TIME AND TIME-FREQUENCY METHODS IN THE ANALYSIS OF HEART RATE VARIABILITY

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1. SUMMARY

Several time and time-frequency methods are applied to the tachograms obtained from arrhythmic ECG recordings. Small segments of the tachograms are used for feature extraction, which are fed into a neural network to classify them as normal or arrhythmic. The methods are tested using the MIT-BIH recordings and results are presented for all combination of features in terms of the obtained sensitivity and specificity.

2. INTRODUCTION

Arrhythmias are disorders of the regular rhythmic beating of the heart. The Electrocardiogram (ECG) of healthy individuals in resting conditions exhibits periodic variation in RR intervals, corresponding to respiratory activity, known as Respiratory Sinus Arrhythmia (RSA). 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].

Heart Rate Variability (HRV) refers to the beat-to-beat alterations of heart rate. HRV believed to be a good marker of the individual's health condition and heart diseases [2,3]. Therefore HRV analysis became an important tool in cardiology. Time domain analysis (statistical measurements, geometrical evaluation [3,4,6-8]) and frequency domain analysis [3,6-8] are the most commonly used methods. Non-linear – chaotic analysis has also been used [3,5,6-8].

Time domain analysis provides essential but not detailed information for HRV. Time-Frequency (TF) analysis, which is based on TF distributions, is a more detailed analysis, which provides with non-stationary information of the HRV. Several TF distributions have been used for TF analysis. The Wigner Ville Distribution has been used for the identification of severe brain stem injury and postural tachycardia syndrome [9-13]. Keselbrener et al. used Selective Discrete Fourier Transform (SDA) and Short Time Fourier Transform (STFT) for cardiovascular control and fast vagal response [14-16]. Chan et al. used Wigner Ville Distribution (WVD) and Smoothed Pseudo Wigner Ville Distribution (SPWVD) for Cheyne-Stokes oscillation detection [17-19]. Bentley et al. used the Choi-Williams Distribution (CWD) for classification of native and bioprosthetic heart valve sounds [20].

In this study we use time and time-frequency analysis to detect arrhythmia in long-term electrocardiograms. In the time domain analysis extract several features by segmentation of the corresponding tachograms. In TF analysis STFT and a number of distributions belonging to the Cohen's class are applied on the segmented signals. The obtained characteristics are fed into a neural network. The latter provides with arrhythmia diagnosis. The proposed methods are used in MIT-BIH arrhythmia database and the corresponding results are presented.

3. MATERIALS AND METHODS

The dataset used in our research are the MIT-BIH arrhythmia database recordings [21]. The database consists of 48 ECG recordings, which are divided into 23 recordings of 100 Series and 25 recordings of 200 Series. The length of each recording is 30 minutes, which results to a total of 112,568 RR intervals.

Our analysis is carried out in several stages. At first a preprocessing procedure is used to extract the tachogram from the ECGs. Next, time domain or time-frequency methods are applied to extract several features. Finally a classification technique based on neural network's methodology is applied.

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. We used the RDNN software, included with the MIT-BIH database, to extract tachogram from the database recordings. In the second step we use segments of 32 points and we characterize each segment. A segment is characterized "Normal" if it contains more than 95% "Normal" annotated RR intervals of the total 32 RR intervals, otherwise is characterized "Arrhythmic". The total number of segments in the segmented dataset is 3,431. The above process is shown schematically in Fig. 1.

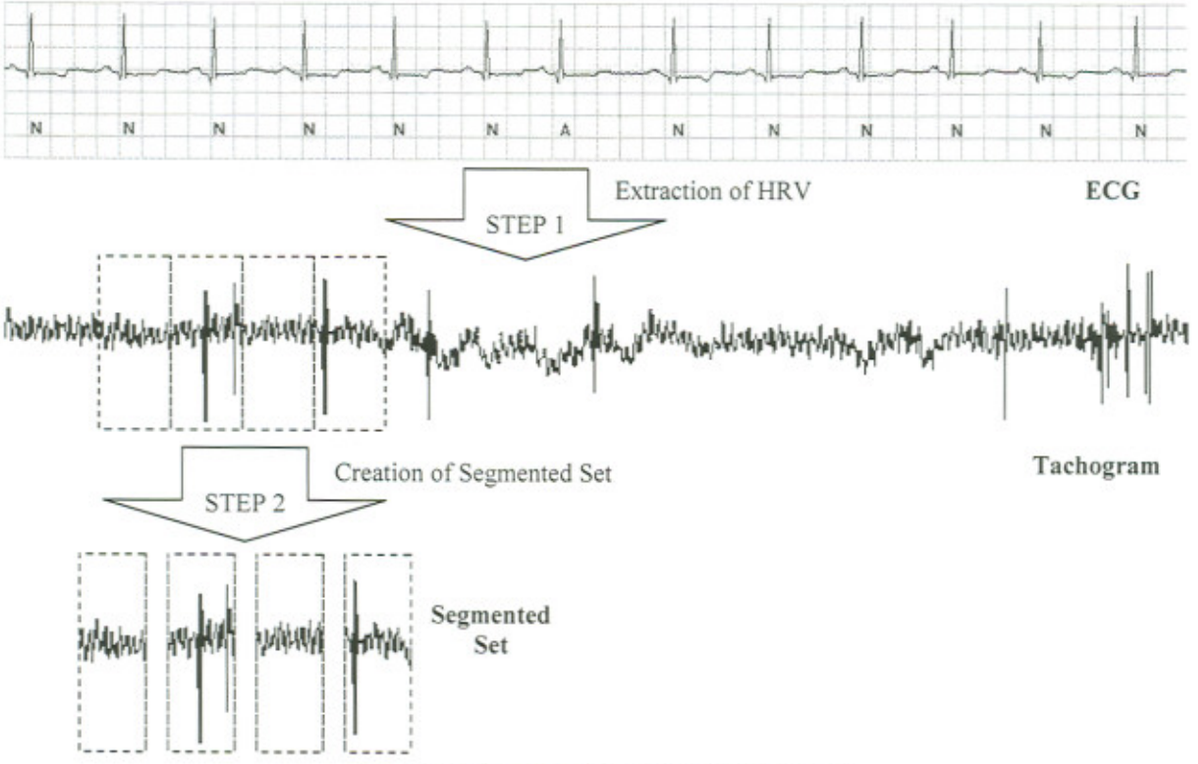

Figure 1: Preprocessing of the ECG signal.

Time domain methods

In the first step of the time domain methods the features shown in Table 1 are extracted from the segmented dataset.

Table 1: Time domain features.

	Feature	Description
1	SDNN	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	Percent of RR intervals > 5msec
5	pNN10	Percent of RR intervals > 10msec
6	pNN50	Percent 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. In addition, we apply the Principal Component Analysis (PCA) for all the features (*SDNN, r_MSSD, SDSD, pNN5, pNN10, pNN50*). That gives us a total of 64 inputs with 3,431 patterns each. All inputs, feature combinations and PCA, are shown in Table 2.

Table 2: Combinations of time domain features.

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

In the second stage we train and test a feed-forward back-propagation neural network, for each input, using 2000 patterns as training set and 1431 patterns as testing 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 final "Normal" or "Arrhythmic" classification depends on the selection of the decision rate. If the output is greater than the decision rate then the result is "Arrhythmic" segment otherwise is a "Normal" segment. The training of the neural network ends when the square error is less than 0.01 or the training epochs are more than 2000. The procedure followed for the time domain methods is shown in Fig. 2.

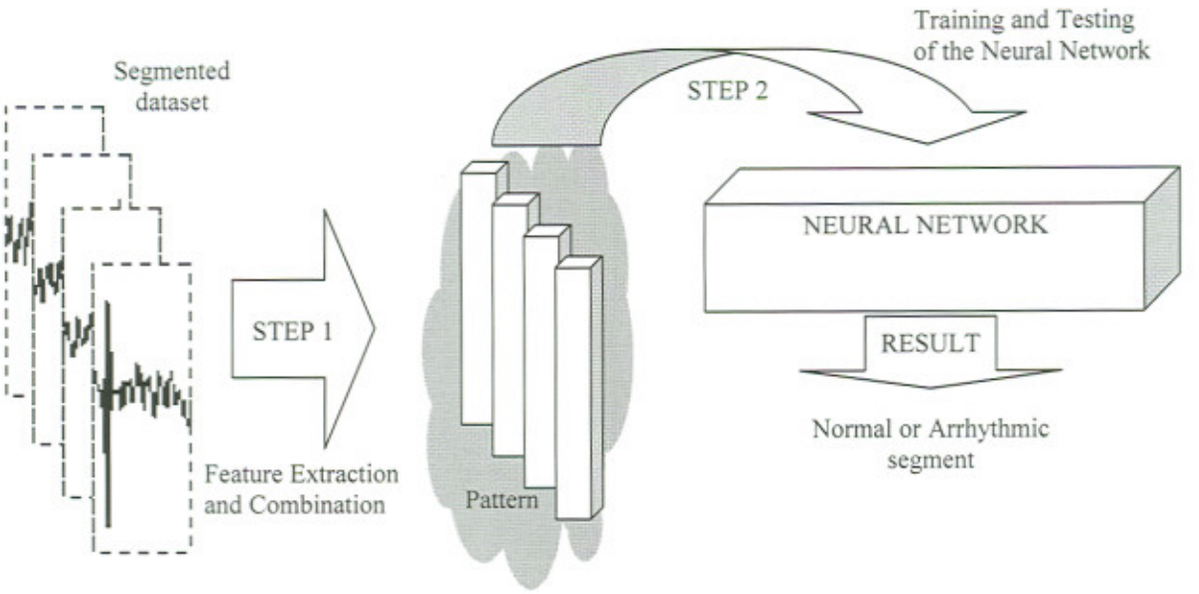

Figure 2: Time domain methods procedure.

Time-frequency methods

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

Table 3: Time-frequency distributions.

	Distribution	Name
1	Born-Jordan distribution	BJ
2	Butterworth distribution	BtWth
3	Choi-Williams distribution [5]	CW
4	Generalized rectangular distribution	GenRect
5	Margenau-Hill distribution	MarHil
6	3.a.1 Pseudo Margenau-Hill distribution	PsMarHil
7	Margenau-Hill-Spectrogram distribution	MarHilSp
8	Page distribution	Page
9	Pseudo Page distribution	PsPage
10	Wigner-Ville distribution [6]	WV
11	Pseudo Wigner-Ville distribution	PsWV
12	Smoothed Pseudo Wigner-Ville distribution [7]	SmPsWV
13	Rihaczek distribution	Rih
14	Reduced interference distribution with Bessel window	RIBes
15	Reduced interference distribution with Hanning window	RIHan
16	Reduced interference distribution with binomial window	RIbio
17	Reduced interference distribution with triangular window	RItria
18	Zhao-Atlas-Marks distribution	ZAM
19	Short Time Fourier Transform	STFT

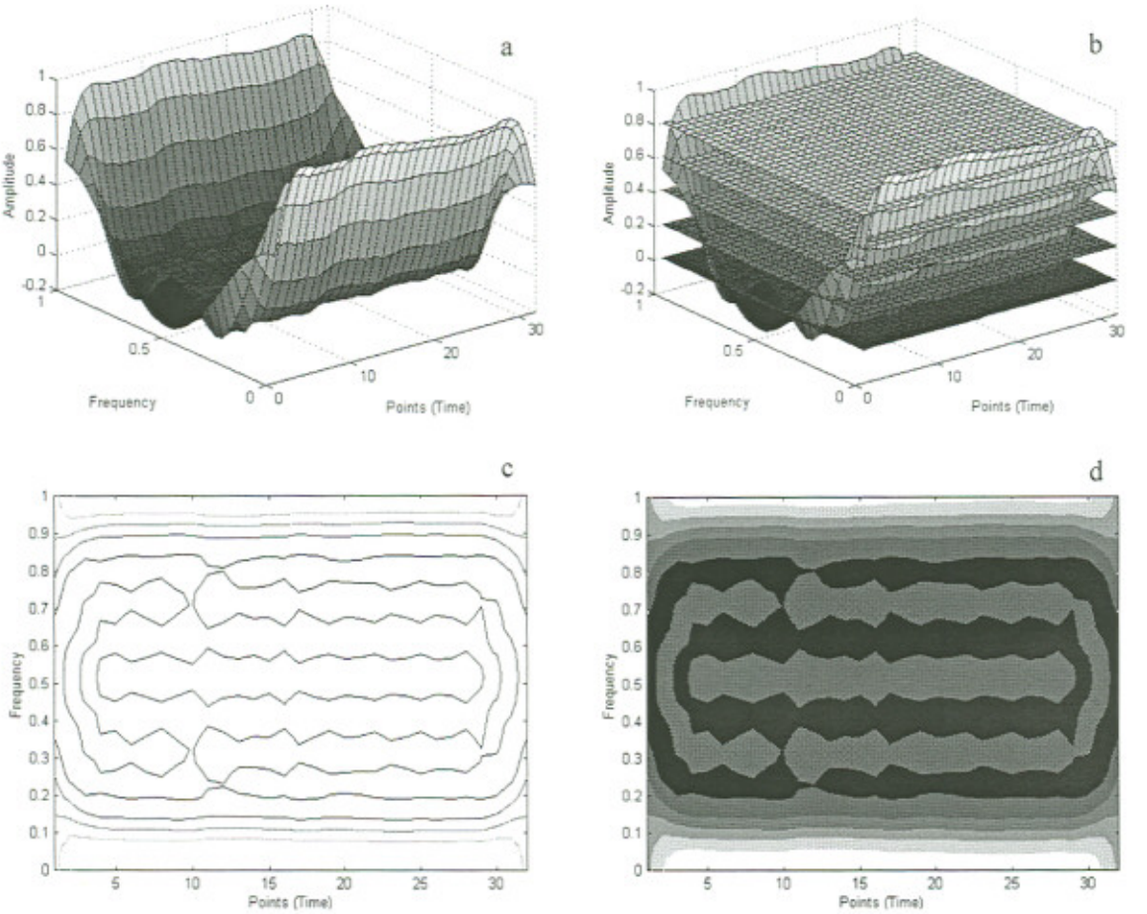

Figure 3: a. Distribution, b. Traces c. Areas, d. Features for time-frequency methods

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. The features extracted from each TFD of the segments in the segment set are summarized in Table 4.

Table 4: Time-frequency features

	Feature
1	Area below Amplitude ≤ 0
2	Area between 0.0 < Amplitude ≤ 0.2
3	Area between 0.2 < Amplitude ≤ 0.4
4	Area between 0.4 < Amplitude ≤ 0.6
5	Area between 0.6 < Amplitude ≤ 0.8
6	Area between 0.8 < Amplitude ≤ 1.0

Six features for each TFD are computed. This leads to a total of 19 inputs with 3,431 patterns each.

For each TFD we train and test a feed-forward back-propagation neural network, with a standard architecture: six inputs, one hidden layer with 20 neurons and one output being a real number in the interval [0,1]. The final "Normal" or "Arrhythmic" decision depends upon

the used decision rate. If the output is greater than decision rate then the result is "Arrhythmic" segment otherwise the segment is classified as "Normal". Schematically, the time-frequency procedure is presented in Fig. 4.

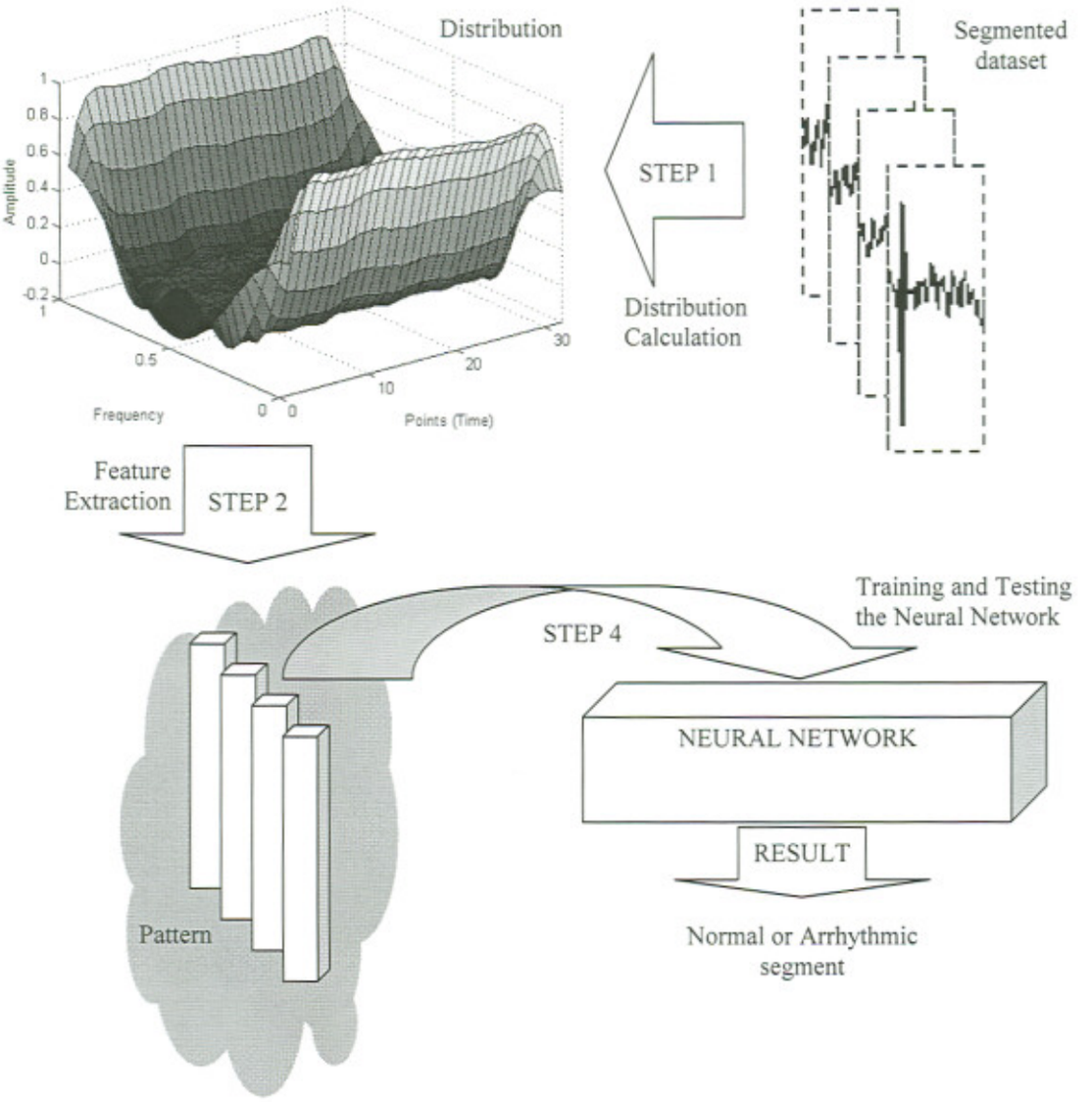

Figure 4: Time-frequency methods procedure.

4. RESULTS

For each input and combination of time domain features or TFD features, we calculate the corresponding sensitivity and specificity, using a decision rate equal to 0.5. We derive the Receiver Operating Characteristic (ROC) curve calculating sensitivity and specificity for multiple decision rates, from 0.0 to 1.0 with 0.05 step. Based on ROC curves the Area Under Curve (AUC) marker is also calculated.

Time domain results

Table 5 contains the ten best results for sensitivity, specificity and AUC marker of the total 63 combinations. Results are shown also for PCA. The results are obtained for all MIT-BIH recordings.

Table 5: Time domain methods summary of results for the MIT-BIH recordings.

	Best Sensitivity			Best Specificity			AUC	
	Features	Sensitivity	Specificity	Features	Sensitivity	Specificity	Features	AUC
1	6	95%	36%	126	85%	71%	1346	86.4%
2	56	91%	39%	12356	85%	71%	126	85.9%
3	46	90%	40%	12346	84%	69%	136	85.9%
4	234	89%	53%	1356	83%	69%	12356	85.8%
5	34	89%	48%	1236	86%	68%	1236	85.5%
6	456	89%	41%	1246	86%	68%	12346	85.3%
7	23	88%	50%	1256	84%	68%	1256	85.1%
8	5	88%	33%	136	86%	67%	1246	84.9%
9	12456	87%	61%	12	83%	67%	36	84.8%
10	235	87%	54%	1346	86%	66%	12456	84,5%
11	pca	83%	60%	pca	83%	60%	pca	83.5%

The combination 6 (only pNN50) shows the highest sensitivity (95%) but the specificity is very low (36%). The combination 12456 (SDNN, r_MSSD, pNN5, pNN10, pNN50) indicated 87% sensitivity and 61% specificity. The best specificity is obtained for combinations 126 (SDNN, r_MSSD, pNN50) and 12356 (SDNN, r_MSSD, SDSD, pNN10, pNN50) which corresponds to 71% specificity and 85% sensitivity. Use of PCA leads to 83% sensitivity and 60% specificity. Using the AUC marker the best result (86.4%) is obtained using the 1346 combination (SDNN, SDSD, pNN5, pNN50) and the use of PCA leads to 83.5%.

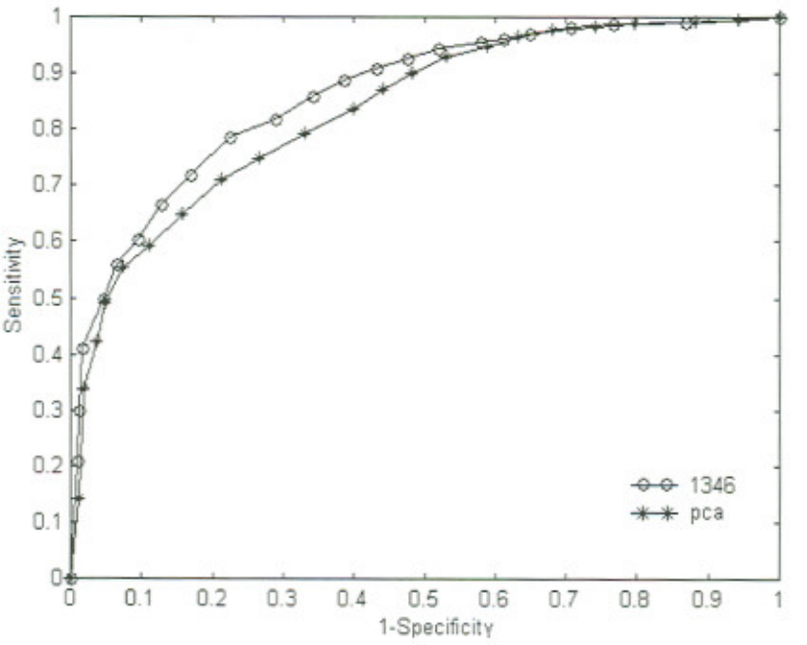

Figure 5: ROC curve for feature combination 1346 and PCA result

Time-frequency results

Table 6 contains the results for sensitivity, specificity and AUC marker of the nineteen TFD methods used for the MIT-BIH database recordings.

Table 6: Time-frequency methods summary of results for the MIT-BIH recordings

	Best Sensitivity			Best Sensitivity			ACU	
	Features	Sensitivity	Specificity	Features	Sensitivity	Specificity	Features	AUC
1	MarHilSp	80%	70%	MarHil	73%	75%	PsPage	83.6%
2	PsPage	80%	69%	Page	73%	75%	MarHilSp	82.7%
3	ZAM	80%	69%	Rihaczek	75%	73%	ZAM	82.1%
4	CW	76%	64%	MarHilSp	80%	70%	MarHil	80.3%
5	RIBes	76%	61%	PsPage	80%	69%	Rihaczek	80.2%
6	Rihaczek	75%	73%	ZAM	80%	69%	SmPsWV	79.4%
7	SmPsWV	75%	63%	GenRect	74%	69%	Page	78.5%
8	RIHan	75%	58%	PsWV	70%	67%	GenRect	78.3%
9	GenRect	74%	69%	BtWth	71%	65%	PsWV	76.8%
10	PsMarHil	74%	62%	RIBio	71%	65%	CW	76.7%
11	MarHil	73%	75%	CW	76%	64%	PsMarHil	76.3%
12	Page	73%	75%	BJ	72%	64%	RIBes	76.0%
13	RITria	73%	61%	SmPsWV	75%	63%	RIBio	75.2%
14	BJ	2%	64%	STFT	70%	63%	BtWth	74.4%
15	BtWth	71%	65%	WV	69%	63%	RITria	73.8%
16	RIBio	71%	65%	PsMarHil	74%	62%	RIHan	73.8%
17	PsWV	70%	67%	RIBes	76%	61%	STFT	73.5%
18	STFT	70%	63%	RITria	73%	61%	BJ	72.5%
19	WV	69%	63%	RIHan	75%	58%	WV	71.2%

Margenau-Hill-Spectrogram distribution has the highest sensitivity (80%) and the corresponding specificity is 70%. The Pseudo-Page and Zhao-Atlas-Marks distributions perform also well indicating 80% sensitivity and 69% specificity. The use of STFT leads to 70% sensitivity and 63% specificity. The corresponding AUC markers are 83.6% for Pseudo-Page distribution, 82.7% for Margenau-Hill-Spectrogram, 82.1% for Zhao-Atlas-Marks distribution and 73.5% for STFT.

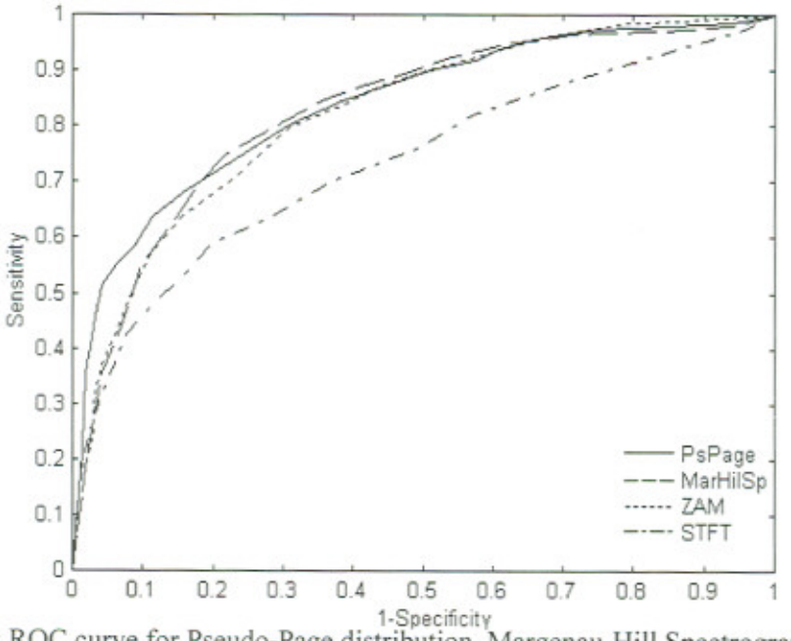

Figure 6: ROC curve for Pseudo-Page distribution, Margenau-Hill Spectrogram distribution, Zhao-Atlas-Marks distribution and Short Time Fourier Transform.

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