Design and specification of analog artificial neural network

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Abstract

In this paper, we have implemented, using Matlab Simulink an analog artificial neural network for breast cancer classification. Simulated results with ideal building blocks exhibit a total error of classification of 2.6%. Thanks to this value, we have modified Simulink models of the building blocks (i.e. multiplier, activation function and its derivative) in order to take into account their non-idealities. This study allows to determine their influence on the classification quality and to extract some specifications of these building blocks.

Keywords Neural network · MLP · Breast cancer · Non-ideal blocks · Simulink

1 Introduction

Artificial Neural Networks (ANN) are used in many fields such as medical domain (the current paper application), communication, power control and other applications.

ANN have two methods of implementation:

1. Implementation by using software.
2. Implementation by using hardware.

The first method uses software like C++, MATLAB, LabVIEW and other software using different algorithm like Multilayer perceptron with Back-propagation (MLP), Radial Basis Function (RBF), Support Vector Machine (SVM) [1–3]. Some published papers use the Fuzzy logic method [4] and others use the normalized Multilayer perceptron with Back-propagation (MLP) [5].

In the second method, we have two options:

1. Digital hardware implementation.
2. Analog hardware implementation.

In the first one, digital devices are used for example the Field Programmable Gate Array (FPGA) [6–8] and [9].

The second way is based on analog implementation of ANN [10], this type of artificial neural networks is particularly interesting for CMOS VLSI implementations because every parallel element (neuron or synapse) is relatively simple, allowing the complete integration of big networks on a single chip [11]. Multipliers [12], non-linear function and its derivative [13, 14] are essential key elements in the analog signal processing in particular for analog VLSI implementation of artificial neural networks. In this article, we create a design for breast cancer detection and classification (i.e. malignant or benign) by using the artificial neural network MLP (Multi-Layer Perceptron) with back-propagation [14–16], based on the Wisconsin Data Base [17]. In a previous work, we have demonstrated that the most efficient architecture consists of 9 inputs neurons corresponding to 9 attributes of the Data Base, 10 neurons in the hidden layer and 2 for the output layer (two output classes: Benign or malignant), named 9-10-2 without biases [18]. The main objective of this work is to determine the influence of the non-idealities of the analog building blocks on the quality of the classification and to determine the specifications of each building block. Thanks to the HCMOS9A 130 nm

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STMicroelectronics technology [12], we create non-ideal multiplier, activation function and its derivative blocks, under Simulink Matlab R2016a [19].

This paper is organized as follows. Section 2 highlights the Simulink implementation of the neural network. Ideal models of building blocks are created and simulated results are presented in Sect. 3. In Sect. 4, these models are modified in order to take into account the limitations of the CMOS analog implementation of these building blocks. Finally, conclusion and trends are given in Sect. 5.

2 Definition of cancer

All blocks of body were created from cells [20]. In normal case cells grow and divide to form new cells and when cells grow out of control will be a cancer. If these cells grow inside the breast form a tumor [21], and will be benign (not cancer) or malignant (cancer). From different parts of the breast, the breast cancers can begin [21].

3 Wisconsin breast cancer dataset

The Wisconsin Breast Cancer database [22] is located in the UCI Machine Learning Repository and it is applied in this research.

Breast-cancer-Wisconsin dataset has:

- 699 instances (Benign: 458 Malignant: 241).
- 9 integer-valued attributes.
- 2 classes: 212 malignant and 357 benign, or (65.5% malignant and 34.5% benign).
- Missing attribute values: none.

We can find also this database from the following link: <ftp.cs.wisc.edu/cd/math-prog/cpo-dataset/machine-learn/WDBC/>.

4 Dataset description [17]

The Wisconsin Breast Cancer dataset [17] is applied, to classify malignant (cancerous) from benign (non-cancerous) samples. A brief specification of this dataset

Table 1 Specification of the breast cancer dataset

Dataset	No. of attributes	No. of instances	No. of classes
Wisconsin breast cancer (original)	9	699	2

is presented in Table 1 [17]. The dataset consists of some classification patterns with a set of numerical attributes.

5 Data set information [17]

Dr. Wolberg reports his clinical cases periodically and grouping this dataset by recorded date. The detail of this dataset is listed in the following Table 2. Table 3 represents the 9 attributes with small description and will be 9 inputs to the neural network.

Classification is one of the most significant and fundamental tasks in neural network. Wisconsin breast cancer medical datasets used to classify breast cancer and will be the output of the neural network:

1. Benign or 0.
2. Malignant or 1.

Table 2 distribution of 699 instances

Group	Instance	Date
1	367	January 1989
2	70	October 1989
3	31	February 1990
4	17	April 1990
5	48	August 1990
6	49	Updated January 1991
7	31	June 1991
8	86	November 1991
Total	699	As of the donated database on 15 July 1992

Table 3 Wisconsin breast cancer dataset attributes

Id number	Attribute	Domain
1	Clump thickness	1–10
2	Uniformity of cell size	1–10
3	Uniformity of cell shape	1–10
4	Marginal adhesion	1–10
5	Single epithelial cell size	1–10
6	Bare nuclei	1–10
7	Bland chromatin	1–10
8	Normal nucleoli	1–10
9	Mitoses	1–10

6 Simulink neural network implementation

6.1 Feed forward neural network

The design of the Artificial Neural Network without Biases is presented in Fig. 1a and the equivalent scheme created in Simulink is shown in Fig. 1b.

The equations, without biases, for the hidden and the output layers are given by Eqs. (1) and (2).

$$a_j = g_j \left(\sum_{i=1}^9 w_{ij} * x_i \right) \quad j = 1, 2 \dots 10 \quad (1)$$

$$s_k = g_k \left(\sum_{j=1}^{10} w_{jk} * a_j \right) \quad k = 1, 2 \quad (2)$$

where x_i are the inputs (the 9 Cancer attributes of the Wisconsin Data Base), w_{ij} (or w_H) are the 90 coefficients

of the hidden layer, a_j are the 10 outputs of the hidden layer (i.e. the inputs of the output layer), w_{jk} (or w_O) are the 20 coefficients of the output layer and s_k are the 2 outputs of the neural network. g_j is the activation function of the hidden layer and g_k is the activation function of the output layer. A logsigmoid function was chosen as activation function for both hidden and output layers [18].

Due to the HCMOS9a technology and the power supply of the circuits (± 0.9 V [12]), we have chosen a dynamic of -0.9 to 0.9 for the coefficients (i.e. the weights, w_{ij} and w_{jk} , of the neurons). Our reference for breast cancer detection and classification are located in neural network toolbox of Matlab R2016a [19]:

1. Number of inputs equal to 9.
2. Number of outputs equal to 2 = Number of neurons in output layer.
3. Number of neurons in hidden layer equal to 10.
4. Number of samples equal to 699.

a Architecture of the Neural Network without Biases

b Feed-forward neural network

Fig. 1 **a** Architecture of the Neural Network without Biases, **b** feed-forward neural network

Fig. 2 Hidden layer details

5. Number of samples for learning process equal to 489.
6. Number of epochs equal to 14.
7. Learning rate equal to 0.25.

6.2 Memory package

Before starting the learning process in our model, we must initialize the weights in hidden layer w_H and the weights in output layer w_O (cf. Fig. 1b) by applying the random function that creates a random value between -0.9 and 0.9 . This value will be stored in the memories package w_H and w_O and will be used in the future as inputs for analog CMOS multiplier.

The “Read storage weights for output layer” block is used to read the weight’s values in output layer, and the “Read storage weights for hidden layer” block is used to read the weight’s values in hidden layer.

6.3 Hidden and output layers

The CancerTargets, the target output and the connection between hidden and output layers, are realized with Simulink routing [23]. We can find the Simulink method to build the artificial neural network in several papers for example the radial basis function RBF [24] or self-organizing map SOM artificial network [25].

Fig. 3 Single neuron

The details of “Hidden Layer” block in Fig. 1 are presented in Fig. 2.

We choose through the submatrix block the corresponding weights for each neuron and we find in Fig. 3 the details for each neuron block in Fig. 2 and equivalent to the equation:

$$a_j = \text{Logsig} \left(\sum_{i=1}^9 w_{ij} * x_i \right) \quad j = 1, 2 \dots 10 \quad (3)$$

The same for the output layer in Fig. 1b, the “Desired Output” block represents the target category, which is considered benign in element 1 and malignant in element 2 [23]. The “CancerInputs” block represents the nine attributes of 699 biopsies.

To separate the desired output 1 and desired output 2, the Demux block is used, and the “Subtract” block is used to generate the subtraction between the target outputs (1 or 2) and the neuron output (1 or 2).

Figure 4 shows the details of multiplication of inputs and weights values equivalent to the Eq. (4).

$$\sum_{i=1}^9 w_{ij} * x_i \quad j = 1, 2 \dots 10 \quad (4)$$

6.4 Back-propagation

To obtain the full design, depicted in Fig. 5, we add the back-propagation blocks and the feed-forward blocks.

Fig. 4 Cancer inputs and weights multiplication

Fig. 5 MLP neural network Simulink model

Fig. 6 Back-propagate error signals and update new values for weights

The equivalent architecture “Back-propagate error signals” block in Fig. 5 is shown in Fig. 6.

To calculate the local gradients of the output layer, δ_k , used in Fig. 6, the “Back-propagate error signal O” (cf. Fig. 5) is given by Eq. 5, and is then updated with the newest weight values through the “To store the new values for output neuron” block based in the Eq. 6 (cf. Fig. 6).

$$\delta_k = g'_k(z_k) E(d_k, S_k) \quad k = 1, 2 \quad (5)$$

$$w_{jk} = w_{jk} + \eta a_j \delta_k \quad j = 1, 2 \dots 10 \quad \text{and} \quad k = 1, 2 \quad (6)$$

To calculate the local gradients of the hidden layer, δ_j , used in Fig. 6, the “Back-propagate error signal H” is given by Eq. 7, and is then updated with the newest weight values through the “To store the new values for hidden weights” block based in the Eq. 8 (cf. Fig. 6).

$$\delta_j = g'_j(z_j) \sum_{k=1}^2 \delta_k w_{jk} \quad j = 1, 2 \dots 10 \quad k = 1, 2 \quad (7)$$

$$w_{ij} = w_{ij} + \eta a_i \delta_j \quad i = 1, 2 \dots 9 \quad \text{and} \quad j = 1, 2 \dots 10 \quad (8)$$

7 Simulation and results

7.1 Signals generator

Design and analysis of analog implementation are the main objectives of this work, but before opening the model, a small program written in MATLAB generate signals and determine the times for stopping the learning and beginning the testing. This program is based on the following organization chart:

A similar organization chart was used to create signals generator and successfully tested by using the Microcontroller PIC18F2680 through software PIC C and Proteus 4.8 SF0 Pro [26], the unit time can be 0.1 μ S, 1 μ S,...1 s depending on the application used.

Fig. 7 Nine attributes signals

The duration time for learning phase and testing phase was calculated during running the small program that launch the model and it's equal respectively to $tL = m * n$ [0 to $m * n - 1$] and $tT = [0 + m * n$ to $m * n + tT - 1]$.

Two switches block determine the end of the learning phases and the beginning of the testing phase, through the variable tL , for example when not achieved this value during running the model, we still in learning phase.

During each unit time and during the learning phase the first switch lets the model read the weights (memories block) from the hidden layer during the first half of unit time and write the updated weights during the second half and at the end of the learning time. At the beginning of the testing phase, this switch lets the model read only from the memories block (weights in Hidden layer).

The same procedure for the second switch for the Output layer.

7.2 Artificial neural network signals

Before running the design shown in Fig. 5, we must use the following variables as [18]:

- Number of sample $NS = 489$
- Number of epochs = 14
- Learning rate = 0.25.

The needed times for learning and testing phases in our model are equal to $6845 \mu s$ (i.e. $489 * 14 \mu s$) and $7545 \mu s$ (i.e. $6845 + 699 \mu s$) respectively.

Figure 7 below shows the nine attributes signals of 699 biopsies as CancerInputs. These values, initially between 1 and 10 in the database, are converted first into 0.1 to 1 for Matlab Simulink and into 10 mV to 100 mV for the analog implementation.

After executing the structure (see Fig. 5), we have the following results:

- The desired output curves for the first category (benign) and the neuron output in Fig. 8
- The desired output curves for the second category (malignant) and the neuron output in Fig. 9
- The updated weight values curve in hidden layer in Fig. 10
- The updated weight values curve in output layer in Fig. 11

Figures 8 and 9 are certainly difficult to interpret as is, but serve only as illustration. To facilitate the analysis of these curves, we have added a comparison block, presented in the next section (cf. Fig. 12). Much more interesting, Figs. 10 and 11 present the evolution of the weights in the hidden layer and that of the exit. Let us remind that these weights are 90 in the hidden layer, which is constituted by 10 neurons

Fig. 8 First category as benign and the output produced by the neural networks

Fig. 9 Second category as malignant and the output produced by the neural networks

having each 9 inputs (9 attributes of every biopsy presented in Fig. 7). They are 20 in the output layer.

On Figs. 10 and 11, we can notice that at the end of 6845 μ s (learning phase), the weights do not vary any more.

7.3 Classification results

The diagram illustrated in Fig. 12, was created to obtain the number of wrong answers produced by the neural network and the equivalent percentage shown in Fig. 13. Thanks to the structure of comparison, the number of error

and thus its percentage can be calculated and offer a result easier to interpret.

As a result, we can obtain the difference between the desired output and the output created by the neural network for the first category and the second category in the upper and lower curves respectively in Fig. 13. On this figure, one 1 means the presence of a cell corresponding to its class of origin (benign for the output 1 and malignant for the output 2). For reading reasons, we printed only a part of the phase of test (upper time in 6845 μ s). Although this figure is easier to interpret than the results illustrated by Figs. 8 and 9, the matrix of

Fig. 10 Variations of weights in hidden layer

Fig. 11 Variations of weights in output layer

confusion, presented in Fig. 14, is a much simpler and more visual tool to analyse the quality of the artificial neural network.

This final result giving a total error of 2.6% was obtained with ideal blocks: multipliers, logsigmoid function and its derivative as activation function. This result serves as a reference for the following studies.

8 Non-idealities implementation

8.1 Introduction

In order to determine the influence on the non-idealities of these building blocks on the quality of the classification, we have to take into account their limitations and

Fig. 12 Calculation of wrong answers of neural networks

Fig. 13 Difference between the desired output and the output created by the neural network

drawbacks. This study will allow us to determine some specifications of these circuits.

8.2 Creating a non-ideal multiplier block

Two characteristics of the multiplier will be extracted from this study: dynamics and noise. The dynamics will be given

by the extreme values of the weights (inputs) and the noise by the influence of their accuracy.

We add a random error to the multiplier block to obtain the influence of the non-ideal multiplier block on the number of wrong answers of our neural network. Figure 15 shows the diagram of this non-ideal multiplier.

Output Class	1	2	
	1	2	
1	446 63.8%	6 0.9%	98.7% 1.3%
2	12 1.7%	235 33.6%	95.1% 4.9%
	97.4% 2.6%	97.5% 2.5%	97.4% 2.6%

Fig. 14 Matrix of confusion with ideal building blocks

Fig. 15 Non-ideal multiplier

For example, if we choose $V1 = 3$ and $V2 = 2$, we obtain the result of $V0$ presented in Fig. 15 for “noisy” multiplier. The ideal value has to be equal to 6, which is the mean value of the signal presented in Fig. 16. The aim of the following study is to determine the maximum amplitude of this random generator (i.e. the maximum input noise of the multiplier) which offers a suitable error of the classification.

By replacing the ideal multiplier block with another noisy block in the Simulink model, we create an error in the multiplier block and in the derivative function at the same time. In fact, the activation function $f(x)$ is the log-sigmoid and its derivative is equal to $f(x) * (1 - f(x))$. For this reason, we changed at the same time the multiplier and the derivative function.

We made a series of simulations where the maximal value of the “noise” increases in relative value compared

with the inputs of the multiplier. The results are summarized in the Table 4 below. The first line, with 0% of error, corresponds to the ideal case the results of which were presented previously, with a total error of 2.6%.

The variables $er1$ and $er2$ (the first 2 columns) represent the percentages of error range between two values added to the multiplier block. The next two columns provide the total number of errors during the classification on the 699 biopsies and the corresponding percentage respectively. So, 18 total errors (cf. first line with $er1 = er2 = 0\%$, 12 errors for the benign class and 6 errors for the malignant class as shown in the confusion matrix, cf. Fig. 14) give a percentage error of $18/699 = 2.6\%$. wH and wO represent the extreme values (minimum and maximum) of the weights for hidden and output layers.

These results show that an error lower than 10% on the input of the multiplier, and so on the value of the weights, does not modify the quality of the classification; 20% with a final error of 3.3% (compared with 2.6%) and 50% (with an error of 6.2%) can also suit our application. Moreover, the worst case gives a dynamic (extreme values) of $[-3.8; 3.5]$. If we consider a scale of 5 mV for a weight of 0.01, a weight of 3.8 will be corresponding to a voltage of 760 mV. A final input dynamic of the multiplier, equals to ± 800 mV, will be enough and easily to achieve with the HCMOS9A 130 nm technology and a power supply of ± 900 mV [12]. Also, a maximum input noise of the multiplier of 80 mV (10% of error) is not a difficult constraint.

8.3 Create a non-ideal log-sigmoid block

By using the same previous approach, we add an error to the real log-sigmoid block presented in Fig. 17 below.

By changing the ideal logsigmoid block with another non-ideal logsigmoid block, we obtain the results presented in Table 2.

As we see in Table 5, the maximum acceptable error varies between -20 and 20% to keep the number of errors in the classification at lower value, so the activation function is very sensitive to the result of neural network.

The final step is to change the real multiplier, activation function and its derivative by other non-ideal blocks at the same time; this produces the results presented in Tables 6 and 7. Table 3 shows that the maximum acceptable range for the multiplier block is from -50 to 50% when the error range for the log-sigmoid block varies between -10 and 10% .

Table 7 shows that the maximum acceptable range for the multiplier block is from -20 to 20% when the error range for the logsigmoid block varies between -20 and 20% .

Fig. 16 Results of multiplication of 3 and 2 with the noisy multiplier

Table 4 The non-ideal multiplier and non-ideal derivative function blocks

er1 (%)	er2 (%)	Nb errors	% Error	Extreme values: wH	Extreme values: wO
0	0	18	2.6	-1.37 → 1.17	-3.54 → 3.48
-10	10	19	2.7	-1.6 → 1.4	-3.8 → 3.5
-20	20	23	3.3	-1.7 → 1.2	-3.2 → 3.8
-30	30	26	3.7	-1.7 → 1.2	-3 → 3
-40	40	31	4.3	-1.7 → 1.5	-3 → 3.2
-50	50	43	6.2	-1.7 → 1.2	-3 → 2.8
-60	60	68	9.7	-1.7 → 1.3	-3 → 2.8
-70	70	77	11.0	-1.8 → 1.6	-2.8 → 3
-80	80	86	12.3	-2.5 → 1.8	-2.5 → 3.1
-90	90	92	13.6	-2.4 → 1.8	-2.7 → 2.5
-100	100	98	14.0	-2.8 → 1.8	-2.7 → 2.5

Fig. 17 Non-ideal log-sigmoid block

9 Results analysis

In analog CMOS circuits we can't find, create or fabricate an ideal multiplier or an ideal activation function. For this reason, a non-ideal multiplier and a non-ideal log-sigmoid were designed to verify the acceptable range to be used in the analog CMOS circuits.

wH and wO represent respectively the weights in Hidden and Output layers and these weights change during the learning phase. In software world no limits for range contrary to CMOS world where this range varies from circuit to another.

From Table 4 we can deduce that in CMOS world for example:

Table 5 The non-ideal logsigmoid block

er3 (%)	er4 (%)	Nb errors	% Error	Extreme values: wH	Extreme values: wO
– 10	10	24	3.4	– 1.6 → 1.4	– 3.2 → 3.8
– 20	20	49	7.0	– 1.7 → 1.2	– 4 → 6.2
– 25	25	241	34.5	– 1.7 → 1.2	– 4 → 16

Table 6 Error changes between – 10% and 10% for logsigmoid block

er1 (%)	er2 (%)	er3 (%)	er4 (%)	Nb errors	% Error	Extreme wH	Extreme wO
– 10	10	– 10	10	22	3.1	– 1.6 → 1.2	– 3.9 → 4.1
– 20	20	– 10	10	24	3.4	– 1.6 → 1.3	– 3.6 → 3.6
– 30	30	– 10	10	28	4.0	– 1.4 → 1.5	– 3 → 3
– 40	40	– 10	10	30	4.3	– 1.6 → 1.0	– 4 → 3.4
– 50	50	– 10	10	38	5.4	– 1.7 → 1.5	– 3.2 → 3.4
– 60	60	– 10	10	241	34.5	– 5.2 → 6.5	– 6 → 48

Table 7 Error changes between – 20% and 20% for logsigmoid block

er1 (%)	er2 (%)	er3 (%)1	er4 (%)	Nb errors	% Error	Extreme wH	Extreme wO
– 10	10	– 20	20	48	6.9	– 2.2 → 1.2	– 4 → 6.2
– 20	20	– 20	20	241	34.5	– 2.1 → 2.3	– 3.8 → 11

Case 2 (row 2) when we have an error between – 10 and +10% applied to the multiplier the extreme values for wH and wO respectively will be – 160 mV → 140 mV and – 380 mV → 350 mV.

The same for the activation function for example from Table 5:

Case 2 (row 2) when we have an error between – 20 and + 20% applied to the log-sigmoid the extreme values for wH and wO respectively will be – 170 mV → 120 mV and – 400 mV → 620 mV.

When we choose the blocks together and from Table 7:

Case 1 (row 1) when we have an error between – 10 and + 10% applied to the multiplier and when we have an error between – 20 and + 20% applied to the log-sigmoid, the extreme values for wH and wO respectively will be – 220 mV → 120 mV and – 400 mV → 620 mV.

These results show that a ± 800 mV input dynamics of the multiplier is sufficient, since it gives a very high sensitivity of 5 mV for a 0.01 accuracy of the coefficients (i.e. weights of the neurons), well beyond than we need. Likewise, an error of 10% (or 20%) on these inputs corresponds to an input noise of the multiplier of 80 mV (or 160 mV respectively). These specifications will be very easy to perform with the chosen 130 nm CMOS HCMOS9A technology and with a power supply of the electronics of ± 900 mV [12].

In addition, to simplify the final realization of the artificial neural network, we chose a current output of the multipliers. Thus, the addition of multipliers' outputs is realized by using simply the Kirchhoff law for feeding the activation function. The constraints of this latter are not in

voltage but in current; its dynamics will therefore depend on the realization of the multiplier with however a noise constraint which not exceed 10% of the value.

10 Conclusion

After creation and simulation for different errors on the non-ideal blocks for the multiplier, activation function and its derivative, this procedure gives us information about the acceptable error when we want to create a neural network by using the analog CMOS circuits.

From this study, we conclude that the activation function log-sigmoid block is very sensitive to the wrong answer for the classification of breast cancer detection.

In future projects, we will try to build the activation function log-sigmoid by using the analog CMOS circuit, taking into consideration the maximum acceptable range for this block.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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