ECG Arrhythmias Classification by Combined Feature Extraction Method and Neural Network

Khalooq Y. Al Azzawi
Electromechanical Engineering Department, University of Technology/ Baghdad
Email: kynal9@yahoo.com

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ABSTRACT

Electrocardiogram (ECG) became one of the most crucial tool for heart status diagnosis. Generally, several arrhythmias may appear based on different heart rate or ECG signal morphology variation. In this paper, a novel combined feature extraction method to present ECG arrhythmias is proposed. The combination between Wavelet Packet Transform (WPT) entropies and Power Spectrum Density (PSD) is suggested. For classification, Feed Forward Backpropagation Neural Network (FFBPN) is utilized. The experimental results showed that the proposed method can be beneficial for ECG signal arrhythmias classification. MIT-BIH Arrhythmia Database was used for algorithm testing. The proposed method was compared with three state of art methods, where was of better performance reached about 80%. The proposed method as well as other methods was tested in noisy environment for comparison investigations. The suggested method is promising approach for arrhythmias classification. However, enormous testing data set might significantly improve the results.

Keywords: ECG, Wavelet, PSD, Arrhythmia. FFBPN.

تصنيف عدم الانتظام بإشاره قلب الانسان باستخدام أسلوب مركب والشبكه العصبونيه

الخلاصة

إشارة تخطيط القلب أصبحت واحدة من أكثر الأدوات الحاسمة في تحليل حالة القلب بشكل عام . قد تظهرمعالم للعديد من عدم إنتظام ضربات القلب بناء على معدل ضربات القلب المختلفة أو شكل إشارة تخطيط القلب .

في هذا البحث تم إقتراح طريقة لأستخراج الملامح (Feature Extraction Method) لعدم انتظام ضربات القلب . وقد جمع بين الإنتروبيا لتحويلة المويجات وكثافة طيف الطاقة لغرض التصنيف,حيث أظهرت النتائج التجريبية أن الطريقة المقترحة يمكن أن تكون مفيدة لتمييز حالات عدم انتظام ضربات القلب, حيث تم استخدام قاعدة بيانات معهد ماساتشوستس للتكنولوجيا لأختبار الخوارزمية , وقد تم الحصول على أداء أفضل من الأساليب الاعتيادية بحصوله على النسبة 80%.

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2412-0758/University of Technology-Iraq, Baghdad, Iraq

INTRODUCTION

The ECG is the electrical work signal of the human heart, which is totally significant in heart problems analyses, where every arrhythmia in ECG signals may be associated to a heart disability. The main contest in heart disease judgment for ECG is that the conventional ECG can vary for each human being or for single disease has special signs on diverse patient's ECG signals.

Moreover, two separate syndromes could have just about the same effects on normal ECG signals. These complications confuse the ECG and disease recognition. Hence, employment of sample classifier procedures may suggest an enhanced an ECG arrhythmia judgment [1-3]. For instant, Atrial fibrillation (AF) has in current era been the subject of deep study in framework of attaining a superior understanding of its system and refining its running. It is the most shared continued cardiac arrhythmia, taking place in 1-2% of the overall people. more than 6 million Europeans suffer from this arrhythmia, and its occurrence is expected twice in the next 50 years as the residents ages. AF is an arrhythmia in which electrical action in the atria is confused as a substitute of the sinus node given that the usual electrical signals to the atrium, speedy circulating waves of irregular electrical signals constantly stimulate the atrium. Scientists, who tried to discover AF previous to, mostly utilized time-frequency study techniques, statistical tools and sequential study methods. For example, Stridth et al have performed time-frequency analysis to construct trends of AF frequency. Wigner-Ville sharing technique and Choi-Williams sharing were utilized for the short term and long term time-frequency investigation. They have establish that chronic AF has time varying characteristics [4-6]. Tateno et al. have analyzed AF in order to discover the AF based on RR intervals. Their manner utilizes typical density histograms and experimental density histograms of RR intervals and the time distinction between sequential RR intervals. When two histograms are not considerably different from each other, the ECG is classified as AF [7].

Another work on recognition of AF was conducted by Christovet al [8]. They used sequential analysis to test the absence of P-wave, existence of ventricular arrhythmia and atrial activity. Stridth and Sornmo have investigate to distinguish AF centered on time-frequency sharing of the QRST canceled ECG signals [9]. Records concerning sequential variations in fibrillation frequency and waveform nature was extracted and discovered. Cerutti et al. test the dynamics of RR intervals in standard SR and AFECGs by using parameters ensuing during an autoregressive modeling and corrected provisional entropy methods [10].

Guler et al. proposed ECG beat classifier utilizing Physiobank database and shared artificial neural network (ANN) model, with superior accuracy of 97% when compared to the use of stand-alone neural network model [11]. ANN is a well-known classifier that could be utilized for ECG arrhythmias classification. Multi-layerperceptron (MLP) is presented to be able to identify and categorize ECG signals more precisely than other ANN methods. Still, MLP with backpropagation exercise algorithm suffers from limited convergence to local and universal minima and from arbitrary settings of weights and initial values[12]. Development of ANN's quality has been the topic of involved researches on ECG arrhythmias arrangement by different feature extraction procedures. Ozbay et al. compared the capability of fuzzy clustering neural network architecture with multilayered perceptron with backpropagation exercise algorithm for classification of arrhythmias.

The research proved the dominance of the presented scheme in term of classification time which is a result of decreasing the number of segments by grouping analogous segments in training data with fuzzy c-means clustering [13,7]. Discrete wavelet transform is used to develop the quality of MLP with (BP) training algorithm and also compared with additional feature extraction algorithms and data reduction methods [13]. Many researchers has shared the MLP neural network with DWT for superior accuracy [14]. Besides an ECG strike classification system based on DWT and probabilistic neural network (PNN) [4, 23] is proposed to differentiate six ECG strike types [15]. The ECG recordings were treated by means of CWT [6] and DWT to expect the maintenance of sinus rhythm after cardio edition in patients with detected atrial fibrillation[16],[1].

Numerous typical methods of system study have been used to morphological classification of the Set[19]. Both ANN [17], and system modeling [18] have been shown to be advanced over traditionally frequency field and signal-averaged ECG methods that accomplished an accuracy of about 85%. In [21], author found good reasons for testing the value of a wavelet- linear discriminant analysis set classification scheme. First, while the utilize of wavelets for analysis and classification of biomedical signals, with some components of the ECG are well documented [19],[20], wavelet analysis particularly of the Set has not received much revision. Wavelets offer a considerable information-rich parameterization method for data reduction of the ECG time-series. Secondly, neural networks functionally diverse from linear discriminant study (i.e. those with a hidden layer) require huge samples due to the huge number of parameters to be expected. This is often not sensible. Third, linear discriminant analysis is relatively guess free, dissimilar model-based approaches. The results by [19] for the individual Set approach normally outperformed the typical cardio logical measures and the signal-averaged P-wave attitude. Our purpose is to develop the quality technique for numerous types of arrhythmias classification. For this cause many published techniques are studied. The construction of this article, we present the wavelet packet transform feature extraction algorithm, followed by classification methods. Subsequently results will be available. At the end, conclusion is given.

WAVELET TRANSFORM

The Wavelet Packet Transform (WPT) and the Discrete Wavelet Transform (DWT) are almost very similar, with some clear differences in the coefficients decomposition, while the DWT performs the decomposition process on approximations; the WPT decomposes coefficients in both details and approximations.

The mother wavelet function is presented in equation (1), and the wavelet transform is taken by the inner product of the data function $x(t)$ and the mother wavelet $\psi(t)$ [23]:

$$\psi_{a,b}(t) = \psi\left(\frac{t-b}{a}\right) \quad .....(1)$$

$$W_{\psi}x(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi*\left(\frac{t-b}{a}\right)dt \quad ...(2)$$

where a and b are the scale and shift parameters, respectively. By means of varying the parameters a and b, the mother wavelet $\psi(t)$ will be scaled and translated. Technically, wavelet packet (WP) customs a pair of low pass and high pass filters to produce two sequences. The two wavelet orthogonal bases made from a previous node are defined as:

$$\psi_{j+1}^{2p}(k) = \sum_{n=-\infty}^{\infty} h[n]\psi_j^p(k-2/n) \qquad \ldots(3)$$

$$\psi_{j+1}^{2p+1}(k) = \sum_{n=-\infty}^{\infty} g[n]\psi_j^p(k-2/n) \qquad \ldots(4)$$

where $h[n]$ and $g[n]$ are the low-pass and high-pass wavelet functions (filters), respectively. $\psi(n)$ represents the wavelet function, while the parameters *j* and *p* represents the number of decomposition levels and nodes of the previous node, respectively [23].

ENTROPY

The entropy is a communal theory in the academic community, predominantly in image and signal processing. Typical entropy-based benchmark defines information-related possessions for a precise representation of a given image. Entropy is commonly used in image processing; it possesses information about the concentration of the image [27]. In contrast, a method for measuring the entropy appears as a supreme tool for measuring the ordering of non-stationary processes With the purpose of investigating a better ECG features, different types of entropy is being tried [27],

The non-normalized Shannon entropy,

$$E(s) = -\sum_{\tau} s_{\tau}^{2} \log(s_{\tau}^{2}) \qquad \ldots(5)$$

The log-energy entropy,

$$E(s) = \sum_{\tau} \log\left(s_{\tau}^{2}\right) \qquad \ldots(6)$$

The Threshold entropy,

$E(s) =$ the number of times where $|s_{\tau}|$ is greater than the threshold $\mathbb{P}$ … (7)

Where s is the input, and s_{τ} are the coefficients within the input signal.

METHOD

In this paper, a combination of three sets of coefficients obtained from the real ECG signals for ECG feature vector constructing to be used for arrhythmias diagnosing. The first set is composed of several features calculated from the direct ECG signal. The second set is composed of several features calculated from the power spectrum density of ECG signal. And the third set contains features obtained from WPF. The feature extraction method is summarized as follows.

- Pre-processing: Before the signal is given to the feature extraction unit, the ECG signals is to be pre-processed and normalized to remove probable drift of baseline[3], interferences, noises[2], etc.

- Direct data feature set: to compose this set we calculate the first five R-R intervals, first five P wave time duration and first five T wave time duration. The characteristic points (Onset, Offset and location of the peak of R is found based on the work in [3]). Also, standard deviation max and min and mean value of the direct ECG signal are obtained.

$$S1 = \{R - R_1, \dots, R_{R_{10}}, P_1, \dots, P_{10}, T_1, \dots, T_{10}, m, Max, Min, \sigma\} \qquad \dots(8)$$

where $R - R_1$ is time interval between two subsequent R waves, P is time interval between two subsequent P waves, T is time interval between two subsequent T waves, m is the mean value, and Max, Min are the maximum and minimum, respectively. σ is the standard deviation.

- PSD data feature set: the set here is obtained from PSD of the ECG signal. Advantage of such approach is to find out the energy behaviors over the frequency domain. This set is composed of the first ten local maximas, and the correspondent frequency for these maximas.

$$S2 = \{LM_1, \dots, LM_{10}, f_1, \dots, f_{10}\} \qquad \dots (9)$$

where, LM is the local maxima and f is the frequency.

- WPT data feature set: this set contains the Shannon entropy, threshold entropy and log energy entropy, getting out from each node of WPT tree at level 3.

$$S1 = \{SE_1, \dots, SE_{10}, TU_1, \dots, TU_{10}, LE_1, \dots, LE_{10}\} \qquad \dots (10)$$

where, SE is the Shannon entropy, TU is the threshold entropy and LE is the log energy entropy.

- The feature vector that presents ECG signal is built from these three sets and is fed as an input for classification, and is formed as:

$$S1 = [S1 \;\; S2 \;\; S3] \qquad \dots (11)$$

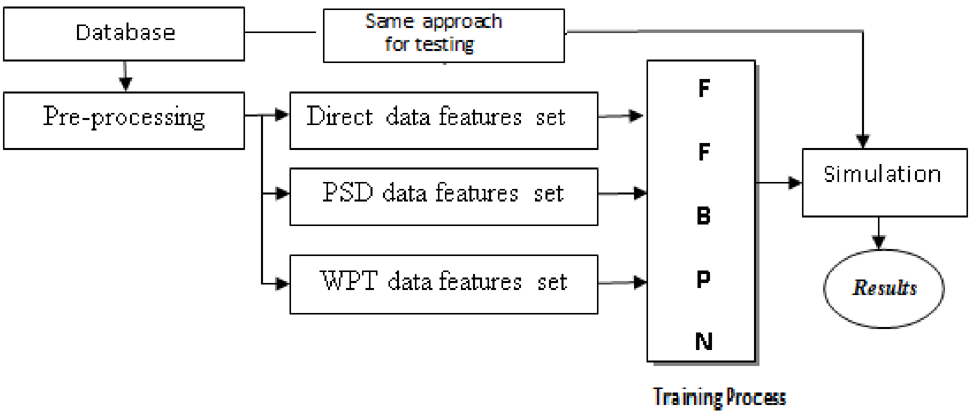

Figure (1) The flow chart of the proposed procedure. After training the certain number of patterns by means of FFBPN, testing process is performed for recognition the feature vectors of the testing samples. The output of the training process is given to the testing stage, where the simulation process for testing features is performed. The output of the simulation process will determine the class.

CLASSIFICATION

In this work, FFBPN is proposed for arrhythmias classification. The training parameters used in this work were taken for the best performance. These parameters are: four Input layers (with 20 neurons), two hidden layers (with 10 neurons) and two output layers (with 5 neurons). Weight function used in the algorithm is DOTPROD and training function is Levenberg-Marquardt Backpropagation with activation function Log- sigmoid, performance function (mse) is 10^{-5} and number of epochs is 20.

The feature vectors are fed as columns in the training matrix, which presents all four arrhythmias types to the FFBPN classifier. The last layer is the network output (target) is constructed as a five binary digits for each features vector [24]:

$$T = \begin{bmatrix} 0\,0\,0 \ldots 1 \\ 0\,0\,0 \ldots 0 \\ 0\,0\,0 \ldots 0 \\ 0\,1\;\,1 \ldots 1 \\ 1\,0\;\,1 \ldots 0 \end{bmatrix} \quad \ldots (12)$$

24 ECG signal feature vectors are trained. Six signals for each arrhythmia type are trained. After training the certain number of patters by means of FFBPN, testing process is performed for recognition the feature vectors of the testing samples. The output of the training process is given to the testing stage, where the simulation process for testing features is performed. The output of the simulation process will determine the class

The testing signals simulation result is compared with each of the 24 patterns target code to get the decision.

RESULTS

In this paper, MIT-BIH Arrhythmia Database was used for algorithm testing. The used database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, taken by the BIH Arrhythmia Laboratory between years 1975 and 1979. The recordings sampling frequency is 360 Hz per channel with 11-bit resolution over a 10 mV range [25] [26]. ECG signals taken from MIT-BIH are utilized for training and testing. The proposed algorithm is based on feature extraction and classification as shown in the flow chart (Fig.1). In the experiments three types of arrhythmias were used for algorithm testing: atrial fibrillation AF, normal sinus rhythm NSR and congestive heart failure CHF as seen in figure (2) and Figure(3). 80 signals of 15 second were used for each type. 6 signals were for training and the remaining was for testing. The table 1 presents the typical performance results in term of classification rate. The tabulated results show that the method is beneficial in arrhythmia classifications. The best results was achieved for AF with classification rate reached 83.78%.

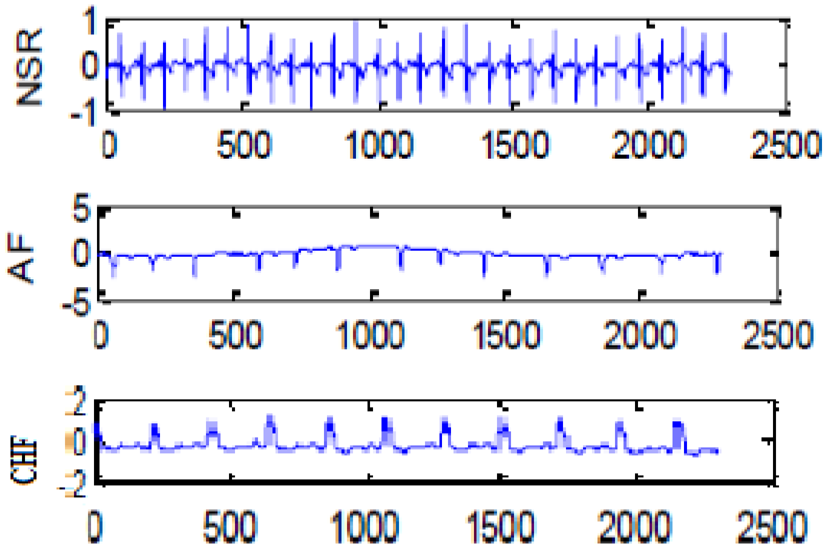

Figure (2) Three types of arrhythmias were used for algorithm testing: atrial fibrillation AF, normal sinus rhythm NSR and congestive heart failure CHF.

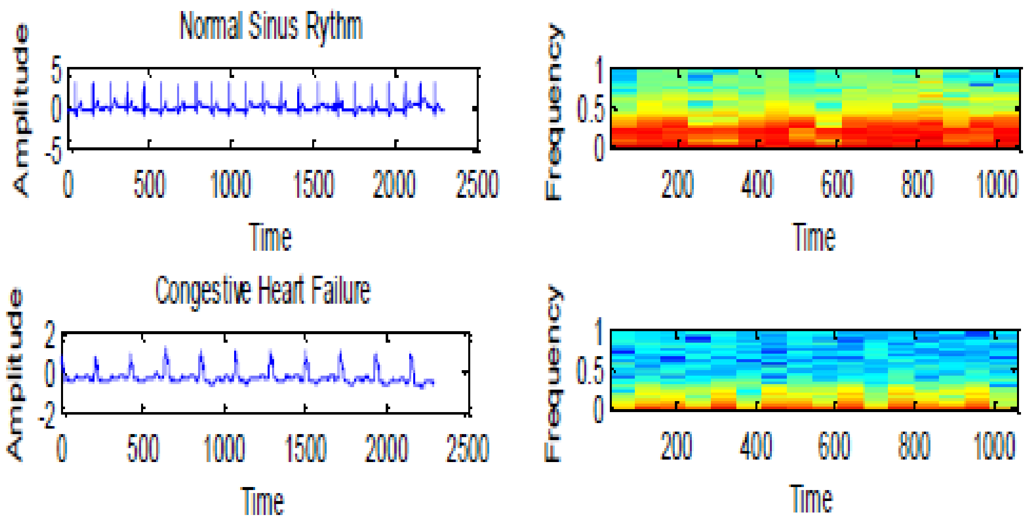

Figure (3) Illustration of normal atrial rhythm signal and congestive heart failure signal by means of spectrogram using a Short-Time Fourier Transform (STFT). We can notice the distinct illustration between the two types by the spectrogram.

Table(1) Typical performance results in term of classification rate.

Arrhythmia type	Number training/testing	Classified Correctly	Classification Rate
NSR	6/74	57	74.02%
AF	6/74	62	83.78%
CHF	6/74	61	82.43%

In the next experiment Table (2), several methods were investigated for comparison. Shannon entropy with probabilistic neural network (SEPNN) [14], fast Fourier transform and FFBPN (FFTNN) [4], time-frequency and FFBPN (TFNN) [8], were studied for comparison. The best result was achieved for our method.

Table(2) Comparison between several methods in term of classification rate.

Method	Classification Rate
SEPNN	64.43%
FFTNN	74.59%
TFNN	73.78%
CFNN	79.52%

Table (3) presents a comparison between the methods presented in Table (2) in noisy environment. The used noise is a real noise taken from ECG signal after filtration. The methods were performed in the noise existing of 0 dB SNR and 5 dB SNR. The proposed method could accomplish reasonable performance, particularly in 5 dB SNR.

Table(3) Comparison between several methods in term of Classification rate in noisy environment.

Method	Classification Rate 5 dB	Classification Rate 0 dB
SEPNN	43.34%	20.45%
FFTNN	54.10%	40.00%
TFNN	61.53%	53.41%
CFNN	68.67%	57.47%

In the last experiment, the correlation coefficient as evaluation measure is performed. Two methods are involved in the experiment. WPT and entropy used in the set three of our feature extraction method at level three denoted by (WPEF). The second method is DWT at level five with the same three entropies used in set three denoted as (DWTEF). For evaluation the performance of these method, correlation coefficient between the features set of an ECG signal of one arrhythmias case and another of same arrhythmias case is calculated for 40 signal pairs. The results are illustrated in the Figure (4), where we can notice that WPEF is better in term of correlation coefficients. This proves that our choice of WPT in set three was valid.

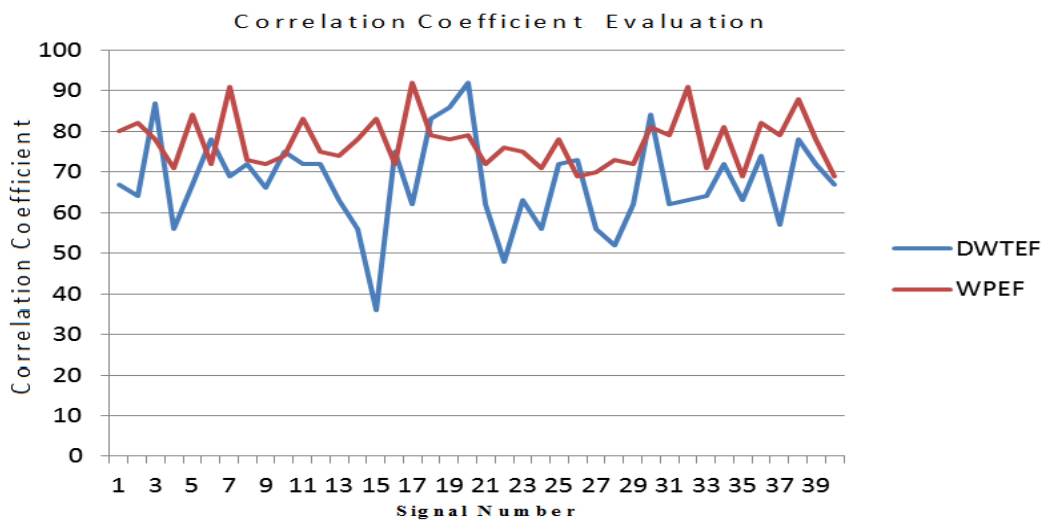

Figure (4) The correlation coefficient as evaluation measure of two methods: WPT and entropy at level three (WPEF). The second method is DWT at level five with the same three entropies used in set three (DWTEF).

WP transform has overcome DWT in the task of arrhythmia recognition. The reason behind that is the possibility of decomposing the signal from the low pass frequency subsignals as well as high pass frequency subsignals. This enriches the feature vector with more detailed features.

CONCLUSIONS

The recent paper presents a proposed combination of several features for ECG arrhythmias classification. The method extracts the arrhythmias distinguishing coefficients over three sets of features. The sets construction is based on three ideas: direct data features, wavelet features and spectral features. For classification FFPBN has been proposed, which has been fed by the feature vectors in columns forms to be trained. Three types of arrhythmias NSR, AF, and CHF have been tested. Two types of wavelet transform WPT and DWT, were used. As a matter of fact, the proposed method performed good results in term of classification rate. For comparison, three published method were used. The experimental results showed that the proposed method is superior. The method performs better results in noisy environment, with comparison with the conventional methods. WPT has overcome the DWT in term of correlation coefficient evaluation. The wavelet transform utilization in the feature extraction procedure could enhance the results significantly overcoming the conventional methods. The reason behind that is the possibility to get features thru the different wavelet transform subsignals.

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