Variable Admittance Human-Robot Collaborative Control Based on Motion Intention Prediction

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Abstract: This paper proposes a variable compliance control method for human-robot collaborative tasks. When the operator is towing the robot for collaborative motion, the motion trajectory of the operator's arm is unknown. In order to meet the different motion control needs of the robot in each stage of motion, a motion intention prediction strategy for the operator is designed, and the admittance controller is adjusted through fuzzy reasoning. The experimental results show that this method can effectively improve the controllability and adaptability of the robot in the process of compliant control.

1 INTRODUCTION

In human-robot collaborative tasks such as robot-assisted surgery and robot-assisted assembly, the robot needs to be used as an intelligent tool with its movement guided by humans. This control mode can not only give full play to the auxiliary role of the robot, but also reflect the wisdom of humans. Robot compliance control makes the robot dynamically respond to the feedback information of the external environment force through a certain control strategy[Hogan N, 1984]. Among them, impedance control and admittance control are widely used in engineering compliance control strategies. Impedance control can control the contact force between the robot and the environment by correcting the deviation of the end feedback position and velocity. The admittance control makes the robot respond to the external force information and adjust the desired position to track the force movement.

When the operator pulls the end-effector of the robot, the input of the control system is the interactive force information exerted by the operator, and the output is the expected movement of the robot, so that the robot can follow the operator's arm to move, the admittance control can meet this control demand. The admittance model is shown in Figure 1, its expression form is described as equation (1):

$$F = M(\ddot{X} - \ddot{X}_0) + B(\dot{X} - \dot{X}_0) + K(X - X_0) \tag{1}$$

where F is the interactive force exerted by the operator, M is the virtual mass coefficient, B is the virtual damping coefficient, K is the virtual stiffness coefficient, $\ddot{X}_0$, $\dot{X}_0$ and X_0 are the acceleration, velocity and position of the robot in Cartesian space, $\ddot{X}$, $\dot{X}$ and X are the expected acceleration, velocity and position of the robot in Cartesian space.

When the operator pulls the robot, the virtual stiffness coefficient K will cause the robot to generate a certain restoring force and the end of the robot will show a tendency to maintain the initial position, which is not in line with the control purpose of the robot following the interactive force. The virtual stiffness coefficient should be set to 0. Moreover, this motion method does not refer to the target position, thus the expected motion state variables ($\ddot{X}_0$, $\dot{X}_0$ and X_0) need to be ignored. In this case, the transfer function of the admittance controller is described in equation (2).

$$G(s) = \frac{\dot{X}(s)}{F(s)} = \frac{1}{Ms + B} = \frac{\frac{1}{B}}{\frac{M}{B}s + 1} \tag{2}$$

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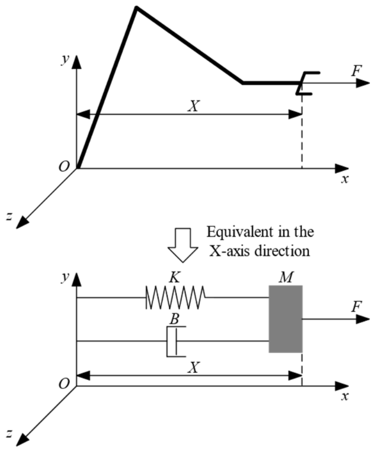


Figure 1: The admittance model.

The traditional admittance control model is preset and fixed, and the control system shows poor adaptability when facing the changing working environment in practical application. When the operator pulls the end effector of the robot to accelerate, the robot should have a certain acceleration performance to quickly reach the desired speed, and when the robot decelerates, it needs better braking performance. At this time, a single admittance model obviously cannot meet the control requirements of each stage of the traction robot movement. In order to improve the performance of the control system, the control system needs to be able to sense the external environment and adjust the control model autonomously. At present, many researchers have proposed adaptive admittance control methods (Shaodong Li - Tsumugiwa), which pay more attention to system stability during human-robot interaction. In order to solve the adaptability and compliance problems in the process of human-robot interaction, it is also necessary to enable the control system to predict the future motion state and make dynamic adjustments accordingly. In this paper, a motion state perception strategy is proposed to predict the operator's motion control intention and adjust the control system online by fuzzy reasoning.

2 MOTION STATE PERCEPTION STRATEGY

Dynamically adjusted admittance models generally require known future motion instructions as a reference. There is no track to follow when the operator pulls the robot, and it is difficult to establish a mathematical model by simply relying on the operator's operation intention to generate the motion track because it contains personal factors. In this paper, the motion intention of the operator is perceived by combining the traction force information in the direction of the robot's end motion speed and component.

2.1 Motion State Perception Strategy

In equation (2), the system gain ‘$1/B$’ is related to the output amplitude of the control system, which will directly affect the robot's motion speed and acceleration and deceleration performance (Ikeura R,1994). Although large virtual damping will make the operator feel obvious resistance and limit the acceleration ability of the robot, and damage the smoothness and flexibility of human-robot interaction, large virtual damping will also bring better deceleration ability for the robot when braking, and enable the operator to control the robot movement more accurately. On the contrary, a small virtual damping will make the operator feel less resistance when pulling the end of the robot, and the robot shows better acceleration ability during the interaction process. The operator can make the robot move at the expected speed with a small force, but the reduction of virtual damping will also limit the braking performance of the robot, resulting in the overshoot phenomenon and reducing the stability of the system. Therefore, after obtaining the motion intention, the virtual damping coefficient B of the admittance model should be adjusted so that the robot can quickly adapt to the control demand at the next moment.

The perception strategy is shown in Figure 2, taking the single-degree-of-freedom motion of the robot in Cartesian space as an example, when the interaction force and the end velocity direction of the robot do not reach the set threshold, the robot maintains the current motion state without changing the control system. When the interaction force and velocity reach the threshold value, when the two directions are the same, it is determined that the operator intends to pull the robot to accelerate the movement, and then the admittance controller is adjusted to appropriately reduce the virtual damping coefficient to make the robot accelerate rapidly. When the interaction force and the velocity are reversed, the motion is inferred as deceleration, and the virtual damping coefficient of the admittance controller is appropriately increased, so that the robot speed decreases rapidly. In addition, when the robot is moving with six degrees of freedom in

Cartesian space, the admittance controller should adjust the virtual damping and virtual mass coefficient of its six degrees of freedom direction respectively, because the operator may decelerate the robot in one direction and accelerate the robot in the other direction when pulling the robot.

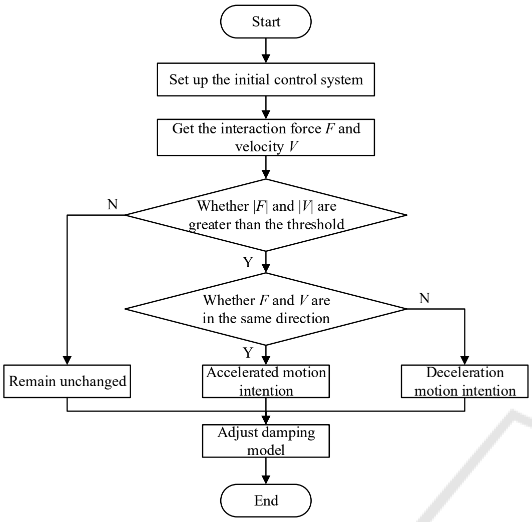


Figure 2: Perception strategy of the operation intention.

2.2 Variable Admittance Control System based on Fuzzy Reasoning

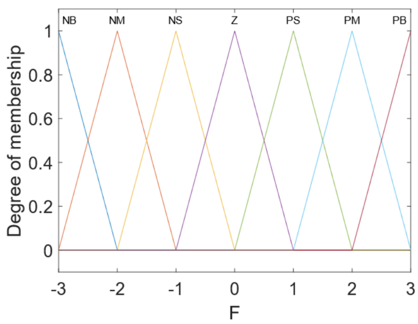
Fuzzy control can only infer the possible state according to the input and output of the controlled object without the precise model of the object, and then make adaptive adjustments to build a nonlinear time-varying control system that can accurately control the complicated and uncertain process, which can meet the control requirements of this paper to change the motion state according to the operation intention. When the motion state of the robot changes due to personal intention during the following traction movement, the virtual damping coefficient B can be adjusted in real time according to the intention perception strategy in Figure 3 with the help of the fuzzy reasoning method to adapt to the motion demand. Compared with the discrete data rules used by computers, the human-robot interaction control system is described by linguistic fuzzy variables, and the control mode of obtaining control action set through fuzzy reasoning simplifies the complexity of system design (Prabhu, 1998). Therefore, a fuzzy inference system was established in this paper to blur the interaction force exerted by the operator, the robot's end motion speed and the virtual damping coefficient of the admittance controller, and adjust the virtual damping coefficient of the system by fuzzy inference according to the operation intention. The fuzzy system can independently adjust the virtual damping coefficient of the 6 degrees of freedom of the admittance controller.

The fuzzy reasoning system in this study is a fuzzy system with two inputs and one output. The system input is the interaction force F and the robot terminal velocity V imposed by the doctor on the robot, and the output is the virtual damping coefficient B. Assuming that the variation ranges of the input and output variables are $[F_{max}, F_{min}]$, $[V_{max}, V_{min}]$ and $[B_{max}, B_{min}]$ respectively, the method for determining the minimum virtual damping coefficient is as follows:

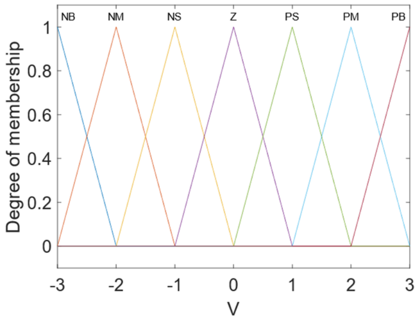
$$B_{min} = \frac{F_{min}}{V_{max}} \tag{3}$$

where V_{max} is the maximum velocity at the end of the robot in Cartesian space, and F_{min} is the minimum force that causes the velocity at the end of the robot to reach V_{max}.

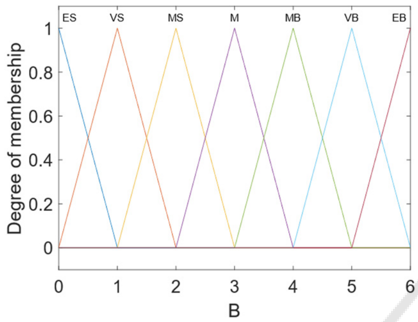
The input and output domains of fuzzy systems are defined as F:[-3,3], V:[-3,3], B:[0,6]. Then the fuzzy set and membership function are defined in the input and output variable theory domain of the fuzzy inference system. In order to take into account the simplicity and control effect of the fuzzy reasoning system, the fuzzy language of interaction force F and velocity V is described as {NB (negative big), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medium), PB (positive big)}. The fuzzy language of virtual damping coefficient B is described as {ES (extremely small), VS (very small), MS (medially small), M (medium), MB (medially big), VB (very big), EB (extremely big)}. All fuzzy subsets are described by triangular membership functions, and the membership function distribution of each fuzzy set is shown in Figure 3.



(a) Membership function of the force.



(b) Membership function of the velocity.



(c) Membership function of the virtual damping coefficient.

Figure 3: Membership functions of fuzzy sets in fuzzy inference system.

This paper adopts linguistic fuzzy rules (Mamdani), whose expression is as follows:

$$\begin{aligned}&If\ \tilde{F}_1\ is\ D_1^j\ and\ \cdots\ \tilde{F}_m\ is\ D_m^k\ and\ \tilde{V}_1\ is\ E_1^p\ and\ \cdots\tilde{V}_m\ is\ E_m^q\\&Then\ \tilde{B}_n\ is\ W_n^{k,\cdots,l,p,\cdots,q}\end{aligned} \tag{4}$$

where $\tilde{F}_m$ and $\tilde{V}_m$ are the fuzzy inputs of the fuzzy system, $\tilde{B}_n$ is the fuzzy output of the fuzzy system, D_m^a and the a-th linguistic values of E_m^a are $\tilde{F}_m$ and $\tilde{V}_m$ respectively. $W_n^{j,\cdots,k,p,\cdots,q}$ is the language value of the $\tilde{B}_n$. Then the fuzzy mapping relationship of a two-input single-output fuzzy system is established:

$$R_n^{k,\cdots,l,p,\cdots,q}=(D_1^j\times\cdots\times D_m^k)\times(E_1^p\times\cdots\times E_m^q)\times W_n^{k,\cdots,l,p,\cdots,q} \tag{5}$$

The fuzzy inference rules based on the operation intention perception strategy are shown in Table 1. After the fuzzy inference conclusion is clarified by the area-centric method, the fuzzy system outputs a clear virtual damping coefficient B value. The input and output responses of the fuzzy reasoning system are shown in Figure 4.

Table 1: Fuzzy reasoning rules.

B		*V*						
		NB	NM	NS	Z	PB	PM	PB
	NB	ES	VS	MS	M	MB	VB	EB
	NM	VS	VS	MS	M	MB	VB	VB
	NS	MS	MS	M	MB	M	MB	MB
F	Z	M	M	MB	VB	MB	M	M
	PS	MB	MB	M	MB	M	MS	MS
	PM	VB	VB	MB	M	MS	VS	VS
	PB	EB	VB	MB	M	MS	VS	ES

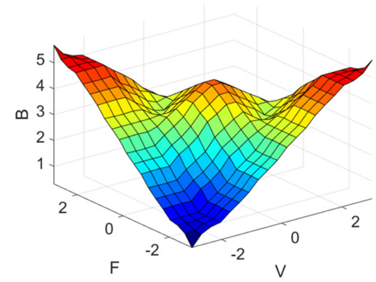


Figure 4: The response diagram of the fuzzy inference system.

According to the analysis of equation(2), when adjusting the damping of the control system, if the virtual mass coefficient M is kept constant and only the virtual damping coefficient B is changed, the system time constant M/B will be changed. The change of the system response time will change the dynamic characteristics of the system, and eventually affect the smoothness and flexibility of human-robot interaction. In order to avoid this problem, the virtual mass coefficient M should be adjusted synchronously with the virtual damping coefficient B, so as to maintain the dynamic characteristics of the control system and minimize the impact on the operating experience.

When the initial parameters of the control system increase or decrease the virtual damping, the system response curve generated when M/B is fixed or changed respectively is shown in Figure 5. As can be seen from the figure, when the virtual damping coefficient B is changed and the time constant M/B is kept constant, the response time of the control system is the same as that of the initial control system under different virtual damping. However, the response time of the output curve of the system whose M/B changes only by changing the virtual damping coefficient B changes to different degrees, which indicates that it is necessary for the controller to adjust the virtual mass synchronously to keep M/B unchanged during the movement of the robot under the control of variable admittance.

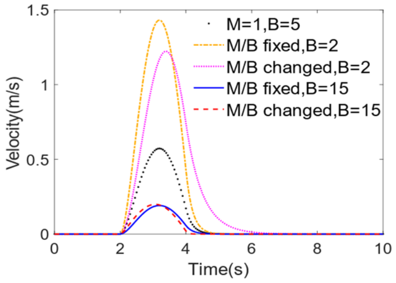
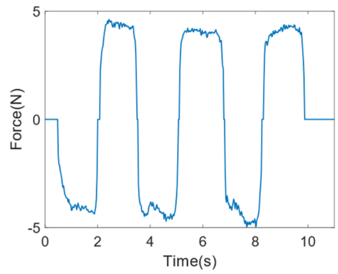


Figure 5: The response curve of a variable admittance model.

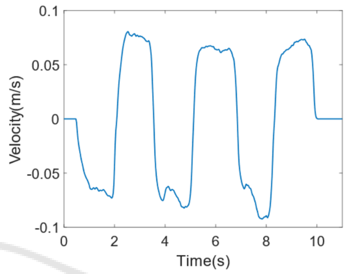
3 EXPERIMENTAL EVALUATION

In this section, the KUKA LBR iiwa robot will be used to verify the proposed variable admittance control algorithm. The SRI M3714A force sensor is installed at the end of the robot to collect the force.

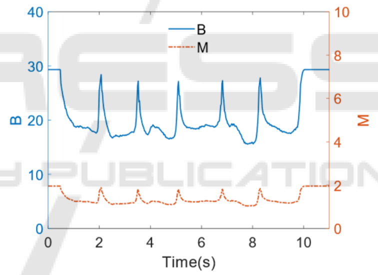
The operator drags the end of the robot to move so that the acceleration and deceleration of the end of the robot change frequently. As can be seen from Figure 6, when the interaction force begins to increase, the control system determines that the operator intends to accelerate the motion according to the interaction intention inference strategy, and correspondingly reduces the virtual damping coefficient of the admittance control model, so that the end of the robot quickly reaches the expected speed and follows the movement trend of the operator's arm, making it easier to start. On the contrary, when the direction of the interaction force reverses and is opposite to the direction of motion, the control system judges that the operator intends to slow down, the virtual damping coefficient of the admission control model increases, and the end of the robot quickly brakes and changes the direction of motion or stops under the operator's expected posture, effectively reducing the overshoot. In addition, the virtual mass coefficient changes in a fixed proportion with the virtual damping coefficient, so that the dynamic response performance of the control system is stable under constantly changing conditions, and the control effect of the robot's end following the interactive force is improved. The experimental results show that the variable admittance compliance control strategy based on fuzzy reasoning can dynamically adjust the damping of the control system to quickly respond to the operator's control intention while maintaining the dynamic response performance of the robot control system. This method improves the controllability of the robot's movement and the ability to adapt quickly to different operator habits, making the robot follow the operator's arm movement more flexibly and naturally.



(a) Interaction force.



(b) The velocity at the end of the robot.



(c) Admittance controller parameters.

Figure 6: Variable admittance compliance control based on fuzzy reasoning.

In order to further verify the control effect of the dynamic adjustment admittance controller based on fuzzy reasoning, two control methods (constant admittance and variable admittance) are used to pull the robot to move back and forth between two points, as shown in Figure 7.

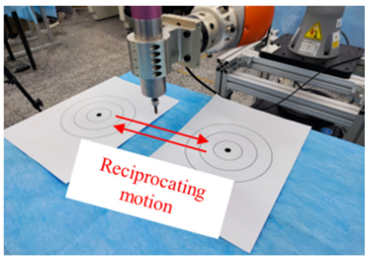
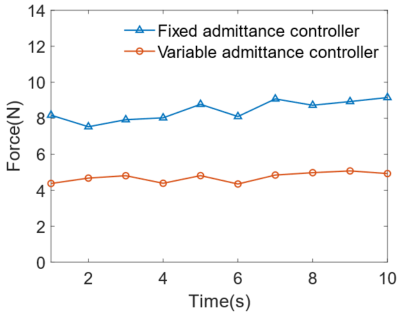
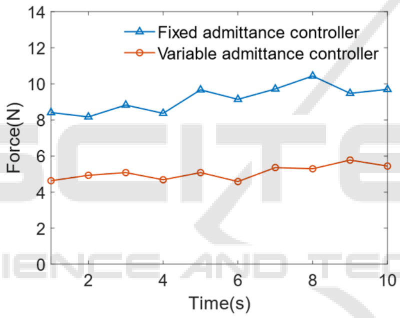


Figure 7: Reciprocating experiment.

The interactive force applied during the experiment is shown in Figure 8. It can be seen that the average and peak value of traction force applied under variable admittance control are significantly lower than those under constant admittance control, which proves that this strategy can make the robot more labor-saving and sensitive to follow the operator's intended movement, effectively reduce the operation intensity, and improve the human-robot interaction experience to a certain extent.



(a) Average interaction force.



(b) Peak interaction force.

Figure 8: Comparison of two control methods for applying interactive forces.

4 CONCLUSION

In this paper, a fuzzy variable admittance control method is proposed to solve the problem of single characteristics of the traditional admittance control model. A dynamic adjustment admittance control model of the fuzzy inference system is designed based on the perception strategy of the robot's end interaction force and velocity direction. The experimental data show that the variable admittance control method proposed in this paper can significantly improve the flexibility and adaptability of the control system when changing the robot's motion state.

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REFERENCES

Hogan N. Impedance control: An approach to manipulation[C], *1984 American control conference*. IEEE, 1984: 304-313. https://doi.org/10.23919/ACC.1984.4788393.

Shaodong Li. Research on robot-assisted minimally invasive spine surgery system and navigation and force control technologies applied in system[D]. *Harbin Institute of Technology*, 2020: 82-94. https://doi.org/10.27061/d.cnki.ghgdu.2020.005036.

Ranatunga I, Lewis F L, Popa D O, et al. Adaptive admittance control for human-robot interaction using model reference design and adaptive inverse filtering[J]. *IEEE Transactions on Control Systems Technology*, 2016, 25(1): 278-285. https://doi.org/10.1109/TCST.2016.2523901.

Jiang Z, Sun Y, Gao P, et al. Compliance control based on PSO algorithm to improve the feeling during physical human-robot interaction[J]. *Robotics and biomimetics*, 2016, 3(1): 1-7. https://doi.org/10.1186/s40638-016-0052-0

Tsumugiwa T, Yokogawa R, Hara K. Variable impedance control based on estimation of human arm stiffness for human-robot cooperative calligraphic task[C]. *Proceedings 2002 IEEE International Conference on Robotics and Automation*. IEEE, 2002, 1: 644-650. https://doi.org/ 10.1109/ROBOT.2002.1013431.

Ikeura R, Monden H, Inooka H. Cooperative motion control of a robot and a human[C]. *Proceedings of 1994 3rd IEEE International Workshop on Robot and Human Communication*. IEEE, 1994: 112-117. https://doi.org/10.1109/ROMAN.1994.365946.

Prabhu S M, Garg D P. Fuzzy-logic-based reinforcement learning of admittance control for automated robotic manufacturing[J]. *Engineering Applications of Artificial Intelligence*, 1998, 11(1): 7-23. https://doi.org/10.1016/S0952-1976(97)00057-2.