

## ECG FREQUENCY DOMAIN FEATURES EXTRACTION: A NEW CHARACTERISTIC FOR ARRHYTHMIAS CLASSIFICATION

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**Abstract**-This article describes a new ECG spectrum feature that allows the classification of dangerous arrhythmia. In order to check the classification effectiveness of this variable, the statistical method known as Anova has been used. The results obtained show that this parameter could be an effective classification feature of dangerous arrhythmia with an approximated probability of error of 0.00%.

**Keywords** – ECG Signal Processing, Feature Extraction

### I. INTRODUCCION

In last decade many papers have been published regarding arrhythmias classification based on the features extraction in Time, Frequency and Time-Frequency domains [1]. Very recently others more exotic domains like Time-Scale, have been used in order to classify correctly these non-stationary signals [2]. This increment in the complexity of analysis provokes a time consuming CPU computer implementation of these algorithms. Depending on the application, the ECG processing have to be done in real time and carried out by a low-voltage low-power mobile device. Due to many of algorithms proposed in the literature are not valid for these applications so that simple and computationally effective solutions have to be used.

Frequency domain is usually a good method for characterizing and classifying ECG signals [3-6]. Using classical and more elaborated spectrum techniques, many results of interest have been reported in the literature. Based on experimental results this domain is proposed as a good alternative to time domain providing simpler and more efficient classifying methods.

In this article we will report detailed research of the Frequency domain features extraction and will propose a new characteristic for classifying life-dangerous arrhythmias into two groups: on the one hand arrhythmias requiring an emergency treatment, on the other the rest of them.

### II. MATERIAL AND METHODS

#### A.- ECG Signals

Signals from different databases have been selected. We have used signals from MIT-BIH Arrhythmia Database, MIT-BIH Malignant Ventricular Arrhythmia Database, Creighton University Ventricular Tachyarrhythmia Database, MIT-BIH Supraventricular Arrhythmia Database, MIT-BIH Normal Sinus Rhythm Database, as well as ECG

signals obtained in cooperation with *Hospital of Navarra*, Pamplona, Spain.

387 representative fragments from different cardiac arrhythmias were selected, and were grouped into 33 different types according to Cardiology Academies' criteria and Cardiologist from *Hospital de Navarra*, Table I.

TABLE I

Arrhythmia types grouped according to Cardiologist Academia's Criteria used in this research work.

00 NORMAL RHYTHM	
01 Normal Sinus Rhythm	89
02 Sinusal Arrhythmia	4
03 Pacemaker Rhythm	4
10 HIPERACTIVE ARRHYTHMIA	
11 Supraventricular Extrasystoles	25
12 Sinus Tachycardia	13
13 Supraventricular Tachycardia (SVT)	
13-1 SVT with narrow QRS	15
13-2 SVT with wide QRS	8
14 Atrial Flutter	8
15 Atrial Fibrillation (AF)	12
16 Ventricular Extrasystoles (VES)	
16-1 Isolated Unifocal VES	14
16-2 Frequently Unifocal VES	25
16-3 Multifocal VES	7
16-4 Short VT	3
16-5 Double VES	7
16-6 Double-Triple VES	13
17 Ventricular Tachycardia (VT)	57
18 Ventricular Flutter	7
19 Ventricular Fibrillation	50
20 HIPOACTIVE ARRHYTHMIA	
21 Sinus Bradicardia	2
22 Sinus-Atrial blockade	0
23 Node Rhythm	5
24 Idioventricular rhythm	3
25 AV blocked 1° grade (AVB1)	4
26 AV blocked 2° grade (AVB2)	5
27 AV blocked 3° grade	5
28 Heart Failure	2
<b>TOTAL</b>	<b>387</b>

Numerous groups such as Normal Sinus Rhythm were taken in order to serve as a reference point for the comparison with other groups or with the abnormal cases. Ventricular Tachycardia and Ventricular Fibrillation are also

widely represented, as they are the most life-dangerous arrhythmias.

Signal length was established between 5 and 15 seconds, most of them having 10 seconds length. Sample frequency was set up to 250 Hz.

#### B.- Feature extraction.

Direct observation of ECG signals spectrums were performed showing that depending on what kind of characteristic was analyzed, a proper signal classification may be done. Figure 1 shows the material used in this research work.

Following features that could lead to their classification were proposed.

1. Mean of the energy samples.

$$\bar{m} = \frac{1}{n} \sum_{i=1}^n m_i$$

2. Variance of the energy samples.

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (m_i - \bar{m})^2}$$

3. Average frequency.

$$\bar{f}_p = \frac{\sum_{i=1}^n f_i \cdot m_i}{\sum_{i=1}^n m_i}$$

4. Half Point of the function energy, HaPo.
5. Maximum value of energy.
6. Frequency of the maximum energy.
7. Minimum value of energy.
8. Frequency of the minimum energy.

After performing a statistical study, the variable getting the best results was Half Point variable, HaPo. This variable represents the frequency that divides up the spectrum into two parts of the same area.

Figure 2 shows the values of HaPo variable for the different ECG groups analyzed.

#### C.- Statistical Study

In order to check the classification effectiveness of this variable, the statistical method known as Anova, Analysis of Variance, has been used [7]. This analysis tries to check whether the performance of the quantitative variable, in our case HaPo variable, is different depending on which group it belongs to.

For this analysis, all the observations were classified into groups according to the type of arrhythmia. All these groups

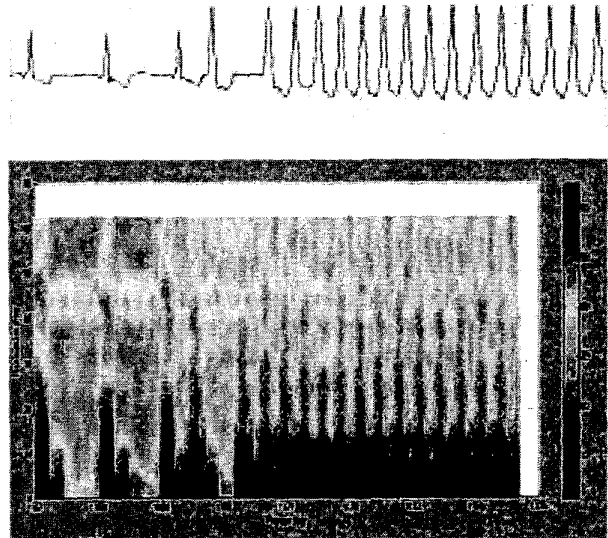
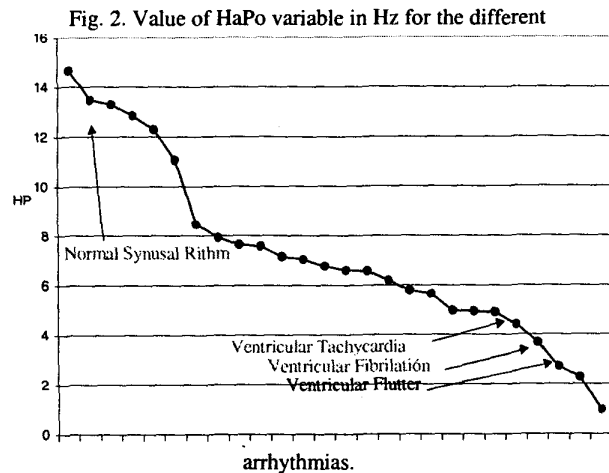


Fig. 1. ECG depicts a Normal Sinus Rhythm that degenerates into a Ventricular Tachycardia. Its spectrogram is shown in the bottom part.



were compared with the group of control, i.e. Normal Sinus Rhythm, determining whether they could indeed be considered different groups by taking as the representative statistic of each group the statistical mean of HaPo variable.

### III. RESULTS

From this Anova tests comparing the most important arrhythmia groups with Normal Sinus Rhythm, the results summarized in the following Table II were obtained.

The results in this table are sorted out by Resultant Probability value column. This parameter represents the value obtained in the F-Test [7]. Thus, we can find out what kind of arrhythmias is more similar to Normal Sinus Rhythm, i.e., those for which the Resultant Probability is greater. We can corroborate that the most life-dangerous arrhythmias are easily classified using this feature.

In a later Anova analysis all the ECG records used in this work were divided up into two groups. On the one hand a group contained Ventricular Tachycardia, Ventricular Flutter and Ventricular Fibrillation, and a second group gathering the rest of signals. Comparing the means of HaPo variable for each group the result obtained was that both groups were statistically different with an error probability of 0.00%

#### IV. CONCLUSIONS

Based on the Anova statistical study a new Frequency domain feature named Half Point, HaPo, could be used for classifying life-dangerous arrhythmias. Due to the computational simplicity for processing this variable, it is worthy reporting that a classifying algorithm based on this method would have a low computing cost. Moreover, other Frequency domain features could be used in order to improve the efficiency and accuracy of this possible classifying algorithm. The authors are working towards the computationally efficient implementation of this proposal.

#### ACKNOWLEDGMENT

We would like to thank the Cardiologist from *Hospital de Navarra* who from their comments improved this research work, which was financially supported by grant FIS 00/0786 from *Ministerio de Sanidad y Consumo*.

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TABLE II  
Anova results obtained using Normal Sinus Rhythm group as reference

Arrhythmia	Resultant Probability	Performance similar to Normal
Sinusal Tachycardia	48.90874087%	YES
Paroxistic SVT	33.91486074%	YES
Supraventricular Extra-systole	12.41474939%	YES
Isolated unifocal VES	1.46716573%	NO
Unifocal frequently VES	0.16574338%	NO
Double-Triple VES	0.05464772%	NO
Atrial Fibrillation	0.04773785%	NO
Ventricular Tachycardia	0.01304667%	NO
Ventricular Fibrillation	0.00000305%	NO