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Intelligent reconfigurable universal fuzzy flip-flop

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Abstract: In this paper a universal fuzzy flip-flop is proposed that can be reconfigured as a fuzzy SR, D, JK, or T flip-flop. When integrated with a multi layer neural network, the resulting reconfigurable fuzzy-neural structure showed excellent learning ability. The sigmoid activation function of neurons in the hidden layers of the multilayer neural network was replaced by the quasi-sigmoidal transfer characteristics of the universal fuzzy flip-flop in the reconfigurable fuzzy-neural structure. Experimental results showed that the reconfigurable fuzzy-neural structure can be effectively trained using either a large or sparse set of data points to closely approximate nonlinear input functions.

Keywords: reconfigurable fuzzy flip-flop, function approximation

Classification: Science and engineering for electronics

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1 Introduction

With advances in technology, fuzzy logic applications have been implemented using dedicated hardware at chip level and are therefore conducive to embedded applications. Several researchers have proposed designs of fuzzy gates [1] and fuzzy flip-flops [1, 2, 3, 4] for dedicated fuzzy logic systems. Using the fuzzy flip-flop as a basic building block, researchers have also proposed combining it with neural networks to design intelligent fuzzy state machines [5], while other researchers have extended this further to approximate nonlinear functions [6]. The integration of fuzzy logic and neural networks produces intelligent machine-learning hardware with the ability to learn from its input data. In the literature, most applications focused on individual fuzzy flip-flops.

In this paper, we propose the design of a reconfigurable universal fuzzy flip-flop that can be configured as a fuzzy SR flip-flop, fuzzy D flip-flop, fuzzy JK flip-flop or fuzzy T flip-flop. Such a building block is useful for rapid prototyping and designing complex fuzzy systems. The reconfigurable universal fuzzy flip-flop is integrated with a neural network to form a fuzzy-neural structure that has the benefits of both a neural network and a fuzzy system. The ability of the resulting fuzzy-neural structure to learn any nonlinear input function and generate an output that closely approximates the input is studied.

2 Proposed reconfigurable universal fuzzy flip-flop design

Unlike existing fuzzy flip-flops that are treated as individual fuzzy logic devices, the proposed universal fuzzy flip-flop building block has the flexibility to reconfigure the appropriate fuzzy memory element for a given application. The reconfiguration is easily implemented to (a) meet design specifications, (b) select an alternate fuzzy memory computing structure in the event of component failure, or (c) incorporate design modifications when additional features are added or changed. Fig. 1 (a) shows the four modes of the proposed reconfigurable universal fuzzy flip-flop controlled by signals X and Y. For each mode, the inputs A and B of the universal fuzzy flip-flop generate fuzzy output signals. The characteristic equation Q+ of the proposed universal fuzzy flip-flop is obtained by transforming the binary operators of logical product, logical sum, and complement to corresponding fuzzy logic operators. The logical product is transformed to fuzzy intersection operator referred to as a t-norm ($\mathcal{T}$) or triangular norm operator. The logical sum is transformed to a fuzzy union operator referred to as an s-norm ($\mathcal{S}$) or t-conorm operator and the logical complement is replaced by fuzzy negation operator ($\mathcal{N}$). In the literature, there are several definitions of t-norms and s-norms. In this paper, we use algebraic norms where, $(a\ \mathcal{T}\ b) = a.b$, $(a\ \mathcal{S}\ b) = a + b - ab$, and $\mathcal{N}\ (a) = 1 - a$. Using the algebraic fuzzy norms, the binary characteristic equation of the reconfigurable universal flip-flop defined in Eq. (1),

$$Q+ = (A + Q)(Y + A + \bar{B})(X + \bar{Y} + A)$$

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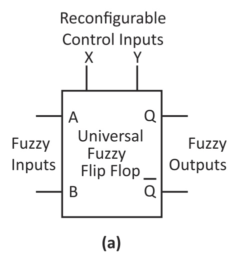
$$(\bar{X}+\bar{A}+\bar{B}+\bar{Q})(\bar{X}+\bar{Y}+\bar{A}+\bar{Q}) \quad (1)$$

is transformed to the fuzzy characteristic equation given by,

$$\begin{aligned} Q+ = {} & (1-X)(1-Y)[(A+Q-AQ)(AB-B+1)] + \\ & (1-X)Y[A(A+Q-AQ)] + \\ & X(1-Y)[(1-ABQ)(A+Q-AQ)(AB-B+1)] + \\ & XY[(AQ-1)(ABQ-1)(A+Q-AQ)] \end{aligned} \quad (2)$$

Control inputs X and Y are binary while the inputs A and B of the universal fuzzy flip-flop take any value from 0 to 1. Each input combination yields a large number of output sequences for the present state Q, and next state $Q+$. Fig. 1 (b)–(e) shows a representative sample of the fuzzy dynamic output characteristics between the present state Q and the next state $Q+$ for different values of A and B, and for different modes of the universal fuzzy flip-flop. This unlimited output response patterns makes the universal fuzzy flip-flop a powerful building block for fuzzy logic system design.



Control Inputs		Flip Flop Inputs		Universal Fuzzy Flip Flop Mode
X	Y	A	B	
0	0	S	R	SR
0	1	D		D
1	0	J	K	JK
1	1	T		T

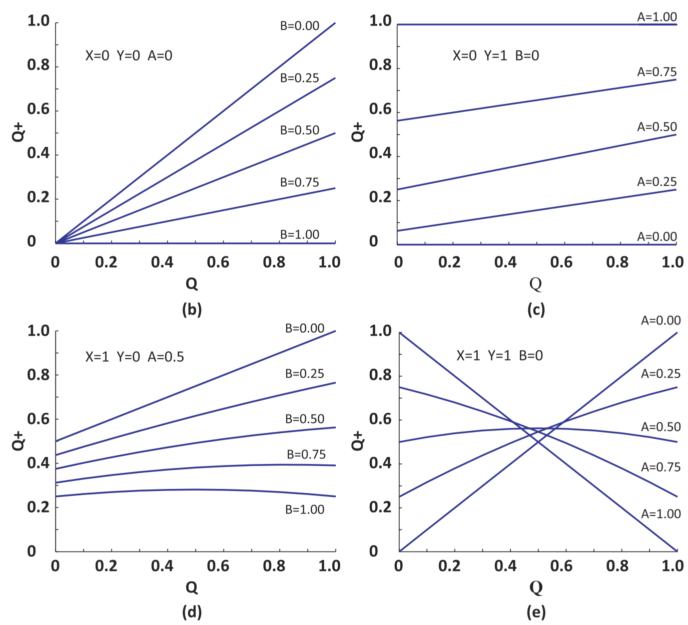


Fig. 1. (a) Reconfigurable universal fuzzy flip-flop and its dynamic characteristics in four operating modes (b) SR FFF (c) D FFF (d) JK FFF (e) T FFF

3 Proposed reconfigurable fuzzy-neural structure

In this section, we will use the proposed reconfigurable universal fuzzy flip-flop to learn any nonlinear input function and generate an approximate func-

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tion at the output. It is well known that feedforward multilayer neural networks can uniformly approximate any nonlinear continuous function. Fig. 2 shows a multilayer feedforward fuzzy-neural network with two hidden layers. In general, the output $\boldsymbol{F}$ is expressed as a function of the input $\boldsymbol{x}$ and interconnection weights $\boldsymbol{w}$.

$$\boldsymbol{F}(\boldsymbol{x}, \boldsymbol{w}) = \varphi_0\left(\sum_{h_2} w_{y_i h_2}\varphi_2\left(\sum_{h_1} w_{h_2 h_1}\varphi_1\left(\sum_i w_{h_1 i}x_i + b_{h_1}\right) + b_{h_2}\right) + b_{y_i}\right) \quad (3)$$

where $i = 1, 2, \ldots, n$; $w_{h_1 i}$ is the synaptic weight between input x_i and a neuron in the first hidden layer; $w_{h_2 h_1}$ is the synaptic weight between a neuron h_1 in the first hidden layer and a neuron h_2 in the second hidden layer; and $w_{y_i h_2}$ is the synaptic weight between a neuron h_2 in the second hidden layer and a neuron y_i in the output layer. b_{h_1}, b_{h_2}, b_{y_i}, are the bias vectors of the first hidden layer, the second hidden layer and the output layer.

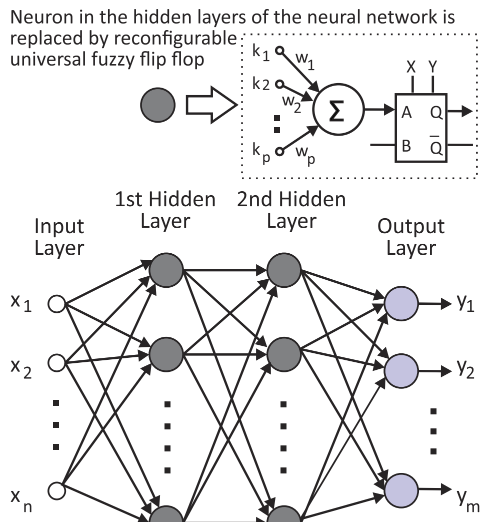

Fig. 2. Fuzzy-neural network structure

In the proposed reconfigurable fuzzy-neural structure, the sigmoid activation functions $\varphi_1(.)$ and $\varphi_2(.)$ are defined by the quasi-sigmoid transfer characteristics of the universal fuzzy flip-flop as delineated in the fuzzy characteristic Eq. (2). The output sigmoid activation function $\varphi_0(.)$ in the feedforward neural network is a linear transfer function. This reconfigurable fuzzy-neural structure will demonstrate the learning ability to perform nonlinear input-output mapping for function approximation.

4 Experimental results

To study the performance of the proposed reconfigurable fuzzy-neural structure when approximating complex nonlinear input functions, we considered two functions $y_1(x)$ and $y_2(x_1, x_2)$. The first complex function was represented by $y_1(x) = [sin(4x)cos(20x)/2.5] + 0.5$. Using this function, a large number of data points (1000) was generated. We next considered a second

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nonlinear complex function represented by $y_2(x_1, x_2) = (1 + x_1^{-2} + x_2^{-1.5})^2$ where $1 \leq (x_1, x_2) \leq 5$. For our experiment, a sparse dataset (50 data points) identical to the data points used by other researchers for similar applications was chosen, providing a baseline for comparing the efficacy of the proposed reconfigurable fuzzy-neural network with previously published results [7, 8]. In the case of the first nonlinear complex function $y_1(x)$, we compared the performance of the proposed reconfigurable fuzzy-neural network with the feedforward neural network using the hyperbolic tangent sigmoid activation function (*tansig*) which yielded the best performance. These two datasets show the learning ability when the data points are large and when the data points are sparse. Furthermore, since the proposed universal fuzzy flip-flop can be reconfigured to a fuzzy SR flip-flop, fuzzy D flip-flop, fuzzy JK flip-flop or fuzzy T flip-flop, we further studied the performance of function approximation in each of these modes.

When approximating the function $y_1(x)$ using the multilayer neural network, we sampled the data points uniformly and the corresponding values of $y_1(x)$ were evaluated. The pairs of data points were used to train the multilayer neural network using the Levenberg-Marquardt algorithm with a maximum of 120 epochs. In our experiment, each hidden layer had 20 neurons and each neuron in the first and second hidden layers had a *tansig* activation function. The neurons in the output layer had a linear transfer function. The initial weights were randomly assigned small values. The approximated function generated by the multilayer neural network and the proposed reconfigurable fuzzy-neural structure for each mode of the universal fuzzy flip-flop are shown in Fig. 3 (a). The graphs show that the function approximation of the fuzzy-neural structure for each mode closely matched the performance of the feedforward neural network. The mean squared error (MSE) was calculated for all five cases representing the fuzzy-neural structure, based on the four modes of the reconfigurable universal flip-flop and the multilayer neural network with *tansig* activation function in the hidden layers. These results are shown in Fig. 3 (b). The average MSE values were obtained after running the experiment 150 times. The best approximation of the function $y_1(x)$ was obtained when the universal fuzzy flip-flop was configured in the fuzzy T flip-flop mode. The results are comparable to those obtained with the multilayer neural network using *tansig* activation function.

In the first hidden layer, a subset of neurons extracts the local features of the nonlinear function by partitioning the input space into regions. The remaining neurons in the first layer learn the characteristics of these individual regions. In the second hidden layer, each neuron learns the global features of each individual region in the first layer and is combined to generate the approximated function at the output. Higher accuracy is obtained by increasing the number of neurons in the hidden layers.

Next the function $y_2(x_1, x_2)$ was approximated with only 50 data points, as used in similar experiments by other researchers [7, 8]. The universal fuzzy flip-flop in the fuzzy-neural structure was reconfigured in the fuzzy T flip-flop mode to obtain the best performance. We ran the tests 30,000 times

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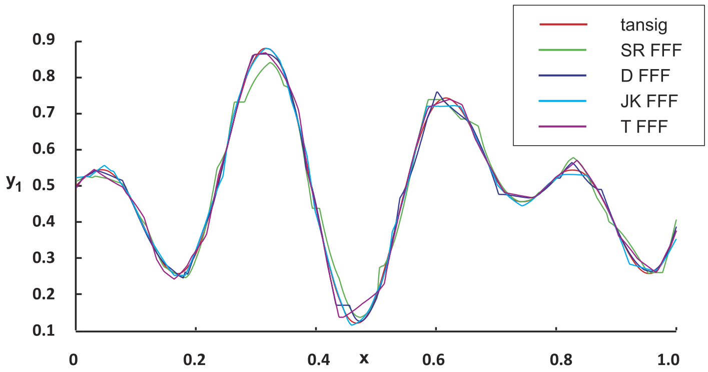

(a)

Dataset	Mean Squared Error (M S E)						
	tansig	SR FFF	D FFF	JK FFF	T FFF	Sugeno [7]	Scherer[8]
Large	1.18E-02	1.90E-02	2.12E-02	1.43E-02	8.95E-03		
Sparse					2.67E-01	2.81E-01	2.73E-01

(b)

Fig. 3. (a) Performance of reconfigurable universal fuzzy-neural structure as function approximator (b) Quantitative comparison

to be consistent with the experimental design of previously published work. Fig. 3 (b) compares the results of MSE obtained by the proposed fuzzy-neural structure when the universal flip-flop is configured in the fuzzy T flip-flop mode with the results obtained by Sugeno et al. [7] and by Scherer [8]. The results show that even with the sparse dataset, the reconfigurable neuro-fuzzy structure has good learning ability and performed better as a function approximator compared with the recently proposed relational neuro-fuzzy system [8] and the results reported in [7].

5 Conclusion

In this paper we proposed the design of a reconfigurable universal fuzzy flip-flop, as an alternative to previous designs that have focused on selected individual fuzzy flip-flops such as fuzzy JK, D or T flip-flops. The functionality of the reconfigurable universal fuzzy flip-flop is extended to generate a myriad of responses to optimize the performance for specific applications. We integrated the reconfigurable universal fuzzy flip-flop in the hidden layers of a multilayer neural network. This replaced the sigmoid activation function of the neurons by the quasi-sigmoid transfer characteristics of the universal fuzzy flip-flop. The learning ability of the resulting reconfigurable fuzzy-neural structure was demonstrated by a function approximation application. The universal fuzzy flip-flop was configured in each of the four modes by selecting different values for the fuzzy inputs. The learning ability of the proposed reconfigurable fuzzy-neural structure was studied when the available data points were large and when the data points were sparse. The MSE results obtained by using two nonlinear complex functions showed that the fuzzy-neural structure has very good learning ability, as demonstrated in the function approximator application.

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