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FPGA Implementation of Wavelet Neural Network for Epilepsy Detection

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Abstract:-This paper introduces implementation of a wavelet neural network (WNN) with learning ability on Field Programmable Gate Array for epilepsy detection. The electro-encephalography (EEG) signals were first pre-processed using discrete wavelet transforms (DWTs). Three different activation functions were used in the hidden nodes of WNNs – Gaussian, Mexican Hat, and Morlet wavelets. The best combination to be used was the WNNs that employed Morlet wavelet as the activation function, with Daubechies wavelet of order 4 in the feature extraction stage. A more suitable method is the particle swarm optimization (PSO) that is a population-based optimization algorithm. 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.

***Key words-:* Wavelet neural networks (WNN); Field programmable gate array (FPGA); Particle swarm optimization (PSO). EEG signals, epilepsy, epileptic seizure, wavelet transform.**

I. INTRODUCTION

In recent years, artificial neural networks (ANN) have been widely used in many fields, such as chemistry [1], diagnosis [2], control [3], and image processing [4].]. The most commonly used artificial neural network 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 binary classification task of epileptic seizure detection. The main objective of this paper is to investigate on the feasibility of WNNs in the binary classification task of epileptic seizure detection. . In this paper, a novel hybrid system was proposed. The EEG signals of interest were first pre-processed using DWT. The method of DWT was chosen because this transform has the superiority of capturing the details of the non-stationary signals. The frequency and abrupt changes in the biomedical signals can be traced and studied effectively using DWT. After the feature extraction stage, a dimensionality reduction stage was performed before the data was fed into the proposed WNNs, with three different activation functions. WNNs were 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 to 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 has 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.

II. THE PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is a recently invented high performance optimizer that possesses several highly desirable attributes, including the fact that the basic algorithm is very easy to understand and to implement. 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

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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 solves the problem. Using the local best position (Lbest) and the global best position (Gbest), a new velocity for each particle is updated by

$$\vec{v_i}(k+1) = \omega * \vec{v_i}(k) + \varphi_1 * rand() * \left(Lbest - \vec{x_i}(k)\right) + \varphi_2 * rand() * \left(Gbest - \vec{x_i}(k)\right) \quad [1]$$

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 $\vec{v_i}$ is limited to the range $\pm \vec{v}_{max}$. If the velocity violates this limit, it will be set at its proper limit. The concept of the updated velocity is illustrated in Fig. 3. 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.

III. WAVELET NEURAL NETWORKS

The data were then fed into the proposed WNNs. 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, 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:

$$y(\mathbf{x}) = \sum_{i=1}^{n} w_{ij} \frac{1}{\sqrt{|d|}} \psi\left(\frac{\mathbf{x} - \mathbf{t}_i}{d}\right) \quad [2]$$

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, ψ 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:

(i) Gaussian wavelet, $\psi_1(t) = -t.\exp(-0.5t^2)$

(ii) Mexican Hat Wavelet, $\psi_2(t) = (1-t^2).\exp(-0.5t^2)$

(iii) Morlet Wavelet, $\psi_3(t) = \cos(5x).\exp(-0.5t^2)$

The Graphical Representations Of The Three Functions Are Shown In Fig. 1.

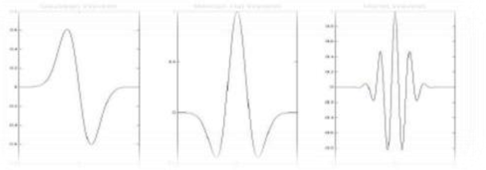

Fig. 1.Graphical Representations of Gaussian Wavelet, Mexican Hat Wavelet, and Morlet Wavelet.

IV. METHODOLOGY

In this work, the EEG signals that were obtained from the benchmark dataset were first pre-processed using DWT (db2 or db4). After the feature extraction stage, the dimension of the date was further reduced through the feature selection stage, where two sets of input feature were considered (set I and II). 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. A summary of the methodology used in this paper is given in figure 2.

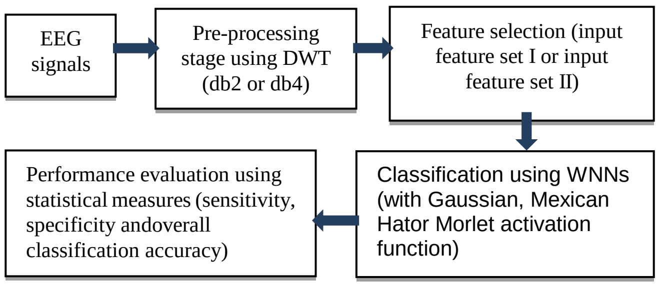

Fig. 2. Block Diagram for the Proposed Wnns

V. HARDWARE IMPLEMENTATION

In this section, the study will introduce the hardware implementation of the WNN structure and its learning algorithm.

A. Wavelet Unit

The main part of the WNN structure is the wavelet layer. The input layer can directly transmit a value to the wavelet layer. The product layer will be multiplied by the output of the wavelet layer individually. The overall of components of WNN Model is shown in Fig 3. The overall structure of WNN block is shown in Fig 3-4. 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.

B. Learning unit

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. PSO Learning Block is shown in Fig 5.

C. Evaluation fitness block

The evaluation fitness block calculates the cost function in order to evaluate the performance. 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. Evaluation fitness block is shown in Fig 6.

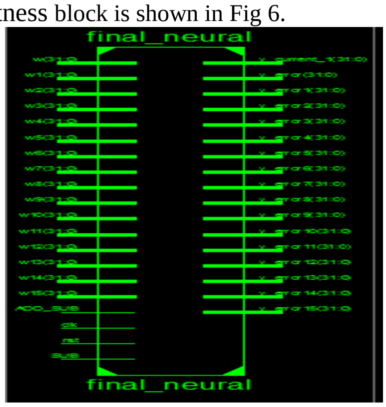

Fig 3. The Overall Structure of WNN Block

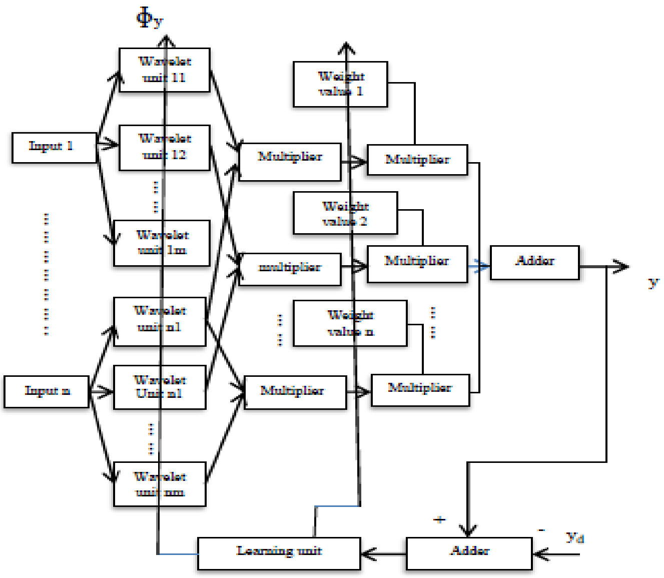

Fig. 4 the Overall of Components of WNN Mode

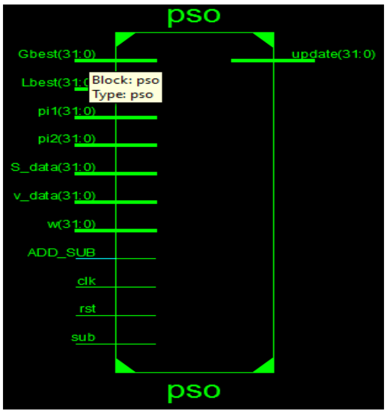

Fig.5 PSO Learning Block

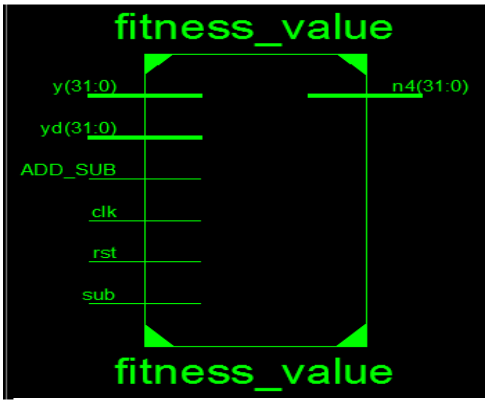

Fig.6 Evaluation Fitness Block

D. The comparator block.

The block begins with a multiplexer to account for the initial state, where the fitness value is fixed to FFh. 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. Comparator block shown in fig7.

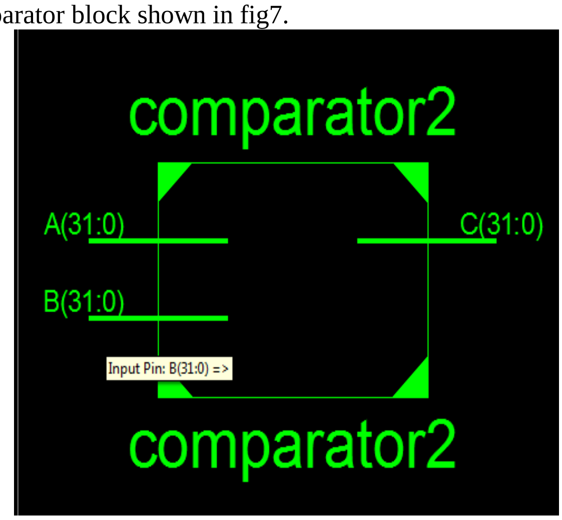

Fig.7 Comparator Block

E. Update block

The rand() function is uniformly distributed random numbers in [0, 1], it is not implemented with hardware circuit

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directly. The random number generator uses a linear feedback shift register (LFSR). The linear feedback shift register counts through 2n −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.

VI. RESULTS AND DISCUSSION

The results of the binary classification problem, with different parameters setting, were displayed in Table 1. In this work, 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.

Daubechies Wavalet	Performance matrix	Activation functions		
		Gaussian	**Mexican hat**	**Morlet**
Db2 (Input feature set I, set II)	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 (Input feature set I, set II)	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**

Table 1. The performance metric obtained using different Daubechies wavelets, input features, and activation functions

Classifier	Feature selection	Classification accuracy	Reference
ANN	Time frequency analysis	97.73	[23]
MLP	DWT with line length feature	97.77	[24]
MLP	DWT with k-means algorithm	99.60	[25]
WNN	DWT	98.66	This paper

Table 2. Performance comparison of the proposed WNNs with other classifiers

VII. CONCLUSION AND FUTURE WORK

In this paper, implementation of wavelet neural networks with 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. In the future, a recurrent wavelet neural network will be proposed for solving identification and control problems.

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