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Fuzzy control based on "true and false" philosophy for mechatronics systems

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For man, possessing the ability to recognize the specific situation that has arisen at any instant of time and taking the appropriate decision without using a mathematical model is what 'adaptation' means. Adaptive principles are being extended to more complex systems in widely different areas, in which we need to replace the traditional metaphor of a fixed environment with a dynamic and constantly changing one. Each mechatronic system, for example, is usually, faced with a multiplicity of choices and objectives of the system change with it. Its modeling requires more than a mathematical model that is based on clear definitions and axioms using the rules of logic deduction theory. To solve this problem, the new concept of system integration by software control, such as real-time multi-tasking operating system using fuzzy logic, is emphasized in the education of modem mechatronics engineering. In this paper, I would like to return, firstly, to the fundamental element of truth measure, which we can use as basis for constructing a way to spread the binary philosophy rather than its rejecting and to increase our ability to describe the real world. Next, in order to explanation into details one aspect of real-time software using fuzzy logic, applied in control of mechatronic systems, we present a fuzzy control technology that combines artificial intelligence and control methodologies. It achieves control purposes based on expert knowledge and experience expressed in the form of IF-THEN rules (Sugeno-type) or neural networks using neuro-fuzzy based intelligent control scheme in order to create a real-time-adaptive control process. Application of this technology is presented in numerical example of trajectory control of PUMA 560 robot manipulators using Fuzzy Artificial Neural Network, FANN, rather than using Artificial Neural Network, ANN, only.

Keywords: fuzzy control, neural network, fuzzy-neural network, mechatronics, real-time software.

1. Introduction

Innovations in mechanical engineering and in electronics have accelerated the progress of many technological advances. The development of these new high technologies has given birth to the academic interdisciplinary field of Mechatronics, which provides new insights into an integrated consideration of mechanics, electronics and information processing and communication technology. The terminology "mechatronics" was first introduced by a Yaskawa Electric engineer in 1969. Firstly, mechatronics was confined to large programmes in the aeronautics, space and arms industries. It then developed in parallel in industrial design workshops and research laboratories. The IEEE has published its first issue of "IEEE Trans. on Mechatronics" on March 1996. The International Federation for the Theory of Machines and Mechanism (IFTMM), provides a formal definition of mechatronics *"Mechatronics is the synergetic integration of mechanical engineering with electronic and real-time control in the design and manufacturing of industrial products and processes"*. Although mechatronics has a wide scope of applications and is a technology with multiple engineering disciplines - we consider it to be a technology requiring competences: electronics, automation, mechanical engineering and Information Technology (IT), its key roles are computer including hardware, software and integration of them. In order to implement the real-time control, it is necessary to have substantial computing power. The great advances in microelectronics with Very-Large-Scale Integration (VLSI) technology such as the TMS320C30 Digital Signal Processor and a broad from DSP research with intelligent I/O module are effectively used to realize advanced control schemes. Due to its fast computation speed, the DSP has replaced much of the complex control hardware by ROM-based software. This development trend has made software control to reach a new horizon in the applications of power electronics and motion control. Intelligence comes from the decision making of command and feedback. Flexibility comes from the self-organization and adaptation to environment changes.

During the last four decades, many "model based" control strategies have been proposed by the researchers. The proposed fuzzy controller uses the capability of fuzzy logic to control systems, without prior knowledge of the dynamic characteristics, that are nonlinear in nature and for which a mathematical model is not well suited for dealing with ill-defined and uncertain systems, or unavailable. Although, these important capabilities of fuzzy logic are gained at the cost of rejecting the "true or false" philosophy, as indicated by Klir [5]. Interest in Fuzzy Systems (FS) was sparked by Seiji Yasunobu and Soji Miyamoto of Hitachi, who provided simulations that, demonstrated the superiority of Fuzzy Control (FC) systems for the Sendai railway. Canon developed an auto-focusing camera that uses a Charge-Coupled Device (CCD) to measure the clarity of the image in six regions of its field of view and uses the information provided to determine if the image is in focus. Work on FSs is also proceeding in the US and Europe. The US Environmental Protection Agency has investigated FC for energy-efficient motors, and NASA has studied FC for automated space docking. Firms such as Boeing, General Motors, Allen-Bradley, Chrysler, Eaton, and Whirlpool have worked on fuzzy logic for use in low-power refrigerators, improved automotive transmissions, and energy-efficient electric motors etc.. The scope of this paper is, firstly, to return to the fundamental element of truth measure, which we can use as basis for constructing a way to spread the binary philosophy rather than its rejecting and to increase our ability to describe the real world. Next, it is limited to the application of a modern FC technology that combines artificial intelligence and control methodologies. It achieves control purposes based on both mathematical results and expert knowledge expressed in the form of if-then rules using neuro-fuzzy based intelligent control scheme in order to create an Adaptive Network-based Fuzzy Inference System, ANFIS [4], rather than using Artificial Neural Network, ANN, only as indicated by Ali T.Hasan *et al.*, for robotic manipulators [1].

2. "TRUE AND FALSE" PHILOSOPHY

The Chinese philosopher Trang Chau (369-298 BC) developed an alternative to the binary idea: "the being or the non-being"/"True or False" of Confucianism (see [7]). In his philosophy, "knowledge is created in our head, depending on our perception rather than mathematical analyses", in which, truth is uncertain - true contains an amount of false and false contains an amount of true; they have common sense which is subjective and approximate in nature. It is today the multi-valued logic (see [6]) and fuzzy logic, in which, truth values, τ, are represented by numbers of the unit interval $[0, 1]$. The many-valued logic, which Zadeh takes as a basis model for his model of linguistic reasoning with vague statements named fuzzy logic [10], is Łukasiewicz's infinitely valued logic. In this fuzzy logic, linguistic variable is viewed as a fuzzy set of points having the form of a clump of elements drawn together by similarity.

Using truth values, it is clear that:

$$A \vee B \vee C = \begin{cases} (A|\,\tau = 1) \wedge (B|\,\tau = 0) \wedge (C|\,\tau = 0) \\ (A|\,\tau = 0.3) \wedge (B|\,\tau = 0.5) \wedge (C|\,\tau = 0.2) \\ (A|\,\tau = 0) \wedge (B|\,\tau = 0) \wedge (C|\,\tau = 1) \end{cases} \tag{1}$$

It indicates that we can extend the "T or F" philosophy using truth values, τ, in order to obtain a new philosophy called "T and F" philosophy/human philosophy (see [9]), which is described graphically in Fig. 1.

Further, conclusions resulted from analytical analysis we call knowledge while knowledge including truth values, τ, – expert knowledge resulted from both analytical analysis and expert's

Fig. 1. From “T or F” to “T and F” philosophy

experiences called meta-knowledge. Generally, “True or False” philosophy is considered as product of human brain for the purposes of mathematical analysis. Whereas, “True and False” philosophy simulates the way human make decision by self-assertion using meta-knowledge – human intelligence. It is more practical importance. In this framework, “fuzzy” is seen as truth values, τ, in the sense of Łukasiewicz’s logic, attached to individual logical assertions. Let consider the fuzzy variable: consolidation state (I_D) for example. It can be divided into three linguistic variables: ‘loose’, ‘medium consolidation’ and ‘consolidation’. These variables refer to assertion in fuzzy logic that have truth values, τ, determined by truth functions (see [8]). It is shown in Fig. 2.

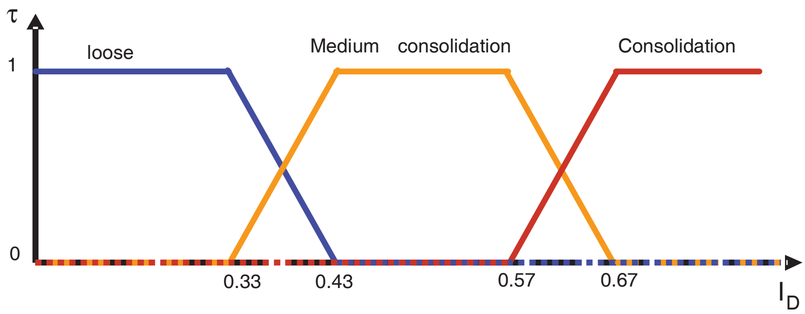

Fig. 2. Truth values attached to individual assertions

The truth function of the linguistic variable ‘loose’, for example, could be defined by:

$$\tau_{loose}(I_D) = \begin{cases} 1 & \text{for } I_D \in [0, 0.33]\,, \\ 1 - \frac{I_D - 0.33}{0.1} & \text{for } I_D \in [0.33, 0.43]\,. \end{cases} \tag{2}$$

It is interesting to note that, in the framework of “T or F” philosophy, we have loose state of soil for $I_D = 0.33$ and medium consolidation state of soil for $I_D = 0.35$. That is to say, large difference (‘loose’ – ‘medium consolidation’) of soil condensed states vs small difference (0.33 – 0.35) of I_D. While, in the framework of “T and F” philosophy we have soil condensed states determined as:

- for $I_D = 0.33$,

  ‘loose’ with truth value $\tau = 1.0$ and ‘medium consolidation’ with truth value $\tau = 0.0$,

- for $I_D = 0.35$,

  ‘loose’ with truth value $\tau = 0.6$ and ‘medium consolidation’ with truth value $\tau = 0.4$.

It is true that: small difference of soil condensed states according to small difference of I_D. In this case, “T and F” philosophy leads to more practical presentation of soil condensed states.

3. An adaptive neuro-fuzzy inference system (ANFIS)

Neural networks have two main benefits, which are capable of learning non-linear mapping of numerical data and performing parallel computation. However, the knowledge of the system is usually distributed into the whole network as synaptic weights. It is very hard to understand the meaning of these weights, and the incorporation of prior knowledge into the system is usually impossible. We may draw plausible inferences using our existed belief deriving from our experiences in the "IF....THEN" form [3]. Then, fuzzy logic based on "T and F" philosophy uses human understandable linguistic terms to express the knowledge of the system. It makes possible to a close interaction between the system and human controller which is very desirable property.

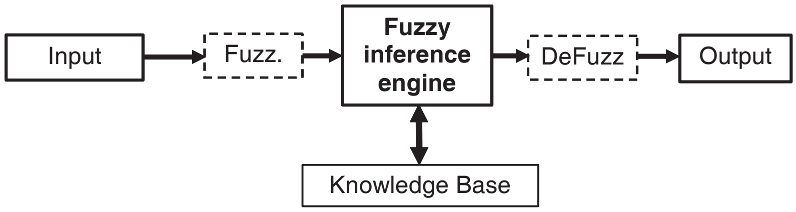

Fig. 3. The structure of the fuzzy inference system

The basic Fuzzy Inference System (FIS) is presented in Fig. 3, where Fuzz is fuzzification in which the crisp inputs are transformed to fuzzy values, and DeFuzz is defuzzification in which the outputs of fuzzy rules are combined to a crisp output. Inference is the decision making unit performs the inference operations on the fuzzy rules which is described in the form:

$$\text{IF } \underbrace{\text{input 1 is big AND input 2 is small}}_{\text{Antecedent part}} \text{ THEN } \underbrace{\text{output in medium}}_{\text{Consequence part}}$$

The Knowledge Base consists of the data base and the rule base. The Fuzzy inference engine performs fuzzy reasoning rules taking fuzzified inputs of FIS as inputs and delivering the fuzzy result to the defuzzifier, which produces the output of FIS.

ANFIS is a fuzzy inference system implemented within the architecture and learning procedure of adaptive networks. It is a cross between an artificial Neural Network and a Fuzzy Inference System. ANFIS can be used to optimize membership functions to generate stipulated input–output pairs and has the advantage of being able to subsequently construct fuzzy "if–then" type rules representing these optimized membership functions. The ANFIS structure used in this paper consisted of a 5-layer Takagi & Sugeno type architecture – is similar to the Mamdani structure in many respects. The main difference between Mamdani-type of fuzzy inference and Sugeno-type is that the output membership functions are only linear or constant for Sugeno-type fuzzy inference. This technique provides a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to tract the given input-output data. A typical example is shown in Fig. 4.

Here, two inputs are used (x_1, x_2) and one output (y), i.e. there is only a single obtained output. In the first layer, all nodes are adaptive; μ_{Ai} is the degree of the membership of the input to the fuzzy membership/truth function represented by node:

$$O_{li} = \mu_{Ai}(x), \quad i = 1, 2, 3, 4, \tag{3}$$

where O_{li} is the output of the node i in a layer l. In the second layer the nodes are fixed (i.e. not adaptive). Nodes in this layer are labeled Π and multiply the signal before outputting. The outputs are given by:

$$O_{2i} = w_i = \mu_{Ai}(x_1)\,\mu_{Aj}(x_2), \quad i = 1, 2, \quad j = i + 2. \tag{4}$$

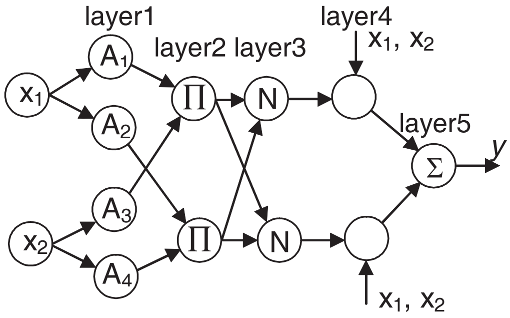

Fig. 4. A 5-layer ANFIS structure

Each node output in this layer represents the firing strength of the rule. In the third layer, every node is also fixed and labeled with an N and performs a normalization of the firing strength from the previous layer. The output of each node is given by:

$$O_{3i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \tag{5}$$

In the fourth layer, all nodes are adaptive. The output of a node is the product of the normalized firing strength and a first order polynomial and is given by:

$$O_{4i} = \overline{w_i} y_i = \overline{w_i} \left(p_i x_1 + q_i x_2 + r_i \right), \quad i = 1, 2, \tag{6}$$

where p_i, q_i, r_i (p, q, r are all constants) is the modifiable parameter set, referred to as consequent parameters since they deal with the THEN part of the fuzzy rule. Finally, layer 5 is a single node labeled with Σ which indicates that the function is that of computing the overall output as the summation of all incoming signals:

$$O_{5i} = y = \sum_i \overline{w_i} y_i = \frac{\sum_i w_i y_i}{\sum_i w_i}, \quad i = 1, 2. \tag{7}$$

The general Takagi & Sugeno rule structure is: IF $f(x_1 \text{ is } A_1, x_2 \text{ is } A_2, \ldots, x_k \text{ is } A_k)$ THEN $y = g(x_1, x_2, \ldots, x_k, p, q, r, \ldots)$. Here f is a logical function that connects the sentences forming the condition, y is the output, g is a function of the inputs and p, q, r, ... are the parameters pertaining to the node output – consequent parameters, which are updated according to given training data and a gradient-based learning procedure. Generally, suppose that a given adaptive network has L layers. We can define the error measure for the p-th entry ($1 \leqslant p \leqslant P$, where P is number of training data set) of training data entry as sum of squared errors:

$$E_p = \sum_{m=1}^{L} \left(T_{m,p} - O_{m,p}^{L} \right)^2, \tag{8}$$

where, $T_{m,p}$ is the m-th component of p-th target output vector, $O_{m,p}^{L}$ is the m-th component of actual output vector produced by the presentation of the p-th input vector. In order to develop a learning procedure that implements gradient descent in the overall error measure E over the parameter space. The error rate for the output node at (L, i) can be calculated by:

$$\frac{\partial E_p}{\partial O_{i,p}^{L}} = -2 \left(T_{i,p} - O_{i,p}^{L} \right). \tag{9}$$

To obtain better results, we can use a hybrid learning rule that combines the gradient method and the least squares estimate to identify parameters (presented in other paper).

4. Robotic manipulators

Trajectory control of robotic manipulators traditionally consists of a pre-programmed sequence of last link's end (called the end-effector (*eef*)) movements. Robot control usually requires control signals applied at the joints of the robot while the desired trajectory – or sequence of arm end positions is specified for the *eef*. To make the arm move, desired coordinates of the *eef* point are fed to the robot controller for generating the joint angles for the motors that move the arm. The *eef* of the Puma 560 robot arm, for example, can reach a point within its workspace from any direction. The six degrees of freedom are controlled by six brushed DC servo motors. To perform *eef* position control of a robotic manipulator, Inverse Kinematics problem (IK) needs to be solved.

Forward and Inverse Kinematics: Usually the *eef* point is one of the two points that are of interest in manipulating. The second is the base of the manipulator, also called the base frame. The calculation between these two points is called kinematics and is the tools for answering the questions "where is the *eef* with this configuration?" and "what configuration gives this *eef* position?". These two questions are the forward and inverse kinematics, respectively.

Forward Kinematics (FK): Normally when working with manipulators, the position and orientation of the *eef* is of more interest than the individual joints. From a given set of joint angles, it is straight forward to calculate the position and orientation of the *eef* using quite simple trigonometric functions, given a serial structure of rigid body where all link parameters are known. A robot manipulator is mathematically modelled by a set of Denavit-Hartenberg (DH)-parameters [2]. The Puma 560 with the DH parameters is shown in the Fig. 5.

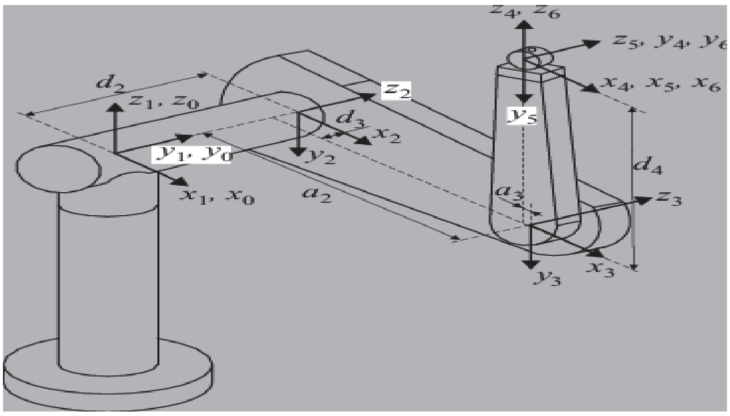

Fig. 5. The DH parameters of PUMA 560 robot

From the four parameters d, a, α, θ_I we can describe the position and orientation of a link frame with respect to the preceding link frame along the chain. When these parameters are associated with joint i, a homogeneous matrix is obtained as:

$$\boldsymbol{A}_i = \begin{bmatrix} \cos\theta_i & -\sin\theta_i\cos\alpha_i & \sin\theta_i\sin\alpha_i & a_i\cos\theta_i \\ \sin\theta_i & \cos\theta_i\cos\alpha_i & -\cos\theta_i\sin\alpha_i & a_i\sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{10}$$

The position and orientation of the robot *eef* is likewise described by a 4×4 matrix:

$$\boldsymbol{P} = \begin{bmatrix} n_x & b_x & t_x & P_x \\ n_y & b_y & t_y & P_y \\ n_z & b_z & t_z & P_z \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{11}$$

The kinematic equation for a 6-DOF robot is given by:

$$\boldsymbol{P} = \boldsymbol{A}_1\boldsymbol{A}_2\boldsymbol{A}_3\boldsymbol{A}_4\boldsymbol{A}_5\boldsymbol{A}_6. \tag{12}$$

For a set of joint angles $\boldsymbol{\Theta} = [\theta_1, \theta_2, \ldots, \theta_n]$ the *eef* coordinates P_x, P_y, P_z are found with the help of the FK of the robot arm. This can generally be described as: $\boldsymbol{P} = \mathrm{fk}(\boldsymbol{\Theta})$, where $\mathrm{fk}(\boldsymbol{\Theta})$ is the function executing the FK mapping.

Inverse Kinematics (IK): In most cases it is desired to place the *eef* at a desired position and orientation in the work space, which means that joint values resulting in such position and orientation have to be calculated. This leads us to the IK problem in the Lyapunov's idea "Finding sequences of inputs that guarantee the uniform convergence of system". From a given point, the position of each joint is generally described by: $\boldsymbol{\Theta} = \mathrm{fk}^{-1}(\boldsymbol{P})$. For most manipulators, the IK problem can be solved analytically. However there is no general IK solution for all manipulators that can be computed with a "one step analytical calculation", which also meets real-time requirements. On the other hand, the control of a robotic manipulator is hampered by complex kinematics, non-linear motion and uncertainties. The chosen method uses the forward kinematic equations to generate a collection of data relating the joint angles to the resulting cartesian coordinates of the end effector. Next, a Fuzzy Neural Network ANFIS is trained to solve the IK problem with the simple FK solution of PUMA560, so that the nonlinear mapping from the joint space, $\boldsymbol{\Theta}$, to the operation space, $\boldsymbol{P}$, is accomplished quite accurately. It is integration model described in Fig. 6. General schema of ANFIS, used in this paper, is shown in the Fig. 7.

The first step, the ANFIS algorithm generates the membership functions and number of rules. Next, the ANFIS was trained with the test data and the resultant accuracy was determined. The

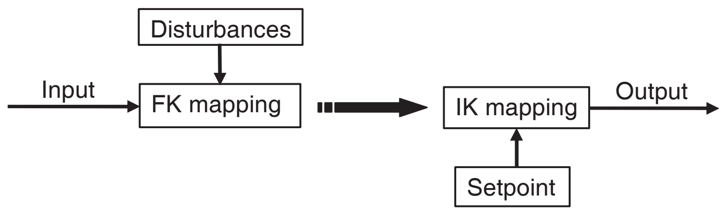

Fig. 6. Feedforward and Feedback integration model for robot control

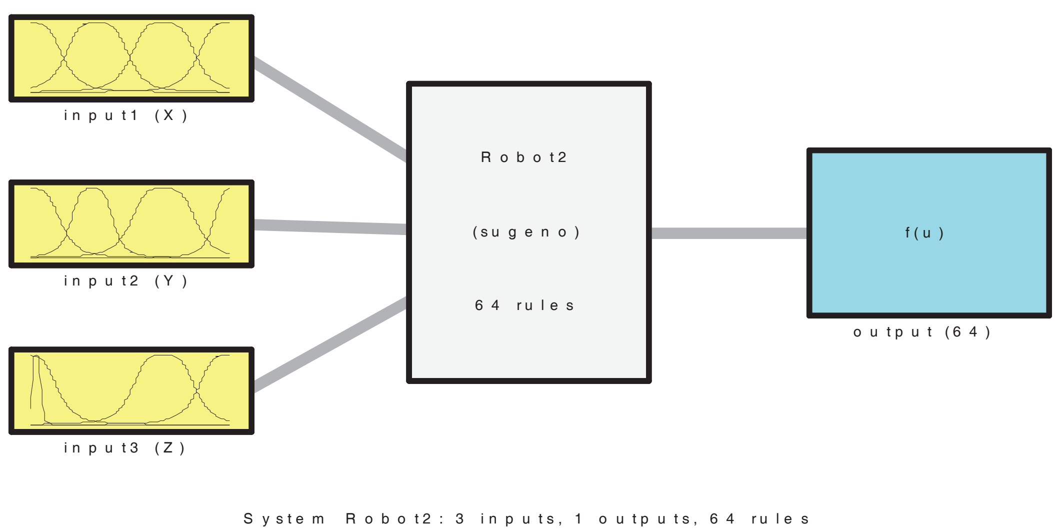

Fig. 7. A block diagram of ANFIS

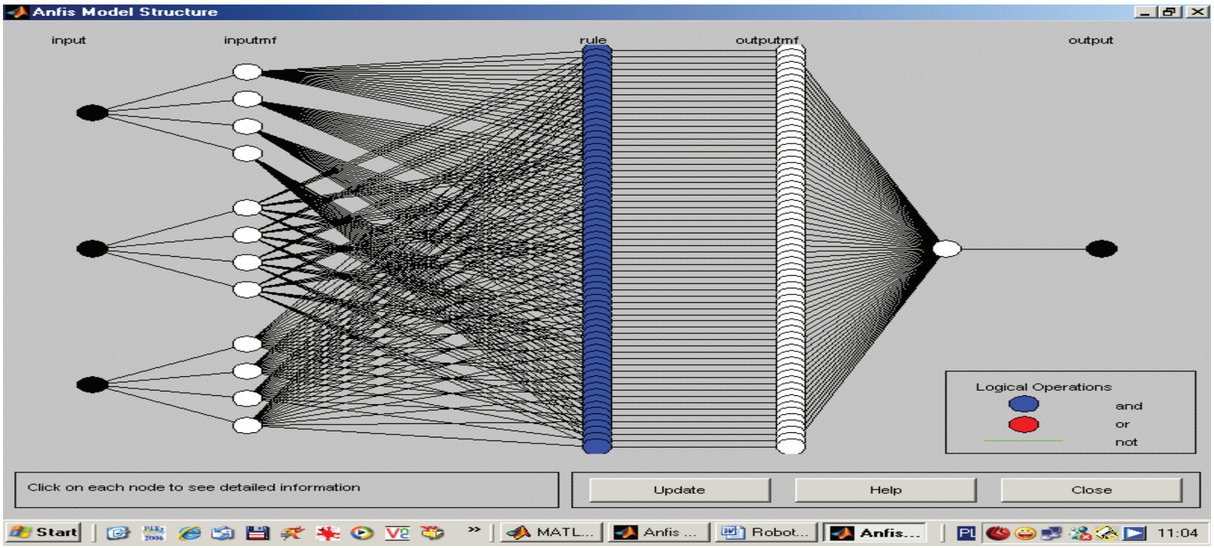

Fig. 8. FAM model structure for fuzzy controller

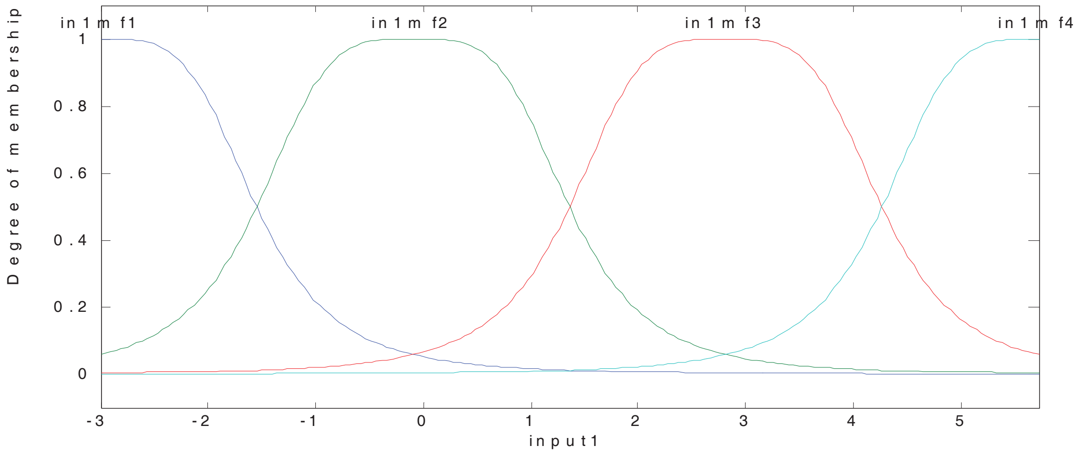

Fig. 9. Four initial membership/truth functions for input 1

Table 1. Relative error for $\zeta = 0.1$

	θ_6 [°]				
	1	2	3	4	5
Desired values	60.0173	54.2878	-157.5978	165.6994	20.8499
ANFIS results	60.0173	54.2878	-157.5978	164.1467	22.4084

network-type shown in Fig. 8 similar to that of a neural network, which maps inputs through truth functions and associated parameters, and through output with associated parameters to output, is used to interpret the input-output map. Figure 9 shows the initial membership/truth functions for input 1. The resultant mapping after training for 50 epochs is shown numerically in the Tab. 1 and graphically in Fig. 10 as follows.

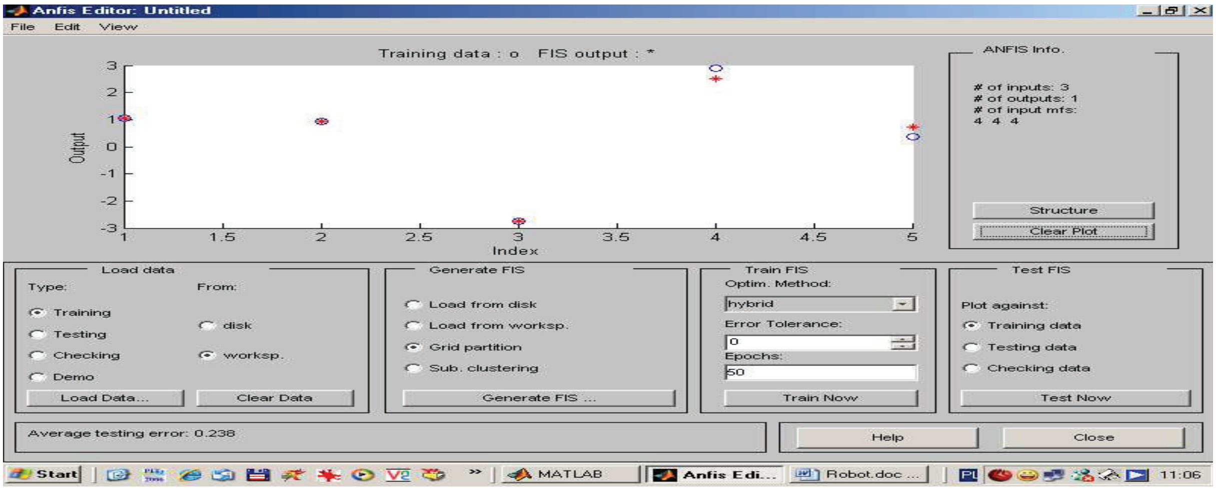

Fig. 10. Desired values and ANFIS learning results of joint angle θ_6 after 50 epochs

5. Conclusions

The nature of fuzziness and how fuzzy operations are performed, how fuzzy rules can incorporate the underlying knowledge are discussed in this paper. There are differences between the philosophy for mathematics and philosophy for practices. To recognize of them is no great matter. We should from that, however, better understand the real world by dealing with uncertainty in logic ways through truth-measures and fuzzy rules – fuzzy logic, where change of the real world is sometimes unpredictable, and our beliefs about the real world change and may be uncertain. "True and False" philosophy, extended from "True or False" philosophy indicates good promise in consumer products and decision support systems. It enables us to build a mathematical model including both knowledge and meta-knowledge. In the framework of this philosophy, instead of using complex mathematical equations only, we can use, in addition, linguistic descriptions to define the relationship between the input and the output information. It provides a convenient and user-friendly front-end to develop control programs, helping designers to concentrate on the functional objectives in the intelligent way. It is a way to make mechatronic systems more intelligent enabling them to reason in a fuzzy manner like humans. This computing technology with its adaptive ability suggests a new approach to apply "smart" engine technology, through active feedback control using ANFIS (in Fuzzy Logic Toolbox, MATLAB program). In this technique, active control is based on real time measurements rather than open-loop scheduling for improvement quality of multiple-input control systems. It is seen actually to drive the technological development for mechatronic systems such as robot or any intelligent structures. However, in order to prove the effectiveness of this technique for real-life situations it will be necessary to prove the concept from more experimental studies.

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