ARRHYTHMIA DETECTION WITH TIME AND TIME-FREQUENCY ANALYSIS OF HEART RATE VARIABILITY

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ARRHYTHMIA DETECTION WITH TIME AND TIME-FREQUENCY ANALYSIS OF HEART RATE VARIABILITY

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Abstract: **In this paper we use the tachograms obtained from arrhythmic ECG recordings to detect arrhythmia. Tachograms are segmented and time and time-frequency methods are applied to those segments in order to extract several features. Neural networks are used for arrhythmia detection and the results are presented for the MIT-BIH arrhythmia database in terms of the obtained sensitivity and specificity.**
Keywords: **Heart Rate Variability, Time-Frequency Analysis, Time Domain Analysis, Arrhythmia**

I. Introduction

Arrhythmias are disorders of the regular rhythmic beating of the heart. Respiratory Sinus Arrhythmia (RSA) is of periodic variation in RR intervals, corresponding to respiratory activity. Non-natural arrhythmias can take place in a healthy heart and be of minimal consequence, but they may also indicate a serious problem and lead to heart disease, stroke or sudden cardiac death [1]. Therefore automatic arrhythmia detection in short-time ECG recordings and in 24 hours holter recordings has become a serious issue because it can provide vital information for the individual.

The electrocardiogram (ECG) provides critical information about heart's condition [1]. Heart Rate Variability (HRV), extracted from ECGs, believed to be a very good marker of the individual's health condition and heart diseases. HRV refers to the beat-to-beat alterations of heart rate at any instant in time and represents the resultant of many influences on the sympathetic and parasympathetic centers. Therefore HRV analysis became an important tool in cardiology providing information about body activities strongly related to heart diseases [2].

Time domain analysis (statistical measurements, geometrical evaluation [3]) and frequency domain analysis [4] are the most commonly used methods that provide essential but not detailed information for HRV. Time-Frequency (t-f) analysis, which is based on Time-Frequency Distributions (TFDs) and wavelet analysis, is a more detailed method and provides with non-stationary information of the HRV. Wigner Ville Distribution (WVD) and Smoothed Pseudo Wigner Ville Distribution (SPWVD), Selective Discrete Fourier Transform (SDA), Short Time Fourier Transform (STFT) and Choi-Williams Distribution (CWD) are some of the distributions used for t-f analysis of HRV [6-17]. Non-Linear – Chaotic analysis has also been used [5].

In this study we use time and time-frequency analysis of the HRV to detect arrhythmia in long-term electrocardiograms. The dataset used in our research are the MIT-BIH arrhythmia database recordings [18]. For each recording the corresponding tachogram has been extracted and segmentation has performed for all tachograms. In time domain analysis we extract several statistical features from each segment; in t-f analysis STFT and a number of distributions belonging to the Cohen's class are applied and t-f features extracted. The obtained time and t-f features are fed into a set of neural networks. The latter combined with a decision rule provides with arrhythmia diagnosis.

II. Methodology

Our analysis is carried out in several stages. At first a preprocessing procedure is used for the extraction and segmentation of the tachograms from the ECGs. Next, time domain and time-frequency methods are applied to extract several features and a classification technique based on a set of neural networks is applied followed by a decision rule on the neural networks' results.

The MIT-BIH arrhythmia database consists of 48 ECG recordings, which are divided into 23 recordings of 100 series and 25 recordings of 200 series. In this study we use all the recordings from both series. The length of each recording is 30 minutes, which results to a total of 112,568 RR intervals.

The analysis is carried out on MatLab ver. 5.2. The RDNN DOS software, included in MIT-BIH arrhythmia database, was used to extract the tachograms from the database recordings. The calculation of the TFDs was made with the Time-Frequency Toolbox ver. 2.0 for MatLab [19].

A. Preprocessing stage

Preprocessing is carried out in two steps. In the first step we extract the tachograms from the ECG recordings. Tachogram is the signal, which indicates the RR interval duration. In the second step using the MIT-BIH arrhythmia database annotation we characterize each RR interval as follows; RR interval with annotation N, P, f, p, Q, |, +, s, t and ~ were characterized as "Normal" and RR interval with annotation L, R, A, a, J, S, V, F, [, !,], e, j, n and E were characterized as "Arrhythmic". A segment is characterized "Normal" if it contains more than 95% "Normal" RR intervals of the total 32 RR intervals, otherwise is characterized "Arrhythmic". The total number of segments in the segmented dataset is 3,426.

B. Time Domain Analysis

The features shown in Table 1 are extracted from each segment in the segmented dataset.

Table 1: Time domain features.

	Feature	Description
1	SDRR	Standard deviation of all RR intervals
2	r_MSSD	Square root of the sum of the squares of differences
3	SDSD	Standard deviation of differences
4	pNN5	% of RR intervals > 5msec
5	pNN10	% of RR intervals > 10msec
6	pNN50	% of RR intervals > 50msec

We use all possible combinations among these features in order to create the pattern set for the classification stage. This leads to a total of 63 feature combinations. That gives us a total of 63 inputs with 3,426 patterns each. All inputs are shown in Table 2.

Table 2: Combinations of Time Domain Features.

Combination	Combination Name (Feature Numbers)	Features
1	1	SDRR
2	2	r_MSSD
3	12	SDRR, r_MSSD
4	3	SDSD
5	13	SDRR, SDSD
6	23	SDRR, r_MSSD
7	123	SDRR, r_MSSD, SDSD
8	4	pNN5
...	...	...
60	3456	SDSD, pNN5, pNN10, pNN50
61	13456	SDRR, SDSD, pNN5, pNN10, pNN50
62	23456	r_MSSD, SDSD, pNN5, pNN10, pNN50
63	123456	SDRR, r_MSSD, SDSD, pNN5, pNN10, pNN50

In the sequel, we train a feed-forward back-propagation neural network, for each input, using 1,426 patterns as training set. The architecture is always the same; N inputs, one hidden layer and one output. N is the number of features used in the specific input, the hidden layer has 20 neurons and the output is a real number between 0 and 1. The training of the neural network ends when the square error is less than 0.01 or the training epochs are more than 2,000.

C. Time-frequency Methods

We calculate multiple TFDs for each segment of the segmented dataset. All TFDs belong to the Cohen's class except Short Time Fourier Transform (STFT). The TFDs used are shown in Table 3. The TFDs are normalized in the [-1,1] interval.

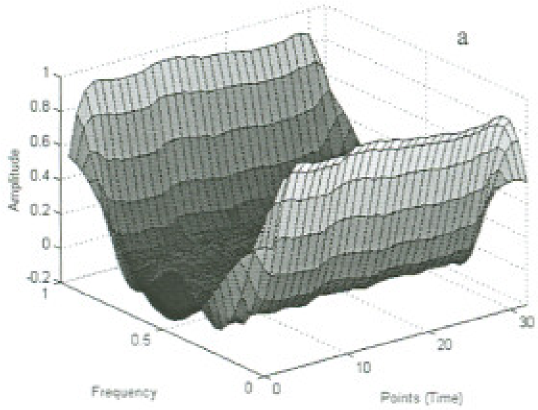
Table 3: Time-frequency distributions.

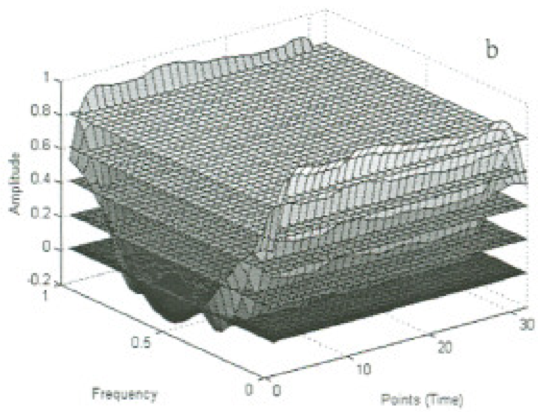
	Distribution
1	Born-Jordan distribution
2	Butterworth distribution
3	Choi-Williams distribution [5]
4	Generalized rectangular distribution
5	Margenau-Hill distribution
6	Pseudo Margenau-Hill distribution
7	Margenau-Hill-Spectrogram distribution
8	Page distribution
9	Pseudo Page distribution
10	Wigner-Ville distribution [6]
11	Pseudo Wigner-Ville distribution
12	Smoothed Pseudo Wigner-Ville distribution [7]
13	Rihaczek distribution
14	Reduced interference distribution Bessel window
15	Reduced interference distribution Hanning window
16	Reduced interference distribution Binomial window
17	Reduced interference distribution Triangular window
18	Zhao-Atlas-Marks distribution
19	Short Time Fourier Transform

For each distribution we create multiple traces with amplitude = 0.0, 0.2, 0.4, 0.6, 0.8 and 1.0. Then we calculate the area below 0.0 and the areas between adjacent traces. Fig. 3 shows the distribution, traces and areas calculated.

Six features (areas) for each TFD are computed. This leads to a total of 19 inputs with 3,426 patterns each.

For each TFD we train a feed-forward back-propagation neural network, with the following architecture; six inputs, one hidden layer with 20 neurons and one output which is a real number in the interval [0,1]. The training set consists of 1,426 segments. Training of the neural network ends when the square error is less than 0.01 or the training epochs are more than 2,000.





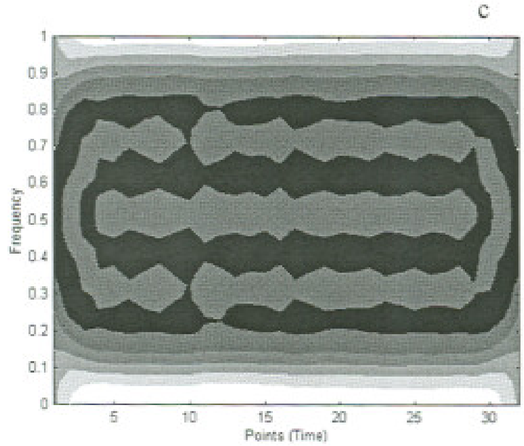


Fig. 3: a. Distribution, b. Traces c. Areas

D. Arrhythmia Detection

For both time domain and t-f analysis we use 2000 segments as test set. We feed each segment into all the neural networks trained (63 for time domain analysis and 19 for t-f analysis) and use all the corresponding results to determine the final "Normal" or "Arrhythmic" decision using the following three decision rules.

- Average: For each segment we calculate the average of the results of all neural networks and threshold 0.5 for the final decision.
- Vote: For each segment all neural networks vote if it is arrhythmic, with threshold 0.5. If more than half votes are accumulated then the decision is "Arrhythmic", otherwise "Normal".
- Weight Vote: Each neural network votes by the following equation;

$$\text{weight} = \begin{cases} 0 & |y_i - 0.5| \leq 0.1 \\ y_i - 0.5 & \text{otherwise} \end{cases}$$

where y_i is the result of the i^{th} neural network. If all the neural network results have weight 0 then the weight is calculated as;

$$\text{weight} = y_i - 0.5$$

After calculating the weights for all neural networks we use the average of all weights and threshold 0.0 for the final decision.

III. RESULTS

For both time domain analysis and t-f analysis we calculate sensitivity and specificity using the above decision rules. The results for time domain analysis average and vote criterion were almost identical, nearly 81% and 78% for sensitivity and specificity, respectively. Weight Vote leads to 87.5% sensitivity and 89.5% specificity. Time-frequency analysis resulted nearly 88% sensitivity and specificity for average and vote decision rules. Weight vote had the best results among all experiments, 90% sensitivity and 93% specificity. The obtained results are shown in Table 4.

Table 4: Time and t-f analysis results for sensitivity and specificity.

Analysis	Decision Rule	Sensitivity	Specificity
Time	Average	80.68%	78.18%
	Vote	82.60%	78.43%
	Weight Vote	87.53%	89.48%
T-F	Average	87.64%	88.65%
	Vote	86.84%	89.25%
	Weight Vote	89.95%	92.91%

IV. DISCUSSION

We use time domain and t-f analysis characteristics to detect arrhythmias annotated in the MIT-BIH arrhythmia database. Our goal is the creation of an automatic arrhythmia detection system that detects all types of arrhythmia and isolates the arrhythmic segments in an ECG recording.

Average and vote decision rules are common methods for combining more than one result. Using average and vote the final result depends on all networks results, including networks results that are close to 0.5, which is not a clear decision. In weight vote all those networks results are measured as 0 and they don't effect the final decision.

V. CONCLUSIONS

The proposed arrhythmia detection system based on time characteristics results in 81% sensitivity and 78% specificity for average and vote decision rules and t-f analysis resulted nearly 88% sensitivity and specificity. Weight vote gave better results in both cases, 87.5% and 89.5% for time analysis and 90% and 93% for t-f analysis. Clearly t-f analysis resulted higher sensitivity and specificity than time analysis.

Future work includes identical detection systems for other domains of HRV analysis, such as frequency and non-linear analysis, in order to develop a complete automatic arrhythmia detection system in each domain and a hybrid system that combines the best features from each domain for arrhythmia detection.

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