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ORIGINAL ARTICLE

FPGA-based system for artificial neural network arrhythmia classification

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Abstract
The automatic detection and cardiac classification are essential tasks for real-time cardiac diseases diagnosis. In this context, this paper describes a field programmable gates array (FPGA) implementation of arrhythmia recognition system, based on artificial neural network. Firstly, we have developed an optimized software-based medical diagnostic approach, capable of defining the best electrocardiogram (ECG) signal classes. The main advantage of this approach is the significant features minimization, compared to the existing researches, which leads to minimize the FPGA prototype size and saving energy consumption. Secondly, to provide a continuous and mobile arrhythmia monitoring system for patients, we have performed a hardware implementation. The FPGA has been referred due to their easy testing and quick implementation. The optimized approach implementation has been designed on the Nexys4 Artix7 evaluation kit using the Xilinx System Generator for DSP. In order to evaluate the performance of our proposal system, the classification performances of proposed FPGA fixed point have been compared to those obtained from the MATLAB floating point. The proposed architecture is validated on FPGA to be a customized mobile ECG classifier for long-term real-time monitoring of patients.

Keywords Electrocardiogram · Discrete wavelet transform · Artificial neural network · Multilayer perceptron · Xilinx system generator · FPGA

1 Introduction

The continuous monitoring and the early detection of heart diseases are essential tasks to develop new health policies for preventing and controlling cardiovascular failures. Since the introduction of electrocardiography (ECG) monitoring in hospital units, monitoring objectives have been expanded from basic rhythm and simple heart rate monitoring to more sophisticated means of detecting and diagnosing complex arrhythmia and preventing heart attacks [1]. This continuous monitoring can help to defeat the lack of human supervision in hospitals. It can help in permanent medical surveillance in school medicine and in remote diagnosis and treatment of patients through telemedicine. It provides to heart failure of patients a medical supervision without requiring a heavy and expensive hospital management. For that, the improvement of a real-time monitoring system is required. The system can combine ECG signal acquisition and processing in the same hardware architecture.

Through the last decades, several algorithms have been developed to identify and classify ECG abnormalities. The development of methods used in these algorithms resulted in a clear improvement in signal processing and information [2]. For example, a robust ECG classification method has been proposed [3]; it was based on a powerful algorithm series in terms of characterization of the ECG signal (DWT), feature reduction (PCA) and discrimination between classes. This led to achieving a very important classification rate. The classification was based on Statistical and Mixture Modeling Features [4, 5]. In addition, the researches used another kind of classifiers: artificial neural networks (ANN) [6–9]; linear quantization vector classification (LQV) [10], genetic algorithm [11, 12] and support vector machine (SVM) [13–18]. The research has been expanded also to the image processing methods. The

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research works [19–21] have been used to interpret and diagnose some cardiac condition. A combination of signal processing algorithm based on discrete wavelet transform and artificial neural network is used in order to classify and detect cardiac diseases. The classification systems showed a robustness during testing [21–23]. An intelligent method of classifying ECG signal based on the neuro-fuzzy adaptive system resulting from the approach of fuzzy logic is presented in [24]. Another combination of quartermaster analyzing algorithms, wavelets transform and artificial neural networks by acting on the number of multilayer perceptron node gave interesting results in accuracy and execution time [25]. All the techniques mentioned previously have achieved a very high classification rate due to the good selection of the best discriminating features by exploiting an advanced signal processing technique. Only the feature number involved to reach this classification rate is important [26].

The fast technology evolution was not only limited to the software arrhythmia classification methods but it had been extended to the real-time implementation. Most of these architectures are implemented using digital signal processor (DSP) [27, 28] or field programmable gate array (FPGA) [29–34]. The hardware implementation using the FPGA is considered to be the most widely used among the recent technologies. These techniques face a great challenge and this through the reorganization of the time and material constraints of existing technologies. The FPGA circuits are preferred due to their specific purpose circuits, their low-cost, their reconfigurable characteristics, and their parallel and interconnected architectures. A real-time architecture implemented on FPGA in order to accelerate ECG signal processing, including QRS detection, feature extraction, and preliminary diagnosis is presented [29]. A new real-time R-wave detection algorithm implemented on FPGA was described in [30], the ECG signal had been processed by the wavelet lifting and the R-wave was detected using the differential operations. The simulation is performed by MATLAB and System on Programmable Chip. A new ECG heart rate detection system is implemented. The system is based on the Shannon energy envelope and developed by basic VHDL blocks for implementation in FPGA [31]. Parallel field programmable gate arrays (FPGA) implementation of fault-tolerant ANN for ECG arrhythmia classification (FPAAC) is developed [32]. Using the PCA as feature extraction technique and the ANN, the FPAAC classifies the ECG in three classes of arrhythmia, premature ventricular contraction (PVC), fusion (F), and normal (N) beats. As a sequel of the results realized [32], authors proposed a reduced-size ANN architecture and they implemented it in two different representations: 32-bit floating and 16-bit fixed-point numerical on the same FPGA [33].

Our proposed classification system is mainly based on three principal units: feature extraction, classification and decision by applying an optimized and efficient approach. Also, it has been implemented on FPGA chip, using the Xilinx System Generator for DSP. Therefore, this paper proposes three main contributions. The first appears in the development of optimized software-based medical diagnostic system that can best classify ECG signals into normal and arrhythmia classes. The system requires only one statistical feature (the variance). This will reduce the size of the processed data and the memory space requirement. The second contribution is the hardware implementation on the FPGA chip. This system is a continuation of the first contribution. It combines the speed and the good precision of discrete wavelet transform with the high performance of MLP classifier. This would lead to self-diagnosis of medical heart conditions. Also, the system will be able to extract pertinent information from the ECG signal to detect the arrhythmia diseases. The third contribution is the real-time validation on the Nexys-4 FPGA evaluation kit using the Analog Discovery device. To achieve that, this paper is organized as follows: After the Sect. 1, materials, theory and basics of the proposed method have explained in details in Sect. 2. Section 3 presents the implementation and the design of the proposed architecture on MATLAB and FPGA. In Sect.4, a comparative study between the MATLAB and FPGA was presented. Finally, we discussed and concluded our work in Sect. 5.

2 Theory and method

The proposed ECG arrhythmia classification method consists of three principal units: feature extraction based on the wavelet transform to select the most relevant features, the classification and class decision. The classification unit consists of a multilayer perception (MLP) to classify and detect the ECG arrhythmia classes. Once weights and biases of neurons were calculated in the training stage, and then the proposed procedure was validated in MATLAB; the hardware implementation was designed, synthesized, and simulated on FPGA (Fig. 1).

2.1 Database

In order to design and validate the proposed arrhythmia classification system, we have used the annotated ECG records available in Physiobank database and developed largely by the Massachusetts Institute of Technology (MIT) and the Beth Israel Hospital in Boston (BIH) [35]. The database composed of 78 half-hour records, obtained from ambulatory ECG recordings, to supplement the examples of supraventricular arrhythmias in the MIT-BIH

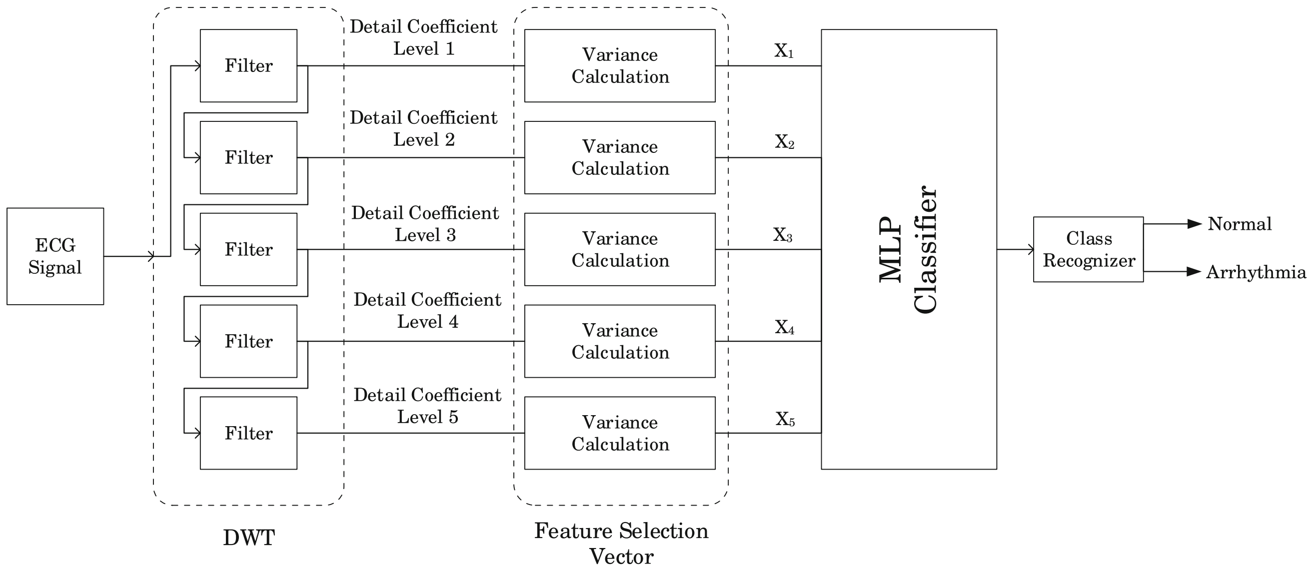


Fig. 1 Procedure of the proposed algorithm

Arrhythmia Database. From each ECG record, we have selected a 10s to create a 240 datasets divided evenly between the two classes. A 120 sets randomly taken from these 240 examples are used in training, and we kept the remaining 120 examples for testing the proposed system. The records are sampled at 128 Hz. The latest was used to evaluate performance of the proposed architecture for cardiac arrhythmia classification.

2.2 Feature extraction method

2.2.1 Discrete wavelet transform

In data analysis, the wavelet transform became one of the important new time–frequency decomposition tool. It has been found to be useful for nonstationary signals analysis, such as the ECG signal. The wavelet transform has the ability to study the signal concurrently in both time and frequency domains. This enables to extract more features from nonstationary signals. Generally, the concept leads to define the representative wavelet transform equation:

$$W(a,b) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \Psi^{*}\left(\frac{t-b}{a}\right) \mathrm{d}x \tag{1}$$

where the * indicates the complex conjugate operation symbol. $W(a, b)$ is the mother wavelet function, b is the translation factor, and a is a scale factor. In order to produce the minimum number of coefficients required to accurately recover the original signal using bilateral transformations, it would be preferable to use the discrete wavelet transform (DWT). This transform ensures this reduction by restricting the variation in translation and scale. In contrast to the continuous transform, where the wavelet is expanded and translated continuously, the discrete wavelet transform translates and dilates the wavelet according to discrete values. The coefficients a and b will be discretized as follows:

The variation steps of the translation parameters in time b and in the scale (frequency) a depend on each other and are defined by:

$$\begin{aligned} &a = a_0^i \quad \text{and} \\ &b = k * b_0 * a_0^i \quad \text{with} \quad a_0 > 1 \quad \text{and} \quad b_0 > 0 \quad i,k \in N \end{aligned} \tag{2}$$

The wavelets are constructed in the same way as in the continuous transform, by:

$$\Psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} \Psi\left(\frac{1}{a_0^m} t - nb_0\right) \tag{3}$$

These wavelets are used to compute the coefficients of the transform by discrete scalar products:

$$\mathrm{DWT}_x^{\Psi} = \frac{1}{\sqrt{a_0^i}} \int_{-\infty}^{+\infty} x(t) \quad \Psi\left(\frac{1}{a_0^i} - kb_0\right) \mathrm{d}x \tag{4}$$

The DWT is computed with a cascade filtering using two finite impulse response (FIR) filter banks. The signal is decomposed into low- and high-frequency parts. The high-pass part (g) is associated with the discrete mother wavelet and produces detail information. The low-pass part (h) is the mirror version associated with the scaling function and produces coarse approximations. In order to keep the same number of inputs and outputs, the convolution product caused by the filters is subsampled by a factor of 2. Only the details of approximation are processed by these two filters according to the level number. The dominant frequency of the signal contributes to the identification of decomposition level number [36]. Therefore, the coefficients of the DWT approximation (A_i) and details (D_i) are given by the following functions:

$$A_i = \sum_k h[k]S[2n+1] \tag{5}$$

$$D_i = \sum_k g[k]S[2n+1] \tag{6}$$

where n and k indicate discrete time coefficients and S represents the input signal for each level. i represents the number of decomposition levels [37, 38].

The ECG records are sampled at 128 Hz. In accordance with the Nyquist rules $f_e \geq 2f_{\max}$, the frequency band of real ECG signals is between 0–64 Hz.

Table 1 summarizes the bandwidth of the different frequency bands corresponding to different levels of DWT decomposition from the first to the fifth level. According to the wavelet decomposition, the ECG energy concentration lies in the five first levels of DWT details. Over the fifth level, the ECG energetic information is almost nonexistent.

In any application of wavelet transform, we are confronted with the problem of selection of the optimal wavelet. As there are several families of wavelets, we started with the most simple as Haar up to the high level such as the orthogonal and biorthogonal wavelets. They are selected according to their waveform and their capacity to analyze signals in the application. The Daubechies family is the best known among orthogonal wavelet families [39]. These wavelets are generally referred in this kind of application. Their energy is concentrated around the lower frequencies and they are similar in form to the QRS complexes [22, 40, 41]. In our study, we have selected the Daubechies of order 3 (DB3), which represent by Fig. 2.

2.2.2 Selection of feature vector

Feature selection is a very important task required for the learning process. The big challenge of selection algorithms is the enormity of the size/dimensionality of datasets. Usually, we can say that a feature is good when it is highly correlated with the class, but not otherwise [42]. We developed an approach with a minimum number of characteristics that can best classify ECG signals into normal and arrhythmia signals. Therefore, from each subband ($D1$–$D5$), a set of one statistical feature is computed which is the variance of wavelet coefficients at each level. For a single details coefficient D_i of size N, the general equation for calculating the variance (var) is defined by:

$$x_i = \frac{1}{N_i}\sum_{i=1}^{N} D^2_{(j,i)} - \left(\frac{1}{N_i}\sum_{i=1}^{N} D_{(j,i)}\right)^2 \tag{7}$$

Over the set of the wavelet details coefficients, five statics were used from the first level to the fifth. The obtained results presented good performance for our study. It can be noted that our contribution appears in the reduction of the number of pertinent features compared to existing researches. That will be described in details in Sect. 4. This choice leads to the reduction the processed data and the memory space requirement in the hardware implementation.

Table 1 Bandwidths of frequencies corresponding to five decomposition levels for Daubechies 3 filter wavelet with a sampling frequency of 128 Hz

Details	Frequency bands (Hz)
$D1$	32–64
$D2$	16–32
$D3$	8–16
$D4$	4–8
$D5$	2–4

2.3 MLP classification

Artificial Neural Network (ANN) is a computational model based on the structure of biological neural networks. One of the most common types of neural network is the multilayer perceptron (MLP). The MLP is known as a supervised learning technique because it is intended to generate rules from a learning database containing cases already processed and validated. The purpose of MLP model is to map a set of input data onto a set of appropriate outputs using a known database. Afterward, we can produce output results when the desired output is unknown [21]. Figure 3 shows the artificial neural network diagram.

The mathematical model which represents the artificial neuron is given by the following functions:

$$v^h_j = \sum_{i=1}^{m} w^h_{j,i} x_i + w^h_{j,0} \quad \text{with} \quad j = 1, \ldots, N \tag{8}$$

$$y^h_j = \phi_h(v^h_i) \tag{9}$$

where v^h_j is the answer of the j-th hidden neuron; x_i is the i-th of m input signals; and $w^h_{(j,i)}$ is the weight associated with the i-th input layer. $w^h_{(j,0)}$ is the bias of the j-th hidden neuron. ϕ_h is the activation function of the j-th hidden neuron. y^h_j represents the output of the j-th of the hidden layer neuron. In the same manner, the output of each neuron k, in output layer is given by:

$$v^o_k = \sum_{i=1}^{m} w^o_{k,i} y^h_j + w^o_{k,0} \quad \text{with} \quad k = 1, \ldots, N \tag{10}$$

$$y^o_k = \phi_o(v^o_k) \tag{11}$$

where $w^o_{(k,i)}$ is the synaptic weight connecting the output of the j-th hidden layer neuron to the k-th neuron of the output

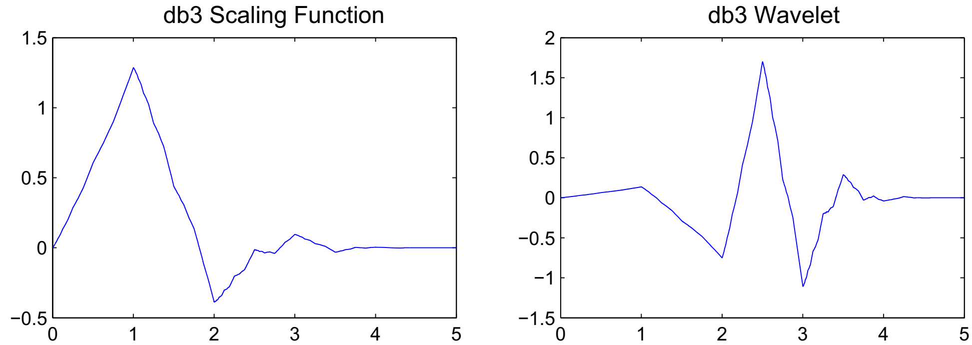


Fig. 2 Shape and scaling function representation of Daubechies 3 (db3)

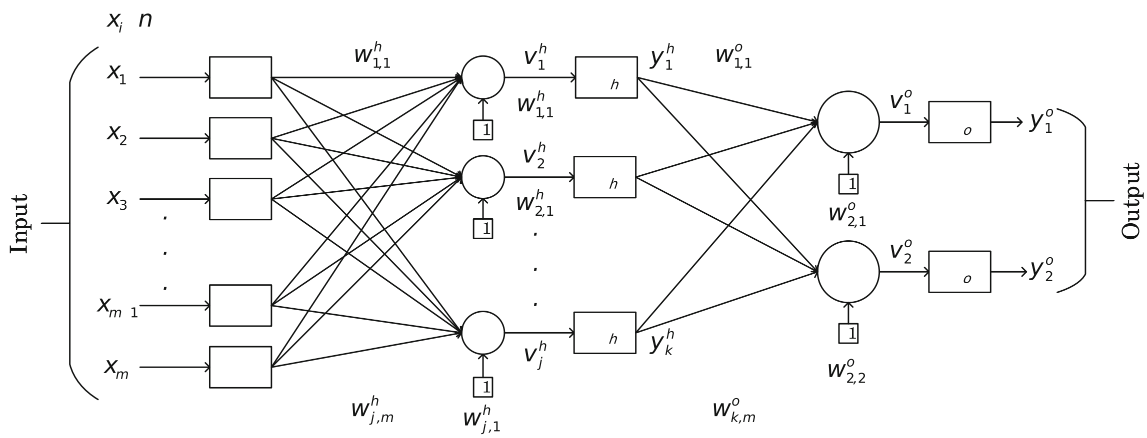


Fig. 3 Diagram of MLP network

layer, and the $w^o_{k,0}$ is the bias associated with the k-th neuron. y^k_o represents the output of the k-th of the hidden layer neuron [43]. The selection of neural network inputs is the most important part in the conception of the neural network classifier. Indeed, the best classifier performs poorly if the input is not very well chosen. The network proposed employs a three-layered architecture with a five-input layer, it depends on the size of the input feature vector and two output layers presenting the normal and the arrhythmia classes in which the feature vector is classified. While the selection of hidden nodes is chosen empirically depending on their effects on the obtained accuracy rate results. We have applied the hyperbolic tangent and the sigmoid as activation functions for the hidden and the output layers, respectively, where the hyperbolic function is presented by:

$$\phi_h = \frac{2}{1 + \mathrm{e}^{-2x}} - 1 \tag{12}$$

While the sigmoid function is given by:

$$\phi_h = \frac{1}{1 + \mathrm{e}^{-x}} \tag{13}$$

These functions are privileged due to their proximity to the linear origin. They are nearly saturating fairly quickly when they digress from the origin and its practically mathematically computed [44].

3 Implementation method

In this paper, we have performed two different implementation methods of the arrhythmia classification system. The first on MATLAB-based system to test and verify the methodology. The second on FPGA-based system to develop the prototype on hardware.

3.1 Software implementation

As a preface to FPGA implementation, the proposed classification system has been implemented in MATLAB. It presents a high-level programming tool. It allows to prior test performance of algorithms with complex calculation tasks. The MATLAB-based software implementation will help to build up the hardware implementation and to evaluate its effectiveness.

3.2 Hardware implementation

In this section, we presented how the hardware implementation was performed. We started with the Xilinx System Generator designing, followed by testing and validating the designed architecture on FPGA from MATLAB/Simulink (hardware co-simulation). Finally, we ended with testing the implementation in real time.

3.2.1 XSG design

Our aim is to provide a hardware architecture of arrhythmia ECG recognition by the artificial neural network (ANN) classifier. The best choice to carry out this architecture is the FPGA devices, which combine the high performance of ASICs and the flexibility of DSPs. Using Xilinx System Generator and the Nexys4 Artix7 evaluation Kit, the implementation has been designed. The XSG is a high-level tool that allows using MATLAB/Simulink environment to create and to verify Xilinx FPGAs designs in a quick and easy way. It provides a library of bits and cycles in both accurate floating-point and fixed-point implementations. Moreover, the DSP block is able to build high-performance DSP systems in Simulink using the Xilinx Blockset, which contains functions for signal processing, error correction, arithmetic, memories and digital logic. The Xilinx System Generator includes a code generator that automatically generates a synthesized VHDL code from the created model, which can be implemented in the FPGA [43]. Figure 4 describes the top-level diagram of the suggested architecture, and it consists of four main subsystems: feature extraction block including both the discrete wavelet transform and the feature vectors extraction blocks, classification and class recognition blocks. Moreover, a block to download the ECG signals from MATLAB, gateway in/out to pass from floating-point MATLAB to FPGA fixed point and a display to show the appropriate classes. In the following, we will describe in details the main parts of each subsection.

In the feature extraction block, the five-wavelet analysis levels are implemented on FPGA using a pair of low-pass and high-pass filters corresponding to the h and g wavelet transform filters. Figure 5 describes the top-level diagram of the discrete wavelet transform. Using the basis of convolution defined in Eqs. (4, 5), the hardware implementation of the two main filters has been achieved. ECG signal is multiplied by the coefficients represented by constants in (Fig. 5b, c). These constants correspond to the coefficients of DB3 wavelet filters. Table 2 represents the six coefficients corresponding to the two filters computed using the 'wfilters' MATLAB function.

In order to give wavelet detail and approximation coefficients, we have multiplied the signal with coefficients extracted from Daubechies filters, related by adders to perform the weighted sum. The outputs of each low- and high-pass filter blocks are followed by a downsampling provided by XSG library. To guarantee the best precision of details coefficients, it is necessary to take into account the application of delays. The equalization of the filter path delays is obtained by inserting appropriate additional delays in corresponding paths. The DB3 filters group delays are computed using groupdelay functions of MATLAB. The group delay in each critical path for the given filter h is obtained by summing delays of the cascaded filters using the Noble identities represented in [45, 46]. The five-wavelet decomposition levels sequence is constructed by processing only the approximation coefficients using low and high blocks. We have retained the same filter blocksets in each level. The final architecture obtained is represented in Fig. 5a.

After that, using the outputs of previous unit and according to Eq. (7) describing the variance calculation, representing each operation by its corresponding block from the XSG library, we have designed the block of feature extraction. The five vectors of details coefficients

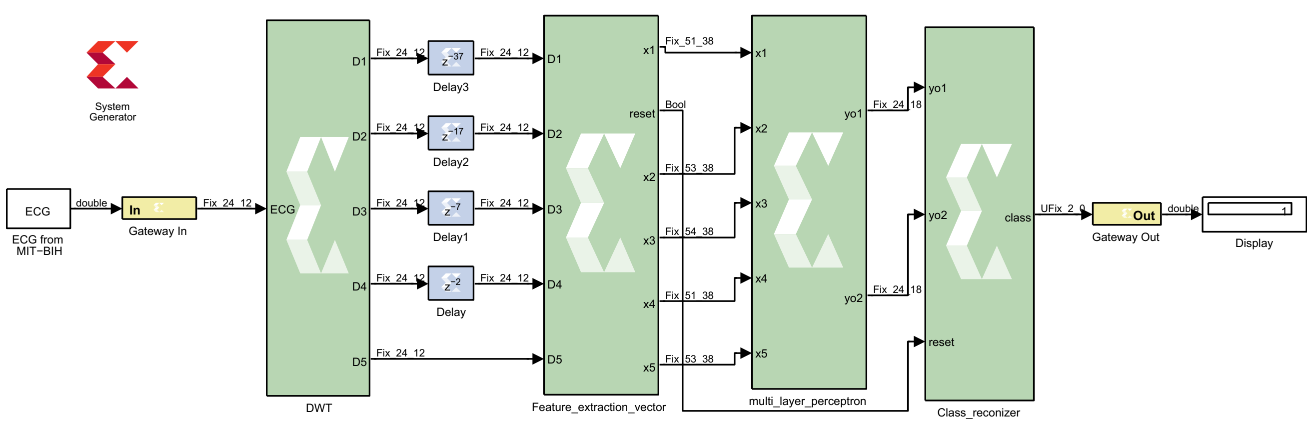
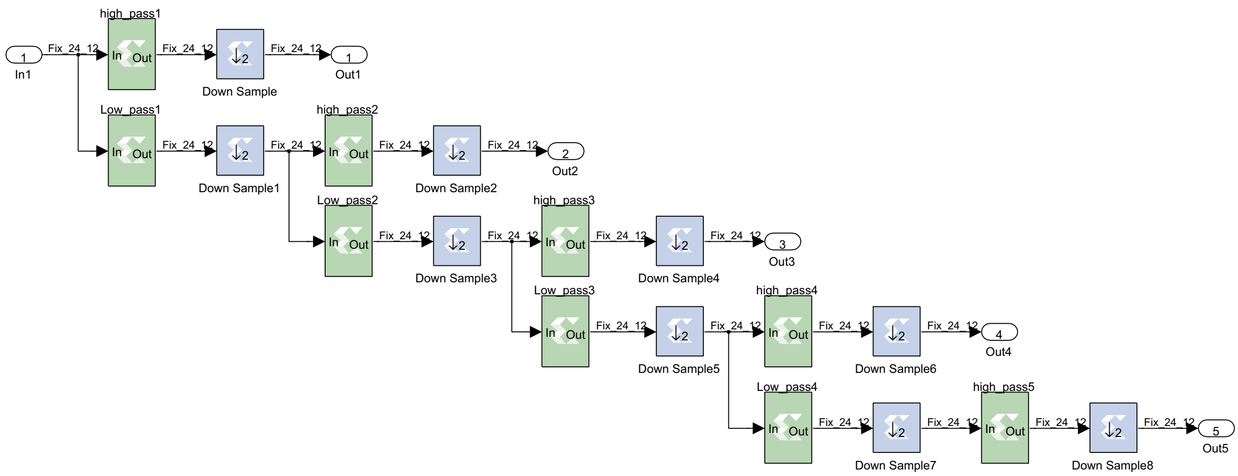
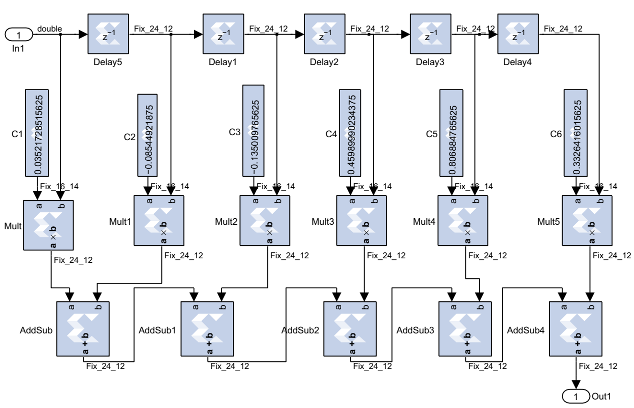


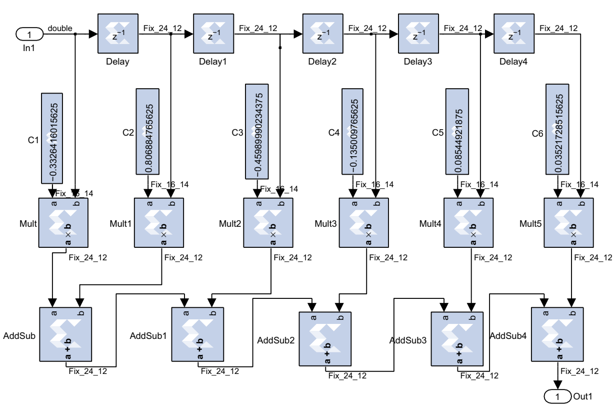
Fig. 4 Top-level diagram of ECG arrhythmia NNA classifier architecture



(a) Discrete wavelet transform scheme



(b) Low pass filter



(c) High pass filter

Fig. 5 Top-level diagram of discrete wavelet transform

Table 2 Coefficients of filters based on Daubechies 3 wavelet

Tap	Low pass (h)	High pass (g)
C1	0.035226291882101	– 0.332670552950957
C2	– 0.085441273882241	0.806891509313339
C3	– 0.135011020010391	– 0.459877502119331
C4	0.459877502119331	– 0.135011020010391
C5	0.806891509313339	0.085441273882241
C6	0.332670552950957	0.035226291882101

extracted from the treatment block (DWT) are accumulated with current scale stored values using an accumulator, a counter defining all the values of details coefficients as it is represented in Table 1, and a multiplier with a constant to introduce the division. We have used adders, multipliers and constants to perform the successive sums of details coefficients, a register to save its feature values enabled by the counter corresponding to each level. Figure 6 describes the top-level diagram of feature vectors selection block. As shown in Fig. 4, the procedure is repeated at each stage of the five decomposition levels.

After the extraction of the feature vector, the obtained data are ready for the MLP classification. Implementation of the artificial neural network architecture contains two main blocks: the processing and the activation functions. This architecture is implemented according to mathematical Eqs. (7–10) [43, 48] describing the MLP classifier in Sect. 2. The coming inputs from the feature extraction unit are weighted by multiplying the weight vector calculated in the MATLAB training stage. The sum of these weighted inputs is implemented using a binary tree of two input adders in order to minimize the critical path [47], as represented in Fig. 7c. In that case, the constants are used as a support to load the values of synaptic weights of the input layers, as shown in Fig. 7b.

The sum of the weighted inputs and bias constitute the hyperbolic activation function block input, where ϕ_h is implemented using a look-up table (LUT) scheme [48].

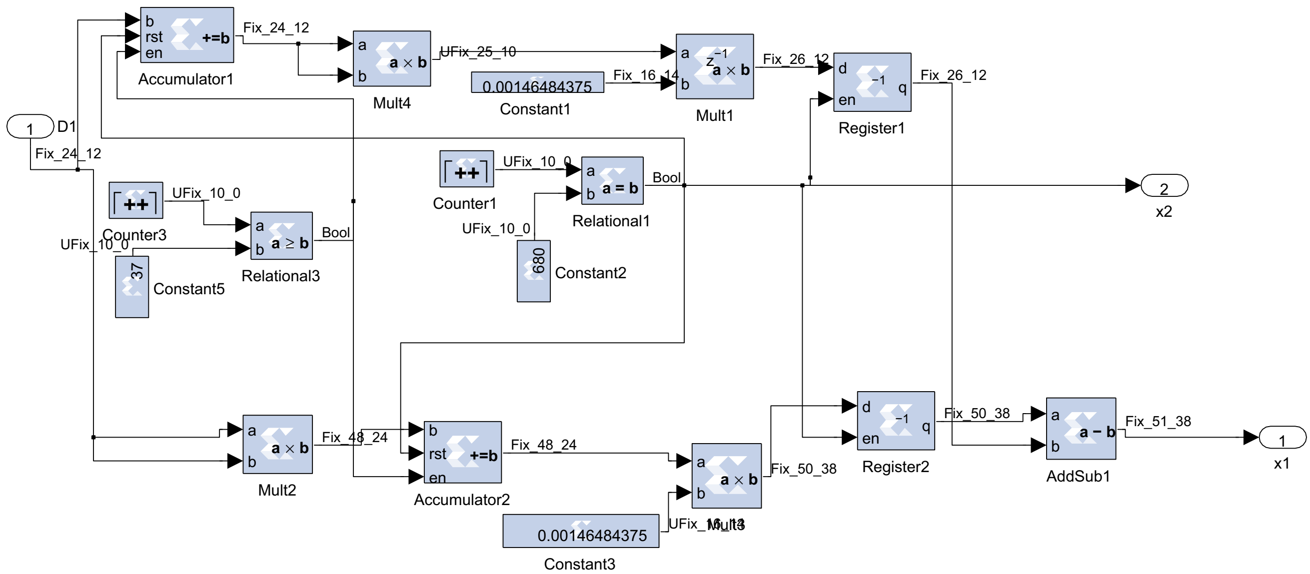


Fig. 6 Feature vector selection

The computation of this activation function is based on the use of a distributed memory (ROM). In order to convert the positives values of the hyperbolic function in their corresponding addresses, outputs of the weighted sum v_j^h are multiplied by $2^{11}/40$, where the number 40 represents the maximum amplitude of the hyperbolic function inputs generally limited between -40 and 40. According to asymmetry characteristics, i.e., $\phi_h(-v) = -\phi_h(v)$, negative values of the activation function are represented using a block negate $(-x)$ provided by XSG library. Figure 7d shows the internal block of the activation function.

The output of each neuron in the output layer is implemented, in the same manner as the hidden layer as shown in Fig. 8. Constants blocks represent the synaptic weights and the bias of the hidden layer inputs and the binary tree of adder is to perform the weighted sum of the outputs layers as shown in Fig. 8a, b, respectively. Figure 8c shows the block of implementation of the sigmoid function. The activation function of positive values is implemented such as the implementation of hyperbolic function positive values. However, the negative values of sigmoid function are obtained using another ROM with 2^{11} according to the symmetrical characteristic of sigmoid function $\phi_o(v^o) = 1 - \phi_o(v^o)$, as shown in Fig. 8c. As described above, the top-level diagram of the whole artificial neural network architecture is represented in Fig. 7.

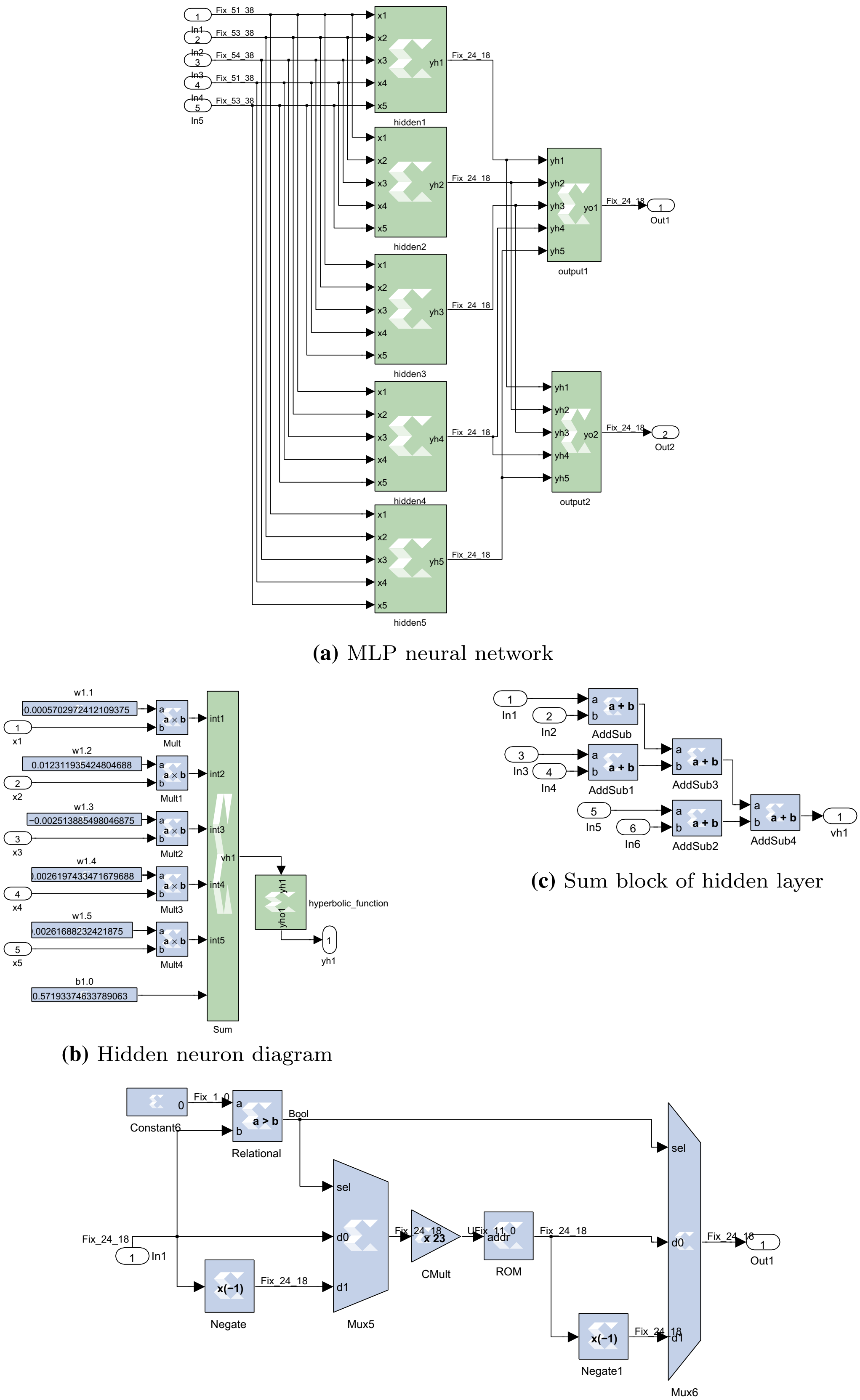
In order to visualize the output type of the system, we have realized the block class decision, which compares the MLP outputs results and assigns them to the appropriate class. As shown in Fig. 9, the block contains a multiplexer and comparator associated with the previous block results to evaluate the difference between the two MLP outputs y_o1 and y_o2. The constants represented by the values 1 and 2 correspond to the normal and arrhythmia class, respectively.

3.2.2 Co-simulation test

After the successful simulation using XSG blocksets, the designed architecture is ready to be transferred into the FPGA board. The XSG can be executed on FPGA from MATLAB, using the hardware co-simulation offered by the System Generator block, the compiled model is transferred directly from simulink MATLAB to FPGA board. The compilation creates automatically the bitstream and compiles the JTAG block. When the compilation is in progress, the data are transferred simultaneously between the computer and the board. Therefore, it is possible to read the outputs of classification from JTAG and display them in simulink as shown in Fig. 10.

3.2.3 Real-time test

The real-time implementation of the proposed XSG-based architecture can be uploaded and tested independently into MATLAB/Simulink environment. For this aim, we have used some electronics modules. Firstly, the analog discovery device has been used to provide and generate the ECG signal, by applying the waveform tool. The analog ECG output signal has been transferred to Nexys 4 board through an analog-to-digital converter (PmodAD1). The obtained results have been shown using additional configured components: the RGB lightening into red and green and one digit 7-segment display provided by the



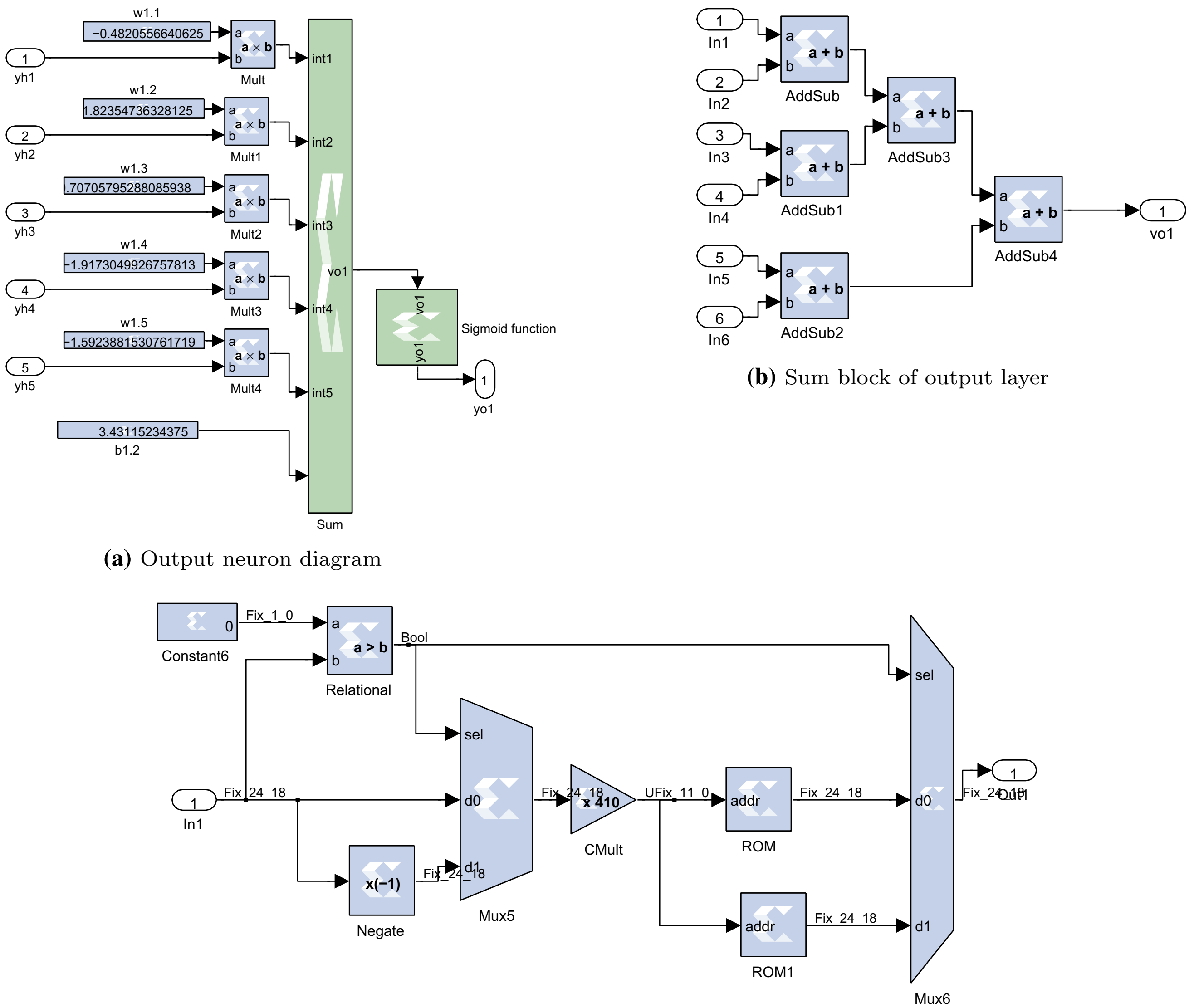
(a) MLP neural network

(b) Hidden neuron diagram

(c) Sum block of hidden layer

(d) Tangent hyperbolic function

Fig. 7 Top-level diagram of MLP neural network and diagram of hidden neuron



(a) Output neuron diagram

(b) Sum block of output layer

(c) Sigmoid function

Fig. 8 Top-level diagram of output neuron

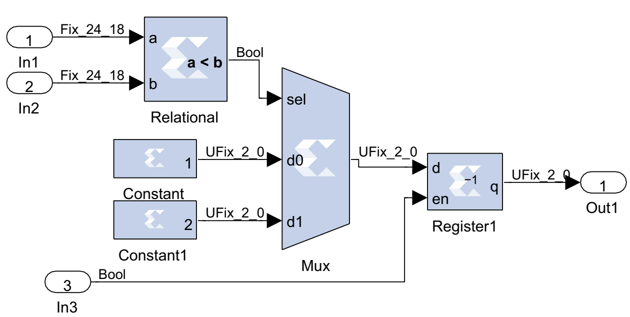
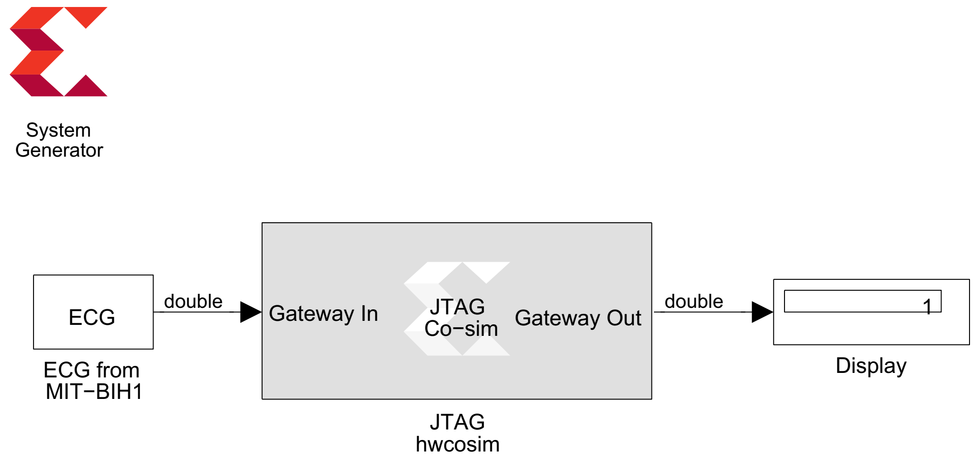


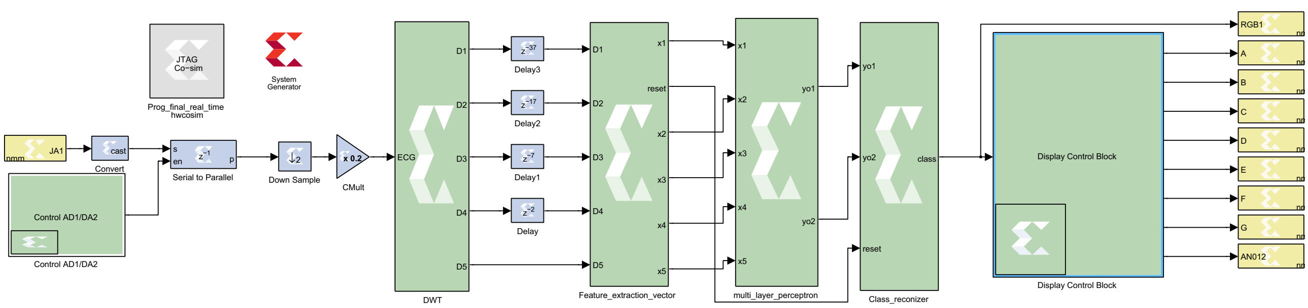
Fig. 9 Diagram of class decision

board, to indicate the signal class: normal or arrhythmia. Figure 11 presents the XSG design of the real-time implementation.

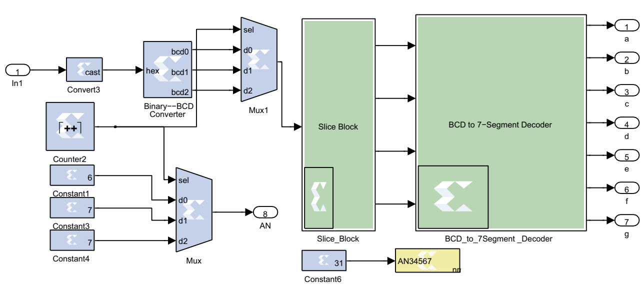
The data of developed architectures are quantized using 2'complement signed fixed-point format, whatever the number of bits used. For example, the constants in DWT and feature extraction selection units are all coded by 16 bits including 14 fractional. While in the classifier unit, some of the weight constants couldn't be coded by 16, so it has been configurated by 18 bits; however, the multipliers and accumulators are 24 bits with 11 bits for addressing the ROM. To avoid increase in word lengths, the truncation method has been used by changing parameters within the different programmable blocks. Table 3 describes the resource list required in hardware, which is mean the Artix 7 device resource estimator. It gives the ability to calculate the hardware resources needed for the System Generator design. Notice that, the real-time implementation requires more resources due to the manually and configured added components in the architecture.

Fig. 10 diagram of hardware/software implementation of ECG arrhythmia MLP classifier

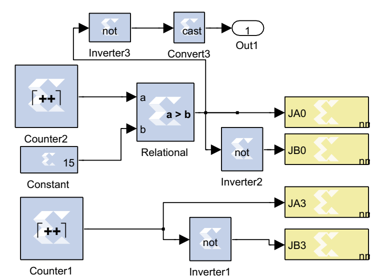




(a) Real time diagram



(b) Display control block



(c) Control AD1 DA2

Fig. 11 Diagram of real-time implementation of ECG arrhythmia MLP classifier

Table 3 The resources estimation required by our proposed method on Nexys 4

Architecture	Hardware co-simulation	Real-time
Resource utilization		
Slices (15,850)	2535 (15%)	2650 (16%)
LUTs (63,400)	7298 (11%)	7598 (11%)
Flip-flops (126,800)	2474 (1%)	2763 (2%)
Bonded IOBs (210)	27 (12%)	42 (20%)
DSP48E1s (240)	214 (89%)	214 (89%)
Number of used memory (19,000)	99 (1%)	98 (1%)
Maximum frequency	98.209 MHz	98.209 MHz

4 Experimental results

The performance of the proposed approach is determined by the most common statistical parameters. These parameters are calculated both MATLAB and FPGA implementations using the confusion matrix:

$$\text{Accuracy (Tc)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \tag{14}$$

$$\text{Sensitivity (tpr)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{15}$$

$$\text{Positivepredictivity (ppr)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{16}$$

$$\text{Specificity (tnr)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{17}$$

where TP represents the true positive: arrhythmia subjects correctly identified as abnormal. FP defines the false positive: normal people incorrectly identified as abnormal. TN represents the true negative: normal subjects correctly identified as normal. FN is the false negative: arrhythmia subjects incorrectly identified as healthy.

4.1 MATLAB simulation

To implement the arrhythmia ANN classifier in hardware, we must first go through the training stage. It has complex algorithm in the software application. The training phase of our proposed method was performed using MATLAB(R2011a)on an Intel(R)core (TM)i7 CPU TM-4790 3.60 Ghz with Windows 7 as operating system. The performance of our technique is evaluated using 240 datasets from the standard database (MIT-BIH Arrhythmia database); we have used 120 signals for each type of ECG class.

In the feature extraction part, we have used the wavelet toolbox from MATLAB. Applying the DWT to ECG signals, the input is decomposed into low -and high-frequencies parts. The decomposition of the input data requires the uses of specifics wavelets. Given a large number of existing wavelets, a comparative study over the set of Daubechies family has been performed. This allowed us to see the impact of this choose on the results and select the most appropriate wavelet for our work. Table 4 shows the different accuracy rates achieved by the uses of the Daubechies family.

The principal advantage in feature selection part appears in the feature vector minimization compared to the existing method. Therefore, firstly we have made a statistical study over a set of the following statistics:

- Mean of the wavelet coefficients in each level.
- Standard deviation in each level.
- Variance of the wavelet coefficients in each level.

We have found an average value of 90% of variance distribution is concentrated on the first five detail levels. Over the fifth level, the ECG energetic information is almost nonexistent. We observe that the band on the first level of detail $D1$, ranging [32–64 Hz] presents the details of the ECG signal outside the wave characteristics of this signal, the third and the fourth levels $D3$, $D4$ corresponding to [8–16 Hz], [4–8 Hz] frequency bands contains the information of the QRS complex. The fifth level $D5$ [2–4 Hz], include the information of the T and P waves. To prove that, this statistical study has been applied for our entire database and it shows the same characteristics. The statistical study result over the set of statics gives the following accuracy rates. For the mean of the wavelet coefficients in each level, we have found 73.33%. However, standard deviation and variance give a 97.5%, 98.3%, respectively. According to the obtained results, we have proved that with only one feature vector which is the variance is sufficient to properly separate the signals affected by the arrhythmia compared to normal signals. While, in the proposal neural network part, several techniques of high-level performing training such as Resident Backpropagation (trainrp) and the Memory Levenberg Marquet (trainlm) has been carried out. The results obtained by applying those techniques are given by 97.5%, 98.3%, respectively. The training parameters were chosen according to their effects on the obtained accuracy rate results. The proposed method gives an accuracy rate of 98.3% with 1.7% error rate. In addition, the values of sensitivity, specificity, and positive predictive value are 100%, 96.7% and 96.6% respectively.

The overall performance of the optimized approach is compared with some existing arrhythmia classification methods in the literature. The comparison has been

Table 4 The effect of Daubechies family selection on the accuracy rate

Daubechies wavelets	Accuracy rate (%)	Daubechies wavelets	Accuracy rate (%)
db1	90	db6	50
db2	90	db7	97.5
db3	98.3	db8	92.5
db4	92.5	db9	95
db5	85.8	db10	98.2

Table 5 Comparison between other related works and our proposed method

Research	Method	Data	The used ECG classes	Training data	Set of features	Feature dimensionality	Performance (%)
Prasad et al. [23]	DWT and ANN	10 files (MIT-BIH arrhythmia database)	NB, RBBB, APB, AAPB, NPB, VPB, FVNB, VFW, NEB, VEB, PB beat FPNB	30,293 Beats	Ci, RR1, RR2	25	96.77
Guler et al. [7]	DWT and MLP	(Physiobank database)	NB, CHF, VT, AF	360 Vectors	Mean, Ap, Std, Mad	19	96.94
Sarkaleh et al. [22]	DWT and ANN	10 files (MIT-BIH arrhythmia database)	NB, PB, APB	90 Vectors	Max, Min, Var	24	96.5
Thomas et al. [8]	(DTCWT) + trainrp (ANN)	10 files (MIT-BIH arrhythmia database)	CV, NEB, SA	10,675 Beats	Max, Min, Mean, Std	20	96.76
Ceylan [26]	DWT-ANN	10 files (MIT-BIH arrhythmia database)	NB, RBBB, APB, AAPB, NPB, VPB, FVNB, VFW, NEB, VEB, PB beat FPNB	318 Vectors	Energy	50	98.43
Our proposal method	DWT and MLP	Normal beat, MIT-BIH supraventricular arrhythmia database	NB, SA	120 Vectors	Var	5	98.3

NB normal beat, *LBBB* left bundle branch block, *RBBB* right bundle branch block, *APB* atrial premature beat, *AAPB* aberrated atrial premature beat, *NPB* nodal (junctional) premature beat, *VPB* ventricular premature beat, *FVNB* fusion of ventricular and normal beat, *VFW* ventricular flutter wave, *NEB* nodal (junctional) escape beat, *VEB* ventricular escape beat, *PB* paced beat, *FPNB* fusion of paced and normal beat, *CHF* congestive heart failure beat, *VT* ventricular tachyarrhythmia beats, *AF* atrial fibrillation beat, *CV* the complex ventricular, *SA* supraventricular arrhythmias, *DTCWT* dual-tree complex wavelet transforms

Table 6 System Generator confusion matrix

	Confusion matrix	
	Normal (NB)	Arrhythmia (SA)
Normal (NB)	59	5
Arrhythmia (SA)	1	55

achieved in terms of feature vector sizes and accuracy rate. For example, Guler et al. [7] proposed a combined neural network model for ECG beats classification. They used the following statistical features: mean (Mean), average power (Ap), standard deviation (Std), ratio of the absolute mean values (Mad) of adjacent subbands over 265 wavelet coefficients. The dimensionality of the feature vector has been reduced from 256 features to 20. Thomas et al. [8] proposed feature extraction technique based on dual-tree complex wavelet transform (DTCWT) for automatic classification of cardiac arrhythmia. From the first level to the fifth, they computed four statistical parameters: the maximum value (Max), the minimum value (Min), the mean (Mean) and the standard deviation (Std) of the wavelet coefficients. In total, they used 20 statistical features. Sarkaleh et al. [22] proposed an expert system for ECG arrhythmia classification. They used 24 statistics over the whole set of eight-level-wavelet coefficients. They used three features per level: the maximum (Max), the minimum (Min) and the variance (Var). Prasad et al. [23] described a method which accurately classifies ECG arrhythmia through a combination of wavelets and artificial neural networks (ANN). They presented twenty-three (23) DWT coefficients (Ci) selected from A4, *D*4, *D*3 as a feature vector, in addition to the RR interval between the processing beat and the previous beat (RR1), and the interval between the processing beat and the next beat (RR2). Ceylan [26] presented a work which accurately classifies ECG arrhythmia through a combination of wavelets and artificial neural networks (ANN). They applied two-level DWT (here the number of features is 50). Table 5 summarizes performances of our method compared to other researches in terms of features selection.

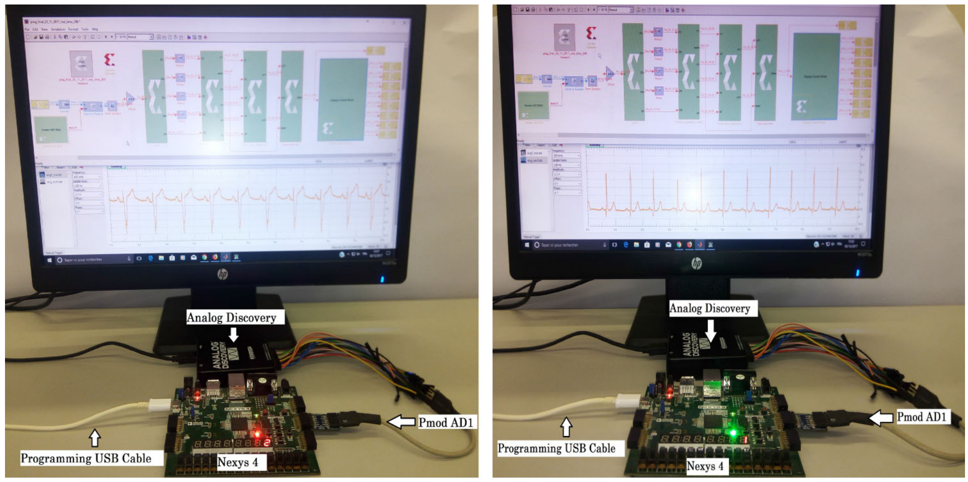
The results reported in Table 5 show on the whole that our method performed better than other works, despite the fact that it is based on only one feature. This optimization in the feature vector size will automatically affect the FPGA hardware implementation list of resources.

4.2 Hardware co-simulation

After creating the JTAG block, it is possible to read and display the outputs classification results from hardware co-

Table 7 System Generator Simulation Results compared with MATLAB

Performance	tps (%)	tnr (%)	ppr (%)	Tc (%)	Error rate (%)	Number of misclassified
MATLAB	100	96.7	96,6	98.3	1.7	6
XSG	98.33	98.2	92.2	95.00	5	2



(a) Arrhythmia case **(b)** Normal case

Fig. 12 Real-time implementation of MLP classification system

simulation block in the same time on Simulink (Fig. 10). Classification obtained results of the combined neural network architecture was presented by a confusion matrix. The confusion matrix showing the true and misclassified classes for our fixed-point model (Table 6).

Here, the diagonal represents the number of correctly classified signals in their respective classes. According to the obtained results, the proposed FPGA architecture gave an accuracy rate of 95.00% with an error of 5.00%. In addition, the values of sensitivity and positive predictivity values are, respectively, 98.33% and 92.2%.

In order to evaluate the performance of our method, we have compared the results of the implementations of floating-point MATLAB and fixed-point XSG as shown in Table 7.

As presented, it is clear the difference between the XSG fixed-point and floating-point MATLAB results, and this is due to the quantification error and the vector's data size.

4.3 Real-time evaluation

To build and validate the proposed system in real time, several electronic modules have been used. The ECG signal was provided by the Analog Discovery device from MIT-BIH database, using the WaveForms tool installed on the PC. The analog ECG signal was then acquired by the FPGA through the PmodAD1 at a sampling frequency of 128 Hz. The proposed method has been implemented on the FPGA-based system and the results of class recognition were sent to the 7-segment display and the RGB-Led provided by the Nexys 4 evaluation kit. The first 7-segment digit displays a value of one with the green lightening when the ECG is that of a normal case. However, it displays the value 2 with red lightening for the arrhythmia case (as shown in Fig. 12).

5 Conclusion

We proposed and realized a real-time implementation of ECG arrhythmia classification system. The system was successfully implemented on Nexys4 Artix-7 FPGA. We developed an optimized software algorithm that can best classify ECGs into normal and arrhythmia and using real ECG signals. The method requires a minimum number of statistical features which leads to optimize memory space requirement. Then, this method had been implemented in a real-time FPGA-based system in order to provide a system which is able to help patients and doctors for heart diseases monitoring and diagnosis. The system had been implemented on FPGA using the basic Xilinx System Generator for DSP blocks like arithmetic blocks, memories, and digital logic. We evaluated the method and adapted it to the real-time system by the use of additional electronic modules. To evaluate the performance and the effectiveness of the proposed Arrhythmia classification system, we have used standard MIT-BIH arrhythmia database. The performance is evaluated in terms of sensitivity (tpr %), positive predictive value (ppr %), specificity (tnr %) and accuracy (Tc%) which are calculated from true classified class(TP), false negative (FN) and false positive (FP). Both MATLAB and hardware implementations were conducted to evaluate our system performance. Our FPGA design achieved an average accuracy of 95% with an error of 5%, an average sensitivity and positive predictive value of, respectively, 98.33%, 92.2%, while MATLAB performance gave an accuracy rate of 98.3%.

Our proposed software-based method gave a better response than the existing methods based on ECG signal processing. Moreover, the FPGA implementation for arrhythmia classification provided satisfactory results. It has been proven to be powerful and advantageous on FPGA due to their convergence performance with the floating-point format results of MATLAB software.

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References

1. Drew BJ, Califf RM, Funk M, Kaufman ES, Krucoff MW, Laks MM, Macfarlane PW, Sommargren C, Swiryn S, Van Hare GF (2004) Practice standards for electrocardiographic monitoring in hospital settings. Circulation 110(17):2721–2746
2. Moavenian M, Khorrami H (2010) A qualitative comparison of artificial neural networks and support vector machines in ECG arrhythmias classification. Expert Syst Appl 37(4):3088–3093
3. Afsar F.A, Arif M, (2008) Robust electrocardiogram beat classification using discrete wavelet transform. In: 2008 2nd international conference on bioinformatics and biomedical engineering, IEEE, pp 1867–1870
4. Afkhami RG, Azarnia G, Tinati MA (2016) Cardiac arrhythmia classification using statistical and mixture modeling features of ECG signals. Pattern Recognit Lett 70:45–51
5. Elhaj FA, Salim N, Harris AR, Swee TT, Ahmed T (2016) Arrhythmia recognition and classification using combined linear and nonlinear features of ECG signals. Comput Methods Programs Biomed 127:52–63
6. Kadbi MH, Hashemi J, Mohseni HR, Maghsoudi A (2006) Classification of ECG arrhythmias based on statistical and time-frequency features. In: IET 3rd international conference on advances in medical, signal and information processing, MEDSIP 2006. IET, pp 1–4
7. Güler I, Übeyl ED (2005) ECG beat classifier cesigned by combined neural network model. Pattern Recognit 38(2):199–208
8. Thomas M, Das MK, Ari S (2015) Automatic ECG arrhythmia classification using dual tree complex wavelet based features. AEU-Int J Electron Commun 69(4):715–721
9. Rai HM, Trivedi A, Shukla S (2013) ECG signal processing for abnormalities detection using multi-resolution wavelet transform and artificial neural network classifier. Measurement 46(9):3238–3246
10. Homaeinezhad MR, Tavakkoli E, Habibi M, Atyabi SA, Ghaffari A (2011) Combination of different classifiers for cardiac arrhythmia recognition. World Acad Sci Eng Technol 5:1189–1200
11. Kumari V, Rajesh K (2015) Optimization of multi-layer perceptron neural network using genetic algorithm for arrhythmia classification. J Commun 3:150–157
12. Diker A, Avci D, Avci E, Gedikpinar M (2019) A new technique for ECG signal classification genetic algorithm wavelet kernel extreme learning machine. Optik 180:46–55
13. Übeyli ED (2008) Support vector machines for detection of electrocardiographic changes in partial epileptic patients. Eng Appl Artif Intell 21(8):1196–1203
14. Jankowski S, Oreziak A, Skorupski A, Kowalski H, Szymanski Z, Piatkowska-Janko E (2003) Computer-aided morphological analysis of Holter ECG recordings based on support vector learning system. Comput Cardiol 30:597–600
15. Osowski S, Hoai LT, Markiewicz T (2004) Support vector machine-based expert system for reliable heartbeat recognition. IEEE Trans Biomed Eng 51(4):582–589
16. Acr N (2005) Classification of ECG beats by using a fast least square support vector machines with a dynamic programming feature selection algorithm. Neural Comput Appl 14(4):299–309
17. Song MH, Lee J, Cho SP, Lee KJ, Yoo SK (2005) Support vector machine based arrhythmia classification using reduced features. Int J Control Autom Syst 3(4):571
18. Acr N (2006) A support vector machine classifier algorithm based on a perturbation method and its application to ECG beat recognition systems. Expert Syst Appl 31(1):150–158
19. Mohamed B, Issam A, Mohamed A, Abdellatif B (2015) ECG image classification in real time based on the haar-like features and artificial neural networks. Procedia Comput Sci 73:32–39
20. Sharma J, Kumar V, Ayub S, Saini JP (2012) Uniform sampling of ECG waveform of MIT-BIH normal sinus rhythm database at desired intervals. Int J Comput Appl 50(15):6–9
21. Wang J-S, Chiang W-C, Hsu Y-L, Yang Y-TC (2013) ECG arrhythmia classification using a probabilistic neural network with a feature reduction method. Neurocomputing 116:38–45
22. Sarkaleh MK, Shahbahrami A (2012) Classification of ECG arrhythmias using discrete wavelet transform and neural networks. Int J Comput Sci Eng Appl 2(1):1
23. Prasad GK, Sahambi JS (2003) Classification of ECG arrhythmias using multi-resolution analysis and neural networks. In: TENCON 2003. Conference on convergent technologies for the Asia-Pacific region, vol. 1. IEEE, pp 227–231
24. Güler I, Übeyli ED (2004) Application of adaptive neuro-fuzzy inference system for detection of electrocardiographic changes in patients with partial epilepsy using featur extraction. Expert Syst Appl 27(3):323–330
25. Dokur Z, Ölmez T (2001) ECG beat classification by a novel hybrid neural network. Comput Methods Programs Biomed 66(2–3):167–181
26. Ceylan R (2018) The effect of feature extraction based on dictionary learning on ECG signal classification. Int J Intell Syst Appl Eng 6(1):40–46
27. Minami K-i, Nakajima H, Toyoshima T (1999) Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network. IEEE Trans Biomed Eng 46(2):179–185
28. Gutiërrez-Gnecchi J A, Morfin-Magaña R, Lorias-Espinoza D, del Carmen Tellez-Anguiano A, Reyes-Archundia E (2017) DSP-based arrhythmia classification using wavelet transform and probabilistic neural network. Biomed Signal Process Control 32:44–56
29. Gu X, Zhu Y, Zhou S, Wang C, Qiu M, Wang G (2016) A real-time FPGA-based accelerator for ECG analysis and diagnosis using association-rule mining. ACM Trans Embed Comput Syst (TECS) 15(2):25
30. Ma Y, Li T, Ma Y, Zhan K (2016) Novel real-time FPGA-based R-wave detection using lifting wavelet. Circuits Syst Signal Process 35(1):281–299
31. Panigrahy D, Rakshit M, Sahu PK (2016) FPGA implementation of heart rate monitoring system. J Med Syst 40(3):1–12

32. Özdemir AT, Danisman K (2011) Fully parallel ANN-based arrhythmia classifier on a single-chip FPGA: FPAAC. Turk J Electr Eng Comput Sci 19(4):667–687
33. Özdemir AT, Danisman K (2015) A comparative study of two different FPGA-based arrhythmia classifier architectures. Turk J Electr Eng Comput Sci 23(Sup. 1):2016–2089
34. Alfaro-Ponce M et al (2017) Automatic detection of electrocardiographic arrhythmias by parallel continuous neural networks implemented in FPGA. Neural Comput Appl. https://doi.org/10.1007/s00521-017-3051-3
35. Mark R, Moodly G (2011) MIT-BIH arrhythmia database. https://physionet.org/physiobank/database/mitdb/. Accessed 12 July 2011
36. Subhashrao DP, Halahlli SR (2015) Low complexity algorithm for extraction of ECG fiducial points. Int J Eng Sci Res Technol 1(4):65–74
37. Dhubkarya DC, Dubey S (2009) High quality audio coding at low bit rate using wavelet and wavelet packet transform. J Theor Appl Inf Technol 6(2):194–200
38. Vanisree K, Singaraju J (2011) Automatic detection of ECG RR interval using discrete wavelet transformation. Int J Comput Sci Eng (IJCSE) 3(4):1599–1605
39. Daubechies I (1992) Ten lectures on wavelets, vol 61. Siam, Philadelphia
40. Mahmoodabadi S, Ahmadian A, Abolhasani M, Eslami M, Bidgoli J (2006) ECG feature extraction based on multiresolution wavelet transform. In: 27th annual international conference of the engineering in medicine and biology society, 2005. IEEE-EMBS 2005, IEEE, pp 3902–3905
41. Saritha C, Sukanya V, Murthy YN (2008) Ecg signal analysis using wavelet transforms. Bulg J Phys 35(1):68–77
42. Silipo R, Marchesi C (1998) Artificial neural networks for automatic ECG analysis. IEEE Trans Signal Process 46(5):1417–1425
43. Bahoura M (2014) FPGA implementation of high-speed neural network for power amplifier behavioral modeling. Analog Integr Circuits Signal Process 79(3):507–527
44. Bishop CM (1995) Neural networks for pattern recognition. Oxford University Press, Oxford
45. Bahoura M, Ezzaidi H (2012) FPGA-implementation of discrete wavelet transform with application to signal denoising. Circuits Syst Signal Process 31(3):987–1015
46. Matlab (2010) Signal processing blockset 7 users guide. The MathWorks Inc., Natick
47. Bahoura M, Park C-W (2012) FPGA-implementation of dynamic time delay neural network for power amplifier behavioral modeling. Analog Integr Circuits Signal Process 73(3):819–828
48. Bastos JL, Figueroa HP, Monti A (2006) FPGA implementation of neural network-based controllers for power electronics applications. In: Twenty-first annual IEEE applied power electronics conference and exposition, 2006. APEC'06. IEEE, p 6