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Performance Analysis of ECG Signal by Wavelet Transform, Independent Component Analysis and Fast Fourier Transform

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ABSTRACT

ECG plays a vital role in the analysis of various heart diseases as the shape of the ECG waveform consist of vital information about heart conditions such as its electrical conduction or muscle activity. Inspite of the conventional method the extraction of ECG features is of major significance and benefit for the diagnosis of numerous harmful or even critical cardiac diseases. The feature extraction plays a vital role in diagnosis of the various cardiac diseases. Each cycle of an ECG signal contains of the P-QRS-T waves. This scheme of feature extraction describes and provides the amplitudes and intervals in the ECG signal for further investigation. The amplitudes and intervals value of P-QRS-T segment shows the operation of heart. Recently, various techniques have been evolved for analysis of the ECG signal. This paper discusses three most widely used methods used to extract the different features of Electrocardiograph (ECG) signals namely Wavelet Transform (WT), Fast Fourier Transform (FFT), Independent Component Analysis (ICA). The study conveys the information that the Fast Fourier Transform method gives better performance in frequency domain for the ECG feature extraction. Accuracy of Wavelet Transform is 92.20%, of the Fast Fourier Transform is 92.47%, and of the Independent Component Analysis is 90.13%. It has been observed that FFT shows better performance regarding the ECG signal analysis. Moreover, provides efficient estimation of the PSD from noise corrupted signals. But the limitation of this method is the leakage decreases the ability of FFT to resolve two frequencies of close space. But by the use of a window function will reduce this leakage.

Keywords : ECG feature extraction, Wavelet Transform, ICA, FFT.

I. INTRODUCTION

ECG basically plays the vital role in the cardiac arrhythmia diagnosis. It is generally the graphical representation of the electrical activity of the heart muscles. As we know that in the current era, numerous feature extraction techniques have been developed in order to determine the up to date circumstances of heart activity through investigation of rhythms and distortions found in ECG. The timing statistical-based features [1] which have been extracted from ECG signal that includes P and QRS widths, PQ/PR and QT intervals, P and T amplitudes, QRS height, and ST level. The extracted features include both the persistent and non-stationary characteristics of the ECG signal. The investigation of both the temporal and spatial assessments of cardiac activities has proved the dominance of spatial investigation for characterizing and classifying the ECG features [2] especially for the ventricular arrhythmias. This study provides a review of the three most common techniques used for ECG feature extraction.

II. METHODS AND MATERIAL

A. Wavelet Transform (WT)

Although the Wavelet transform can provide good localization in frequency and time domain simultaneously, yet it performs significantly for the local analysis of non-stationary signals. [3] Can define a single wavelet:

$$\Psi^{a.b}(x)=|a|^{-\frac{1}{2}}\Psi(\frac{x-b}{a}) \qquad (1)$$

The inner product of $\Psi^{a,b}$ and function *f* gives wavelet transform as follows [3]:

$$W_{\Psi}(f)(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\Psi(\frac{t-b}{a})d(t) \qquad (2)$$

Lipschitz exponents have been used as a method to measure a function local regularity [4]. A function is defined as Lipschitz α (α is denoted as Lipschitz exponent) at x_0, if and only if two constants *A* and h_0 (>0) can be presented such that for $h \leq h_0$:

$$f(x_0+h)|-P_n(h)\leq A|h|^a \qquad (3)$$

Where p_n (h) represents a polynomial of order n being a positive integer.

If the wavelet transform of a function has no modulus maxima within a given interval, the function is Lipschitz α while α is close enough to one in that specific interval. In other words it can be concluded that a function cannot be singular if its wavelet transform does not have any modulus maxima of fine scales in that particular neighborhood [3]. The meticulous processing of ECG signal through detecting its modulus maxima and also by performing the Wavelet multi-scale decomposition of the signal a zero cross is obtained. As a result the number and location of the QRS complexes can be defined accurately through this analysis. Despite the great superiority of wavelet method, there are also some conditions which this method may not perform properly. The presence of arrhythmia which may lead to inaccurate detection of QRS complexes or by the application of 3-lead actual gathering system of ECG signal causes loss of some vital and useful information of the signal are among the conditions which can limit the efficiency of the Wavelet transform.

B. Fast Fourier Transform (FFT)

FFT is a method to extract out useful information from the statistical features of ECG signal. Assuming T_0 as period and the periodic signal *f(t)* that is been represented by the Fourier series [7, 8]:

$$f(t)=A_0+\frac{1}{2}\sum_{n=-\infty}^{+\infty} a_n - jb_n\, e^{j2\Pi n/T0} \qquad (4)$$

α_n represents complex coefficients of the Fourier series and can be shown in exponential form:

$$\alpha_n = \frac{1}{T_0}\int_{-\frac{T_0}{2}}^{\frac{T_0}{2}} f(t)\, e^{-\frac{j2\pi nt}{T_0}} dt$$

$$n = 0, \pm 1, \pm 2, \ldots \qquad (5)$$

As ECG frequency bands are limited to 0.05-40 Hz therefore restricted numbers of frequency coefficient are enough to monitor. The efficiency of FFT algorithm is good but it suffers from two disadvantages. These are firstly; the quantization value in discrete spatial domain is the reciprocal of the time duration. The big space as a result of short data records makes it very difficult to portrait the modification in the dominant frequencies of ventricular fibrillation over short time periods. Secondly, the presence of finite epochs in data produces frequency components in the observed data that doesn't respond to the frequency components of discrete spectrum. This causes the spectrum peaks to increase [9, 10]. This leakage decreases the ability of FFT to resolve two frequencies of close space. But by the use of a window function will reduce this leakage [11].

C. Independent Component Analysis (ICA)

Independent component analysis (ICA) is a method that searches multivariate statistics which are statistically independent [13]. The ICA method has various application is various areas such as in the field of biomedical signal processing including Electro Gastrogram (EGG) separation [14], separation of fetal and maternal ECG signals [15], EEG and MEG recordings analysis [16], and feature extraction and classification of ECG signals [17, 18]. However, ICA usually produces a large number of independent components (ICs) which are in an arbitrary order that provides necessary dimension reduction in the feature space. On the other side, random order of the ICs makes it difficult to determine the relative significance of each IC to be obtained in the task. It produces a set of random variables in terms of linear combinations of statistically ICs [19]. Assuming the observed m random variables $x_1(t)\ldots x_m(t)$ are modeled at time instant *t*, as linear combinations of *n* random variables $s_1(t), \ldots, s_n(t)$. Applying the vector matrix notation, the mixing model is [19-22]:

$$X=A.S \qquad (6)$$

where $x(t) = [x_1(t), \ldots, x_m(t)]T$ represents the mixing signal, $s(t) = [s_1(t), \ldots, s_n(t)]\ T$ is the source signal, and A shows the mixing matrix with real coefficients a_{ij} ($i = 1,\ldots,m$; $j = 1,\ldots,n$).

III. RESULTS AND DISCUSSION

Performance Analysis of Methods Used

Performance of the three ECG feature extraction techniques and sensitivity and specificity of these feature been extracted are calculated using quantitative parameters. The results are provided in Table I and II [2, 5, 7, 12, 23-25] by the application of ventricular late potential detection in terms of their sensitivity and specificity.

Table I. Comparing Three ECG Feature Extraction Methods In Terms Of Sensitivity and Specificity

METHOD USED	WAVELET TRANFORM	FAST FOURIER TRANSFORM	INDEPENDENT COMPONENT ANALYSIS
SENSITIVITY	61%	81%	97.8%
SPECIFICITY	75%	98%	99%

Here ICA showed better results as compared to FFT [26]. However, FFT model results in so many missing and null values while all of the spectral components can be obtained using ICA.. Furthermore it has been shown that for both FFT and ICA methods their reproducibility significantly decreases for short-term recordings [27]. Table II presents a brief summary of the feature extraction methods along with their characteristics [2, 5, 7, 12, 23-25, 28].

TABLE II. AN OVERVIEW OF COMPARING THREE DIFFERENT FEATURE EXTRACTION METHODS

FEATURE EXTRACTION METHOD	APPLICATION DOMAIN	COMPETENCE	SUITABLE CLASSIFICATION METHOD	ACCURACY
WAVELET TRANFORM	Time-frequency	Local investigation of fast time varying and irregular signals	ANN	92.20%
FATS FOURIER TRANSFORM	Time-frequency	Short-term heart rate variability	ANN	92.47%
INDEPENDENT COMPONENT ANALYSIS	Time-frequency	Linear mixtures of independent sources	Fast ICA	90.13%

IV.CONCLUSION

The ability of the applied feature extraction techniques provides an accurate representation of the original signal show great importance while calculating its efficiency. WT, FFT and ICA are discussed in this paper for extracting features of the ECG signal. However, the sensitivity and specificity of the applied methods still are not agreeable. As a result, it can be said that among other methods, FFT has been shown better performance regarding the ECG signal analysis. Moreover, it can provide efficient estimation of the PSD from noise corrupted signals. One disadvantage of this method is the leakage decreases the ability of FFT to resolve two frequencies of close space. However, by the use of a window function will reduce this leakage.

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