ADAPTIVE ECG SIGNAL TIME FREQUENCY ANALYSIS AND SIGNAL QUALITY ASSESSMENT USING AI

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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.

Keywords—Feature Extraction, SVM, PSO, ECG, DWT.

I. INTRODUCTION

Signal processing today is performed in the vast majority of systems for ECG analysis and interpretation. The objective of ECG signal processing is manifold and comprises the improvement of measurement accuracy and reproducibility (when compared with manual measurements) and the extraction of information not readily available from the signal through visual assessment. In many situations, the ECG is recorded during ambulatory or strenuous conditions such that the signal is corrupted by different types of noise, sometimes originating from another physiological process of the body. Hence, noise reduction represents another important objective of ECG signal processing; in fact, the waveforms of interest are sometimes so heavily masked by noise that their presence can only be revealed once appropriate signal processing has first been applied. Electrocardiographic signals may be recorded on a long timescale (i.e., several days) for the purpose of identifying intermittently occurring disturbances in the heart rhythm. As a result, the produced ECG recording amounts to huge data sizes that quickly fill up available storage space. Transmission of signals across public telephone networks is another application in which large amounts of data are involved. For both situations, data compression is an essential operation and, consequently, represents yet another objective of ECG signal processing. Signal processing has contributed significantly to a new understanding of the ECG and its dynamic properties as expressed by changes in rhythm and beat morphology. For example, techniques have been developed that characterize oscillations related to the cardiovascular system and reflected by subtle variations in heart rate. The detection of low-level, alternating changes in T wave amplitude is another example of oscillatory behavior that has been established as an indicator of increased risk for sudden, life-threatening arrhythmias. Neither of these two oscillatory signal properties can be perceived by the naked eye from a standard ECG printout [1-5].

II. RESEARCH MOTIVATION

The rapid advancement in the fields of electronic and communication technologies and new developments in computational algorithms such as deep learning and big data analysis have resulted in new ways of providing health care [6]. The bulky medical apparatus have been replaced by smaller electronic gadgets connected with personal computers, laptops and smart phones. For example, the company Bio Telemetry, Inc., [7] offers remote healthcare services to over one million patients over the internet [8]. One of the key components of the computerized remote health care systems is the automatic analysis and understanding of ECG signal by advanced computer algorithms. The accuracy of the analysis usually depends on the quality of the input ECG signal. The recorded ECG signal has low amplitude and is often contaminated with multiple types of noises such as power line interference (PLI), electro surgical noise, lead wire problems, base-line drift and high frequency noise components [9]. Several signal filtering methods exists in the literature to remove specific types of noise component from the ECG signal to improve its SNR. In this paper, we perform a comparative evaluation of four basic types of filtering methods including Least Mean Square (LMS), Normalized LMS (NLMS), Log LMS, and Sign LMS for ECG signal enhancement and remove the high frequency noise from the ECG signal. The high frequency is generated due to electromyography (EMG) and instrumentation noise [10].

III. DIGITAL FILTERS

The aim of the pre-processing is to achieve a noise free signal and enhance its features accurately. Digital filters can be categorized into two major types as shown in Fig. 4, i.e. fixed type of filters where the coefficients of the filters are fixed and adaptive filter where the coefficients change adaptively. Fixed filters are well suited for stationary environment and can be used for eliminating the powerline interference 60/50 Hz noise [11]. When we know which frequency is to be eliminated, fixed filters are the best choice. In case of nonstationary signals such as ECG, filters designed using advanced learning algorithms are the optimum choice. After reviewing the literature carefully, we have chosen adaptive filters as a potential candidate for the processing of ECG signal because of its flexibility to adapt to the changes in the signal. As ECG is a non-linear signal, adaptive filters are well suited for its processing [12-15].

IV. ADAPTIVE ECG SIGNAL TIME FREQUENCY ANALYSIS

Spectrum has twice the resolution as compared toFourier domain spectral representation. Thus, looking at such advantages, FBSE-EWT (Fourier–Bessel series expansion (FBSE)-based empirical wavelet transform (EWT) (FBSE-EWT) method) is used instead of EWT for extracting different modes from the given signal. New FB-based spectral entropy, such as Shannon spectral entropy (SSE), log energy entropy (LEE), and Wiener entropy (WE), have been proposed, which are used as features from the obtained modes. Then, smoothing of the feature values is performed by applying moving average over obtained features values, which is then given as input to KNN classifiers for emotional class identification. The block diagram of the proposed methodology is shown in Figure 1.

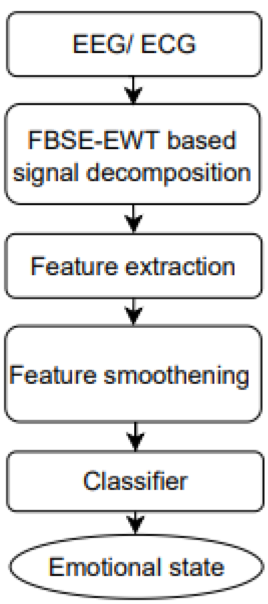

Fig.1. Flow chart and Block diagram for the proposed methodology.

Analyzing non-stationary signals such as ECG is difficult as the signal is time-varying in nature and its properties also change continuously. In order to understand the properties of such signals, decomposing them into narrow-band simpler components can help to make it easier to understand; therefore, the preprocessed signal was given to a signal decomposition algorithm, which will decompose the input ECG signal into various modes.

Raw ECG data contains some noise and artifact components that alter the shape of the ECG trace from the ideal structure, which render the clinical interpretation inaccurate and misleading; consequently, a pre-processing step for improving the signal quality is a necessity. The types of noises contaminating ECG signal include Power line Interference, Baseline Wandering, Muscle Tremor noise, Electrosurgical noise, Instrumentation noise and other less significant source of noise [3]. Among these noises, the power line interference and the baseline wandering are the most significant and can strongly affect ECG signal analysis. It is essential to reduce disturbances in ECG signal and improve the accuracy and reliability for better diagnosis. We have used Pan Tompkins algorithm, which removes baseline wander, power line noise and muscle noise in linear filtering stage using bandpass filter having passband of 5-12 Hz [6].

V. PROPOSED ALGORITHM

The KNN is one of prospective statistical classification algorithms used for classifying objects based on closest training examples in the feature space. It is a lazy learning algorithm where the KNN function is approximated locally and all

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computations are deferred until classification. No actual model or learning is performed during the training phase, although a training dataset is required, it is used solely to populate a sample of the search space with instances whose class is known, for this reason, this algorithm is also known as lazy learning algorithm. It means that the training data points are not used to do any generalization and all the training data is needed during the testing phase. When an instance whose class is unknown is presented for evaluation, the algorithm computes its *K* closest neighbors, and the class is assigned by voting among those neighbors. In KNN algorithm, training phase is very fast but testing phase is costly in terms of both time and memory [1].

The KNN algorithm consists of two phases: Training phase and Classification phase. In training phase, the training examples are vectors (each with a class label) in a multidimensional feature space. In this phase, the feature vectors and class labels of training samples are stored. In the classification phase, *K* is a user-defined constant, a query or test point (unlabelled vector) is classified by assigning a label, which is the most recurrent among the *K* training samples nearest to that query point. In other words, the KNN method compares the query point or an input feature vector with a library of reference vectors, and the query point is labeled with the nearest class of library feature vector. This way of categorizing query points based on their distance to points in a training data set is a simple, yet an effective way of classifying new points.

Parameter *K* and distance metric

One of the advantages of the KNN method in classifying the objects is that it requires only few parameters to tune: *K* and the distance metric, for achieving sufficiently high classification accuracy. Thus, in KNN based implementations the best choice of *K* and distance metric for computing the nearest distance is a critical task. Generally, larger values of *K* reduce the effect of noise on the classification, but make boundaries between classes less distinct. The special case where the class is predicted to be the class of the closest training sample (i.e. when *K* = 1) is called the nearest neighbor algorithm. In binary classification problems, it is helpful to choose *K* to be an odd number as it avoids tied votes. Thus, the value of *K* is defined in such a way that it produces the highest correct classification rate [1]. In this work the different values of *K* which have been tested are 1, 3, 5, 7 and 9. Further, the different distance metrics which are used in this work are Euclidean distance, City Block and Correlation.

VI. RESULT AND SIMULATION

In this paper, peak detection was performed using KNN algorithm. After comparative analysis of transforms, we found that EWT gives zero distortion and Wavelet transform gives distortion in the range of 10- 11 after reconstruction of signal. The signals were decomposed up to 4 levels using biorthogonal 4.4 wavelet family.

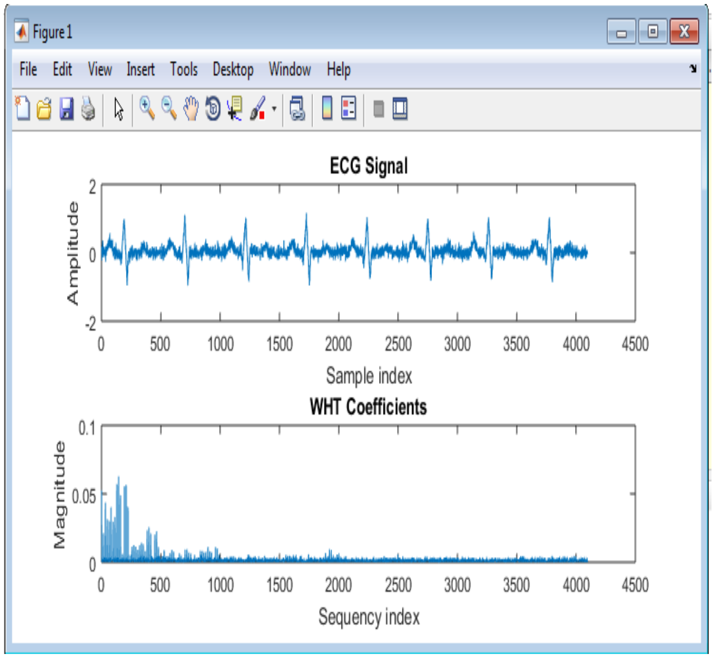

Fig.2. ECG magnitude.

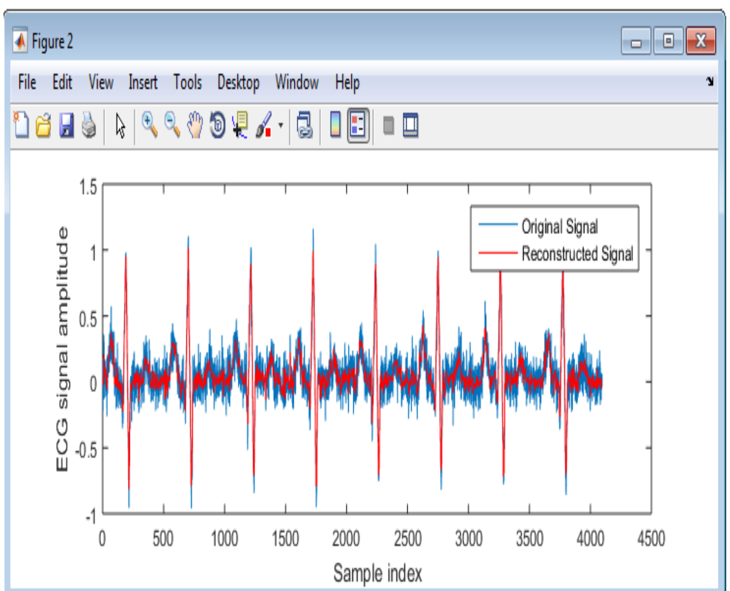

Fig.3. Sample index.

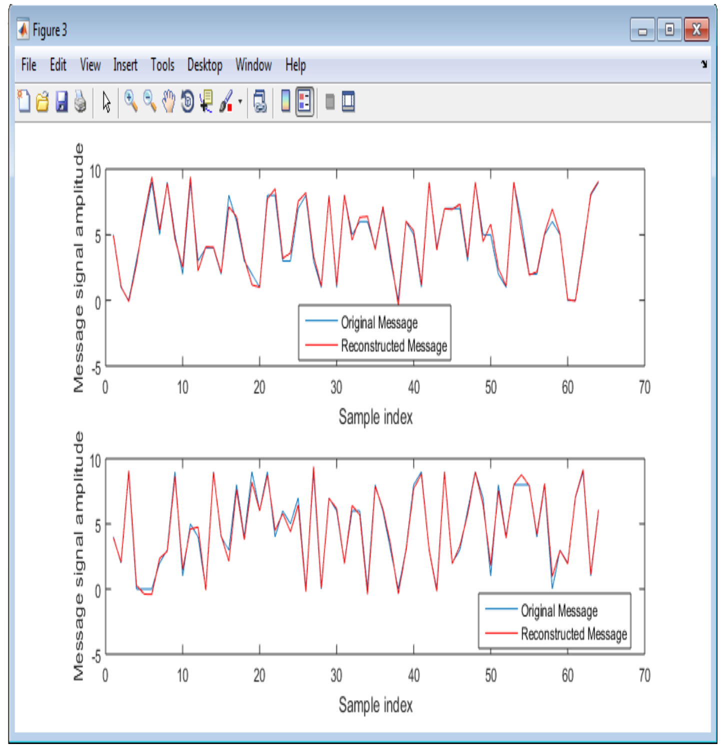

Fig.4. Both Comparison.

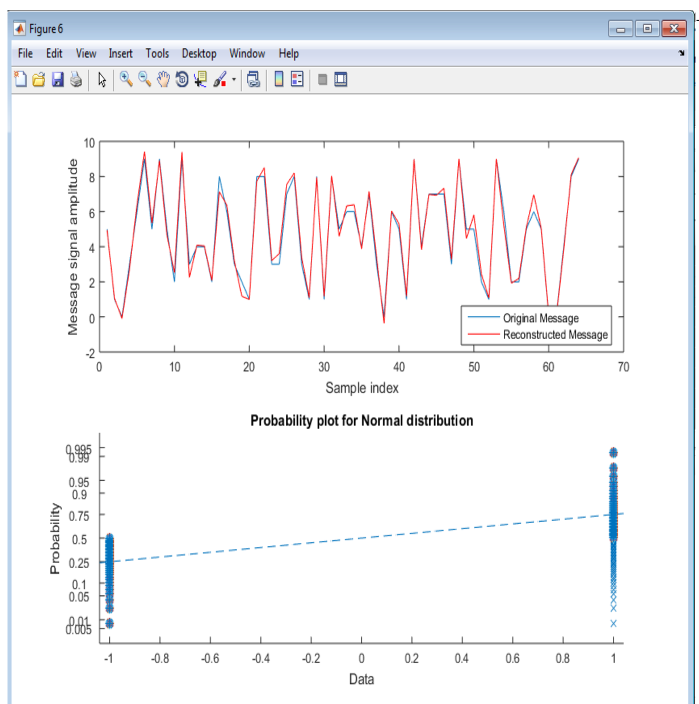

Fig.5. KNN Peak classification

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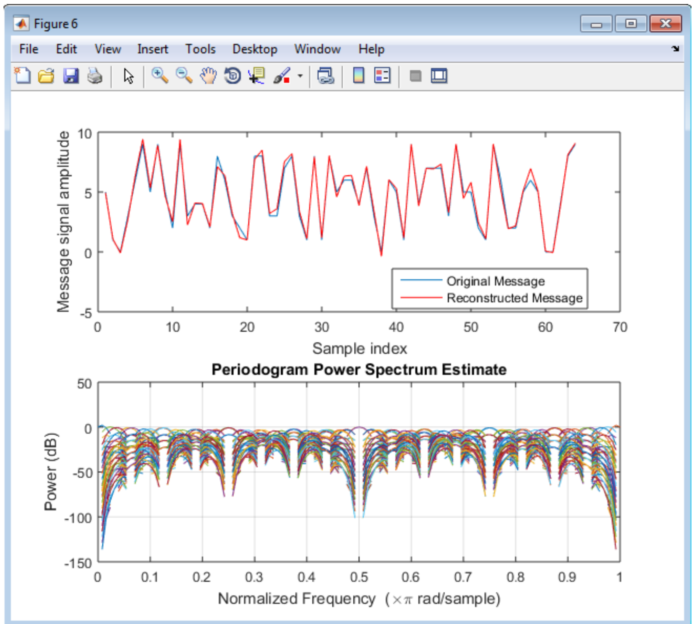

Fig.6. Power spectrum estimation.

VII. 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 knn Probability of 0.25% to 0.75%. ARTFA reduces the overall burden on the KNN classifier. Therefore, KNN has been improved detection rate about 50%. These results will definitely enhance the application of the proposed methodology in expert systems for making decisions.

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