Adaptive Feature Extraction for QRS Classification and Ectopic Beat Detection

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Abstract

Automatic procedures to classify the QRS complex are very useful in diagnosis of cardiac disfunctions. In this work we present an adaptive system to extract, in real time, the features that characterize the QRS with the Hermite functions model. The adaptive system is based on the multiple-input adaptive linear combiner, where the primary input signal is the succession of the QRS complexes, and the reference inputs are the Hermite functions. The weight vector becomes an estimation of the coefficients that represent the QRS complex in the Hermite function base. To adapt these weights we use the LMS algorithm. We have incorporated a procedure to adaptively estimate a width parameter (b) that best fits each QRS complex. We present applications of this system to classify QRS in case of ECG signals affected by the phenomenon of bigeminy and to detect ectopic beats using the b parameter. In both cases we have obtained correct pattern classification.

1 Introduction

The ECG signal is characterized by its recurrent or periodic behaviour with each beat. The most characteristic wave in each recurrence is the QRS complex. This complex represents the depolarization phenomenon of the ventricles and therefore gives useful information about the heart behaviour. The beat-to-beat classification of the QRS complexes will help us to follow heart evolution and to detect arrythmias like Premature Ventricular Contractions (PVC).

Usually, this classification is performed through pattern recognition techniques that represent the data by a feature set [1]. The election of these features is a key point to obtain a low dimension feature space with retention of maximum signal information and enhancement of distance between different classes of QRS.

In a previous work Sörnmo et al. [2] propose a set of features that consists on the coefficients of the QRS complex modelled with the Hermite functions. These functions are orthogonal, thus each feature has not redundant information and the signal can be represented with a low number of coefficients. For that, this model seems appropriate to efficiently classify QRS complexes, allowing fast data transmision, low memory spend, and fast signal processing for diagnosis. All these properties are of great importance in health care units that need data transmision to a central processing unit.

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Early detection and classification of QRS changes is of great interest in real-time monitoring such as cardiac critical care units or operating room environments. In these circumstances it is important to develop on-line signal processing techniques that allow the on-line feature obtention and subsequent classification of QRS patterns. Adaptive signal processing [3] is appropriate for on-line estimation of non-stationary signals that present a recurrent behaviour like the ECG signal. In this work we present an Adaptive Hermite Model Estimation System (AHMES) for on-line extraction of the QRS complex features using the Hermite model [4]. This model incorporates a width parameter that can be considered as a feature used for ectopic beat detection given that these beats have larger width than normal ones. We present applications of this system to classify real QRS complexes and to detect ectopic beats.

2 The Hermite function model

Orthogonal function modelling is a general method for approximating functions with a finite number of parameters. We can consider $s'(t)$ signal as composed of the noise free QRS signal ($QRS(t)$) over its definition interval (T_0) and extended to $-\infty$ and $+\infty$ with a zero extension.

$$s'(t) = \begin{cases} QRS(t) & |t| < \frac{T_0}{2} \\ 0 & |t| > \frac{T_0}{2} \end{cases} \qquad (1)$$

This $s'(t)$ function represents the QRS complex and is an element of the linear vectorial space $L_2(-\infty,\infty)$ given that it satisfy $\int_{-\infty}^{\infty} s'^2(t)\, dt < \infty$. The Hermite functions ($\Phi_n(t)$, n=0, ..., ∞) form an orthonormal base in the $L_2(-\infty,\infty)$ space, and are expressed as

$$\Phi_n(t,b) = \frac{1}{\sqrt{b\, 2^n\, n!\, \sqrt{\pi}}} e^{-\frac{t^2}{2b^2}} H_n(t/b)\ , \qquad (2)$$

where $H_n(t/b)$ are the Hermite polinomials. We have introduced the b parameter in order to have a scale factor related to the width of the QRS complex. These function remains orthonormal for any width paramenter b. With these base functions we can consider a N order approximation of $s'(t)$ as

$$s'(t) \simeq \sum_{n=0}^{N-1} c_n(b)\, \Phi_n(t,b)\ . \qquad (3)$$

In this approximation the QRS complex is characterized by the N coefficients, $c_n(b)$, and the b parameter.

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3 The adaptive Hermite model estimation system

In this section we present the Adaptive Hermite Model Estimation System (AHMES) that we use to adaptively calculate the c_n coefficients and b parameter. It is based on the multiple-input adaptive linear combiner [3]. The primary input to this AHMES is the digitized QRS signal and the reference inputs are the digitized Hermite functions.

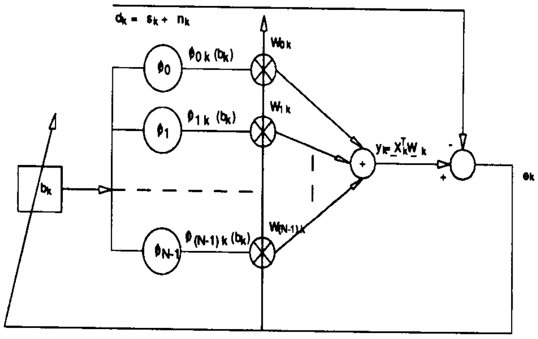

Figure 1: *Adaptive Hermite Model Estimation System (AHMES).*

Figure 1 displays the AHMES where there are two adaptation process: the weights and the b parameter adaptation. The b parameter acts as an input to the Hermite function base generator that produces the elements of the reference input signals in the AHMES.

To synthesize the primary input signal (d_k) of the AHMES we proceed as follows. We apply a QRS detector on the digitized ECG signal. Centered on the QRS detection mark, we define a signal window (200 ms) that contains the QRS complex. This signal window is extended with a zero flat line on the right and on the left to form the s'_k signal. Given that this s'_k signal is zero outside this window, we construct a new signal s_k as the subsequent linking of finite intervals (L samples) of s'_k signal from each QRS, where the first order Hermite functions are significatively different from zero. The time interval L is selected according to b and model order N values. The primary input signal d_k is the sum of the deterministic signal s_k and the noise (n_k) that contaminates the former ($d_k = s_k + n_k$).

Each reference input is formed by one of the N Hermite functions considered in the model. The construction of this input is analogous to the construction of d_k. We concatenate sequences of the Hermite funcion signal defined in an interval of duration L and centered around the synchronization point (middle point of the interval). The reference inputs Φ_{nk} (n=0, ..., N-1) at the Ath QRS recurrence is defined as

$$\Phi_{nk}(b) = \Phi_n\left(kT - L\left(A - \frac{1}{2}\right)T\ ,\ b\right) \qquad (4)$$

where T is the sampling period. The b parameter is continuously recalculated and acts as input to the Hermite function generator.

The output signal of the system is y_k, and results from the sum of the Hermite functions, each one afected by a weight factor w_n. These weight factors are the features that characterize the QRS complex in this model. According to the standard notation for the adaptive linear combiner [3] we express the output signal model as

$$y_k = \sum_{n=0}^{N-1} w_{nk}\ X_{nk}(b) = \mathbf{W}_k^T\ \mathbf{X}_k(b)$$

$$\mathbf{X}_k(b) = \left[X_{0k}(b), X_{1k}(b), ..., X_{(N-1)k}(b)\right]^T\ , \mathbf{W}_k = [w_{0k}, w_{1k}, ..., w_{(N-1)\ k}]^T \qquad (5)$$

where $X_{nk}(b) = \Phi_{nk}(b)$, $\mathbf{W}_k$ is the weight vector and $\mathbf{X}_k$ is the reference vector. The error signal e_k is defined as

$$e_k = d_k - y_k(b) = d_k - \mathbf{W}_k^T\mathbf{X}_k(b)\ . \qquad (6)$$

The mean-squared error $\left(\xi = E[e_k^2]\right)$ is expressed [3] as

$$\xi = E[e_k^2] = E[d_k^2] + \mathbf{W}^T\mathbf{R}\mathbf{W} - 2\mathbf{P}(b)^T\mathbf{W}$$

$$\mathbf{P}(b) = E[d_k\mathbf{X}_k(b)]\ , \qquad \mathbf{R} = E[\mathbf{X}_k(b)\mathbf{X}_k^T(b)] \qquad (7)$$

where $\mathbf{R}$ and $\mathbf{P(b)}$ are the input correlation matrix and the cross-correlation vector, respectively. Given that the Hermite functions remain orthogormal for any b parameter, and noise n_k are supposed to be not correlated with the deterministic signal s_k, the $\mathbf{R}$ and $\mathbf{P}(b)$ matrixes result

$$\mathbf{R} = \frac{1}{L\,T}\mathbf{I} \quad \text{and} \quad \mathbf{P} = \frac{1}{L\,T}[c_0(b), c_1(b), ..., c_{(N-1)}(b)]^T\ . \qquad (8)$$

Then, the optimum weight vector $\mathbf{W}^*(b)$ that minimizes ξ is [3]

$$\mathbf{W}^*(b) = \mathbf{R}^{-1}\mathbf{P(b)} = [c_0(b), c_1(b), ...c_{N-1}(b)]^T\ . \qquad (9)$$

The $\mathbf{W}^*(b)$ vector elements, that depend on b parameter, are the sequence of the coefficients that describes the deterministic component s_k of the primary input signal d_k in the Hermite model, defined by the reference inputs $X_{nk}(b) = \Phi_{nk}(b)$.

In the steady state the AHMES output is

$$y_k = \mathbf{W}^{*T}(b)\mathbf{X}_k(b) = \sum_{n=0}^{N-1} w_n^*(b)X_{nk}(b) = \sum_{n=0}^{N-1} c_n(b)\Phi_{nk}(b). \qquad (10)$$

That means y_k is the N order approximation of the QRS complex in the Hermite model (equation 3), for a given b parameter.

4 The adaptive algorithms

The AHMES includes two adaptation process: the estimation of the optimum Hermite model coefficients (weight vector) and width parameter b. To adjust the weight vector we use least-mean-square (LMS) algorithm [3]

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu_1 e_k\mathbf{X}_k(b)\ . \qquad (11)$$

To adjust the b parameter we consider a gradient search method ($b_{k+1} = b_k - \mu_2\nabla_k$) with the same approximation [3] used to obtain the LMS algorithm $\left(\nabla E[e_k^2] \simeq \nabla e_k^2 = 2e_k \nabla e_k\right)$, and then from (6) we can write

$$\frac{\partial E[e_k^2(b)]}{\partial b} \simeq 2e_k(b)\frac{\partial e_k(b)}{\partial b} = -2e_k(b)\frac{\partial y_k(b)}{\partial b}\ , \qquad (12)$$

that leads to the following recursive expression to adapt b

$$b_{k+1} = b_k + 2\mu_2 e_k(b_k)\frac{\partial y_k(b_k)}{\partial b_k} = b_k + 2\mu_2 e_k(b_k)\sum_{n=0}^{N-1} w_n \frac{\partial \Phi_{nk}(b_k)}{\partial b_k}\,. \quad (13)$$

We have considered different μ factors, μ_1 and μ_2, for the weight vector and b parameter, respectively. The implementation of the recursive equation (13) needs to know the value of $\partial\Phi_{nk}(b_k)/\partial b_k$ in each time instant k. This value can be proved to be a linear combination of w_n and $\Phi_{nk}(b_k)$ [5].

$$\frac{\partial \Phi_n(t,b)}{\partial b} = \frac{1}{2\,b}\left[-\sqrt{n(n-1)}\,\Phi_{n-2}(t,b) + \sqrt{(n+2)(n+1)}\,\Phi_{n+2}(t,b)\right]. \quad (14)$$

From (13) and (14) it results evident that b_{k+1} can be calculated from $\mathbf{W}_k$ and $\mathbf{X}_k(b)$ directly with no additional calculations.

The two adaptation process acts simultaneously, and thus one interacts with the other. In a first approximation we study the convergence of weight vector and b parameter while the other remains fixed. This is not the real situation but the experimental results show that predictions with this approximation are in accordance with results when both adaptations act simultaneously.

4.1 Convergence of the weight vector

The LMS algorithm converge [3] when the μ_1 parameter satisfies the condition

$$0 < \mu_1 < \frac{1}{tr[\mathbf{R}]} = \frac{L\,T}{N}\,, \quad (15)$$

and the convergence time associated to each weight w_n (τ_{w_n}) is given by

$$\tau_{w_n} = \frac{1}{2\,\mu_1\lambda_n} = \frac{L\,T}{2\mu_1} \quad (16)$$

where λ_n is the nth eigenvalue of $\mathbf{R}$ matrix. In this case all the eigenvalues have the same value $\left(\lambda_n = \lambda = \frac{1}{L\,T}\right)$. Convergence time is expressed in number of samples.

Therefore, the gain constant μ_1 controls the stability and the speed of convergence. The convergence of weights can be obtained in the first record ($\tau_{w_n} < L$), if an appropriate value of μ_1 is selected. This possibility will be very useful for tracking variations in time-varying deterministic QRS signals.

4.2 Convergence of the b parameter

To study the convergence conditions and speed of the b adaptation algorithm as function of μ_2 we consider expected values in the recurrent adaptation expression (13) of b. In [5] it is proved that the algorithm converges when μ_2 satisfies

$$\mu_2 < \frac{L\,T\,b^{*2}}{SE}\,. \quad (17)$$

This condition depends on the primary input signal energy (SE) and the optimum b value (b^*). Then, the μ_2 factor has to consider the signal that will be studied. If this signal energy changes with time it could be necessary to readjust μ_2. The convergence time (τ_b) of the b parameter can be estimated [5] as

$$\tau_b < \frac{L\,T\,b^{*2}}{2\mu_2\,SE} \quad (18)$$

5 Estimation of real QRS sequences

We apply the AHMES to real ECG signals. In order to avoid baseline variations be modelled as QRS, the QRS window signals (200 ms) are extracted from a high-pass filtered ECG signal. The windows are extended to to 400 ms adding 100 ms of zero value on the right and on the left (L = 100 samples). The signal is sampled at 250 Hz (T = 4 ms). The model order of the AHMES is selected to be N=10. The weights are initialized to zero ($w_{n0} = 0$) and the b parameter to 25 ms (b_0 = 25 ms). The convergence limit for μ_1 is

$$\mu_1 < \frac{L\,T}{N} = 40\,. \quad (19)$$

We select $\mu_1 = 0.75$. The convergence limit for μ_2 is calculated with the SE estimated in the first QRS recurrence (figure 2), $SE = 1.25 \cdot 10^{10}$, and assuming $b^* = 20$ ms.

$$\mu_2 < \frac{L\,T\,b^{*2}}{SE} = 1.28 \cdot 10^{-5}\,, \quad (20)$$

and considering a safety factor we select $\mu_2 = 10^{-8}$.

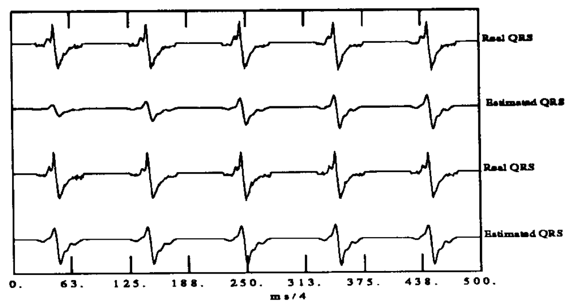

Figure 2: *QRS complex estimation in a normal sequence.*

In figure 2 we have the sequence of 10 consecutive QRS (first and third rows). Below the original QRS signal is the estimated by the AHMES after each QRS adaptation.

According to equation (16) the predicted convergence time for the weights is

$$\tau_{w_n} = \frac{L\,T}{2\mu_1} = 266.7 \text{ samples} \simeq 2.7 \text{ QRS recurrences} \quad (21)$$

In figure 2 we can corroborate that after the third recurrence adaptation the reconstructed signal has converged towards more than the 60% of the final signal energy.

According to equation (18) the predicted convergence time τ_b for the b parameter (in this case the obtained b^* is 18 ms) can be estimated as
$\tau_b < 518.4$ samples, that supposes five QRS recurrences.

5.1 Ectopic beat detection

In this section we consider the case where there are QRS complexes that belong to abnormal beats like PVC. In this case it is important to detect and discriminate this abnormal beats. Normaly, PVC beats are characterized by larger width than in normal cases. Given that b parameter is related to the width of the Hermite functions, we analyse and study the capability of the AHMES for detecting PVC through the b parameter.

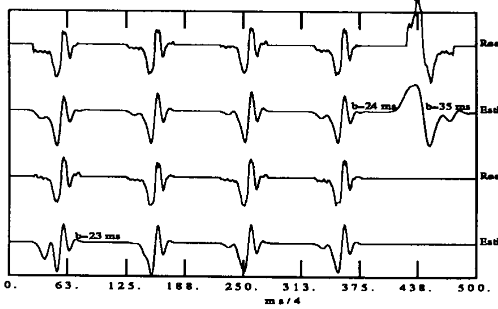

Figure 3: *Detection of PVC beats.*

We take a QRS sequence of nine beats that includes a PVC at the fifth beat (figure 3). We applied the AHMES over this beat sequence with $\mu_1 = 3.4$ in order to have a weight convergence in less than one recurrence (from (16) we reach $\tau_{w_n} < 1$ QRS recurrence) and then be able to track beat-to-beat variations like isolated PVC. μ_2 remains with the same previous value (10^{-8}) given that the QRS sequences have been normalized to satisfy the same convergence condition. In figure 3 we have the b parameter value after adaptation of: the QRS previous to the PVC beat (24 ms), the PVC (35 ms), and the QRS next to the PVC (23 ms). This result shows that the b parameter value can be used to classify PVC beats, even if they appears once in the QRS sequence. The detection can be implemented in real time through a threshold decision rule that will require experimentation with a broad PVC patterns to adjust the PVC detection threshold level.

5.2 QRS complex classification

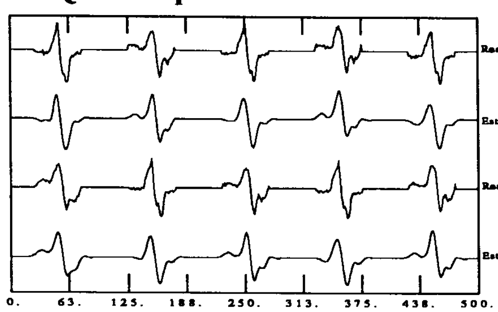

Figure 4: *Estimation of shape variable QRS complexes.*

To study the capability of the AHMES for QRS classification, we have selected a QRS sequence from a patient affected by the bigeminy phenomenon (figure 4). The QRS signal presents beat-to-beat periodic variations that basically generates two different QRS patterns. We have applied the AHMES to this sequence with the same μ_1 and μ_2 values than in the PVC case. The b parameter in this case remains stable (Table 1), and it is not significative to classify the QRS complex sequence. By other hand the w_n parameters are able to track the QRS shape variations as can be corroborate by following the shape estimation recovery in figure 4. As an example in table 1 we enumerate the w_1 values from the sixth to the tenth QRS. It results evident that w_1, and best all the w_n parameter set, are adequated to classify the QRS complexes in the two basic shapes (figure 4), following classical pattern recognition techniques described in [1].

Beat	*6th*	*7th*	*8th*	*9th*	*10th*
b (ms)	27.8	26.5	26.8	27.1	27.4
w_1	11205	-56008	2490	-64493	34644

Table 1: *b and w_1 feature values after QRS adaptations.*

6 Conclusions

An adaptive system based on the Hermite functions (AHMES) have been proposed to adaptively estimate and track the QRS complexes in the ECG signal with few and nonredundant parameters. The AHMES allows the on-line estimation of the QRS model parameters with the presence of an on-line QRS detector and a Hermite function generator especially designed for this purpose.

It is possible to select the AHMES constants μ_1 and μ_2 in such a way that the convergence is achieved in less that one recurrence. Because that it is able to estimate beat-to-beat changes in the deterministic QRS signal through the Hermite model features evolution. The simple inspection of b parameter can be used for on-line detection of PVC beats. We have presented a application example of the AHMES in case of ectopic beat detection and QRS complex classification, showing the viability of the AHMES for this applications.

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