FPGA Synthesis of Soft Decision Tree (SDT) for Classification of Epilepsy Risk Levels from Fuzzy Based Classifier using EEG Signals

R. HariKumar, M. Balasubramani

Abstract*— The objective of this paper is to design, simulate, and synthesis a simple, suitable and reliable Soft Decision Trees for classification of epilepsy risk levels from EEG signals. The fuzzy classifier (level one) is used to classify the risk levels of epilepsy based on extracted parameters like energy, variance, peaks, sharp and spike waves, duration, events and covariance from the EEG signals of the patient. Soft Decision Tree (post classifier with max-min and min-max criteria) of three models is applied on the classified data to identify the optimized risk level (singleton) which characterizes the patient's risk level. The efficacy of these methods is compared with the bench mark parameters such as Performance Index (PI), and Quality Value (QV). A group of twenty patients with known epilepsy findings are analyzed. High PI such as 95.88 % was obtained at QV's of 22.43 in the SDT model of (16-4-2-1) with Method-II (min-max criteria) when compared to the value of 40% and 6.25 through fuzzy classifier respectively. It was observed that the simulated and synthesized Field Programmable Gated Array (FPGA) SDT models are good post classifier in the optimization of epilepsy risk levels which is closely follows the mat lab version. the deterministic character of dynamics of the underlying system.

***Index Terms*— EEG Signals, Epilepsy, Fuzzy Logic, Soft Decision Trees, Risk Levels, FPGA synthesis**

I. INTRODUCTION

Medical expert systems are a challenging field, requiring the synergy of different scientific areas. The representation of medical knowledge and expertise, the decision making in the presence of uncertainty and imprecision, the choice and adaptation of suitable model, are some issues that a medical expert system should take under consideration [1]. Uncertainty is traditionally treated in probabilistic manner; recently, however, methods based on fuzzy techniques have gained ground [2]. The model's parameter adaptation (training) amounts to optimizing a properly constructed "error" function. There is a variety of methods with diverse features that may properly understand the subtleties of the optimization procedures and is a key to choose effective training approach [9]. These characteristics of a decision tree classifier is very attractive where one has to determine the appropriate feature subsets and the decision rules at each internal node [10].

Manuscript received May 30, 2011.

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A. General Techniques

EEG is an important clinical tool for diagnosing, monitoring and managing neurological disorders related to epilepsy. This disorder is characterized by sudden recurrent and transient disturbances of mental function and/or movements of body that results in excessive discharge group of brain cells [3]. The presence of Epileptiform activity in the EEG confirms the diagnosis of epilepsy, which sometimes confused with other disorders producing similar seizure like activity [4]. The different types of epileptic seizures are characterized by different EEG waveform patterns. With real-time monitoring to detect epileptic seizures gaining widespread recognition, the advent of computers has made it possible to effectively apply a host of methods to quantify the changes occurring based on the EEG signals .One of them is a classification of risk level of epilepsy using Fuzzy techniques [6].This paper addresses the FPGA Synthesis of SDT models towards optimization of fuzzy outputs in the classification of epilepsy risk levels.

II. MATERIALS AND METHODS

The E EEG data used in the study were acquired from twenty epileptic patients in the Neurology Department of Sri Ramakrishna Hospital, Coimbatore, India. A paper record of 16 channel EEG data is acquired from a clinical EEG.

A. Artifact Rejection and Acquisition of EEG Data

A. With the help of neurologist, artifact free EEG records with distinct features were selected scanned by Umax 6696 scanner with a resolution of 600dpi. EEG records are divided into epochs of two second duration each by scanning into a bitmap image of size 400x100 pixels which is long enough to detect any significant changes in activity and presence of artifacts and also short enough to avoid any repetition or redundancy in the signal. Each epoch is sampled at a frequency of 200Hz. Each sample corresponds to the instantaneous amplitude values of the signal, totaling 400 values for an epoch. The different parameters used for quantification of the EEG are computed using these amplitude values by suitable programming codes. The parameters are obtained for three different continuous epochs at discrete times in order to locate variations and differences in the epileptic activity. Twenty EEG records were used for both training and testing. These EEG records had an average length of six seconds and total length of 120 seconds. The patients had an average age of 31 years. A total of 960 epochs of 2 seconds duration are used.

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B. Fuzzy System as a Level One Classifier

The following seven parameters are extracted from EEG signals which are

1. The energy in each two-second epoch is given by [7]

$$E = \sum_{i=1}^{n} x_i^2 \qquad (1)$$

Where x_i is signal sample value and n is number of samples. The scaled energy is taken by dividing the energy term by 1000.

2. The total number of positive and negative peaks exceeding a threshold is found.

3. Spikes are detected when the zero crossing duration of predominantly high amplitude peaks in the EEG waveform lies between 20 and 70 ms and sharp waves are detected when the duration lies between 70 and 200ms.

4. The total numbers of spike and sharp waves in an epoch are recorded as events.

5. The variance is computed as σ given by [5]

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \qquad (2)$$

Where $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$ is the average amplitude of the epoch.

6 .The average duration is given by [5]

$$D = \frac{\sum_{i=1}^{p} t_i}{p} \qquad (3)$$

Where t_i is one peak to peak duration and p is the number of such durations.

7. Covariance of Duration. The variation of the average duration is defined by [7]

$$CD = \frac{\sum_{i=1}^{p}(D - t_i)^2}{pD^2} \qquad (4)$$

The energy is compared with the other six input features to give six outputs which are classified into five levels namely *normal, low, medium, high* and *very high*. In this fuzzy system we have five linguistic sets such as Very low, low, medium, high and very high for all the seven parameters. With energy being a constant input and others parameters are selected in sequential manner [6]. These inputs will form (2×1) fuzzy system works with 25 rules. We obtain a total rule 150 rules based on six sets of 25 rules each corresponding to six fuzzy systems [6].

C. Estimation of Risk Level in Fuzzy Outputs

An optimization of the outputs of the fuzzy system is necessary as the output of a fuzzy logic represents a wide space of risk levels. A specific coding method processes the output fuzzy values as individual code such as a string of alphabets as shown in table. I

Table. I Representation of Risk level Classifications

Risk Level	Representation
Normal	U
Low	W
Medium	X
High	Y
Very High	Z

A sample output of the fuzzy system with actual patient readings is shown in fig. 1 for eight channels over three epochs. It can be seen that the Channel 1 shows medium risk levels while channel 8 shows very high risk levels. Also, the risk level classification varies between adjacent epochs.

Epoch 1	Epoch 2	Epoch 3
YYYYXX	ZYYWYY	YYYXYZ
YYYXYY	ZZYZZZ	YYYXYZ
YYYYYY	ZZYZZZ	ZYYYZZ
ZYYYZZ	ZZYZYY	YYYXXZ
YYYYYY	YYYXYY	YYYYYZ
YYYYYY	YYYXYY	YYYXYY
YYYYYY	YYYYYY	YYYYYY
ZZYZYZ	ZZYZZZ	ZZYZZZ

Figure .1 Fuzzy Logic Output

D. Rhythmicity of Fuzzy techniques

Encoding each output risk level of the fuzzy output gives us a string of six chromosomes, the value of which is calculated as the sum of probabilities of the individual genes. Now the each input patterns are encoded in the numerical form of the range 0-1. Table II represents the code representation of risk levels as follows

Table.II Binary Representation of Risk levels

Risk Level	Code	Binary String	Weight	Probability
Very high	Z	10000	16/31=0.51612	0.086021
High	Y	01000	8/31=0.25806	0.043011
Medium	X	00100	4/31=0.12903	0.021505
Low	W	00010	2/31=0.06451	0.010752
Normal	U	00001	1/31=0.03225	0.005376
		11111=31	Σ=1	

Now we are about to identify the Rhythmicity of Fuzzy techniques which is associated with nonlinearities of the epilepsy risk levels. Let the Rhythmicity is defined as [8]

$$R = C/D \qquad (5)$$

Where C= No of categories of patterns; and D=Total number of patterns which is 48 in our case. For an ideal classifier C is to be one and R= 0.0208. Table III shows the Rhythmicity of the fuzzy classifier for each subject.

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Table III. Rhythmicity of Fuzzy Techniques

Patient	No of categories of patterns	Rhythmicity R=C/D
1	9	0.187
2	7	0.1458
3	13	0.271
4	10	0.208
5	7	0.1458
6	9	0.187
7	12	0.25
8	13	0.271
9	14	0.292
10	18	0.375

It is observed from the table III that the value of R is deviated from its ideal value therefore it is necessary to optimize the fuzzy outputs to endure a singleton risk level. Soft Decision Trees (SDT) is used for this purpose.

III. SOFT DECISION TREES FOR OPTIMIZATION OF FUZZY OUTPUTS AS HYBIRD CLASSIFIER

Our objective is to merge the epilepsy risk level representation, with approximate reasoning capabilities, and symbolic decision trees. The high dimensionality problem associated with multi criteria decision and minimum training samples are curtailed by the use of SDT [9].

Apart from several advantages there are some pertinent drawbacks associated with decision trees which are as follows i) Errors may accumulate from level to level in a large tree. Therefore one cannot simultaneously optimize both accuracy and efficiency ii) Increased in number of terminals when number of classes is large and this lead to increase the search time and memory space requirements. iii) Finally, there may be difficulties involved in designing optimal SDT. The problem of designing a truly optimal SDT is a very difficult one[9]. They also conjecture that no sufficient algorithm exists and thereby supply motivation for finding efficient heuristics for constructing near-optimal decision trees.

A. Algorithm for SDT Optimization

The various heuristic methods for construction of SDT can roughly be divided into four categories: Bottom-up approaches, Top-Down approaches the hybrid approach and tree Growing – pruning approaches[10]. A decision tree using bottom-up approach was constructed and studied. Using max-min soft decision measures, pair wise distances between a priori defined classes are computed and at each step the two classes with the node decision are merged to form a new group, and this process is repeated until one is left with one group at the root which will be the optimized epilepsy risk level patterns [10]. From a processing point of view, these types of trees are highly recommended. The generic representation of SDT optimization is explained, let W= $[P_{ij}]$ be the co –occurrence matrix with (i,j) elements which represents fuzzy based epilepsy risk level patterns of single epoch. There are 48 (16x3) epochs are available. Three models of SDT such as (16-8-4-2-1), (16-4-2-1), and (16-2-1) were selected for optimization of fuzzy patterns. A decision strategy of Method –I (Max-min) or Method –II (Min-max) were applied at each nodes in the above three SDT models. Therefore six types of SDT models were obtained.

In the case of (16-8-4-2-1) model an epoch of (16x1) elements were considered as the leaf nodes of the tree. The next level of tree was named as B with eight decision nodes, which was followed by C level with four soft decision nodes. Further level was designated as D level with two nodes and the final level was the E level with single node which was the root of the tree. The following decisions were performed at the each node of the tree.

Max-Min Method I.

The above algorithm is depicted in the figure 2.Each SDT model is trained and tested by means of MSE Function. Since our model is patient specific in nature, we are applying 48 (3x16) patterns for each SDT model. As the number of patterns in each database for training is limited, each model is trained with one set of patterns (16) for Minimum Mean Square Error (MSE) condition and tested with other two sets of patterns (2x16). After network is trained using these, the classification performance of test set is recorded. The testing process is monitored by the Mean Square Error (MSE) which is defined as [11]

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(O_i - T_j)^2 \qquad (6)$$

Table .IV Estimation of MSE in SDT models

SDT Models	Mean Square Error (MSE) Index		Confidence score
	Training	Testing	$C_i=\exp(-\lambda e_i^2)$
Method-I			
16-8-4-2-1 (AR1)	5.2E-03	5.9E-03	0.9941
16-4-2-1 (AR2)	8.9E-03	8.4E-03	0.9916
16-2-1(AR3)	9.1E-03	9.32E-03	0.9961
Method-II			
16-8-4-2-1 (AR1)	1.66E-02	7.24E-03	0.9927
16-4-2-1 (AR2)	9.6E-04	2.04E-03	0.998
16-2-1 (AR3)	1.66E-02	0.101	0.989

The squared error (e_i^2) from equation (6) between the input and the output of the SDT is converted into the confidence score using relation $\mathbf{C_i=exp\ (-\lambda e_i^2)}$ where refers to the SDT index [11]. In this paper λ=1was chosen. The average confidence score for each SDT model is also tabulated in the table IV. SDT (16-4-2-1) model with method –II (Min-max criteria) provided better training and testing MSE. Hence, SDT (16-4-2-1) model with method-II was selected as an appropriate post classifier for optimization of fuzzy outputs in epilepsy risk level classification.

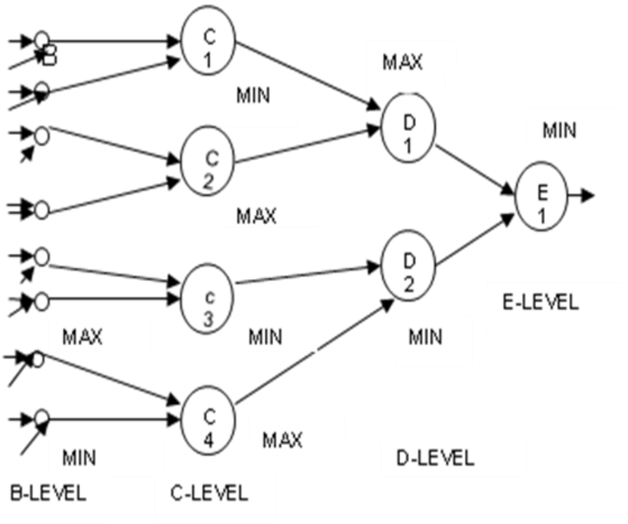

Figure. 2 Optimization of Epilepsy Risk Levels through STD (16-8-4-2-1) model with (Max-min) Method I

IV. VHDL SYNTHESIS AND PROGRAMMING XILINX BOARD (SPARTAN 3) USING ISE

In recent years, VHSIC (Very High Speed Integrated Circuit) Hardware Design Language (VHDL) has become a sort of industry standard for high-level hardware design. Since it is an open IEEE standard, it is supported by a large variety of design tools and is quite interchangeable (when used generically) between different vendors' tools [17]. It also supports inclusion of technology-specific modules for most efficient synthesis to VLSI.

A. VHDL Test Bench Processes

In order to examine the VHDL code for correct functionality, VHDL tools provide a feature called simulation. Simulation takes the VHDL code and simulates how it would work in hardware. In order to do this, the designer must provide to the simulator valid inputs to produce expected outputs. An efficient and common method of simulating VHDL code is through the use of a special type of VHDL code called a test bench as per Xilinx manual (2006)[18]. Test benches effectively surround the VHDL code the designer wishes to simulate and also provide stimulus to the tested entity. While designing the parallel system, the following points are to be noted 19].

(i) Identify the maximum number of sub blocks.

(ii) The logic of sub blocks can be modified to reduce the number of logic transitions.

(iii) Implement all the sub blocks under parallel architecture such that all blocks will work concurrently which increases the processing speed, this may reduce the power dissipation of the entire system.

The synthesis process transforms the VHDL model into a gate –level net list. The target technology contains technology – independent generic blocks such as logic gates and register-transfer level (RTL) blocks, such as arithmetic-logic-units and multiplexers, comparators interconnected by wires [12]. A second program called RTL module builder is necessary. The purpose of this builder is to build, or acquire from a library of predefined components, each of the required RTL blocks in the user-specified target technology. Having produced a gate-level net list, a logic optimizer reads in this net list and optimizes the circuit for the user-specified area and timing constraints [13]. These area and timing constraints may also be used by the module builder for appropriate selection or generation of RTL blocks. Different synthesis system support different VHDL subsets for synthesis, each synthesis system may provide different mechanism to model a flip-flop or a latch [14]. Each synthesis system defines its own subset of VHDL language including its own personalized modeling style [15].

Spartan -3 families offers densities ranging from 50,000 to five million system gates. It is programmed by loading configuration data into robust, reprogrammable, static CMOS configuration latches (CCL) that collectively control all functional elements and routing resource s[16]. Embedded capabilities make Spartan-3 devices ideal as coprocessors or pre-and post-processors, offloading highly computational functions from a programmable DSP to enhance system performance.

V. SYNTHESIS OF SDT SYSTEM

The synthesis part of the SDT system is depicted in the figure 3 which includes two main blocks, max function, and min function. The summary of Mapped resource for the SDT system synthesis is tabulated in Table.V and shows that only less part of the resources is used for the VHDL synthesis process.

Table. V Mapped Resources Summary

MAPPED RESOURCES	USED/TOT	PERCENTAGE
Macro cell	20/32	62
Product terms	38/112	34
Function block	19/80	24
Registers	14/32	44
Pins	18/33	55

Figure 3 depicts only the major Entity blocks of the SDT system. But each block internally uses numerous components to synthesis the output Function [17],[18],[19]. By using the RTL schematic internal components also be analyzed

VI. RESULTS AND DISCUSSION

To study the relative performance of these Fuzzy techniques and STD models with mat lab and FPGA simulation, we measure two parameters, the Performance Index and the Quality Value. These parameters are calculated for each set of twenty patients and compared.

A. Performance Index

A sample of Performance Index for a known epilepsy data set at average value is shown in table VI. It is evident that the STD optimization model and FPGA charts a better performance than the fuzzy techniques because of its lower false alarms and missed classifications.

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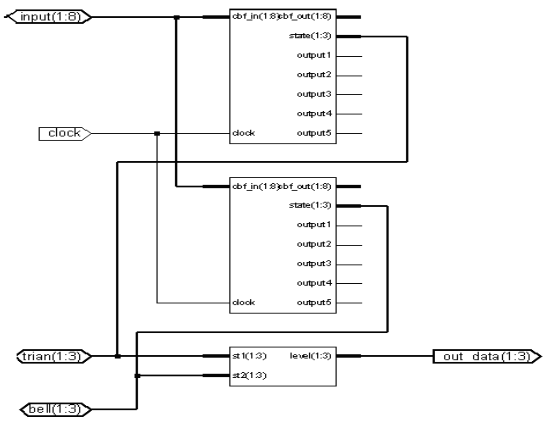

Figure 3 Synthesis of SDT systems

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A. Performance Index

A sample of Performance Index for a known epilepsy data set at average value is shown in table VI. It is evident that the STD optimization model and FPGA charts a better performance than the fuzzy techniques because of its lower false alarms and missed classifications.

Table VI. Performance Index

Methods	Perfect Classific-ation	Missed Classific-ation	False Alarm	Performance Index
Fuzzy Technique	50	20	10	40
SDT Method				
AR1	96.03	2.91	1.04	95.88
AR2	94.59	2.08	3.33	94.28
AR3	97.29	0	2.71	97.21
FPGA Method				
AR1	96.04	2.29	1.66	95.88
AR2	98.125	0.625	1.25	98.74
AR3	95.42	1.458	3.125	95.2

B. Quality Value

In Order to compare different classifier a measure that reflects the overall quality of the classifier was needed. The quality value was determined by three factors. Classification rate, Classification delay, and False Alarm rate. The quality value Q_V was defined as [5}

$$Q_V = \frac{C}{(R_{fa} + 0.2) * (T_{dly} * P_{dct} + 6 * P_{msd})} \quad (7)$$

Where, C is the scaling constant, R_{fa} is the number of false alarm per set, T_{dly} is the average delay of the on set classification in seconds, P_{dct} is the percentage of perfect classification and P_{msd} is the percentage of perfect risk level missed. A constant C is empirically set to 10 because this scale is the value of Q_V to an easy reading range. The higher value of Q_V, the better the classifier among the different classifier, the classifier with the highest Q_V should be the best.

Table. VII Results of Classifiers taken as Average of all Twenty Patients

Methods	Weighted delay (s)	False-alarm rate/set	Performance Index %	Quality value
Fuzzy logic	4	0.2	40	6.25
SDT Method				
AR1	2.095	1.04	95.88	22.68
AR2	2.0166	3.33	94.28	21.25
AR3	1.945	2.71	97.21	22.63
FPGA Method				
AR1	2.0582	1.66	95.88	22.43
AR2	2	1.25	98.1	23.52
AR3	1.908	3.125	95.2	22.65

It wa It is observed from table VII that STD and FPGA are performing well with the higher performance index and quality values.

VIII. CONCLUSION

In this paper, we consider generic classification of the epilepsy risk level of epileptic patients from EEG signals. The parameters derived from the EEG signal are complied as data sets. Then the fuzzy logic is used to the risk level from each epoch at every EEG channel. The target was to classify perfect risk levels with high rate of classification, a short delay from onset, and a low false alarm rate. Though it is impossible to obtain a perfect performance in all these conditions, some compromises have been made. As a high false alarm rate ruins the effectiveness of the system, a low false-alarm rate is most important. Since, the fuzzy outputs are highly nonlinear in nature with dynamic probability functions. STD based optimization technique to optimize the risk level by incorporating the above goals was chosen. FPGA simulation of SDT was carried out and it closely follows the mat lab version. Further research is in the direction to compare these hybrid models with Fuzzy Support Vector Machine (SVM) model to solve this open end problem.

ACKNOWLEDGEMENTS

The authors thank the Management and the Principal of Bannari Amman Institute of Technology, Sathyamangalam for providing excellent computing facilities and encouragement. The authors are grateful to Dr.Asokan, Neurologist, Ramakrishna Hospital Combiatore and Dr. B.Rajalakshmi, Diabetologist, Govt. Hospital Dindigul for providing the EEG signals.

This research is also funded by AICTE RPS.:F No 8023/BOR/RID/Rps-41/2009-10 , dated 10th Dec 2010.

REFERENCES

1. K. P.Adlassnig, "Fuzzy Set Theory in Medical diagnosis", IEEE Transactions on Systems Man Cybernetics, vol,16 , March 1986, pp 260-265.
2. R.Harikumar, Dr.(Mrs.). R.Sukanesh, P.A. Bharathi, "Genetic Algorithm Optimization of Fuzzy outputs for Classification of Epilepsy Risk Levels from EEG signals," Journal of Interdisciplinary panels I.E. (India), vol.86, no.1, May 2005,pp1-10.
3. Leon D.Iasemidis etal., Adaptive Epileptic SeizurePrediction System, IEEE Transactions on Biomedical Engineering, May 2003,50(5): 616-627.
4. Alison A Dingle et al, A Multistage system to Detect epileptic form activity in the EEG,IEEE Transactions on Biomedical Engineering,1993, 40(12):1260-1268.
5. Haoqu and Jean Gotman, A patient specific algorithm for detection onset in long-term EEG monitoring possible use as warning device, IEEE Transactions on Biomedical Engineering, February 1997,44(2): 115-122.
6. Dr.(Mrs.).R.Sukanesh, R.Harikumar, A Simple Recurrent Supervised Learning Neural Network for Classification of Epilepsy Risk Levels from EEG Signals, I.E.India Journal of Interdisciplinary panels Vol.87,no.2,pp 37-43, Nov 2006
7. Celement.C etal, A Comparison of Algorithms for Detection of Spikes in the Electroencephalogram, IEEE Transaction on Bio Medical Engineering, April 2003, 50 (4): 521-26.
8. Nurettin Acir etal., Automatic detection of epileptiform events in EEG by a three-stage procedure based artificial neural networks, IEEE transaction on Bio Medical Engineering January 2005,52(1):30-40.
9. M.W.Kurzynski, "The optimal Strategy of a Tree Classifier," Pattern Recognition, vol 16, 1983, pp 81-87.
10. Philippe Salembier, Luis Garrido, "Binary Partition Tree as an Efficient Representation for Image Processing, Segmentation, and Information Retrieval," IEEE Transactions on Image processing,vol.9, no.4, April 2000,pp-561-576.
11. K.Srirama murty and B.Yegnannarayana, "Combining Evidence from Residual Phase and MFCC Features for Speaker Recognition", IEEE Signal Processing Letters, vol,13,no.1, 2006, pp 52-55.
12. K.Paramasivam, R.Harikumar, K.Gunavathi Simulation of VLSI Design using Parallel Architecture for Epilepsy risk level Diagnosis in Diabetic Neuropathy, Proc. Of National conference on VLSI Design and Testing, Coimbatore, India, Feb.21st and 22nd 2003.
13. Mahamoud A Manzoul, D.Jayabharathi , FPGA for Fuzzy Controllers, IEEE Tran. System Man Cybernetics Vol.25, No. 1 Jan. 1995.
14. Verilog HDL Language Reference Manual, IEEE, 2001.
15. Zoran Salcic, High Speed Customizable Fuzzy logic Processor: Architecture and Implementation, IEEE Tran. System Man Cybernetics Vol.31, No. 6, pp 731-736, November 2001.
16. Giuseppe ascia, Vincenzo catania, Marco Russo, Lorenzovita, Rule Driven VLSI fuzzy processor, IEEE Micro, Vol.16, no.3, pp 62-74, June 1996.
17. C.Maxfield, "The Design Warrior Guide to FPGA," *Mentor Graphic's Corporation and Xilinx Inc*.,USA, 2006.
18. R. Freeman, "User-Programmable Gate Array," *IEEE Spectrum,* pp.32-35, December 1988.
19. J. Di Giacomo, "Design Methodology," in VLSI Handbook, J. Di Giacomo, Editors, New York: McGraw-Hill, pp. 1.3-1.9, 1989.

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