Cardiac Arrhythmia Help – Diagnosis System Using Wavelets and Hidden Markov Models

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Abstract: - This paper reports the development of a help-diagnosis system where the physician is required to analyze some ECG pulses that can not be accurately classified by the system. A confidence measure is estimated on the basis of massive experimental tests on data from MIT-BIH Arrhythmia Database, and was set on a threshold above which no classification errors were obtained. Cardiac arrhythmia detection and classification is performed by using Wavelets and Hidden Markov Models (HMMs). The types of beat being selected are normal (N), premature ventricular contraction (V) which is often precursor of ventricular arrhythmia, two of the most common class of supra-ventricular arrhythmia (S), named atrial fibrillation (AF), atrial flutter (AFL), and normal rhythm (N). Experimental results are obtained in real data from MIT-BIH Arrhythmia Database and a developed Data-Acquisition System.

Key-Words: Hidden Markov Models, Wavelets, Cardiac Arrhythmia Diagnosis.

1 Introduction

Electrical instability of the heart, which can be identifiable in the ECG, leads to an abnormal synchronized contraction sequence reducing pumping efficiency. This phenomenon named arrhythmia can be classified as frequent or infrequent (sporadic). Infrequent arrhythmias can be evaluated by long-term ambulatory ECG monitoring (Holter), which produces a quantity of beats greater than 10^5. This huge quantity of data requires automatic diagnosis equipment which allows reducing the time required for diagnosis, increasing the quality of life.

Atrial fibrillation (AF) is perhaps the most common arrhythmia encountered in clinical practice, affecting about 0.5-1% of the general population. AF is not only related to frequent symptoms and reduced quality of life but also constitutes a major risk factor for stroke and mortality from cardiovascular and all other causes [1]. AF pathology is usually diagnosed based on ECG analysis.

Normally continuous monitoring over an extended period of time is required in order to increase the understanding of patient's cardiac abnormalities. Such situations require continuous monitoring by the physicians or alternatively the aid of automated arrhythmia detection equipment, which can be able to identify different types of arrhythmias.

This problem of cardiac arrhythmia detection can be viewed as a pattern recognition problem, since it is possible to identify a finite number of different patterns (arrhythmias).

HMMs have been successfully applied to pattern recognition problems in applications spanning automatic speech recognition [2], image segmentation [3], ECG modeling [4] and cardiac arrhythmia analysis [5]. The most common approach regarding HMMs training is finding the stochastic distribution that best fits the data. Usually this data is derived from the waveform from some type of signal processing usually known as feature extraction method. Recently advanced signal processing techniques as Fourier Transform, Linear Predictive Analysis, Lyapunov Functions [6] and Multivariate Analysis (MA) have been used in order to feature extraction in the HMMs framework. MA allows observing the signal at various scales emphasizing some hidden particularities not viewed at other scales. Wavelet Analysis (WA) is perhaps the most common form of MA. Recently WA was been successfully combined with HMMs especially regarding ECG segmentation [7].

The Wavelet Transform (WT) has the advantage over conventional techniques that time/frequency representation can be more accurately modeled by decomposing the signal in the corresponding scales. When the composition level decreases in the time domain it increases in the frequency domain providing zooming capabilities and instantaneous characterization of the signal [8].

The baseline system is a Bakis or left-to-right Continuous Density Hidden Markov Models (CDHMMs) with a Gaussian Mixture Model (GMM) associated to each model transition. The ECG signal is previously sliced in singular pulses by using the Pan-Tompkins [9] algorithm and each pulse class is modeled by a six state model, modeling the Q-S, S-T, T, T-P, P and P-Q events. Experimental results from the MIT-BIH Arrhythmia Database using more than 2000 training pulses and 3400 testing pulses are presented. Additionally more than 600 pulses acquired by our Data-Acquisition System from patients of the Braga Hospital were tested under supervision of a Cardiologist.

2 Data-Acquisition System

The developed Data-Acquisition System has two components. The hardware acquisition system is based on a custom printed-circuit board with pre-amplifier, filters and interface for short term Ag/AgCl electrodes [10]. Usually, the electrodes position follows the vector cardiogram distribution (left and right arms and left and right legs). However, modified limb lead II (MLII) and modified lead V1 carry sufficient information regarding automatic diagnosis purposes. Figure 1 shows a five leads standard Holter.

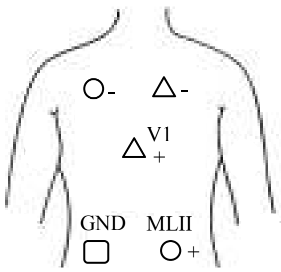

Fig.1 A five leads standard Holter

The electrical activity of the heart is filtered, amplified and converted in a digital signal. A data-acquisition board, NI 6014, set in differential mode is used to control the acquisition hardware and A/D conversion.

The software for acquisition and filters were developed in MATLAB [10]. Afterwards, MLII and V1 signal named 300 and 301 were converted in to MIT-BIH 212 signal format.

3 Wavelets

The most usual way to sample the time-scale plane is on a so-called "dyadic" grid, which means that sampled points in the time-scale plane are separated by a power of two. This procedure leads to an increase in computational efficiency for both WT and Inverse Wavelet Transform (IWT). Under this constraint the Discrete Wavelet Transform (DWT) is defined as

$$\psi_{j,k}(t) = s_0^{-j/2}\psi\left(s_0^{-j}t - k\tau_0\right) \qquad (1)$$

which means that DWT coefficients are sampled from CWT coefficients. A "dyadic" scale is used and therefore $s_0=2$ and $\tau_0=1$, yielding $s=2^j$ and $\tau=k2^j$ where j and k are integers.

As the scale represents the level of focus from the which the signal is viewed, which is related to the frequency range involved, then digital filter banks are appropriated to break the signal in different scales (bands). If the progression in the scale is "dyadic" the signal can be sequentially half-band high-pass and low-pass filtered.

The output of the high-pass filter represents the detail of the signal. The output of the low-pass filter represents the approximation of the signal, for each decomposition level, and will be decomposed in its detail and approximation components at the next decomposition level, and the process proceeds iteratively in a scheme known as wavelet decomposition tree. After the filtering half of the samples can be eliminated according to the Nyquist's rule, since the signal now has only half of the frequency. This very practical filtering algorithm yields as Fast Wavelet Transform (FWT) and is known in the signal processing community as two-channel subband coder [11]. One important property of the DWT is the relationship between the impulse responses of the high-pass (g[n]) and low-pass (h[n]) filters, which are not independent of each other and they are related by

$$g[L-1-n] = (-1)^n h[n] \qquad (2)$$

where L is the filter length in number of points. Since the two filters are odd index alternated reversed versions of each other they are known as Quadrature Mirror Filters (QMF). Perfect reconstruction requires, in principle, ideal half-band filtering. Although it is not possible to realize ideal filters, under certain conditions it is possible to find filters that provide perfect reconstruction. The most famous ones were developed by Ingrid Daubechies and they are known as Daubechies wavelets. In the ambit of this work only Daubechies wavelets with 2 vanishing moments (db-4) were used.

The multiresolution analysis based on the DWT can enhance small differences if the signal is viewed at the most appropriate scale. Figure 2 shows the result of the application of the DWT one cycle of a normal ECG. From the figure we can observe that d1 level (frequency ranges of 90-180Hz) emphasize the high frequency content of complex QRS when compared with P and T waves . D2 and d3 levels show clearly that other waves of small frequencies not seen at d1 scale are just appearing.

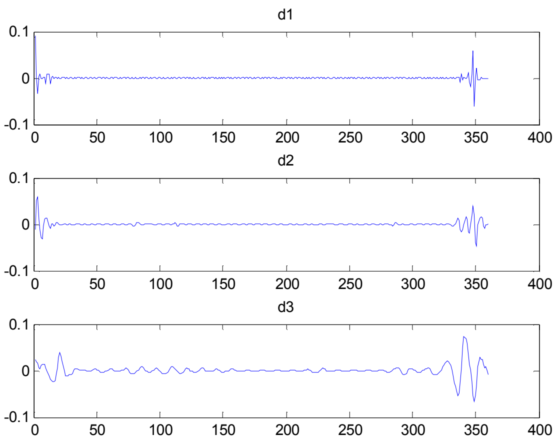

Fig.2 One ECG pulse viewed at scales d1, d2 and d3.

The features used in the scope of this work are simultaneous observations of d1 and d2 scales, therefore the observation sequence generated after the parameter extraction is of the form $\mathbf{O}=(\mathbf{o}_1, \mathbf{o}_2, \ldots \mathbf{o}_T)$ where T is the signal length in number of samples and each observation $\mathbf{o}_t$ is a bi-dimensional vector. Each element of the observation vector is derived from the IWT of the selected scale.

4 Hidden Markov Models

HMMs are a doubly stochastic process in which the observed data are viewed as the result of having passed the hidden finite process (state sequence) through a function that produces the observed (second) process.

In the pattern recognition paradigm each class of beat is represented by a separate model and after decoding, the class for the which the probability (likelihood) of occurrence is greater is selected. Since the ECG is characterized by a time sequence waves occurring almost always in the same order which reflects the sequential activity of the cardiac conduction system an HMM structure where the states are connected in a left-to-right order was adopted. In [4] it is shown that a full connected HMM is eventually more appropriate for HMM modeling since the beat sequence reproduced by this kind of HMM is almost perfect. Figure 3 shows the model structure adopted for the several pathologies considered in the ambit of this paper.

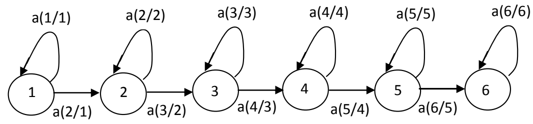

Fig.3 A left-to-right HMM with 6 states

The next issue is the choice of the number of Gaussian mixtures. For CDHMMs, it has been found that it is more convenient and sometimes preferable to use diagonal covariance matrices with several mixtures, rather than fewer mixtures with full covariance matrices. The reason is the difficulty in performing reliable re-estimation of the off diagonal components of the covariance matrix from the necessarily limited training data. The HMMs in this work use five Gaussian mixtures per transition.

The output probability density function, which defines the conditional likelihood of observing a set of features when a transition through the model takes place, is usually a multivariate Gaussian mixture for the most engineering applications involving HMMs. These probability density functions are associated with the transitions which configures a CDHMMs Mealy machine and are given by

$$f(y/u_t) = \sum_{i=1}^{C} b_{u_t,i} G(y_t, \mu_{u_t,i}, \Sigma_{u_t,i}) \qquad (3)$$

Where c is the number of components in the Gaussian mixture, G(…) stands for bi-variate normal distribution with mean vector and covariance matrix for the i^{th} mixture component and transition u_t given respectively by $\mu_{u_t,i}$ and $\Sigma_{u_t,i}$. As the components of observation vector are assumed iid G(…) function in equation (3) is simply the product of five Gaussian functions. The mixture coefficients $b_{u_t,i}$ satisfy, for each transition u_t , to

$$\sum_{i=1}^{C} b_{u_t,i} = 1 \qquad (4)$$

so that, equation (3) is a probability density function.

In our experiments the observations were modeled by five components in the Gaussian mixture (C=5) in order to fit best data with multimodal distributions.

The Estimation of HMMs parameters from a set of representative training data can be done by using the Baum-Welch algorithm which is based on the decoding of all the possible state sequence, or alternatively by using the Viterbi algorithm which is based on the most likely state sequence [2]. The adopted training was the MLE procedure in the Viterbi framework, which goal is to maximize iteratively the following probability density function. The model reestimation formulas can be found in [2]. This usual parameter estimation technique maximizes iteratively the model parameters that best fit the training data.

5 Experimental Results

Experimental results were evaluated by using the MIT-BIH Arrhythmia Database. Normal (N) and premature ventricular contraction (V) beats, in atrial fibrillation (AF), atrial flutter (AFL) and normal (N) rhythms were selected.

The training set contains the 121, 122, 221 and 222 records and the testing set contains the 105, 112, 121, 122, 210, 221 and 222 records of the MIT-BIH arrhythmia database, 300 and 301 of the Data-Acquisition Systems. For the training set 1445 normal (N) pulses of 121 (N rhythm) and 122 (N rhythm), 682 normal and premature ventricular contraction (V) pulses of 221 (AF rhythm) and 197 normal pulses of 222 (AFL rhythm) records were used. The testing set contains 3024 pulses of 105, 112, 121, 122, 300 and 301 records, 1011 pulses of 210 and 221 records and 246 pulses of 222 record, which means that data for training and testing purposes was obtained from different patients, which is normally known as patient-independent analysis. Table 1 shows the HMM based pulse classification system using features from wavelets.

Table 1 – The confusion matrix associated DWT

	AFN	AFV	AFLN	NN	Total	Pr+
AFN	864	0	0	0	864	1
AFV	0	114	0	0	114	1
AFLN	0	0	237	0	237	1
NN	33	0	9	3024	3066	0.98
Total	897	114	246	3024	4281	
Sensitivity	0.96	1	0.96	1		

Both MLII and V1 signals were used each one with their own HMM. A pulse is considered classified if the score from both models agree, otherwise the pulse is considered wrong. The row labeled "Total" means the total number of beats used in experiment for each class listed in the corresponding column.

Figure 4 shows a pulse were the confidence measure is below the threshold, hence it was select for posterior analysis by the physician. This pulse is clearly an "A" pulse so not belonging to the considered arrhythmia classes. In this case it was well selected by insufficient likelihood.

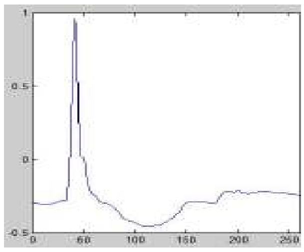

Fig.4 Selected pulse for posterior analysis by the physician

6 Conclusion

This paper reports a robustness help-diagnosis system regarding the cardiac arrhythmia detection by the physician. Uncertainty about classification by the automatic recognizer is signaled and the physician is required to make diagnosis based on medical knowledge.

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