Coordinated Control of Two Arms Using Fuzzy Inference

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Abstract

Recently, complicated and dexterous tasks with two or more arms are needed in many robot manipulator applications which can not be accomplished with one manipulator. In general, when two arms manipulate an object, the dynamics of the arms and the object should be considered simultaneously.

In order to control the force of the arms, we can use various control schemes based upon dynamic modeling. But, there are difficulties in solving inverse dynamics equations, and the environment where a manipulator performs various tasks is usually unknown, and we can not describe a model precisely, for instances, the effect of the joint flexibility, and the friction between the arm and the object.

Therefore, in this paper, we suggest a new force control method employing fuzzy inference without solving dynamic equations. Fuzzy inference rules and parameters are designed and adjusted with the automatic fuzzy modeling method using the Hough transform and gradient descent method.

I Introduction

In case of tasks in which two manipulators hold and move an object as shown in Fig. 1-1, the arms can be controlled by solving the dynamic equations of the system. However, it is usually difficult to solve the equations and there may be some singular points where it is impossible to position the object and arms. Therefore, we use fuzzy inference instead of solving the dynamic equations.

It is assumed that one of the two robot arms serves as a master arm in performing a task, that is, the master arm is only controlled by position-control scheme to move to a desired position holding an object and the other robot arm is to follow the movement of the object using force-control scheme. We adopt the fuzzy inference method in the force control of the slave arm. The force and torque given to the object are observed through the force-torque sensor attached to each arm wrist, and using sensor information, the movement of the slave arm is determined by fuzzy inference.

In case of cooperation of multi-manipulators such as explained above, analytic approaches are based on the assumption that the dynamics of the manipulators are all known, but the exact dynamics is hard to obtain due to the measurement error and uncertain effects such as friction and disturbance. Moreover, though we know all about the robot dynamics, the dynamic equations is not easy to solve because of its excessive calculation time and complexity of the equations.

In previous studies, Nakano et al. and Arimoto et al. proposed a scheme to control one as a master(by position control) and the other as a follower (by force control). Antti J. Koivo et al.[1] surveyed the problems and recommendation for the future research. About coordinated multiple robot manipulators, he suggests several problems in cooperation of multiple arms, such as load distribution and constraints caused by formation of a closed chain.

This paper is organized as follows. In section 2, we discuss robot manipulator fuzzy control, and in section 3, show how to make a fuzzy model , and how to implement in simulation. Then in section 4, we prove the effectiveness of this method using fuzzy modeling by experiment. Finally, in section 5, we make conclusions.

II Manipulator Control Using Fuzzy Inference

For the cooperative task moving object with two arms, we adopt the force control of the slave arm using the fuzzy inference. The force and torque given to the object are observed through the force-torque sensor attached to each arm wrist. The control variables of the slave arm is determined from the sensor information. There are some suggestions of fuzzy inference and modeling methods. In this paper we use the fuzzy model of Takagi-Sugeno[4] as expressed by the following equations:

$$L^i: \text{If } x_1 \text{ is } A_1^i \text{ and } x_2 \text{ is } A_2^i, \dots x_m \text{ is } A_m^i \quad \text{then } y^i = a_0^i + a_1^i x_1 + \dots + a_m^i x_m \qquad (2-1)$$

$$y = \frac{\sum_{i=1}^{n} w^i y^i}{\sum_{i=1}^{n} w^i} \quad \text{where } w^i = \prod_{j=1}^{m} A_j^i(x_j^0) \qquad (2-2)$$

Where L^i(i = 1,2,...n) represents i-th implication and x_j(j=1,2,...,m), an input variable and y^i, the output from

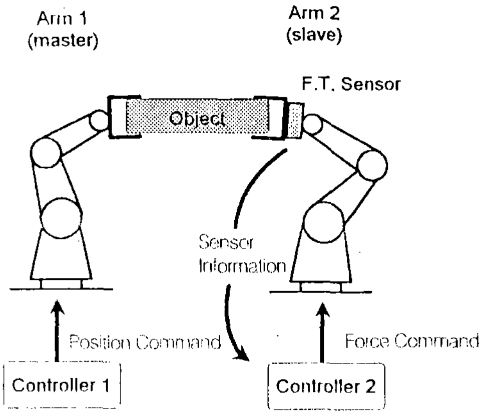

Fig. 1-1 Coordinated control of two manipulators.

the i-th implication. a_j^i is a consequent parameter and $A_1^i, A_2^i, \ldots, A_m^i$ are fuzzy variables. As shown in Eq.(2-1) and (2-2), this fuzzy model describes the nonlinear input-output relation with piecewise linear equations for the divided input space.

Because the consequent part of the fuzzy model is composed of linear equations, the control system can be analyzed utilizing classical control methods. But the design and identification algorithm proposed by Takagi-Sugeno is difficult to implement and time-consuming due to its complexity. When the number of input variables is large, the number of the possible structure becomes combinationally large. This method is based on the idea to find a set of piecewise-linear structure to describe a nonlinear process. In this approach, we have to build dynamic model using only input-output data. This stage of modeling is usually referred to as identification. In this paper, we use a new identification method based on a fuzzy model suggested by Takagi and Sugeno to solve above problems.

III Fuzzy Model Identification

The identification of a fuzzy model using input output data is divided into two kinds: structure identification and parameter identification. The former consists of premise structure identification and consequent structure identification. The latter also consists of premise parameter identification and consequent parameter identification. The consequent parameters are the coefficients of linear equations.

As shown in Eq.(2-2), the output is determined by premise parameter w_i and consequent parameter a^i. Because the output is affected by the consequent parameter more than the premise parameter, determining the premise part prior to the consequent part makes the identification algorithm inefficient. Therefore, we first identify consequent part and then identify premise part. The consequent parameters are identified by the Hough transform, which is used to find a set of linear equations and make it unnecessary to set initial values of linear equations. Then we suggest a gradient descent algorithm to fine-tune the parameters of a fuzzy model. According to the consequent structure and parameters included in the linear equations, the premise structure and parameters are determined.

The Hough Transform

To describe the given system with piecewise linear equations, the input space should be partitioned. Once the input space is partitioned, each area is used to form a fuzzy rule of the fuzzy model. In case of a single input and single output system, the input and output of the system can be mapped into a point of 2-dimensional plane as (x_i, y_i). Then a Hough transform method[10] is used to find straight line segments and identify the parameters of the fuzzy model.

Although the Hough transform is usually used for 2-dimensional data (especially in image processing), it is applicable to any function of the form g(x, c) = 0, where x is a vector of coordinates and c is a vector of coefficients. So the Hough transform method can also be applied in case of a multi-input and multi-output system.

Consequent and Premise Identification

There can be several selected cells by a fixed threshold in a small area after the Hough-transformed and which can cause undesirably large number of lines corresponding to a almost linear group of input and output data. To avoid those problems, the local maximum points of the accumulator cells in the transformed plane are chosen as candidate cells and some of them are merged by clustering methods.

After clustering of consequent identification, the center and variance of clusters are used to form the premise parameters of the fuzzy model. In this paper, all membership functions are Gaussian function(bell-type) expressed as follows:

$$A_i(z_i, s_i, x) = \exp\{-((x - z_i) / s_i)^2\} \tag{3-1}$$

,where z_i is the center of the i-th cluster and s_i is the standard deviation of the cluster.

Fine Tuning by Gradient Descent Algorithm

By the gradient descent method, an appropriate algorithms to fine-tune the parameters of a fuzzy model can be derived. Let p_{jk}^i be the k-th variable which constructs the linguistic variable of j-th premise part in the i-th rule. Then the premise parameter of a fuzzy model can be fine-tunned by the following learning method :

The following equation is the fine-tuning algorithm for the premise parameter of the fuzzy model represented by Eq. (2-1) and (2-2):

$$\Delta p_{jk}^i = \gamma(y_{des} - y^*)(y - y^*)\frac{1}{\sum_{i=1}^{m} w^i}\frac{\partial w^i}{\partial p_{jk}^i} \tag{3-2}$$

,where γ denotes the learning rate, y_{des} denotes the desired output and y^* denotes output obtained from a fuzzy model.

The consequent parameters can be tuned by the following learning method :

$$\Delta\alpha_j^i = \gamma(y_{des}-y^*)\frac{1}{\sum_{i=1}^{m} w^i} w^i x_j \qquad (3-3)$$

(proof)

Given Sample data (X, y_{des}), we define the difference between y_{des} and y^* as error e,

$$e = y_{des} - y^* = y_{des} - \frac{\sum_{i=1}^{m} w^i y^i}{\sum_{i=1}^{m} w^i}$$

The premise parameter should be fine-tunned to reduce the squared error e. Therefore, the variation of the premise parameters are derived by the following procedure:

$$\Delta p_{jk}^i = -\gamma \frac{\partial}{\partial p_{jk}^i}\left(\frac{e^2}{2}\right) = -\gamma e \frac{\partial e}{\partial p_{jk}^i}$$

$$= \gamma(y_{des}-y^*)\frac{\frac{\partial}{\partial p_{jk}^i}\left(\sum_{i=1}^{m} w^i y^i\right)\times\sum_{i=1}^{m} w^i - \sum_{i=1}^{m} w^i y^i \times \frac{\partial}{\partial p_{jk}^i}\left(\sum_{i=1}^{m} w^i\right)}{\left(\sum_{i=1}^{m} w^i\right)^2}$$

$$= \gamma(y_{des}-y^*)\frac{\frac{\partial w^i}{\partial p_{jk}^i} y^i \times \sum_{i=1}^{m} w^i - \sum_{i=1}^{m} w^i y^i \times \frac{\partial w^i}{\partial p_{jk}^i}}{\left(\sum_{i=1}^{m} w^i\right)^2}$$

$$= \gamma(y_{des}-y^*)\frac{\partial w^i}{\partial p_{jk}^i}\left(\frac{y^i}{\sum_{i=1}^{m} w^i} - \frac{\sum_{i=1}^{m} w^i y^i}{\sum_{i=1}^{m} w^i}\frac{1}{\sum_{i=1}^{m} w^i}\right)$$

$$= \gamma(y_{des}-y^*)\frac{\partial w^i}{\partial p_{jk}^i}\frac{1}{\sum_{i=1}^{m} w^i}(y^i - y^*)$$

$$= \gamma(y_{des}-y^*)(y^i - y^*)\frac{1}{\sum_{i=1}^{m} w^i}\frac{\partial w^i}{\partial p_{jk}^i}$$

The consequent parameter should be tuned to reduce the squared error e like the premise part using a gradient descent algorithm.

By the gradient descent method,

$$\Delta\alpha_j^i = -\gamma\frac{\partial}{\partial \alpha_j^i}\left(\frac{e^2}{2}\right) = -\gamma e \frac{\partial e}{\partial \alpha_j^i}$$

$$= \gamma(y_{des}-y^*)\frac{\partial y^*}{\partial \alpha_j^i}$$

$$= \gamma(y_{des}-y^*)\frac{1}{\sum_{i=1}^{m} w^i} w^i x_j \qquad (Q.E.D)$$

IV Results of Fuzzy Modeling

To make the modeling procedure simple, only z-axis sensor data corresponding to the movement of the object is used in the fuzzy modeling(single input and single output). Using the input and output data shown in Fig. 4-1 the construction of fuzzy model is accomplished. Fig. 4-2 shows the linear equations of the fuzzy model obtained from the Hough transform and clustering. To adjust the premise and consequent parameters and minimize error, fine-tunnig based on the gradient descent method is accomplished and the premise and consequent parts are settled down diminishing error during the learning procedure. Fig. 4-3 is the input and output of the model trained using the explained fuzzy modeling method. It shows that the fuzzy modeling algorithm constructs the model of the given system successfully and the output of the fuzzy model can be used for the control of the slave robot arm according to the input sensor data. If 3-dimensional force input of xyz direction and the movement of the object are used in the modeling procedure, it can be possible to apply this controller to the real robot movement in 3-dimension.

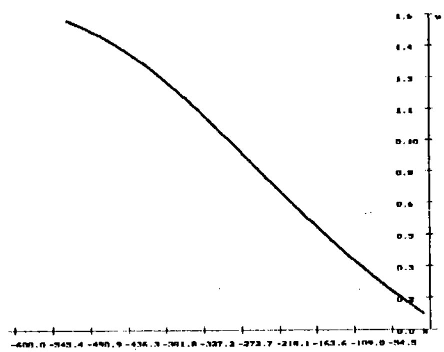

Fig. 4-1 Input/output data of the given system.

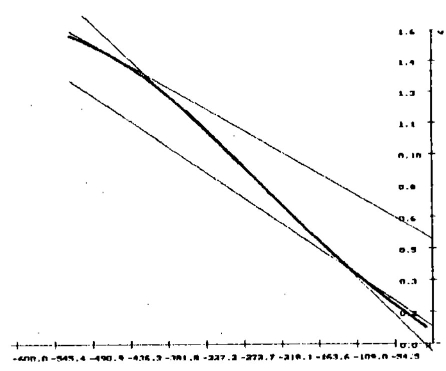

Fig. 4-2 Linear equations obtained from the Hough transform and clustering.

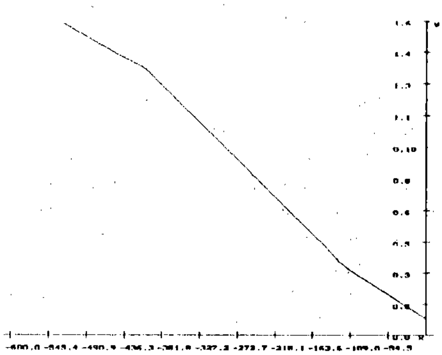

Fig. 4-3 Output of the fuzzy model after fine-tuning.

V Conclusions

When two arms manipulate an object, the dynamics of the arms and the object should be considered simultaneously but it is not easy to solve the dynamic equations. Therefore, in this paper, we employs the fuzzy inference without solving dynamic equations and the fuzzy modeling algorithm to design and determine the fuzzy inference structure and parameters. Fuzzy inference rules are constructed automatically using the Hough transform and clustering method and the gradient descent method is used for parameter adjustment. The slave arm can be controlled by the fuzzy inference with the force-torque sensor input data.

In this paper, we show the modeling procedure and the results of fuzzy modeling with the data from the force-torque sensor attached to the slave robot wrist in one axis. It can be applied to 3-dimensional applications of the cooperative tasks of manipulatorusing the similar modeling method. We are planing further researches including a simulation and experiment for the real world applications.

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