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Fuzzy model reference learning control in surgical robots

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Abstract: *This paper proposes to apply the fuzzy model reference learning control method based on the guide control to the collaborative human-machine dragging process of the surgical robot. Variable damping coefficient adjustment parameter rules for fuzzy conductance controllers are trained by an offline learning mechanism in order to achieve the best human-machine interaction control effect. The surgical risk caused by the doctor's misoperation is lowered. Through the simulation experiment results, the speed curve tracking error is reduced by 70%. Trajectory curve tracking error is reduced by 57%. The both results prove that the strategy can reduce the error of the surgical robot and ensure the safety of robotic surgical operation.*

Keywords: *human-machine interaction, fuzzy control, reference learning control, surgical robot*

1. Introduction

As the country has become more industrialized, many manual operations have been replaced by robots, which even perform a series of complex operations. In the medical field, there are many unforeseen situations when doctors perform surgical work, especially when medical personnel work for a long time, may lead to decreased surgical accuracy and increased surgical risk. To further improve physician ergonomics, robots have been introduced into surgical operations [1]-[6].

At the same time, as the complexity, nonlinearity, and coupling of the controlled object increases, it is so difficult to establish an accurate mathematical model for traditional control that the desired control effect cannot be achieved. Therefore, fuzzy control theory was introduced [7]-[9]. The most classic fuzzy controller is the Mamdani-type fuzzy controller, which was first adopted by Mamdani in the UK in 1973 with the rules of the fuzzy language proposed by Zadeh to achieve automatic control of small boiler-steam engines. In modern medical surgical robots, the application of fuzzy control can effectively guide the surgeon in the process of dragging the robot to keep the surgical tool on the predetermined line as much as possible even if it is not operated properly, which ensures the safety of the surgery [10][11]. Fenglong Sun [12][13] constantly adjusting the damping parameter adjustment rules of fuzzy controller through learning mechanism, the mapping relationship between the doctor's input force and the robot's output speed is realized based on the admittance control method, form a variable damping admittance control method based on fuzzy reference learning [14] [15].

Therefore, in the paper the fuzzy model reference learning control method is applied in this paper based on the conductance control to the collaborative human-robot dragging process of the surgical robot. The damping parameters of the conductance control is automatically adjusted by means of offline learning to achieve the best control effect to improve the safety and flexibility of the doctor-robot interaction. The safety hazards caused by the error operation during the surgery can be addressed.

2. Basic principles of fuzzy control and its structure

Based on the mapping relationship between the doctor's input force and the robot's output velocity established by the conductance control method, this mapping relationship can be characterized by using a fuzzy controller that conforms to human logic thinking. The mapping relationship is dynamically adjusted by using the motion characteristics of the human arm under natural conditions as a reference model, thus forming a variable conductance control algorithm based on fuzzy reference learning to achieve the best human-robot interaction.

One of the more commonly used methods for collaborative human-machine control of surgical robots is conductance control, which can combine the high-precision characteristics of robots with the high decision-making ability of humans to achieve high surgical output results. Derived from mechanical impedance, conductance theory is an equivalent network idea based on generalized inertia, damping, and stiffness. The conductance theory centers on establishing a mapping relationship between the operator input force and the robot end output motion:

$$M_d(x_{ref}-x)+B_d(x_{ref}-x)+K_d(x_{ref}-x)=F_h \tag{1}$$

Here, M_d, B_d, K_d are the generalized inertia, damping and stiffness of the machine, respectively. F_h is the force applied by the operator at the end of the robot. x is the actual displacement at the end of the robot. x_{ref} is the reference displacements at the end of the robot. And the generalized inertia M_d has a negligible effect in the man-machine collaborative system. Thus equation (3-1) can be simplified as:

$$B_d * V + K_d * X = F_h \tag{2}$$

Here, is the output speed of the robot end. Since this chapter focuses on the flexibility of dragging the robot over a wide range in surgery, the virtual stiffness is set to zero for the moment without considering the motion limitation. Therefore, the guide control is essentially a velocity control mode that reveals the correspondence between the physician's operating force on the robot and the robot's output velocity.

Further, according to the fuzzy control theory, the doctor-applied force, the actual speed of the robot and the damping parameters in the conductance control are fuzzified to establish a two-input single-output fuzzy mapping relationship. And then the minimum acceleration model under the natural motion of the human body is introduced as the reference model. Finally, the fuzzy mapping relationship is adjusted by the off-line learning method to achieve the optimal control effect with the reference model as the control target.

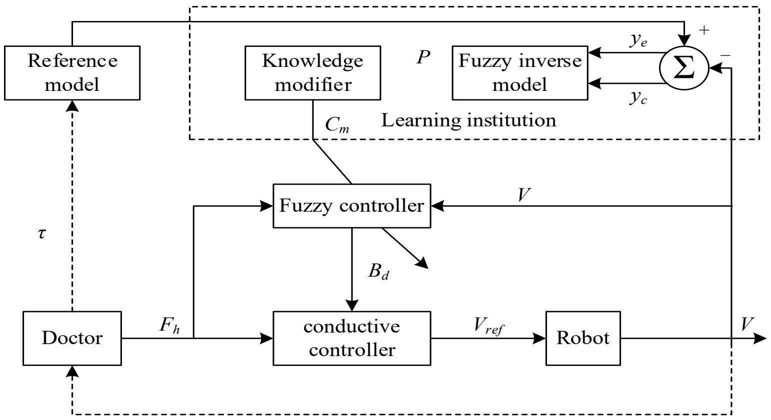

Figure 1: Block diagram of the fuzzy model reference learning controller architecture

The structure block diagram of the fuzzy model reference learning controller is shown in Figure 1, which mainly includes: the guide controller, the fuzzy controller, the learning mechanism, and the reference model. Among them, the function of the guide controller is to get the reference output speed at the end of the robot based on the doctor's input force and the output damping parameters of the fuzzy controller. Then, send the reference speed to the robot as a command to realize the robot following the doctor's movement. The fuzzy controller is mainly used to select the appropriate damping parameters based on the current doctor's input force and the actual output speed of the robot in order to optimize the output performance of the conductive controller. The reference model is a kinematic model of the human arm based on the principle of minimum plus acceleration. Theoretically, the human-robot collaboration achieves the optimal interaction effect when the output motion of the robot is consistent with the reference model. The learning mechanism consists of a knowledge base modifier and a fuzzy inverse model, whose role is to receive feedback information from the reference model as well as the actual motion of the robot and to modify the parameters in the fuzzy controller as a result.

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3. Fuzzy model reference learning controller design

3.1 Fuzzy controller design

The fuzzy controller in this study is a two-input, single-output system, where the inputs are the force F_h applied by the doctor on the robot and the actual output velocity V of the robot. The outputs are the derivative control damping parameters B_d. If the maximum F_{max} and minimum F_{min} values of the applied force on the robot are and the maximum V_{max} and minimum V_{min} values of the actual output velocity of the robot are and, then the theoretical domain of the fuzzy controller inputs are $F_h[F_{max},F_{min}]$ and $V_h[V_{max},V_{min}]$. The input affiliation function is a trapezoidal affiliation function and divides and into 5 classes each on its theoretical domain. Considering the directionality of the force and velocity, these 5 classes can be defined as 9 fuzzy subsets:

$$\widetilde{F_{hb}} = \{-4,-3,-2,-1,0,1,2,3,4\} \tag{3}$$

$$\widetilde{V_b} = \{-4,-3,-2,-1,0,1,2,3,4\} \tag{4}$$

Similarly, the theoretical domain of the output of the fuzzy controller is determined experimentally. The output affiliation function utilizes a single-valued affiliation function and will be divided into five fuzzy subsets over its domain:

$$\widetilde{B_{dn}} = \{1,2,3,4,5\} \tag{5}$$

The fuzzy rule can be explained by the following sentence:

(1) If the value of the applied force is large (-4 or 4), and at the same time the actual speed at the end of the robot is high (-4 or 4), then the value of the damping is small (1).

(2) If the value of the applied force is moderate (-2 or 2) and the actual speed at the end of the robot is moderate (-2 or 2), then the value of the damping is also moderate (3).

(3) If the value of the applied force is small (0) and the actual speed at the end of the robot is also small (0), then the value of the damping is high (5).

Therefore, the initial rule table of fuzzy control shown in Table 1 can be formed.

Table 1: Table of initial rules for fuzzy controllers

$\tilde{B}_{dn}$	$\tilde{F}_{hb}$									
		-4	-3	-3	-1	0	1	2	3	4
$\tilde{V}_b$	-4	1	1	2	2	3	3	4	4	5
	-3	1	2	2	3	3	4	4	5	4
	-2	2	2	3	3	4	4	5	4	4
	-1	2	3	3	4	4	5	4	4	3
	0	3	3	4	4	5	4	4	3	3
	1	3	4	4	5	4	4	3	3	2
	2	4	4	5	4	4	3	3	2	2
	3	4	5	4	4	3	3	2	2	1
	4	5	4	4	3	3	2	2	1	1

3.2 Reference model

The motion of the human arm in the natural situation conforms to the minimum acceleration model (equation (3-4)). The kinematic information (velocity, acceleration) of the human arm that conforms to the principle of minimum acceleration can be used as a reference model for the output motion of the robot during a wide range of dragging in human-machine collaborative orthopedic surgery, so that the human-machine interaction can achieve the most supple effect.

$$X(\tau) = X_0 + \left(X_f - X_0\right)(6\tau^5 - 15\tau^4 + 10\tau^3) \tag{6}$$

Here, and denote the beginning and end positions of the human arm motion, respectively. r=t/ is the time proportionality constant. t is the motion time.

The target velocity value of the reference model is taken as and the following can be obtained by differentiating the minimum acceleration model:

$$V_{jerk} = \frac{dX(t)}{dt} \tag{7}$$

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The error between the target velocity value of the reference model velocity and the actual output velocity of the robot is

$$y_e(kT) = V_{jerk}(kT) - V(kT) \tag{8}$$

Here, is the actual measured speed of the robot at the moment of and is the sampling time of the fuzzy controller.

When 0, it can be assumed that the robot achieves the optimal output, i.e., the human-robot interaction is optimal, and the learning mechanism will no longer adjust the parameters of the fuzzy controller.

3.3 Design of learning institutions

In Table 2, the input to the fuzzy inverse model is the error between the robot output velocity and the reference model and the rate of change of the error:

$$y_e(kT) = V_{jerk}(kT) - V(kT) \tag{9}$$

$$y_c(kT) = (y_e(kT) - y_e(kT - T))/T \tag{10}$$

The output is. Similar to the fuzzy controller in the previous section, by fuzzifying the input and output of the fuzzy inverse controller, the fuzzy rule can be expressed as:

$$IfY_{el}^{j} and \cdots Y_{es}^{k} andY_{cl}^{j} and \cdots Y_{cs}^{k}\ ThenP_{n}^{j,\cdots k,l,\cdots,m} \tag{11}$$

Here, and denote the linguistic values of error and error rate of change, respectively.

The fuzzy inverse controller rule can be explained by the following sentence:

(1) If the value of is zero and also the value of is zero, then the value of P is zero.

(2) If the value of is positive and the value of is also positive, then the value of P is taken as negative.

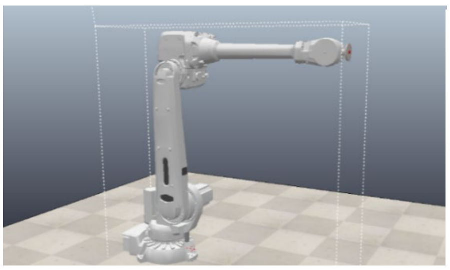
(3) If the value of is negative, and the value of is also negative, the value of P is positive.

The table of fuzzy inverse control rules is shown in Table 2.

Table 2: Table of fuzzy inverse control rules

P		y_c										
		-5	-4	-3	-2	-1	0	1	2	3	4	5
y_c	-5	1	1	0.7	0.7	0.5	0.5	0.3	0.3	0.1	0.1	0
	-4	1	0.7	0.7	0.5	0.5	0.3	0.3	0.1	0.1	0	-0.1
	-3	0.7	0.7	0.5	0.5	0.3	0.3	0.1	0.1	0	-0.1	-0.1
	-2	0.7	0.5	0.5	0.3	0.3	0.1	0.1	0	-0.1	-0.1	-0.3
	-1	0.5	0.5	0.3	0.3	0.1	0.1	0	-0.1	-0.1	-0.3	-0.3
	0	0.5	0.3	0.3	0.1	0.1	0	-0.1	-0.1	-0.3	-0.3	0.5
	1	0.3	0.3	0.1	0.1	0	-0.1	-0.1	-0.3	-0.3	-0.5	-0.5
	2	0.3	0.1	0.1	0	-0.1	-0.1	-0.3	-0.3	-0.5	-0.5	-0.7
	3	0.1	0.1	0	-0.1	-0.1	-0.3	-0.3	-0.5	-0.5	-0.7	-0.7
	4	0.1	0	-0.1	-0.1	-0.3	-0.3	-0.5	-0.5	-0.7	-0.7	-1
	5	0	-0.1	-0.1	-0.3	-0.3	-0.5	-0.5	-0.7	-0.7	-1	-1

4. Experimental procedures



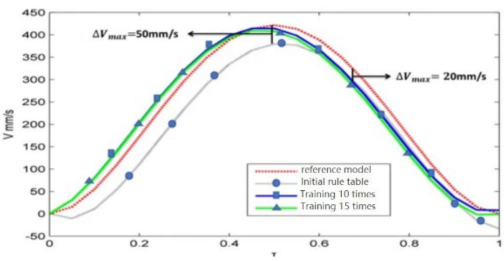


Figure 2: ABB-TRB simulation robot model *Figure 3: Comparison chart of the reference model*

As shown in Figure 2, we use ABB-TRB simulation robot for experiment, figure 3 shows that the fuzzy model reference learning control method based on the conductance control is applied to the human-machine collaborative dragging process of the surgical robot. The surgical robot automatically adjusts

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the damping parameters of the conductance control by means of offline learning. By comparing the analysis with the reference model, it can be seen that when t=0-0.5, there is still a large gap between the output motion speed of the robot and the reference model. When t=0.5-1, with the increase of training times and the extension of time, the output motion speed of the robot gradually converges with the reference model. It can be considered that the human-robot collaboration gradually tends to achieve the optimal interaction effect. In summary, with the increase of the number of experiments and the extension of the experimental time, the output motion of the robot tends to be infinitely consistent with the reference model. It can be considered that the human-robot collaboration achieves the optimal interaction effect. Thus, the safety and flexibility of the interaction between the doctor and the robot are improved to solve the safety hazards caused by the error operation during the operation. The safety of the operation is effectively guaranteed.

5. Conclusion

In order to solve the safety problems caused by the doctor's misoperation and the complexity of the surgical space in the human-machine collaborative surgery, the fuzzy model reference learning control method is applied in this paper based on the conductance control to the human-machine collaborative dragging process of the surgical robot. The damping parameters of the conductance control is automatically adjusted by the offline learning method. Simulations were also carried out using Matlab and V-REP software. With the gradual increase in the number of experiments and the extension of the experimental time, progressive convergence of the robot’s output motion of the reference model is demonstrated. The human-robot collaboration tend to achieve the optimal interaction effect.

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