International Journal of Engineering Research ISSN:2319-6890)(online),2347-5013(print)
Volume No.3, Issue No.5, pp : 318-320 01 May 2014

Embedded ANFIS as a Supervisory Controller for a 6-DOF Robotic Arm

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Abstract— This paper implements multi-layered ANFIS controller in PIC16F886 micro-controller as a supervisory control for a 6 DOF robotic arm. The complexity in mathematical modelling demands for machine-learning techniques, which rely less on precise mathematical analysis. ANFIS is one such machine learning technique which helps in decision making for the control of robotic arms. Standard PD controllers could be used as servos to guarantee precise tracking. Based on real physical parameters of Dexter ER-1, a model is developed in Sim –Mechanics to capture the actual dynamics of robot arm. The time dependent reachable set is generated out of which it gave nearly 40,000 data samples. This data is used as inverse training data for ANFIS network and is implemented as a supervisory controller in microcontroller. The controller is tested with predefined paths and random position targets and results are shown to act satisfactorily.
Keywords- ANFIS, micro controller, PIC, fuzzy logic, Clustering, Sim-Mechanics

INTRODUCTION

Robotic manipulators, especially of the SCARA type have found wide range applications from small scale sectors to high end industries. They are generally used in inaccessible places, space and robotically assisted surgeries.

Traditional modeling and control of arms using first principles are precise, but, the complexity is proportional to DOF of manipulators. For a 6-DOF robotic arm these methods becomes inaccurate because of increased complexity in mathematical modeling and computation management. Soft computing techniques offer a useful approach in modeling and control of such systems. Systems with less knowledge could be controlled successfully with neural networks, and systems with incomplete knowledge but predictive responses could be modeled and controlled using Fuzzy systems [1]. ANN's had the limitation with complexity and in higher DOF robotic arms lack of intuition makes fuzzy modeling tough. It is well known that the solution exists in ANFIS systems where the learning ability of neural networks will assist Fuzzy systems to represent the knowledge expressed in the form of linguistic rules[3][6][5]. However, there is no specific method to decide the number of membership functions and choice of ANN architecture in order to start up the design process right away. This problem multiplies in the case of large data sets to train ANFIS.

This paper focuses on application of ANFIS on robotic arms with higher DOFs and huge reachable sets. For a six DOF arm this has reached to 40,000 data points with 1cm resolution in end effecter positioning. The number of neural networks and the number of member ship functions in each ANFIS controller need to be optimized in order to obtain satisfactory control performance and reduce computational cost. Obtaining the optimum number of membership functions for each ANFIS is described in section 3. Training each ANFIS with respective positions as inputs and joint angle as output is explained in section 2. Section 4 describes an algorithm for implementing generated ANFIS on an 8-bit microcontroller. Programmed micro controller is used as supervisory control and tested Dexter ER-1 arm for random positions and predefined paths. Section 5 shows that the controller worked satisfactorily for given target positions.

I. GENERATION AND TRAINING DATA

Usual procedure of generating training data is to predict with Kinematic analysis of robotic manipulator using forward kinematics equations. Neural Networks obtained out of such training data could not account for dynamics of the system. The best solution for this is to generate training data from real system. But generating all possible combinations out of real systems is challenging to interface and operate in safer limits. In this paper a Sim-Mechanics model is developed taking physical parameters of Dexter ER-1 which includes inertia, mass, motor dynamics etc. This model behaves as a real arm under gravity and generates dynamic data easily without the hassle of sensor interfaces and communication lags. A plot of generated data for 1cm resolution in the positioning of end effecter is shown in Figure 1. This data is used as inverse training data to create an ANIFS controller as explained in following sections.

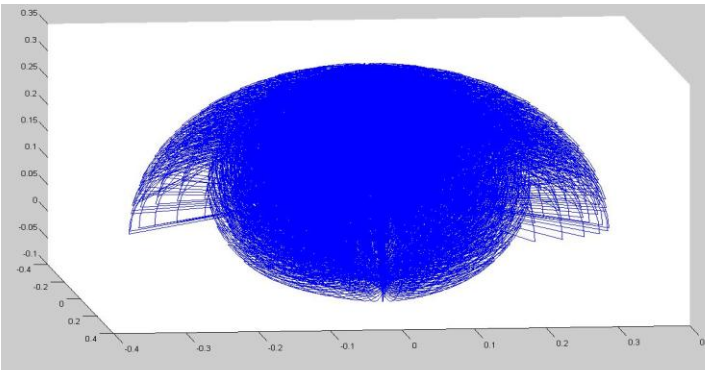

Fig.1.Reachable set of *DEXTER ER-1*.

II. ANFIS ARCHITICTURE

ANFIS is a neural network with hybrid learning rules based on Sugeno type fuzzy interface system (FIS). Mamdani FIS supports MIMO structure but leads to complexities in centroid calculations. Sugeno MISO structure demands for 4 separate networks for 4 links but de-fuzzification method supports embedded limitations. Several test showed overall efficiency in Sugeno multi-layered network is more than Mamdani's FIS. This paper implements ANFIS with implication method as minimum function and weighted averaged defuzzification.

A. *Formulation of ANFIS*

The typical rule set for 2 inputs and 1 output first order Sugeno type rule base can be expressed as

Rule 1: If input 1= x and input2 =y then $f_1 = a_0 x + a_1 y + a_3$

Similarly $f_2 = b_0 x + b_1 y + b_3$.

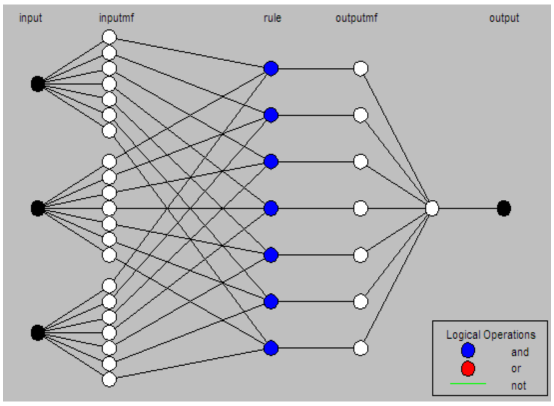

Fig.2.ANFIS Architecture obtained in MATLAB for *DEXTER*.

Figure 2 shows the ANFIS architecture developed to control each link of Dexter. Inputmf is the input membership function, where the each node denotes the membership functions of fuzzy sets and they are multiplied and t-norm operations are done and their average is calculated based on weights taken from fuzzy rules as shown in equation 1and 2.

$$w_i = \varepsilon_{Ai}(x_1).\varepsilon_{bi}(x_2) \qquad (1)$$

$$\overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad (2)$$

Outputmfs are output membership functions which are obtained from Sugeno type fuzzy rules as equation 3.

$$f_i\overline{w_i} = \overline{w_i}\ (a_i x_1 + b_i x_2 + c_i) \qquad (3)$$

Weighted average method is chosen for defuzzification process

$$\mathrm{f} = \frac{\sum_i^N w_i f_i}{\sum_i^N w_i} \qquad (4)$$

Where N is the number of rules, w is weights and $\overline{w_i}$ is the average calculated based on weights taken from fuzzy rules[10].

B. *Clustering*

Data clustering is the process of dividing the data set into clusters based on several statistical criteria[2]. The whole reachable set of a 6 DOF robotic arm cannot be formulated as membership functions with much accuracy. More over the process is quite time consuming and cumbersome. In this scenario it is strongly advisable to use clustering methods to segregate the reachable set into several regions with some mathematical relation. This procedure reduces the burden on ANFIS training to find out the membership relations. Choosing the proper number of clusters one can achieve reasonable number of membership functions with better accuracy and quick training. In this paper C-mean clustering is used and the whole 3-D space is clustered into 10 regions. Table 1 shows the summary of ANFIS architecture developed to control Dexter ER-1.

III. ANFIS IN PIC16f886

Always mobility is the major concern in robotic manipulators. In order to improve the mobility of the arm the ANFIS network shown above need to be programmed in micro controller. This section explains the techniques and modifications followed in implementing MATLAB generated ANFIS into an 8-bit micro controller. To implement ANFIS in micro controller, generated FIS is modified to triangular membership functions[8]. Weights of rules can be obtained from the trained data obtained from the Sim-mechanics simulation. Output equations are de-fuzzified using Sugeno fuzzy Inference method and finally the output angles are obtained using weighted average method. The flow chart for micro controller implementation of ANFIS is shown in figure 3.

1. TABLE
2.

Networks	ANFIS 1	ANFIS 2	ANFIS 3	ANFIS4
Number of nodes	62	54	54	46
Number of linear parameters	28	24	24	20
Number of Nonlinear parameters	42	36	36	30
Total parameters	70	60	60	50
Number of training data pairs	40320	40320	40320	40320
Number of checking data pairs	0	0	0	0
Number of fuzzy rules	7	6	6	5

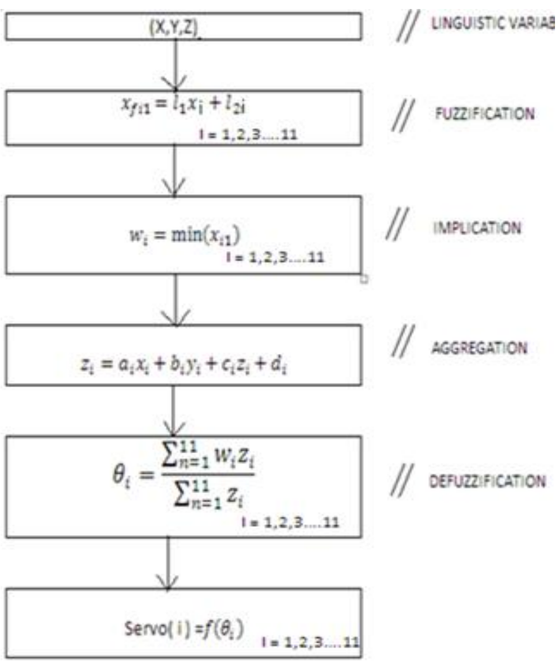

Fig.3.Micro-Controller implementation of ANFIS Flow chart

ISSN:2319-6890)(online),2347-5013(print)
01 May 2014

IV. SIMULATION AND RESULTS

Figure 4 shows the errors between desired angles generated by MATLAB and micro controller. Results shows micro controller implementation is satisfactorily accurate to implement directly on DEXTER ER-1.

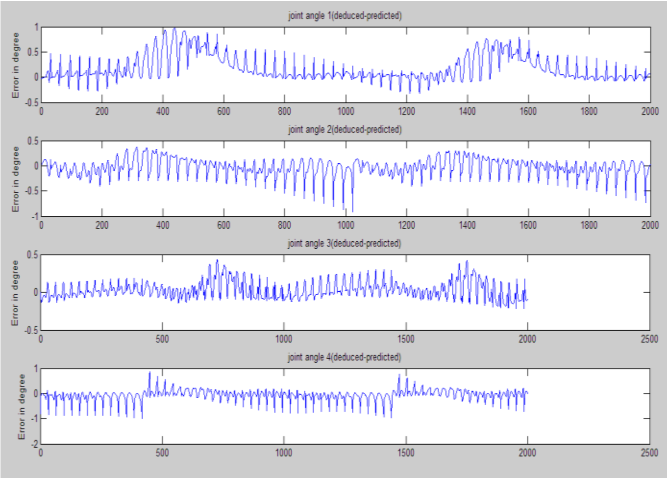

Fig.4.Difference in theta deduced and the data predicted with ANFIS trained

REFERENCES

i. Jang, J.-S.R., "ANFIS: adaptive-network-based fuzzy inference system," Systems, Man and Cybernetics, IEEE Transactions on , vol.23, no.3, pp.665,685, May/Jun 1993

ii. James C.Bezdek, Robert Ehrlich and William Full,"FCM: The Fuzzy c-mean clustering algorithm", Computers and Geosciences, vol 10, no 2-3,pp.191-203,1994.

iii. K.V.Lakshmi and Mashuq-un-nabi,"An Adaptive Neuro-Fuzzy Control Approach for Motion Control of a Robotic Arm",IEEE.OSA/IAPR International Conference On informatics, Electronics &vision.

iv. Nair B, Krishnan R, Nizar N, Radhamani R, Rajan K, Yoosef A, Sujatha G, Radhamony V, Achuthan K, Diwakar S. Role of ICT-enabled visualization-oriented virtual laboratories in Universities for enhancing biotechnology education – VALUE initiative: Case study and impacts, FormaMente, Vol. VII, n. 1-2, ISSN 1970-7118, 2012.

v. Layne J.R, Passino K. M, "Fuzzy Model Reference Learning Control", Journal of intelligent and fuzzy systems , Vol.4, No.1,pp, 33-47,1996.

vi. J. Godjevac and N. Steele, "Neuro-fuzzy control of a mobile robot", in Neurocomp., vol.28 pp. 127-143, 1999.

vii. Bach Hoang Dinh, "Approximation of the inverse kinematics of a robotic manipulator using a neural network", Heriot-watt university, july.2009.

viii. Nicholas hay cotton, "A Neural Network implementation in Embedded systems", Auburn University, Alabama 2010.

ix. Kevin M., Passino, Stephen Yurkovich, "FUZZY CONTROL", Addison Wesley long man, inc., 2725 sand hill road, Menlo park, California, 94025.

x. Jeffery r. layne and Kevin m passino," Fuzzy model reference learning control", The Ohio state University