HRV analysis using wavelet package transform and Least Square Support Vector Machine

Gley Kheder, Abdennaceur Kachouri and Mounir Samet

Abstract — In this study we are interested in the feature extraction of HRV which includes Ventricular Fibrillation (VF) and ventricular tachycardia (VT) and its classification by the least square support vector machine (LS-SVM). In the first stage, we are interested in the demonstration of the efficacity of the signals' analysis HRV by WPT compared to the analysis by DWT. Since the DWT analysis of the HRV causes frequency decomposition. In this study we are going to present new solution using WPT to decompose the HRV signal into HF and LF frequency ranges. The obtained frequency bands are too close to LF and HF bands. RMS measure the signal power contained in the specified frequency bands LF and HF. The index of sympathovagal balance (LF/HF) was examined by RMS of wavelet coefficients. The second part is devoted to evaluating the performance of the features extraction method using the outputs towards an LS-SVM classification algorithm. The classifications include exploratory data analysis, optimal input variable selection, parameter estimation, and performance evaluation via Receiver Operating Characteristic (ROC) curve analysis. LS-SVM model with Radial Basis Function (RBF) kernel achieve a best performance.

***Keywords*—**Feature extraction, Heart Rate Variability, Least Square Support Vector Machine, Sympathovagal balance, Wavelet Package,

I. Introduction

An electrocardiogram (ECG) is an electrical signal that represents the heart's cardiac activity. This signal is recorded by means of certain number of electrodes which are pasted on the body. The typical ECG is constituted by P, QRS and T waves. The P wave corresponds to the atrium's depolarization. The QRS complex results from the ventricular depolarization. The T wave corresponds to the polarization of the ventricle [1].

In this study we are interested on the RR intervals. RR intervals are defined by the time between successive R-waves. Thus, RR tachogram variability is essential for heart function's measure. Variations' analysis of this tachogram is known as Heart Rate Variability (HRV) analysis [2]–[3].

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G. Kheder is with the Laboratory of Electronics and Technologies of Information (LETI) in the National School of Engineers, Sfax ; B.P.W, 3038 Sfax, Tunisia (phone:(216) 23927790.;e-mail: kheder_enis@yahoo.fr)

A. Kachouri is with the National School of Engineers Sfax ; B.P.W, 3038 Sfax, Tunisia (e-mail: abdennaceur.kachouri@ enis.rnu.tn).

M. Samet is with the National School of Engineers Sfax ; B.P.W, 3038 Sfax, Tunisia (e-mail: mounir.samet@ enis.rnu.tn).

The parameters extracted from Heart Rate Variability signal used in assessing Autonomous Nervous System (ANS). HRV, described by the extraction of the physiological rhythms embedded within its signal, is the tool through which adaptations of activity of the ANS have been widely studied. In this study we are interested in the feature extraction of HRV witch includes Ventricular Fibrillation (VF) and ventricular tachycardia (VT). The VF and VT are life-threatening cardiac arrhythmias. The exact detection and classification of these cardiac anomalies can diminish the rate of mortality from such cardiac diseases. While VT is represented as a series of three or more repetitive complexes that originate from the ventricles, is defined as three or more ventricular extra systoles in succession at a rate of more than 120 beats/min. However VF which is usually defined as a primary cardiac event is the commonest arrhythmia that causes sudden death out of hospital.

The measurement of the HRV's non-stability presents a challenge to the signal processing techniques, especially in the dynamic conditions of functional testing [4]. The most common mathematical used to analyse HRV is the Fourier transform, which is limited to stationary signal. The best transformation of the signal expansion is to localize a given basis functions in time and in frequency. The limits of Fourier Transform, while analyzing the functions used are infinitely sharp in their frequency localization. They exist at one exact frequency but have no time localization due to their infinite extends [5]. In fact, to overcome this very limitation, we applied the Wavelet Transform (WT). This transformation is the most efficient method to quantify HRV in non-stationary conditions [4]–[6]–[7]–[8]. In our precedent studies we had to use DWT to analyse the HRV, but we encountered frequency decomposition problem [10]. This paper presents new solution using the wavelet package transform (WPT) to decompose the HRV signal into HF and LF frequency ranges and the evaluation of the performance of the features extraction method using the outputs towards an least square support vector machine (LS-SVM) classification algorithm.

Support Vector Machine (SVM) is the most know form among kernel methods, based on Vladimir Vapnik statistical theory of learning. SVM is a binary classification method by supervised learning introduced by Vapnik in 1995[15]. This method is therefore a recent alternative classification. This method relies on the existence of linear classifier in appropriate space. Since it is a twos classes-classification problem, this method uses a learning dataset to learns the model parameters. It is based on the use of the Kernel Function, which allows an optimal data separation. The Least Square SVM (LS-SVM) classifier formulation above implicitly corresponds to a regression interpretation with binary targets $y_i = \pm 1$ [16].

II. Methods

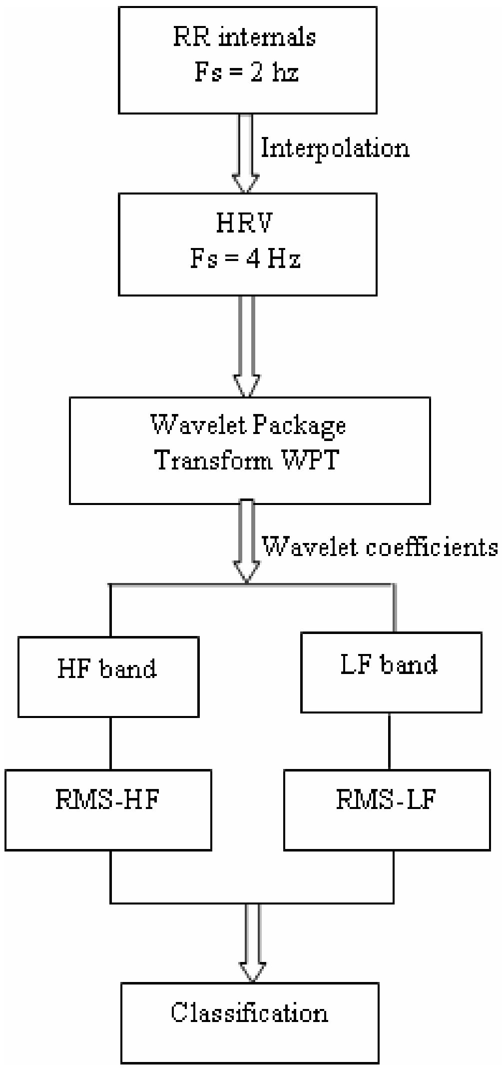

Fig. 1 the structure of the proposed system

A. HRV analysis

The nervous system's sympathetic branch increases the heart rhythm resulting in shorter beat intervals whereas the parasympathetic branch decelerates the heart rhythm leading to longer beat intervals. The spectral analysis of the HRV has led to the identification of two fairly distinct peaks: high (0.15-0.5 hz) and low (0.05-0.15 hz) frequency bands. Fluctuations in the heart rate, occuring at the spectral frequency band of 0.15-0.5 hz, known as high frequency (HF) band, reflect parasympathetic (vagal) activity, while fluctuations in the spectral band 0.05-0.15 hz, known as low frequency (LF) band are linked to the sympathetic modulation, but includes some parasympathetic influence (sympathetic-vagal influences) [10]. In fact, the level of physical activity is clearly indicated in the HRV power spectrum.

For its analysis are used widely wavelets, these problems limit process ability and investigations can be canalized different points. Both of these this bands LF and HF energy frequency bands shift to unwanted frequency regions when DWT is used to determine them. This is very important for determination and interpretation of sympathovagal balance (LF/HF) [11]. In this work, WP is needed to move frequencies in between required bands. The classification is used by the least square support vector machine (LS-SVM). Experimental studies, including training and test of the classifiers, concentrated on the recognition between two types of HRV signal classes. The proposed classifier show in Fig.1, in general, is an HRV parameter time-frequency measuring system.

B. Dataset

The dataset used in this study is obtained from physioBank entitled "Spontaneous Ventricular Tachyarrhythmia Database" [12]. This database contains 135 pairs of RR interval time series, recorded by implanted cardioverter defibrillators in 78 subjects. Each series contains between 986 and 1022 RR intervals. One series of each pair includes a spontaneous episode of ventricular tachycardia (VT) or ventricular fibrillation (VF), and the other is a sample of the intrinsic (usually sinus) rhythm. The ICD maintains a buffer containing the 1024 most recently measured RR intervals. Sampled signals are interpolated using cubic spline interpolation and resampled in 4 Hz.

C. Wavelet theory

A wavelet family $\psi_{a,b}$ is the set of elemental functions generated by dilations and translations of a unique admissible mother wavelet $\psi(t)$,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

The discrete wavelet transform (DWT) achieves this parsimony by restricting the variation in translation and scale, usually to powers of 2. When the scale is changed in powers of 2, the discrete wavelet transform is sometimes termed the dyadic wavelet transform. Discrete wavelet function can be described by (1)

$$\psi_{m,n} = 2^{-m/2}\psi(2^{-m}t - n), \qquad (2)$$

Here m is related to a as: $a = 2^m$; b is related to n as $b = n2^m$ and $n, m \in Z$

The wavelet computations are equivalently performed simply using the filtering processes as

$$\phi_{m+1,n}(t)=\frac{1}{\sqrt{2}}\sum_k c_k\phi_{m,2n+k}(k)\,, \qquad (3)$$

$$\psi_{m+1,n}(t)=\frac{1}{\sqrt{2}}\sum_k b_k\phi_{m,2n+k}(t)\,, \qquad (4)$$

Where $\phi(t)$ is scaling function, $\psi(t)$ is wavelet function, c_k are scaling coefficients, b_k are wavelet coefficients, and k is location index of transform coefficients. Approximation and detail coefficients can be formulized respectively as

$$G_{m+1,n}=\frac{1}{\sqrt{2}}\sum_k c_k A_{m,2n+k}=\frac{1}{\sqrt{2}}\sum_k c_{k-2n}A_{m,k}\,, \qquad (5)$$

$$H_{m+1,n}=\frac{1}{\sqrt{2}}\sum_k b_k A_{m,2n+k}=\frac{1}{\sqrt{2}}\sum_k b_{k-2n}A_{m,k}\,.$$

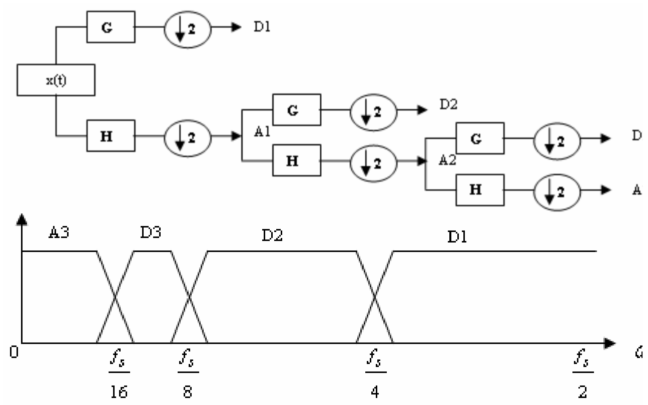

Fig. 2 DWT at level 3

(6)

Approximation (A) and detail (D) components is obtained with reconstruction of approximation and detail coefficients as

$$A_M(t)=G_{M,n}\phi_{M,n}(t)\,, \qquad (7)$$

$$D_m(t)=\sum_{n=0}^{2^{M-m}-1}H_{m,n}\psi_{m,n}(t)\,, \qquad (8)$$

Where M is last decomposition level.

A M-level decomposition of orthogonal wavelet basis is illustrated in Fig. 3, that is, detail coefficients at all the M levels (D1, D2…, DM) and approximate deepest decomposition level (AM). Approximate coefficients often resemble the signal itself.

Initial signal X is reconstruct as

$$X=A_M(t)+\sum_{m=1}^{M}D_m(t)\,,\ m=1, 2, \ldots, M. \qquad (9)$$

Wavelet packet (WP) transform are a generalization of DWT. In WP signal decomposition, both the approximation and detail coefficients are further decomposed at each level. In DWT, detail coefficients are transferred down, unchanged to the next level. However, in WP, all coefficients are decomposed in each stage. WP function includes third additional index as j and is described as

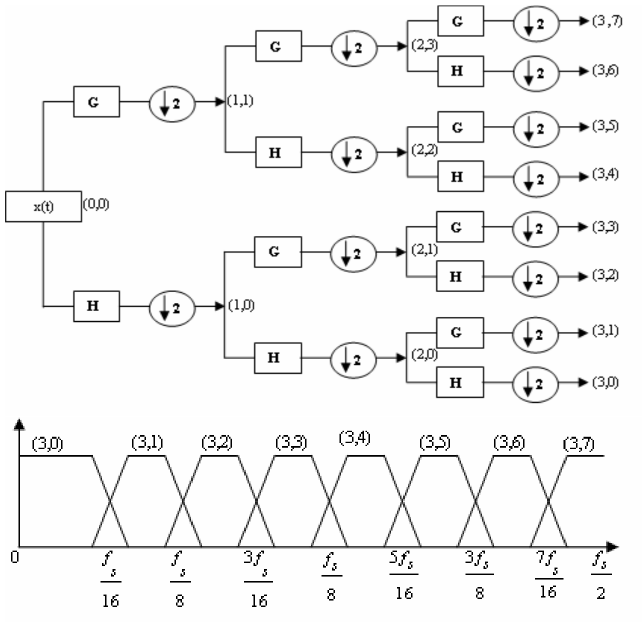

Fig. 3 WPT at level 3

$$W_{m,j,n}(t)=2^{-m/2}W_j(2^{-m}t-n)\,, \qquad (10)$$

Where $j\in N$ denote node index in each m level [13].

D. Wavelet package feature extraction

Feature extraction is a transformation of a pattern from its original form to a new form suitable for further processing. The first step in performing the feature extraction process should wavelet domain in mapping the data of distorted signal [13].

Wavelet packet decomposition at level j of HRV signal give 2^j sets of sub-band coefficients of length $N/2^j$. The total number of such sets located at the first level to the jth level inclusive is $(2^{j+1}-2)$. The order of these sets at the jth level is $m=1,2,\ldots,2^j$. Then, each set of coefficients can be viewed as a node in a binary wavelet packet decomposition tree. Wavelet packet coefficient, $\{P_{j,m}(k)\mid k=1, 2, \ldots, N/2^j\}$, correspond to node (j,m). These vectors reflect the change of the signal with time in the frequency range of $\left[(m-1)F_s/2^{j+1}, mF_s/2^{j+1}\right]$, where F_s is the sampling frequency [14].

There are many wavelets that can be needed to analyse the distorted signal and extract the feature vector. In this work the Daubechies “db4” wavelet function is used to analyse the signal by WPT. In fact, we obtained maximum energy localization using db4 and db8 when compared to the other type of wavelets [13].

The 6 levels decomposition of WP provides high resolution. The obtained frequency bands are too close to LF and HF bands. The resultant resolution of a terminal node is (6,r), r=0, 2, …, 63. The LF band is localized in the nodes (6,1), (6,2), (6,3) et (6,4). However HF band is localized in the nodes (6,5), (6,7), (6,8), (6,9), (6,10), (6,11), (6,12), see Table I.

HRV produce variations in the relative energy associated with the different frequency bands and in their degree of importance. RMS (Root Mean Square) measure the signal power contained in the specified frequency band LF and HF. The index of sympathovagal balance (LF/HF) was examined by RMS of wavelet coefficients used (12).

Wavelet package energy is determined depending on w values that is obtained reconstruction of $W_{m,j,n}$.

TABLE I
THE FREQUENCY RANGES WITH RESPECT TO NODES

HRV Bands	Node	Frequency Range (Hz)
	(6,0)	0 – 0,03125
	(6,1)	0,03125 – 0,0625
LF	(6,2)	0,0625 – 0,09375
	(6,3)	0,09375 – 0,125
	(6,4)	0,125 – 0,15625
	(6,5)	0,15625 – 0,1875
	(6,6)	0,1875 – 0,21875
	(6,7)	0,21875 – 0,25
HF	(6,8)	0,25 – 0,28125
	(6,9)	0,28125 – 0,3125
	(6,10)	0,3125 – 0,34375
	(6,11)	0,34375 – 0,375
	(6,12)	0,375 – 0,40625
	.	.
	.	.
	.	.
	(6,63)	1,96875-2

$$e(m,j)=\sqrt{\frac{1}{N}\sum\left|w_{m,j}(r)\right|^{2}} \qquad (11)$$

$e(m,j)$ are RMS values of interested band.

$$\frac{LF}{HF}=\frac{e(6,1)+...+e(6,4)}{e(6,5)+...+e(6,12)} \qquad (12)$$

E. LS-SVM classifier

Support Vector Machine SVM is a classification method that shows good performance is salving various problems. This method has proved its effectiveness in many areas of applications such as image processing, texts categorization, medical diagnostic and in a very large scale data set dimension. Least Square Support Vector Machine LS-SVM is reconstructed from the standard SVM which lead to solving linear KKT systems [17]. The achievement of training program by LS-SVM leads to the solving of optimization a problem involving a resolution system in an area of considerable dimension. The use of these programs lays mainly a selecting a good kernel function family and regulating the parameters of these functions. The choices as usually made by a cross-validation technique, in with we estimate the system performance by measuring it on examples that have not been used in the training phase [18]. The idea is to look for the parameters allowing obtaining maximum performance. If the implementation of an LS-SVM algorithm is generally expensive in terms of time, we must, however, expect that the finding of the best parameters many request larger test phase [19]-[20].

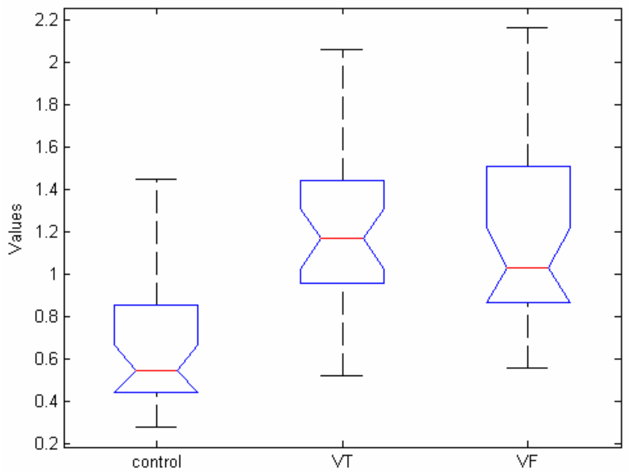

Fig. 4 Variation of SB

In this work we use an optimization program from the MATLAB Toolbox to calculate these parameters [21]-[15].

III. Results and Discussion

A. Feature extraction

The number of signals used in this simulation recorded from subjects with different ages (between 20 and 75 years old). Among which, 29 signals are normal used as control groups, the two other signal groups (of 29 signals) are respectively VT

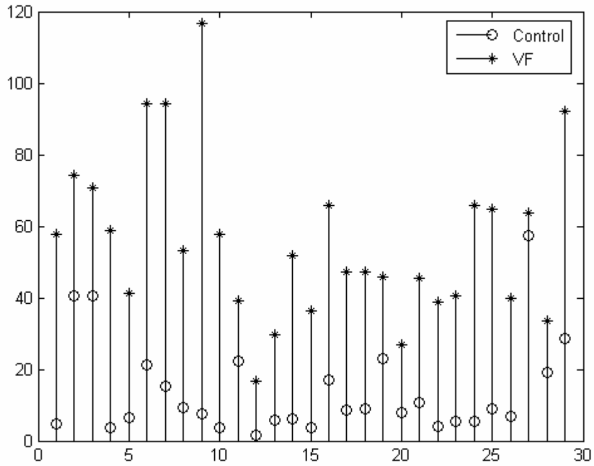

Fig. 5 Standard deviation of VF arrhythmias and controls in LF ranges

and VF arrhythmias.

Fig. 1 presents an efficient analysis of sampatovagal balance variations. The domination of sympathetic activity is well detected when this is higher than 2.1. If this ratio is smaller

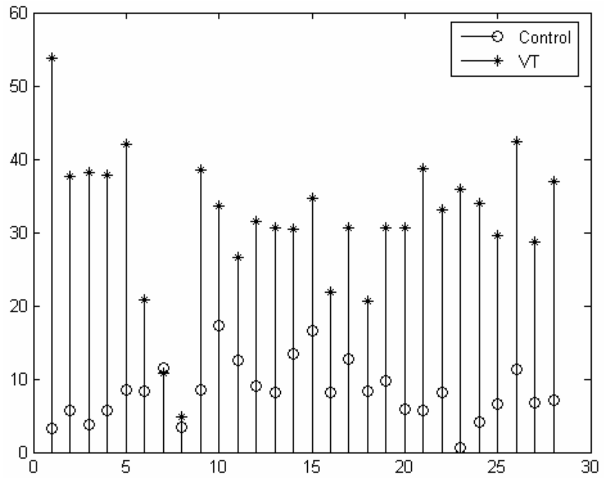

Fig. 6 Standard deviation for VT arrhythmias and controls in LF ranges

1.4, it denotes domination of parasympathetic activity. These two activities are well detected while analysing the VT and VF signals by means of WP.

The variations of the ratios, measured by means of wavelet coefficients energy, of the signals with VT and VF anomalies gives significant differences ($p<0.0002$) in accordance with normal signals.

The standard deviation measures the spread of the data about the mean value. Both Fig. 2 and Fig. 3 present the variation of the wavelet coefficients using the standard deviation of the LF band in the signals with VT and VF arrhythmias, we note that when the role of the parasympathetic nervous system marked by variation in the LF band is prevalent, the sympathetic and parasympathetic nervous

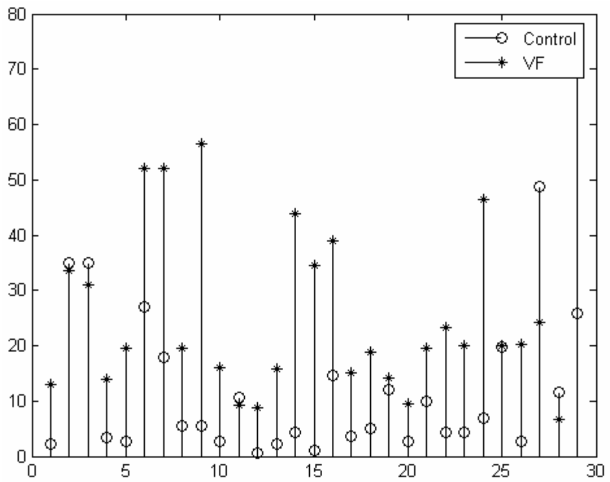

Fig. 7 Standard deviation of VF arrhythmias and controls in HF ranges

systems play a role in the development of the LF as efferent nerves of the autonomous nervous system.

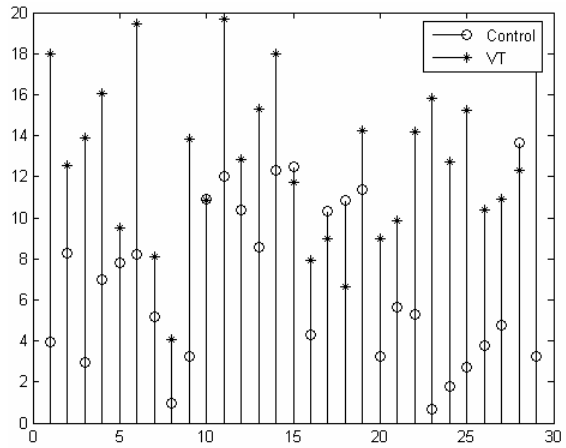

Fig. 8 Standard deviation for VT arrhythmias and controls in HF ranges

Fig. 4 and Fig. 5 show the standard deviation of wavelet packet coefficients at the frequency ranges HF of HRV with VT and VF arrhythmias. A change in standard deviation in the wavelet package coefficients corresponds to a change in signal power at that frequency range. We consistently observed that the standard deviation of the sympathetic activity of the subjects with VT and VF arrhythmias as increases as compared to the respective standard deviations of the control groups.

B. Classifications

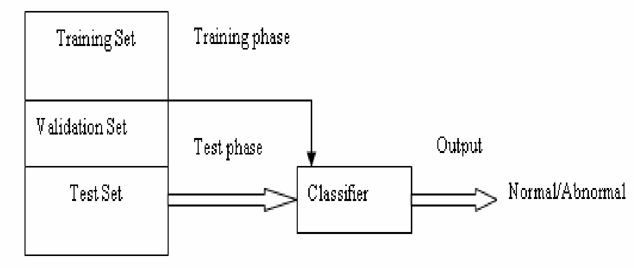

Fig. 9 The classification method

After feature extraction by wavelet package transform at level 6, we employ the LS-SVM classifier for classification phase. As Show in Fig. 9, finally, the classification is implemented using LS-SVM MATLAB ToolBox [21].

Fig. 10 and Fig. 11 show the input space of the classifier.

The training data constructed by two classes (Normal=+1 and Abnormal=-1).

In the first stage we need two extra parameters for LS-SVM:

- γ (gamma) is the regularization parameter, determining the trade-of between the fitting error minimization and smoothness.
- σ^2 of the RBF kernel

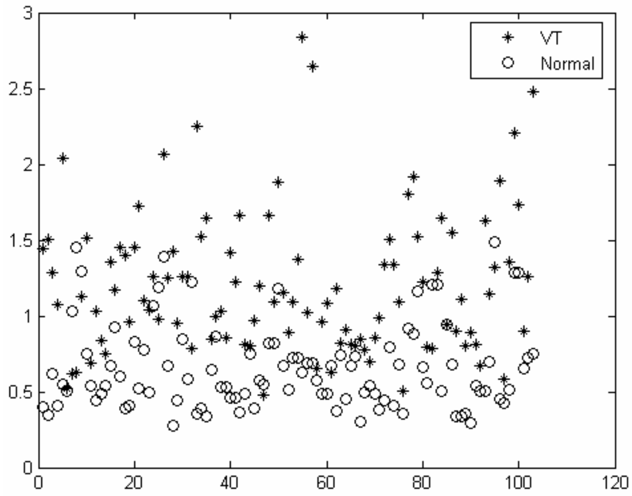

Fig. 10 LF/HF variation HRV with VT and Normal

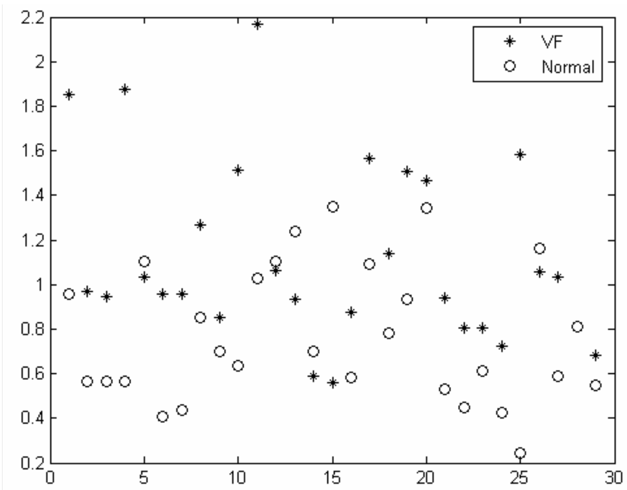

Fig. 11 LF/HF variation HRV with VF and Normal

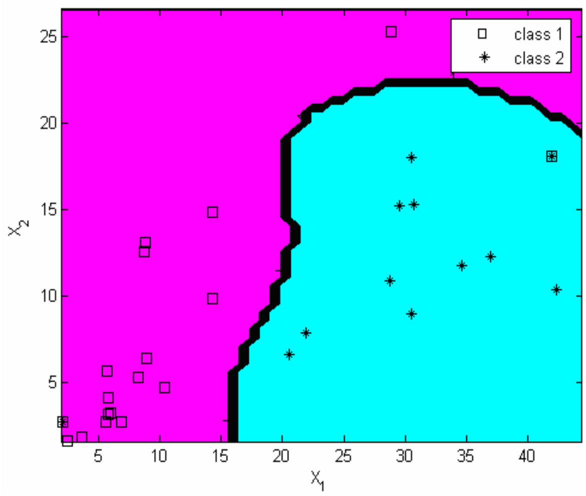

Fig. 12 LS-SVM two class example with Normal and Abnormal data set

Fig. 12 present an example of determination of optimal γ value is 20.0855 and optimal σ^2 value is 3.7796 for good diseases.

The classification results could be provided thanks to the following statistical parameters:

- True positive (TP), which represents pathological state HRV (including VT or VF), is classified as pathological state.
- True negative (TN), that represents a normal beat, is classified as normal.
- False positive (FP) represents a normal beat. This is misclassified as a pathological state.
- False negative (FN) representing a pathological beat being misclassified as normal.

Added to that, we can define sensitivity (SE), specificity (SP) and accuracy (AC) as:

$$SE = \frac{TP}{TP + FN} \times 100$$

$$SP = \frac{TN}{TN + FP} \times 100$$

$$AC = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

TABLE II
CLASSIFICATION PERFORMANCE

Classifier	SE	SP	AC
Normal/VT	91%	92%	91.5%
Normal/VF	95%	97%	96%
Normal/Abnormal	89%	90%	89.5%

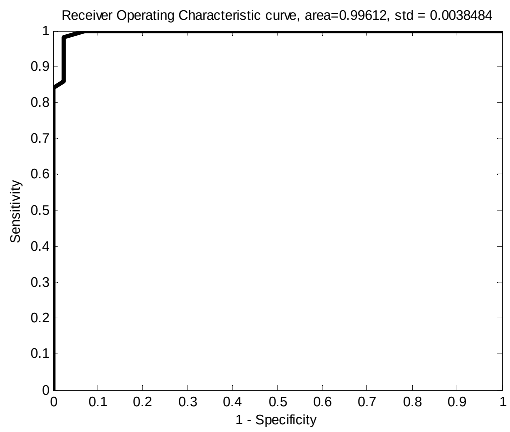

Fig. 13 ROC curve

In this work these parameters are calculated by ROC curves, as presented in TABLE II and Fig.13.

ROC curves is a statistical comparing method which uses the rates of true positive and false positive. Therefore, it provides a trade-off between sensitivity and specificity. In this example Fig. 13 area value is 0.99612, this area we evaluate these classifiers performances.

The stated results show that the LS-SVM with RBF can make an efficient interpretation.

IV. CONCLUSION

In this study, for the diagnosis of Heart Rate Variability HRV Arrhythmia, a novel medical decision support system based on DWT and LS-SVM. We have presented HRV analyse using wavelet package transform and classification using Least Square Support Vector Machine LS-SVM. The wavelet packet utilized an optimized division. The wavelet package analysis is a flexible approach, because the division of the frequency spectrum can be regular performed schemes. Wavelet package transform has been made to adapt to the signal characteristics by calculating an optimized decomposition for the whole HRV time series. WPT give an efficient extraction of the two frequencies ranges LF and HF. RMS measure the signal power contained in the specified frequency band LF and HF. We obtained maximum energy localization using “db4” wavelet function. We use LS-SVM to classify the extracted features. Performances of LS-SVM classifier are calculated by ROC (Receiver Operator Characteristic) method. The percentage of accuracy obtained by the set test data for validating the classifier is mean at 90%.
These results demonstrate considerable potential in applying wavelet package transform in HRV analysis and suggest superior performance of LS-SVM in biomedical classification.

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Gley Kheder was born in Gafsa, Tunisia in 1978. He received the electrical engineering degree in 2002 and Master degree in electronics and telecommunication in 2003, both from National School of Engineers of Sfax, Tunisia (ENIS). She currently is working toward the Ph.D. degree in electronic at the same school. Her research interest is to feature extraction of the electrocardiogram using signal processing technique.

Abdennaceur Kachouri was born in Sfax, Tunisia, in 1954. He received the engineering diploma from National school of Engineering of Sfax in 1981, a Master degree in Measurement and Instrumentation from National school of Bordeaux (ENSERB) of France in 1981, a Doctorate in Measurement and Instrumentation from ENSERB, in 1983. He “works” on several cooperation with communication research groups in Tunisia and France. Currently, he is Permanent Professor at ENIS School of Engineering and member in the “LETI” Laboratory ENIS Sfax.

Mounir Samet was born in Sfax, Tunisia in 1955. He obtained an Engineering Diploma from National school of Engineering of Sfax in 1981, a Master degree in Measurement and Instrumentation from National school of Bordeaux (ENSERB) of France in 1981, a Doctorate in Measurement and Instrumentation from ENSERB, in 1981 and the Habilitation Degree (PostDoctorate degree) in 1998. He "works" on several cooperation with medical research groups in Tunisia and France. Currently, he is Permanent Professor at ENIS School of Engineering and member in the "LETI" Laboratory ENIS Sfax.