Improvement of a FPGA-based Detection of QRS Complexes in ECG Signal using an Adaptive Windowing Strategy

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Abstract: This paper presents an FPGA-based algorithm for automatic detection of QRS complexes in ECG signals, first step for the estimation of cardiac intervals. The proposed algorithm is divided into 3 parts : Filtering, Contrast Enhancement, and finally a Detection block based on an adaptive windowing and a thresholding of the enhanced data. The entire detection scheme was developed in accordance with embedding constraints and in the perspective of a real-time use. We evaluated the algorithm on manually annotated databases, such MIT-BIH Arrythmia and QT databases. The FPGA-based algorithm correctly detects 91,85 % percent of the QRS complexes, with a very limited ratio of false detection (only 5%) on standard databases, while for real-time records obtained from young subjects between 20 and 25 years, the sensitivity reaches 93,77 % with a false detection ratio of only 4 %. These results are in accordance with the most recent state-of-the-art off-line algorithms on the same database, and improves significantly FPGA-based ones that were tested on a limited number of ECG extracted from the MIT-BIH set of data only.

1 INTRODUCTION

Heart disease is the first cause of death in western world. In France, 32% of deaths are caused by cardiovascular disease and in United States, only 10.6% of people survived after an emergency medical services. Hence, algorithms, providing good interpretation of ECG signals, represent a big priority in Biomedical Engineering nowadays. For example many studies have shown that segment abnormalities are good indicators of particular cardiovascular diseases (Spodick, 1973; Baljepally and Spodick, 1998).

A standard non-pathological ElectroCardioGram (ECG) signal is composed of five different waves (in chronological order, the *P*, *Q*, *R*, *S* and *T* waves), each one corresponding to a particular physiological excitation of Atria and Ventricles of the heart (Einthoven, 1912). The *QRS* complex is the name given to the combination of the *Q*, *R*, and *S* deflections: It is usually the central and most visually obvious part of the tracing as illustrated in Fig. 1. The *QRS* complex corresponds to the depolarization of the right and left ventricles of the human heart.

A precise time-detection of this complex is the first and necessary step in the perspective of physiological feature extractions. In fact, the shape, the moment of occurrence and the frequency of the *QRS* complex are primary characteristics of the heart condition (Ohkawa S, 1981). Nevertheless, *QRS* detection is still a difficult task because of the various types of noise which can be present in the ECG signal, particularly, muscle noise, power-line interference, baseline wander and in some cases, it happens that the *P* waves and *T* waves present with high-frequency characteristics, similar to *QRS* complexes (Stolojescu, 2008).

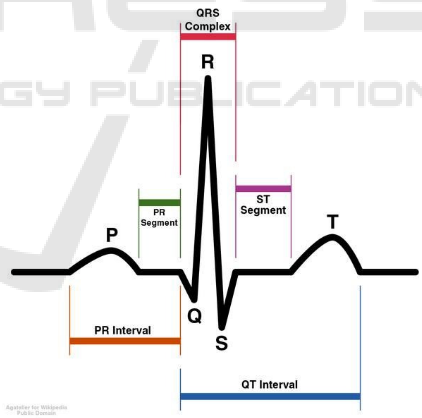

Figure 1: Illustration of a standard ECG signal.

Moreover, in the particular context of “Connected Systems for Healthcare”, the need for efficient em-

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bedded algorithms is definitely on the increase. The main challenge is, then, to propose low-power detection algorithms with real-time processing capabilities and a limited level of complexity.

Many QRS detection method are present in the literature (see (Zine-Eddine, 2006) for an overview). A brief description of the most used ones, as well as their performance when available, are given below:

In Pan and Tompkins (Pan and Tompkins, 1985) authors propose a method based upon digital analysis of slope, amplitude and width of different waves of the ECG signal. It includes a bandpass filtering, a differentiation and a nonlinear transformation of the ECG signal. Applied on the standard 24h MIT/BIH arrhythmia database, this method detects 99.3 percent of the QRS complexes. This approach remains currently the most cited paper of the IEEE Transactions in Biomedical Engineering.

Laguna (Laguna et al., 1990) leads to delineate QRS complexes and T waves by applying a differentiation and low-pass filter on the ECG signal. For the T wave detection, a search window is defined using R-position. Then, the T peak is detected by searching the zero of the differentiation output inside this window. Due to both a low complexity and an easy implementation, this method is heavily used.

The method of Ying Sun et al. (Meissimilly et al., 2003) is based on an adaptive amplitude thresholding. It includes three steps : a differentiation, a nonlinear transformation and a thresholding. It has been tested on eight records of the American Heart Association database. It detects 99.20 percent of the QRS complexes. The weakness of this method is the lack of post-processing for eliminating acquisition noise.

Martinez (Martinez et al., 2004) proposed to use a wavelet transform for the detection of QRS complexes. Each QRS complex is delineated and the determination of P-waves and T-waves peaks, onsets and ends is performed. The algorihm was tested on MIT-BIH Arrythmia, QT, European ST-T and CSE databases. For the QRS complex detection, the algorithm reaches 99.66 % of sensitivity and 99.56 % of specificity.

The method of Dubois (Dubois et al., 2007) is widely inspired on the method of Pan and Tompkins (Pan and Tompkins, 1985). The algorithm includes six steps : a bandpass filtering, a differentiation, a nonlinear transformation, an integration, a low-pass filtering and an adaptive thresholding. Compared to the method of Pan and Tompkins, he adds an adaptive thresholding to avoid the detection of P and T waves with high amplitudes.

The method of Saurabh (Suarabh and Madhuchhanda, 2009) presents a multiresolution wavelet transform based system for detection and evaluation of QRS complex, P and T waves. It was tested on the Physionet PTB diagnostic database. The test result shows over 99% true detection rate for R peak and over 97%, 96%, 95%, 98% for heart rate, P wave, QRS complex and T wave respectively.

And finally, the method of Guven (Guven et al., 2014) presents a method for ECG baseline drift removal. For this, authors propose to detect onset and end of QRS complex and a point of T-P segment. Then, the algorithm finds the isoelectric line using an interpolation method.

If each of the aforementioned methods proposes efficient algorithms for various types of wave detections in ECG, none of them addresses the embedding issue, whereas it has become for the last 5 years a primary need with the increase of the “Smart Embedded Systems for Health” market.

In (El Hassen et al., 2015), we proposed an automatic QRS-complex detector based on a significant improvement of the Dubois’ approach using a systematic search of maximas on a fixed-size neighborhood was proposed. This particular algorithm was developed both in software, using MATLAB code, and in hardware (VHDL). Simulations performed on the MIT-BIH Arrythmia Database from the Physionet database project (www.physionet.org) showed a sensibility of 99.9 % and a specificity of 96.57 % using MATLAB and a sensibility of 95.35 % with a specificity of 91.80 % using RTL simulations. These results were in accordance with the most recent state-of-the-art off-line algorithms tested on the same database, and improved significantly FPGA-based one of Yu et al. (Yu et al., 2013) that reaches a 98.68% sensibility but considering only a limited number (only 11) of ECG extracted from the MIT/BIH set of data (48 recordings in total), excluding the most challenging ones. Nevertheless, the experiments were limited to one database with no real-time recordings included; The size of the search-window for maxima detection was manually tuned to obtain the best performance on the considered database showing a lack of robustness of this parameter; and finally the proposed hardware architecture could be improved to fully take advantage of the parallelism capabilities of FPGA platform.

In this paper we propose to address these limitations in the following ways: First of all an adaptive windowing strategy, which allows the system to adapt, in a flexible way, to all types of ECG signals is proposed and validated on different kind of databases, including real-time acquisitions. Secondly, if the real-time processing of multiple simultaneous channels can improve considerably the detection rate, their implementation must be optimized in order to reduce power consumption, area, latencies, etc. For this purpose, a time sharing processing seems to be the best tradeoff as illustrated in Figure 2. Indeed, the overall duration of all the processing scheme should be less than the time period over which the ECG is stored in a RAM block.

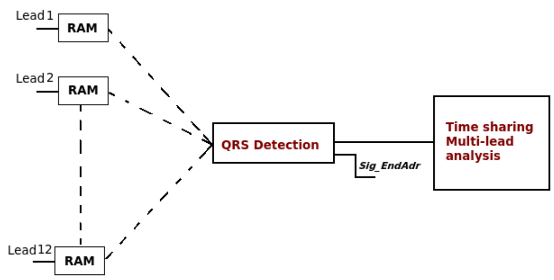

Figure 2: Real-time processing of several simultaneous leads.

To address this, we propose an architecture of a minimal time processing and energy consumption as it will be shown in the Experiments section.

The remainder of this article is organized as follows: In section 2, the overall proposed processing scheme is presented with a focus on the adaptive windowing for maximum detection. Section 3 introduced the proposed architecture for hardware implementation of the proposed methods for automatic QRS detection. Section 4 is focuses on performance evaluation of the proposed approach on several type of databases. And finally conclusions and perspectives are proposed in last section.

2 METHODS

As introduced in (El Hassen et al., 2015), the all processing scheme for QRS detection is composed of 3 main blocks : A "Bandpass Filtering" in order to eliminate the baseline wander, P waves and T waves in low frequencies, and to remove the electromyographic interferences in high frequencies. Based on (Thakor et al., 1984) and the ECG power spectrum, the bandwidth of this filter is chosen between 9Hz and 15Hz. A "Contrast Amplification" block which increases the contrast of QRS complexes and avoid false detections and finally, a "Detection" block based on an adaptive maxima detection and an amplitude and time thresholding for QRS localization.

Main originality of this article lies in the improvement of the maxima detection block and in the corresponding proposal for an hardware implementation in accordance with the real-time processing time constraint.

This part of the algorithm consists in finding maxima in a sequence of N_S window containing N_W samples each, such as $N_S \times N_W = N_T$, the total number of samples of the considered ECG recording. In (El Hassen et al., 2015), N_W was chosen empirically using a manual tuning that maximizes the performance detection (estimated using a ROC Curve strategy). If obtained detection results were very satisfying on the MIT BIH database (**?**) originally considered (99.70 % of sensitivity and 96.57 % of specificity), unfortunately, N_W had to be tuned again for a different database making difficult a systematic use of the proposed approach.

In this paper, an adaptive approach is proposed. More precisely, N_W parameter is automatically estimated using information brought by the last five previous R-R intervals: The size of the search window is then calculated according to the following pseudo-code where *flagIndRRD* is a flag permitting the automatic counting of the 5 last R-R intervals.

Algorithm 1: Adaptive windowing.

```
if flagIndRRD = 1 then
    WindowSize = mean(R-R intervals).
else
    WindowSize = 100.
```

As a consequence, the size of the window detection can be adapted automatically to the characteristics of the ECG signals, like arrhythmia pathologies for instance.

In the following, the architecture for implementation is presented and the improved performance presented and discussed.

3 FPGA-BASED PLATEFORM

For hardware implementation of the different previous IP corresponding to the different processing blocks, we chose on purpose to design the global architecture using handwritten VHDL code. It allows us to design the corresponding architecture with a low level of abstraction and to optimize the code with respects to the implementation constraints related to a FPGA use. Furthermore, it permits us to migrate from one hardware support to another without starting from scratch each time.

The global architecture is shown in Figure 3.

A shift register and a "FP Removal" blocks have been added in addition to the processing steps presented in **Section 2** in order to reduce the false rate

Figure 3: Description of the algorithm: Blocks in blue are clocked at CLK and blocks in green are clocked at CLK_1 (variable because of the adaptive windowing). The block ”FP Removal” contains 2 blocks : a shift register and an amplitude thresholding.

and to improve the specificity. Noticing that a false positive is, in general, surrounded by two true positives, we propose to place a shift register after the IP ”Thresholding” to store three peaks. Then, the ”FP Removal” IP leads to compare each peak with 53 percent of the average of the amplitudes of the previous and following one.

In Figure 4, the efficiency of the proposed strategy for the automatic estimation of the size of the detection window N_W is illustrated on a simulation using proposed architecture.

Inside the red ellipses are shown the False Positive (FP) detection on the ECG signal considered for this experiment. First row is for the adaptive windowing and second row for the previously proposed fixed-size strategy (optimal value). One can clearly notice here that if 3 FP were detected with the non adaptive windowing, this amount is lower down to 3 with the new approach.

4 IMPLEMENTATION AND EXPERIMENTAL RESULTS

4.1 Data

In order to compute significant performance and to make sure that our detection scheme is efficient in terms of sensibility and specificity, we have compared our detection indexes with the annotations provided by cardiologists in standard databases, such as MIT Arrhythmia and QT databases. We also added real-time acquisitions provided by *Sahloul Hospital of Sousse - Tunisia*. Again, the automatic detected QRS complexes are compared with the ground truth provided by the clinical staff.

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60 percent) and outpatients (about 40 percent) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

The QT database contains 105 fifteen-minute records, representing a wide variety of QRS and ST-T morphologies, in order to challenge QT detection algorithms with real-world variability. These records are chosen from among seven ECG databases of PhysioNet[1]. The distribution of the 105 records according to original databases is shown in **Table 1**. All records are sampled at 250 Hz. The 67 chosen records are : the European ST-T Database records, the MIT-BIH Arrythmia Normal Sinus Rythm Database records and the Sudden Death Database records whose names in **Table 1** are respectively European ST-T, MIT-BIH NSR DB and Sudden Death. Each record has 8 annotation files. The annotation file used for the performances calculation is a manual annotation file, provided by a cardiologist.

The twelve real-time ECG records are obtained from young healthy subjects, between 20 and 25 years old, of the hospital of Sahloul in Tunisia. Three of these records are sampled at 200 Hz and nine of them are sampled at 256 Hz. Before processing, the sampling frequency has been changed to 250 Hz. The aim of testing our algorithm on these records is to be more in line with a real-time processing.

4.2 Implementation Plateform

Our algorithm is implemented using the DE2-115 board of Altera. This board contains a CYCLONE IV 4CE115 FPGA device, including 114,480 logic elements, 432 M9K memory blocks, 3,888 Kbits embedded memory and 4 PLLs. The 7-segment displays on the DE2-115 board are used to display the number of detected QRS complexes.

4.3 Performance Results

Simulations and testing have been carried out on a total of 127 different ECG signals, presenting different characteristics and provided from the different databases presented in previous section. Results are shown in **Table 2**.

The resource occupation of the overall detection system on the FPGA device use for experiments is shown in **Table 3**.

[1] physionet.org : offers free web access to large collections of recorded physiologic signals

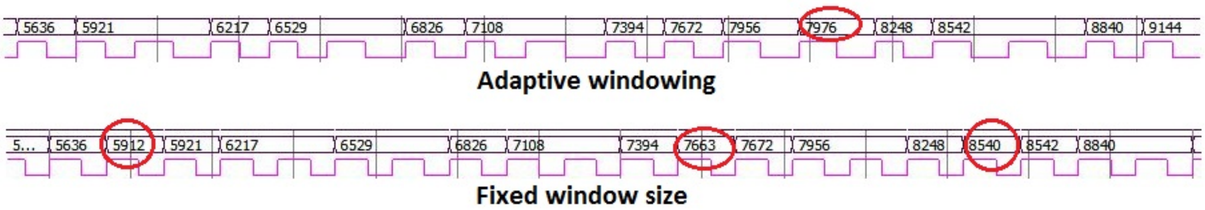

Figure 4: False positive ratio improvement using the adaptive windowing strategy proposed in this article. This chronogramm is generated during the simulation mode of the proposed corresponding hardware architecture.

Table 1: Distribution of the 105 records according to the original Database.

MIT-BIH Arryth.	MIT-BIH ST DB	MIT-BIH Sup.Vent.	MIT-BIH Long Term	**European ST-T**	**MIT-BIH NSR DB**	**Sudden Death**
15	6	13	4	33	10	24

Table 2: Results.

Results	Sensitivity	Specificity
MIT-BIH Arrythmia Database	94.93%	92.81%
European ST-T	89.15%	95.31%
MIT-BIH NSR DB	96.79%	95.48%
Sudden Death	86.79%	97.65%
Total on standard DB	91.85%	94.59%
Real signals (Sahloul Hospital)	93.77%	97.37%

Table 3: FPGA Hardware utilization.

Resource Name	*Occupied*	*Total Number*	*Proportion*
Logic elements	33747	114480	29%
Combinational functions	32084	114480	28%
Logic registers	3899	114480	3%
I/O	45	529	9%
GCLK	1	3	33.33%

In addition, it can be noticed than the total power consumption of the proposed architecture is only of 148.79 mW, while the dynamic power consumption is close to 0 mW.

According to the timing analyzer report, maximum frequencies of the system are about 25.86 MHz for CLK and 4.57 MHz for CLK_1 (see Figure 3). The latence of the whole system is equal to $5 * CLK + 5 * CLK_1$. Considering the values of frequencies, we can treat one minute of a MIT-BIH database signal (with a sampling rate of 360 Hz) in 28.31 ms and a QT database signal (with a sampling rate of 250 Hz) in 19.31 ms.

5 CONCLUSION AND DISCUSSION

In this paper, we proposed a FPGA-Based algorithm for the QRS complex detection in ECG signals. The original signal goes through a series of processing steps allowing to eliminate the various types of noise present in ECG signal. Then, a "Detection" step, composed of a R-peak search using an adaptive window and thresholding, is proposed. To reduce the false positives rate, an "FP Removal" has been also proposed in order to increase the specificity of the system detection. The algorithm has been validated on the MIT-BIH arrhythmia database, the QT database and finally on 12 real-time acquisitions. The all algorithm was finally synthesized and tested on a DE2 FPGA Platform: the corresponding performance are of real interest considering the recent literature on this particular aspect both in terms of performance and compatibility power consumption: obtained results shows that the sensitivity reaches 91.85 % and the specificity 94.59% in standard databases and 93.77 % of sensitivity with 97.37 % of specificity on real signals. These results are in accordance with the most recent state-of-the-art off-line algorithms on the same database, and improves significantly FPGA-based one of Yu et al. (Yu et al., 2013) that reaches a 98.68% sensibility but considering only a limited number (only 11) of ECG extracted from the MIT/BIH set of data (48 recordings in total), excluding the most challenging ones. Furthermore the dynamic power consumption of Yu et al. (Yu et al., 2013) system is around 20 mW, while our is close to 0 mW.

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