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Cardiac Diagnostic system based on time-frequency features

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Abstract: Cardiovascular diseases are one of the most frequent and dangerous problems in modern society nowadays. Therefore, it is very difficult to take immediate measures without real time electrocardiogram information. Unfortunately ECG signals, during their acquisition process, are affected by various types of noise and artifacts. This paper presents a diagnostic method which is based on time-frequency features of the ECG signals to classify four types of electrocardiograms (ECG): normal case, or one of the following three types of arrhythmias VCouplet, VTachy, VBigeminy. The proposed diagnostic method uses features which are computed based on Short Time Fourier Transform (STFT) and then projected onto a lower dimensional feature space using Discrete Cosine Transform (DCT). The DCT coefficients serve as a feature vector; this feature vector is used as an input for a feed forward neural network (FFNN). The proposed method was tested using real ECG signals from the MIT-BIH arrhythmia database. The proposed method showed good results, assuring a good classification with 100% for the normal case and more than 90% well classified signals for the other type of ECG arrhythmias.
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1. Introduction

The electrocardiogram (ECG) is a diagnostic tool that describes the activities of the heart. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of an arrhythmia, therefore, its analysis represents an efficient way to detect and treat different kinds of cardiac diseases. The standard ECG signal, as shown in **Fig. 1**, consists of P-wave, PR-interval, PR-segment, QRS complex, ST-segment, and T-wave. The QRS complex is a very important signal that is useful in the diagnosis of Arrhythmias diseases.

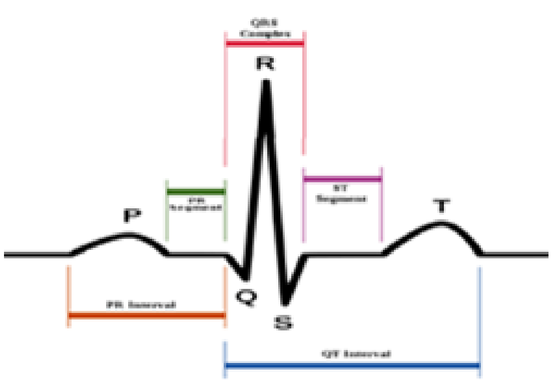

Fig. 1 standard ECG waveform

Real-time automated ECG analysis in clinical settings is a great assistance to clinicians in detecting cardiac arrhythmias, which often arise as a consequence of a cardiac disease, and may be life-threatening and require immediate therapy. Challenging problem is the characteristics of ECG signal show significant variations for different patients and under different temporal and physical conditions.

In general, ECG classification systems (shown in Fig. 2):

Fig. 2 ECG classification system

Most classification systems are designed to get robust and accurate detection of ECG heart beat patterns which propose feature extraction process depend on the morphological characteristics of ECG signals. And all are trying to improve the way of getting various QRS-waves of different patient which is the main source of these morphological characteristics of ECG signals. During the last years, many studies was introduced for analyzing the ECG signal using a real-time algorithms which interesting in detection ECG signal patterns as QRS-peaks and duration, R-R interval , amplitude and duration of P,R and T-waves. However, an accurate ECG signal, unaffected by low-frequency and high-frequency interferences, is rarely found in practice. The most common disturbing perturbations are: baseline wonder, muscular noise (EMG) or electrode motion artifact. All these unwanted phenomena make the interpretation of the ECG signal difficult and sometimes even impossible [1] using only the time-domain signal analysis.

The ECG signals or any other biomedical signals are non-stationary, meaning that they change their statistical properties over time. Other studies were proposed for classification of ECG signals using the time-frequency analysis as the Wavelet Transform (WT) [2-8] and Fourier Transform [9-11] which introduce a good tool to detect the variation of the signal with time. The advantages of this tool are the good representation of non-stationary signals such as ECG signals and the possibility of dividing the signal into different window to follow up the variation of the frequency over all time. In this paper, we present an approach for ECG signal classification that is based on time-frequency analysis using Short Time Fourier Transform (STFT) and Discrete Cosine Transform (DCT). The rest of the paper is arranged as, section 2 presents the data base used in the research, the proposed methodology explained in section 3, and finally the result and the discussions in section 4.

2. Database

The ECG samples used in this study are taken from the world-famous MIT-BIH arrhythmia database [12]. The database is arranged in 4 categories, each is a group of 96 1080-sample signals with 360 samples/second. The first group is representing Normal ECG signal, the second one is representing Ventricular Couplet, the third one is representing Ventricular Tachycardia and the fourth is representing Ventricular Bigeminy as shown in Fig. 3.

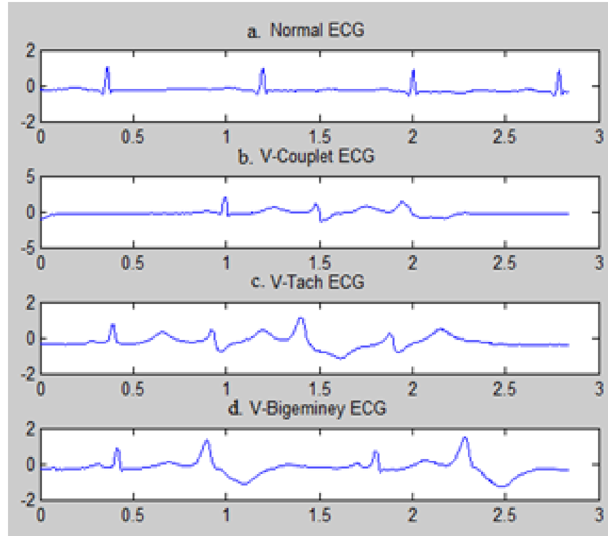

Fig. 3 ECG signals

3. The proposed methodology

a. Feature Extraction Technique

Our feature extraction technique consists of the following steps:

1. The signal is divided into a number of windows N, where N is determined according to the window size and the overlap between windows, to capture all the variations in the signal. Fig. 4 shows an example of a 256 samples window (0.711 sec).
2. Each signal window was multiplied with hamming window before transformation to smoothly decrease the boundary of the ECG signal to zero and removing its discontinuity.
3. The FFT (Fast Fourier Transform) is computed for each window of the N windows in the same ECG signal, and then the first K low-order FFT-coefficients are taken and the high order coefficients are neglected because of their smaller amplitudes, where K is determined experimentally.
4. The K FFT-coefficients of each window is represented using DCT (Discrete Cosine Transform) expansion of order M, where M<K. Therfore we have NxM frequency DCT-coefficients for each ECG signal as :

W1 = (dct1, dct2, dct3,……....…, dctM)
W2 = (dct1, dct2, dct3,……....…, dctM)
W3 = (dct1, dct2, dct3,……....…, dctM)
.
.
WN= (dct1, dct2, dct3,……....…, dctM)

Take the first L DCT-coefficients which represent each pattern, the taken numbers of these coefficients can be changed until we get the optimum numbers of coefficients that represent the pattern and give a good classification results.

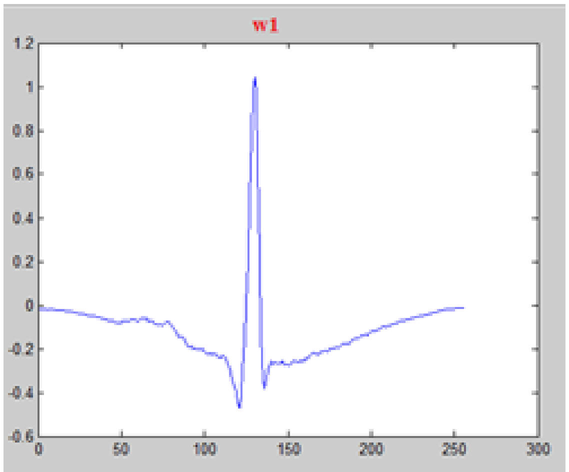

Fig. 4 single window from ECG signal

5. A time series expansion (DCT expansion) of order L, where L<N, is computed for each of the M dct coefficients over the N windows. This expansion can be explaned as follows:the following vector represents the i**th** dct coefficients over the N windows:

DCTi **=(DCT**i**(w1), DCT**i **(w2), DCT**i **(w3),……….., DCT**i **(wN)** ,

Where **DCT**i(**w**j) is the i**th** dct coefficients of the j**th** window.

For this vector we perform a dct expansion to represent the time variation of this i**th** dct. This expansion is performed for each of the M dct to represent the time variation of each in dct. At this step each ECG signal is represented with a feature vector of order MxL.

6. In this step the feaure vectors are scaled to reduce the effect of their amplitudes to the classification process.

b. Neural network Classifier

A feed-forward neural network is used as a classification technique in this study [13-18], we have performed classification by using neural network toolbox in Matlab [19]. The network was configured to have one input layer, one hidden layer and one output layer is proposed as shown in the **Fig. 5**. The input layer consist of MxL nodes, equivalent to the number of features in the feature vector. The hidden layer consists of R neurons with the transfer function of log-sigmoid whereas the output layer consists of four neurons with the linear transfer function. The number of output nodes equals the number of classes (4 classes). Once the network weights and biases were initialized, the network was ready for training. The training process required the assessment of a set indicating the desirable network behavior. This set should include the network inputs (P) and their corresponding target outputs (T). In our case the input training set consisted of 384 ECG signals. Each one of them was fully defined by a (Mxk) element vector. These vector elements corresponded to time-frequency features of the ECG signals.

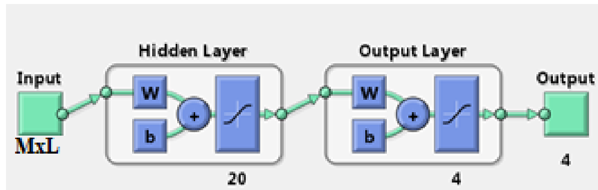

Fig. 5 the structure of the utilizes neural network

4. Simulation Results and Discusion

The proposed diagnostic system includes several parameters that to be optimized for obtaining high classification performance. The first parameter to be determined is the number of FFT-coefficients (K), the second parameter is the order (M) of the frequency DCT-expansion which is used to represent the K spectral coefficients. The thired parameter to be determined is the order (L) of the time DCT-expansion that is used to represents each frequency DCT-coefficients over time. Therefore several simulation experiments were conducted to optimize these three parameters. We use a neural network classifier with fixed setting through the whole experiments as single hidden layer of 20 neurons with the transfer function of log-sigmoid and an output layer with four neurons. The input and the targets vectors were divided into three sets. Precisely 75% of the vectors were used to train the network and validate how well the network generalizes, the last 25% of the signal vectors provided a clear testing set of the network generalization using data that the network has never encountered before.These experiments are as follows:

Expeiment. 1 : Selecting the number of fft-coefficients.

To determine the optimum number of FFT-coefficients, an experiment was conducted by dividing each ECG signal into 17 windows, each of length 256 samples, and is spaced by 50 samples. A hamming window was multiplied by each of these 17 windows. The FFT was computed for each of these windows. We chose M=25 and L=5 and we run the experiment for K equal 25, 30, 40, 50, 75, 100, and 128. The results of this experiment are shown in **Fig. 6**, From this figure, the best classification accuracy is obtained at K=50. In the rest of experiments we will use this K.

Experiment. 2 : selecting the order (M) of the frequency DCT-expansion.
To determine the order (M) of the frequency DCT-expansion that is used to represent the K spectral coefficients. We used K=50 and L=5 and we ran the experiment for M equal 15, 20, 25, 30, 35, 40, 45, and 50. The results of this experiment are shown in **Fig. 7** From this figure, the best classification accuracy is obtained at M=20.

Experiment. 3 : selecting the order (L) of the time DCT- expansion that is used to represents each frequency DCT-coefficients over time.
We use K=50 and M=20 and we run the experiment for L equal 3, 4, 5, 6, 7, 8, 9 and 10. The results of this experiment are shown in **Fig. 8**. From this figure, the best classification accuracy is obtained at L=3.

We can observe from the previous three experiments that the proposed technique gives the best classification results (93%) at setting K=50, M=20, and L=3. As we observe from **Fig. 10** that the ECG signal in the time domain has a lot of variations (non-stationary), and the DCT over the signal can detect these variations of the frequency over all time and most of the data are concentrated in the first part of that signal as explained in **Fig. 11**, and these time-frequency DCT coefficients introduce a features which is discriminative and good representive to the signal.

Experiment. 4 : applying WT on the same data
We apply WT on the same ECG signals with different number of windows and we find the best classification accuracy with 8-windows as shown in **Fig. 9**.

In [20] an algorithm was developed for detection and classification using the DWT and statistical features. In [21] the DWT was replaced with the SWT. In [22] a combination of the wavelet transform and artificial neural network is presented. Three kinds of features in a very computationally efficient manner are computed as follows: joint Time-Frequency features (discrete wavelet transform coefficients), time domain features (R-R intervals), and Statistical feature (Form Factor).The classification results are showed in **Table. 1** compared to the algorithm proposed in [20], [21], and [22], the proposed method in which the input signals are decomposed using the time-frequency features show higher classification percentage.

Table. 1 Comparison between classification percentages using the DWT, SWT and the proposed technique

DWT[20]	**74%**
SWT[21]	**80 %**
DWT + ANN [22]	**90 %**
Proposed technique	**93 %**

Having in mind that the above procedure is a simple successful classification method of ECGs using FFT and DCT with a non-linear neural network model, it is clear that it can be applied to more complex medical conditions, acting as an additional tool of diagnosis by a doctor.
Finally, it should be mentioned that the proposed methodology, will not be used in order to replace a doctor, but only in means of an additional evaluation method. A medical informative system, which will be based on time-frequency features and ANNs, would be a significant means for the offer of advanced health services.

5- CONCLUSION

In this work, we presented an ECG classification method depend only on the time-frequency features of the ECG signal which is suitable to analyze non-stationary signals, especially biomedical signals, like the ECGs.
The results indicate that the proposed technique is able to work and to perform a good ECG classification, and offers an alternative method to the wavelet transform.
Improvements have to be made to add the morphological characteristics of the ECG signal and to work with a larger set of signals; also we can use different type of classifier to improve the final classification result.

References

[1]. Bronzino J. D. The biomedical engineering handbook. 2nd ed.vol. 1 Boca Raton FL: CRC Press LLC; 2000.
[2]. Addison P. S. Wavelet transforms and the ECG: a review. Physiological Measurement 26: 155-199; 2005.
[3]. Mahamoodibad S.Z., Ahmadian A., Abolhasani M.D., ECG feature extraction using Daubechies wavelets. Proceedings of Fifth IASTED International Conference: 343–348; 2005.
[4]. Vijaya V., Kishan Rao K., and Rama. V., Arrhythmia Detection through ECG Feature Extraction using Wavelet Analysis. European

Journal of Scientific Research 6(3): 441-448; 2011.
[5]. Provaznık I. and Kozumplık J., Wavelet transform in electrocardiography data compression. International Journal of Medical Informatics. 45(1-2): 111-128, 1997.
[6]. Mallat S. A Wavelet Tour of Signal Processing. 2nd ed.: Academic Press; 1999.
[7]. Daubechies I. Orthonormal bases of compactly supported wavelets. Communications on Pure and Applied Mathematics 41 (7): 909-996; 1988.
[8]. Shensa M. J. The discrete wavelet transform: wedding the à trous and Mallat algorithms. IEEE Trans. Sig. Proc. 1992; 40:2464-2482.
[9]. Minami, K., Nakajima, H., Toyoshima, T., 1999. Real-time discrimination of ventricular tachyarrhythmia with Fourier transform neural network. IEEE Trans. Biomed. Eng. 46, 179–185.
[10]. Himanshu Gothwal. Cardiac arrhythmias detection in an ECG beat signal using fast fourier transform and artificial neural network, J.Biomedical Science and Engineering, 2011, 4, 289-296, doi:10.4236/jbise.2011.44039 Published Online April 2011.
[11]. Minami, K., Nakajima, H. and Toyoshima, T. (1999) Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network. IEEE Transactions on Biomedical Engineering, 46, 179-185. doi:10.1109/10.740880
[12]. MIT Database available from : http://www.physionet.org/physiobank/database/mitdb/.
[13]. Haykin, S. (2005) Neural networks—A comprehensive foundation. Prentice Hall.
[14]. Hagan, M.T., and Menhaj, M.B. (1994) Training feed forward networks with the marquardt algorithm. IEEE Transactions on Neural Networks, 5, 989-993. doi:10.1109/72.329697
[15]. G. Karraz, G.M. (2006) Automatic classification of heartbeats using neural network classifier based on a Bayesian framework. 28th Annual International Conference of the IEEE Publication, 4016-4019.
[16]. Yu1, S.-N. and Chou, K.-T. (2006) Combining independent component analysis and back-propagation neural network for ECG beat classification. Proceeding of IEEE Engineering in Medicine and Biology Society, 1, 3090-3093.
[17]. Issac, N.S., Shantha, S.K.R. and Sadasivam, V. (2005) Artificial neural network based automatic cardiac abnormalities classification. 6th International Conference, 41-46.
[18]. Fu, L.M. (2004) Neural networks in computer intelligence.McGraw-Hill Inc., 153-264.
[19]. Neural Network Toolbox. Available: http://www.mathworks.com .
[20]. Stolojescu C. Estimation of Noise in ECG Signals Using Wavelets. 11th International conference OPTIM 4: 113-118; 2008.
[21]. Cristina STOLOJESCU, ECG Signals Classification using Statistical and Time-Frequency Features. Applied Medical Informatics, Vol. 30, No. 1 /2011, pp: 16-22.
[22]. Hashemi, J. ; Mohseni, H.R. ; Maghsoudi, A, Classification of ECG Arrhythmias Based on Statistical and Time-Frequency Features, Advances in Medical, Signal and Information Processing, 2006. MEDSIP 2006. IET 3rd International Conference.

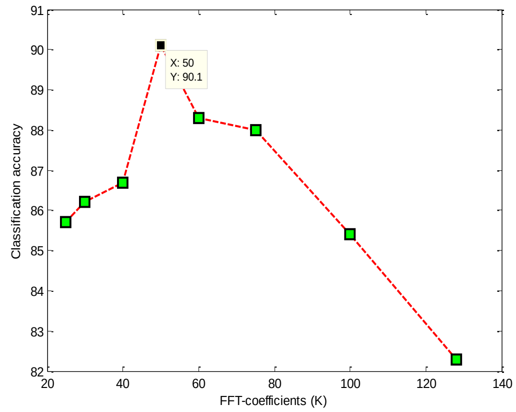

Fig. 6 classification percentage versus FFT-coefficient (K)

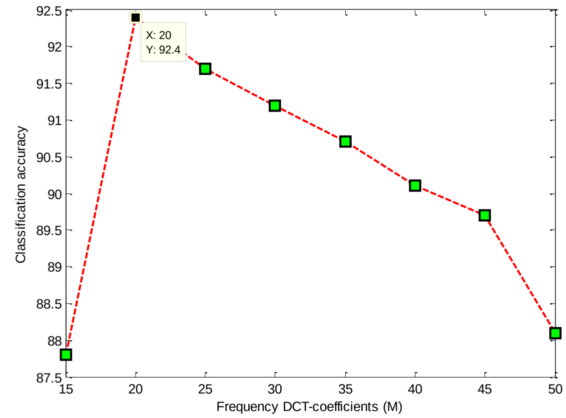

Fig. 7 classification percentages versus freequency DCT-coefficient (M)

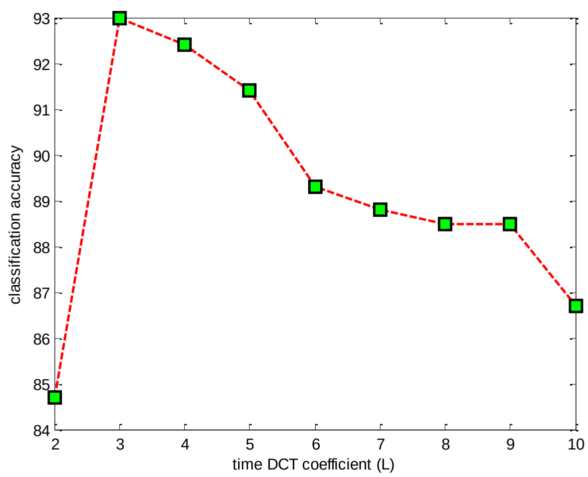

Fig. 8 Classification percentages versus time DCT-coefficient (L)

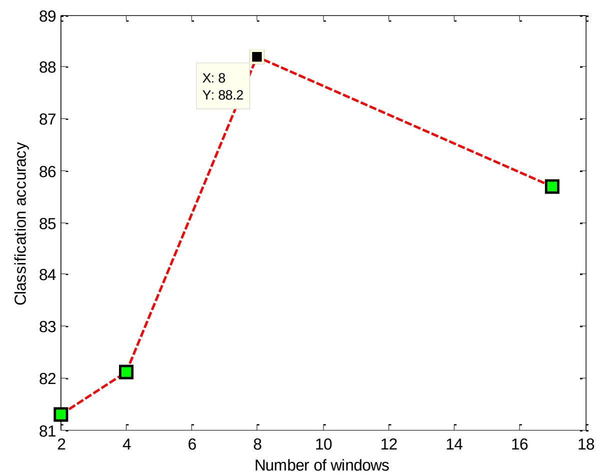

Fig. 9 Wavelet classification accuracy versus number of windows

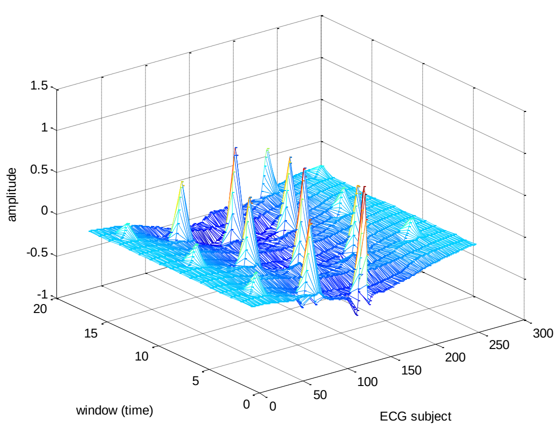

Fig. 10 ECG signals variation through all windows

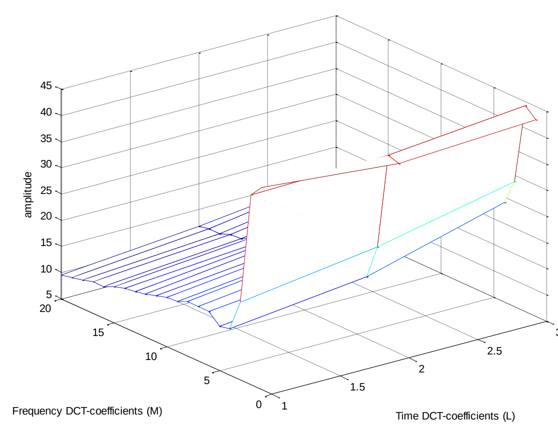

Fig. 11 time-frequency features for subject# 1

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