A Fuzzy Knowledge-Based Controller to Tune PID Parameters

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Abstract

In this paper integration of fuzzy knowledge-based control with the hard control technique is purposed. The fuzzy knowledge-based is implemented as a set of fuzzy rules with an inference mechanism to tune the PID controller in the system. A software is developed in which users can define the rule base. The program generates the fuzzy decision table based on all inputted information and in a descriptive fashion. Then, the decision table is used to modify the parameters required by the fuzzy tuner in on-line operations. A simulation environment based on MATLAB® and SIMULINK® is used for demonstration purpose. Two control systems with the same structures are constructed. One system is using a fuzzy knowledge-based tuner and the other one is using a conventional PID control loop. Simulation results show improvement on system response of fuzzy knowledge-based control structure.

I. Introduction

There are many reasons for the practical deficiencies of control systems. Unconsidered conditions or any changes in environment may result in undesired outputs in a control system. For example, if the model of the process is inaccurate, model-based control can provide unsatisfactory results. Even with an accurate model, approximations are applied if parameter values are partially known or vague. Algorithmic control based on such incomplete information will not usually give satisfactory results. Often, the environment with which the process interacts may not be completely predictable and it is normally not possible for a hard control to respond accurately to a condition that it did not anticipate [1].

However, use of intelligent control may improve the performance and efficiency of such systems [1-5]. Intelligence can be embedded into a controller in the form of a knowledge base typically expressed as a set of rules and an associated inference mechanism.

Human knowledge and experience are gained not through on-line generation of control signals manually, but through performing parameter adjustments and tuning operations. A knowledge-based controller may be more effective in a monitoring and tuning capacity than in direct generating control signal capacity since human experts are quite effective in tuning operations.

In this paper, we apply a fuzzy knowledge-based to tune control parameters of a proportional-integral-derivative (PID) controller of a robot joint. It is not recommended to include a knowledge-based controller within a servo loop to generate drive signals for a high-speed process such as a robot joint controller. Thus, a control structure is considered which utilizes the advantages of a hard algorithmic control and a knowledge-based soft control.

A robot system with one revolute joint is shown in the figure 1. A robotic manipulator with *n* joints could be linearized and decoupled into *n* single joints with the same controller for each of the joints.

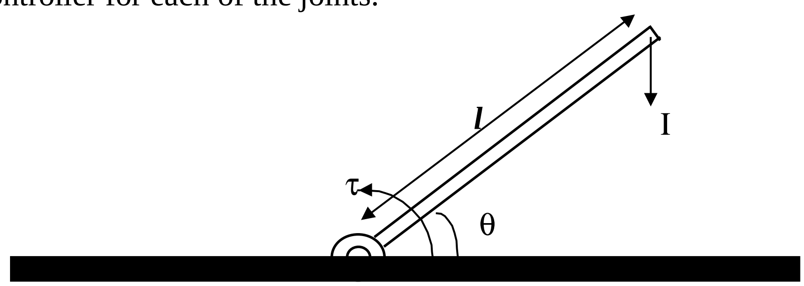


Fig. 1: A revolute joint scheme

$\tau = I\,\alpha + B\,\omega$

where $\alpha = -(B / I)\,\omega + (1 / I)\,\tau$ and $\omega = d\theta/dt$

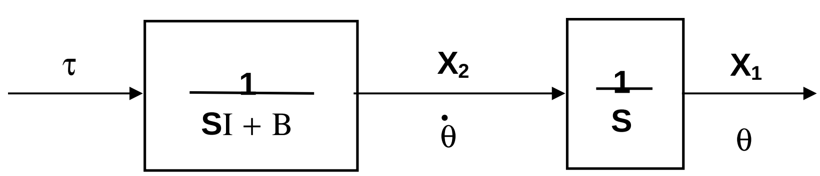
Let :

$x_1 = \theta \quad \Rightarrow \quad dx_1/dt = x_2$

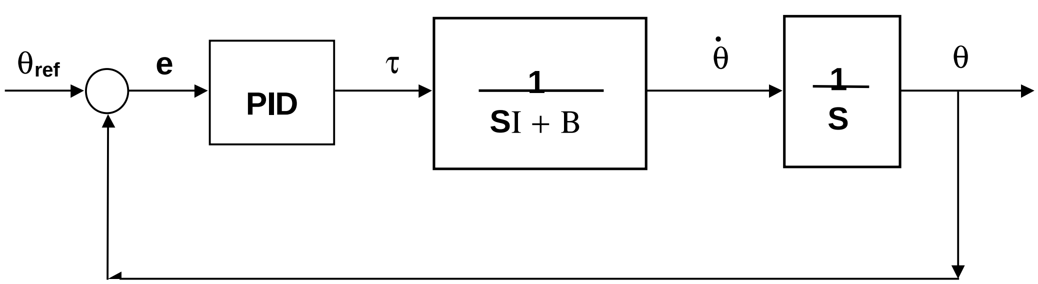
$x_2 = \omega \quad \Rightarrow \quad dx_2/dt = -(B / I)\,x_2 + (1 / I)\,\tau$

where I represents inertia, τ denotes torque, θ is degree of the link with horizon, and B shows friction coefficient.

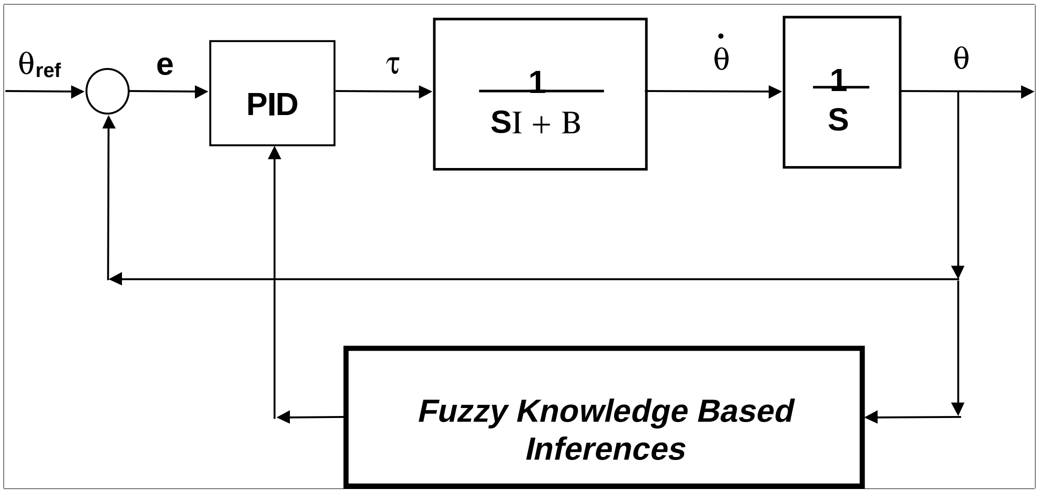
The block diagram of above system can be shown as follow:



A closed-loop control system with a conventional PID controller for above system is shown below:



A knowledge-based tuner can be used to determine response status of the system with respect to the inputs and also for tuning parameters of the PID controller as follows:



In above system, an error monitoring period is chosen and response error is sampled during this period. If the total time of operation is T and P is the period of time required for gathering data via sampling of response error, inferences would be made in T/P intervals. After each inference, fuzzy tuner can make the desired changes on the values of PID control parameters.

II. The Concept of Fuzzy

The fuzzy set proposed by Zadeh [3] extends the traditional set theory to resolve problems generated by the nothing-or-all classifications of Aristotelian logic. Traditionally, a logic condition or expression could only be one of the two possibilities of completely true or completely false. However, in fuzzy logic all statements have some degree of truth between 0 and 1. By incorporating this degree-of-truth concept, fuzzy sets can be defined qualitatively using linguistic terms such as tall, warm, active, near, etc. with the elements of the sets having assigned degree of membership.

The fuzzy system can monitor, evaluate, and control an external system through its system inputs and outputs. The system inputs contain status information about the external system. Each system input is associated with a group of qualitative classifications called fuzzy sets. An input has some degree of membership in each of its fuzzy sets defined by a function called membership function. For example, possible fuzzy sets for the system input temperature include such classifications as cold, cool, warm, and hot. The process of determining a value to represent an input's degree of membership in each of its fuzzy sets is called fuzzification. Figure 2 shows possible configuration of fuzzy sets for temperature as the input.

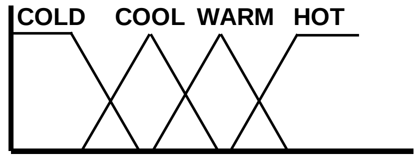


Fig. 2 : A fuzzy set for temperature

Usually, simple shapes such as triangles are used to define membership within fuzzy sets. To provide relationship between imprecise data and the system's behavior an expert develops a set of rules. Each rule is presented in the form of an if-then statement. The if side of the rule contains conditions and the then side shows actions. An inference mechanism is used for rule evaluation. During rule evaluation, rule strengths are computed based on condition values and then are assigned to the rule's fuzzy outputs. The fuzzy outputs are converted to exact or crisp values through a process called defuzzification.

III. Fuzzy Knowledge-Based Tuner

The first step for developing a fuzzy knowledge-based tuner is gathering expert knowledge about tuning a PID controller. The expert knowledge is expressed as a set of linguistic statements with fuzzy quantities. Using if-then implication and replacing fuzzy quantities by its notations, each fuzzy rule is expressed as a fuzzy relation by converting the linguistic statements into the rules in tabular form. Next, membership functions are established for the fuzzy quantities presented in the fuzzy rules. The resulting set of tables form the rule base of the fuzzy tuner. Rule matching can be accomplished by application of the compositional rule of inference [5]. The on-line rule matching is generally time consuming process and it may slow down the speed of tuning.

Since the universe of discourse of the system conditions and the tuning actions are discrete and finite, computational efficiency can be significantly improved by applying the compositional rule of inference off-line. The output of this off-line processing is a decision table which can be used by knowledge-based tuner to perform on-line PID tuning during process operation.

Consider the following statements which are linguistic rules that reflect the actions of human expert in tuning a PID control by observing the response error of the system.

> *if* the response error does not have an offset; *then* don't change the proportional , integral, and derivative parameters of the control;

or

> *if* the response error has an offset; *then* make a large increase in the proportional gain, a slight increase in integral rate, and a large increase in the derivative time constant.

> *if* the response error dose not steadily diverge; *then* don't change the proportional , integral, and derivative parameters of the control;

or

if the response error steadily diverges; *then* slightly increase the proportional gain and the integral rate and make a large increase in the derivative time constant.

if the response error is not oscillatory; *then* don't change the proportional and derivative parameters of the control;

or

if the response error is oscillatory; *then* make a large increase in the proportional gain and a large increase in the derivative time constant.

Of course, more rules can be added and the resolution of the fuzzy quantities can be increased to improve accuracy. The above linguistic statements can be expressed in the condense form as follows:

if	OFF	=	OKY	then	KP	=	NC
if	OFF	=	OKY	then	KI	=	NC
if	OFF	=	OKY	then	KD	=	NC
if	OFF	=	NOK	then	KP	=	PH
if	OFF	=	NOK	then	KI	=	PL
if	OFF	=	NOK	then	KD	=	PH
if	DIV	=	OKY	then	KP	=	NC
if	DIV	=	OKY	then	KI	=	NC
if	DIV	=	OKY	then	KD	=	NC
if	DIV	=	NOK	then	KP	=	PL
if	DIV	=	NOK	then	KI	=	PL
if	DIV	=	NOK	then	KD	=	PH
if	OSC	=	OKY	then	KP	=	NC
if	OSC	=	OKY	then	KD	=	NC
if	OSC	=	NOK	then	KP	=	PH
if	OSC	=	NOK	then	KD	=	PH

where the fuzzy condition variables are denoted as:

- OSC = Oscillations in the response error
- DIV = Divergence of the response error
- OFF = Offset in the response error

fuzzy condition values are presented as:

- OKY = Satisfactory
- NOK = Unsatisfactory

fuzzy action variables are shown as:

- KP = Change (relative) of the proportional gain
- KI = Change (relative) of the integral rate
- KD = Change (relative) of the derivative time constant

and fuzzy action values are denoted as:

- NC = No Change
- PL = Positive Low
- PH = Positive High

The main idea in defining membership functions is to transform triangular shape of the fuzzy sets into discrete form. In tables 1 and 2 membership functions are defined for the fuzzy quantities.

		0	1
OSC	OKY	1.0	0.2
OSC	HIG	0.2	1.0
DIV	OKY	1.0	0.2
DIV	NOK	0.2	1.0
OFF	OKY	1.0	0.2
OFF	NOK	0.2	1.0

Table 1: Membership functions for the fuzzy conditions

		0	1	2
KP	NC	1.0	0.2	0.1
KP	PL	0.2	1.0	0.2
KP	PH	0.1	0.2	1.0
KI	NC	1.0	0.2	-
KI	PL	0.2	1.0	-
KD	NC	1.0	-	0.1
KD	PH	0.1	-	1.0

Table 2: Membership functions for the fuzzy actions

The number of elements required to express membership functions is equal to the values that can be assigned to them. For example, the fuzzy action KP can take one of the three fuzzy values of NC, PL, and PH. The membership function of NC for instance, should be assigned a universe having only three elements such that each element presents one of the three fuzzy values. Actual numerical values assigned to the elements in a universe of a fuzzy quantity are of significance only in a relative sense. However, an appropriate physical meaning should be attached to each value. For example in defining KP, the numerical value 2 is chosen to represent a positive high change in the proportional gain. This choice is compatible with the choice of 1 to represent a low positive change.

In order to demonstrate how a decision table is developed, we present the necessary steps required for one of the conditions. The necessary steps needed to develop the rules that relate the condition OSC to the action KP are illustrated in Table 3.

To construct the fuzzy relation table, for instance *R1*, perform the following steps:

1. select the membership function of OKY for OSC and membership function of NC for the KP.
2. form the Cartesian product space of these membership functions.
3. place the lower value of each pair of membership grades to the corresponding location in the Cartesian space.

After constructing the relation tables for each category of rules (for this example, category of OSC $\rightarrow$ KP), the composite relation table *R* is obtained by combining all of the relation tables for each rule, for instance R1, R2, … .

R1:	if	OSC	=	OKY	Then	KP	=	NC

		KP		
		0	1	2
OSC	0	0.1	0.1	0.1
	1	1.0	0.2	0.1

R2:	if	OSC	=	NOK	Then	KP	=	PH

		KP		
		0	1	2
OSC	0	0.1	0.2	1.0
	1	0.1	0.1	0.1

R: R = R1 $\vee$ R2

		KP		
		0	1	2
OSC	0	0.1	0.2	1.0
	1	1.0	0.2	0.1

Table 3: Fuzzy relation table for (OSC $\rightarrow$ KP)

Establishment of the decision table is the final step in the development of fuzzy knowledge-based tuner. Suppose that after a monitoring period and based on the sampled data, fuzzy tuner determines the response error is oscillatory, in fact OSC = NOK is inferred. This inference has the membership function $\mu_{OSC} = [1.0 \;\; 0.1]$. This context has to be matched with rule base R presented in table 3. This is accomplished by applying the compositional rule of inference as follows:

$\mu_C = \mathit{Sup\ min}(\mu_D , \mu_R)$

where μ_C is the membership function of tuning (control) action, μ_D denotes the membership function of the data base (μ_{OSC}), and μ_R represents the membership function of the rule base (R).

Next, we compare the μ_{OSC} vector with each column of R. To do this, first we choose the lower value of each pair of compared elements. Then, we take the larger value of the two elements in each column of the resulted table.

This gives us μ_{DP}=[0.1 0.2 1.0].

The membership function of the tuning action on proportional gain corresponds to inferred context. The result should be defuzzified in order to obtain a crisp value for the tuning action. There are a number of techniques available for defuzzification. We use the center of gravity method as follows:

$$((0.1 * 0) + (0.2 * 1) + (1.0 * 2)) / 3 = 0.733$$

Finally, fuzzy decision table is obtained by following the above steps for all rules in the rule base. Resulted decision table is shown in table 4.

	KP	KI	KD
OKY	0	0	0
DIV=NOK	0.467	0.5	1.0
OFF=NOK	0.733	0.5	1.0
OSC=NOK	0.733	0	1.0

Table 4: Fuzzy decision table

Note that the updating values for satisfactory conditions (OKY) should be zero for all tuning actions, even if we obtain different values for them during the processing. The relation used for updating a PID parameter is:

$$P_{new} = P_{old} + \Delta P \; (P_{max} + P_{min})$$

where P_{new} is the updated value of the PID parameter, P_{old} shows the previous value of the PID parameter, ΔP is the incremental coefficient, P_{max} represents upper bound for a parameter, and P_{min} is lower bound for a parameter.

IV. Simulation and Results

A program is developed which can be used for off-line processes. To use the software, first the fuzzy conditions and fuzzy actions with their values should be provided. Next, the rule base consisting of if-then type rules and membership functions for each fuzzy quantities are defined. Then, the program generates the fuzzy decision table based on all inputted information and in a descriptive fashion.

Finally, the decision table can be used for on-line control of the system. We used MATLAB® and SIMULINK® to simulate and construct two identical control loops. The fuzzy knowledge-based tuning is implemented in one of the controller loop and the other control loop uses a conventional PID. The same initial values are applied to both systems. Total time of the simulation is 100 seconds. In the system with fuzzy tuner, response error is sampled each 0.05 second and 300 samples are used for discovering the status of the response error. In other words, every 15 seconds tuning action is performed, if so required. After starting the simulation, response errors of both systems are obtained and in every 15 seconds intervals knowledge-based tuner modifies the control parameters of the first system. Each modification causes improvement in the response error of the first system while the response error of the second system remains unchanged. The result of tuning with knowledge-based tuner and the improvement on the system response are shown in figures 3, 4, and 5.

Figure 3 shows the response error of both systems. Steady offset is found at the 30th second of the simulation and the required modifications are applied. Offset in the response error is decreased for the first system while the response error of the second system remains the same. Steady offset in the first system is inferred again at 75th second of the simulation and modifications are repeated.

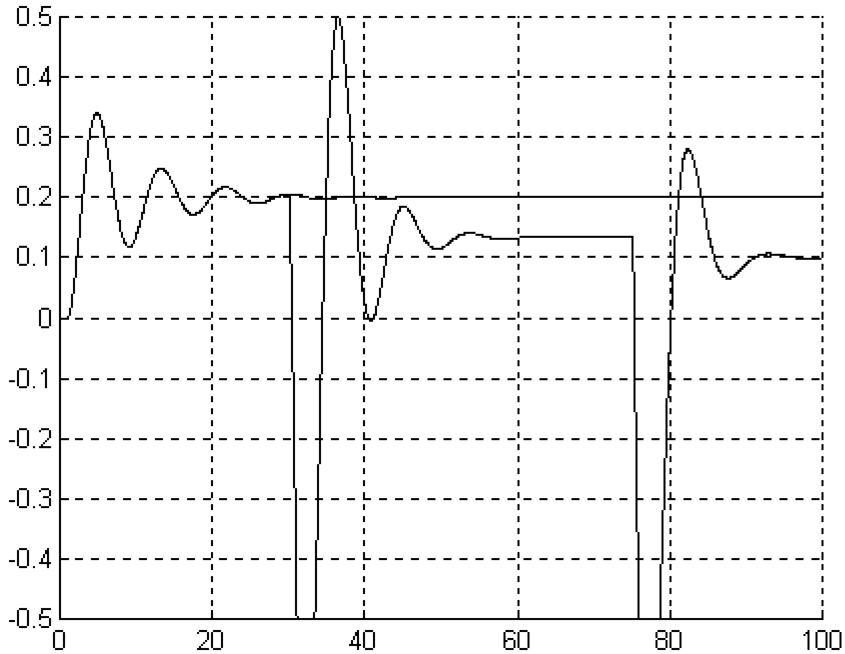


Fig 3: Correction of steady offset in the response error by the fuzzy knowledge-based tuner in 30th and 75th second of the simulation.

In figure 4, improvement on the first system response after fuzzy knowledge-based tuner discovers divergence of the response error is shown. After modification in parameters of the first system controller, response error is converged and in the 60th second steady offset is inferred by the fuzzy tuner and required modification is applied.

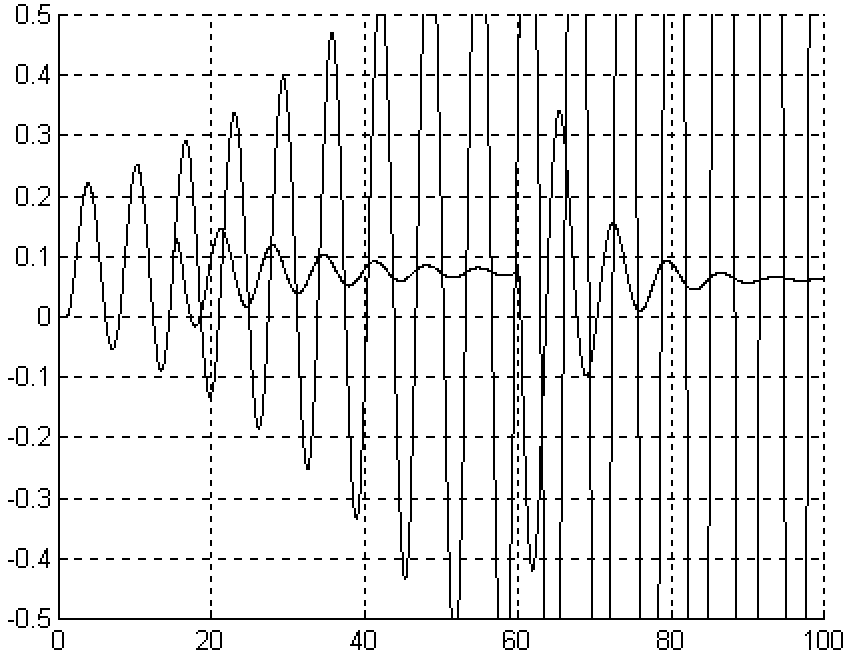


Fig 4: Correction of Divergence in the response error by the fuzzy knowledge-based tuner in 15th second and correction of steady offset in 60th second of the simulation.

Correction on the oscillatory error response of the first system is depicted in fig. 5. After oscillation correction, steady offset is inferred in the response error of the first system at 45th and 75th second of the simulation. Improvement on each modification is shown.

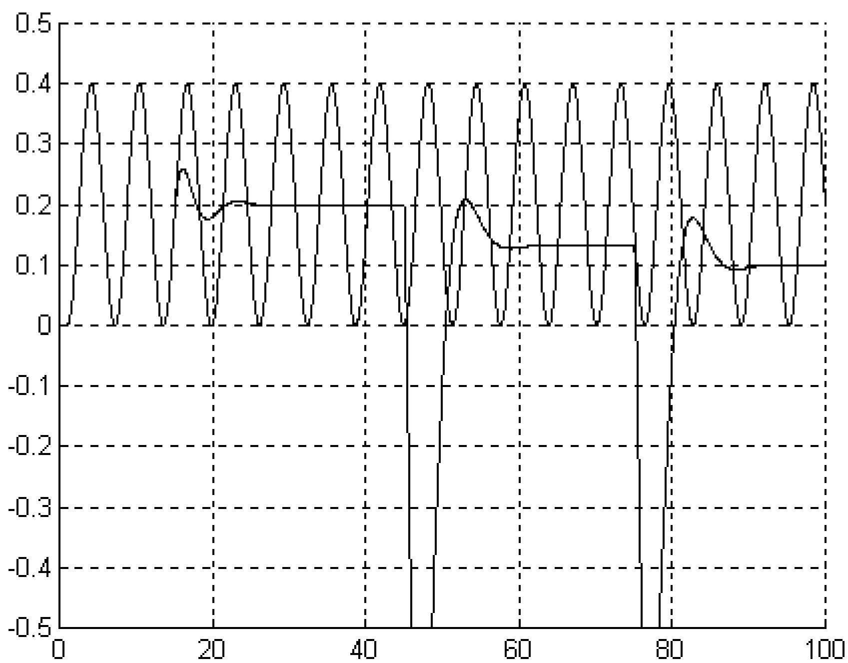


Fig 5: Correction of oscillation in the response error by the fuzzy knowledge-based tuner in 15th second and correction of steady offset in 45th and 75th second of the simulation.

V. Conclusions

Integration of fuzzy knowledge-based control with the hard control is presented. The fuzzy knowledge-based can be incorporated as a set of fuzzy rules with an inference mechanism. On-line inferences are time consuming and significantly decrease the speed of the processes. Computational efficiency can be improved by applying the compositional rule of inference off-line. For this purpose, a program is developed which generates the decision table from the expert knowledge. Then, the fuzzy tuner uses the decision table to modify the required parameters in on-line operations. Simulation results show improvement of system response in such a control structure.

VI. Acknowledgment

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Bibliography

1. DeSilva, C.W. and MacFarlane, A.G. J.; “Knowledge-Based Control Approach For Robotic Manipulators”, Int. J. Control, vol. 50 , No. 1, pp. 249-273, 1989.
2. Mizutani, E., Jang, J.S.R., Nishio, K., Takagi, H., and Auslander, D.M.; “Coactive Neural Networks With Adjustable Fuzzy Membership Functions and Their Applications”, Proceedings of the Int. Conf. On Fuzzy Logic and Neural Networks, Iizuka, Japan, pp. 581-582, August 1994.
3. Zadeh, L.A., “Fuzzy Sets”, Information and Control, Vol. 8, pp. 335-353, 1965.
4. Jang, J.S.R., Sun, C.T., and Mizutani, E.; Neuro-Fuzzy and Soft Computing, Prentice Hall, NJ, 1997.
5. Mamdani, E. H.; "Application of Fuzzy Logic to Approximate Reasoning Using Linguistic Synthesis", IEEE Trans. on Computers, Vol. 26, pp. 1182-1191, 1987.

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