HERMITIAN TRANSFORM APPROACH IN CLASSIFICATION OF ECG SIGNALS

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Abstract

The continuous Hermite functions have been used for continuous signal approximations for some time. Vectors called discrete Hermite functions are presented in this paper that model digital signals in a similar way, often with excellent compression capabilities. When used in conjunction with ANNs (artifical neural networks) Hermite founctions can effectively reduce computational load and provides faster classification. In this work we purpose a method for classification of ECG signals using Hermite basis functions.

Keywords: Hermite, ECG, ANN

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1. Introduction

The electrocardiogram (ECG) is the signal of electrical activity of the heart and is the most important data to investigate heart diseases and conditions [1].When interpreting ECG signals QRS complex is considered as the most important part of signal.By analyzing this complex automatic diagnosis systems differantiate between normal and arhythmia beats . Various features are obtained from the ECG signal such as morphological features [2], heartbeat temporal intervals [3], frequency domain features [4], and wavelet transform coefficients [5]. Classification techniques of ECG patterns include linear discriminant analysis [2], support vector machines [6], and artificial neural network [7]. Unsupervised clustering of ECG complexes using self-organizing maps has been studied [8].

The neural network models were used to classify the ECG heartbeat in MIT-BIH Arrhythmia Database [10]. The neural models are basically based on the perceived work of the human brain. The artificial model of the brain is known as Artificial Neural Network (ANNs) or simply Neural Networks (NNs). Generally, the ANNs are a cellular information processing system designed and developed on the basis of the perceived notion of the human brain and its neural system. The influence of neurons changes by altering the effectiveness of the synapses and so that learning occurs. Also note that the rapid, efficient propagation of electrical and chemical impulses is the distinctive characteristic of neurons and the nervous system in general. The neurons operate collectively and simultaneously on most for all data and inputs which performs as summing and nonlinear mapping junctions. In some cases they can be considered as threshold units that fire when total input exceeds certain bias level. Neurons usually operate in parallel and are configured in regular architectures. They are often organized in layers, and feedback connections both within the layer and toward adjacent layers are allowed. Strength of each connection is expressed by a numerical value called a weight which can be updated. Also they are characterized by their time domain behavior which is often referred as dynamics. In general, the neuron could be modeled as a nonlinear activated function of which the total potential inputs into synaptic weights are applied.

The aims of this study are to purpose a method for both classifing and storing heartbeaths with minimal computation and storage requirements. To achieve this we first expand each beat into

Hermite polynomials and make a neural network classification based on these coefficents. Expansion into the Hermite coefficents do not require much calculation due to it's nature so a reduction in input nodes of neural network can be achieved using this method. We tested system with varying number of Hermite coefficentts and compared results.

The ECG Signal

The electrocardiogram is a time-varying signal that measures the electrical activity (on the surface of the human body) of the heart. The standard parameters of the ECG waveform are the P wave, the QRS complex and the T wave. But most of the information lies around the R peak.Additionally a small U wave (with an uncertain origin) is ocassionally present. The cardiac cycle begins with the P wave, which corresponds to the period of atrial depolarization in the heart. This is followed by the QRS complex, which is usually the most relevant (recognizable) feature of an ECG waveform. The T wave follows the QRS complex and corresponds to the period of ventricular repolarization. The end point of the T wave represents the end of the cardiac cycle (presuming the absence of U wave). The durations (time between the onset and offset) of particular parameters of the ECG (referred as an time interval) is of great importance since it provides a measure of the state of the heart and can show the presence of certain cardiological conditions. In practice, interval measurements, wave interpretations are carried out manually by ECG specialists [9].Figure 1 illustrates the normal clinical features of the electrocardiogram, which include wave amplitudes and interwave timings.

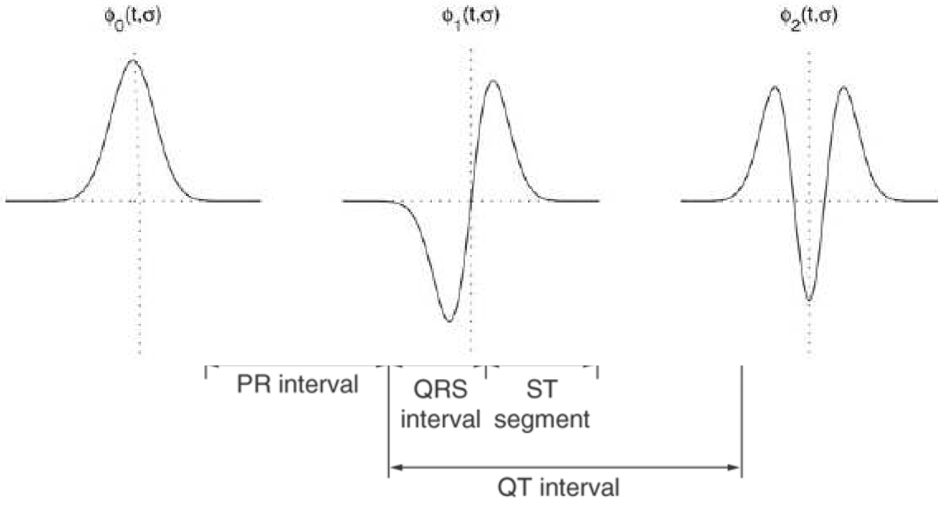


Figure 1. An example of Normal ECG trace

Hermite Basis Functions

Mathematically Hermite basis functions play the same role with the Fourier series.This functions can be used to reproduce an approximation of a signal wtih with a small error. The number of the coefficents used to approximate the signal defines the error between original teh reproduced signal.

The higher order of coefficents are used the more accurate representation of original signal is obtained. Hermite basis functions are given by the following expression;

$$\theta n(t,\sigma) = \frac{1}{\sqrt{\sigma 2^n n! \sqrt{\pi}}} e^{-t^2/2\sigma^2} H_n\left(\frac{t}{\sigma}\right) \quad (1)$$

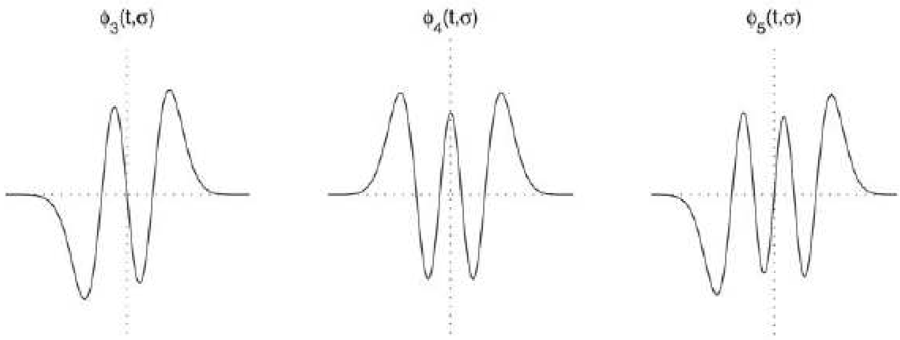


Figure 2. The first six Hermite basis functions

Hermite polynomials are given recursively by;

$$\begin{aligned} &H_0(x)=1 \\ &H_1(x)=2x \\ &H_n(x)=2xH_{n-1}(x)-2(n-1)H_{n-2}(x) \end{aligned} \qquad (2)$$

and ECG complex can be expressed as sum of these functions.

$$\xi(t)=\sum_{n=0}^{N-1} c_n(\sigma)\theta n(t,\sigma)+e(t,\sigma) \qquad (3)$$

where e(t,σ) is error between the real and reonstructed ECG signal.

2. Method

In this study we used the MIT-BIH arrhythmia database. This database include 48 recordings, which contains the two-channel 30-min ECG signals. There are approximately 110,000 heartbeats, and each of the beats is annotated as 15 different heartbeat classes [10]. We tested our study with two ECG sample dataset taken from record 102. This record belong to 84-years female patient In these dataset we only studied pacemaker fusion beats. Prior to appling input data to neural network.a QRS detection algorithm is used to find fiducial pointsof QRS complexes. Because we focused on ECG classification, we used Pan-Tompkins algorithm described in [11]. For reconstruction of ECG signal from Hermite functions we only used first 15 Hermite coefficents.

Artificial Neural Network

ANNs consist of a great number of processing elements, which are connected with each other; the strengths of the connections are called weights. Input feature (information) selection constitutes an essential first step. The feature space needs to be chosen very carefully to ensure that the input features will correctly reflect the characteristics of the problem. [12]. Another major task of the ANN design is to choose network topology. This can be done experimentally through a repeated process to optimize the number of hidden layers. Unlike the input and output layers, one starts with no prior knowledge as the number of hidden layer. A network with too few hidden nodes would be incapable of differentiating between complex patterns leading to only linear estimate of the actual trend. If the network has too many hidden nodes it will follow the noise in the data due to overparmeterization leading to poor generalization for untrained data. The most popular approach to finding the optimal number of hidden layers could be determined by trial and errors [13].

To classify ECG signals, we used ANN and output layer's activity is outlined below

Step 1: Compute the total weighted input x_j, using the formula:

$$X_j = \sum_i y_i W_{ij}$$

Step 2: Calculates the activity (sigmoid function) y_j

$$y_j = \frac{1}{1 + e^{-x_j}}$$

Step 3: To determine all output unit activities, Compute error *E*, which is defined by the expression:

Backpropagation learning algorithm is used for training in this neural system. Detailed information is found in [14]

3. Results

Classification of ECG heartbeat patterns using various number of hidden nodes is summarized in Table 1. True positive (TP) and true negative (TN) indicate the correct classification of normal and abnormal patterns. False negative (FN) refers to misclassification of normal patterns as abnormality and false positive (FP) defines misclassification of abnormal patterns into normality. Classification accuracy is then defined as the ratio of the number of correctly classified patterns (TP and TN) and the total number of patterns.

	45 coefficents	**30 coefficents**	**15 coefficents**
10 nodes	98.09%	97.51%	98,9%
15 nodes	98.09%	97.13%	98.9%
20 nodes	97.94%	97.18%	98.17%

Table 1 : Classification accuracy versus number Hermite coefficents and umber of neurons in hidden layer

Left row in the table 1 states number of hidden neurons called nodes in neural networks and columns in up state number of hermitian coefficients used as input of neural network. As seen the table 1, the highest classification accuracy is obtained for 15 hermitian coefficients and the optimal hidden nodes are found as 10 and 15. Actually, it was expected that the success of the classification accuracy increases when the number of coefficients do increase. However; in our case, the highest classification accuracy is found for 15 coefficients. On the other hand, the best classification accuracy for the ECG signals is obtained by the use of the lowest coefficients since 15 coefficients cause less complexity and computational cost.

4. Conclusion

In this paper, to classify the ECG heartbeat in MIT-BIH Arrhythmia Database, Hermitian Transform and Neural Network methods are used. ECG classification systems have two stage. In the first stage, feature extraction process is applied. Hermitian Transform is utilized for this. Thus, feature vectors are reduced 15, 30 and 45 coefficients. In the second stage, Neural Network is applied to classify the ECG signals. At the end of the classification process, the highest classification accuracy is calculated as 98.9% for 15 Hermitian coefficients and 10 hidden nodes.

5. REFERENCES

[1] Hu YH, Palreddy S, Tompkins W. A patient adaptable ECG beat classifier using a mixture experts approach.IEEE Trans Biomed Eng 2007;44:891-900

[2] P. de Chazal, M. O'Dwyer, and R. B. Reilly, "Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features," *IEEE Trans. on Biomedical Engineering*, Vol. 51, No. 7, pp.1196-1206, July 2004.

[3] C. Alexakis, H. O. Nyongesa, R. Saatchi, N. D. Harris, C. Davis, C. Emery, R. H. Ireland, and S. R. Heller, "Feature Extraction and Classification of Electrocardiogram (ECG) Signals Related to Hypoglycaemia," *Computers in Cardiology*, Vol. 30, pp.537-540, 2003.

[4] I. Romero and L. Serrano, "ECG Frequency Domain Features Extraction: A New Characteristic for Arrhythmias Classification," *Proc. Int'l. Conf. on Engineering in Medicine and Biology Society (EMBS'2001)*, pp.2006-2008, October 2001.

[5] P. de Chazal and R. B. Reilly, "A Comparison of the ECG Classification Performance of Different Feature Sets," *Computers in Cardiology*, Vol. 27, pp.327-330, 2000.

[6] S. Osowski, L. T. Hoai, and T. Markiewicz, "Support Vector Machine-based Expert System for Reliable Heartbeat Recognition," *IEEE Trans. on Biomedical Engineering*, Vol. 51, No. 4, pp.582-589, April 2004.

[7] Y. H. Hu, W. J. Tompkins, J. L. Urrusti, and V. X. Afonso, "Applications of Artificial Neural Networks for ECG Signal Detection and Classification," *Journal of Electrocardiology*, Vol. 26. (Suppl.), pp.66-73, 1994.

[8] M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt, and L. Sörnmo, "Clustering ECG Complexes Using Hermite Functions and Self-organizing Maps," *IEEE Trans. on Biomedical Engineering*, Vol. 47, No. 7, pp.838-848, July 2000.

[9] Z. German-Sallo "Applications of Wavelet Analysis in ECG Signal

Processing",Summary Of Phd. Thesis pp.5, 2005

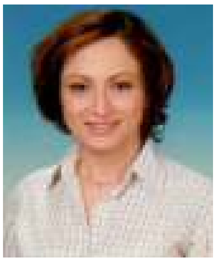
[10] Mark R, Mody G. MIT-BIH Arrhythmia Database. 1997 Online available : http://www.physionet.org/

[11] V. Afonso, W. Tompkins, T. Nguyen, and S. Luo, "ECG beat detection using filter banks," IEEE Trans. Biomed. Eng., vol. 46, no. 2, pp. 192--202, Feb. 1999

[12] Fausett, L, (1994). Fundamentals of neural networks architectures, algorithms and applications, Englewood Cliffs, NJ: Prentice Hall.

[13] Ubeyli, E.D., Güler, I., 2003. Neural network analysis of internal carotid arterial doppler signals: prediction of stenosis and occlusion. Expert system with applications. 25,1-13.

[14] Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986. Learning representations by back-propagating errors. Nature. 323, 33-536.



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