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New Frame Work for QRS Complex Monitoring

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Abstract

The paper at hand presents a framework for the monitoring of the QRS complex of an electrocardiogram. Such a complex is made up of three waves Q, R and S and carries the most important information in an ECG because it influences the ventricular contraction and relaxation of the heart. This framework is divided into two main parts: the detection of the QRS complex by the continuous wavelet transform and its control by the analysis of the principal linear component. The first step consists in determining the localizations of the waves of the QRS complex by leaning on the properties of the regularity and the detection of the singularities offered by TOC. This step allows for the definition of a multivariable matrix presenting several measurements of the various amplitudes of the waves and the segments of the QRS complex. The second step allows studying the data matrix through the multi-scale linear PCA so as to define the fault variables by using the principle of the fault detection and the fault localization of the PCA. This framework is applied to some ECG of the MIT/BIH base and is evaluated by comparing it with the data of this same base.

Keywords: ECG, QRS complex, CWT, PCA, fault detection, fault localization

I. Introduction

The ECG signal is a set of waves determined by letters ranging from P to U. In particular, the grouping of the three waves Q, R and S, with the so particular profile, is called QRS complex. Many previous works were inclined to the study of this complex by integrating various tools. Some of these works approached the problem of detecting the waves of the QRS complex. In this respect, several researches used traditional methods such as the filters and the first and the second derivative [1, 2,3 and 4]. Still, modern tools have recently been introduced to detect the QRS complexes. The very tools are based on the wavelets [5, 6 and 7].

Another part of these preceding works tackled the problem of classifying the cardiac arrhythmias by referring to the analysis of the QRS complexes. Lagerholm et al. [8] suggest a method for the classification of the QRS complexes of the ECG by integrating the basic functions and the neuron networks with autonomous organization. Lagerholm et al. validated their approach by using the arrhythmia MIT-BIH database. The resulting groups are found with a degree of classification error of 1, 5%.

Tsipouras et al. [9] developed an approach to the automatic generation of a fuzzy expert system (FES). The classification results of the asynchronous pulses gave a percentage of precision equal to 96,43%. In [10], Chazal et al. propose a process for the automatic treatment of an electrocardiogram (ECG) resulting from the MIT/BIH database for the classification of the pulsations. The independent evaluation of the performances of this configuration gave a sensitivity of 75,9%, a positive predictive value of 38,5%, and a rate of positive faults of 4,7% for the ESV class. The sensitivity was 77,7%, the positive predictivity was 81,9%, and the rate of positive faults was 1,2% for the EV class. Maater and Lachiri [11] proposed to develop a system of classification of the QRS made up of 8 arrhythmias by integrating the hidden models of Markov. This work proved a rate of maximum classification of 82.14%.

This paper presents an approach which deals with the detection of the QRS complexes as well as the analysis of their evolutions to classify the arrhythmias. On the one hand, we introduce the continuous wavelet transform so as to detect the waves Q, R and S. The obtained results are gathered in a matrix. The variables of such a matrix are the amplitudes of the waves and the segments of the QRS complex. On the other hand, a new method is introduced in order to analyze the evolution of the QRS of the ECG which is based on the analysis of the main component. This approach statistically analyzes the QRS complexes for the detection and the localization of the defective variables which will indicate the type of arrhythmia. Our approach is implemented on the ECG MIT/BIH database and the results are compared with the data of this base.

II. Proposed frame work for complex QRS monitoring

II.1. Processing

In this part, we start with the presentation of the step of the plan of the suggested work for the analysis of the QRS complexes which is composed of two main parts: the detection of the waves of the QRS and the identification of the arrhythmias. These two parts are described by the following diagrams.

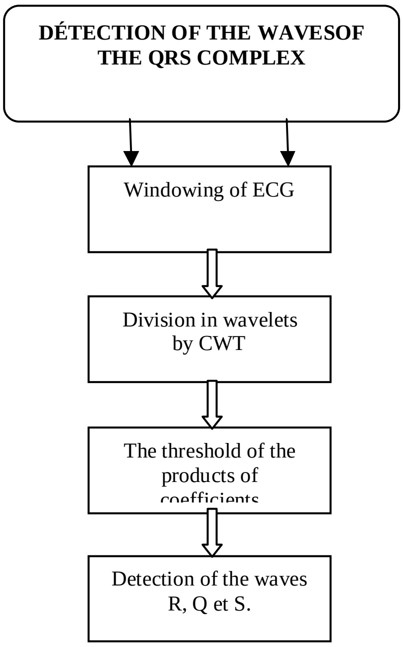

Fig.1. the step of detecting the QRS complexes

Figure 1 presents the approach to the detection of the waves of the QRS complexes. We begin by windowing the ECG taken from the MIT BIH international base to facilitate the analysis of the totality of the long signal. For each window, we apply the continuous wavelet transform to three successive levels. The used mother wavelet is the first derivative of Gaussian. The product of the three coefficients (P) will be started in keeping with the maximum module of the product P according to the following equation:

$$S = \beta \times max(P) \tag{1}$$

The parameter β lies between 0 and 1, its choice depends on the obtained results of detection. In this work, we fixed this parameter to the value $\beta = 0.6$.

Finally, the waves R are detected according to the principle of the passage by zero of the extremums of Gaussian on its first derivative.

The wave Q is localized by the first module which precedes the modules of the wave R and the wave S is localized by the first module which follows it.

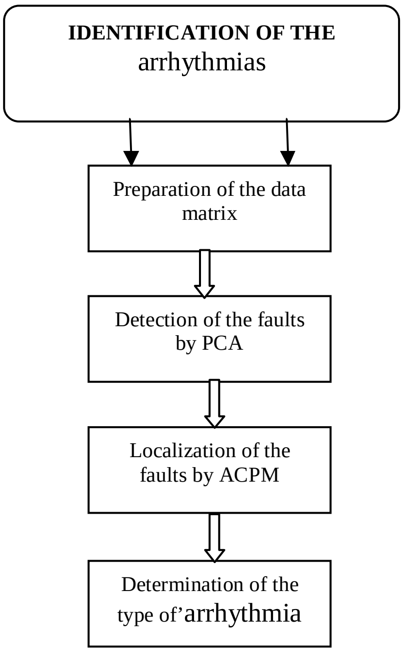

Fig.2. The step of determining the arrhythmias of the QRS

Figure 2 describes a diagram which presents the various steps identifying the arrhythmias by taking the evolution of the QRS complexes as a basis. The first step consists in preparing a three-variable-data matrix: RR is the heart frequency presented by the interval which separates two successive waves R, RA is the amplitude of the wave R, QS is the interval which measures the width of the QRS complex. We take about 200 measurements of the studied variables.

Statistically, we will analyze the matrix obtained by the principal components analysis. This method has the property of detecting and localizing the data faults. The defective variables will be analyzed to identify the arrhythmias.

II.2. Continuous wavelet transform (CWT)

The wavelet transform divides up the signals into a relocated and dilated family of wavelets. A wavelet is a function $\psi \in \mathbf{L}^2(\Re)$ of null average. It is standardized to $\|\psi\| = 1$, and centered in the neighborhood of t = 0. A family of time-frequency atoms is obtained by dilating the wavelet ψ by a factor s, and by relocating it by u:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \qquad (2)$$

These atoms are of the norm 1: $\|\psi_{u,s}\| = 1$. The continuous wavelet transform of the signal $x(t)$ in time u and at the scale s is given by the following equation:

$$W\,x(u,s) = \langle x(t), \psi_{u,s}(t)\rangle = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t-u}{s}\right)dt$$

In this expression, s is the scale factor and u is the dilation parameter. The parameter s plays the role of the opposite of the frequency: the smaller s is, the more the wavelet support is reduced; therefore, the central frequency of its spectrum is high.

The continuous wavelet transform can be rewritten as a signal convolution product with a pass-band filter characterizing the wavelet function. The convolution allows calculating the wavelet transform using dilated band-width filters. Just like a Fourier window transform, a wavelet transform allows measuring the evolution of the frequencial components in time. With this intention, we need to use a complex analytical wavelet in order to separate the phase and the amplitude. Yet, the real wavelets are often used for the detection of the fast transitions of a signal.

1. **Analytical wavelets:** To analyze the temporal evolution of the spectral components of a signal, it is necessary to use an analytical wavelet (Fourier null transform for the negative frequencies), this wavelet allows separating the information of the amplitude and the phase. An analytical wavelet transform is calculated with an analytical wavelet ψ. An analytical wavelet transform defines a density of energy in time-frequency $P_W f$, which measures the energy of f in the box of Heisenberg of each wavelet $\psi_{u,s}$ centered at the point $(u, \xi = \eta/s)$ with η is the frequency term. This energy density is called scalogramme.

$$P_W\,x(u,\xi) = |W\,x(u,s)|^2 = \left|W\,x\left(u, \frac{\eta}{\xi}\right)\right|^2$$

2. **Real wavelets:** The real wavelets are often used to characterize the regularities of the signals in the neighborhood of a given moment. Let us suppose that ψ is a real wavelet, with a null average, $W\,x(u,s)$ measures the variation of $x(t)$ in the neighborhood of *u* with a proportional size to *s*. When *s* tends towards 0, the decrease of the coefficients of the wavelets characterizes the regularity of $x(t)$ in the neighborhood of *u*. This property has very important applications to detect the brutal transitions which can be contained by a signal. The literature proposes panoply of real wavelets. The most famous are the wavelets of daubechies, the Mexican hat and the splines.

The continuous wavelet transforms are parameterized by two real numbers, the scale factor *s* and the relocation step *u*. These transforms are actually very redundant because the time-frequency space is continuously covered, but, in practice, there is always a discretization of the parameters in the operated calculation. This redundancy is reduced by sampling the time-frequency space. The family containing wavelets is replaced by a family indexed by discrete variables of time $u = n\,u_0 s_0^m$ and of the scale $s = s_0^m$ (with $s_0 > 0\,; b_0 > 0$, $n, m \in Z$). We, then, obtain the discrete wavelet transforms in which the redundancy is generally present but reduced. Such a sampling does not inevitably provide good wavelet bases; in particular, the dual base necessary to rebuild the signal is not necessarily a wavelet base. The calculation of the discrete wavelet transform uses Mallat fast algorithm which is based on the algorithm with holes. The dyadic wavelet coefficients are calculated by convolution operations in cascade with dilated filters.

II.3. Principal component analysis (PCA)

- **Objective**

The principle of PCA lies in transforming, linearly, the correlation of the variables of the source in a subspace in which there is no correlation between its variables. Otherwise, the principal components analysis allows transforming a set of correlated variables into another one in which the variables are not correlated.

Let us consider a vector containing centered measurements, that is to say $x = [x_1, x_2, ..., x_m]^T \in \Re^m$, the variation of the data matrix $X \in \Re^{mxn}$ is presented by a symmetrical covariance matrix $\Sigma \in \Re^{mxn}$. For each vector of X we associate a vector $t \in \Re^m$. This vector allows optimizing the maximization of the variation t and the minimization of the estimation error.

The first principal component is given in the form of linear combination of x which is expressed as:

$$t = p^T.x \tag{3.5}$$

The condition of maximizing the projected variance is determined by the following equation:

$$(\Sigma - \lambda_i I)p_i = 0 \tag{3.6}$$

with:

- I is an identity matrix
- λ_i are scalars
- are vectors closed by the combination coefficients.

Considering the real solutions of λ_i:

$$|\Sigma - \lambda I| = 0 \tag{3.7}$$

The solution of this equation gave us scalar solutions λ_i which are called eigenvalues of the matrix Σ. We obtain, thereafter, the eigenvector p_i with

$p_i^T p_j = 1 \forall i, j$ forming an orthogonal base whose variables are not correlated. In addition, the eigen vectors which check the condition forms an orthonormal base expressed as follows:

$$P^T P = P P^T = I_n \tag{3.8}$$

We break up the following matrix linear transformation:

$$T_{N\times m} = X_{N\times m} P_{m\times m} \quad et \quad X_{N\times m} = T_{N\times m} P^T_{m\times m} \tag{3.9}$$

With:

- $X \in \Re^n$: matrix of N observation and m variables.
- $P \in \Re^{m\times n}$: matrix of the eigen vectors.
- T: score matrix (the matrix of the principal components).
- $P = [P_1, P_2, ..., P_m]$: the whole of vectors in $\Re^{m\times n}$.

- **Fault detection method by PCA**

We introduce two statistical tools to detect the faults: the statistics of the square of the predictive error SPE and the statistics of Hotelling T².

Figure 3.7 described the process of fault detection by SPE and T².

The data T² and SPE Fault decision

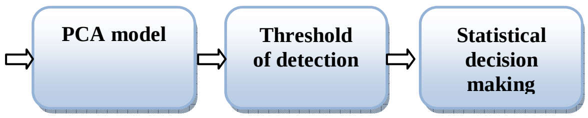

Fig.3. Principle of fault detection by PCA

The SPE statistics are given by the following equation:

$$SPE = \|\tilde{x}\|^2 = x^T \tilde{P}\tilde{P}^T x = x^T \tilde{C} x \tag{3.21}$$

with

$e = (I - \tilde{P}\tilde{P}^T)x$ presenting the residues of the vector x.

The statistics T² allows measuring the variation of the score vector in the space of CP, it is expressed as:

$$T^2 = t^T \Lambda^{-1} t = x^T P \Lambda^{-1} P^T x = x^T D x$$

with A is the diagonal matrix which contains the CP used in the model of PCA and $D = PA^{-1}P^{T}$ is a semi-positive matrix.

The faults are detected by comparing the two statistics with their control limits.

- **The threshold of the detection of T²**

Let us consider x with measurements of m variables of normal distribution and $\sum$ is a covariance matrix. We check, after that, if μ the multivariable parameters average follows an average population throughout the Khi-two statistics calculation which is defined as:

$$\chi^2 = (x-\mu)\Sigma^{-1}(x-\mu)^T \tag{3.23}$$

The limiting threshold for a confidence interval α is given by $\chi^2_{\alpha,n}$.

$$T^2 \le \chi^2_\alpha(\ell) = \tau^2 \tag{3.24}$$

With ℓ is the degree of freedom of the Khi-two law. If the variance matrix is unknown, we can use the statistics T² to estimate it:

$$T^2 = (x-\mu)S^{-1}(x-\mu)^T \tag{3.25}$$

With S is the estimate of the variance matrix $\sum$. In order to determine the detection limit we introduce, Fisher distribution [12]. The limits of control are given by the degree of confidence α :

$$LCL = \frac{m(N^2-1)}{N(N-P)} F_{1-\alpha}(m, N-m)$$

$$UCL = \frac{m(N^2-1)}{N(N-P)} F_{\alpha}(m, N-m) \tag{3.27}$$

With LCL is the high detection limit at a degree of confidence $1-\alpha$, UCL is the confidence limit lower than a degree of confidence α.

- **The threshold of detection of SPE**

We consider the measurement vector x which follows a normal distribution $N(0,\Sigma)$ with $\lambda_i, i=1,...,m$ are the eigenvalues of Σ. The detection limit for SPE was expressed by Jackson and Mudholkar [13] as follows:

$$C_\alpha = \theta_1 \left[\frac{1-\theta_2 h_0 (1-h_0)}{\theta_1^2} + z_\alpha \frac{(2\theta_2 h_0^2)^{1/2}}{\theta_1} \right]^{1/h_0}$$

with

$$\theta_1 = \sum_{i=1}^{m} \lambda_i, \theta_2 = \sum_{i=1}^{m} \lambda_i^2, \theta_3 = \sum_{i=1}^{m} \lambda_i^3, h_0 = 1 - \frac{2\theta_1 \theta_3}{3\theta_2^2}$$

- **Localization of the faults**

Here we describe the principle of calculating the contributions to localize the faults. Suppose that the total number of the variables indicated by m and ℓ is the number of CP to be retained in the model PCA, then the dimension of subspace of the residues is given by $m-\ell$. Once the statistical tests T² and SPE exceed the thresholds of detection, the contributions of the various variables are determined. The faults are localized with the variables having high contributions compared to the others.

The calculation of the contribution for a variable by the method SPE is given by considering the large residue with the square associated with only one variable:

$$SPE_i = \tilde{x}_i^2 \quad (3.29)$$

Qin[14] gave the following equation to calculate the contribution by the statistics of Hotelling T²:

$$T_i^2 = \left\| \Lambda^{-1/2} P(:,i)\, x_i \right\|^2$$

Generally, the statistics of the fault detection have the quadratic form which is defined as follows:

$$statistique(x) = x^T B x = \|x\|_B^2 \quad (3.31)$$

with B is equivalent to $\tilde{C}$ for the model SPE and to D for that of Hotelling T².

The statistics (x) is given by:

$$statistique(x) = \sum_{i=1}^{M} (\xi_i^T B^{1/2} x)^2 = \sum_{i=1}^{M} c_i^{statistique} \qquad (3.32)$$

The contribution of x_i is indicated by $c_i^{statistique} = (\xi_i^T B^{1/2} x)^2$, and ξ_i is th column of the matrix of identity and direction x_i.

For the statistics SPE, the calculation of the contribution for a variable is defined in [15] as:

$$c_i^{SPE} = (\xi_i^T \tilde{C}^{1/2} x)^2 = \tilde{x}_i^2$$

For the statistics of T², the contributions are calculated in [16] by this equation

$$c_i^{T^2} = (\xi_i^T D^{1/2} x)^2$$

III. Implementation of the proposed frame work

III.1. Database

Our suggested framework for the analysis of the QRS complexes and the identification of the arrhythmias is validated on the ECG MIT/BIH international base [17]. The studied arrhythmias are the ventricular tachycardia existing in the ECG 106, 200, 203, 205, 221 et 223.

III.2. Results

- **Detection of the QRS complexes**

First of all, we will apply the wave-detection algorithm to determine the positions of the various waves Q, R and S by employing the continuous wavelet transform. In the following table, we have the results of this step, with Se is the sensitivity, P+ is the positive predictive value which is defined as follows:

$$S_e = \frac{TP}{FN + TP}$$

$$P_+ = \frac{TP}{FP + TP}$$

These parameters are calculated according to other parameters related to the results of the algorithm of detection of the adapted waves; that is to say,

TP: true positive: to detect the waves which are true waves of the ECG.

FP: false-positive: to detect the waves which do not exist in the ECG.

FN: false-negative: not to detect a wave which exists in the ECG.

TABLE I

	TP	FP	FN	SE	P+
106	2016	9	198	91%	99%
200	1561	26	522	75%	98%
205	1561	26	522	75%	98%

RESULTS OF THE QRS COMPLEX DETECTION

The detection results are assessed by the parameters Se and P+, many factors can reduce the performance of the detection algorithm such as the noises and the characteristic of the forms of the waves of the ECG.

- **Data matrix**

We comprise a data matrix (500x6), which is presented in 2, the variables of which stem from the characteristics of the waves Q, R and S. QA, RA and SA are respectively the amplitudes of the waves Q, R and S, QS is the width of the complex, QR is the interval between the wave Q and the wave R and RR is the heart rate (interval between two successive waves R).

- **Détection**

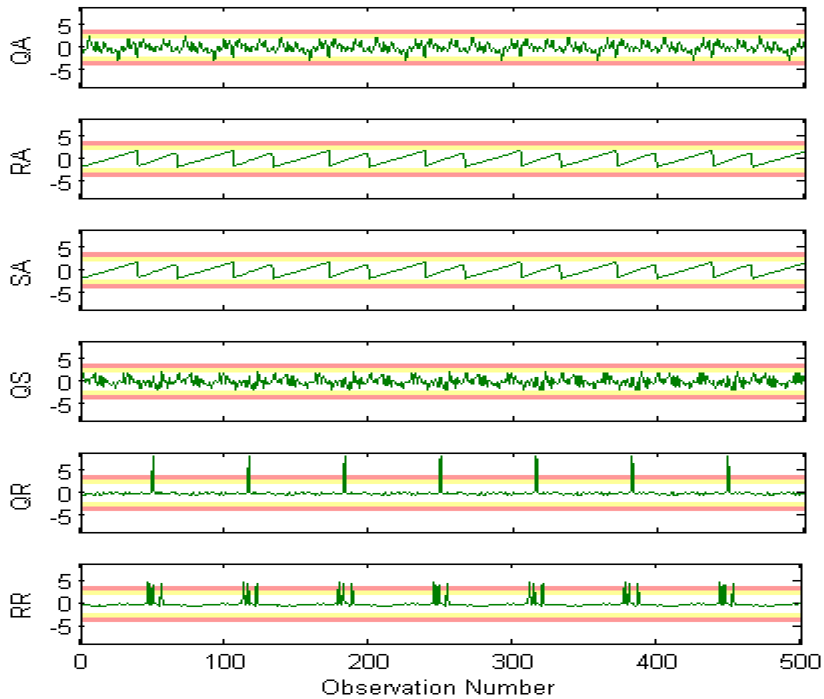

Fig.4. data matrix

- **Arrhythmias detection**

In this section, we attempt to introduce the principal component analysis (PCA) to detect the arrhythmias in an ECG by analyzing the evolution of the data matrix. The PCA has the property of detecting the faults by means of various tools. In this, figure 3 shows the results of the fault-detection by the statistics of Hotteling T^2 and SPE statistics. The excess of the control-thresholds proves the existence of faults and, thus, arrhythmias.

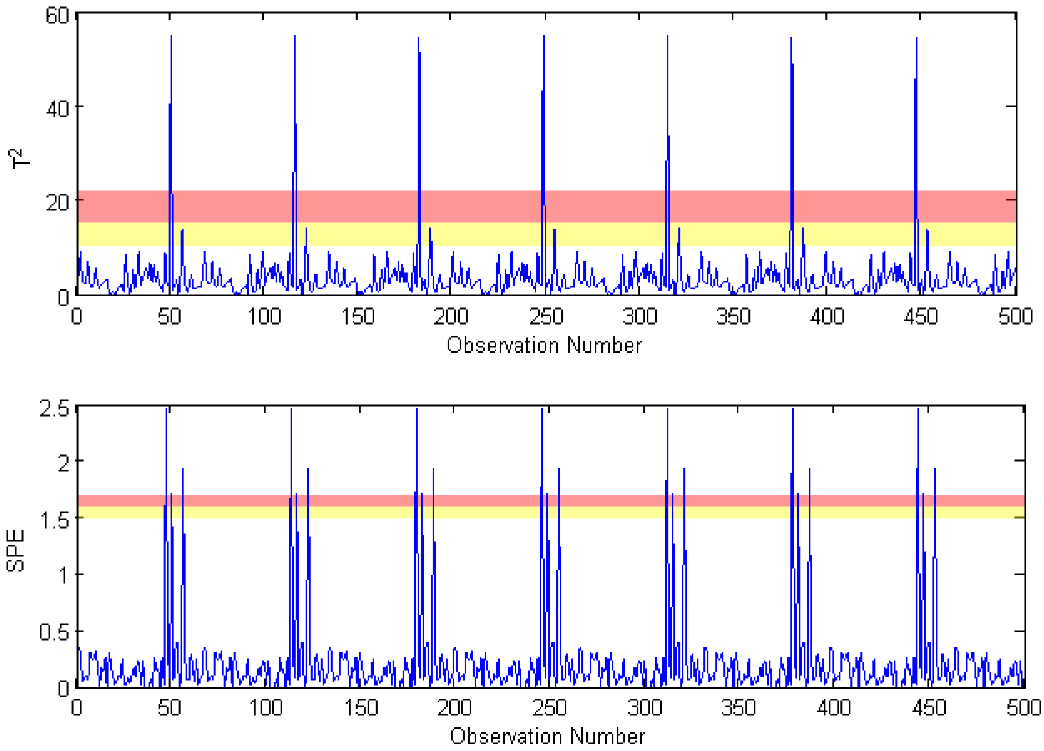

Fig.5. Détection des arythmies par la détection des défauts utilisant SPE et T^2

To identify the type of arrhythmias, we refer to the localization of the faults by calculating the contributions for each variable of the data matrix as shown in figure 4. In fact, we notice that the variable RR has the highest contribution; therefore, we consider this variable to be defective. The variable RR describes the heart rate; accordingly, the detected arrhythmia is a ventricular tachycardia. In sum, this approach is applied to the whole of the selected ECG and proves the existence of a ventricular tachycardia in each one.

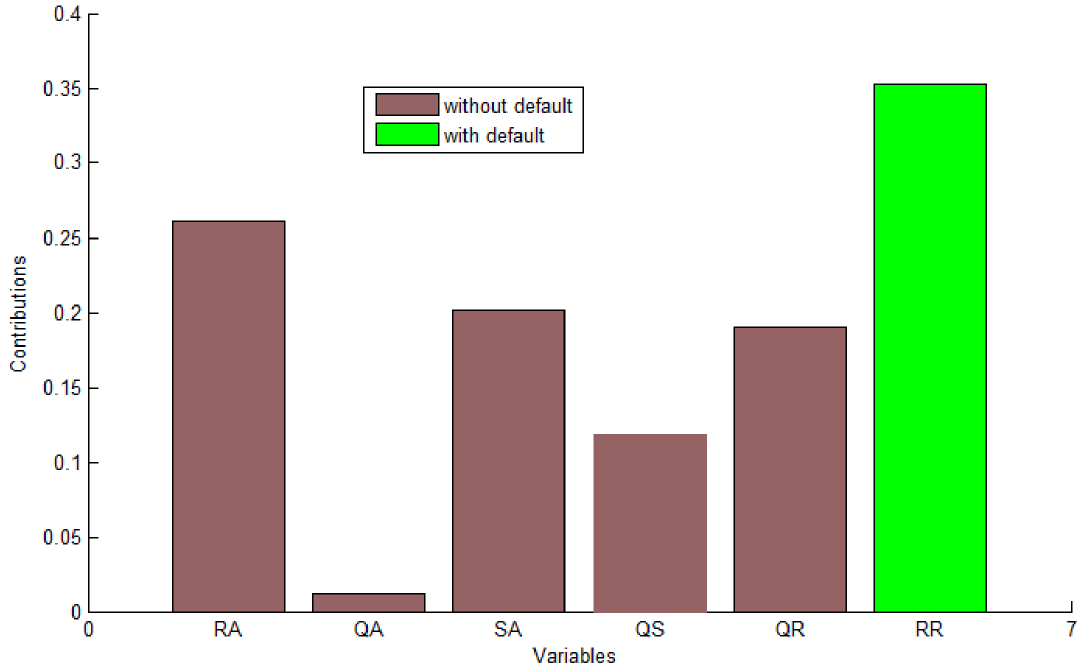

Fig.6. Identification of the type of arrhythmia

IV. Conclusion

This paper presents a framework for the control of the QRS complexes in an ECG. This work is divided into two parts: the detection of the QRS complexes through the continuous wavelet transform and the identification of the arrhythmias through the principal component analysis. In the first part, we employed the property of detecting the singularities provided by the continuous wavelet transform to detect the waves R and, then, the waves Q and S. The validation of this method was applied to some ECG signals of the MIT/BIH base and showed satisfying results. We comprise a data matrix (500X6) in which the variables stem from the properties of the QRS complexes. The second part deals with the detection and the identification of the arrhythmias. The PCA allows for the detection of the faults by the statistics of Hotteling T^2 and SPE and, thereafter, for the detection of the arrhythmias. To identify the type of the detected arrhythmia, we resort to the localization of the faults by calculating the contributions. The variable RR has the highest contribution. Thus, it can be deemed as the source of fault. The existing fault in this variable, which describes the heart rate, shows that the detected arrhythmia is a ventricular tachycardia.

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