Position and Impedance Force Control of Tele-operated Mater-slave Robot Hand

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The paper considers the position control with neuro-fuzzy inverse model velocity controller of multi-finger robot hand in tele-operated system - an active master-slave robot hand system for demining. For neuro-fuzzy network training, the well-known backpropagation method is employed where adaptive learning rate is used in order to accelerate the speed of convergence. In the force loop position-based impedance force control with a two posture recognize NN to realize smoothly releasing action of the master-slave hand is considered. The results of experiment show that the position tracking of the master-slave hand has strong robustness, and position-based impedance force control with a two posture recognizes NN can realize stable grasp and release action of master-slave hand.

Key words: Neuro-fuzzy, Tele-operated master-slave robot hand system, Adaptive learning rate, Impedance force control

1. Introduction

Many tele-operated robotic systems have been used to dangerous and unreachable environment protecting people from hazardous works. Our research group provided an active tele-operated master-slave robot hand with completely different structure. In this paper, the system characteristics are introduced firstly, then a neuro-fuzzy inverse model control in velocity loop is proposed. In order to incorporate learning ability into the drive system, an artificial neural network with fuzzy structure is used here. For neuro-fuzzy network training, the well-known backpropagation method is employed where the learning rate is adapted in each iteration step in order to accelerate the speed of convergence. It is shown that an appropriate selection of the learning rate results in stable training in Lyapunov sense(5).

In the force control loop we used impedance force control and put human hand outside of force control loop. And at last, in order to realize smoothly releasing action of the master-slave hand a two posture recognize NN is employed.

2. Configuration of tele-operated robot hand system

![Configuration of tele-operated robot hand system](image)

2.1 Master hand

Our research group considers tele-operated robot hand that has been using a dataglove with 22 position sensors and an exoskeleton force feedback glove(2); there is a direct mapping from the human hand to the robot slave hand. Generally, the finger positions of the human master are translated to the robot and visual or force feedback is returned from the slave hand to the master, the master hand are equipped with "actuators" on the exoskeleton giving the operator a very important feeling coming from grasped object. In this system master and slave hand have totally different structure, and the operation of human hand has some degrees of dithering, so we should consider how to reduce the response of slave hand to this dithering and to mimic human noise response.

2.2 Slave hand characteristics

Slave hand consists of four fingers and every finger is composed of a proximal joint (upper joint) and a distal joint (Fig.1). Every joint of the slave hand comprises of one hydraulic cylinder, four individually actuated two-way, two-position valves and one potentiometer as shown in Fig.2, where the valves are solenoid (SOL) valves with PWM signal trigger.

2.3 Analysis of system

The requisite for our grasping operation is the accurate position tracking and the compliant feeling of contact force of the finger tip. There are some problems associated with the tele-operated system, 1) Master and slave hand have totally different structure

2) Hydraulic system with on-off valve have strong nonlinear characteristics

3) The image from the display interface is not clearly display tactile information of all fingers.

4) The force of slave hand cannot be controlled to a specified level, relying on the operator to adjust the pressure that he, or she, is feeling.

5) A model of the interaction between the robot and environment will be modeled according to different tactile objects.

In order to solve above mentioned problem, a neuro-fuzzy inverse model control in velocity loop is proposed, in the force loop we used impedance force control.

3. Neuro-fuzzy control system

The basic structure of the neuro-fuzzy control system proposed is
shown as in Fig.3. It consists of two main parts: (1) the main feedback external loop is P position loop that gives the joint velocity reference value, and (2) the internal part which is responsible for the velocity of the joint robot where a neuro-fuzzy inverse model controller is employed with the RBF (Radial Basis Function), isosceles triangular and trapezoid membership function (in order to overcome dead zone).

Layer (E) is the defuzzified part, the crisp out value \( u \) is calculated by the center of gravity method as:

\[
  u = \frac{\sum_{i=1}^{m} \mu_{B_i}(w_i)w_i^*}{\sum_{i=1}^{m} \mu_{B_i}(w_i)}
\]

where \( w_i^* \) is defined to satisfy \( \mu_{B_i}(w_i^*) = 1 \).

### 3.2 Neuro-Fuzzy Algorithm

Our goal of off-line training is to get an approximate velocity inverse model, then copy the inverse model as a velocity controller, and at the same time use P position control output as reference velocity input to velocity inverse controller generate robust control signals to the joint make position tracking with stable speed and high accuracy. Method gives an initial rule base starting with an empty rule base (1). And we define the cost function as

\[
  E = \frac{1}{2}(r_k - y_k)^2 = \frac{1}{2} v_k^2
\]

In the training process off-line \( r_k \) is the duty cycle that is the target output data of training data set shown as Fig.6. The joint velocity is the input of the neuro-fuzzy network. Here we use backpropagation algorithm to update the controller parameters with an adaptive learning rate for improving the convergent speed. The adaptive learning rates \( \eta_{c_i}(k), \eta_{\sigma_i}(k), \eta_{w_i}(k) \) and \( \eta_{w_i}(k) \) are chosen as

\[
  \eta_{c_i}(k) = \frac{\alpha}{2} \left( \frac{w_i^* - u_i}{z} \right)^2, \quad \forall k
\]

\[
  \eta_{\sigma_i}(k) = \frac{\alpha}{2} \left( \frac{w_i^* - u_i}{z} \right)^2, \quad \forall k
\]

\[
  \eta_{w_i}(k) = \frac{\alpha}{2} \left( \frac{R_i}{z} \right)^2, \quad \forall k
\]

\[
  \eta_{w_i}(k) = \frac{\alpha}{2} \left( \frac{1}{z} \right)^2, \quad \forall k
\]

where \( \alpha \in (0,1) \). Choice of coefficient \( \alpha \) is a result of trade-off between the speed and stability of training algorithm for each specific case. A lower value of \( \alpha \) guarantees more stable adaptation of weights.

### 4. Position-Based Impedance Force Control

To provide the operator with more workspace feedback, force reflecting systems are available where the forces being exerted on the remote slave robot can be 'felt' by the operator through an active master mechanism. However, our system has some limited effectiveness as additional burden is actually placed on the operator who is now part of the control loop. Furthermore, the forces cannot be controlled to a specified level, relying on the operator to adjust the pressure that he, or she, is feeling without force sensor of master finger tip. Therefore, here we remove the operator from the loop in fact as Fig.5. Position-Based force control uses an external force control loop which surrounds an internal position or velocity loop which provides the control to the actuators, Figure 5, where IK is Inverse
Kinematics. In this system, one direction force sensor is used; here we just consider one direction force control.

In order to reach the desired force quickly the system performance impedance is regulated by Eq. (6):

\[ E(t) = F(t) - F(t) \]

\[ M \frac{d^2}{dt^2}[X(t) - X(t)] + B \frac{d}{dt}[X(t) - X(t)] + K[X(t) - X(t)] = F(t) \]  

(6)

\( M, B, K \) are the desired inertia, damping coefficient and stiffness respectively, here we just consider stiffness affect. The calibration of force sensor is mapped from [0, 10] kgf to voltage [0, 5] V.

5. Posture recognition of grasp and release

In fact, after impedance force control begins to work, position reference data from the data glove do not work again, so here an NN of two posture recognition is employed to realize release action, where one is grasp posture, another is release posture.

6. Experimental results

6.1 Position part results

The training data set of the proximal joint is shown as Fig.6. The training result and training error are shown as Fig.7, 8, 9, respectively. The position tracking experimental results of robot joint with neuro-fuzzy controller are shown as Fig.10 to compare with the result with P controller. The control scheme of the paper has strong robustness. In order to do force controller more easily, the opposite finger active at the same posture, means the opposite finger use the same data-glove data as reference value.

6.2 Force control part results

The reference force of finger tip is set to 1.6kgf, 2kgf, 3kgf to different object, respectively. The calibration of force sensor is [0-10]kgf to [0-5]V. The result is shown as Fig.11-Fig.22. Here in order to get Fig.13-16 easily, for soft bottle we just let slave side to work to track sine wave and then put the object between the opposite fingers, other results are master-slave together to work. Here, one finger of the opposite fingers is controlled using impedance force controller after contacting.

1) Soft bottle
2) Wooden box

Fig.17 finger tip force without force control

Fig.18 finger tip force with force control

3) Heavy mine

Fig.19 finger tip force with force control

Fig.20 finger tip force without force control

6.3 Comparison of grasping and releasing action

This part compared grasping action with impedance controller with grasping action according human’s feeling and presented releasing action result with recognition NN.

1) Finger2,4 using impedance force control

Fig.21 finger2,4 tip force with force controller

2) Finger1,3 according human’s feeling

From Fig.21, we can see the releasing action using recognition NN is smoothly enough. Compared Fig.21 and Fig.22, we can see according human’s feeling the force of slave hand will become to larger more easily.

7. Conclusions

From the experimental results, we can see the position tracking of the master-slave system with neuro-fuzzy control scheme have strong robustness, and impedance force control with two posture recognition NN realized specified level grasp and stable release action of master-slave hand.

In the future, we will consider establishing much better virtual reality environment and using intelligent impedance strategy or hybrid position/force control.

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