



A Flexible Link Radar Control Based on Type-2 Fuzzy Systems

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Abstract

An adaptive neuro fuzzy inference system based on interval Gaussian type-2 fuzzy sets in the antecedent part and Gaussian type-1 fuzzy sets as coefficients of linear combination of input variables in the consequent part is presented in this paper. The capability of the proposed method (we named ANFIS2) for function approximation and dynamical system identification is remarkable. The structure of ANFIS2 is very similar to ANFIS but in ANFIS2 a layer is added for purpose to type reduction. An adaptive learning rate based backpropagation with convergence guaranteed is used for parameter learning. Finally the proposed ANFIS2 are used to control of a flexible link robot arm that can be used in radar. Simulation results shows the proposed ANFIS2 with Gaussian type-1 fuzzy set as coefficients of linear combination of input variables in the consequent part has good performance and high accuracy but more training time.

Keywords: Flexible Link Radar, ANFIS, Interval Type-2 Fuzzy Sets.

Article history: Received 29- SEP-2017; Revised 12- OCT-2017; Accepted 16-NOV-2017.

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1. Introduction

Parallel processing, adaptability and high computation ability are the important advantages of neural networks [1]. Using the knowledge of expert man as if-then rules and having real concept of parameters are the advantages of fuzzy systems. Among hybrid fuzzy neural networks, ANFIS is very popular and widespread. ANFIS is very simple and intelligible so it has affected many areas such as geography, medical Sciences, meteorological science, chemical and petroleum engineering and etc. [2, 3]. A flexible link arm is a distributed parameter system of infinite order, but must be approximated by a lower-order model and controlled by a finite-order controller due to onboard computer limitations, sensor inaccuracy, and system noise. The so-called “control spillover” and “observation spillover” effects then occur, which under certain conditions can lead to instability [4].

In recent ten years, type-2 fuzzy logic with more capabilities and more flexibility than type-1 fuzzy logic has been investigated. Castillo et al. investigated type-2 fuzzy logic in more details [5].

Huang and Chen [6] used the combination of quantum inspired bacterial foraging algorithm (QBFA) and recursive least squares (RLS) to tune a type-2 fuzzy system. Tavoosi et al. proposed a different architecture of interval type-2 takagi-sugeno-kang fuzzy neural network [7]. They proposed an ANFIS based on type-2 fuzzy sets. Shahnazi [8] used type-2 fuzzy systems to approximate the unknown nonlinearities in MIMO systems control problem. He derived all the adaptive laws via Lyapunov synthesis approach.

Not much study has been done on fuzzy systems with type-1 (or type-2) fuzzy sets in the consequent part. In most of papers the consequent part is singleton [9] or interval type-1 fuzzy sets [10-12] up to now. In continue some of the works in this area are reviewed. In [13] interval type-2 fuzzy integrators in ensembles of ANFIS models for the time series prediction is used. Genetic algorithm is used to optimize of the proposed model. The equations of Type-2 ANFIS and its optimization are not presented. In [14] interval type-2 adaptive network-based fuzzy inference

system with type-2 non-singleton fuzzification have introduced. Interval type-1 fuzzy sets have been used as consequent parameters. Mendez and Hernandez [15] presented a type-2 fuzzy ANFIS that interval type-1 non-singleton fuzzy numbers are the inputs and type-2 TSK FLS is the output and the consequent parameters are estimated by the recursive least-squares (RLS) method. They didn't provide further details of learning equations. Bhattacharyya et al. [16] proposed a type-2 fuzzy ANFIS that an interval type-2 fuzzy logic is used to combine the different outputs of the ANFIS classifiers to produce a final optimal result.

2. A Review on Type-2 Fuzzy Systems

In dealing with a lot of uncertainties, the performance and efficiency of type-1 fuzzy systems is not suitable. The membership degree of type-1 fuzzy sets is a crisp number while the membership degree of type-2 fuzzy sets is a type-1 fuzzy number.

Some difficulties of type-1 fuzzy logic can be solved by using type-2 fuzzy logic. In some systems such as time-series prediction, the exact membership degree is determined in a very difficult manner due to their complexity and their noisy information [25]. So using type-2 fuzzy systems for describing behaviour of these systems can be useful. In [26], some disadvantages of type-1 fuzzy sets are mentioned.

Fig.1. shows the Gaussian primary membership function and Gaussian secondary membership function. For example if $m = 0, \sigma = 1$ and $x = 1$ then degree of membership is 0.6, if this membership degree is too fuzzy or $\tilde{0.6}$ then primary membership is Gaussian type-1 fuzzy set with $m = 0, \sigma = 1$ and secondary membership is Gaussian type-1 fuzzy set with $m = 0.6, \sigma = 0.1$.

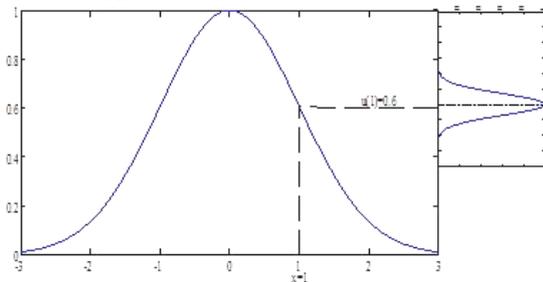


Fig. 1. Gaussian primary and secondary membership functions

Note that, when secondary membership is not Gaussian type-1 fuzzy set and it is equal to one and in other words secondary membership function is interval set with one magnitude, then fuzzy set called interval type-2 fuzzy set.

Two cases of interval type-2 fuzzy sets are shown in Fig. 2. In Fig. 2-a, a case of a fuzzy set

characterized by a Gaussian membership function with mean m and a standard deviation that can take values in $[\sigma_1, \sigma_2]$ and in Fig. 2-b, a case of a fuzzy set with a Gaussian membership function with a fixed standard deviation σ , but an uncertain mean, taking values in $[m_1, m_2]$ and are shown.

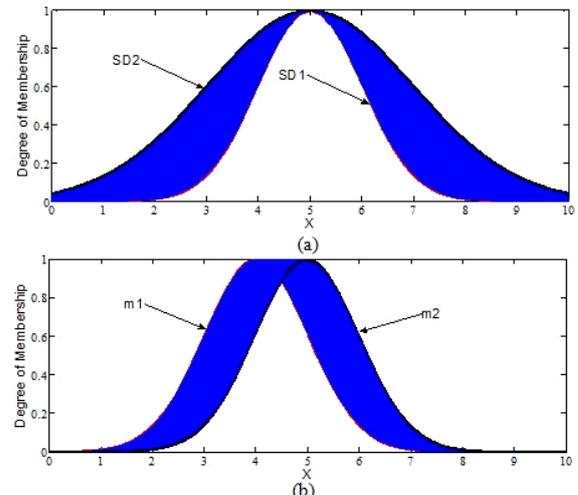


Fig. 2. a) Uncertainty in standard deviation b) uncertainty in mean

In this paper Gaussian membership function with fixed standard deviation σ and uncertain mean is used (Fig. 2. b).

3. Adaptive Neuro Fuzzy Inference System by Type-2 Fuzzy Sets (ANFIS2)

Similar to type-1 TSK fuzzy systems, the output of type-2 TSK fuzzy systems is a function of their inputs. But in type-2 fuzzy systems the output and its coefficients are type-1 fuzzy sets. In this paper, the proposed ANFIS2 has seven layers that its structure is shown in Fig 3. The two rules of ANFIS2 can be described as follows:

$$\begin{aligned}
 R^1: & \text{if } x_1 \text{ is } \tilde{A}_1 \text{ and } x_2 \text{ is } \tilde{B}_1 \text{ then } \tilde{y}_1 = \tilde{r}_1 + \tilde{p}_1 x_1 + \tilde{q}_1 x_2 \\
 R^2: & \text{if } x_1 \text{ is } \tilde{A}_2 \text{ and } x_2 \text{ is } \tilde{B}_2^k \text{ then } \tilde{y}_2 = \tilde{r}_2 + \tilde{p}_2 x_1 + \tilde{q}_2 x_2
 \end{aligned}
 \tag{1}$$

Where $x_i (i = 1,2)$ are inputs, $\tilde{y}_k (k = 1,2)$ is output of the k th rule which it is type-1 fuzzy set (since it is a linear combination of Gaussian type-1 fuzzy sets), \tilde{A}_i^k are antecedent interval type-2 fuzzy sets, \tilde{r}_k, \tilde{p}_k and $\tilde{q}_k (k = 1,2)$ are Gaussian type-1 fuzzy sets. For simplicity in description we select only two inputs and two rules but the proposed ANFIS2 can be generalized to n -inputs and m -rules ($n, m \in N$).

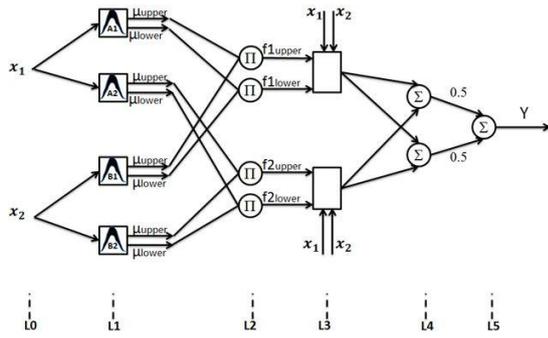


Fig. 3. The structure of ANFIS2

The forward-propagation procedure is described as follows:

Layer 0: This layer is inputs layer. The number of nodes in this layer is equal to the number of inputs.

Layer 1: This layer is fuzzification layer. The output of this layer as follows:

$${}^1\mu_{k,i}(x_i, [\sigma_{k,i}, {}^1m_{k,i}]) = e^{-5\left(\frac{x_i - {}^1m_{k,i}}{\sigma_{k,i}}\right)^2} \quad (2)$$

$${}^2\mu_{k,i}(x_i, [\sigma_{k,i}, {}^2m_{k,i}]) = e^{-5\left(\frac{x_i - {}^2m_{k,i}}{\sigma_{k,i}}\right)^2} \quad (3)$$

Where $m_{k,i} \in [{}^1m_{k,i}, {}^2m_{k,i}]$ is uncertain mean for k th rule and i th input.

$$\bar{\mu}_{k,i}(x_i) = \begin{cases} {}^1\mu_{k,i}(x_i, [\sigma_{k,i}, {}^1m_{k,i}]), & x_i < {}^1m_{k,i} \\ 1, & {}^1m_{k,i} \leq x_i \leq {}^2m_{k,i} \\ {}^2\mu_{k,i}(x_i, [\sigma_{k,i}, {}^2m_{k,i}]), & x_i > {}^2m_{k,i} \end{cases} \quad (4)$$

$$\hat{y}_l = \frac{\sum_{k=1}^N \bar{f}^k(m_{r_k}\sigma_{r_k} + m_{p_k}\sigma_{p_k}x_1 + m_{q_k}\sigma_{q_k}x_2) + \sum_{k=N+1}^M \bar{f}^k(m_{r_k}\sigma_{r_k} + m_{p_k}\sigma_{p_k}x_1 + m_{q_k}\sigma_{q_k}x_2)}{\sum_{k=1}^N \bar{f}^k(\sigma_{r_k} + \sigma_{p_k} + \sigma_{q_k}) + \sum_{k=N+1}^M \bar{f}^k(\sigma_{r_k} + \sigma_{p_k} + \sigma_{q_k})} \quad (8)$$

$$\hat{y}_r = \frac{\sum_{k=1}^L \bar{f}^k(m_{r_k}\sigma_{r_k} + m_{p_k}\sigma_{p_k}x_1 + m_{q_k}\sigma_{q_k}x_2) + \sum_{k=L+1}^P \bar{f}^k(m_{r_k}\sigma_{r_k} + m_{p_k}\sigma_{p_k}x_1 + m_{q_k}\sigma_{q_k}x_2)}{\sum_{k=1}^L \bar{f}^k(\sigma_{r_k} + \sigma_{p_k} + \sigma_{q_k}) + \sum_{k=L+1}^P \bar{f}^k(\sigma_{r_k} + \sigma_{p_k} + \sigma_{q_k})}$$

Layer 5: The single node in this layer computes the output.

$$\hat{y} = \frac{\hat{y}_l + \hat{y}_r}{2} \quad (9)$$

Gradient descent with adaptive learning rate back propagation is used for learning phase [7].

4. Flexible Link Robot Arm (Used in Radar)

Consider a single-link robotic manipulator coupled to a brushed direct current motor with a no rigid joint. When the joint is modeled as a linear tensional spring, from the Euler–Lagrange equation, the equations of motion for such an electromechanical system can be derived as:

$$J_1\ddot{q}_1 + F_1\dot{q}_1 + K\left(q_1 - \frac{q_2}{N}\right) + mgd \cos q_1 = 0 \quad (10)$$

$$\underline{\mu}_{k,i}(x_i) = \begin{cases} {}^2\mu_{k,i}(x_i, [\sigma_{k,i}, {}^2m_{k,i}]), & x_i \leq \frac{{}^1m_{k,i} + {}^2m_{k,i}}{2} \\ {}^1\mu_{k,i}(x_i, [\sigma_{k,i}, {}^1m_{k,i}]), & x_i > \frac{{}^1m_{k,i} + {}^2m_{k,i}}{2} \end{cases} \quad (5)$$

Where $\bar{\mu}_{k,i}$ is upper membership degree and $\underline{\mu}_{k,i}$ is lower membership degree.

Layer 2: This is rule layer. Each output node represents the lower (\underline{f}^k) and upper (\bar{f}^k) firing strength of a rule:

$$\underline{f}^k = \prod_{i=1}^n \underline{\mu}_{k,i} \quad ; \quad \bar{f}^k = \prod_{i=1}^n \bar{\mu}_{k,i} \quad (6)$$

Layer 3: This is consequent layer.

$$\begin{aligned} \tilde{y}_1 &= \tilde{r}_1 + \tilde{p}_1x_1 + \tilde{q}_1x_2 \\ \tilde{y}_2 &= \tilde{r}_2 + \tilde{p}_2x_1 + \tilde{q}_2x_2 \\ &\vdots \end{aligned} \quad (7)$$

$$\tilde{y}_k = \tilde{r}_k + \tilde{p}_kx_1 + \tilde{q}_kx_2$$

\tilde{r}_k, \tilde{p}_k and \tilde{q}_k ($k = 1, 2$) are consequent coefficient that they are Gaussian type-1 fuzzy sets. Note that (7) can be extended to \tilde{y}_k ($k = 1, \dots, n$). In this paper k is 2.

Layer 4: This layer is used for consequent lower–upper firing points [27].

$$\begin{aligned} J_2\ddot{q}_2 + F_2\dot{q}_2 + \frac{K}{N}\left(q_1 - \frac{q_2}{N}\right) &= K_t i \\ LDi + Ri + K_b\dot{q}_2 &= u \end{aligned}$$

where q_1 and q_2 are the angular positions of the link and the motor shaft, i is the armature current, and u is the armature voltage. The inertias J_1, J_2 , the viscous friction constants F_1, F_2 , the spring constant K , the torque constant K_t , the back-emf constant K_b , the armature resistance R and inductance L , the link mass M , the position of the link's center of gravity d , the gear ratio N and the acceleration of gravity g can all be unknown.

A flexible link robot arm is shown in Fig. 4.

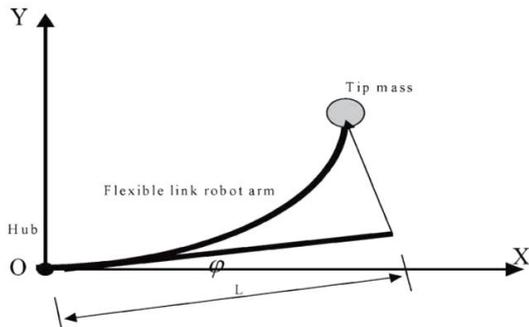


Fig. 4. Configuration of flexible-link robot arm.

5. Simulation Results

In this section, a flexible link robot arm is controlled using ANFIS2. The structure of the robot arm and ANFIS2 based controller is shown in Fig 5. Where the reference signal (desired angle in here) is applied to system then the error between reference signal and the output of robot system (angle of link in here) is calculated. This error must be minimized, so ANFIS2 is adapted to minimize the error.

In order to illustrate the effectiveness of the proposed results, the simulation will be conducted to control system, where $J_1 = 1.625 \text{ kg m}^2$, $J_2 = 1.625 \text{ kgm}^2$, $R = 0.5 \text{ } \square$, $K_t = 0.9 \text{ N m/A}$, $K = 0.5868$, $K_b = 0.9 \text{ N m/A}$, $M = 4.34 \text{ kg}$, $L = 25.0 \times 10^{-3} \text{ H}$, $g = 9.8 \text{ N/kg}$, $F_1 = 1.625 \times 10^{-2} \text{ N m s/rad}$, $F_2 = 1.625 \times 10^{-2} \text{ N m s/rad}$, $N = 2$, $d = 0.5 \text{ m}$.

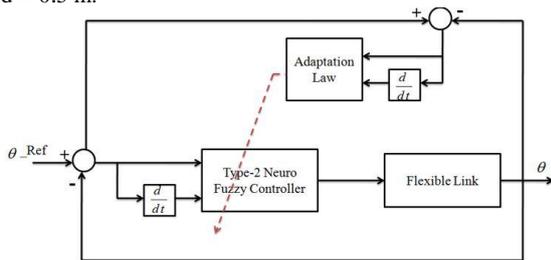


Fig. 5. The structure of the robot arm and ANFIS2 based controller

The performance of ANFIS2 with sine angle reference is shown in fig. 6.

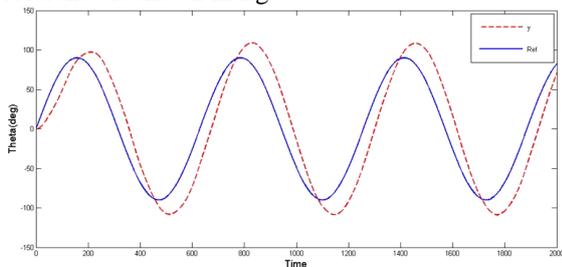


Fig. 6. ANFIS2 based controller with sine angle reference

The performance of ANFIS2 with step angle reference is shown in fig. 7.

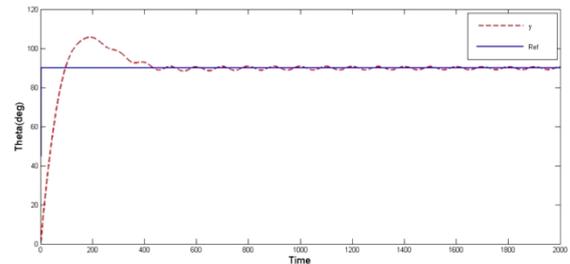


Fig. 7. ANFIS2 based controller with step angle reference

The performance of ANFIS2 with ramp angle reference is shown in Fig. 8.

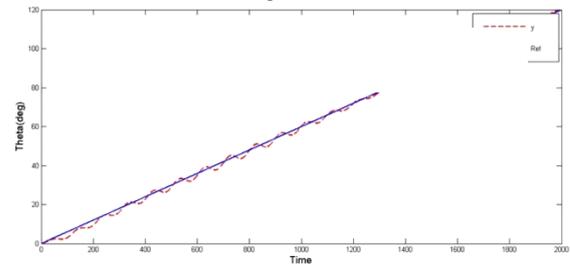


Fig. 8. ANFIS2 based controller with ramp angle reference

Figures 5-8 show that adaptive inverse control based on ANFIS2 is suitable and robust strategy to control of a flexible link robot arm.

6. Conclusion

In this paper, a novel ANFIS2 was proposed for identification of nonlinear dynamical systems. The proposed ANFIS2 is based on interval Gaussian type-2 fuzzy sets in the antecedent part and Gaussian type-1 fuzzy sets as coefficients of linear combination of input variables in the consequent part that it helps to improve modeling of highly nonlinear systems. Adaptive learning rate helps to prevent the ANFIS2 from trapping into a local minima and it helps to fast convergence of training algorithm. The test results show the importance and necessity of ANFIS2 to modeling the inverse of uncertain systems and control it.

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