An FPGA based arrhythmia recognition system for wearable applications

A. Armato, E. Nardini, A. Lanatà, G. Valenza, C. Mancuso, E.P. Scilingo, D. De Rossi
Department of Information Engineering & Interdepartmental Research Center "E.Piaggio"
University of Pisa
Pisa, Italy
antonino.armato@ing.unipi.it

Abstract— **The aim of this paper is constituted by the feasibility study and development of a system based on Field Programmable Gate Array for the most significant cardiac arrhythmias recognition by means of Kohonen Self-Organizing Map. The feasibility study on an implementation on the XILINX Virtex®-4 FX12 FPGA is proposed, in which the QRS complexes are extracted and classified in real time between normal or pathologic classes. The whole digital implementation is validated to be integrated in wearable cardiac monitoring systems.**

Keywords: QRS complex, Real-time arrhythmia recognition, Neural Networks, FPGA.

I. INTRODUCTION

The QRS complex is the spiked shape part of the ECG trace which maximally corresponds to the depolarization of ventricles. As well know it corresponds to the higher information content of ECG. In particular duration, morphology and amplitude of the QRS complex in an ECG signal provide significant contributions to physicians diagnosing various arrhythmias. Usually the analysis of this kind of data is off-line [1]. However the development of a portable system that analyzes ECG in real-time is an important goal in order to monitor high-risk cardiac patients. Such a device requires a very accurate QRS recognition, which is difficult, mainly for the physiological variability of the QRS complexes, but also for various typologies of noise overlapped on the ECG signal [2].

In the last twenty years many new approaches to QRS detection have been proposed.

A real time algorithm to extract the QRS complex extraction in the time domain is the well known algorithm of Tompkins and Hamilton[2][3]. This algorithm is suitable for implementing the QRS detection in hardware like FPGA devices[4].

Beyond QRS detection, many works have been published in related fields; e.g. ECG signal enhancement or pattern classification. At intention an adaptive wavelet algorithm was proposed by Lin [1] in order to recognize normal beat and six cardiac arrhythmias. The recognition system consists of two sub-networks cascade connected. In the first sub-network, the activation functions take the Morlet wavelets and were responsible for extracting features from each ECG signal. The second sub-network, a probabilistic neural network (PNN) [5], is used to classify cardiac arrhythmias.

The morphologic features of QRS complex could be also performed in the frequency domain in order to find changes in QRS complex power spectra between normal and arrhythmic waveforms [6]. In this case Fourier transform shows the changes in QRS complex due to rhythm origination and conduction path in order to discriminate by a neural network three kinds of rhythms.

A more deep analysis of ECG Fourier Transform for QRS features extraction and classification was proposed [7].

In this work a more effective real-time ECG signal analysis is reported, and normal beat and five different cardiac arrhythmias are classified, by means of a QRS extraction algorithm and Kohonen Self-Organizing Map (KSOM) both implemented into Xilinx Virtex®-4 FX12 device.

II. METHODS

The early stage of the system used in this work allows the input signal digitalization through an incremental ADC with sampling rate of 360 Hz according with MIT-BIH Arrhythmias Database [8] records sampling rate, and with 12 bit resolution. Following stages implemented the arrhythmia detection algorithm and were comprised of three modules (Fig. 1):

1) QRS complex extraction,
2) Discrete Fourier Transform calculation,
3) Arrhythmia classification by using Artificial Neural Network (ANN).

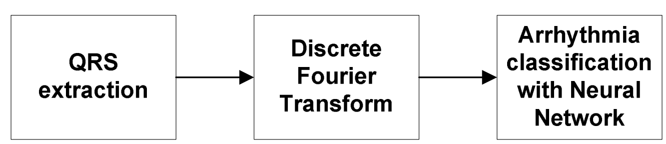

Figure 1. Arrhythmia detection system humane

In the Figure 2 the classified arrhythmia morphologies are shown.

A. *QRS extracted*

According to Hamilton and Tompkins [3] and to Shulka [4], the detection of QRS wave is preceded by a data filtering in order to detect the QRS complex frequency. We first processed the ECG signal through a low-pass IIR filter, and then through a high-pass IIR filter we suppressed the

978-0-7695-3872-3/09 $26.00 © 2009 IEEE
DOI 10.1109/ISDA.2009.246

high frequency noise and attenuated P and T waves in the signal, all the filters used were flat in the frequency band of interest.

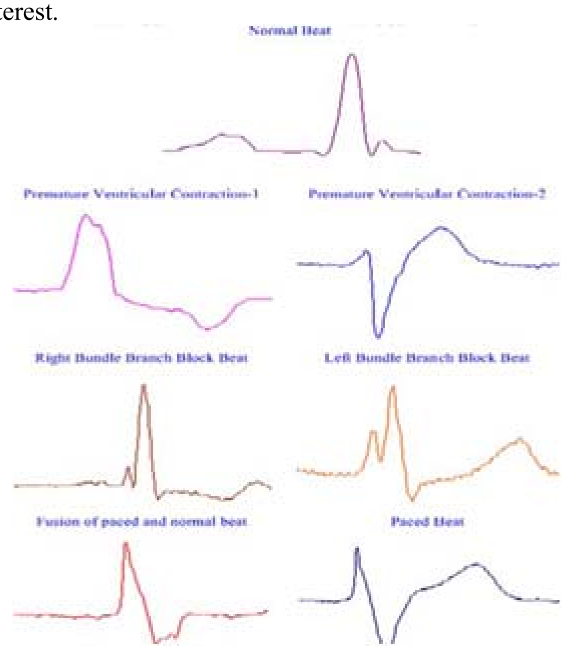

Figure 2. Typical arrhythmias in time domain humane (from [1])

We recorded two seconds of ECG in a internal buffer in order to preserve the original shape of the signal. Therefore, in a copy of this buffer, a QRS detection method were applied as [2][3] that include a derivative filter to emphasizes the QRS complex, a squaring stage that makes all data points positive and accentuates the QRS slope and a moving window integrator that points out waveform feature information.

Thus, for features extraction, we have considered only the samples of original ECG into the buffer corresponding at non zero values of the buffer copy. We can realized this method thanks to the use of Virtex® 4FX12 FPGA on demo board ML403 that provides large memory space in order to allocate a large amount of signal samples and a PowerPC in order to implement a hybrid hardware/software solution.

B. *Discrete Fourier Transform*

To reduce the number of samples and thus to minimize the number of input layer neurons, a Fast Fourier Transform (FFT) is applied with a frequency resolution of 3.6Hz as suggested in [7].

The Fast Fourier Transform is an efficient algorithm to compute the Discrete Fourier Transform (DFT) and its inverse that reduces the number of calculations to be done. The DFT is a numerical approximation of an analytically-defined Fourier Transform in a digital domain. The DFT X(k), k=0..N-1, of a sequence x(n), n=0..N-1 is defined as

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-jnk2\pi/N} \quad (1)$$

where N is the transform size and j=$\sqrt{-1}$ [11]. The inverse DFT (IDFT)

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(K) e^{jnk2\pi/N} \quad (2)$$

[11]. To evaluate the spectrum of a continuous signal $x(t)$ a sampling is performed every T seconds. The signal evaluated with t=nT is represented by a finite length sequence x(n). The length of the temporal window and the sampling-interval T, introduces numerical errors and approximations.

C. *Neural Networks: Kohonen Self-Organizing Map*

In order to classify the arrhythmia we used ANN which can adapt according to several algorithms that can be classified in two major families: *Unsupervised learning, Supervised learning*. In unsupervised learning the neural network learns some properties of the input pattern distribution without any feedback from the environment or from the user. The limited resources of the FPGA architecture were considered. Thus the ANN block implements a minimal KSOM (2x2 neurons for two input classes) for each cardiac arrhythmia. Self-organizing maps (SOM) are different than ANN in the sense that they use a neighborhood function to preserve the topological properties of the input space. A SOM consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space [9]. The choice of this kind of neural network is justified because KSOM requires only the storage of weight and the output is performed with a simple sum of products. According to the Kohonen map topology, all the elements of the input vector are connected to all the artificial neurons of the KSOM [9]. A KSOM maps the original space into a two-dimensional net of neurons in such a way that close neurons respond to similar signals, in order to solve classification tasks and to find structures in data. In Figure 3 is reported the 2x2 KSOM structure.

The winner-takes-it-all training strategy was adopted using a distance-based learning method: the neurons compete with each other to be the one to fire [9]. The neuron that fires is called the winner and this neuron has the weight vector most similar to the current input vector. Training phase was performed in offline mode with DFT data provided by hardware block. After training process the content of the synaptic weight vectors were placed on corresponding memory block of the neurons.

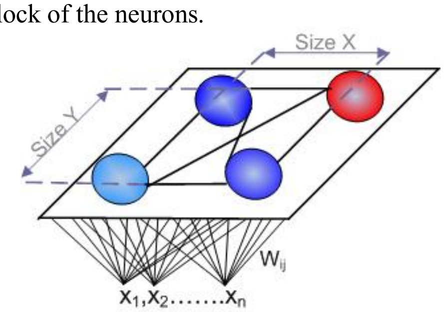

Figure 3. 2x2 Kohonen map architecture

First 10 point of DFT of the detected QRS were processed, and one of following six classes returned as output: normal beat, premature ventricular contraction, right bundle branch block beat, left bundle branch block beat, paced beat, and fusion of paced and normal beat.

Training set was achieved from 70% of MIT-BIH database [8] records and the last 30% were used to test the hardware prototype.

III. Design on FPGA

ML403 board with Virtex®-4FX12 FPGA was used. The board includes dedicated DSP slices, high-speed clock management circuitry, RS-232 serial port, 16-character x 2-line LCD display, PS/2 mouse and keyboard connectors, JTAG configuration port for use with Parallel Cable IV cable [10].

The proposed model is constituted by an arrhythmia recognition block which is composed by three major blocks as reported in Fig.4: an FFT block, a control unit and a processing neural block (neural network, maximum output calculus block) . The clock signals and corresponding clock enable signals do not appear in the Simulink® block diagrams using Xilinx System Generator® libraries, but are automatically generated when an FPGA design is compiled.

The FFT block was a standard block provided by Xilinx library. The FFT core provides three architecture options to offer a trade-off between core-size and transform time [11], Pipelined is used, Streaming I/O solution which pipelines several radix-2 butterfly processing engines in order to offer continuous data processing. The FFT block returns real and imaginary part used to calculate the module.

The control unit managed the control signal of the processing neural block in order to initialize and command the components of the processing neural block.

The processing block is designed to calculate the neural output and the winning neuron according to maximum output of the neurons. The current design used 68% resources. However, it results the better choice in terms of cost between data accuracy and area occupied for these kinds of arrhythmia.

A. *Processing block*

The processing block is the main block of the recognition design. It incorporated both the Kohonen neural networks and the logic for the winning neuron.

The kind of the neuron was linear. The structure of the neuron, reported in Fig. 5, consisted of one memory block for weights, one multiplier and one accumulator.

B. *Test of the algorithm in hardware*

In order to develop a fast prototype of ECG processing system a proprietary design tools Xilinx System Generator® for DSP was used, which is a tool for creating DSP designs using graphical methods. The design was tested on data records obtained from the MIT-BIH database as previous described. In detail, the data were sent to the ML403 board with Virtex®-4FX12 FPGA through JTAG cable [12] and a co-simulation has been generated in order to establish the

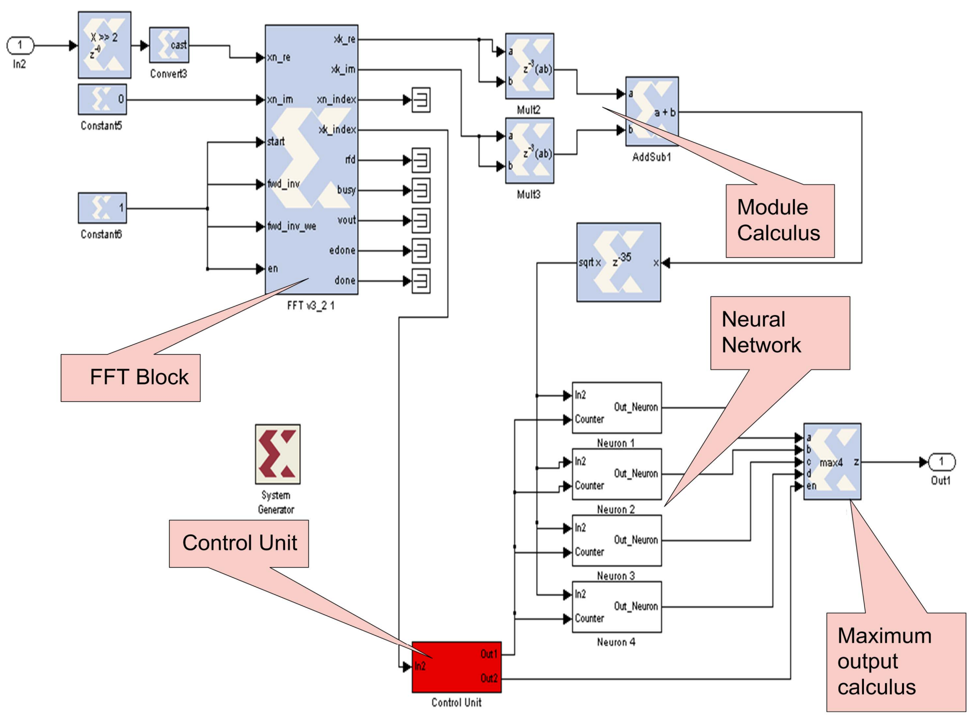

Figure 4. Design of Arrhythmia recognition block

accuracy and the logical operation of the digital implementation.

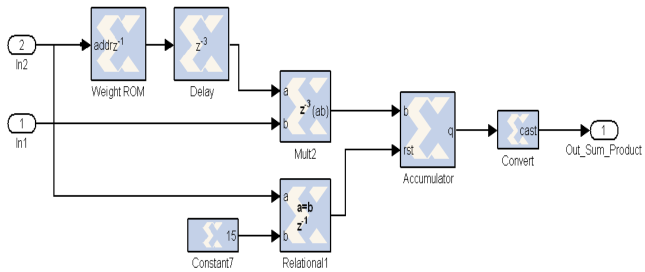

Figure 5. Design of the linear neuron

IV. RESULTS

As above mentioned, results were performed by applying the system to the MIT-BIH arrhythmia database records. In particular only the cases showed in Table 1 have been processed.

According to [13] essentially two parameters should be used to evaluate the algorithms; they are the sensitivity:

$$Se=TP/(TP+FN) \qquad (3)$$

and the positive predictivity:

$$+P=TP/(TP+FP) \qquad (4)$$

TABLE I. MIT-BIT ARRHYTHMIA DATABASE RECORDS INCLUDED IN OUR STUDY

Heartbeat	N.QRS	Record	Record Patient
Normal	1543 1743 2621 923 244 2031 314 2230	MIT-119 MIT-200 MIT-209 MIT-212 MIT-217 MIT-221 MIT-231 MIT-233	Female,age51 Male, age 64 Male, age 62 Female,age32 Male, age 65 Male, age 83 Female,age72 Male, age 57
Paced	2078 1542	MIT-107 MIT-217	Male, age 63 Male, age 65
Left Bundle Branch block	2492 2123 2003	MIT-109 MIT-111 MIT-214	Female,age64 Female,age47 Male, age 53
Right Bundle Branch block	2166 1531 1825 1254 397	MIT-118 MIT-124 MIT-212 MIT-231 MIT-232	Male, age 69 Male, age 77 Female,age32 Female,age72 Female,age76
Fusion of Paced and Normal	260	MIT-217	Male, age 65
Premature Ventricular Contraction	444 826 256 396 831	MIT-119 MIT-200 MIT-214 MIT-221 MIT-233	Female,age51 Male, age 64 Male, age 53 Male, age 83 Male, age 57

where *TP* denotes the number of true positive detections, *FN* the number of false negatives, and *FP* the number of false positives.

Results showed both accurate discriminations (see Table 2) and faster processing time during pathological QRS classification, when used FFT and KSOM. The results showed good specificity, but in some cases lower sensitivity (Fusion of Paced and Normal, Right Bundle Branch block). Moreover the positive predictivity of Fusion of Paced and Normal was low because a low number of pathologic QRS to training the neural networks.

V. DISCUSSION AND CONCLUSIONS

The algorithm chosen in this work allows recognizing normal beat and five cardiac arrhythmias by a suitable implementation into FPGA. The algorithm of Hamilton and Tompkins isolated the QRS complex while the FFT algorithm extracted the features sent to the KSOM. Hardware architecture of QRS recognition and artificial neuron were presented. In order to design and to implement the system, a proprietary design tools Xilinx System Generator® for functional specification and to co-simulate the hardware was used.

The method is proved to be advantageous and feasible on FPGA device. Moreover, the board used for the design still has about 10% resources available, which can be used timely for implementing additional functionality like on-chip learning.

Future works will be addressed to implement the digital design on FPGA in order to develop wearable systems and to realize on-chip learning so to speed up the training task.

TABLE II. EXPERIMENTAL RESULTS

Heartbeat	Specificity	Sensitivity	+P
Paced	97.36%	99.69%	92.17%
Left Bundle Branch block	97.11%	96.05%	94.74%
Fusion of Paced and Normal	93.13%	91.53%	22.71%
Right Bundle Branch block	97.10%	92.45%	95.16%
Premature Ventricular Contraction	98.70%	94.10%	95.43%

REFERENCES

[1] C. Lin, Y. Du, T. Chen, "Adaptive wavelet network for multiple cardiac arrhythmias recognition"; Expert Systems with Applications, vol. 34, pp. 2601–2611, 2008.

[2] J. Pan and W. Tompkins, "A real-time QRS detection algorithm," IEEE Transactions on Biomedical Engineering, vol. BME-32, no.3, pp. 230-236, March 1983.

[3] P. Hamilton and W. Tompkins,"Quantitative Investigation of QRS Detection Rules Using MIT/BIH Arrhythmia Database,"IEEE Transactions on Biomedical Engineering, vol. BME-33, no.12, pp. 1157-1165, December 1986.

[4] A. Shulka, L. Macchiarulo, "A Fast and Accurate FPGA based QRS detection System", 30 Annual International IEEE EMBS Confernce, , Vancouver ,British Columbia, Canada, August 20-24 2008.

[5] Specht, F. Donald, “Probabilistic neural network for classification mapping, or associative memory”, In Proc. IEEE Int. Conf. Neural network, San Diego, CA, Vol. 1,pp. 525–532, July.1988.

[6] K. Minami, H. Nakajima, T.Toyoshima, “Real-Time Discrimination of Ventricular Tachyarrhythmia with Fourier-Transform Neural Network”; IEEE transactions on Biomedical Engineering, Vol. 46, N.2, February 1999.

[7] G. Valenza, A. Lanatà, M. Ferro, EP. Scilingo, “Real-Time Discrimination of Multiple Cardiac Arrhythmias for Wearable Systems Based on Neural Networks”, Computers in Cardiology (CinC'08), Bologna (Italy), 2008.

[8] PhysioBank: www.physionet.org.

[9] Kohonen T., “Self organizing Maps”, Berlin, Springer-Verlag, ed.2001.

[10] Xilinx inc., “ML401/ML402/ML403 Evaluation Platform User Guide”,May, 2006.

[11] Xilinx inc., “Xilinx LogicCore Fast Fourier Transform v3.2”, DS260 January 11, 2006.

[12] Xilinx inc, “System Generator® for DSP User Guide”, Release 9.2.01 October, 2007.

[13] ANSI/AAMI EC57: “Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms (AAMI Recommended Practice/American National Standard)”, 1998. Available: http://www.aami.org; Order Code: EC57-293.