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FPGA IMPLEMENTATION OF A WAVELET NEURAL NETWORK WITH PARTICLE SWARM OPTIMIZATION LEARNING FOR EPILEPTIC SEIZURE DETECTION

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ABSTRACT

The main objective of this paper is to model and implementation of Field Programmable Gate Array (FPGA) for a Wavelet Neural Network (WNN) with Particle Swarm Optimization (PSO) learning ability to detect epileptic seizure. The electro-encephalogram (EEG) signals were first pre-processed using Discrete Wavelet Transforms (DWTs) haar, dB2, sym8, and dB4. This was followed by the feature selection stage, where a set of four representative statistics were computed. The features obtained were fed into the input layer of WNNs. A more suitable PSO method is selected for is a population-based learning algorithm for WNN. In the approximation of a nonlinear activation function, we use a Taylor series and a look-up table (LUT) to achieve a more accurate approximation. A group of twenty epileptic patients were studied in this research. The accuracy of 98.27% is obtained for dB4 wavelet with Morlet activation function.

Key words: Wavelet Neural Networks (WNN); Field Programmable Gate Array (FPGA); Particle Swarm Optimization (PSO). EEG signals, Epilepsy, Epileptic seizure, Wavelet Transform.

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1. INTRODUCTION

For the past three decades, Artificial Neural Networks (ANN) has been widely used in many fields, like product design [1], diagnosis [2], control [3], signal and image processing [4]. The most commonly used ANN is the multilayer Perceptron (MLP) proposed by Gibson et al. [5].The MLP is a full connection structure that uses sigmoid functions as hidden node functions. MLP equipped with global transfer functions active over a large range of input values has been widely used to perform global approximations [6]. Inspired from its biological counterpart, ANNs are powerful mathematical models that mimic the learning mechanisms of neuron cells in the brain. A survey of the literature found that various models of ANNs have been considered and proposed in the task epileptic seizure detection. The main objective of this paper is to investigate on the feasibility of WNNs in the classification of epileptic seizure detection from EEG signals. In this paper, a novel hybrid system of WNN with PSO learning was proposed. The EEG signals were first pre-processed using DWT. The frequency and abrupt changes in the biomedical signals can be traced and studied effectively using DWT.WNNs was selected as the mathematical models because of their compact architecture and faster learning rate. Wavelet neural networks (WNN) are examples of spatially localized networks that have been applied in many fields.

WNNs train their parameters iteratively using a learning algorithm. The common training method used is the gradient descent (GD) method. The gradient descent algorithm including the Least Mean Squares (LMS) algorithm and back-propagation [7], [8] for neural networks, are not suitable because they are likely to converge in the local minimum. Thus, this study also introduces a novel algorithm called particle swarm optimization (PSO) to achieve global optimum capability. The particles in a swarm share the information among themselves. There have been successful applications of the PSO for several optimization problems, such as for control problems [9]–[10] and feed forward neural network design [11], [12].The contribution of this work as a classifier with high predictive accuracy to perform the task of epileptic seizure detection is proposed. Digital integrated circuits in the form of field programmable gate arrays (FPGA) [13]–[14] make the hardware designing process flexible and programmable. In addition, the usage of very high speed integrated circuit hardware description language (VHDL) results in easy and fast compilation in complicated circuits. Hence VHDL has lots of benefits, such as high capacity, speedy, duplicate designs, and low cost. Many of the literature have proposed hardware implementation of neural networks, but it does not have learning ability [13]–[15]. Some researchers have proposed hardware implementation of neural networks with on-chip learning that uses the BP algorithm [16].Since the wavelet function is a nonlinear activation function; it is not easy to implement using the hardware. A lookup table (LUT) has been traditionally used for implementing the nonlinear activation function in which the amount of hardware required could be large and the degree of approximation is not accurate enough. In this paper, the nonlinear activation function is approximated to accomplish a more accurate approximation using the Taylor series and LUT. The remaining part of the paper is organized as follows. In Section 2, the outline of the materials and methods is given. Section 3 discusses the hardware implementation of a WNN using FPGA. In Section 4, results are presented. Section 5 concludes the paper.

2. MATERIALS AND METHODS

In this work, the EEG signals that were obtained from the benchmark dataset were first pre-processed using DWT (haar, db2, sym8,and db4). The obtained featured were then fed into WNNs with varying activation functions (Gaussian, Mexican Hat or Morlet wavelet). Finally, performance evaluation was reported using three statistical measures, namely sensitivity, specificity, and overall classification accuracy. Figure 1 shows the block diagram of WNN based Epilepsy detection.

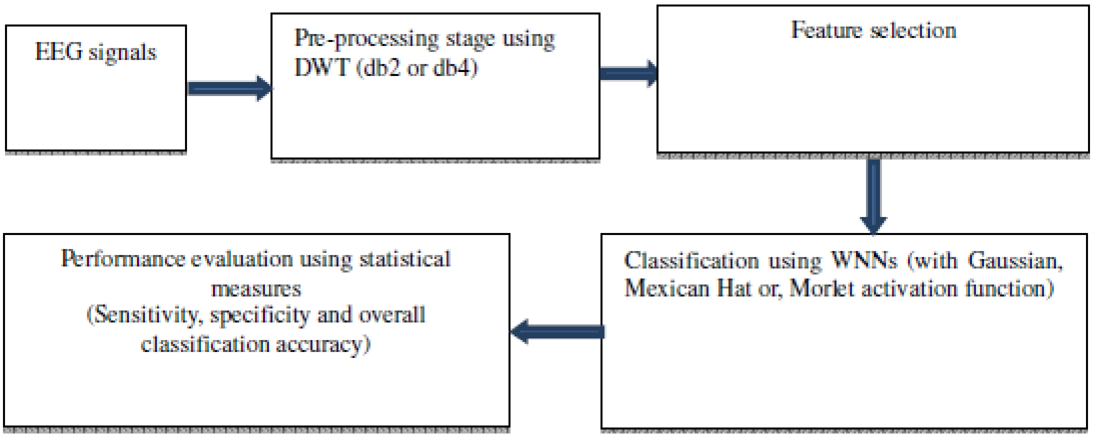

Fig. 1. Block Diagram for the WNN Based Epileptic Detection

2.1. Feature Extraction Using Discrete Wavelet Transform

In the pre-processing stage, the signals were analyzed using DWT. Four different types of wavelets, namely Daubechies wavelet of order 2 (db2) and order 4 (db4),Haar, and sym 8 were considered. Four-level decomposition was employed. At each decomposition level, the signals under study were decomposed into coarse approximation, **a,** and detail information, **d**. The iterated process then yielded the following coefficients with their corresponding frequency: $d1$ (43.4 – 86.8 Hz), $d2$ (21.7 – 43.4 Hz), $d3$ (10.8 –21.7 Hz), $d4$ (5.4 – 10.8 Hz) and $a4$ (0 – 5.4 Hz).After the feature extraction stage, a total of four summary statistics was derived from the generated wavelet coefficients. They are maximum, minimum, and mean of the absolute values of the wavelet coefficients in each sub band, and standard deviations of the wavelet coefficients from each sub band [13] are considered. The maximum and minimum values were replaced with the 90th percentile and 10th percentile of the values of the coefficients, respectively. This was done to trim out possible outliers that might present in the data. The raw EEG signal of two second non overlapping epoch sampled at 200Hz was analyzed. A total of four epochs, of two second duration of EEG signals in sixteen channel bipolar measurement were chosen per epileptic patient. This study is performed in a group of twenty all male epileptic patients and whose min age is 17 years and maximum age is 67 years with an average of 32 years. The wavelet coefficients were generated from each signal and the $d4$ coefficients were extracted. The data were then fed into the proposed WNNs.

2.2. Wavelet Neural Network

WNNs, which were first introduced by Zhang and Benveniste [17], are a variant of ANNs. Due to their capability of rapid identification, analysis of conditions, and diagnosis in real time, ANNs have found a widespread of use in the field of biomedical signal processing; the most prominent ones being speech recognition, cardiology, and neurology [18]. ANNs also demonstrated their feasibility of use in medical diagnosis as they are not affected by several undesirable factors, such as human fatigue, emotional states, and habituation [18]. Specifically, WNNs have been implemented successfully in many biomedical related problems, such as prediction of blood glucose level of diabetic patients [19] and multiclass cancer classification of microarray gene expression profiles [20]. The WNNs proposed consist of three layers – the input layer that receives the input data are with wavelet nodes, the hidden layer that performs the nonlinear mapping, and the output layer that determines the nature or the class of the input data. The mathematical equation that describes the modeling is given by the following equation:

$$y(X) = \sum_{i=1}^{n} w_{ij} \frac{1}{\sqrt{|d|}} \left(\frac{X-ti}{d}\right) \quad (1)$$

where y is the output, n is the number of hidden nodes, j is the number of output nodes, w is the weight matrix that minimizes the error goal, ω_{ij} is the wavelet function, x is the input vector, t is the translation parameters vector, and d is the dilation parameters vector. Three localized continuous wavelet activation functions were investigated. The three functions are as follows:

1. Gaussian wavelet, $\Psi_1(t) = -t.\exp(-0.5\ t^2)$
2. Mexican Hat wavelet, $\Psi_2(t) = (1-t)^2.\exp(-0.5\ t^2)$
3. Morlet wavelet, $\Psi_3(t) = \cos(5x).\exp(-0.5\ t^2)$

2.3. The Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a bio inspired high performance optimization algorithm that possesses several highly desirable attributes. It is similar to genetic algorithms and evolutionary algorithms, but requires less computational memory and fewer lines of code. Consider an optimization problem that requires the simultaneous optimization of variables. A collection or swarm of particles are defined, where each particle is assigned a random position in the N-dimensional problem space so that each particle's position corresponds to a candidate solution to the optimization problem. At each time step, each of these particle positions is scored to obtain a fitness value based on how well it reaches the solution. Using the local best position (Lbest) and the global best position (Gbest), a new velocity for each particle is updated by

$$\overleftarrow{v_i}(k+1) - \omega * \overleftarrow{v_i}(k) + \varphi_1 * \mathrm{rand}(\,) * \left(\mathrm{Lbest} - \overleftarrow{x_i}(k)\right) + \varphi_2 * \mathrm{rand}(\,) * \left(\mathrm{Gbest} - \overleftarrow{x_i}(k)\right) (2)$$

Where $\omega, \varphi_1, \varphi_2$ are called the coefficient of inertia, cognitive and society, respectively. The rand () is uniformly distributed random numbers in [0, 1]. The term $\overrightarrow{v_i}$ is limited to the range $\pm\overrightarrow{v_{max}}$. If the velocity violates this limit, it will be set at its proper limit. Changing velocity enables every particle to search around its individual best position and global best position. Based on the updated velocities, each particle changes its position according to the following: When every particle is updated, the fitness value of each particle is calculated again. If the fitness value of the new particle is higher than those of local best, then the local best will be replaced with the new particle. If the fitness value of the new particle is higher than those of global best, then the global best will be also replaced with the new particle. The algorithm repeats the above updating process step by step, the whole population evolves toward the optimum solution. The detailed flowchart is shown in Fig. 2.

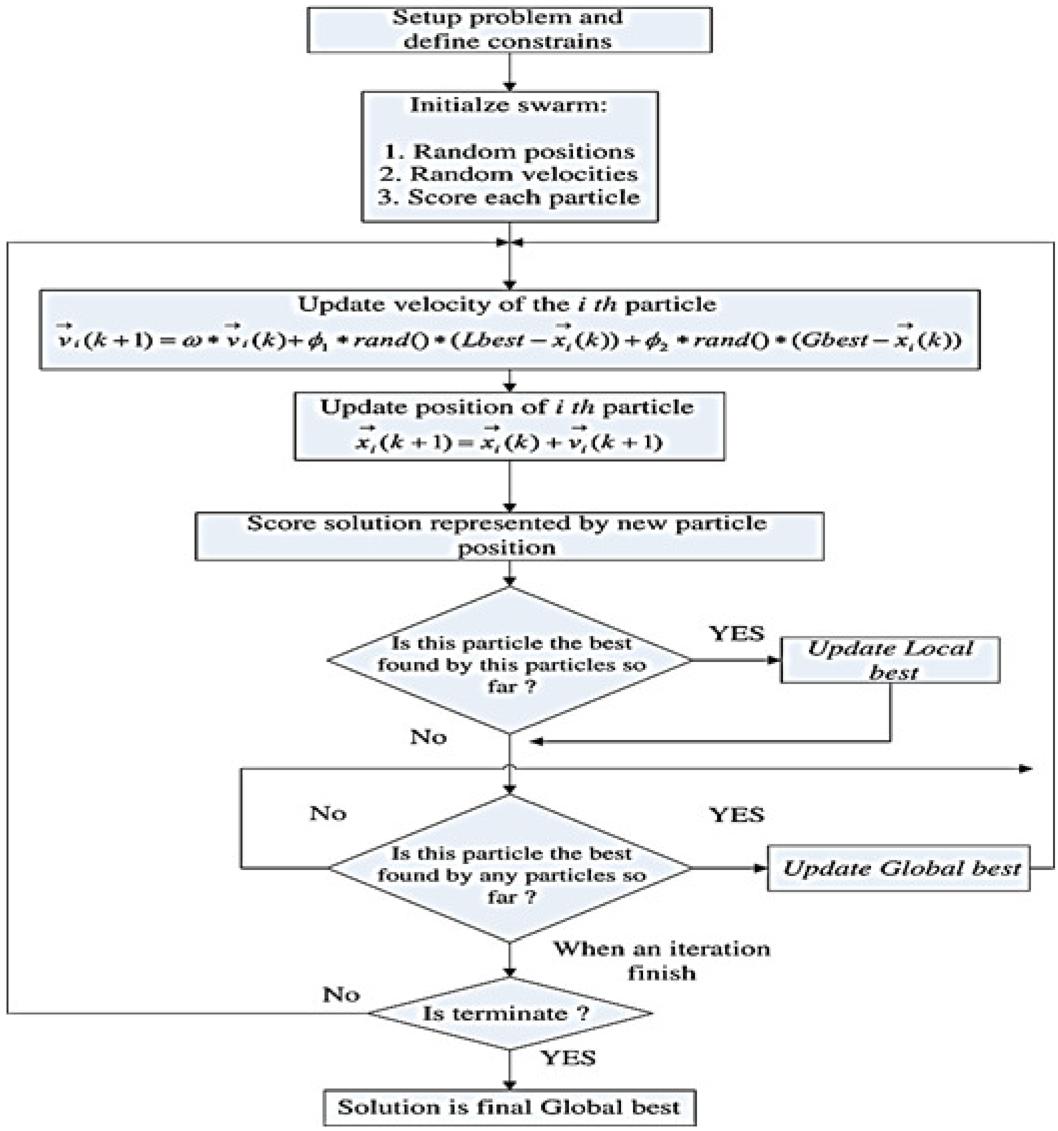

Fig. 2. PSO Algorithm Flowchart to Illustrate The Steps and Update Equations

3. HARDWARE IMPLEMENTATION OF WNN

In this section, we discussed the hardware implementation of the WNN structure and its PSO learning algorithm. The overall component of the WNN model is shown in Fig. 3. The hardware implementation of the WNN model includes two kinds of units: a wavelet unit and a learning unit.

3.1. Wavelet Unit

As shown in Fig. 3, the main part of the WNN structure is the wavelet layer. The input layer can directly transmit a value to the wavelet layer. The process does not pass through any operation. The product layer will be multiplied by the output of the wavelet layer individually. The output layer only needs to add up all the outputs of the product layer. The wavelet layer is used to perform nonlinear transformation mainly, and the wavelet function is used as the nonlinear activation function in this layer. Because the wavelet function is very complicated and cannot be easily used to perform the hardware implementation directly, the study uses the Taylor series and LUT to approximate the wavelet function. In Eq. (3), e^{-x} is expressed by the Taylor series as follows:

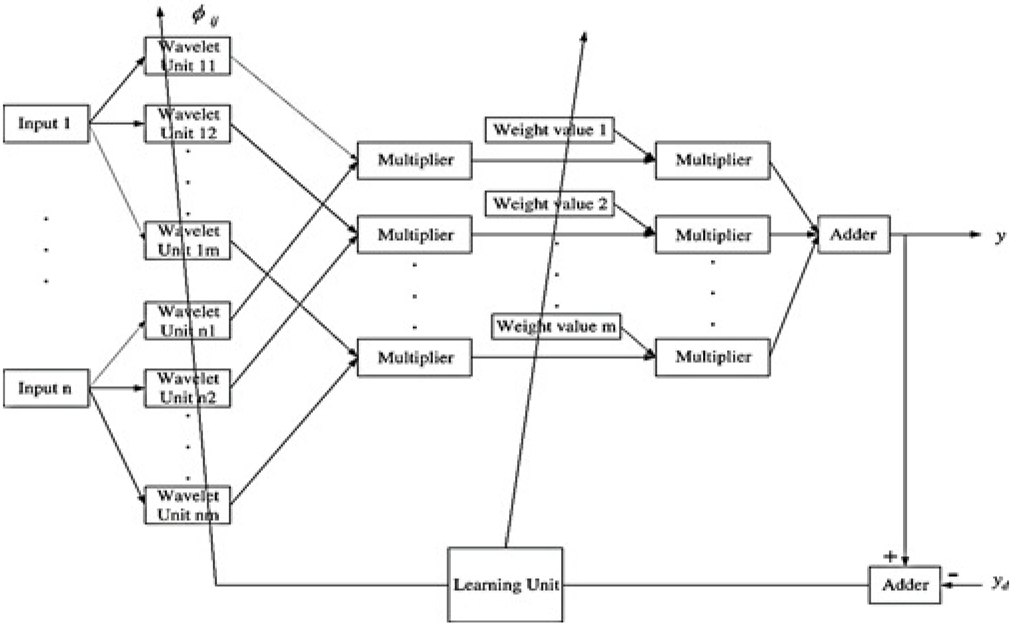

Figure 3 General Blocks for Hardware WNN

$$e^{-x} = 1 - x + \frac{x^2}{2!} - \frac{x^3}{3!} + \frac{x^4}{4!} - \cdots + \frac{x^m}{m!} - \cdots, \qquad (3)$$

Where m is the number of order and x is the input value. A large m leads to a more accurate approximation, but more logic gates and bits are needed. In this paper, the study choose m = 4 to implement the hardware for e^{-x}. Fig. 4 shows a block diagram of the hardware implementation of the Euler function e^{-x}. The implementation uses three multipliers, three dividers, an adder, an LUT, and a multiplexer. The adder adds up the outputs of every order. Some values in the Taylor series are not accurate, such as the input, which is a large negative value, so it needs to compensate for it using the LUT. Therefore, when input is a large negative value, the multiplexer chooses the values in the LUT automatically. The overall component of the wavelet layer is shown in Fig. 3. The wavelet layer consists of a divider, an adder, four multiplier, and the Taylor series e^{-x}. Fig. 5 shows a comparison of the wavelet function and the wavelet function implemented using the Taylor series and the look-up table. The error curve of the reference function (wavelet) and the approximated function is shown in Fig. 6. From Figs. 6 and 7, the implementation can approximate the wavelet function more accurately using the Taylor series and LUT.

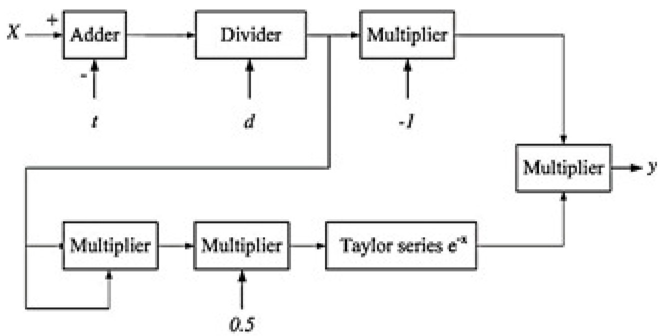

Fig. 4. The Block Diagram of the Hardware Implementations of the Euler Function.

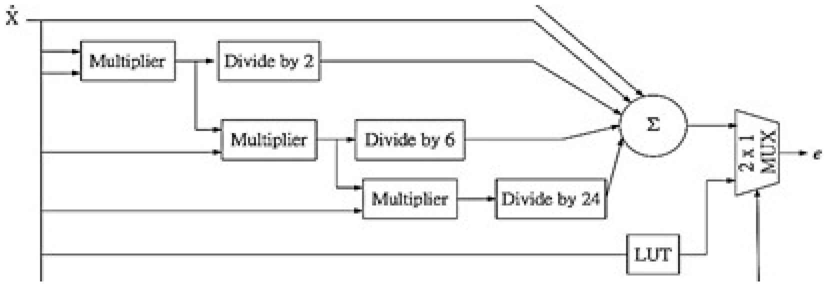

Fig. 5. The Overall Component of the Wavelet Layer Using the First Derivative of the Gaussian Function.

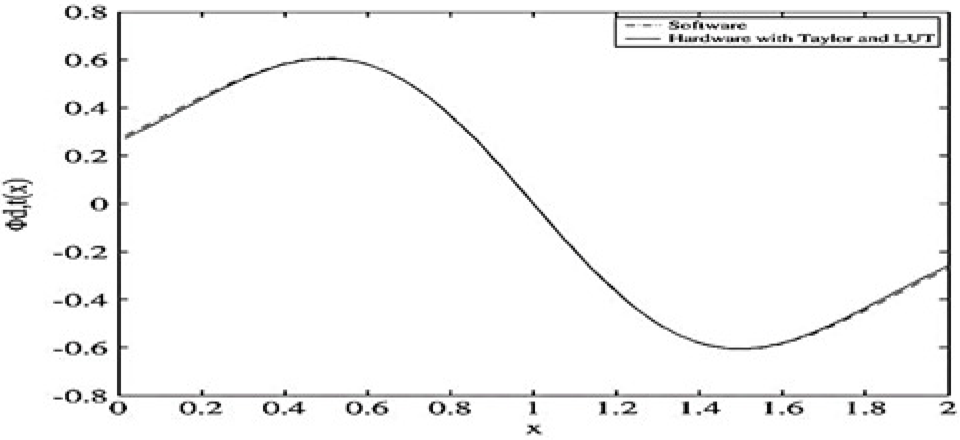

Fig. 6. The Wavelet Function using the first Derivative of the Gaussian function and its Hardware Approximation with Taylor and LUT..

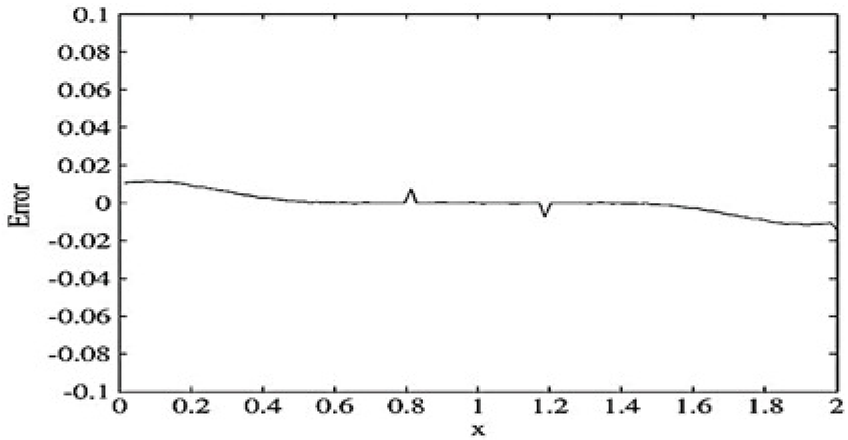

Fig. 7. The Error Curve of the Reference Function (the first derivative of the Gaussian function) and Approximated Function.

3.2. Learning unit

A block diagram of the hardware implementation of the PSO algorithm can be seen in Fig. 8. The design is divided into four main blocks: an evaluation fitness block, a comparator block, an update block, and a control block. The evaluation fitness block calculates the mean square error (MSE) value. The comparator block compares the fitness value to find the best fitness value. The parameters of each particle in a swarm are updated through the update block. The control block manages the counter and generates the enable signal. Because the PSO algorithm needs to record the optimum solution, the memory device is necessary. The implementation uses a RAM as memory device in this study.

3.3. Evaluation Fitness Block

The evaluation fitness block calculates the cost function (objective function) in order to evaluate the performance. The block diagram is shown in Fig. 9. The error value between the actual output and the desired output is calculated by using subtraction and is followed by a square evaluator. Then, the value is accumulated until all the input patterns are calculated.

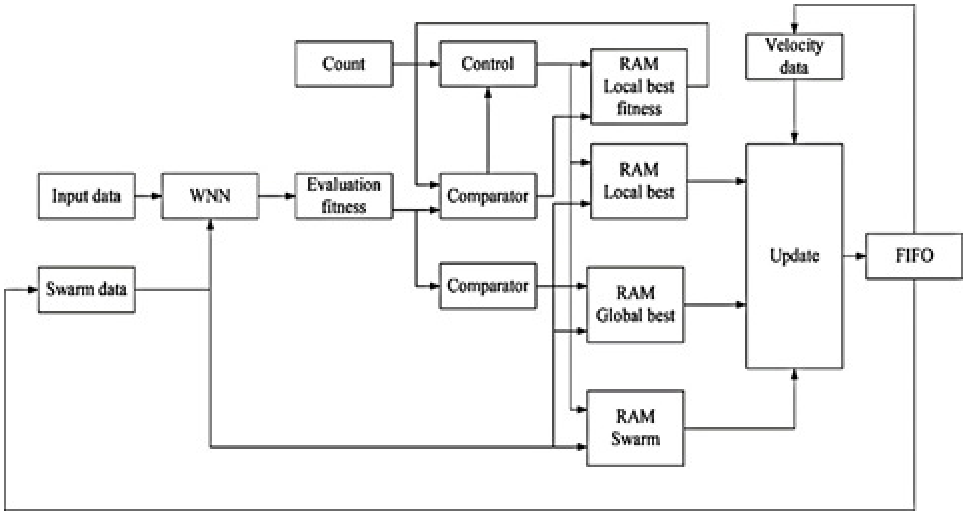

Fig. 8 The Block Diagram of the Hardware Implementation for PSO Algorithm.

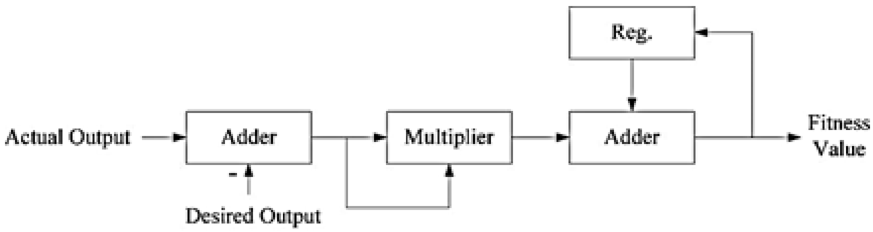

Fig. 9. The Evaluation Fitness Block

3.4. Comparator Block

The comparator block diagram is shown in Fig. 8. The block begins with a multiplexer to account for the initial state, where the fitness value is fixed to FF Hex. Next, the evaluation of a value with a previous best value is compared: If the current fitness value < best and best = current fitness value than store the best in register or RAM. Then, the comparator block delivers an enable signal to the RAM and stores the current position in D-dimensional hyperspace.

Because the rand () function is uniformly distributed random numbers in [0, 1], it is not implemented with hardware circuit directly. The random number generator uses a linear feedback shift register (LFSR). The linear feedback shift register counts through $2^n - 1$ states, where n is the number of bits. The linear feedback shift register state with all bits equal to 1 is an illegal state which never occurs in normal operations. It takes a few clock impulses and watches the output values of the register, which should appear more or less randomly. Depending on the logic used in the feedback path, the register follows a predefined sequence of states. Fig. 9 shows the linear feedback shift register as a random number generator. The update block diagram is shown in Fig. 10. The velocity data is changed and the swarm data is moved by using Eq. (2). As can be seen in Fig. 10, the update can use some simple components to implement such as an adder and a multiplier. The linear feedback shift register with 12 bits is used as a random number generator. The hardware implementation of the PSO uses asynchronous updates, where the swarm and velocity data are updated after each particle with D variables have been calculated by equation(2)rather than waiting until all the particles are updated. This seems to decrease the cost over synchronous updates, although asynchronous updates are not as beneficial to parallel processing as synchronous updates. The control block in fig 8 manages the counter, providing the necessary address for the RAM and determines the RAM to read or write.

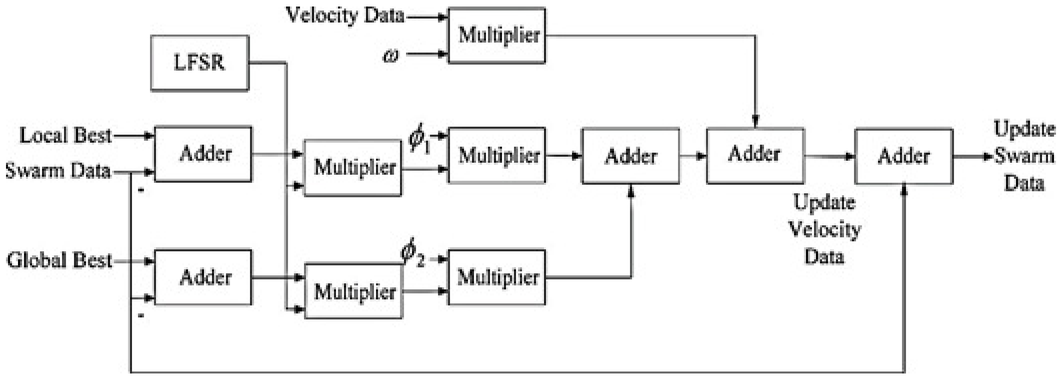

Fig. 10. The Update Block.

4. RESULTS AND DISCUSSION

The results of the binary classification problem, with different parameters setting, were displayed in Table 1.The Mean square Error (MSE) for twent patients with dB4 wavelet at Level 4 decomposition si depicted in the Table 1.

It is observed from the Table 1 that minimum MSE of .0001 is obtained.

Table 1 Mean Square Error Analysis for dB4 at level 4 decomposition with Hard Thresholding

Patient	Epoch1 MSE	Epoch2 MSE	Epoch3 MSE
1	0.00636	0.01178	0.01443
2	0.00970	0.00515	0.00430
3	0.01226	0.00970	0.00496
4	0.00234	0.01131	0.01070
5	0.01313	0.00511	0.04834
6	0.00990	0.00946	0.01412
7	0.00334	0.00149	0.00240
8	0.00119	0.00126	0.00426
9	0.00804	0.00637	0.00650
10	0.00549	0.00428	0.00552
11	0.01083	0.00599	0.01040
12	0.00382	0.00737	0.01077
13	0.01377	0.01317	0.00784
14	0.01298	0.00439	0.00147
15	0.00420	0.00423	0.00770
16	0.00244	0.00208	0.00266
17	0.00535	0.00498	0.00174
18	0.01135	0.01030	0.00463
19	0.01000	0.00524	0.00428
20	0.00483	0.00221	0.00210

Table 2 shows the obtained MSE for hard Thresholding for twenty patients with four types of wavelets such as Harr, dB2, sym 8 and dB4. The obtained MSE values are appreciable in nature for the feature sets.

Table 2 Mean Square Error Analysis for 20 Patients of Hard Thresholding

Patient	HAAR MSE	DB2 MSE	SYM8 MSE	DB4 MSE
1	0.0056789	0.0147772	0.0073068	0.0029908
2	0.0058942	0.0044305	0.0103538	0.0074028
3	0.0129431	0.0065873	0.0123469	0.0049214
4	0.0056552	0.0056826	0.0036491	0.0075474
5	0.0031587	0.0067799	0.0082262	0.0045002
6	0.0071309	0.0078168	0.0107205	0.0074563
7	0.0117516	0.0056351	0.0097812	0.0047875
8	0.0082012	0.0044219	0.0071239	0.0049612
9	0.0055774	0.0058255	0.0090021	0.0052584
10	0.0043798	0.0057518	0.0070282	0.003423
11	0.0039404	0.0071652	0.0053711	0.0038831
10	0.0083923	0.0037305	0.0059748	0.0053505
13	0.0024064	0.0088132	0.0113172	0.0050182
14	0.0147917	0.004166	0.0066333	0.0107044
15	0.0087085	0.0175081	0.0073825	0.0059882
1	0.004351	0.0067021	0.0085577	0.0040473
17	0.00361	0.006374	0.006869	0.0072117
18	0.008835	0.0066595	0.0065988	0.0052709
19	0.0129434	0.0040783	0.0090725	0.0026739
20	0.0058942	0.0044305	0.0103538	0.0074028
Average	0.0072122	0.0068668	0.0081835	0.00554

Table 3 shows the obtained MSE for heursure Soft Thresholding for twenty patients with four types of wavelets like Harr, dB2, sym 8 and dB4. The obtained MSE values are appreciable in nature for the feature sets.

The performance of the FPGA implemented Epilepsy detector is assessed by the following parameters,

The sensitivity S_e is given by [20]

S_e=[PC/(PC+FA)]*100 (4)

The specificity S_p is given by [22]

S_p=[PC/(PC+MC)]*100 (5)

The Accuracy is given by[22]

Overall Accuracy= [Sensitivity+Specificity]/2 (6)

From the Table 4, it was found that the combination that gave the best overall classification accuracy (98.66%) is the WNNs model that employed Morlet wavelet function and used input feature set II with EEG signal preprocessed using db4.As shown in the table, when comparing the types of DWT used, it was found that db4 gave slightly better result compared to db2. This corroborated the finding by [21] that db4 is the most suitable wavelet to be used in the task of EEG signals analysis. As stated in [21], the wavelets of lower order are too coarse to represent the EEG signals that have many spikes, while higher order wavelets oscillate too wildly and this characteristic is not desirable as the wavelets cannot represent the EEG signals well. Also, it was observed that when input feature set II was used, higher overall classification accuracy was obtained. This result showed that the use of 10th percentile and 90th percentile, were indeed, better than the use of minimum and maximum values of the wavelet coefficients. . Regarding the use of three different continuous wavelet functions as the activation functions in the hidden nodes of the WNNs, all three wavelet performed efficiently, with overall accuracy ranging from 96.56% to 98.66%. When the shape of an activation function resembles the shape of the function to be approximate, the WNN performed better by yielding higher approximation accuracy. The Morlet wavelet function used in this paper is derived from the product of the cosine trigonometric function and the exponential function which contribute to the graph's oscillatory behaviour. This oscillating shape resembles the shape of the non-stationary EEG signals used in this study.

Table 3 Soft Thresholding Mean Square Error Analysis for Soft (heursure) epoch values

Patient	HAAR MSE	DB2 MSE	SYM8 MSE	DB4 MSE
1	0.0065161	0.0046182	0.0153171	0.0064092
2	0.0049816	0.0044182	0.0112628	0.0031755
3	0.0076093	0.0037953	0.0050659	0.0078762
4	0.0033859	0.0068597	0.0086387	0.0078378
5	0.0082424	0.0037492	0.0093818	0.0029363
6	0.0011015	0.0105059	0.006973	0.0093212
7	0.0060527	0.0051881	0.0097358	0.0024578
8	0.0021972	0.0035689	0.0165641	0.0043225
9	0.0056063	0.0025795	0.003324	0.0067038
10	0.0065054	0.0063878	0.0018675	0.0026646
11	0.0078764	0.0105974	0.0039378	0.0074752
12	0.0072313	0.0061965	0.0026937	0.0077811
13	0.0062295	0.0024115	0.0035048	0.0022662
14	0.006712	0.0105925	0.0050152	0.0052558
15	0.0096552	0.0089417	0.0021622	0.0029394
16	0.0052083	0.0037208	0.0015951	0.0064044
17	0.0043714	0.0035408	0.0041855	0.0021694
18	0.0081397	0.0026776	0.0188014	0.0065409
19	0.0043098	0.0103235	0.0011655	0.0061514
20	0.0049816	0.0044182	0.0112628	0.0031755
Average	0.005846	0.005755	0.007123	0.005193

Table 4. The performance metric obtained using different Daubechies wavelets, input features and activation functions

Daubechies Wavalet	Performance matrix	Activation functions		
		Gaussian	Mexican hat	Morlet
dB2	Sensitivity	93.83±0.84	86.59±1.57	87.93±1.90
	Specificity	98.05±0.08	99.27±0.21	99.24±0.10
	Overall	97.20±0.13	96.56±0.25	97.02±0.30
	Sensitivity	96.03±0.63	89.51±1.79	92.96±1.52
	Specificity	98.71±0.17	99.50±0.20	99.49±0.21
	Overall	98.14±0.13	97.58±0.26	98.26±0.13
dB4	Sensitivity	93.82±1.18	81.40±1.80	83.61±1.31
	Specificity	97.92±0.27	99.45±0.20	99.69±0.10
	Overall	97.14±0.27	95.88±0.26	96.60±0.15
	Sensitivity	95.78±0.71	92.26±1.31	94.88±0.89
	Specificity	98.83±0.30	99.77±0.18	99.54±0.15
	Overall	98.22±0.21	98.26±0.24	98.66±0.16

The timing diagram of FPGA implementation is also shown in the figure. 11

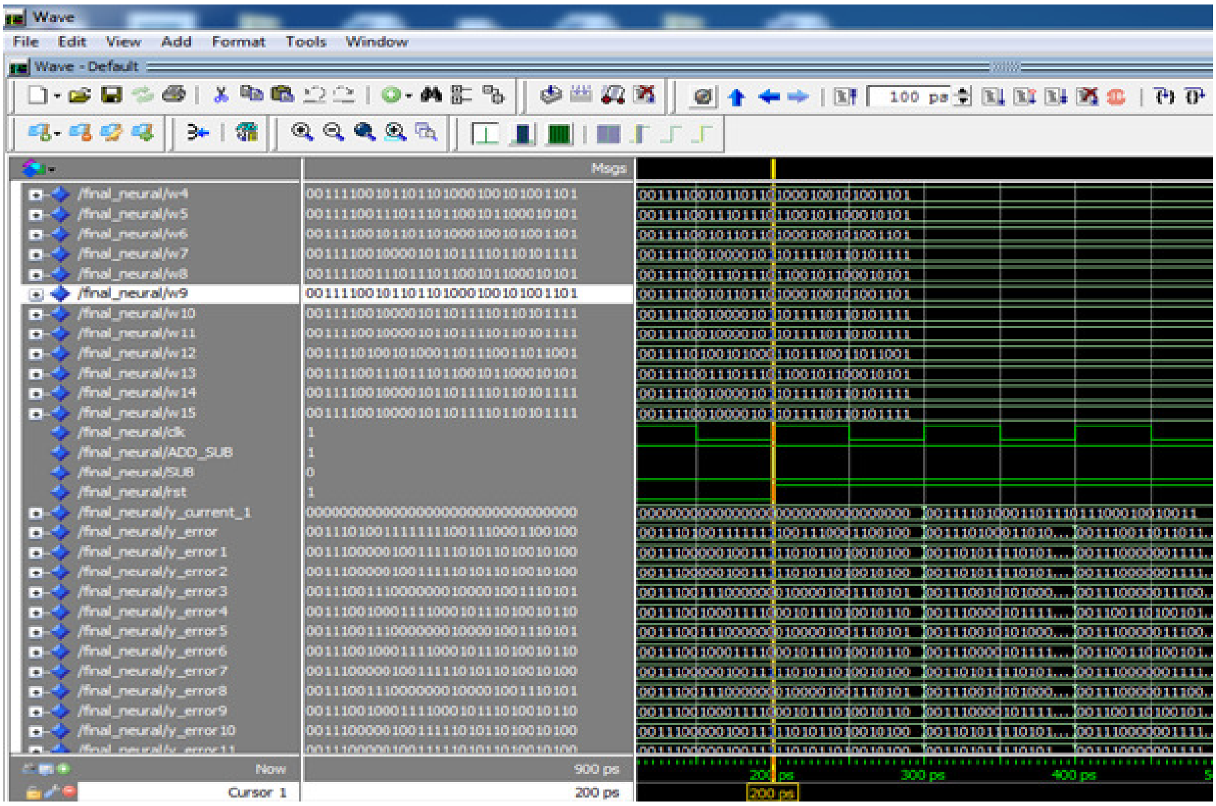

Fig 11. Timing diagram of FPGA Implementation of WNN

Table 5 shows performance comparision of the proposed WNN with other types of neural networks classification. As observed from Table 5 the proposed method provide better classification accuracy of 98.66%.

Table 5 Performance Comparison of the Proposed WNNs with Other Classifiers

Sl.No	Feature Selection	Classifier	Classification Accuracy	Reference
1	Time frequency analysis	ANN	97.73	Tzallas A et.al (2007)[23]
2	DWT with line length feature	MLP	97.77	Guo L, et.al (2010)[24]
3	DWT with k-means algorithm	MLP	99.60	Orhan U, et.al(2011)[25]
4	DWT	WNN	98.66	This paper

5. CONCLUSION

In this paper, implementation of Wavelet Neural Networks with PSO learning ability using FPGA was proposed. Some of the features of the wavelet neural networks with the PSO algorithm can be summarized as follows: (1) an analog wavelet neural network is realized based on digital circuits; (2) hardware implementation of the PSO learning rule is relatively easy; and (3) hardware implementation can take advantage of parallelism. From the results of the experiment with the prediction problem, it can be seen that the performance of the PSO is better than that of the simultaneous perturbation algorithm at sufficient particle sizes. The WNNs models with varied activation functions and different feature extraction techniques were investigated in the task of epileptic seizure classification. Based on the overall classification accuracy obtained, the Morlet wavelet was found to be the best wavelet function to be used. The db4 was also found to be more suitable to be used compared to dB2. By replacing the extreme values of wavelet coefficients with suitable percentiles, the classifiers gave better classification accuracy. The high overall classification accuracy obtained verified the promising potential of the proposed classifier that could assist clinicians in their decision making process. The task of epileptic seizure prediction [22] is another interesting task where it requires the classifier to differentiate between pre-ictal and interictal data.

A major drawback of the existing wavelet neural networks is that their application domain is limited to static problems due to their inherent feedforward network structure. Future research in the direction of recurrent neural network to solve this epileptic detection problem.

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