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Fuzzy variable admittance control for robot based on estimation of environment stiffness

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Abstract.

Abstract. To solve the problem of admittance control performance of manipulator in the process of force/position tracking control under the circumstances of unknown environment stiffness, a fuzzy variable admittance control based on estimation of environment stiffness was proposed. On the basis of manipulator admittance model and manipulator-environment equivalent model, the error of stationary force of the admittance control was analyzed. The environment stiffness was estimated with RBF neural network, and the reference trajectory can be calculated. According to the errors of position, velocity and force, a double fuzzy variable admittance control was proposed to adapt the change of environment parameters, and the better force/position tracking control could be obtained. The result of simulation illustrates: compared with the fixed parameters admittance control, the proposed control method presents a better dynamic performance on force/position tracking. So the method is effective.

Key words. Force/position control, admittance control, fuzzy control, environment stiffness, reference trajectory.

1. Introduction

With the wider and wider application of manipulator in various fields, people become more and more demanding on its level of intelligence. The traditional manipulator position control is no longer applicable to complex environment. Especially when manipulator contacts with the environment, it should be controlled both in position and in force. In the fields of industry, military and so on, both the acting force and displacement of the system should be controlled in using manipulators to complete the task of assembly and dis-assembly, polishing, man-machine collaboration,

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etc.

In recent years, a good number of researches have been made both at home and abroad on the intelligence-controlled admittance / impedance control, so as to improve the performance of force / position control. Mallpragada V proposed the method of environment parameters estimation, and used the neural network to estimate the force control coefficient, thus making the explicit force become less demanding on the environment parameter in impedance control[1]. ZarkoM.Cojbasic made a research on the self-adaptive fuzzy impedance control, and used the fuzzy neural network and the genetic algorithm to compensate for the environmental dynamics parameters in order to adapt to the change of environment[2] . Xu Z L established a fuzzy relation between the expected input and expected output, and used it to train the neural network, for the purpose of achieving online regulation of parameters of the impedance model[3]. Hongyan Wang, studied the position-based impedance control[4]for the pneumatic-hydraulic control device, under the condition that the environment parameters are known, unknown and invariable, and unknown and variable. Zhengyi Li, researched a fuzzy impedance control method of estimating the environment equivalent stiffness based on BP neural network, and used the initial value of impedance parameter and the fuzzy correction factor to adjust the impedance parameter[5] . Fei Wang obtained the environment positional information by means of the reverse engineering, made a fuzzy adjustment of impedance control parameters based on the change of environment stiffness, and finally achieved precise polishing[6] .

In this paper, the authors, based on the above-mentioned researches, analyzes the equivalent model and the steady-state force error for the contact of the manipulator with the environment, and works out the reference trajectory by using the RBF neural network to estimate the unknown environment stiffness. Besides, two fuzzy controllers are used to regulate the target damping parameter and the target stiffness parameter for the admittance control in order to adapt to the change of environment parameter. Finally, better performance in force / position control is achieved.

2. Admittance Control and Manipulator-Environment Equivalent Model

According to the concept proposed by Hogan, the key to admittance control is to adjust the relationship between the acting force and the positional deviation, so as to achieve a high compliance of robot in the operation. It features that the acting force is detected by the external sensor equipped at the end of the manipulator. In this Chapter, the research on manipulator admittance control mainly centers on the compensation for the dynamic and environmental uncertainty of manipulator and the tracking of the expected force [7][8].

$$M_{\mathrm{d}}(\ddot{X}-\ddot{X}_r)+B_d(\dot{X}-\dot{X}_r)+K_d(X-X_r)=F_d-F \tag{1}$$

In the Cartesian coordinate system, $M_d$representshe target inertia matrix, B_d represents the target damping matrix, and $K_d$represents the target stiffness matrix.

All of them have been decoupled, and are set as the diagonal matrix. Suppose that $E = X - X_r$. If the environment position is known and definite at this time, the manipulator end will keep contacting with the environment, and its driving force decides the expected force and exerts a force on the environment [9].

When the manipulator moves in a free space, it has no contact with the environment, during which it is a an independent system and presents the position tracking control only. However, when the manipulator end tool has contact with the environment, it, constrained by the environment, is no longer an independent controlled body, but constitutes an integral dynamic system with the environment. Generally, the manipulator end tool and the environment-contact model are equivalent to a linear spring system, as shown in Formula 2.

$$F = K_e(X - X_e) \tag{2}$$

In this formula, F,X,X_e represent the acting force between the manipulator end tool and the environment, the $n \times 1$dimensional vector of the actual position of the manipulator end, and the $n \times 1$dimensional vector of the environment position of the manipulator end respectively.K_e represents the positive definite diagonal $n \times n$ dimensional matrix of environment stiffness. Hence, the environment stiffness is decoupled in each direction of the Cartesian coordinate system.

Therefore, it is only necessary to consider the kinetic model for the manipulator end and the environment in a certain Cartesian direction, as shown in Figure 1[10].

3. Admittance Control of Manipulator

3.1. Model for Manipulator Admittance Control

The admittance control of manipulator is made up by the inner position loop and the outer admittance loop. The tracking of expected position is completed by inputting the force detected by the sensor equipped at the end of manipulator, the positional offset generated by the admittance control in the outer loop, and the algebraic sum of the current actual position and the reference position of manipulator, into the position controller in the inner loop. The accuracy of admittance control directly depends on the precision of position control in the inner loop. The acting force between the tool and the environment is detected by the force sensor equipped at the end of manipulator, and then is converted into the position offset e. Based on the admittance control, it can be figured out that [11]:

$$F_d - F = M_d\ddot{e} + B_d\dot{e} + K_d e \tag{3}$$

If converted to the frequency domain, it can be figured out that

$$e(s) = \frac{F_d(s) - F(s)}{M_d s^2 + B_d s + K_d} \tag{4}$$

Formula (4) is equivalent to a low-pass filter which exercises lowpass filtering on each element in $F(\mathrm{S})$ to obtain the position offset e. Add this offset and the reference position vector X_r generated by the trajectory planning together, to get the next position in the position control X_c.

$$X_c = X_r + e \tag{5}$$

If the manipulator moves in a free space and F=0, then e=0, and Xc=X_e . When the tool contacts with the environment, then X=X_c if the position controller is precise enough, and e=X-X_r . The method of admittance control is shown in Figure 2.

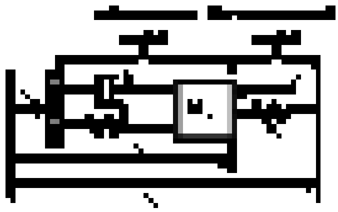

Fig. 1. A Simplified Model for the Contact

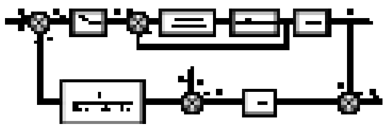

Fig. 2. Model for Admittance Control

When the system is in free movement and has no contact with the environment, then F=0, and the model turns to [12]

$$M_d\ddot{e} + B_d\dot{e} + K_d e = F_{\mathrm{d}} \tag{6}$$

The purpose of adopting admittance control for the end of force-controlled manipulator is to achieve an ideal admittance goal by selecting appropriate admittance parameters, and finally to achieve a stable control of force and position.

3.2. The Influence of Admittance Parameter on the Control Performance

The admittance parameter directly reflects whether the manipulator tool end is rigid or flexible when it has contact with the environment. The influence of admittance parameter on the control system is shown as follows. M$_d$ has a significant influence on the movement with high acceleration and great impact force, B$_d$ has a significant influence on the system in medium-speed movement or with strong interference, and K$_d$ has a significant influence on the low-speed movement near the equilibrium state. The manipulator end, when switching from the free state to the environment-contact state, will produce impact and cause damage to the tool and the environment. Hence, it is quite necessary to adjust the admittance control parameters to make the manipulator properly compliant while position is precisely controlled, thus to achieve the compliance control. When selecting the target stiffness parameter and the target damping parameter, try to have the system under the critical damping state or the overdamping state, so as to ensure the system stability.

4. Method of Admittance Control in Case of Unknown Environment Parameter

4.1. Analysis on Steady-state Force Error and Calculation of Reference Trajectory

It can be concluded from the environmental kinetic equation (2) that,

$$x_r = x_e + \frac{f_d}{k_e} \tag{7}$$

Suppose that $\ddot{x}_r = \dot{x}_r = 0$, and put (7) into the admittance model (1), and f_d is a constant force, so $\ddot{f}_d = \dot{f}_d = 0$. Further, the following result is obtained.

$$m_d \Delta \ddot{f} + b_d \Delta \dot{f} + (k_d + k_e)\Delta f = k_d f_d - k_d k_e (x_r - x_e) \tag{8}$$

In this formula, $\Delta f = f_d - f$
then the steady-state force error is

$$\Delta f_{ss} = \frac{k_d}{k_d + k_e}[f_d + k_e(x_e - x_r)] = \frac{k_d k_e}{k_d + k_e}(\frac{f_d}{k_e} + x_e - x_r) \tag{9}$$

Suppose that $k_{ed} = \frac{k_d k_e}{k_d + k_e}$, which is the equivalent stiffness of the target stiffness and the environment stiffness, so

$$\Delta f_{ss} = k_{ed}(\frac{f_d}{k_e} + x_e - x_r) \tag{10}$$

When it comes stable, the contact force is

$$f_{wd} = f_d - \Delta f_{ss} = k_{ed}(\frac{f_d}{k_d} + x_r - x_e) \tag{11}$$

It can be concluded from Formula (9) and (10) that, the error for the contact force reaching a stable state is
zero, only when $x_r = x_e + \frac{f_d}{k_e}$.

In conclusion, to have a precise tracking of the contact force between the manipulator tool end and the environment, the expected positionx_r must be figured out. Hence, the environment position $x_e$and the environment stiffness $k_e$must become known. However, in the actual control system, the environment is irregular, so the environment-contact positionx_e or the stiffness $k_e$can not be precisely obtained.

Besides, $x_e$exerts a significant influence on the force error. We define $\tilde{x}_e$and$\tilde{k}_e$ as the estimated values of $k_e$and $x_e$respectively, and Δx_eandΔk_e as the deviation between the estimated value and the true value respectively. It can be concluded from Formula (10) that,

$$\Delta f_{ss} = \frac{k_d}{k_d + k_e}(k_e \Delta x_e - \frac{\Delta k_e}{\tilde{k}_e} f_d) \tag{12}$$

It can be seen from the above formula that when the environment stiffness k_e is high, a very small change in the environment position deviation Δx_ewill cause a great force error. Therefore, the environment parameters, $x_e$andk_e, should be obtained in real time, so as to have the admittance control complete the force control in a precise manner. By doing so, the reference trajectory $x_r$for admittance control can be worked out accurately. The environment position is available in the Bibliography. It is only necessary to estimate or figure out the environment equivalent stiffness $k_e$to get the reference trajectory for manipulator admittance control, and thus to achieve the tracking control of force / position when the manipulator contacts with the environment.

4.2. Estimation of Environment Equivalent Stiffness Based on RBF Neural Network

When the manipulator tool end contacts with the environment, the target stiffness parameter in the admittance control exerts a very significant influence on the performance of its force and position tracking. In the equivalent model for the contact of the manipulator tool end with the environment, the equivalent stiffness of the model includes the equivalent stiffness of the environment and the equivalent stiffness of the manipulator system. Therefore, it is necessary to estimate the equivalent stiffness of the environment firstly, so as to adjust the target stiffness parameter in the admittance control system according to environment. In this Section, the features of equivalent stiffness are analyzed based on the experimental data for the environment, and the RBF-neural-network-based algorithm for the environment equivalent stiffness estimation is presented.

In the RBF neural network, it is equivalent to select the neuron transfer function of the hidden layer to form a group of primary functions in order to approximate the unknown function. In this Section, a group of experiments in which the probe equipped at the end of manipulator contacts with the fixed plate were designed, with the manipulator flange equipped with force sensor. To simplify the analysis, the data in the x direction of Cartesian coordinate was collected. In the whole process of contact, move the manipulator slowly to have the probe press the plate little by little. The position value and extrusion force are recorded every 0.03mm the manipulator moves, until the contact force reaches 33N. According to Hooke's law,

$$\mathrm{k}_e = \frac{f_{i+1} - f_i}{x_{i+1} - x_i} \tag{13}$$

Take and calculate the neighbouring two groups of position values and extrusion force values, to figure out the change process of the environment equivalent stiffness.

Firstly, the value for feed displacement and the value of extrusion force are collected from the experiment, so as to obtain the relationship between the extrusion force and the feed displacement, as shown in Figure 3. Then based on Formula (13), the relationship between the environment equivalent stiffness and the extrusion force in the process of contact is obtained, as shown in Figure 4.

It can be seen from Figure 4 that the environment equivalent stiffness and the contact force are in non-linear relationship. The RBF neural network is used to fit the non-linear relationship between the equivalent stiffness and the contact force (the extrusion force) when the manipulator end contacts with the

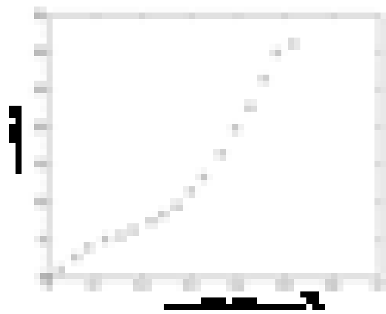

Fig. 3. Relationship between the Extrusion Force and the Feed Displacement

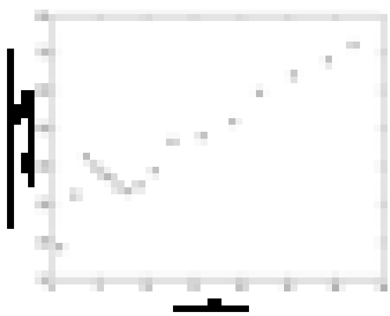

Fig. 4. Relationship between the Environment Equivalent Stiffness and the Extrusion Force

environment. Suppose that the input of the RBF neural network is the contact force between the manipulator tool end and the template f_e, and the output is the environment equivalent stiffness k_e. It is aimed to find out the input-output relationship of the 17 data points.

The RBF neural network designed for this Section is shown in Figure 5.

The non-linear mapping exists between the input layer and the hidden layer. The Gaussian function is selected as the excitation function for the node of the hidden layer. That is,

$$\mathrm{u}_i(x) = \exp[-\frac{(x-c_i)^T(x-c_i)}{2\sigma_i^2}] \qquad (i=1,2,...,q) \tag{14}$$

In this formula, u_i is the output of the node in the i^{th} hidden layer, $\sigma_i$is the standard constant of the node in the i^{th} hidden layer, $q$is the number of nodes in the hidden layer, $x = [x_1, x_2, ..., x_m]$ is the input sample, and c_i is the central vector of the node in the i^{th} hidden layer, which is in the same dimension with the vector of the input sample.

The linear mapping exists between the hidden layer and the output layer. That is,

$$k_k = \sum_{i=1}^{q} w_{ki} u_i \qquad (k=1,2,...,L) \tag{15}$$

In this formula, k_k is the output of thek^{th} node in the output layer, and w_{ki} is the weighting coefficient from the hidden layer to the output layer.

Currently, there is not a uniform reference basis for the determination of number of nodes in the hidden layer. However, it is certain that the greater number of nodes is, the higher degree of network approximation will be, and the higher degree of complexity will be. Hence, a balance shall be achieved between the precision and the complexity in selecting the number of nodes. Here a three-layer RBF network made up by the monolayer hidden layers is chosen, and the number of nodes in the hidden layer is selected according to the formula 2m+1 (m is the number of nodes input). For the web-based learning, the energy function$E$is defined.

$$E = \frac{1}{2}\sum_{s=1}^{S}\sum_{k=1}^{L}(k_k^{(s)} - \tilde{k}_k^{(s)})^2 \tag{16}$$

$\tilde{k}_k^{(s)}$is the expected environment equivalent stiffness shown in Figure 2, and $k_k^{(s)}$is the environment equivalent stiffness actually output from the RBF network, in which s represents the serial number of the sampling value. Similarly, the gradient descent is used to train the network parameters.

$$\begin{aligned} c_k(t+1) &= c_k(t) + \gamma\frac{\partial E}{\partial c_k} \\ \sigma_k(t+1) &= \sigma_k(t) + \gamma\frac{\partial E}{\partial \sigma_k} \\ \omega_k(t+1) &= \omega_k(t) + \gamma\frac{\partial E}{\partial \omega_k} \end{aligned} \tag{17}$$

Take 0.02 as the learning rate γ.

Figure 6 provides the values of environment equivalent stiffness obtained after inputting the sequence of extrusion force in the trained RBF network. The fitting degree of the non-linear stiffness is obtained by comparing the environment equivalent stiffness shown in Figure 6 with the expected stiffness shown in Figure 4 which is concluded from experiment.

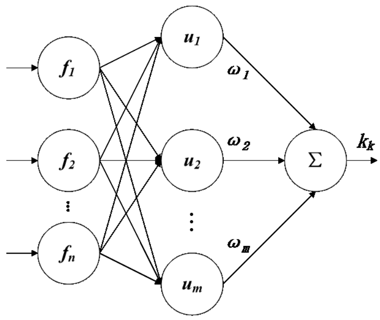

Fig. 5. Structure of the RBF Neural Network

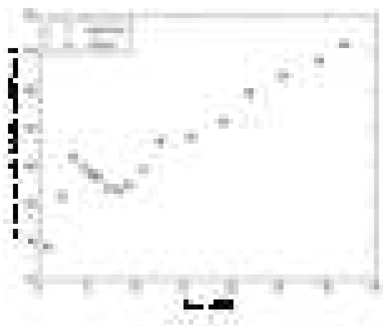

Fig. 6. Comparison between the RBF Network Fitting and the Expected Equivalent Stiffness

It can bee seen that RBF neural network is able to estimate the environment equivalent stiffness k_e.

5. Double Fuzzy Variable Admittance Control

The selection of admittance parameter directly affects the dynamic performance of the control system. The admittance parameters$B_d$and $K_d$are adjusted by fuzzy control in real time, so as to ensure better control of position and force for the object of study in this paper. Within the scope of force error, better position tracking is achieved to reduce overshoot and improve stability. The specific control system is shown in Figure 7.

Two fuzzy controllers are designed. The position error $e_x$and force error $e_f$are input into one fuzzy controller, while the position error change ratio $\dot{e}_x$and the force error $e_f$are input into the other fuzzy controller. The output is set asΔK_d andΔB_d respectively. Two double-input and single-output controllers are formed. The domain of discourse of input variable is [-1,1]. The input and output language variable is divided into 5 fuzzy sets (NB, NS, ZE, PS and PB). The membership function is set to be in triangular distribution. The fuzzy rule table, as shown in Table 1, is prepared as required.

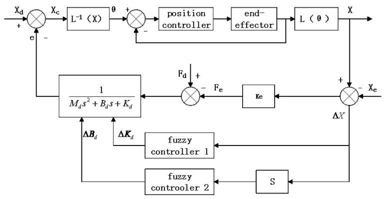

Fig. 7. Double Fuzzy Admittance Control System

Table 1. Table for Fuzzy Control Rule

$\Delta K_d \Delta B_d$		e_f				
		NB	NS	ZE	PS	PB
e_x $\dot{e}_x$	NB	NB	NS	ZE	PS	PS
	NS	NS	NS	ZE	ZE	PS
	ZE	NS	ZE	ZE	ZE	PS
	PS	NS	ZE	ZE	PS	PS
	PB	NS	NS	PS	PS	PB

According to the fuzzy rule table, the output values ΔK_d and ΔB_d of the fuzzy controllers are worked out by means of defuzzification.

6. Analysis on Simulation Experiment

Simulation research on the double fuzzy variable admittance control is done. The initial environment stiffness is set as 5,000N/m, the environment position as 16 cm, the initial position as 0, and the initial admittance parameter as $M_d = I, B_\mathrm{d} = \begin{bmatrix} 300 & \\ & 300 \end{bmatrix}, K_d = \begin{bmatrix} 500 & \\ & 500 \end{bmatrix}$. In the following figure, the force tracking performance curve and the position tracking performance curve are shown.

It can be seen from Figure 8 and 9 that, compared with the fixed-parameter admittance control, the double fuzzy variable parameter admittance control reduces the overshoot of force tracking, and shortens the response time for position tracking. Therefore, the proposed controller achieves a better force / position tracking control under the condition that the environment parameters are known.

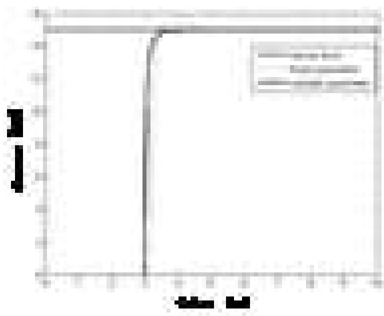

Fig. 8. Force Tracking Curve

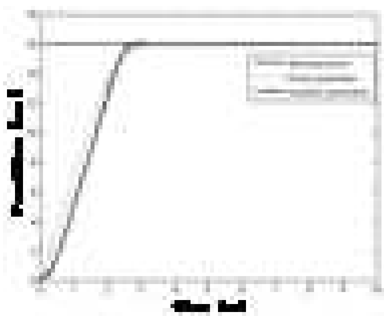

Fig. 9. Position Tracking Curve

7. Summary

Aimed at the problem that the manipulator force / position control is restricted by unknown environment stiffness, the double fuzzy variable parameter admittance control method is proposed, thus solving the dynamic performance problem of manipulator force and position in a constrained environment. In this method, the manipulator admittance model and machine-loop equivalent model are established firstly. To get the reference trajectory, the steady-state force error is analyzed, and the estimation of environment stiffness based on the RBF neural network is presented. Two double-input and single-output fuzzy controllers are designed, with the force error, position error and position error derivative as the input, and with the change of target damping and target stiffness as the output. The admittance control parameters are updated according to the change of environment parameters, so as to achieve better performance in force / position dynamic control. At last, the method is proved effective by the simulation research.

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