Neural-wavelet analysis of cardiac arrhythmias

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Abstract: - Time-frequency wavelet theory is used in combination with neural networks for the detection of life threatening electrocardiography (ECG) arrhythmias. This is achieved through the application of the wavelet transform on the ECG data, and using the resulting data as input to a neural network, which will perform the classification of the arrhythmia into one of three possible cases, those are ventricular fibrillation, ventricular tachycardia and atrial fibrillation. Ventricular fibrillation is characterized by continuous bands in the range of 2-10 Hz; ventricular tachycardia is characterized by two distinct bands: the first is in the range of 2-5 Hz and the second is in the range of 6-8 Hz; and atrial fibrillation is determined by a low frequency band in the range of 0-5 Hz.

Key-Words: - Electrocardiography, Ventricular fibrillation, Ventricular tachycardia, Atrial fibrillation, Wavelet transformation, Neural network.

1 Introduction

There are a number of cardiac arrhythmias that could be catastrophic and life threatening. Among these are ventricular fibrillation (VF), ventricular tachycardia (VT) and atrial fibrillation (AF). VF is considered to be the most life threatening because the heart fails to pump blood effectively, and the patient could die within minutes unless normal heart rhythm is restored using an electrical defibrillator.

The reliable detection and diagnosis of this arrhythmia constitute a challenge, not only in the monitoring of patients in CCU, but also in the design of automatic implantable defibrillators where the electric shock is automatically initiated by the detection of these episodes [12], [9], [15], [17].

The accuracy of VF detection is of extreme importance because failure in detection or false identification is fatal [6]. The detection of VF is difficult because the ECG has a waveform that is different from other abnormal rhythm waveforms [2]. Furthermore, practical problems such as poor electrode contact can produce artifacts that mimic these rhythms [6].

Several research groups have been working on the above problem, and a number of detection and analysis techniques have been used [18], [13], [2], [3], [19], [5]. These include, in general, either time-domain or frequency-domain analysis techniques.

In time domain analysis, threshold crossing intervals (TCI) [8], [19], and autocorrelation (ACF) methods are used [1], [4] TCI was used to detect VF and was characterized by a mean of 105ms that corresponds to a dominant frequency of 9.5 Hz, whereas for TCI = 220ms corresponds to a dominant frequency of 4.5 Hz for the detection of VT [19]. Other research groups have different values [8], [1]. The short-time ACF was used to distinguish between VF and other rhythms; depending on the fact that VF is a periodic signal [1], [4], [3].

In the frequency domain technique, the VF-filter [11], [13] as well as spectral analysis techniques was used [5]. The VF-filter method relies on approximating the VF signal as a sinusoidal waveform. The method is equivalent to using a bandpass filter, the central frequency of which is the mean signal frequency. The spectral analysis technique relies on the fact that the VF frequency contents are concentrated in the bandwidth 4-7Hz [5]. The increased power in this band of frequencies is the major indication of the presence of VF.

The above spectral analysis technique is applied to stationary signals. However, abrupt changes in the non-stationary ECG signal are spread over the whole frequency range. Important time-varying statistical characteristics are lost once the signal has been Fourier transformed. In recent years time-frequency analysis techniques have proved to be useful in experimental and clinical cardiology. These include the detection of ECG late potentials [7], [14] and high-resolution electrocardiography in general [16].

The wavelet theory is used as a time-frequency representation technique to provide a method for enhancing the detection of life threatening arrhythmias, such as AF, VT and VF [10]. It reveals some interesting characteristic features such as low frequency band (0-5 Hz) for AF, two distinct frequency bands (2-5, 6-8 Hz) for VT, and a broad band (2-10 Hz) for VF.

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 above-mentioned arrhythmias.

The back-propagation algorithm (BP) allows experiential acquisition of input/output mapping knowledge within multi-layer networks. BP performs the gradient descent search to reduce the mean square error between the actual output of the network and the desired output through the adjustment of the weights. It is highly accurate for most classification problems because of the property of the generalized data rule.

In the traditional BP training, the weights are adapted using a recursive algorithm starting at the output nodes and working back to the first hidden layer. The above algorithm could be performed using the following equation:

$$W_{ij}(t+1) = W_{ij}(t) + hd_j x_i +$$
$$a(W_{ij}(t) - W_{ij}(t-1)) \ldots (1)$$

Where W_{ij} is the weight value of node i connected to node j from previous layer, x_i is the output at node i, ç and á are the learning rate and the momentum term respectively. ä$_j$ is an error term for node j. If node j is an output node, then

$$d_j = f'(x_j)(d_j - x_j) \ldots (2)$$

Where f(x) is the nonlinear sigmoid logistic function and d_j is the desired output of node j. If node j is an internal hidden node, then

$$d_j = f'(x_j) \sum d_k w_{jk} \ldots (3)$$

Where k is over all nodes in the layer above node j.

Eqs.2 and 3 show that the error term depends basically on the activation function which is given by equation 4. The sigmoid function is chosen because it is a continuous function whose derivatives exist.

$$f(x) = \frac{1}{1 + \exp(-x)} \cdots (4)$$

2 Methods

2.1 ECG data

Performance evaluation was carried out using the MIT-BIH arrhythmia database. This database was developed at MIT and at Boston’s Beith Israel hospital, and can be accessed on the Internet through the physiobank archives. The ECG database at Yarmouk University was also used. This database was developed in cooperation with Kent University in the UK.

2.2 ECG analysis

To quantify the differences between the various groups with the help of the wavelet transform, the densities for different frequency bands were compared. That is, we computed the volume underneath the 3D plots of the square modulus of the wavelet transform for several regions of the time-frequency plane. We divided the time-frequency plane into seven bands ranging from 0 to 15 Hz. For sinus rhythm the energy was calculated within the time intervals T1 and T2 integrated over the whole frequency axis. The time interval T1 was determined by the region of QRS-complex, and the time interval T2 was 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. We refer to this parameter as Tv and define it as the sum of the energy parameters computed within the intervals T1 and T2. Although the signals of AF and VT exhibit a QRS-complex, the parameter value T2 for these signals remains relatively small, owing to the absence of abrupt changes in the region of the T-wave. Therefore the value of Tv will still be smaller than that of the normal subjects.

The classification of the VT, VF, and AF arrhythmia was carried out using a Back-propagation neural network whose input is the energy level calculated by the wavelet transform as described above, the output is a three bit pattern, in which 100 corresponds to AF, and 010 corresponds to VT, and 001 corresponds to VF.

3 Results and discussion

Three layers are used in the classification process: The input, the output and one hidden layer. The input layer has seven nodes representing the seven different frequency bands from 0-15 Hz. The output layer has three nodes that represent the three different types of arrhythmia signals AF, VT and VF. The hidden layer consists of six nodes for effective size of the network and acceptable efficiency. The learning rate and the momentum term are chosen to be 0.7 and 0.3 respectively.

The input to the network is the energy level calculated by the wavelet transform described earlier. We have 45 patterns representing all types of arrhythmia. The network is trained with 13 different patterns: Three AF, five VT, and five VF. It took the learning process approximately 1000 iterations to converge with classification error of .001. The network was then tested with 25 different patterns: Ten AF, six VT and nine VF. Table 2 shows a comparison between the actual and the detected

Positive) and FN (False Negative) and the calculated

Actual Arrhythmia	Detected arrhythmia			Total
	VF	VT	AF	25
VF	9	0	0	9
VT	1	5	0	6
AF	1	0	9	10

Table 1: A comparison between the actual and the detected arrhythmia in terms of the number of patterns

	FP	FN	Sensitivity	Specificity
VF	0	2	77.8	100
VT	1	0	100	83.3
AF	1	0	100	90

Table 2: The Sensitivity and Specificity for the testing set in percent.

The Back-propagation algorithm described in the introduction section was efficient in the classification of the three different types of arrhythmia. Table 1 shows that the BP network misclassified the proper arrhythmia in some cases, one AF case was classified as VF, this is because the energy level in the frequency bands is high and common between AF and VF.

VF arrhythmia can be detected with high specificity (100%) and high sensitivity (78%); the two other arrhythmias gave very good results as well, although the number of testing set is small, the results are encouraging for further development of the methodology using neural networks.

4 Conclusion

Neural-Wavelet analysis has proven to be very useful in detecting life threatening cardiac arrhythmias. The resulting volume parameter defined by the scalogram, which represents the energy of the signal within a specific time interval and a certain frequency band is used as an input parameter to the neural network. A comparison of the results of the neural classification scheme with that of other classification schemes obtained for the same data [10] reveals that much better results are obtained using neural networks.

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