECG test. It is plotted on chart paper and stored in computer for analyzing in the future. Any change in the standard ECG signal leads to heart disease (abnormal) and represented a different clinical diagnostic observation [6,9].Various different factors are responsible for cardiac arrhythmia such as smoking, laziness, hypertension, tobacco, obesity, and cholesterol [3]. Among various heart diseases, Coronary artery disease, is mostly happening in the patient ECG signal and ends the life of a someone worldwide [10]. During the acquisition of the ECG datasets different noises involve. These noises hide the important characteristic of the ECG signal that misleads the signal analysis. Even in some cases

two different heart disease signals are same in view [8]. Therefore, morphological technique is not sufficient for analyzing such types of ECG datasets and medical specialist cannot detect the diseases effectively. Moreover, the cost and length of ECG test are very high. Manual classification of heart disease is very cumbersome and time consuming. It requires automated and intelligent ECG signal analysis technique [4] that extracts other possible features using computerized classification (computer based diagnosis) [6] that give accurate, fast and reliable detection of the disease. Various methods of ECG signal analysis have been proposed by different researchers on the basis of time domain, frequency domain, and nonlinear methods. Time domain techniques work well in the cleaned signal analysis and Frequency domain techniques are prone to spectral leakage problems. For analyzing ECG signals, Time-frequency analysis (TFA) methods offer simultaneous interpretation of the signal in both time and frequency domain. Most famous TFA techniques are wavelet transform (WT), short-time Fourier transform (STFT) and Auto-regressive Time Frequency Analysis (ARTFA). WT needs various computational of the coefficients during the decomposition process. It also depends on the type of selected function for analyzing signals. On the other hand STFT has a leakage problem [11] and proper window function is necessary during signal analysis. For analyzing ECG signals, Time-frequency analysis (TFA) methods offer simultaneous interpretation of the signal in both time and frequency domain. Among existing TFA techniques, Auto-regressive Time Frequency Analysis (ARTFA) offers good time-frequency resolution. ARTFA were used for finding the coefficients in first step and time-frequency, description in the second step. Estimated autoregressive coefficients clearly states about the status of the patient heart. Time-Frequency Analysis depicts the existing R-peak in the patient ECG dataset.

Methods

The proposed methodology is shown in Figure.1.

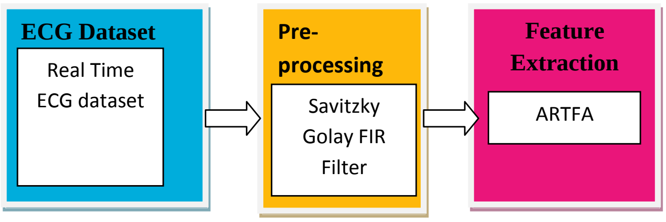


Figure:1 Proposed methodology in the paper

Raw ECG signal

Real-time ECG database

This database prepared at 360 Hz sampling rate under the supervision of a skilled lab boy using two lead arrangements. 43 subjects were involved in this data acquisition program.

Savitzky-Golay Digital Filtering

The Saviztky-Golay filter works on least squares polynomial fitting with sliding window. Usually higher order polynomial permits a good smoothing without loss of the signal information. Filtering by Saviztky-Golay filter preserves all important signal features [12].

If the polynomial fitting model is represented as [13]

$$x(t) = \alpha_o + \alpha_1 t + \alpha_2 t^2 + \cdots \ldots \ldots .. \quad (1)$$

$$x(t) = \sum_{d=0}^{D} \alpha_d \, t^d \quad (2)$$

Then the least square expression can be written as

$$\eta^2 = \frac{1}{\sigma_x{}^2} \sum_{n=-N}^{N} (x(t_n) - x_n)^2 \quad (3)$$

Where $t_n = \cdots \ldots \ldots \ldots \ldots . -3T, -2T, -T, 0, T, 2T, 3T, \ldots \ldots . . , NT$

$$\alpha_d = \sum_{n=-N}^{N} \left(\sum_{k=0}^{D} [[W]^{-1}]_{dk} t_n{}^k \right) x_n \quad (4)$$

The Savitzky-Golay filter is characterized by matrix $[g]$ which has $D + 1$ rows and $2N + 1$ columns.

$$[g]_{dn} = \sum_{k=0}^{D} [[W]^{-1}]_{dk} t_n{}^k \quad (5)$$

Feature Extraction and classification

Autoregressive technique

In AR Modelling the main aim is to choose the appropriate model order because it observes the poles those exists in the model. If it is having very small value of model order, then more power spectrum exists in dominant peaks whilst spurious peaks increase for high values of model order [14].

The time series is defined as: $\{q_1, q_2, \ldots \ldots \ldots \ldots \ldots \ldots \ldots ., q_M\}$

$$y_{j+1} = \theta_1 y_j + \theta_2 y_{j-1} + \cdots \ldots \ldots \ldots \ldots \ldots \ldots . + \theta_m y_{j-m+1} + \lambda_{j+1} \quad (6)$$

For m=1

The time series is associated as

$$y_{j+1} = \theta_1 y_j + \lambda_{j+1} \quad (7)$$

This time series can be expressed in terms of least-squares estimation which involves auto covariance and autocorrelation coefficients.

$$\hat{\theta}_1 = (\phi^T \phi)^{-1} \xi = \frac{\sum_{j=1}^{M-1} y_j y_{j+1}}{\sum_{j=1}^{M-1} y_j{}^2} \quad (8)$$

$$\hat{\theta}_1 = (\phi^T \phi)^{-1} \xi = \frac{\delta_1}{\delta_o} = AR_1 \quad (9)$$

K-Nearest Neighbor (KNN) classifier

KNN is well known and non-parametric lazy learning technique. Measurement of Euclidean distance [15] is generally preferred for measuring distance between the test sample and training sample. Afterwards the classification of the test sample is obtained using known classes of K-nearest training samples. Generally, odd numbers were preferred in selecting the value of K [16].

Results and Discussion

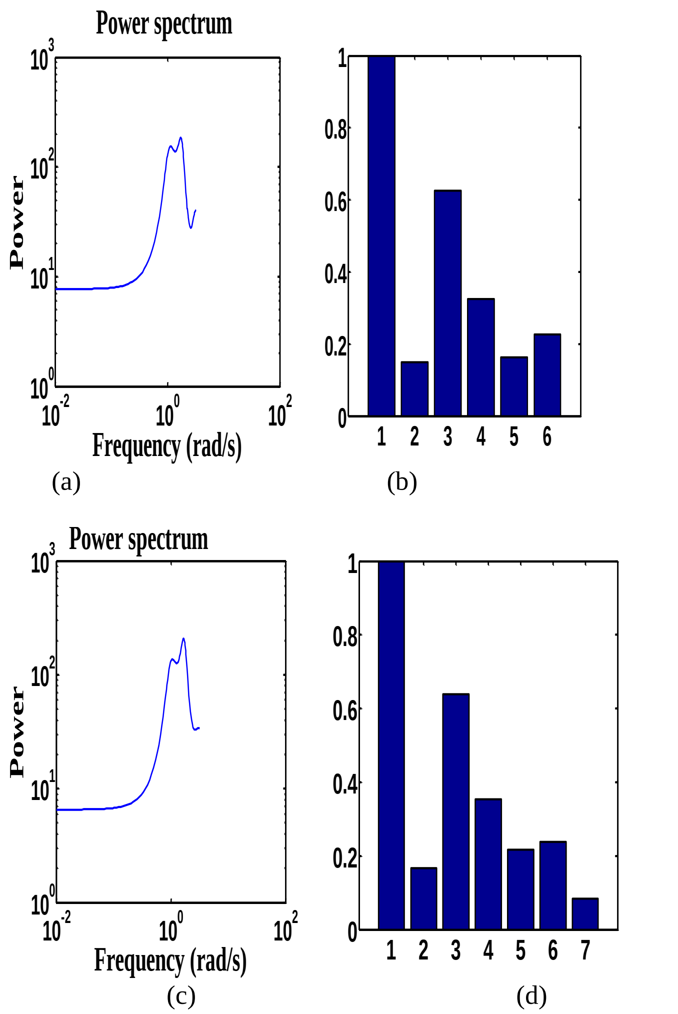
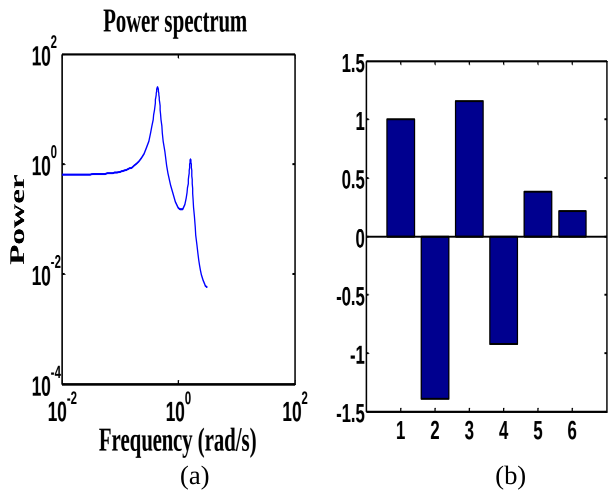


Figure.2 AR Coefficients calculation and power spectrum for Real time ECG database RT_04 at model order- (a) 5, (b) corresponding coefficients, (c) 6, (d) corresponding coefficients.



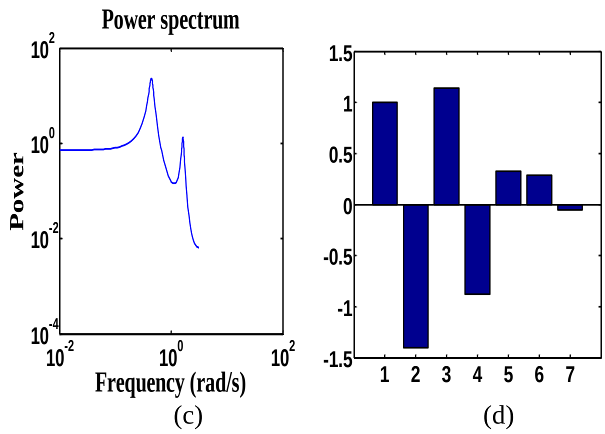


Figure.3 AR Coefficients calculation and power spectrum for Real time ECG database RT_07 at model order- (a) 5, (b) corresponding coefficients, (c) 6, (d) corresponding coefficients.

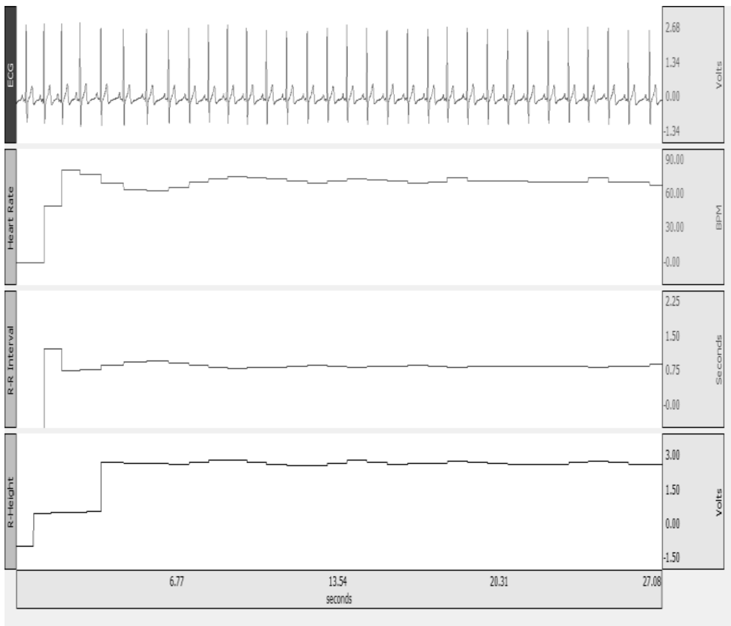


Figure.4 Selected ECG, Heart rate, RR-interval and R-Height signal

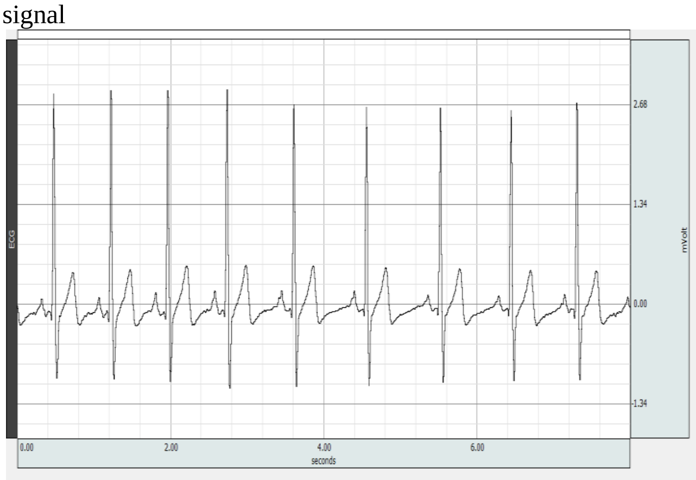


Figure.5 Selected segment of the ECG signal that is to be analyzed

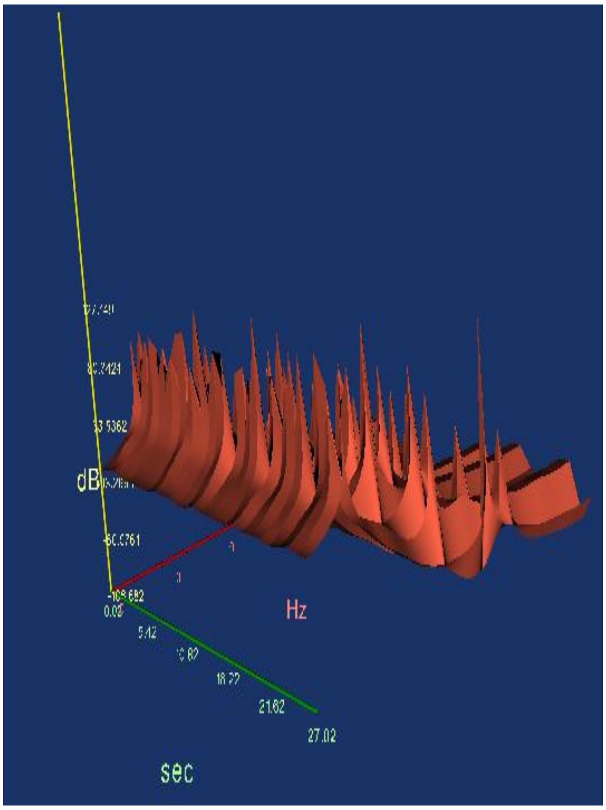


Figure.6 Detected R-peak in RT_04 database at model order 15 using ARTFA

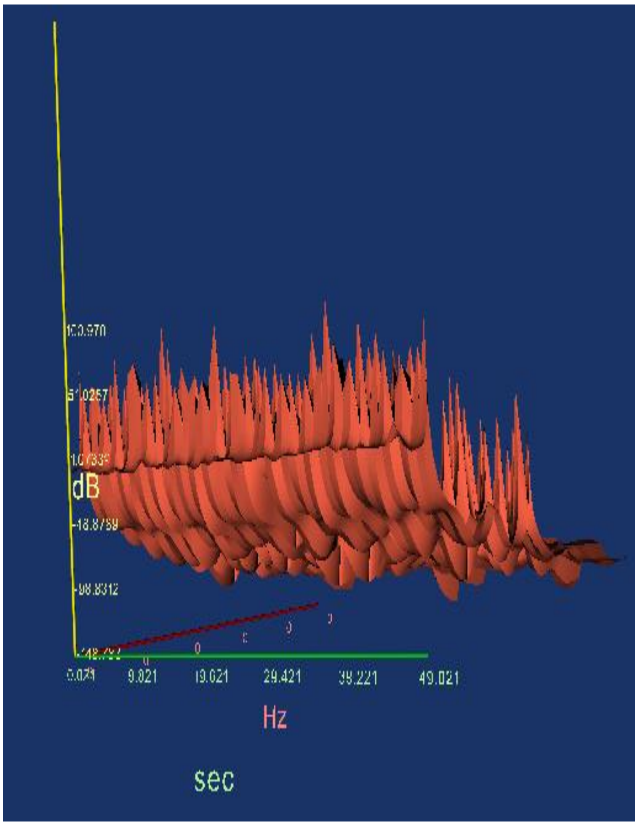


Figure.7 Detected R-peak in RT_07 database at model order 9 using ARTFA

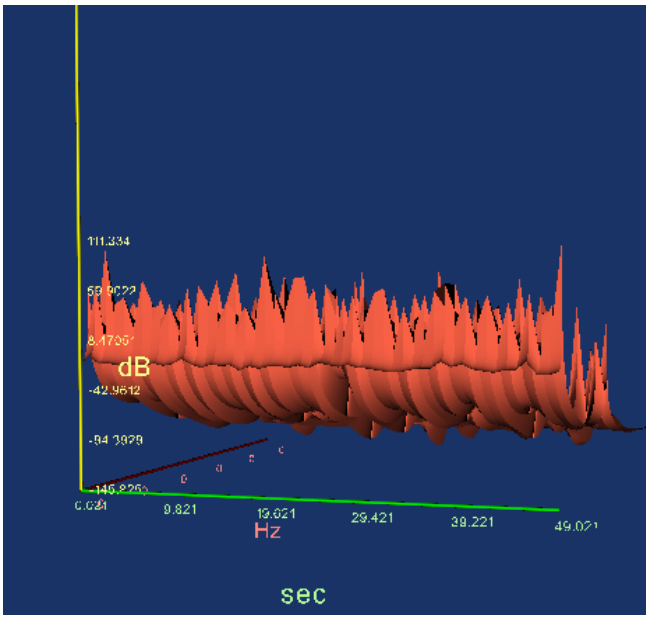


Figure.8 Detected R-peak in RT_08 database at model order 8 using ARTFA

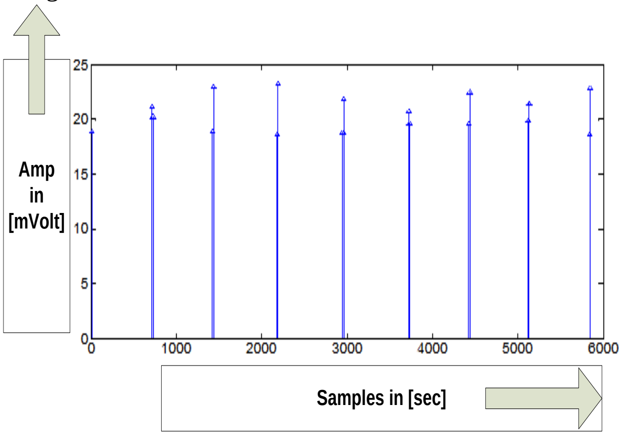


Figure.9 R-peak detection by KNN classifier after ARTFA feature extraction stage.

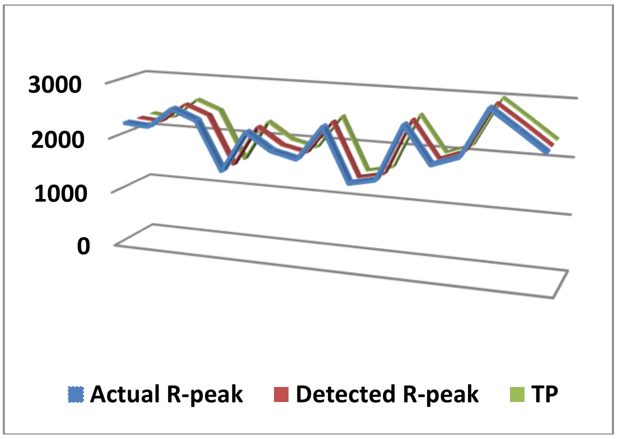


Figure.10 comparison between Actual R-peak, Detected R-peak and TP after feature extraction stage using ARTFA.

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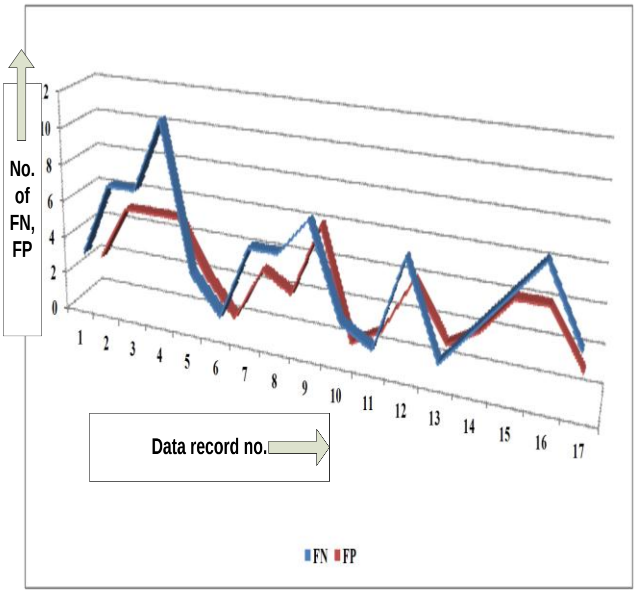

Figure.11 FN and FP values after (ARTFA+KNN) implementation.

Table. 1: Performance evaluation of the ARTFA+KNN approach.

R. T DB	Actual R-peak	Detected R-peak	TP	FN	FP
RT_01	2270	2270	2266	3	2
RT_02	2233	2233	2222	7	5
RT_03	2589	2583	2584	7	5
RT_04	2413	2412	2412	11	5
RT_05	1541	1541	1539	3	2
RT_06	2276	2276	2276	1	0
RT_07	1981	1980	1981	5	3
RT_08	1871	1881	1874	5	2
RT_09	2477	2475	2477	7	6
RT_10	1532	1523	1528	2	0
RT_11	1632	1623	1631	1	1
RT_12	2611	2609	2604	6	4
RT_13	1972	1968	1967	1	1
RT_14	2137	2141	2138	3	2
RT_15	2983	2977	2983	5	4
RT_16	2661	2662	2661	7	4
RT_17	2331	2331	2332	3	1
17 Rec.	37510	37485	37475	77	47

$$\text{Sensitivity}(R_{SE}) = \frac{R_{TP}}{R_{TP}+R_{FN}} = \mathbf{99.79\%}$$

$$\text{Detection Rate}(R_{DR}) = \frac{\text{Total True Positive(TP)}}{\text{Total Actual Peaks}} = \mathbf{99.9\%}$$

ARTFA coefficients states the clear indication of the patient heart towards normal or abnormal conditions. Figure.2 and Figure.3 indicates the arrhythmia status of the patient. It represents the status on the basis of the power spectrum and its stability on the basis of proposed model order. Figure.4 is showing selected ECG, Heart rate, RR-interval and R-Height signal and Figure.5 is showing selected segments of the ECG signal that is to be analyzed. Figure.6 shows detected R-peak in RT_04 database at model order 15 using ARTFA in 3D output. It processed with time interval of 1 seconds, frequency resolution of 1024 points with rounded up to a power of 20.09 Hz/points and amplitude scaling were selected in decibel (dB). Figure.7 is showing detected R-peak in RT_07 database at model order 9 and Figure.8 is showing detected R-peak in RT_08 database at model order 8 using ARTFA. Figure.9 showing R-peak detection by KNN classifier after ARTFA feature extraction stage. Figure.10 clearly indicates comparison between Actual R-peak, Detected R-peak and TP after feature extraction stage using ARTFA. Figure.11 is showing FN and FP values after (ARTFA+KNN) implementation. Table. 1 gives performance evaluation stage of the ARTFA+KNN approach. In [4] the improved threshold denoising algorithm was discussed for solving the problem of constant deviation of the soft threshold function. In [3] hybrid pipeline heart disease risk factor identification system has built for clinical tests that can identify diseases. In [17] AR coefficients were estimated for every 15 second duration of the ECG dataset and feature extraction were achieved using Burg's method. In [18] an efficient heart disease prediction system was proposed using data mining approach. It gave the accuracy of 86.3 % in testing phase and 87.3 % in training phase. In [19] an artificial neural network-based (ANNs) diagnostic model were given for coronary heart disease (CHD). The best accuracy was estimated with a neural network topology of multilayer perceptron with two hidden layers for models included by both genetic and non-genetic CHD risk factors. In [20] comparative study of Support Vector Machine (SVM) and Artificial Neural Network (ANN) classifier were discussed to differentiate three important signal outcomes such as health, pathology and noisy. In [7] QRS complex detection was proposed based on band pass filter, Hilbert transform and the adaptive threshold technique. At decisive stage, the Principal Component Analysis was utilized to extract features from the ECG signal. In [1] autoregressive process based on coupled differential equations in order to obtain the tachograms and the electrocardiogram signals of young adults with normal heartbeats. Results were also compared with Poincare plot and detrended fluctuation analysis (DFA). In [21] a new method was proposed for analyzing the time frequency signals effectively. It is known as Autoregressive Conditional Heteroskedasticity (ARCH) model that is useful to model observed time series. In [22] autoregressive modelling were proposed for analyzing atrial fibrillation database. They were used SVM, LDA, and nearest neighbor(NN) classifier. The performance was observed at MIT-BIH Atrial Fibrillation Database. The best obtained sensitivity, specificity, and positive predictivity were 96.14%, 93.20%, and 90.09%, respectively. In [23] classification of ECG signals were proposed and detected QRS complex, P wave and T wave. They implemented wavelet transform for interpreting the ECG signal components with optimal time-frequency resolutions.

Conclusion

ECG signal is not a pure periodic signal in nature. Even, it changes in every cardiac cycle. Due to the involvement of various types of noises, its characteristic becomes nonlinear and nonstationary in nature. For such types of application ARTFA effectively detected the R-peak in the real time ECG datasets. It gave sensitivity(R_{SE}) of 99.79% and detection rate(R_{DR}) of 99.9%. ARTFA reduces the overall burden on the KNN classifier. Therefore, KNN has been improved detection rate about 3.7%. These results will definitely enhance the application of the proposed methodology in expert systems for making decisions.

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