ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

Arrhythmias Detection based on Wavelet Transform

Fatima Moumtadi, Ph. D, Nicté Mandujano Mayoral, Gabriela Díaz Cartas, Rogelio Alcántara Silva, Ph.D
Department of Telecommunications, School of Engineering
National Autonomous University of Mexico-UNAM Mexico City, Mexico

Abstract*— Currently in Mexico the heart attacks occurs every four seconds and in the adult population (20-69 years) are more than 17 million hypertensive therefore becomes a fundamental part, the detection and diagnosis of heart diseases [14]. In spite of telemedicine progress on the issue of electrocardiographs, the reading to ECG signals is reserved for specialists, delaying the diagnosis and the treatment of patients is getting complicated. Therefore the design and development of a strategy for the classification of arrhythmias: Tachycardia, Bradycardia, and Ventricular Flutter, by detecting the R-R interval of the ECG signal and calculating the heart rhythm in the Wavelet transform representation.

Index Terms— **ECG signals, R-R interval, Wavelet transform.**

I. INTRODUCTION

The heart has two atria and two ventricles, which are the four chambers of the heart, Fig. 1. The atria work together, as well as the ventricles, whose work pumping blood to the lungs and peripheral organs.

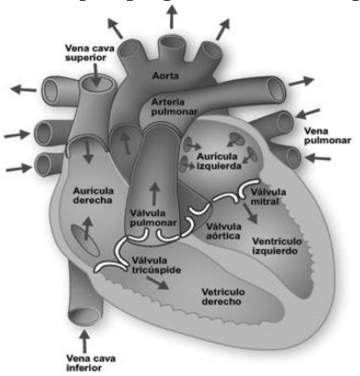


Fig. 1. Heart anatomy

An action potential which causes the heart muscle cells to contract, reducing the volume of the atria and ventricles, respectively. This results in an increased pressure, leading to an outflow through the valve when the pressure before of the valve exceeds the pressure behind of the valve. This process provides the pressure change to open and close the valve and thus perform the pumping function of the heart.

The process of depolarization is a function of the frequency at which the heart muscle receives initiation pulses. In the depolarization and repolarization of the heart in each cycle generates local electrical potential differences, which can be measured in the skin using electronic equipment. This group of signals, called electrocardiogram (ECG) are the most commonly used clinical signs information in the diagnosis of cardiovascular disorders [4].

The use of the electrocardiograph [15] allows defining the heart rhythm, the size and function of the heart chambers and heart muscle through its graphics generated, called ECG signals, and also allows diagnosing cardiovascular diseases, metabolic disorders and predispositions to sudden death.
In order to facilitate and make more accessible the diagnosis at patients, it has tried to automate the diagnosis through digital signal processing (DSP).
Currently, the digital signal processing algorithms for classification of arrhythmias can be divided into three groups: time domain, frequency domain and time-frequency domain [1].

Publications of algorithms for classification of arrhythmias using methods in the time domain as the autoregressive (AR) [2], [3] and the time-frequency domain [4]. The most popular methods use pattern recognition as the R-R interval [9] it using morphological characteristics of the ECG [5], [6].

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

Also you can find techniques using artificial neural networks (ANNs) and its combination with other methods such as Fourier analysis [7], [8] or Wavelet [9], although these techniques successfully derived, their implementation is complicated.

The algorithms for classification of arrhythmias using Wavelet Transform [10], [11] or Wavelet decomposition and QRS complex detection [18] [6], also, wavelets dedicated to each patient fit [12], turn out to be the most used methods today because they allow a better analysis of the ECG signal [13].

For the work developed was used database of Massachusetts Institute of Technology (MIT) - Boston's Beth Israel Hospital (BIH), it is composed of ECG signals from patients both healthy and with arrhythmias, this allows to experiment with these signals, [16], [17].

II. WAVELET TRANSFORM METHOD

The approach used in this project was the Wavelet transform has the ability to allow simultaneous time-frequency analysis with a flexible mathematical basis.

The digital signal processing starts with the baseline removal (Baseline Drift), this is to smooth the signal using Matlab smooth function that uses Moving Average method. Moving average filter can eliminate baseline with an appropriate factor to smooth the signal. This factor is calculated by dividing the period of the ECG signal between the sampling time of the signal (in seconds) [18].

Subsequently Discrete Wavelet Transform will be implemented to remove noise components and unwanted signals and remove the R waves of our original signal.

Mathematically the DWT (Discrete Wavelet Transform) is applied to the original signal $s(t)$ [20]:

$$C(a,b) = \int_R s(t)\frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right) \quad (1)$$

Where:

$C\ (a,b)$ Resulting coefficients of Discrete Wavelet Transform

$s(t)$ Original sign in time.

a Dilation parameter.

b Translation parameter.

φ Wavelet function.

For the Discrete Wavelet Transform' synthesis and understanding, we have a way to understand the results, by mean of scale detail:

$$D_j(t) = \sum_{k\epsilon Z} C(j,k)\varphi_{j,k}(t) \quad (2)$$

$D_j(t)$ Details of high frequency components at a certain level j

There are two types of details which refer to the scale and thickness details which together form what is named approximations:

A_j Approximations of low frequency components at a certain level j

This means that the original signal is decomposed into details and approximations:

$$s = A_j + \sum_{j \le J} D_j \quad (3)$$

The proposed method is the Daubechies Wavelets family, where the original signal will decompose in approximations and details to a corresponding scale [20]-[24].

The wavelet transform of kind Daubechies is defined the same way as the Haar Wavelet Transform, which is calculated averages and differences, it is obtained by the scalar products, scale signals, the only difference between them, consist is how these scale signals and Wavelets are defined.

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

In concept is the same method and equations that must be performed for each Daubechies Wavelets level. The only thing will differentiate them; will be the supports of the scale signals and Wavelets.
The low pass filter coefficients are defined as follows:

$$\alpha_1 = \frac{1+\sqrt{3}}{4\sqrt{2}}, \alpha_2 = \frac{3+\sqrt{3}}{4\sqrt{2}}, \alpha_3 = \frac{3-\sqrt{3}}{4\sqrt{2}}, \alpha_4 = \frac{1-\sqrt{3}}{4\sqrt{2}} \quad (4)$$

Coefficients vectors are defined as:

$$V_1^1 = (\alpha_1, \alpha_2, \alpha_3, \alpha_4, 0, 0, \dots, 0) \quad (5)$$

$$V_2^1 = (0, 0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, 0, 0, \dots, 0) \quad (6)$$

$$V_3^1 = (0, 0, 0, 0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, 0, 0, \dots, 0) \quad (7)$$

$$V_{\frac{N}{2}-1}^1 = (0, 0, \dots, \alpha_1, \alpha_2, \alpha_3, \alpha_4) \quad (8)$$

$$V_{\frac{N}{2}}^1 = (\alpha_3, \alpha_4, 0, 0, \dots, 0, \alpha_1, \alpha_2) \quad (9)$$

These signals scale are similar, as are analyzing the level four, four units of time will be taken. You may notice that the scale signal V_2^1 is the translation of two time units of the scale signalV_1^1, and V_3^1 scale signal is the translation of four units ofV_1^1. Fig. 2 shows the Daubechies approximations as Wavelet function of level 6 (DB6).

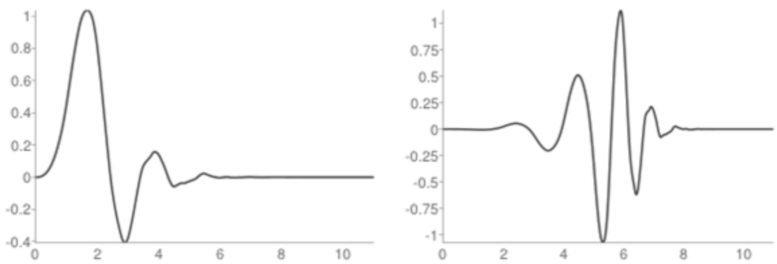


Fig. 2.Daubechies Approximation and function Wavelet Db, of level 6

III. DETECTION AND CLASSIFICATION OF CARDIACS ARRHYTHMIAS

Next, it will a comparison between the methods in which this work was based [23], which presents the automatic detection of R-R interval by Wavelet transform, with the proposed approach. The method is divided into three parts; the first preprocessing of the ECG signal, the second the de R-R interval detection form and the third part is the algorithm, it will classify the different cardiac arrhythmias. Fig. 3 shows a block diagram of the proposed method composition:

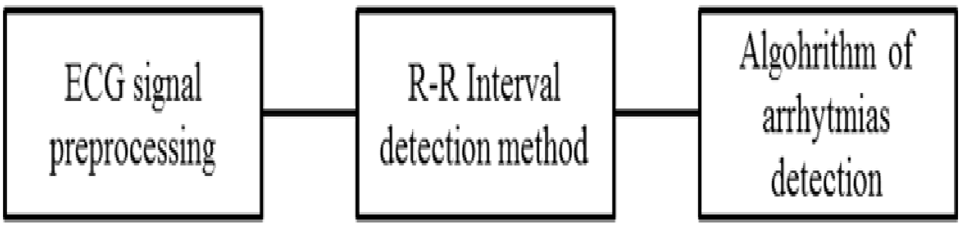


Fig.3. Proposed method

Fig. 4 shows a detailed diagram of the proposed method:

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

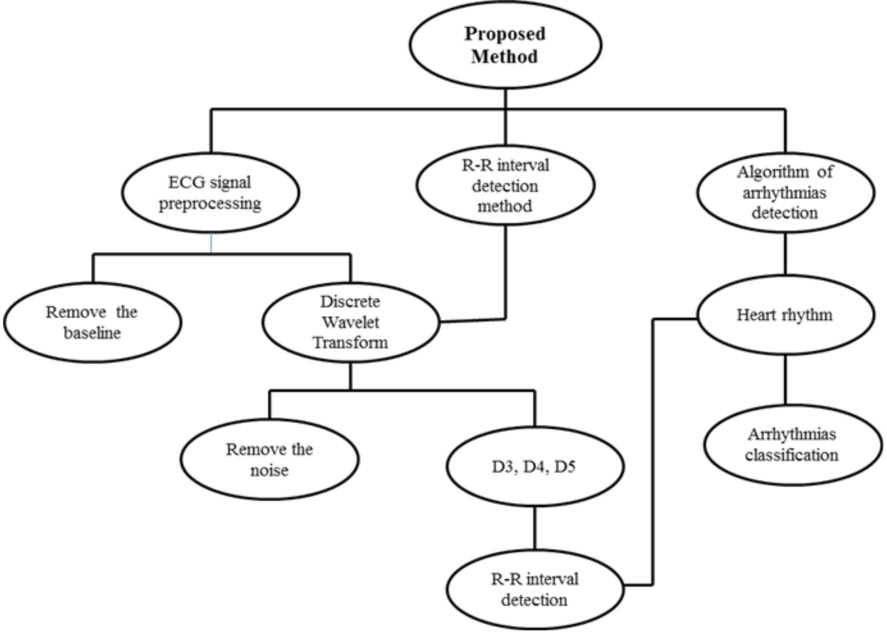


Fig.4.Detailed diagram of the proposed method

Initially this method decomposes the original ECG signal using Discrete Wavelet Transform and Daubechies Wavelet (db6) as the mother wavelet. Remove the low frequency components to eliminate the baseline and remove high frequency components to remove the noise of the original signal. After, use the preprocessed signal to find the R-R interval from ECG automatically. The first step in the digital processing of the ECG signal is the removal of baseline. For this, the signal is smoothed using Matlab function Smooth that uses the Moving Average method [18], the signal 100 of the database MIT-BIH was used, where the signal period is 0.8 seconds and the sampling time is 1/360 seconds, so that the factor used is of 1/300.

Next, in shown Fig. 5 the R-R the interval comparison to that obtained in Fig. 6 where detection of RR interval obtained by K. and Jyothi Vanisree Singaraju.

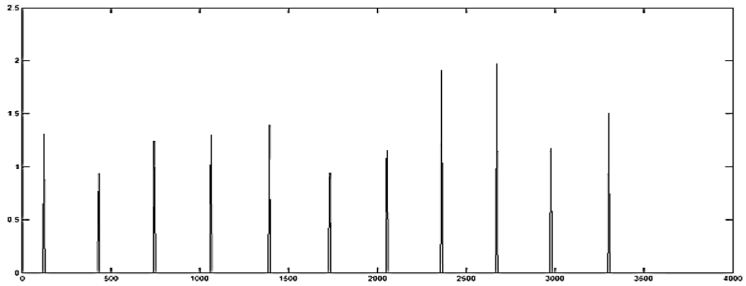


Fig.5. R-R Interval detection obtained.

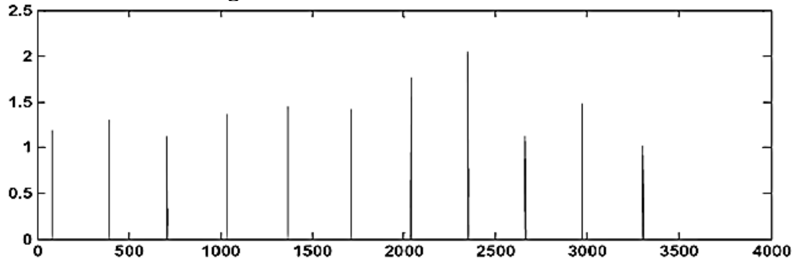


Fig.6. R-R Interval Detection with the method Vanisree K. - Jyothi Singaraju.

The discrete wavelet transform (DWT) allows the decomposition of a discrete signal to diverse scales in its time-frequency components.

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

The wavelet analysis allows the use of large time intervals in those segments where need more precision in low frequency, and smaller regions where information is required at high frequency, this is achieved by a windowing technique with variable-sized regions.

Fig. 7 shows the filter bank to implement the discrete wavelet decomposition.

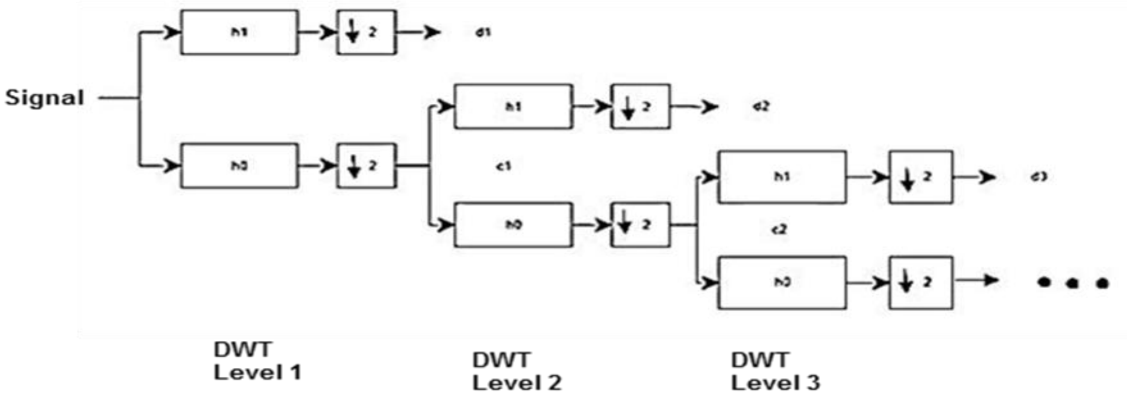


Fig.7. Filter for discrete wavelet decomposition.

The notations h1 and h0 are the FIR filter high pass and low pass respectively. Each filtered signal is submuestrada what length of signal components by a factor of two is reduced.

The notations h1 and h0 are the FIR filter high pass and low pass respectively. Each filtered signal is sub-sampled therefore the length of signal components is reduced by a factor of two.

In this paper the Wavelet transform is used to remove noise and undesired signal components and thus to extract the R-R interval. The signal decomposition is performed at level 8, the mother wavelet used: db6.

The signal is reconstructed from the coefficients d1, which contain the higher frequency components using inverse discrete wavelet transform (IDWT). This reconstructed signal contains the high frequencies detail in the original signal. So the reconstructed signal from d1, d2 and the other coefficients dn is named the detail. To represent these signals we use the notation D1 meaning the detail at level 1, [19], [21].

Although low-frequency components are removed from the original signal, it may still have noise due to high frequency components. To eliminate the noise signal is required to identify which contains noise components and then these identified components of the signal are removed.

When a signal is decomposed by the DWT, we note that the successive approximations become less and less noisy as the high frequency information of the signal is filtered. But to dismiss the entire high frequency information, you can also lose many features of the original signal. An optimal removal of noise requires a subtler approach named Tresholding [21], this means only discard lots of details that exceed a certain limit.

To determine the R-R interval of an ECG signal is necessary to detect the signal peaks. Since these peaks are broader, they can be easily detected. For detecting peaks, certain components of the decomposed signal remain and the other components low and high frequency are removed. Details D3, D4 and D5 are maintained and all other components are removed. For the R-wave to be more remarkable the obtained signal is squared and then a lower limit is applied to remove the pseudo-peaks.

The algorithm performance was analyzed using the following parameters:
Sensitivity (Se): Indicates the percentage of true heartbeats was detected correctly by the algorithm.

$$SE(\%) = \frac{TP}{TP + FN} \quad (10)$$

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015
Positive predictive value (+ P): The percentage of beats detected is true.

$$+P(\%) = \frac{TP}{TP + FP} \tag{11}$$

Detection error rate (DER):

$$TED(\%) = \frac{FP + FN}{\sum R - R} \tag{12}$$

Where:
TP (true positive): Number of true peaks detected.
FP (false positive): Number of false peaks.
FN (false negative): Number of peaks no detected.
$\sum R - R$: Total number of R-R intervals.

ECG paper conventionally has a speed of 25 mm / s, which means that every second there are five large charts of ½ centimeter and there are 300 great charts in 1 minute. To calculate the heart rate HR, the R-R interval is calculated in seconds. By rule of thumb, if there are 300 charts in one minute, in two R-R will be the charts calculated, so 300 is divided by the number of charts on an R-R interval and so it will have the heart rate [Ref 22].
For the pre-diagnosis of cardiac arrhythmias, the R-R interval and the heart rate are analyzed, after a threshold is used to detect arrhythmias.

The parameters used for detection are as follows [22]:
HR normal: 60-100 heartbeats per minute
Normal R-R interval: 0.6 seconds - 1 second

For detection the Bradycardia and Ventricular flutter, the heart rate (HR) and R-R interval were obtained with the following specifications:
HR > 60 heartbeats per minute
R-R interval >1 second

To differentiate Ventricular flutter from the Bradycardia, the behavior of signal is observed where to Ventricular flutter the QRS complex is not well defined and continuous pattern is observed, the implemented program detects a very low HR (much less than Bradycardia) that allows differentiating them.

Therefore, the signal will be detected as ventricular flutter if you show the following specifications:

HR < 40 heartbeats per minute
R-R interval > 1.5 seconds
Otherwise the signal will be detected as Bradycardia.

For the detection of ventricular tachycardia, the heart rate (HR) and R-R interval were obtained with the following specifications:

HR >100 heartbeats per minute
R-R interval < 0.65 seconds

In Fig. 8 shows the classification algorithm of cardiac arrhythmias, where details D3, D4 and D5 are obtained, for that the R wave become more remarkable, and then the R-R interval is detected and the heart rate is calculated. Finally has a threshold to distinguish between Ventricular flutter or Bradycardia and tachycardia and a last threshold for distinguishing between Bradycardia and ventricular flutter, if none of the above is present is taken as normal cardiac rhythm [24].

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

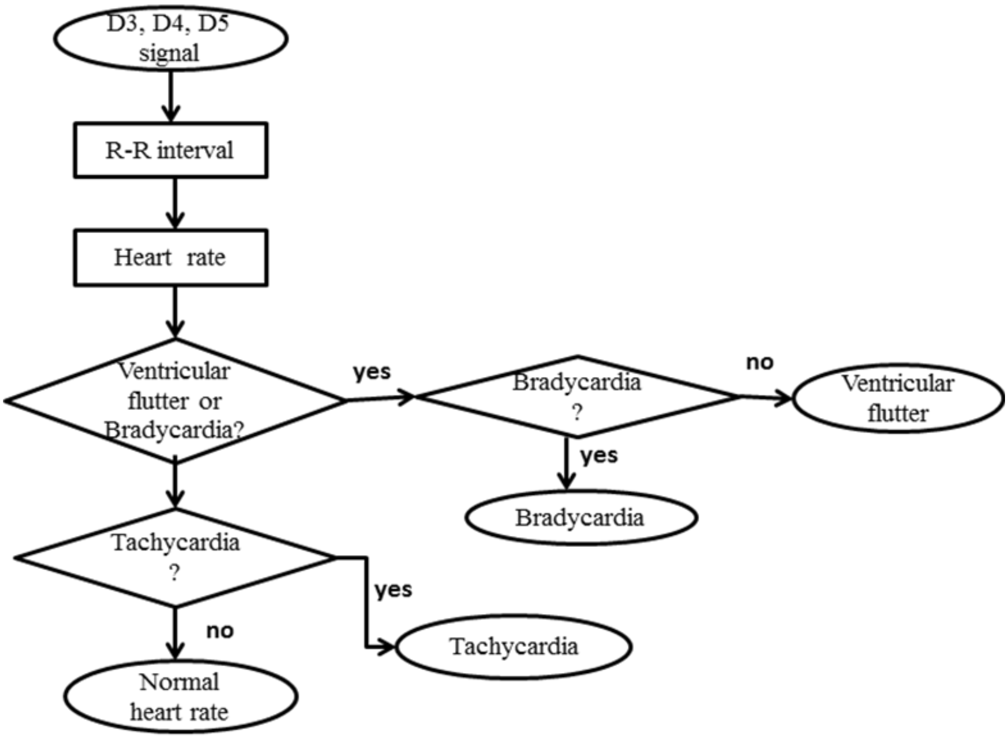


Fig.8. Detection algorithm proposed arrhythmias

In Fig. 9 shows the performance of the detection method of the R-R interval

Signal MIT-BIH	TP	FP	FN	Incorrect detection (FP+FN)	Se (%)	+P (%)	DER (%)
100	25	0	0	0	100	100	0
203	33	2	1	3	97.06	94.29	1.05
232	18	0	0	0	100	100	0
418	7	4	1	5	63.64	87.5	1.33
419	12	0	0	0	100	100	0
420	22	0	0	0	100	100	0
421	32	4	3	7	88.89	91.43	3.1
605	18	0	0	0	100	100	0
8 signals	67	10	5	15	93.69	96.65	0.685

Fig.9. Results of proposed method for the signals database MIT-BIH.

IV. CLASSIFICATION ALGORITHM OF CARDIAC ARRHYTHMIAS

The results were verified with the diagnostics provided by the MIT-BIH database [11], [12].

A. Normal Heart Rate (NHR)

The NHR is considered in this paper when the signal is not classified with any of the above 3 arrhythmias. For the NHR, 20 seconds were used of the next signal.

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

Signal 100

Fig. 10 shows the comparative way of the original ECG signal and R-R interval detection, of the diagnosed signal 100 as NHR by the MIT-BIH database.

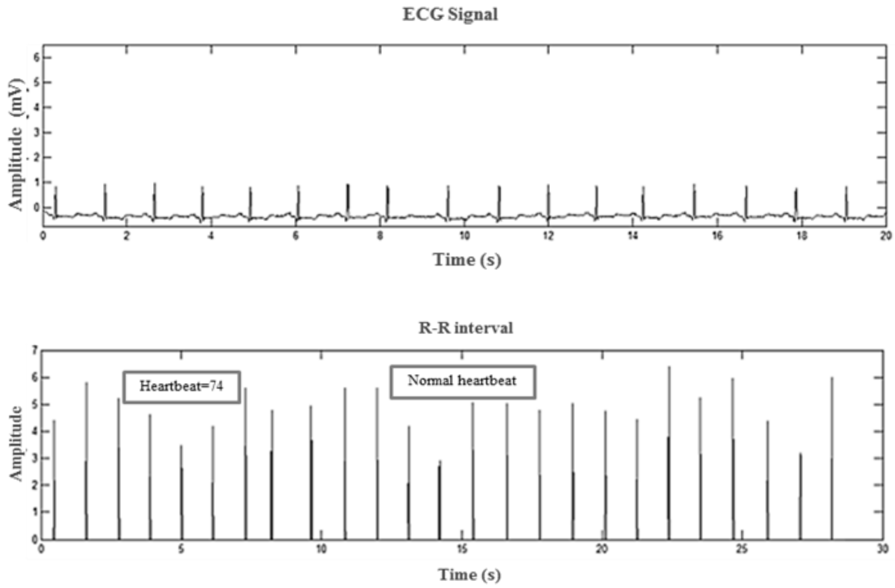


Fig.10. Signal 100

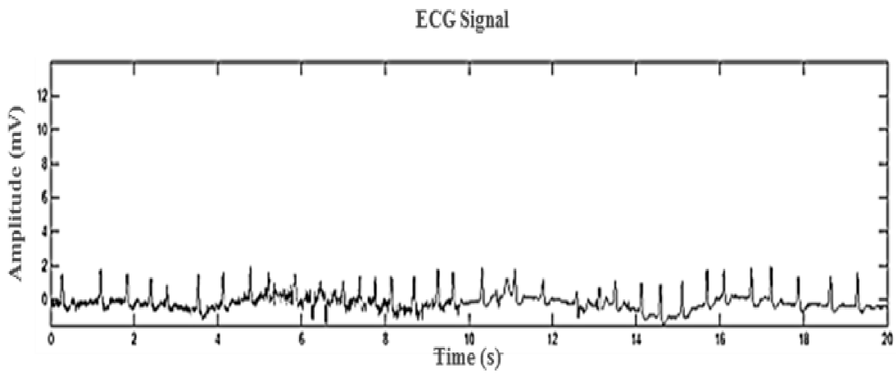
B. *Ventricular Tachycardia (VT)*

For the classification of this arrhythmia, the heart rate (HR) and R-R interval were obtained with the following specifications:

HR > 100 heartbeats per minute
R-R interval < 0.65 seconds
For this arrhythmia, 20 seconds were used of the next signal:

Signal 203

Fig.11 shows the comparative way of the original ECG signal and R-R interval detection, of diagnosed signal 203 as TV by the MIT-BIH database data.



ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

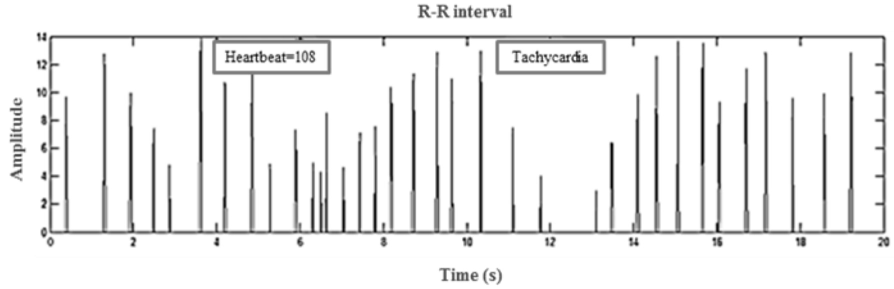


Fig.11. Signal 203

From signal 203, the following characteristics are obtained:
HR = 108 heartbeats per minute.
R-R interval = 0.5925 seconds.
Therefore, the arrhythmia of the signal is classified as tachycardia.

C. Bradycardia

For the classification of this arrhythmia, the heart rate (HR) and R-R interval were obtained with the following specifications:
HR <60 heartbeats per minute
R-R interval> 1 second
For this arrhythmia, 20 seconds were used of the next signal:
Signal 232
Fig.12 shows the comparative way, the original ECG signal and R-R interval detection, of the diagnosed signal 232 as Bradycardia by the MIT-BIH database.

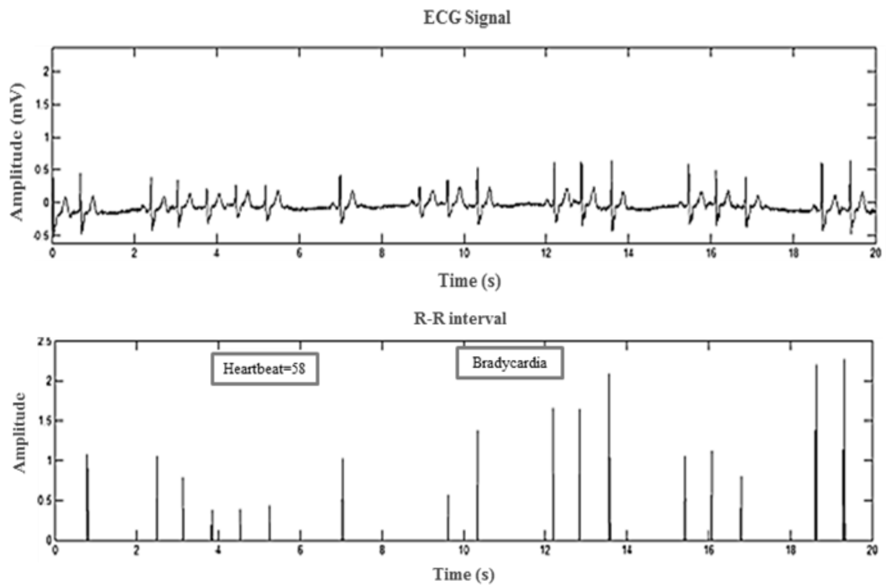


Fig.12. Signal 232

From signal 421, Fig.13, the following characteristics are obtained:
HR = 58 heartbeats per minute.
R-R interval = 1.0222 seconds.
Therefore, the arrhythmia of signal is classified as Bradycardia.

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 4, Issue 3, May 2015

D. Ventricular Flutter (VF)

In this arrhythmia, observing the behavior of the signal where the QRS complex is not well defined and a continuous pattern is observed, the implemented program detects a very low HR (much less than Bradycardia) that allows differentiating between VF and Bradycardia.

For the classification of this arrhythmia, the heart rate (HR) and R-R interval were obtained with the following specifications:
HR <40 heartbeats per minute
R-R interval> 1.5 seconds
For this arrhythmia, 20 seconds were used of the next signal:

Signal 418
Fig.13 shows the comparative way the original ECG signal and R-R interval detection, of the diagnosed signal 418 as VF by database MIT-BIH.

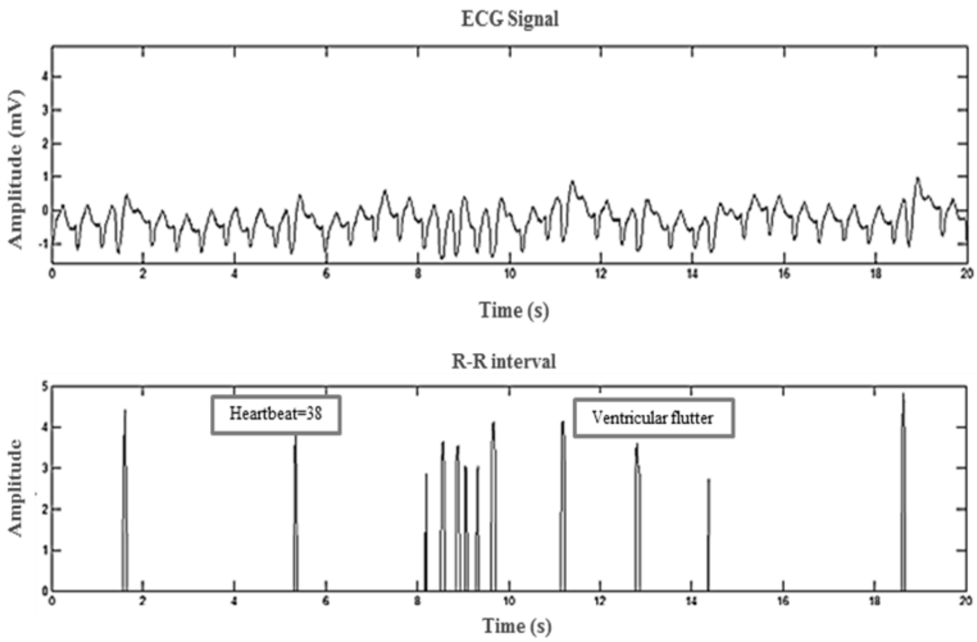


Fig.13. Signal 418

From signal 418 the following characteristics are obtained:
HR= 38 heartbeats per minute
R-R interval = 1.5789 seconds
Therefore, the arrhythmia of the signal is classified as Ventricular Flutter.

V. CONCLUSIONS

In this work, we have developed an algorithm to detect and classify four types of heart rhythms: Ventricular Tachycardia (VT), Bradycardia, Ventricular Flutter (VF) and Normal Heart Rate (NHR).

The result is comparable to other works which talk about the subject , as shown in the results in Fig. 9, the proposed technique obtains performance in arrhythmias detection: Se = 93.69% and P = + 96.65%, and the number of incorrect detection is 0.685%. The proposed method is compared with the MIT-BIH database, in which the signals have an analysis over the cardiac arrhythmia that affects the mentioned medical study.

REFERENCES

[1] John L. Semmlow, “Biosignal and medical image processing”, Boca Raton: CRC Press, 2009.

[2] R Kafieh, A Mehri, "Detection of Ventricular Arrhythmias Using Roots Location in AR-Modelling", Available form: http://www.ieee.org

[3] D Ge, N Srinivasan, S M.Krishnan, "Cardiac arrhythmia classification using autoregressive modeling", BioMedical Engineering OnLine, 2002.

[4] S S. Mahmoud, Q Fang, D M. Davidovic, I Cosic, "A Time-Frequency Approach for the Analysis of Normal and Arrhytmia Cardiac Signals", IEEE Annual International Conference, New York City, USA.

[5] Chazal P., O'Dwyer M., Reilly R. B, "Automatic classification of heartbeats using ECG morphology and heart beat interval features", IEEE Trans. Biomedical Engineering, 2004, vol. 51, pp. 1196/1206.

[6] Shantanu Raghav, and Amit K. Mishra, "Fractal Feature Based ECG Arrhythmia Classification", Member, IEEE, ECE Department, IIT Guwahati, Assam, India.

[7] K Minami, Y Ohkuma, H Nakajima, T Toyoshima, "Real-time Ventricular Arrhythmia Detection with Fourier Analysis and Neural Network", Available form: http://www.ieee.org, Tokyo Japan.

[8] Himanshu Gothwal, Silky Kedawat, Rajesh Kumar, "Cardiac arrhythmias detection in an ECG beat signal using fast fourier transform and artificial neural network", J. Biomedical Science and Engineering, pp. 289-296, April 2011.

[9] Rahat Abbas, Wajid Aziz, Muhammad Arif, "Prediction of Ventricular Tachyarrhythmia in Electrocardiograph Signal using Neuro-Wavelet Approach", National Conference on Emerging Technologies 2004.

[10] K Daqrouq, I N. Abu-Isbeih, "Arrhythmia Detection using Wavelet Transform", IEEE The International Conference on "Computer as a Tool, Warsaw.

[11] C. Saritha, V. Sukanya, Y. Narasimha Murthy, "ECG Signal Analysis Using Wavelet Transforms", Department of Physics and Electronics, S.S.B.N. COLLEGE (Autonomous) Anantapur – 515 001, Andhrapradesh, India, p.76, Feb. 2008.

[12] Jinkwon Kim, Se Dong Min and Myoungho Lee, "An arrhythmia classification algorithm using a dedicated Wavelet adapted to different subjects", Kim et al. BioMedical Engineering OnLine, 2011.

[13] Kayvan Najarian, Robert Splinter, "Biomedical signal and image processing", Boca Raton: CRC Press/Taylor & Francis, 2006.

[14] Martín R., Fause A., "Enfermedad cardiovascular. Primera causa de muerte en adultos de México y el mundo", Archivos de cardiología en México.

[15] Javier G., "Electrocardiógrafo Móvil con Sistema Inalámbrico de Alerta", página 28. Tesis de licenciatura, FI, UNAM.

[16] MIT-BIH Arrhythmia Database, http://www.physionet.ph.biu.ac.il/physiobank/database/mit.

[17] MIT-BIH Malignant Ventricular Arrhytmia Database, http://physionet.org/physiobank/database/vfdb/.

[18] DATAQ Instruments, http://www.dataq.com/m/applicat/articles/an14.htm.

[19] M. Vetterli, "Wavelets and Filter Banks: Theory and Design", IEEE Transactions on Signal Processing, Vol. 40, N°9, September 1992.

[20] Michel M, Yves M, Georges O, Jean Michel P, "Wavelet Toolbox User's Guide", 1996 - 1997 by The MathWorks.

[21] Y Jung, W J.Tompkins, "Detecting and Classifying Life-threatening ECG Ventricular Arrhythmias using Wavelet Descomposition", IEEE International Conference of the IEEE EMBS, Cancun Mexico 2003.

[22] John R. Hampton, "The ECG made easy", International Edition, Edinburgh, Churchill Livingstone, 1997.

[23] Vanisree K , Jyothi Singaraju, "Automatic Detection of ECG R-R Interval using Discrete Wavelet Transformation", International Journal on Computer Science and Engineering (IJCSE).

[24] Gabriela D., Nicté M., 2012, "Detección de Arritmias Basada en la Transformada Discreta Wavelet", Tesis de Licenciatura, FI, UNAM.

AUTHOR BIOGRAPHY

F. Moumtadi, Master of Satellite Broadcasting Systems, by Faculty of Radio and Television by the Technical University of Communications and Informatics in Moscow, Russia. PhD in Television at the Faculty of Radio and Television by the Technical University of Communications and Informatics of Moscow, Russia (MTUCI). Research interest: Study and methods design and equipment for the improvement of the quality of synthetic images in interactive television systems. Optimization study of mobile radio systems, according to its general technical and economic standards.

N. Mandujano Mayoral, Telecommunications Engineer by National Autonomous University of Mexico-UNAM in Mexico.

G. Díaz Cartas, Telecommunications Engineer by National Autonomous University of Mexico-UNAM in Mexico.

R. Alcántara Silva, Electrical Mechanical Engineer (Specialization in Electronics and Communications) of Faculty of Engineering, National Autonomous University of Mexico. Specialization in Control Engineering by National School of Electrical Engineers in Grenoble, France. Master in Control Engineering and Signal Processing of Faculty of Science by the University of Nice in Nice, France. PhD in Control Engineering and Signal Processing by the National School of Telecommunications in Paris, France. Research interest: Communications, Information Processing, Electronics.