FPGA implementation of EEG signal analysis system for the detection of epileptic seizure

Conference Paper · March 2018

DOI: 10.1109/ASET.2018.8379892

4 authors, including:

Afef Saidi
ENICarthage

Slim Ben Othman
University of Carthage

Slim Ben Saoud
University of Carthage

FPGA Implementation of EEG Signal Analysis System for the Detection of Epileptic Seizure

Afef SAIDI, Slim BEN OTHMAN, Wafa KACEM*, Slim Ben Saoud
Advanced Systems Lab - Tunisia Polytechnic School, University of Carthage, BP 743 - 2078 - La Marsa, Tunisia
* Faculty of Medicine of Tunis, University of Tunis El Manar, Campus UFH, BP 94, Tunisia
saidi.afef1986@gmail.com, Slim.benothman@ept.rnu.tn, wafa.riahi.kacem@gmail.com, slim.bensaoud@gmail.com

***Abstract*—Epilepsy is a neurological disorder identified by successive sudden seizures resulting from transient and recurrent electrical discharges in the brain. Their detection is possible by analyzing electroencephalogram (EEG) signals. EEG is the commonly used clinical tool for neurological disorders due to the valuable information that contains about brain activities. The work presented in this paper is oriented towards two parts. A first part is dedicated to the description and the validation of our detection system using the classification algorithm, AntMiner+. The second part focuses on the design and the implementation of our application on the Xilinx ZC702 embedded board.**

Keywords—Epilepsy, EEG, DWT, AntMiner+, Implementation, Embedded Board.

I. INTRODUCTION

EPILEPSY is a neurological disease with prevalence of about 1% of the world's population. This disease is caused due to abnormal electrical activity in the brain. In the EEG recordings of epileptic patient, we can distinguish two categories of abnormal activity: (i) interictal (between seizures) and (ii) ictal (during a seizure).The detection of epileptic seizures remains a challenge even for a proficient neurologist who relies on visual scanning of EEG recordings and on clinical manifestations.

There are commonly five sub-bands on the EEG signal: delta (0–4 Hz), theta (4–8 Hz), alpha (8–15 Hz), beta (15–30 Hz), and gamma (30–60 Hz). These individual frequency sub-bands may better represent brain dynamics than the EEG signal itself. Indeed, they contain more precise information on the neuronal activities and raise some alterations that do not appear in the raw EEG [1].

In recent years, researches on the automatic EEG Signal Analysis System for the Detection of Epileptic Seizure have progressed in two main directions [2]: inter ictal spike detection and epileptic seizure analysis. In our work, we are interested in the last topic.

In this paper, we propose an implementation model of automated system analysis and classification for efficient and fast epileptic seizure detection in EEG signal. Our approach is built around three main stages: (a) filtering operation by FIR filter, (b) feature extraction based on discrete wavelet transform (DWT) and (c) classification by AntMiner+ algorithm. An all Programmable SoC (AP-SoC) implementation are discussed for the EEG feature extraction and seizure detection application.

The rest of this paper is organized as follows. A related works for epileptic seizure detection in EEG is surveyed in section II. Section III explains our proposed method. In section IV, the system design and its implementation is presented. Section V presents our implementation results and analysis. A conclusion of this paper is given in section VI.

II. RELATED WORKS

Most automated seizure detection methods share some common steps: (1) feature extraction and (2) classification.

In literature, feature extraction techniques for EEG signals classification are performed considering either time domain, frequency domain, or wavelet-based domain. Runarsson and Sigurdsson [3] presented a method of detecting epileptic seizures based on peak and minima tracking in the EEG signal. These features are used for the SVM classifier and have reached an accuracy of about 90%. Abdulhamit Subasi et al. [4] examined the use of the autoregressive model (AR) by using artificial neural network for automatic classification of epileptic seizures. Following the use of FFT as preprocessing in the neural network, a classification average of 91% is reached. M. Akin et al. [5] used the wavelet transform of EEG signals to develop an artificial neural network. The accuracy obtained at the outputs of the neural network was too high (97% for cases of epilepsy, 98% for healthy cases).

Assuming that the features extracted are suitable for distinguishing between non-seizure and seizure EEG states, the information is used to decide the class to which the features belong to. A decision-making stage and classification of the data in the feature space are thus required. The classification aims to build a boundary between classes that will be labeled based on their measured features. Several classification techniques have been developed among them SVM (Support Vector Machine) [6], ANN [7], Decision Tree [8], Naive Bayes [9], LDA (Linear Discriminant Analysis) [10] and Ant Colony Classifier [11].

III. PROPOSED METHOD

In order to ensure the automatic detection of epilepsy, the recorded EEG signals in patient undergo several phases of digital treatments. These will be the functional blocks of our system as shown in Fig.1.

978-1-5386-4449-2/18/$31.00 ©2018 IEEE.

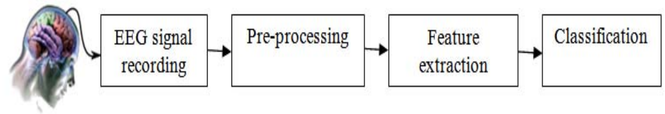

Fig. 1. Functional blocks of the detection system

A. *EEG signal recording*

The main EEG Data used for this work is selected from the database "CHB-MIT" [12]. The data consists of an EEG recording of 23 pediatric patients at Children's Hospital Boston (CHB). In these dataset the electrodes were placed according to the international system "10-20" and generally represent 23 electrodes. Sampling frequency of the data used is 256 Hz.

Another EEG data is considered as validation sources. It consists of EEG recordings made in the neurology department of the Military Hospital of Tunis. The EEG signals from this database are acquired from unipolar montage using 32 electrodes. The signals were sampled at a frequency of 250 Hz.

B. *Data preprocessing*

Wavelet decomposition needs additional processing to extract specific frequency bands of EEG signal. The frequency range of the five EEG sub-bands is delimited between 0-60 Hz and higher frequencies are considered as noise. Therefore, to obtain more easily the frequency sub-bands of the EEG during the wavelet analysis, the EEG is band-limited to 0–64Hz range by convolving with a low-pass finite impulse response (FIR) filter, and then a wavelet filter is employed in order to extract each EEG sub-bands.

Discrete Wavelet Transform (DWT) uses multilevel decomposition in order to convert the EEG signal into finer details. It allows finding the instant of any brusque change. The concept of this wavelet analysis is the decomposition of the signal into two parts: approximations and details.

In this work, we used the Daubechies 4 wavelet transform (db4) to decompose the EEG signals into four levels. This wavelet decomposition yields five groups of wavelet coefficients (A4, D4, D3, D2 and D1) which correspond respectively to the brainwaves: delta (0-4 Hz), theta (4-8 Hz), alpha (8-15 Hz), beta (15-30 Hz) and gamma (30-60 Hz) as shown in Fig. 2.

This decomposition process is based on the successive application of high pass filter (HPF) and low pass filter (LPF). These two filters calculate at each level the wavelet coefficients (details and approximations). To keep the same number of output and input samples, the product of convolution from the filters is down-sampled by a factor of 2. Only the output of the low pass filter, namely the approximation coefficients, is again processed by the two filters.

This procedure is repeated until the specified decomposition level using the following equations:

$$LP(S) = A_{\,j} = \sum_{k} S(k)h(2j-k) \tag{1}$$

$$HP(S) = D_{\,j} = \sum_{k} S(k)g(2j-k) \tag{2}$$

Where :

- *j*: decomposition level.
- *S (k)*: input signal.
- *A1j/D1j*: wavelet coefficients.
- *HP/ LP* : high/ low-pass filter output.
- h/g : filters coefficients.

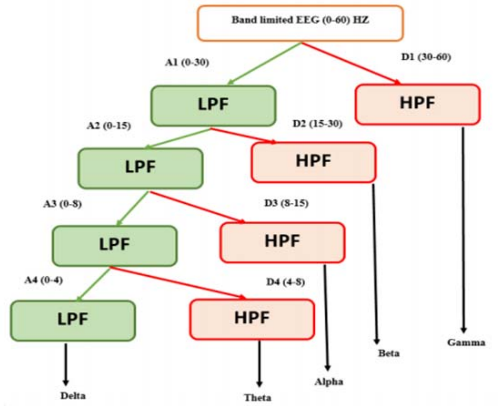

Fig. 2. Wavelet decomposition (db4) of EEG signal

C. *Feature extraction*

In this step, the extracted features are:

(i) Statistic features from the filtered EEG signal (maximum amplitude, minimum amplitude, standard deviation and mean)

(ii) The energy percentages of wavelet details and approximation coefficients. Wavelet energy is calculated using following equations:

$$ED_i = \sum_{j=1}^{N} |D_{ij}|^2 \quad i = 1, 2, \ldots, l \tag{3}$$

$$EA_i = \sum_{j=1}^{N} |A_{ij}|^2 \quad i = 1, 2, \ldots, l \tag{4}$$

Where :

- l: Decomposition level.
- N: Number of detail or approximation coefficients in each level.

D. *Classification*

Classification algorithm uses last extracted features as input, and then it derives classification rules corresponding to the patient state (normal or epileptic). In our work we used AntMiner+ algorithm which is based on the principles of Ant Colony Optimization (ACO) [13].

ACO is a branch of artificial intelligence called swarm intelligence. It is inspired from the behavior of ants by searching for the shortest path between their colony and a food source. These ants communicate with each other by means of a chemical substance called pheromone.

Recently, several works have been made to apply ACO for discovering classification rules. Parpinelli proposed the first ant colony algorithm for this purpose named AntMiner+ [14].

The basic idea of the algorithm is to incrementally construct classification rules from data. The decision list resulting from this algorithm takes the following form: IF (term1) AND (term2) AND ... AND (termn) THEN (class). Each term represents a triple < attribute, operator, value >.

Each rule contains the IF part as the antecedent rule and the THEN part as the predicted class [13, 15]. A preprocessing step for continuous attributes is needed using discretization [16].

In our case study, we have constructed a database named "patient" from 989 EEG signal dataset of normal and epileptic patients. The considered attributes represent the following extracted features: Maximum amplitude (Max), Minimum amplitude (Min), standard deviation (STD), mean (Moy), energy ratio of the approximation coefficients at level 4 (EA4), energy ratio of the details coefficients (ED1, ED2, ED3, ED4). Class attributes for this database are: Normal patient and Abnormal patient.

With "patient" database as input to Ant Miner+, we have succeeded to derive the classification rules with an accuracy of 98.9%.

IV. System Design and Implementation

We implemented our epileptic seizure detection system in the ZC702 XLINX board based on Zynq FPGA which provides an AP-SoC development environment. The Zynq are among the newest FPGA devices. It has two main parts: Programmable Logic (PL) and a complete ARM Processing System with its peripherals (PS).

The development of this project is done in two stages. The first is hardware development using Xilinx Vivado in order to define hardware architecture using the logical elements offered by the board and the FPGA. The second step is the software development using Xilinx SDK and C language in order to define the processor program.

A. Hardware design

In this part, we need to configure the PL part of the Zynq ZC702. The design block is shown in Fig. 3. It encloses the PS configurations and the associated hardware components required for the application.

The design architecture is centered on the ARM processor to which we associate the following interfaces:

- Memory interface. It allows the PS part to control the DDR3 (1GB) memory (which will be used for the storage of the application program and data),
- MIO (Multiple input/Output). It involves interfacing LEDs and push buttons with the processor, as well as a UART block (for serial communication with computer),
- Clock block. It is used to supply the PS part and the AXI bus from a system clock.

At this stage we achieved hardware design. Vivado performs the synthesis process and generates the corresponding bitstream that will be implemented on the board.

A. Software design

After exporting the hardware design to SDK, we started working on the software part. This step consists of developing an optimized C language application for the previously described epileptic seizure detection system.

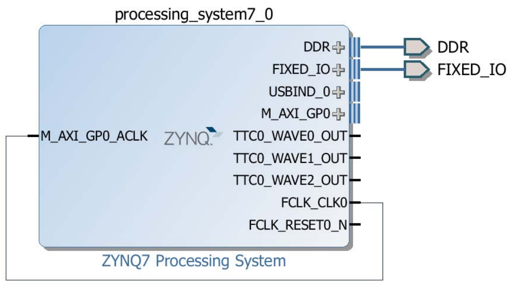

Fig. 3. Block design created on Vivado

The main structure of our program is illustrated by the following flowchart shown in Fig. 4.

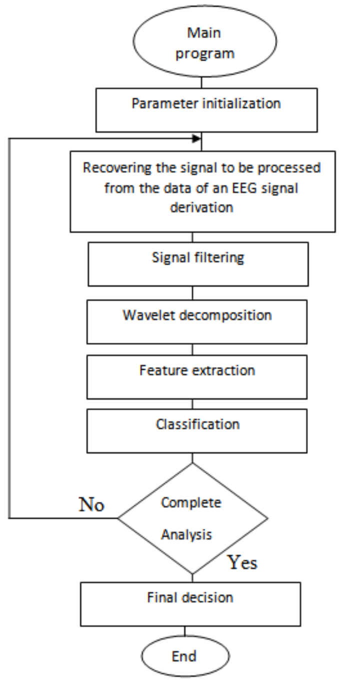

Fig. 4. Flowchart of the main code of our program

We notice that before implement the application code, a further work on Matlab was developed to prepare EEG datasets, design the filters and lead to the classifier rule list.

The filtering part of our C code is based on the digital implementation of a FIR filter and inspired by the principle of the Filtfilt function on Matlab. The basic of this algorithm is given in Fig. 5.

As mentioned in Section 3, wavelet decomposition used the Daubechies 4 which decomposes the data of EEG signal derivation in 4 levels. The output of this decomposition results in five vectors one for the approximation coefficients and four for the detail coefficients corresponding respectively to the five frequency bands of the EEG signal: Delta, Theta, Alpha, Beta, and Gamma. The complete procedure is described by the algorithm on Fig. 6.

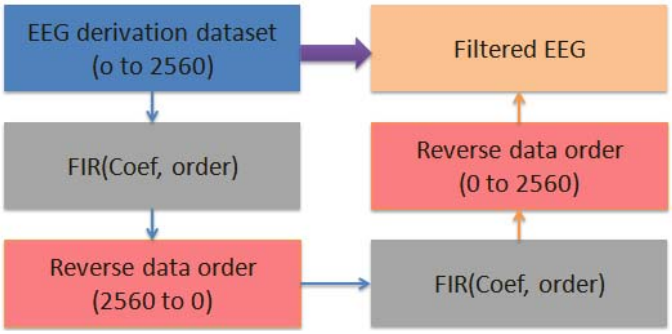

Fig. 5. Implemented EEG Data filtering approach

Input data:

- **Deriv_F** : table containing dataset of filtered derivation EEG signal,
- **hpd** : table of high pass filter coefficients,
- **lpd** : table of low pass filter coefficients,

Sub-functions:

- **FPH()**, **FPB()** : FIR functions of respectively the high pass and low pass filters,

Output data:

- **D1**, **D2**, **D3**, **D4** and **A4**: tables containing the approximation and details coefficients.

Algorithm:

```
: For i =1 to 4 do
:         D[i] = FPH (Deriv_F, hpd)
:         Ap = FPB(Deriv_F, lpd)
:         Deriv_F = Ap
: End For
: D1 = D[1]
: D2 = D[2]
: D3 = D[3]
: D4 = D[4]
: A4 = Ap
: End
```

Fig. 6. Daubechies 4 DWT algorithm

In the feature extraction step, our program first extract statistical features from a filtered derivation EEG signal using simple macro code of max(), min(), mean() and STD(). Obtained values are used later by the classifier model to make a decision about the class of the patient. The program then proceeds to compute energy ratios of details and approximation coefficients by following the procedure described in Fig. 7.

A final step in the computation loop of each derivation on the EEG recordings is the classification function. It consists of applying the decision rule obtained by the AntMiner+ algorithm. The details of this procedure are presented in Fig. 8 and the classification rules are described by Fig. 9.

System analysis is complete when the program achieves decisions of all the derivations on EEG recordings. The final decision on the health state of the patient is made taking into account the intermediate decision results obtained for each derivation of the EEG signal. A patient is epileptic if there is at least one derivation for which the analysis results to an "abnormal" class.

Input data:

- **D1**, **D2**, **D3**, **D4** and **A4**: tables containing the approximation and details coefficients.

Output data:

- **ED1**, **ED2**, **ED3**, **ED4** and **EA4**: Energy ratios of details and approximation coefficients.

Algorithm:

```
: Compute ed1, ed2, ed3, ed4, the details
  coefficients energies using equation (3)
: Compute ea4, the approximation
  coefficient energy using equation (4)
: Tot_Energy = ed1 + ed2 + ed3 +ed4 + ea4
: EDi = 100 * edi / Tot_Energy; (i= 1 to 4)
: EA4 = 100 * edi / Tot_Energy
: End
```

Fig. 7. Energy ratios computing algorithm

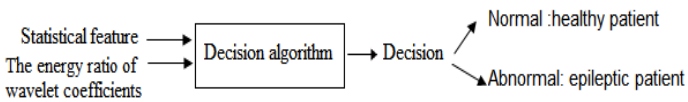

Fig. 8. Classifier block function

Input data:

- **Max**, **Min**, **Mean** and **STD**: Extracted statistical features.
- **ED1**, **ED2**, **ED3**, **ED4** and **EA4**: Energy ratios of details and approximation coefficients.

Output data:

- **Decision** : patient class from EEG derivation

Algorithm:

```
: if  EA4 ≥ 96, 35   then
:          Decision = Normal patient
: else if  (Min ≥ -185, 7) and
:         (STD ≤ 59, 35) and
:         (ED2 ≤ 19, 95) then
:          Decision = Normal patient
: else if  (Max ≥ 200, 4) and
:         (STD ≤ 59, 35) and
:         (ED2 ≤ 19, 95) then
:          Decision = Normal patient
: else if
:          Decision = Abnormal patient
: end if
```

Fig. 9. AntMiner+ classifier model

B. Architecture optimization

The most important thing to optimize in our architecture is the memory occupation either for data or program. The development board used for this project has a memory of 1Gbyte but this is not the case for the majority of embedded boards. In this part, we propose to optimize the memory occupation of our code by partitioning the EEG signal. This solution consists in applying to each derivation of the EEG signal the filtering at the beginning and then divides the filtered signal into four parts as shown in Fig. 10.

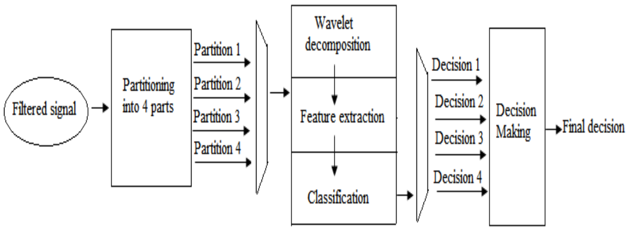

Fig. 10. The optimized solution

The final decision for the condition of the patient per EEG derivation is taken considering the different results obtained for each partition (Decision 1, ..., Decision 4). For a normal patient, we must have for all 4 partitions the "normal" result. While for an epileptic patient it suffices to have only one partition giving an "abnormal" result to conclude that this patient is epileptic.

V. Implementation Results

A. Architecture performances

This section presents the implementation results of our proposed approach for epileptic seizure detection system. Table 1 gives implementation results of our architecture from design tools report generation. Proposed architecture used only a small portion of FPGA resources: a single core of the ARM processor and only 0.16 % of hardware resources. So, it is clear that we will be able to leverage other available resources to move to real-time processing of measurements. This allows us to optimize the performance of our solution and implement additional features to the software part (e.g. hardware accelerator).

TABLE I. Zynq ZC702 device utilization summary

Used resource	Use	Percentage of use
LUT as Logic	89	0.16%
LUT as Memory	0	0%
Core of the ARM processor	1	50%

Afterward, when executing our program on the Zynq ZC702 board, we noticed problems related to the use of memory each time our program attempts to dynamically allocate tables. To overcome this problem, in non-optimized architecture, we are strained to overcome heap section on memory to 7000 bytes. Table 2 shows a comparison of the memory occupation between the first architecture and the optimized one. With the optimized solution, the memory occupation is reduced to 37.7% (vs 38.5% with the non-optimized code) and the application requires less than 1000 bytes on the heap section to execute properly.

TABLE II. Program and data memory occupation

	Memory Occupation (bytes) *Non-optimized code*	Memory Occupation (bytes) *Optimized code*
DATA section	2264	2270
TEXT section	299840	299840
BSS section	101580	93900
HEAP section	7000	1000
Occupancy rate of DDR3 memory	38.5%	37.7%

B. Experimental results

In this section, we display the experimental results of different parts of our proposed approach. A result example of the execution of the filtering function is presented in Fig.11. Spectral analysis of filtered output signal proves that EEG signal is restricted the in the desired frequency band (0-64 Hz).

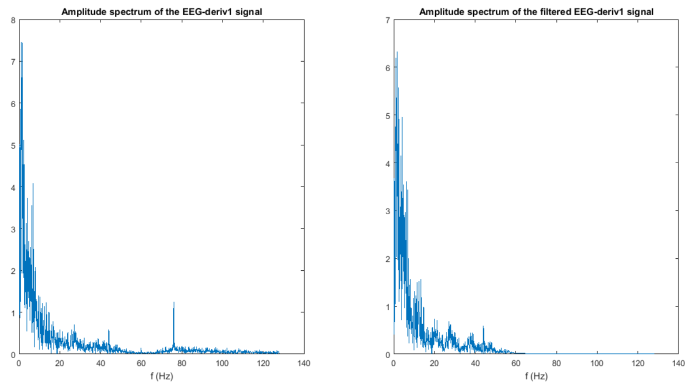

Fig. 11. Filter result

Subsequently, the wavelet decomposition method (db4) allowed us to recover the 5 sub-bands from the filtered EEG signals. DWT results give a better exploration of useful information present in these sub-bands that can't be seen in the raw EEG signal. Therefore, it makes it easier to distinguish between epileptic and normal subject. Fig.12 and Fig.13 illustrates the results of the db4 decomposition for one EEG derivation signal respectively from normal and epileptic subject.

The filtered EEG signals and their sub-bands are used for features extraction process. All intermediate results of our program execution (filtered signals, dwt outputs, statistical features, energy ratios, etc.) are compared with Matlab implementation. We obtained a similarity of all results with a single data representation.

The classification model executed by our embedded program consists of a rules list generated by AntMiner+ classifier running on Matlab. An accuracy of 98.9% is obtained for this model by deploying a set of parameters shown in Table 3. This table depicts also the runtime statistics of the AntMiner+ algorithm to achieve the rues list.

The final rule list achieved by the learning algorithm defines the range of values from extracted EEG characteristics corresponding to a normal class decision.

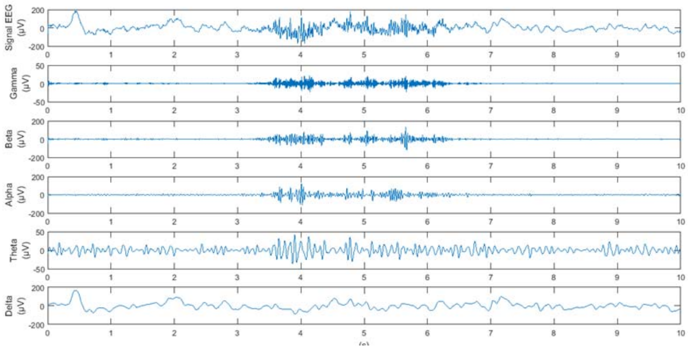

Fig. 12. Result of db4 decomposition of an EEG signal for normal subject

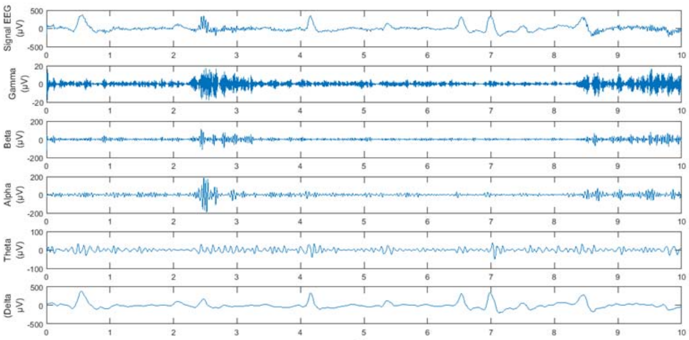

Fig. 13. Result of db4 decomposition of an EEG signal for epileptic subject

TABLE III. ANTMINER+ PARAMETERS AND STATISTICS

Dataset Description	***Size DataSet***	989
	Size Training	309
	Size Validation	231
	Size Test	287
	Ordinal Variables	9
Algorithm statistic	***Accuracy***	98.9%
	Rules number	3
	Total execution time (s)	39.5
	Number of iterations	49

Consequently, an EEG signal is considered as abnormal when its features fall outside the normal range. Fig. 14 gives the range of normal EEG. Limit bands in this figure are used by the classifier model (Fig. 9) of our program to detect epileptic or non-epileptic patient.

- **EA4** ≥ 96, 35
- (**Min** ≥ -185, 7) *and* (**STD** ≤ 59, 35) *and* (**ED2** ≤ 19, 95)
- (**Max** ≥ 200, 4) *and* (**STD** ≤ 59, 35) *and* (**ED2** ≤ 19, 95)

Fig.14. Range of normal EEG

Afterward, the performance of our proposed approach was evaluated using samples of epileptic and normal patient. All experimental tests on our embedded architecture were successful and give the right decision of patient classes. In case of epileptic class, the program is capable to determine which derivations are sources of epileptic seizure.

VI. CONCLUSION

The main contributions of this paper are the study of a functional description of EEG signal analysis system for epileptic seizure detection, the proposal of a classification model using the classification algorithm AntMiner+ and its implementation on an embedded board.

A software optimization solution has been proposed so that our application can be implemented on other less efficient embedded devices.

To improve this implemented system, we propose the implementation of more complex and sophisticated classification methods like ANN or SVM.

REFERENCES

[1] H. Adeli, M. IEEE, S. Ghosh-Dastida and N. Dadmehr, "A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Subbands to Detect Seizure and Epilepsy," *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING,* vol. 54, FEBRUARY 2007.

[2] A. T. Tzallas, M. G. Tsipouras, D. G. Tsalikakis, E. C. Karvounis, L. Astrakas, S. Konitsiotis and M. Tzaphlidou, "Automated Epileptic Seizure Detection Methods: A Review Study", 2012.

[3] S. S. TP Runarsson, "On-line detection of patient specific neonatal seizures using support vector machines and half-wave attribute histograms," *IEEE Xplore,* december 2005.

[4] S. Abdulhamit, K. M Kemal, A. Ahmet and K. Etem, "Neural Network Classification Of EEG Signals By Using AR With MLE Preprocessing For Epileptic Seizure Detection," *Journal of Mathematical and Computational Applications,* vol. 10, pp. 57-70, 2005.

[5] M. Akin, M. Arserim, M. Kiymik and I. Turkoglu, "A New Approach for Diagnosing Epilepsy by using Wavelet Transform and Neural Networks," *IEEE,* 07 November 2002.

[6] S. Abdulhamit, K. Jasmin et A. C. M, «Epileptic seizure detection using hybrid machine learning methods,» *Neural Computing and Applications,* April 2017.

[7] S. Talathi, «Deep Recurrent Neural Networks for seizure detection and early seizure detection system,» 13 June 2017.

[8] L. Ying-Fang et C. Hsiu-Sen, «Automatic Detection of Epileptic Seizures in EEG Using Machine Learning Methods,» *WSEAS TRANSACTIONS on BIOLOGY and BIOMEDICINE ,* vol. 14, 2017.

[9] P. Geethanjali et A. Sharmila, «DWT Based Detection of Epileptic Seizure From EEG Signals Using Naive Bayes and k-NN Classifiers,» *IEEE Access,* vol. 4, 30 June 2016

[10] U. K. Yusuf, R. Nidal et F. Omar, «Automated Seizure Detection in Scalp EEG Using Multiple Wavelet Scales,» *IEEE International Conference on Signal Processing, Computing and Control,* 2012.

[11] S. Osman, N. Amal et M. Ahmed, «Epileptic Seizure Detection From EEG Signal Using Discrete Wavelet Transform and Ant Colony Classifier,» *IEEE International Conference on Communications,* 2014.

[12] "CHB-MIT Scalp EEG Database," [Online]. Available: https://www.physionet.org/pn6/chbmit/.

[13] D. Martens, M. De Backer, R. Haesen, J. Vanthienen, M. Snoeck and B. Baesens, "Classification With Ant Colony Optimization," in IEEE Transactions on Evolutionary Computation, vol. 11, no. 5, pp. 651-665, Oct. 2007.

[14] R. S. Parpinelli, H. S. Lopes, and A. A. Freitas, "An ant colony based system for data mining: Applications to medical data, " in Proc. Genetic and Evol. Comput. Conf., 2001, pp. 791–797.

[15] M. V. S. S. K. Bharat and S. B. Josyula, "Rule Discovery Based Classification On Biological Dataset Using Ant Colony Optimization," *International Journal of Research in Computer and Communication Technology,* vol. 4, August 2015.

[16] R .Seidlová and J .Poživil, "IMPLEMENTATION OF ANT COLONY ALGORITHMS IN MATLAB".*Institute of Chemical Technology; Department of Computing and Control Engineering,*Czech Republic 2012