ARRHYTHMIC ELECTROCARDIOGRAM BEAT DETECTION AND CLASSIFICATION USING HEART RATE VARIABILITY ANALYSIS

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Abstract: **We present a system for automatic arrhythmia detection and classification in ECGs. Arrhythmia detection is based on time and time-frequency domain features of heart rate variability. The RR interval duration signal is extracted from ECGs and segmented into small intervals. Time domain features are extracted and used for the training of a set of neural networks. Short time Fourier transform, and several time-frequency distributions are used in the time-frequency analysis and the obtained features are used for the training of a set of neural networks. The arrhythmia classification is based on a set of rules. The rules use information from the RR interval duration signal and they are applied on a 3 RR interval sliding window. The proposed approach is evaluated using the MIT-BIH arrhythmia database. The results obtained are satisfactory for both sensitivity and specificity for arrhythmia detection. The detected beats are used for testing the classification approach and the results are presented.**
Keywords: **Arrhythmia detection, arrhythmia classification, heart rate variability, time-frequency analysis**

Introduction

Arrhythmic beat detection and classification in electrocardiography is an important subject that provides valuable clinical information about the heart's condition [1]. Several detection algorithms have been proposed, such as the time-frequency [2] and wavelet analysis, complexity measure, multifractal analysis [3] and algorithms based on neural-networks. Many classification algorithms have also been presented. In the paper we explore the use of using only RR interval duration and heart rate variability (HRV) analysis in the detection and classification of arrhythmia.

Materials and Methods

The RR interval duration signal is extracted from ECG recordings. For arrhythmia detection, segmentation is performed on the RR interval duration signal, leading to 3,426 small segments of 32 RR intervals. Each segment is characterized using the MIT-BIH annotation. RR intervals with annotation N, P, f, p, Q, |, +, s, t and ~ were characterized as "Normal" and RR intervals 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". In the time domain analysis several time domain features [4] are extracted (Table 1) from each segment. All possible combinations among these features are used (Table 2) and one neural network is trained for each combination.

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 difference of successive RR intervals > 5msec
5	pNN10	% of difference of successive RR intervals > 10msec
6	pNN50	% of difference of successive RR intervals > 50msec

Table 2: Combinations of time domain features

	Feature Combination	Features
1	1	SDNN
2	2	r_MSSD
3	12	SDNN, r_MSSD
4	3	SDSD
...	...	...
62	23456	r_MSSD, SDSD, pNN5, pNN10, pNN50
63	123456	SDNN, r_MSSD, SDSD, pNN5, pNN10, pNN50

For the time-frequency (t-f) approach several t-f distributions (Wigner-Ville, Pseudo Wigner-Ville and Smoothed Pseudo Wigner-Ville distributions, Margenau-Hill, Pseudo Margenau-Hill and Margenau-Hill-Spectrogram, Born-Jordan, Zhao-Atlas-Marks, Generalized rectangular, Choi-Williams, Rihaczek, Page and Pseudo Page, Butterworth and Reduced Interference Distributions with Bessel, Hanning, Binomial and Triangular window) and STFT are applied [5] on the segments. For STFT and each t-f distribution multiple traces with amplitude = 0.0, 0.2, 0.4, 0.6, 0.8 and 1.0 are created and the area below 0.0 and the areas between adjacent traces are calculated. Six t-f features (areas) are computed. For STFT and each t-f distribution one neural network is trained.

Feed-forward back-propagation neural networks are used, having N inputs, one hidden layer with 20 neurons and one output which is a real number in the interval [0,1]. In the time domain N is the number of features used in the feature combination and in t-f domain N is 6. The training set consists of 1,426 segments. Training of the neural network stops when the square error is less than 0.01 or the training epochs are more than 2,000. For both time domain and t-f analysis 2,000 segments are used as test set. Each segment is fed into all the neural networks trained (63 for time domain and 19 for t-f domain) and all the corresponding results are used to determine the final decision using three decision rules:

- Average: For each segment we calculate the average of the results of all neural networks and use a threshold 0.5 for the final decision.
- Vote: For each segment all neural networks vote for arrhythmia, with threshold 0.5. If more than half votes are accumulated then the decision is "Arrhythmic", otherwise "Normal".
- Selected Vote: All neural networks with output in the interval [0.4, 0.6] are excluded and the average of the rest is used with threshold 0.5 for the final decision. If all outputs are in the interval [0.4, 0.6] then the average of all neural networks if used.

Arrhythmia beat-by-beat classification is performed on segments that are detected as arrhythmic, using a set

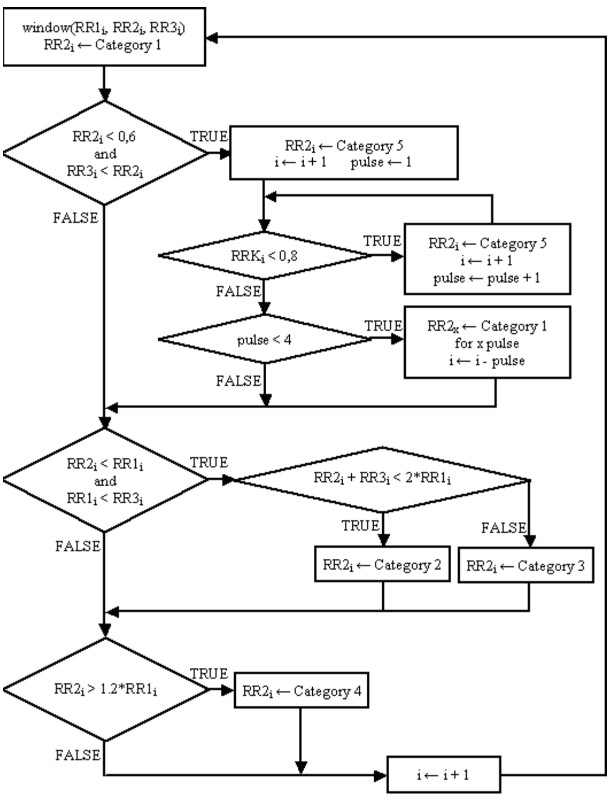

Figure 1: Arrhythmia classification algorithm

of rules. The rules are based on the tachogram and they are applied on a 3 RR interval duration sliding window, characterizing the middle beat. Classification is performed for five categories of beats, which are created using the MIT-BIH annotation. Beats annotated N, P, f, p, Q, |, +, s, t, ~, L and R the first category, A, a, J and S the second, V and F the third, e, j, n and E the forth and [, !, and] the fifth. The classification algorithm is shown in Figure 1.

Results

Results for arrhythmia detection and classification systems are presented in Tables 4a and 4b, respectively.

Table 4: Results for detection (a) and classification (b).

(a)	Time domain		T-f domain	
	Sens.	**Spec.**	**Sens.**	**Spec.**
Average	80.68%	78.18%	87.64%	88.65%
Vote	82.60%	78.43%	86.84%	89.25%
Decision Vote	87.53%	89.48%	89.95%	92.91%

(b)		Classification (# of beats)				
		1	**2**	**3**	**4**	**5**
Annotation (# of beats)	**1**	21630	715	1200	1305	273
	2	312	1185	194	87	157
	3	386	499	3470	226	46
	4	48	5	9	187	2
	5	2	0	1	2	379

Discussion-Conclusions

A system for arrhythmic beat detection and classification in ECGs has been developed. The system uses only RR interval duration and HRV analysis. Time and t-f analysis of HRV and rules based on arrhythmia physiology are used. The system leads to a high sensitivity and specificity system for the detection of arrhythmia and the classification of several arrhythmias. The system proves very useful since it does not uses ECG features (such as P wave), that might be difficult to extract, and operates in real-time.

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