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BOXES-based Cooperative Fuzzy Control for Cartpole System

Sunggyu Kwon

Faculty of Mechanical and Automotive Engineering
Keimyung University
Daegu, Korea

Abstract

Two fuzzy controllers defined by 2 input variables cooperate to control a cartpole system in terms of balancing as well as centering. The cooperation is due to the BOXES scheme that selects one of the fuzzy controllers for each time step according to the content of box that is established through the critic of the control action by the fuzzy controllers. It is found that the control scheme is good at controlling the cartpole system so that the system is stabilized fast while the BOXES develops its ability to select proper fuzzy controller through experience.

Key words : BOXES, inverted pendulum, cartpole system, cooperative fuzzy control

1. Introduction

Control of the cartpole [1] system has been the object of many studies in the literature of control and neural networks. Figure 1 shows the cartpole system composed of a rigid pole and a cart. The pole is hinged on the center of the top surface of the cart that travels along a track of limited length. Thus, the pole can rotate around the pivot in the vertical plane of the cart. The state of the cartpole system is defined by 4 state variables: x and $\dot{x}$, the position and the velocity of the cart and ϕ and $\dot{\phi}$, the angular position and the velocity of the pole. An impulsive force is applied to the cart at discrete time intervals to control the system. The goal of the cartpole system control is to make the pole upright and regulate the cart back to the center of the track.

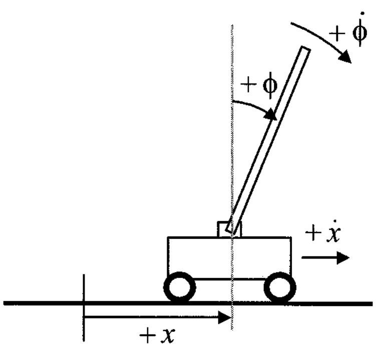

Figure 1. A cartpole system

Some control tasks of the cartpole system are just for balancing the pole without considering the position of the cart. Lee [2] developed an intelligent control scheme by integrating fuzzy control and reinforcement learning techniques. To balance the pole, 7 linguistic labels for the pole angle and 3 labels for the angular velocity of the pole were employed to generate continuous forces as output. Deng [3] proposed a neural-fuzzy BOXES [4] control system with reinforcement learning where the state space is divided into some overlapping fuzzy boxes by defining input membership functions for each state variable. Although the control scheme is expected to yield more generalization and learning abilities, it is only for balancing.

For balancing as well as centering, some fuzzy control techniques make use of the characteristics of the cartpole control. In [5], fuzzy controller was to swing up the pole and the linear state feedback controller was to stabilize the cartpole system. When a system state is within the selected matching states, the fuzzy controller is switched to the linear state feedback controller. It is very interesting to use 2 state variables, the pole angle and the cart position, for the fuzzy controller. In [6], dynamic response of the cartpole system was divided into approach and departure mode. Two types of fuzzy sliding mode controller were designed for two modes of dynamic response. The control scheme was to make the cartpole system in departure mode first and then to make the system in approach mode by switching two types of the controllers. In [7], a fuzzy controller is composed of 4 input state variables and 1 output variable. Each input variable is given with a single input rule module (SIRM) and a dynamic importance degree. The parameters were designed so that balancing has priority over centering. The switching between balancing and centering was realized by adjusting the dynamic importance degrees according to control conditions.

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In some efforts, a neural network and fuzzy controllers are combined to utilize the learning ability of the neural network and the expression of approximate or the rule-based knowledge of the fuzzy control. Berenji [8] proposed a new way of designing and tuning a fuzzy logic controller in which learning is achieved by integrating fuzzy inference into a feedforward neural network. The method was applied to a cartpole control system where 4 labels were employed for each of the 4 state variables and 9 labels for force. 9 fuzzy control rules were involved for balancing and 4 rules for positioning the cart at a specific location on the track. Although the control objective is achieved, some linear oscillation of the cart and angular oscillation of the pole may be present. In [9], a fuzzy-inference-based reinforcement learning algorithm which combines the fuzzy inference engine with dynamic recurrent neural networks is proposed. The algorithm is applied to the cartpole system where 3 input variables, the angular position, the angular velocity of the pole, and the action network's output, were used to generate internal reinforcement according to the 63 fuzzy rules. However, the system performance for hard initial configuration of the cartpole system is questionable. In [10], a fuzzy BOXES scheme for cartpole control is proposed where two BOXES defined by 2 state variables were employed to direct two fuzzy controllers respectively. Hence, for some system states, the direction of fuzzy controllers by BOXES was not proper for the cartpole system.

In this paper, in order to control the cartpole system in terms of both balancing and centering, a BOXES-based cooperative fuzzy control scheme is proposed for cartpole control. Two independent fuzzy controllers, one based on the angular position and the angular velocity of the pole and the other based on the position and the velocity of the cart, are employed to produce the control forces. To apply proper control force to the cart, one of the two fuzzy controllers is selected for every time step due to the content of the BOXES. The BOXES is established through observation of the outcomes of the control action. The behavior of the cartpole system is analyzed to discuss the proposed control scheme.

2. Cooperation of Two Fuzzy Controllers

Although there may be a few cases of using 4 state variables for the fuzzy logic controller for the cartpole system, most fuzzy controllers use 2 state variables, the pole angle (ϕ) and the angular velocity of the pole ($\dot{\phi}$), for the cartpole balancing problem [11]. Unfortunately, with these controllers, there is no way to control the position of the cart while the pole is balanced. In fact, a fuzzy controller using the other 2 state variables, the position of the cart (x) and the linear velocity of the cart ($\dot{x}$), can balance the pole as well as bring the cart back to the center of the track. However, it takes too much time until the controller brings the cart back to the track center.

First of all, it is necessary to discuss the fuzzy controller based on 2 state variables, ϕ and $\dot{\phi}$, (ϕ -fuzzy controller). For the ϕ -fuzzy controller, there are 3 linguistic values for each input state variable and 7 linguistic values for the output variable, force (Figure 2). Triangular membership functions are used for all linguistic values. "Center of gravity" (COG) defuzzification method [11] was used to combine the recommendations represented by the implied fuzzy sets from 9 rules (Table 1).

For computer simulations of the cartpole system, the 4th order Runge-Kutta method with a time step of 0.02 seconds was used to approximate the solution of the friction dynamics equations. The angular displacement of the pole is limited to [-45, +45] (degree) and the moving range of the cart is limited to [-2.4, +2.4] (m). The dynamic equation of the cartpole system and the cartpole parameters are as following [12]:

$$\ddot{\phi} = \frac{g\sin\phi + \cos\phi\left[\dfrac{-F - ml\dot{\phi}^2\sin\phi + \mu_c\,\mathrm{sgn}(\dot{x})}{m_c+m}\right] - \dfrac{\mu_p\dot{\phi}}{ml}}{l\left[\dfrac{4}{3} - \dfrac{m\cos^2\phi}{m_c+m}\right]} \tag{1}$$

$$\ddot{x} = \frac{F + ml\left[\dot{\phi}^2\sin\phi - \ddot{\phi}\cos\phi\right] - \mu_c\,\mathrm{sgn}(\dot{x})}{m_c+m} \tag{2}$$

where $g = -9.8\,m/\sec^2$ is the gravity acceleration, $m = 1.0\,kg$ and $m_c = 0.1\,kg$ are the masses of the pole and the cart, $l = 0.5\,m$ is the half-pole length, $\mu_c = 0.0005$ is the coefficient of friction of the cart on track, $\mu_p = 0.000002$ is the coefficient of friction of the pole on the cart, F is the force (newtons) applied to the cart center.

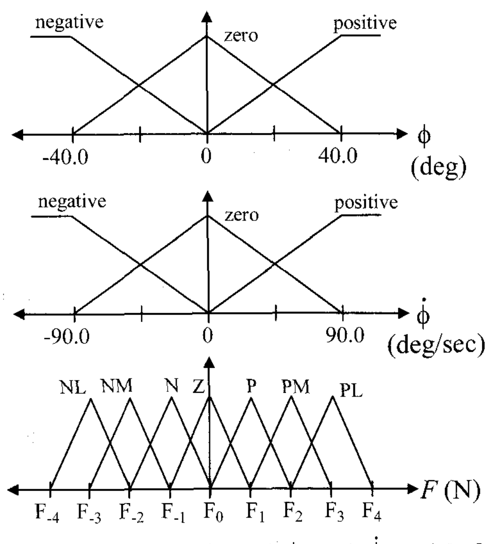

Figure 2. 3 linguistic values of ϕ and $\dot{\phi}$ and 7 of F for the ϕ -fuzzy controller.

Table 1. Rule table with 9 rules for F by ϕ and $\dot{\phi}$.

F		$\dot{x}$		
		N	Z	P
x	N	N4	N1	P2
	Z	N3	Z	P3
	P	N2	P1	P4

Figure 3 shows the cart position and pole angle versus time when the cartpole system operates by the ϕ-fuzzy controller after the system is released at the state of (0.0,0.0,30.0,0.0) [7]. For the output variable (Figure 2), $\Delta F = F_i - F_{i-1}$, $i = 4,3,\ldots,-3$, $\Delta F = 65.5/4$ and $F_4 = 65.5$. The figure illustrates that the controller is able to balance the pole very quickly even though it is impossible to bring back the cart to the center of the track. Therefore, the ϕ-fuzzy controller can balance the pole so that the amplitude of the angular oscillation of the pole decreases quickly.

On the other hand, it is expected that the fuzzy controller based on 2 state variables, x and $\dot{x}$, (x-fuzzy controller) can move the cart back to the center of the track while the pole angle is small. Figure 4 shows the linguistic values of 3 variables for the x-fuzzy controller. There are 3 linguistic values for each input state variable and 9 linguistic values for the output variable. Table 2 is the rule table for the controller.

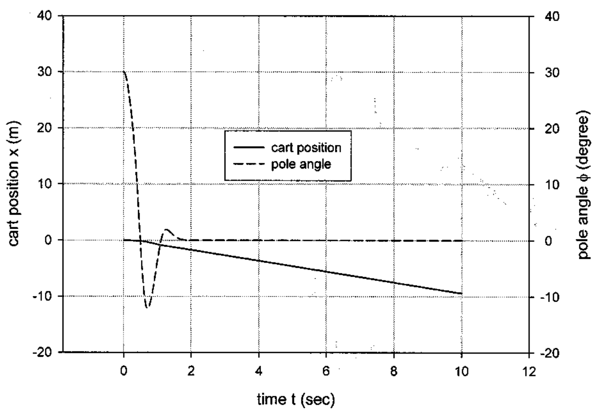

Figure 3. Cart position and pole angle versus time for the ϕ-fuzzy controller.

Figure 5 describes a simple scheme for cooperating two fuzzy controllers. Let $S_C = (x_C, \dot{x}_C, \phi_C, \dot{\phi}_C)$ be the state vector for the current system state and $S_N = (x_N, \dot{x}_N, \phi_N, \dot{\phi}_N)$ be the new system state resulting from a control action for S_C by either of the controllers. At the start, preferentially, the ϕ-fuzzy controller is to produce the control force for S_C. Then, the system state S_N is observed. If $|x_N| \le |x_C|$, the ϕ-fuzzy controller keeps the control over the system. Otherwise ϕ-fuzzy controller loses the control. The x-fuzzy controller produces the control force for S_C. Then, the system S_N is

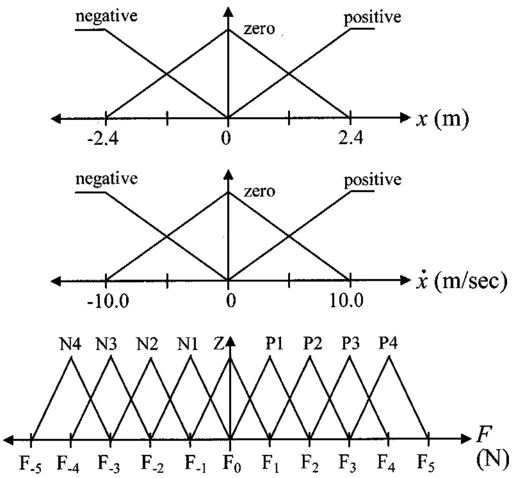

Figure 4. 3 linguistic values of x and $\dot{x}$ and 9 of F for the x-fuzzy controller.

Since the x-fuzzy controller can do nothing alone, it is just not tried to see the system behavior by the controller alone. However, it is expected that the x-fuzzy controller will play its role when it is cooperated with the ϕ-fuzzy controller.

Table 2. Rule table with 9 rules for F by x and $\dot{x}$.

F		$\dot{\phi}$		
		N	Z	P
ϕ	N	NL	NM	N
	Z	N	Z	P
	P	P	PM	PL

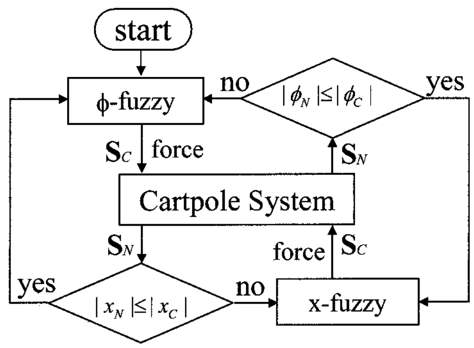

Figure 5. The proposed control scheme is to make use of the two fuzzy controllers.

observed. If $|\phi_N| \le |\phi_C|$, the x-fuzzy controller keeps the control over the system. Otherwise the x-fuzzy controller loses the control. So, this scheme works with the aid of some decision making mechanism that is based on the outcomes of the control action by either of two fuzzy controllers.

Figure 6 shows the system behavior in terms of the changes of x and ϕ due to this control scheme with the ϕ-fuzzy controller and the x-fuzzy controller. For the output variable

(Figure 4) of the x -fuzzy controller, $\Delta F = F_i - F_{i-1}, i = 5,4,\ldots,-4$, $\Delta F = 65.5/5$ and $F_5 = 65.5$ It takes about 30 seconds for the two cooperative fuzzy controllers to move the cart back to the track center while the angular amplitude of the pole decreases quickly within 3 seconds. Although the cart oscillates for quite a long period, the magnitude of the oscillation soon becomes negligible. It is very interesting to see that the cooperation of two fuzzy controllers whose behaviors are quite distinctive comes up with balancing and centering of the cartpole system.

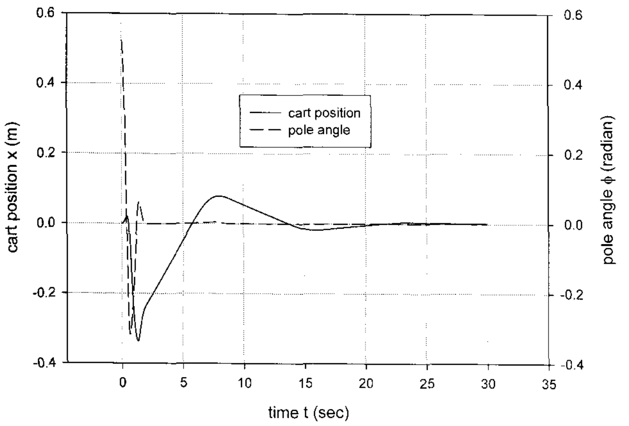

Figure 6. Cart position and pole angle versus time for the control scheme due to the cooperation of the ϕ -fuzzy controller and the x -fuzzy controller.

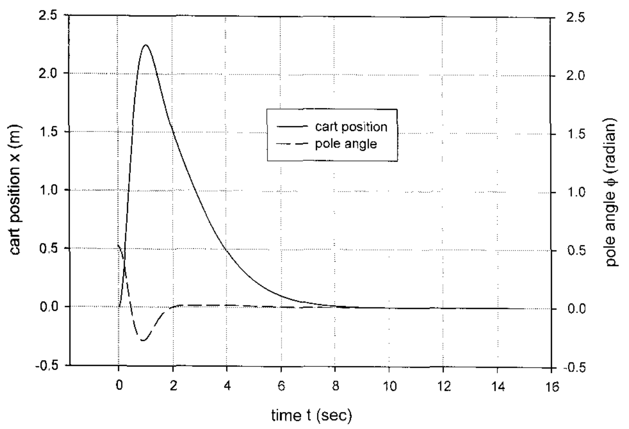

Figure 7. Cart position and pole angle versus time for the controller due to a nonlinear control law [13].

Figure 7 shows the system behavior in terms of the changes of x and ϕ due to a nonlinear control law [13]. This figure is very different from Figure 6. By the cooperative fuzzy control, the cart moves to the negative direction from the beginning while the cart starts moving to the positive direction by the nonlinear control law. The cooperative fuzzy control takes almost 30 seconds before the system stabilizes while the nonlinear control law makes the system stabilized in just 10 seconds. On the other hand, and in both cases, well before the cart arrives at the track center, the pole gets balanced. Moreover, it is obvious that the cooperative fuzzy control does the job to stabilize the cartpole system.

Now, it is noted that both fuzzy controllers are not defined by 4 state variables. Thus, some incomplete state information gets involved with producing the control force. However, the control actions are coordinated by some decision-making mechanism that observes the state variables, keeps the values of state variables of the current and the new state, compares some of them, and selects the proper one between the two fuzzy controllers for the control action. Because of the coordination, the control scheme works well for the plant, even though the mechanism is not capable of producing the control force for the plant. It just makes a simple decision for selecting the right controller for each time step.

According to this scheme, for some time steps, the selection of a fuzzy controller is altered from one fuzzy controller to the other when the magnitude of ϕ is increased due to the x -fuzzy controller or the magnitude of x is increased due to the ϕ -fuzzy controller. This means that the scheme suffers from some wrong selections although the cooperation of the fuzzy controllers is due to the alternating selection between the two fuzzy controllers for some time steps. So, it takes a long time until the cartpole system gets stable and this requires more control actions. For example, for Figure 6, out of the first 1,501 time steps for 30 seconds, the selection of the fuzzy controllers changes 336 times while the ϕ -fuzzy controller acts 1,278 times and the x -fuzzy controller acts 223 times. This amounts to about 22.4 % of the total number of time steps. This means that about 22.4 % of control actions were improper.

The process of selecting the proper one between the two fuzzy controllers can be learned by memorizing the selection process for every system state. The learning will induce the mechanism to select a proper fuzzy controller for every time step by observing the values of the state variables.

3. BOXES-based Cooperative Fuzzy Control

BOXES scheme was proposed by Michie and Chambers [4] and was applied to control the cartpole system. The scheme is to partition the continuous state space into a small number of sub-spaces, or called 'boxes.' Each box is supposed to contain a local demon. The local demon has a switch to select a control action so it determines which system state is entered into its box.

Now, a learning scheme is devised to establish the selection mechanism into the BOXES. Figure 8 shows the diagram of the control system consisting of two fuzzy controllers, the BOXES, a switch, and a critic. Two fuzzy controllers, the ϕ-fuzzy controller and the x-fuzzy controller, are defined respectively by 2 input variables and 1 output variable, as described in the previous section.

The BOXES is composed of all the boxes that correspond to all of the combinations of the intervals that divide each of the 4 state variable axes into small numbers of disjoint regions by quantizing the variables. Due to the content of the box representing the system state for the BOXES at every time step, the switch is set to connect either of the two fuzzy controllers to the plant. The BOXES acts as a decision maker to direct the switch.

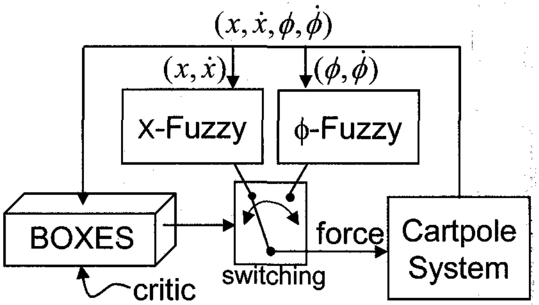

Figure 8. The BOXES-based cooperative fuzzy control for cartpole system is based on the scheme described in Figure 5.

The BOXES is active to update its content for some time steps according to information provided by the critic. The critic observes the state variables of the cartpole system, keeps the values of state variables of the current and the new state, compares some of them, and selects a proper one between two fuzzy controllers for the current state. The selection is based on whether the control action by a fuzzy controller has been proper for the control goal. Then, the critic provides the BOXES with proper information for updating the content of the box representing the current system state. Therefore, the BOXES learns to direct the switch every time step with the aid of the critic.

Through many experiments with the control scheme depicted in the previous section, it is found that the ϕ-fuzzy controller should play a major role in the cooperative control although x-fuzzy controller makes an end of the cooperation by moving the cart back to the track center.

Since all the boxes are initialized with the value 0, the default position of the switch is to connect the ϕ-fuzzy controller to the plant. Then, the very first control action is due to the ϕ-fuzzy controller. Then, for every time step, according to the content of the box corresponding to the system state, one of the two fuzzy controllers is selected to apply control force to the plant. For example, if the value of the box is –1, then the switch is set to connect the x-fuzzy controller to the plant. Otherwise, the switch is not altered to keep the current switch position for the ϕ-fuzzy controller.

Training process for the control system is as following: The content of all the boxes of the BOXES is initialized with value 0 before establishing the control system. For starting with a given current system state $S_C = (x_C, \dot{x}_C, \phi_C, \dot{\phi}_C)$,

(A) The BOXES is called to locate a box that represents the current system state, S_C. Let's call the box, box_C.

(B-1) If the content of box_C is -1, then the switch is set to connect the x-fuzzy controller to the plant. The controller applies a control force to the plant. With the control action, the cartpole system will be in a new state, $S_N = (x_N, \dot{x}_N, \phi_N, \dot{\phi}_N)$.

(B-2) If the content of box_C is not –1, the switch keeps current connection. Then the ϕ-fuzzy controller applies a control force to the plant. With the control action, the cartpole system will be in a new state, $S_N = (x_N, \dot{x}_N, \phi_N, \dot{\phi}_N)$. The switch keeps the default position. If $|x_N| \geq |x_C|$ due to the control action by the ϕ-controller, then the content of the box_C should be set –1. Otherwise, the content of the box does not change and remains, as it is 0.

(C) Then S_N becomes S_C before the procedure goes back to (A).

For the procedure (B-2), the magnitude of x is examined after the ϕ-fuzzy controller applies a control force to the cart in order to see if the control action is good for the system. $|x_N| \geq |x_C|$ means that the control action due to the ϕ-fuzzy controller is not good for the system state S_C. So, the content of box_C is set to be –1. This is the only procedure by which some of the boxes change their content to –1.

However, for the procedure (B-1), the states, S_N and S_C, are not even compared. Since the content of box_C is already set to be –1, the content should not be changed again. The reason is that the ϕ-fuzzy controller was previously not proper for the control at least once for a certain system state. Thus, the content of the box should not be changed in order to prevent box_C from damaging the system behavior in the future. Also, this reflects the preferential application of the ϕ-fuzzy controller. When the distance of the cart starts increasing, the movement should be stopped immediately by calling the x-fuzzy controller. If the ϕ-fuzzy controller keeps the control in that situation, the cart will keep on moving away from the track center and it will take much time for the x-fuzzy controller to make the cart move toward the track center.

As the system operation continues, the BOXES gets training opportunities to update the content of its boxes. Some boxes may be called several times while others might never be called since there might never be a chance to represent the system state by them as the cartpole system operates. Also, some boxes are represented by the neighboring system states and they are to be updated more often than others. In particular, some boxes corresponding to the system states for the configurations near the stabilization will be called very frequently and their contents will be greatly refined to be good for the control goal.

Figure 9 shows the system behavior due to the control scheme described by Figure 8. Without any previous training, the cartpole system was released at (0.0,0.0,30.0,0.0). For 2,501 time steps for 50 seconds, 502 control actions were by the ϕ-fuzzy controller and 1,999 control actions were by the x-fuzzy controller.

4. Discussion and Results

Firstly, let's discuss the problem of constructing the BOXES. With 10 partitions for each state variable, there are $10^4 = 10,000$ boxes for the BOXES. Especially, for the variable of x, only the positive part of the domain was partitioned in order to utilize the odd symmetry of the cartpole system [1]. Every axis is partitioned non-uniformly so that the partition resolutions are smaller near the origin of x axis and ϕ axis. This is to make the cartpole system stabilized with very small values of x and ϕ.

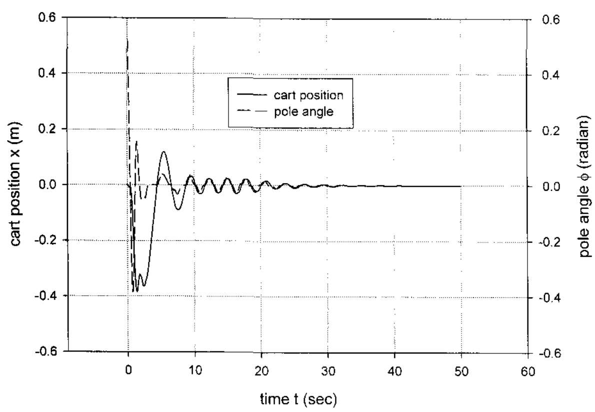

Figure 9. Cart position and pole angle versus time for the control due to the control scheme of Figure 8.

For the control scheme, the ϕ-fuzzy controller has the priority for control action over the x-fuzzy controller. In fact, the x-fuzzy controller had acted 4 times as many as the control actions by the ϕ-fuzzy controller for Figure 9. However, the control action by the x-fuzzy controller is just to assist the ϕ-fuzzy controller to achieve the control goal. For the first 40 seconds, the ϕ-fuzzy controller applied the output to the plant 455 times while the x-fuzzy controller acted 1,546 times. The system behavior by Figure 9 is quite different from that by Figure 6. Also, the control system does not perform as well as that of Figure 6. It takes longer for the cartpole system to stabilize and the cart and the pole oscillate more frequently. However, it is obvious that the control system does its job.

On the other hand, it is hard to estimate that the system behavior by Figure 9 results directly from the correction of the improper selection between two fuzzy controllers discussed in the end of Section 2. At least, it seems that the frequent control actions by the x-fuzzy controller results in frequent oscillation of both the cart and the pole before the cartpole system stabilizes. While the x-fuzzy controller acted 1,546 times for Figure 9 until the cartpole system stabilizes, the x-fuzzy controller acted only 223 times for the system resulted in the system behavior by Figure 6.

By this scheme, the number of boxes of which content is –1 increases while the BOXES learns by the critic and updates the content of its boxes. Then, it is expected that the control system should be able to improve its performance as it operates for the cartpole system. In fact, it performs better as it gets some training through working, although it is not the scope of this paper to analyze the rate of improving its performance.

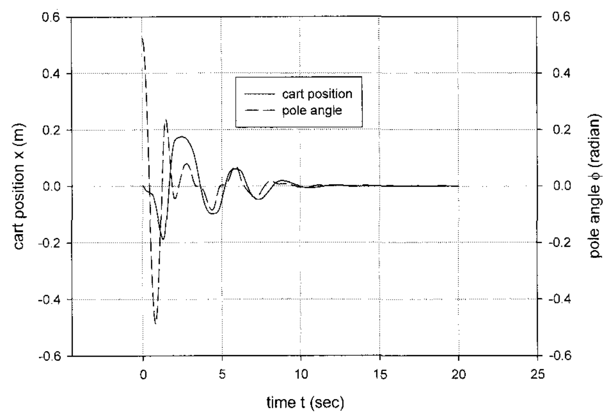

Figure 10. Cart position and pole angle versus time for the control due to the control scheme of Figure 8 after some training.

Figure 10 shows the system behavior when the control system worked for the system state at (0.0, 0.0, 30.0, 0.0) after the system has done its job for 20 different system states previously. While the overall characteristics of the system behavior looks like that of Figure 9, the time for stabilizing the cartpole system decreases more than 20 seconds. This results from the learning capability of the control system. For this figure, for the first 15 seconds, the ϕ-fuzzy controller applied the output to the plant 123 times while the x-fuzzy controller acted 628 times. Although the proposed control system improves its control performance as the system works, the system behavior may be different according to the training history.

Comparing Figure 10 with Figure 7 due to a nonlinear control law, one can see that the system behaviors are quite different from each other while the control system does its job to stabilize the cartpole system. Also, it is obvious that the system behavior by Figure 10 is more like that by Figure 4 than by Figure 7. In fact, it can be said that the control scheme observed by the system behavior due to Figure 6 was the model for the control system depicted in Figure 8. In turn, the control scheme described by the diagram of Figure 8 resulted in the system behavior by Figure 10.

For a comparison, according to [7], some of previous control methods took 8, 12, or 20 seconds while others took more than 20 seconds with various drawbacks in the control systems. The fuzzy controller by [7] took 9 seconds to stabilize the system released at the state of (0,0,30.0,0) while the control system due to Figure 6 took 15 seconds to stabilizes the cartpole system even though $|\phi|$ and $|\dot{\phi}|$ were slightly bigger than that defined by [7] for complete stabilization. However, the controller of [7] works with some special parameters such as the SIRMs and dynamic importance degrees consisting of 2 control parameters and 1 dynamic variable. Also, it requires 24 fuzzy rules while the control system presented in this paper requires only 18 rules for two fuzzy controllers defined by 2 input variables. In addition, the controller by [7] is badly influenced by the sampling time bigger than 0.01 seconds, while the control system proposed in this paper works well regardless of the size of sampling time up to 0.04 seconds.

Moreover, by the previous work [10], the cartpole system released at the state of (1.5, -1.0, -10.0, 40.0) could be stabilized after almost 45 seconds. However, the same system is stabilized in less than 20 seconds with no previous training by the control system depicted by Figure 8.

The control system with the BOXES consisting of 4,096 boxes due to 8 partitions or 1,296 boxes due to 6 partitions for each state variable could stabilize the cartpole system within 25 seconds. Of course, for the variable x, only the positive part of the variable axis was partitioned. Therefore, it is expected that the more boxes for the BOXES the better control performance in terms of fast response.

5. Conclusion

A control scheme was devised to coordinate two fuzzy controllers for the control of the cartpole system in terms of balancing the pole as well as centering the cart to the center of the track. Both fuzzy controllers defined by 2 input variables respectively could be cooperative by the BOXES. The BOXES established with the aid of a critic is good at selecting a proper controller between the two fuzzy controllers. It is found that the control system proposed in this paper is able to control the cartpole system and the performance of the control system improves as the control system works for the cartpole system.

In this paper, the BOXES is just for selecting a proper fuzzy controller for every time step. However, because of the lack of generalization of the BOXES, it tends to require more boxes for better control performance. From that perspective, other neural networks such as CMAC [14, 15] that are equipped with the generalization ability could be used to try to replace the BOXES and to improve the control performance. Moreover, other learning elements could be used to learn the outputs of the two fuzzy controllers. Then, the control system would require more efficient training scheme to build the look-up tables for storing the outputs of the fuzzy controllers. Also, it is expected that the control system could be applied to the ball-beam problem.

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Sunggyu Kwon received the B.S. and M.S. degrees in the Department of Mechanical Engineering, Yonsei University, Korea, in 1980 and 1983 respectively, and Ph.D. degree in the Department of Mechanical Engineering, Louisiana State University in 1990. He worked as a Senior Researcher in the Department of Remote Technology Development, Korea Advanced Energy Research Institute from 1991 to 1994. Since 1995, he has been a faculty of the School of Mechanical and Automotive Engineering, Keimyung University. His current research interests include CMAC applications for robotic engineering and fuzzy control issues.