Non-Invasive, Cardiac Risk Stratification Using Wavelet Coefficients

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Abstract: - In this paper, a non-invasive, cardiac risk-stratification method is introduced based on the discrete wavelet coefficients of an EKG signal. Two groups of signals taken from four EKG databases are compared for cardiac risk: arrhythmic patients' sinus rhythms (APSR) and healthy patients' sinus rhythms (HPSR). The Discrete Wavelet Transform (DWT) is taken using the symlet5 wavelet at a scale of four (4) to locate the 31.25-62.5 Hz frequency information. DWT coefficients are accumulated for the 30s input signal creating the feature dubbed the Accumulated Wavelet Energy (AWE). A Probabilistic Neural Network (PNN) is then trained with half of the APSR and HPSR data sets. Finally, the second half of the data sets are classified with the PNN and performance statistics are calculated. This method demonstrates low computation time and cost, and does not require any lengthy physician training. After fifty random permutations of training and testing sets, an average accuracy of ~83%, a specificity of ~84%, and a sensitivity of ~78% were found.

Key-Words: - Risk Stratification, Sudden Cardiac Death, Wavelets, EKG

1 Introduction

Sudden Cardiac Death, or SCD, is a malfunction of the electrical system that stimulates the contractions of the heart. It occurs suddenly, often with only minutes before death or permanent brain damage sets in. According to the American Heart Association (AHA), SCD is responsible for more than 250,000 deaths in the US each year, about half of all coronary heart disease deaths [1]. This disease is particularly frightening due to the lack of warning for victims. Outwardly healthy people with no known history of heart disease start to have symptoms and are dead in minutes. With immediate emergency treatment, the heart can be shocked back into the normal heartbeat with little or no permanent damage. The critical issue with this disease is time, and the only way to truly treat it is to prevent it through advanced screening and determining who is at risk. Most victims do actually have some underlying cardiac disease. Roughly 75% of SCD victims shows signs of previous heart attack [2] and 85% have signs of coronary artery disease [3].

With high-risk patients, Implantable Cardiac Defibrillators (ICD) can be installed and respond to SCD. The American Heart Association has recommended the deployment of these ICDs in high-risk patients to improve SCD's survival rate.

The true question is how to stratify patients into risk categories before they have cardiac problems. Several methods including QT dispersion, T-wave alternans, signal averaged EKG, HRV, and left ventricle ejection fraction have been used with limited success [3, 4].

In this paper, a non-invasive, cardiac risk-stratification method is introduced using the accumulated energy of the discrete wavelet coefficients of an EKG signal. A probabilistic neural network (PNN) is then used to stratify the different patients into low and high risk groups.

2 A Brief Wavelet Overview

The wavelet transform utilizes a defined function called a "mother wavelet," $g(t)$. This fixed shape signal is then scaled creating "daughter" wavelets with different bandwidths and lengths. These scaled wavelets are convolved with an input signal, $x(t)$, to find the wavelet coefficients. The discrete wavelet transform (DWT), as seen in Fig. 1, employs two sets of functions, called scaling functions and wavelet functions, which are associated with lowpass and highpass filters, respectively. This allows the DWT to output two sets of coefficients, each showing fine and coarse information, respectively.

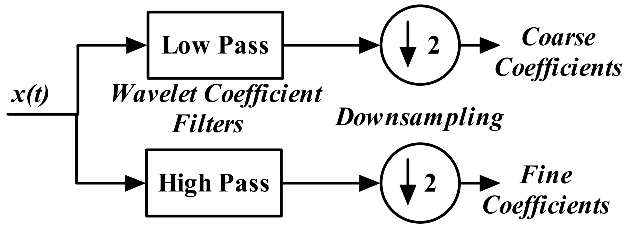

Fig. 1 Discrete Wavelet Coefficient (DWT) Computation

Each of the two outputs contains half of the frequency data from the original at a sampling rate half of the original. For example, when *x(t)* has information in a frequency band from 0-125 Hz, the first level decomposition will output a set of data showing the 0-62.5 Hz information and another showing 62.5-125 Hz information. This can be done recursively, as shown in Fig. 2, showing progressively smaller bands [5].

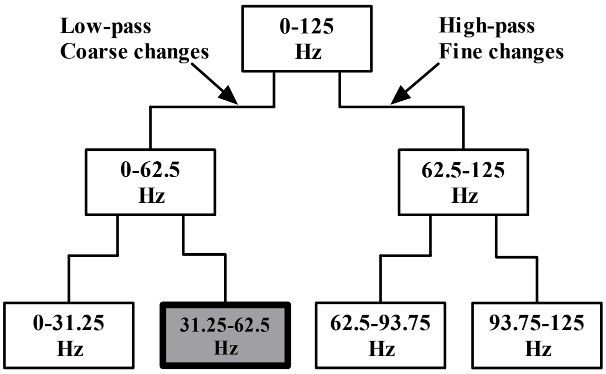

Fig. 2 An example of DWT Frequency Decomposition at a sampling rate of 250 Hz. The 31.25-62.5 band shown in gray is used in this study.

In this paper, the 31.25-62.5 Hz frequency band, marked in gray above, will be studied in the EKG signal.

3 Materials and Methods

All computations were done on a dual Pentium II PC in the Matlab R12 computational program. Three of the databases were downloaded from www.physionet.org.

3.1 EKG Data

For this study, two different groups of data were compared. The first group, dubbed the arrhythmic patient's sinus rhythms (APSR), consists of EKGs of arrhythmia patients when they were not in an arrhythmic rhythm. This is their normal beat that appears most often. The second group, dubbed the healthy patient's sinus rhythm (HPSR), consists of EKGs of patients that have not been diagnosed with a cardiac arrhythmia.

Table 1 Studied databases with patient and segment numbers.

	# of Patients		# of Segments	
Database Name	APSR	HPSR	APSR	HPSR
American Heart Association	8	10	8	55
Fantasia		39		140
Creighton University	27		29	
MIT-BIH Malignant Ventricle	18		29	
Total	53	49	66	195

These two groups, APSR and HPSR, are composed of four different databases all with a sampling frequency of 250 Hz.

Three databases contain APSR signals while only two contain HPSR signals. Each database was first filtered to remove any baseline drift (DC voltage) and 60 Hz noise. Then, multiple thirty-second (30s) segments of minimal artifact noise were taken from each patient.

3.2 Feature Extraction

The DWT of each 30s EKG segment was calculated using the symlet5 wavelet at a scale of four (4) to obtain the 31.25-62.5 Hz frequency band as explained in section two. Most EKG frequency information, including the PQRST waves, exists in the 1 to 30 Hz range [6]. These values are lower than the range investigated in this study. The Accumulated Wavelet Energy (AWE) of an input signal, x, is

$$AWE = \sum_{i=1}^{N} \{DWT_x(i)\}^2 \qquad (1)$$

where N is the length of the DWT of x. The AWE for each signal was then held for comparison and classification.

3.3 Classification

This study uses a supervised learning network called a probabilistic neural network (PNN) to classify the two risk groups. Fig. 3 below shows the flow diagram of this two layer network with a single input. The input is the AWE of the sample being classified. This PNN uses the training set as weighting values, w_N. The function, *f(x),* in the first layer is the radial basis function of the Euclidean distance between the training point and the input sample. The *T* weight values distinguish between the two classes of training data used while *g(x)* is the average of all nonzero inputs. The two outputs are the estimated likelihood of the input AWE being a member of each of the two classes [7].

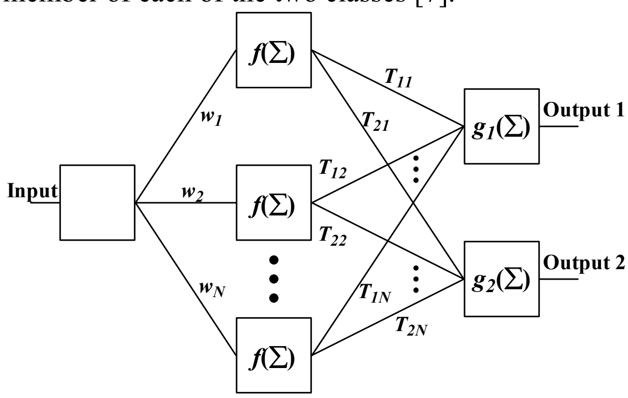

Fig. 3 The flow chart of the PNN used for classification.

The two groups of AWE data, APSR and HPSR, were split into halves for testing and training sets using random permutations. The PNN was trained with the first half and fed the testing half resulting in an output of probabilities of class membership. A probability threshold was set on inspection and apparent low and high-risk class memberships were assigned.

4 Experimental Results

As seen in Fig. 4 (a) and (b), the DWT coefficients of the (a) APSR signal have amplitude lower than those of the (b) HPSR signal. After the AWE is taken, as seen in the bottom of the two plots, (b) HPSR has a much higher value than that of (a) APSR. This feature has a p-value of less than 0.0001 while distinguishing between the two groups of patients.

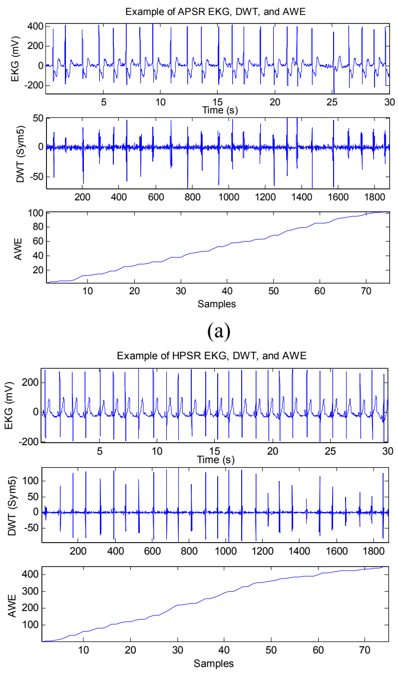

Fig. 4 EKG, DWT, and AWE for a 30s sample from the (a) APSR and the (b) HPSR data sets.

Due to the importance of finding all high-risk patients, false negatives (FN) are minimized to increase sensitivity. The results shown in Table 2 were found with the classifier probability threshold set to 40%. The classifier was run 50 times and the results averaged to allowed many permutations of training and testing sets to be run while gaining reliable output statistics.

Table 2 Experimental Results and statistic Definitions

Statistic	Value	Equation
No. of True Positives (TP)	25.62	
No. of False Positives (FP)	15.18	
No. of True Negatives (TN)	81.82	
No. of False Negatives (FN)	7.38	
Sensitivity	77.6%	$\frac{TP}{TP+FN}$
Specificity	84.3%	$\frac{TN}{TN+FP}$
Positive Predictive Value	62.7%	$\frac{TP}{TP+FP}$
Negative Predictive Value	91.7%	$\frac{TN}{TN+FN}$
Classification Accuracy	82.6%	$\frac{TP+TN}{TP+FP+TN+FN}$

5 Conclusion

In this paper, a non-invasive, cardiac risk stratification method is introduced using the accumulated energy of the discrete wavelet coefficients of an EKG signal. This single feature classified with a PNN produces a high accuracy of ~83% and a sensitivity of ~78% with separate testing and training sets taken from 4 EKG databases.

A limited EKG library was available for research for the two classes of data. Ideally, the two classes should be taken using the same data collection setup (leads, digitizers, filters, etc.) and for long periods of time. Much of the data available was unusable due to large motion artifacts, short length, and/or RF noise. Also, intra-cardiac leads would be beneficial to test due to fewer noise complications.

Future research on this method will be done to determine if there is a causal relationship between this feature and the onset of a life threatening heart arrhythmia. Also, the specified 31.25-62.5 Hz frequency band of the EKG should be further investigated to find reasons this method is successful. Work will also be done to combine other features to increase the sensitivity and accuracy of this method. Further stratification of the low and high-risk categories can also be further divided into more classes and probabilities of SCD could try to be accessed.

Overall, this method contributes to the cardiology community by offering a noninvasive, low complexity, low cost, fast method for cardiac risk stratification. The end result with better classification could be patients being screened at yearly physicals for increasing heart problems before any symptoms occur.

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