International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:5, No:12, 2011

ECG Analysis using Nature Inspired Algorithm

A.Sankara Subramanian, G.Gurusamy, G.Selvakumar, P.Gnanasekar and A.Nagappan

***Abstract*—**This paper presents an algorithm based on the wavelet decomposition, for feature extraction from the ECG signal and recognition of three types of Ventricular Arrhythmias using neural networks. A set of Discrete Wavelet Transform (DWT) coefficients, which contain the maximum information about the arrhythmias, is selected from the wavelet decomposition. After that a novel clustering algorithm based on nature inspired algorithm (Ant Colony Optimization) is developed for classifying arrhythmia types. The algorithm is applied on the ECG registrations from the MIT-BIH arrhythmia and malignant ventricular arrhythmia databases. We applied Daubechies 4 wavelet in our algorithm. The wavelet decomposition enabled us to perform the task efficiently and produced reliable results.

***Keywords*—**Daubechies 4 Wavelet, ECG, Nature inspired algorithm, Ventricular Arrhythmias, Wavelet Decomposition.

I. Introduction

THE cardiac disorders which are life threatening are the ventricular arrhythmias such as Ventricular Tachycardia (VT), Supra Ventricular Tachycardia (SVT), Ventricular Fibrillation (VFIB) and Ventricular Flutter (VFL). The classification of ECG into these different pathological disease categories is a complex task.

Successful classification is achieved by finding the characteristic shapes of the ECG that discriminate effectively between the required diagnostic categories. Conventionally, a typical heart beat is identified from the ECG and the component waves of the QRS, T and P waves are characterized using measurements such as magnitude, duration and area as shown in Fig. 1.

In an arrhythmia monitoring system or a defibrillator, it is important that the algorithm for detecting ECG abnormalities should be reliable. The patient will be losing a chance of treatment if the system is not able to detect the arrhythmia. Also a false positive detection will initiate a defibrillator to give improper therapeutic intervention. Both situations are linked with the patient's life.

A.Sankara Subramanian is with the Department of Electrical and Electronics Engineering, NPA Centenary Polytechnic College, Kothagiri, Tamilnadu – 643217, India (Phone: +91-94434-77578, e-mail: sankar_aru@yahoo.com

G.Gurusamy is with the Department of Electrical and Electronics Engineering, Bannariamman Institute of Technology, Sathyamangalam, Tamilnadu, India (Phone: +91-4295-223671).

G.Selvakumar is with the Annapoorana Engineering College, Salem, Tamilnadu – 636308, India (Phone: +91-93657-33999; e-mail: ngselva_kumar@yahoo.com).

P. Gnanasekar is a research Scholar in the Department of Computer Science & Engineering at the Vinayaka Missions Research Foundation Deemed University, Salem, Tamilnadu, India. e-mail: peegeeyes@gmail.com.

A. Nagappan is the Principal of VMKV Engineering College, Salem, Tamilnadu, India. e-mail: nags_slm@yahoo.com.

Computer based classification algorithms can achieve good reliability, high degree of accuracy and offer the potential of affordable mass screening for cardiac abnormalities.

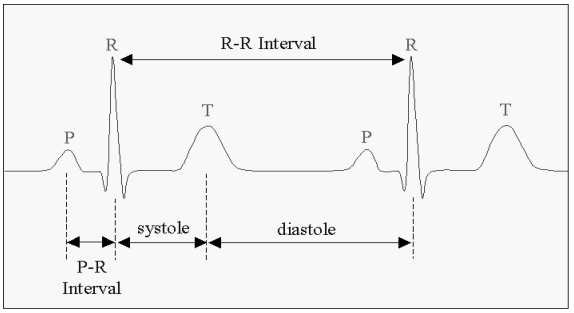

Fig. 1 Normal ECG Waveform

Among the various algorithms used for this task, Wavelet Transform is quite efficient since the discrete Fourier transform only permits analyzing a discrete time signal using frequency components. The Discrete Wavelet Transform (DWT) has been used for analyzing, decomposing and compressing the ECG signals [1].

The wavelet transforms make possible, the decomposition of a signal into a set of different signals of restricted frequency bands. Wavelet processing can be considered as a set of band pass filters [2]. Moreover, the discrete wavelet transform corresponds to a multiresolution analysis [3] which can reduce the redundancy of each filtered signal so that the processing algorithm can be applied effectively to a small data subset of the original signal [4]–[9].

After that a novel classification algorithm based on Ant Colony Optimization (ACO) is developed for classifying arrhythmia types. The system consists of three stages and is constructed as shown in Fig. 2. The first stage of learning phase involves extraction of the feature values. The second stage involves the storage of information over Relational Data Base Management System (RDBMS). The last stage involves the clustering of QRS parameters using the ACO technique to construct arrhythmia classes. Test or control phase is used to control algorithm's efficiency and correctness as shown in Fig. 3. The first stage of testing phase is parameter extraction. Previously built cluster information serves as an input to the testing system.

The ECG registrations from MIT-BIH arrhythmia and malignant ventricular arrhythmia databases are used here. The analysis is done using Daubechies 4 wavelet.

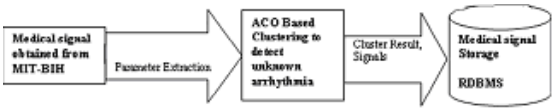

Fig. 2 Training system model

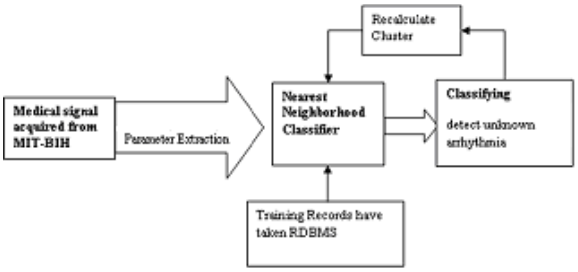

Fig. 3 Testing system model

II. Ventricular Arrhythmia

Arrhythmias are the abnormal rhythms of the heart. They cause the heart to pump the blood less effectively. Most cardiac arrhythmias are temporary and benign. The ventricular arrhythmias are life threatening and need treatment. Such ventricular arrhythmias are Ventricular Tachycardia, Supraventricular Tachycardia, Ventricular Fibrillation and Ventricular Flutter.

Ventricular Tachycardia (VT) is a difficult clinical problem for the physicians (Fig. 4). Its evaluation and treatment are complicated because it often occurs in life-threatening situations that dictate rapid diagnosis and treatment. Ventricular tachycardia is defined as three or more beats of ventricular origin in succession at a rate greater than 100 beats/minute. There are no normal-looking QRS complexes. Because ventricular tachycardia originates in the ventricle, the QRS complexes on the electrocardiogram are widened (>0.12 seconds). Ventricular tachycardia has the potential of degrading to the more serious ventricular fibrillation.

A Supraventricular Tachycardia (SVT) is a rapid rhythm of the heart in which the origin of the electrical signal is either the atria or the AV node. Symptoms can come on suddenly and may go away by themselves. They can last a few minutes or as long as 1-2 days. The rapid beating of the heart during SVT can make the heart a less effective pump so that the body organs do not receive enough blood to work normally. The pulse rate will be in the range of 140-250 beats per minute. The QRS complex has normal duration unless bundle branch block is present. When P waves are identifiable, the P wave morphology is often different from sinus P wave morphology, and the P wave may precede, coincide with or follow the QRS complex.

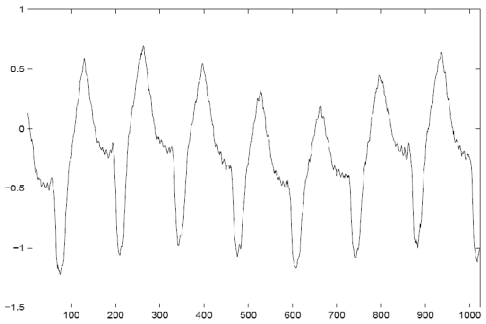

Fig. 4 ECG waveform with VT

Ventricular fibrillation (VFIB) is a condition in which the heart's electrical activity becomes disordered (Fig. 5). During Ventricular fibrillation, the heart's ventricles contract in a rapid and unsynchronized way. It is a medical emergency. If this condition continues for more than a few seconds, blood circulation will cease, as evidenced by lack of pulse, blood pressure and respiration, and death will occur [11].

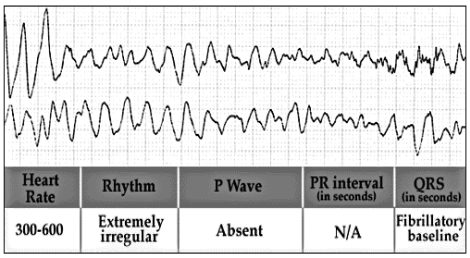

Fig. 5 Ventricular Fibrillation

Ventricular flutter (VFL) is a tachyarrhythmia characterized by a high ventricular rate with a regular rhythm (Fig. 6). The ECG shows large sine wave-like complexes that oscillate in a regular pattern. There is no visible P wave. QRS complex and T wave are merged in regularly occurring undulatory waves with a frequency between 180 and 250 beats per minute. In severe cardiac or systemic disease states, ventricular tachycardia can progress to ventricular flutter, then to ventricular fibrillation.

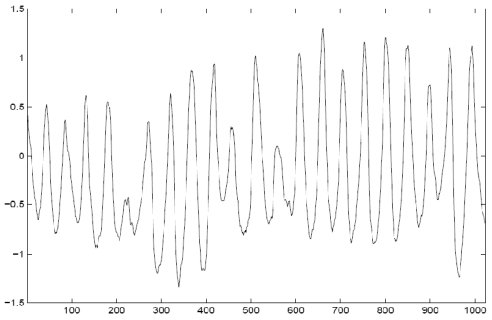

Fig. 6 Ventricular Flutter

III. Wavelet Decomposition

The discrete wavelet transform (DWT) makes possible, the decomposition of ECG at various scales into its time-frequency components. In DWT two filters, a low pass filter (LPF) and a high pass filter (HPF) are used for the decomposition of ECG at different scales. Each filtered signal is down sampled to reduce the length of the component signals by a factor of two. The output coefficients of LPF are called the Approximation while the output coefficients of HPF are called the Detail. The approximation signal can be sent again to the LPF and HPF of the next level for second level of decomposition; thus we can decompose the signal into its different components at different scale levels.

Fig. 7 shows the decomposition process of a signal into many levels. The details of all levels and the approximation of the last level are saved so that the original signal could be reconstructed by the complementary filters. The reconstructed signals at each level are represented by the notations D1, D2, D3 and so on.

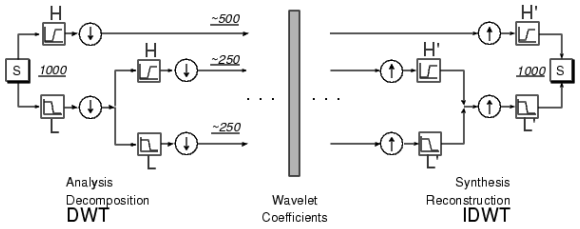

Fig. 7 Wavelet Decomposition and Reconstruction

Fig. 8 shows the ideal frequency bands for a sampling frequency of 360 samples/second.Depending on the scaling function and the mother wavelet, the actual frequency bands and consequent frequency selectivity of the details are slightly different.

In this section we present the algorithm which efficiently detects and classifies the various ventricular arrhythmias using wavelet decomposition and ACO.

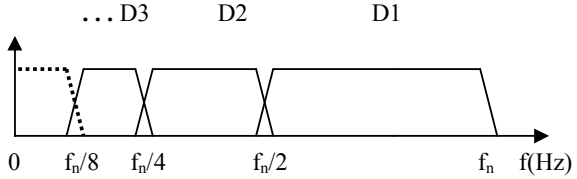

Fig. 8 Ideal frequency bands for the various details

IV. Methodology

A. Description of the Algorithm

The algorithm first decomposes the ECG signals using wavelet transform. The decomposed signals are fed to the feed forward neural network. The wavelet theory is used as a time-frequency representation technique to provide a method for enhancing the detection of life threatening arrhythmias. It reveals some interesting characteristic features such as low frequency band (0-5 Hz) for VFL, two distinct frequency bands (2-5, 6-8 Hz) for VT, and a broad band (2-10 Hz) for VFIB.

A classification scheme is developed in which a neural network is used as a classification tool depending on the above distinctive frequency bands of each arrhythmia. The algorithm is applied to ECG signals obtained from patients suffering from the arrhythmias, mentioned above.

B. ECG Analysis using Wavelet Decomposition

To quantify the differences between the various arrhythmias with the help of the wavelet transform, the densities for different frequency bands are compared. The wavelet transform is performed using Daubechies 4 wavelet since it provides better sensitivity [12].

The algorithm computes the volume underneath the 3D plots of the square modulus of the wavelet transform for several regions of the time-frequency plane. The time-frequency plane is divided into seven bands ranging from 0 to 15 Hz. For sinus rhythm the energy is calculated within the time intervals T_1 and T_2 integrated over the whole frequency axis. The time interval T_1 is determined by the region of QRS complex, and the time interval T_2 is determined by the region of the T-wave.

As the wavelet transform is very sensitive to abrupt changes in the time direction, the energy parameter over the given time intervals attains relatively large values for normal subjects. This parameter is referred to as T_v and it defines the sum of the energy parameters computed within the intervals T_1 and T_2. Although the signals of VFL and VT exhibit a QRS-complex, the parameter value T_2 for these signals remains relatively small, owing to the absence of abrupt changes in the region of the T-wave. Therefore the value of T_v will still be smaller than that of the normal subjects.

The 2D and 3D wavelet transform contours of Normal Sinus Rhythm (NSR), VT and VFL are shown in Fig. 9.

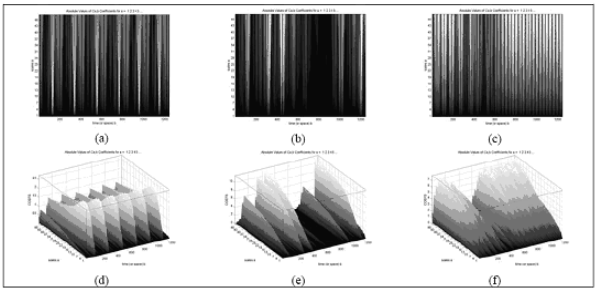

Fig. 9 (a) 2D wavelet of NSR, (b) 2D wavelet of VT, (c) 2D wavelet of VFL, (d) 3D wavelet of NSR, (e) 3D wavelet of VT and (f) 3D wavelet of VFL

V. Ant Colony Optimisation

A. Behavior of Real Ants

Ant Colony Optimization (ACO) techniques are inspired from the behavior of real ant colonies that are used to solve function or combinatorial optimization problems [15]-[17]. Ant colony search algorithms, to some extent; mimic the

behavior of real ants. As is well known, real ants are capable of finding the shortest path from food sources to the nest without using visual cues. They are also capable of adapting to changes in the environment; for example, finding a new shortest path once the old one is no longer feasible due to a new obstacle. The studies by ethnologists reveal that such capabilities are essentially due to what is called "pheromone trails", which ants use to communicate information among individuals regarding path and to decide where to go. Ants deposit a certain amount of pheromone while walking and each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one.

B. The proposed algorithm for clustering

ACO technique can be applied for clustering successfully. The ACO algorithm has been utilized with different favors to solve the clustering problem [17]. In this approach's first stage, ants visit other cities randomly and they lay the pheromone according to inverse proportionality of Gaussian distance. After several iterations, trail intensity (pheromone) between close nodes of trails will be increased; on the other hand, pheromone far between the nodes of trails will be decreased.. In the second stage, ants will favor to visit the closer nodes and then reinforce the trail with their own pheromone. Every ant only needs to visit (1/10) cities not all of the cities, then the ants decreasingly visit the cities every time. Finally, a number of clans (clusters) will be built. The tournament selection technique is used for pa proportionate selection mechanism, and the selection of a new node based on randomly selected lines is continued as shown in Fig. 10. The choice of the previous path [XS] as a next path is prohibited.

Our study is based on these techniques, and some improvements have been implemented. Iteration number is smartly increased and the first and second stages are integrated. Besides, algorithm simplicity is also increased.

The proposed ACO algorithm for clustering can be briefly illustrated as follows.

1. Initialization: Input x data sets and assign y ants randomly to y nodes, and initially y equals x/10.
2. Find the candidate nodes the next time for the ants to visit. These nodes are chosen randomly.
3. Each ant visits the other nodes according to the nearest neighborhood interpolation depending on the Gaussian distribution. Select the nearest neighborhood node.
4. Update the pheromone quantity of the visited trail
5. Repeat 2 through 5 until the iteration number is reached.
6. Perform clustering using the value of pheromone quantity.

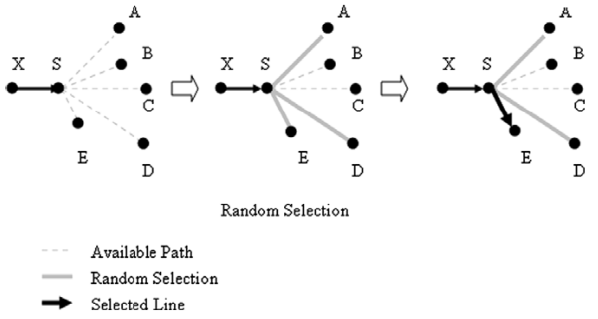

Fig. 10 Tournament Selection Mechanism of ACO Algorithm

C. k- Nearest neighborhood classifier

Nearest neighborhood classifier is used for testing purposes. After a new beat is input to the system, the cluster list is scanned to determine the clusters to which it belongs. If there are two or more such clusters, the beat is placed into the cluster which has the maximum number of nearest members. k is the total number of beat's nearest neighbors and chosen as 5 in this work. The algorithm is mentioned below.

1. Set the member list of the clusters
2. Take the next input vector and find its k nearest members according to the minimum distance measure.
3. Find the cluster which the maximum number of nearest members belong
4. Assign this cluster as the input vector's cluster.
5. Repeat 2 to 4 for all input vectors

VI. Data

The MIT-BIH arrhythmia and malignant ventricular arrhythmia databases were used for the analysis [14]. The VT and SVT episodes were taken from the MIT-BIH arrhythmia database and VFIB and VFL episodes were from MIT-BIH malignant ventricular arrhythmia database. The data files from arrhythmia database were sampled at 360 samples/second and that from malignant ventricular arrhythmia database were sampled at 250 samples/second. The sampling rates of these signals were increased to 360 samples/second by zero padding.

VII. Results And Conclusion

Twenty five signals of VT, ten signals of VFL and five signals of VFIB are used for training. The learning process took approximately 1000 iterations to converge with classification error of 0.001. Thirty signals of VT, fifteen signals of VFL and four signals of VFIB are selected as test set. For decomposition of ECG signal Daubechies 4 wavelet is used. Various levels of decomposition are explored.

In medical statistics, few parameters are important to evaluate the performance of the algorithm. These parameters are sensitivity (Se) and positive predictivity (+P) which can be computed using (1) and (2).

$$Se = \frac{TP}{TP + FN} \quad (1)$$

$$+P = \frac{TP}{TP + FP} \quad (2)$$

Classification results of testing data sets using Ant colony optimization are shown in Table I. The sensitivity and positive predictivity for the various arrhythmias are shown in Table II. The results show that the Ant colony Optimization algorithm is efficient in the classification of all the three types of ventricular arrhythmias.

TABLE I
A COMPARISON BETWEEN THE ACTUAL AND DETECTED VENTRICULAR ARRHYTHMIAS IN TERMS OF THE NUMBER OF PATTERNS

Actual Ventricular Arrhythmia	Detected Ventricular Arrhythmia			Total
	VT	VFL	VFIB	49
VT	30	0	0	30
VFL	1	14	0	15
VFIB	0	0	4	4

TABLE II
SENSITIVITY AND POSITIVE PREDICTIVITY FOR THE TESTING SET

Ventricular Arrhythmia	TP	FP	FN	Positive Predictivity (%)	Sensitivity (%)
VT	29	1	0	96.67	100
VFL	13	1	1	92.85	92.85
VFIB	4	2	0	80	100

Table I shows that the BP network misclassified the proper arrhythmia in some cases, one VFL case was classified as VFIB, this is because the energy level in the frequency bands is high and common between VFL and VFIB. The algorithm is able to classify VT and VFIB with 100% sensitivity. The positive predictivity for VFL episodes is 100%. The algorithm is reliable by providing the overall sensitivity of 95.56% and the overall positive predictivity of 92.22%.

REFERENCES

[1] Anant K., F. Dowla and G.Rodrigue, "Vector quantization of ECG wavelet coefficients", *IEEE Signal Processing Letters*, Vol. 2, No. 7, July, 1995.
[2] M.Vetterli, "Wavelets and filter banks: theory and design", *IEEE Transactions on Signal Processing*, Sep, 1992, pp 2207 – 2232.
[3] R.M.Rao, A.S.Bopardikar, "Wavelet transforms: Introduction to theory and applications", *Addison Wesley Longman*, 1998.
[4] L.Khadra, A.S.Al-Fahoum, H.Al-Nashash, "Detection of life threatening cardiac arrhythmia using the wavelet transformation", *Med. Biol. Eng. Comput*., Vol. 35, 1997, pp. 626-632.
[5] Addison P.S., Watson J.N., Clegg G.R., Holzer M., Sterz F. and Robertson C.E., 'Evaluating arrhythmias in ECG signals using wavelet transforms', *IEEE Engineering in Medicine and Biology Magazine*, Vol. 19, pp. 104-109, 2000.
[6] Dinh H.A.N., Kumar D.K., Pah N.D. and Burton P., 'Wavelets for QRS detection', Proceedings of the 23rd Annual Conference, *IEEE EMS*, Istanbul, Turkey, pp. 35-38, 2001.
[7] Kadambe S., Murray R. and Boudreaux-Bartels G.F., 'Wavelet transform based QRS complex detector', *IEEE Transaction on Biomedical Engineering*, Vol. 46, No. 7, pp. 838-848, 1999.
[8] Romero I., Serrano L. and Ayesta, 'ECG frequency domain features extraction: A new characteristic for arrhythmias classification', Conference of the *IEEE Engineering in Medicine and Biology Society*, 2001.
[9] Szilagyi S.M. and Szilagyi L., 'Wavelet Transform and Neural Network based Adaptive Filtering for QRS Detection', Proceedings of *World Congress on Medical Physics and Biomedical Engineering*, Chicago, USA, 2000.
[10] Rumelhart D.E., Hinton G.E. and Williams R.J., "Learning representations by back-propagation errors", *Nature*, 1986.
[11] V.X.Afonso, W.J.Tompkins, "Detecting ventricular fibrillation", *IEEE Eng. Boil*., March/April, 1995, pp. 152-159.
[12] Selvakumar G., Bhoopathy Bagan K. and Chidhambara Rajan B., 'Wavelet Decomposition for Detection and Classification of Critical ECG Arrhythmias', Proc. of the 8th *WSEAS Int. Conf. on Mathematics And Computers in Biology and Chemistry*, Vancouver, Canada, June 19-21, 2007.
[13] A.S. Al-Fahoum, I.Howitt, "Combined wavelet transformation and radial basis neural networks for classifying life threatening cardiac arrhythmias", *Med. Biol. Eng. Comput*., Vol. 37, 1999, pp. 566 – 573.
[14] MIT-BIH (http://www.physionet.org)
[15] Dorigo M., Caro GD, Gambardella L.M. Ant algorithms for discrete optimization. *Artiff Life* 1999;5, pp 137-142
[16] Dorigo M, Maniezzo and Colomi A. " Ant system: optimization by a clolony of cooperating agents", *IEEE Trans. Systems, Man and Cybernetics*- part B, Vol 26, pp 29-41 Feb 1996
[17] Tsai C-F, Tsai C-W, Wu H-C Yang T . A novel data clustering approach for data mining in large databases, *Journal of System and Software,* 2004 73:133-45