Wavelet Packet and Matched Filter inspired QRS Detector

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Abstract— **For the processing and analysis of the electrocardiogram (ECG), an increasing number of applications require real-time detection of the most prominent complex in the signal, the QRS. In this work we describe a new robust and on-line QRS detection algorithm. This new approach incorporate some classic concepts but has the distinction of being focused on finding the points of maximal similarity between the signal and an atom previously selected from a wavelet packet based dictionary. The proposed algorithm provides the advantage of robust and efficient QRS detection with relatively low computational effort, enabling real-time implementation on 8-bit microcontrollers for general use.**

Keywords— **QRS detection, wavelet packet, matched filter, discrete dictionaries.**

I INTRODUCTION

The electrocardiographic signal gives information about the myocardical electrical activity [1] and it is one of the most widely used noninvasive records for both, the detection of cardiovascular abnormalities, such as accessing information about the autonomic nervous system; respiratory system and even new disciplines such as neuroscience and psychophysiology. The QRS complex is the most prominent portion in this signal and it marks the ventricular depolarization. In the vast majority of ECGs' pattern detection algorithms, all calculations are referred to the R point, hence the importance of QRSs' robust and efficient detection.

Nowadays the computational load of an detection algorithm is been neglected, unless it is to be implemented in embedded systems working in real time and-or are powered by batteries. In the latter case it is imperative to optimize the amount of calculations to be performed by the processing unit, because once calculations are completed, it can be placed in hibernation mode, or shutdown the internal oscillator until the next cycle.

Thinking in these applications, this paper is aimed in detecting the QRS robustly and with the least computational load possible, combining classical concepts with the recent developed techniques in signal processing.

II MATERIALS AND METHODS.

A Wavelet Packet decomposition.

The wavelet analysis is a growing class of signal processing and transformations techniques that use wavelet and related functions,for measuring and efficiently handle non-stationary signals. These techniques can optimize the analysis of such signals, providing adequate resolution in both time and frequency. This feature has made the wavelet analysis the most widely employed in the processing [2], analysis [3], compression and synthesis of ECG signal [4].

The wavelet packet decomposition that is made by the Wavelet Packet Transform (WPT), arises from the use of a suggested reasoning by Wickerhauser [5] that generalizes the multiresolution analysis based on wavelet theory. According to this approach, it is also possible to decompose the high frequency components (details) in the same way as the low frequency components (approximation).

In a more general way, it is possible to see every wavelet packet $\{\psi_k^p\left(t-2^k n\right)\}$ as a function in $L_2(R)$ well localized in both, time and frequency. Then, each of these atoms can be described through their temporal and frequency characteristics. The set of all atoms so defined, is a parametric dictionary of functions with different properties depending on the h and g filters used. This wide variety of morphologies and behaviors allows the correct selection of the wavelet package that best fits the characteristics of the signal of interest.

B QRS Detection Basics

The diversity of arrangements that can be used to design a QRS detector is very wide. Those algorithms that share the characteristics of low computational cost and high performance are called classic or common [6]. Such algorithms share the block structure that is shown in Figure 1.

Fall outside this scheme all algorithms based on neural networks; syntactic approach; adaptive predictors; adaptive filters [7]; genetic algorithms; etc.. Such detectors have been excluded from analysis in this study due, mainly, to their high computational cost (at least in sequential machines) [8].

In the classical scheme of Figure 1 the Linear Filtering

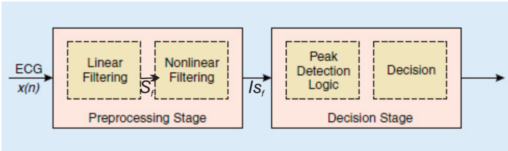

Fig. 1: Typical structure of a classical QRS detector [6].

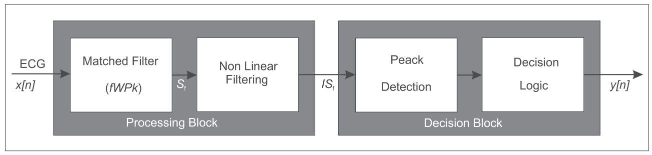

Fig. 2: WAPID scheme.

block has a preprocessing filter which normally extracts all noise that affect the ECG, such as the movement of baseline noise; muscle contraction and power line induction. The linear filter is usually a bandpass type system that allows passing only the content of the signal that matches the bandwidth of the QRS. The ECG signal resulting from linear filtering, is then processed by non-linear filters that aim to emphasize the QRS amplitude [1]. The block which takes the output of non-linear filtering is the peak detection logic. It detects the crossing of the output signal above a threshold that is empirically defined. The threshold is adjusted according to the QRS amplitude signal resulting from the nonlinear filter [9]. Because all detectors must be completed with the application, at least, of a refractory period, the peak detection logic must include a block of decision rules.

C Matched Filters in QRS detection

Those algorithms performing QRS detection scheme based on matched filters, in general, replaces the linear filter block with the matched filter. This is implemented by the classic formula of discrete inner product:

$$y[n] = \sum_{i=0}^{N-1} x[n+i]\, w[i] \tag{1}$$

where $w[i]$ is the QRS template to be detected [10].

As 1 is an inner product between the signal portion analyzed (N samples) and the template, the matched filter generates a signal that is proportional, instant by instant, to the similarity between the signal under study and its template [8].

D Used Data

The MIT/BIH data base [11] is s used to adjust the parameters and estimate the performance of the proposed algorithm. This is because it is one of the most commonly used in this area, is supplied with manual annotations made by medical experts and covers a wide range of arrhythmias.

Attempting to reflect the normal working conditions of a battery-powered and embedded system, all records and entries in the database were resampled, leading to a sampling rate of 250 samples per second before processing. This sampling rate is accepted by the vast majority of works devoted to the detection of ECG patterns [12].

From manual annotations with which is marked each of the records in this database, two performance parameters were estimated, the sensitivity $Se = TP/(TP+FN)$ and positive predictability $P+ = TP/(TP+FP)$, where TP is the total number of true positives, FN the number of false negatives and FP the number of false positives. This work considered a true positive if the difference in time between an annotated beat and an detected beat is no more than 150 ms, in accordance with the requirements of ANSI/AAMI-EC57: 1998 standard's accuracy for QRS detection.

We use the first 22 registers of the database, each record having two different signal derivations, one in the frontal plane and the other in the sagittal plane. Thus, adding the beats for each lead of each record as separated beats (because their morphologies vary considerably) 92 232 beats were analyzed in total. 9,200 beats from 6 records of one derivation randomly chosen were separated to be used in the preliminary tests and the parameter settings of the proposed algorithm.

III The Wavelet Packet and Matched Filter inspired Detector (WAPID)

For the choice of the approach used in the design of the QRS detection algorithm two criteria were considered: complexity and theoretical performance. The algorithm was designed to result relatively simple, so as it could run in real time on 8-bit microcontrollers and not occupy all its time and memory resources. Therefore, in the developed detector the number of multiplications and additions is minimized, avoiding complex calculations, as can be roots or logarithms. Only multiplications and additions in fixed-point arithmetic on the present value of the signal and its past values were applied. To do this, the blocks of preprocessing and linear filtering of Figure 1 is replaced with a block of matched filter. So, the resulting scheme of the QRS detector developed by us, is as shown in Figure 2.

Unlike traditional matched filters that take as template the morphology of a QRS (that is expected to vary in morphology because of the nonstationarity nature of de signal), this

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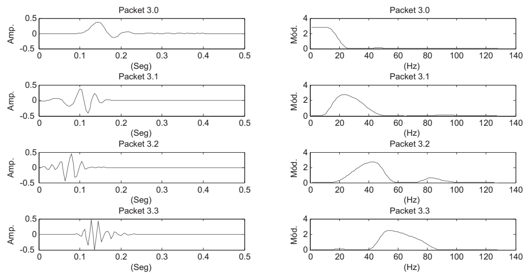

Fig. 3: Different scale 3 atoms of Daubechies mother wavelet with 5 zero null moments with there spectrums. Sampling frequency of 250 Hz.

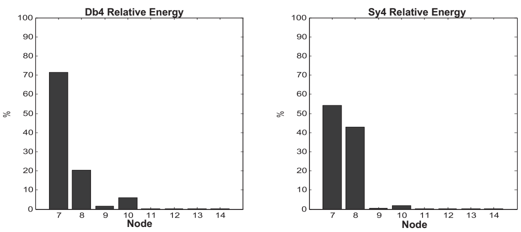

Fig. 4: FWPT relative energy of the 8 terminal nodes of a QRS (where 7 corresponds to node (3,0), 8 to (3,1), etc.). In the left panel the result is obtained by Daubechies 4 mother wavelet and in the right panel with Symmlets 4.

matched filtering scheme is performed using an atom selected from a wavelet packet dictionary.

We decided to try the best filters made up of different atoms obtained from dictionaries generated with the mother wavelets identified in the literature as the most similar in time to QRS [13]. So we worked with Daubechies and Symmlets mother wavelets with 4 and 8 null moments, with the additional aim of comparing results between non-symmetric and quasi-symmetric wavelets.

After defining the mother wavelets with which we were going to work, we need to decide which atoms of the dictionaries were the most similar to the QRS. For that, we use two different criteria, the first one is based on the similarity of its spectrum (see Figure 3) with the spectrum of the QRS, which is centered at 15 Hz and has a bandwidth of 20 Hz [14].

The other criterion for selecting the atoms is based in the fast wavelet packet transform (FWPT) energy distributions in the nodes of scales 3, 4 and 5. We obtain the FWPTs of the different waves in the ECG. Figure 4 presents two examples of FWPT energy distributions in the 8 terminal nodes of level 3 from mothers wavelet Daubechies and Symmlets 4, of the same QRS.

With these kind of graphs we find (comparing the FWPT relative energies of the different nodes of the different waves of the ECG) those atoms which best reflected the information related only to the QRS.

To generate the different atoms ($fWPk$ in Figure 2) we use the MakeWaveletPacket Wavelab function of Matlab [13]. This function generates orthogonal periodizated wavelet packets with a correct temporal support.

We make one Wapid detector for each atom selected, and one set of optimal parameters was found for each, by the use of the 6 registers that were randomly previously chosen.

To obtain the signal S_f, the matched filter output, we decided to implement the inner product as a simplification of the Correlation Waveform Analysis coefficient CWA equation given by [8]:

$$S_f[n] = \frac{\sum_{i=0}^{N-1} \frac{\left(fWPk[n-i] - f\bar{W}Pk\right)}{STD_{fWPk}} x[n-i]}{C} \tag{2}$$

where $\boldsymbol{x}$ is the signal vector under analysis; C is a constant empirically found and $\boldsymbol{fWPk}$ the corresponding wavelet packet atom, $f\bar{W}Pk$ its average value and STD_{fWPk} its standard deviation.

Having explored and tested different alternatives of nonlinear filtering, we decide, based on the performance reported by different authors [15], to implement an nonlinear filtering modulus based on the model proposed by Hamilton and Tompkins scheme (HT) [16].

Thus, on the output of the filtered signal (S_f), the HT algorithm is applied returning IS_f, the integral of the power of S_f (taken with a 100 msecs. time windows, equal to the average length of the QRS). In IS_f an adaptive threshold algorithm is applied in real time, which detects the QRS occurrence [9].

The block that takes the output of the nonlinear filtering (IS_f) is the peak detection logic. This block applies an adaptive threshold algorithm that finds in real time the possible QRS occurrence. For this purpose, it compares IS_f with an threshold function, resulting from the combination of three independent variables $MFR = M + F + R$ [9], where M is the steep slope adaptive threshold; F is the integrative adaptive threshold and R is the expected beat adaptive threshold.

The peak detection logic is completed by a set of decision rules. In the designed detector, these are confined to verify that the detected heartbeat does not fall into the refractory period. Therefore, after a positive detection, the system blocks any possible occurrence of QRS for a period of 270 msec.

IV Results and Discussion

Wapid run on a total of 92,232 QRSs originally annotated in the database and the most important averaged results are presented in Table 1 . Those values were obtained with different atoms from different wavelet packet dictionaries.

To compare the results obtained with the detector designed in this study, against a classical detector based in traditional

Table 1: Wapid performance with different atoms and classical reference algorithm performance.

Wavelet	Atom	Sensib (%)	P. P. (%)
Daubechies 4	3.2	63.91	59.27
	4.1	**88.01**	89.36
	4.2	87.26	**97.91**
	5.2	87.92	**98.16**
	5.3	87.87	95.67
Daubechies 8	3.2	75.45	72.41
	4.1	85.07	89.27
	4.2	80.67	88.67
	5.2	**88.93**	**95.13**
	5.3	70.01	76.12
Symmlets 8	3.2	76.27	76.91
	4.1	89.04	95.22
	4.2	**89.57**	**96.12**
	5.2	88.09	95.13
	5.3	86.09	94.95
Classic		**93.01**	**97.73**

linear filtering, we implement an algorithm which considers all of the blocks of Figure 1. This reference algorithm pre-process the signal using a FIR comb type low pass filter with rejection frequency of 50 Hz cascaded with an high pass IIR filter of order 8 with 0.8 Hz cut-of frequency. The linear filtering block consists of two short IIR filters in cascade, which form a bandpass centered at 15 Hz. Remaining blocks of the reference algorithm share the same characteristics with Wapid.

In Table 1 it is clear that, despite the simplicity of the algorithm, the positive predictability with the best parameter setting is high (98.16 %), but sensitivity is well below (87.87 %) of the classical reference algorithm. This is because the algorithm is very robust against noise and various changes in morphology, but the ectopic ventricular and some not normally conducted beats often complicate the current QRS detection, or the detection of subsequent beats.

It can easily be verified measuring times of run, that the computational load of the traditional detector based on classical filtering is more than 2 times larger than Wapid. On the other hand, we measure the number of elementary operations the two detectors carried out only in those blocks that they differ: the matched filter versus linear filtering and pre-processing. Peak detection and detection logic, which are common to the two algorithms are composed of many conditional statements, which makes that elementary operations do not provide an accurate measure for computational cost involved. For Wapid, optimal filtering assembly with a template generated by node 4.2 (or atom 17) of the wavelet packet dictionary generated by Daubechies 4, optimized for a number of 32 coefficients, reported a total of 32 sums; 32 multiplications and 32 data handling operations (assignments). The classical reference algorithm counts with an 46 coefficients FIR high pass filter, one notch filter of 9 coefficients (generated by convolution of two FIR filters) and a low-pass FIR filter of 13 coefficients. The total count of the classical scheme in pre-processing and linear filtering is 72 sums; 72 multip; 3 divisions and 72 assignments, more than twice the number of elementary operations of Wapid.

V CONCLUSSIONS

In this work a new QRS detection algorithm, based on mixing classical and recent developed signal processing techniques, was presented. The results obtained show its ability to detect QRS complex robustly and efficently. Future works will explore alternatives to improve ectopic beats detection mantaining relatively low computational effort.

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