More Identifiable Stiffness Feedback for Dexterous Hand Teleoperation in Unknown Environment

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Abstract

In dexterous hand teleoperation, effective force feedback is critical for precisely identifying objects in an unknown environment. This paper proposes an object-based motion mapping method to provide more identifiable stiffness perception for an operator to perceive different objects in a teleoperation system. To verify the effectiveness of the proposed method, a three-fingered robot hand (BarrettHand BH8-280) teleoperation system is established which uses a commercial desktop haptic device as the master manipulator. A comparison experiment is carried to identify the stiffness of five different objects with two different motion mapping methods: constant motion mapping, and object-based motion mapping. The results show that the object-based motion mapping is more reliable and effective as compared with constant mapping method.

Keywords: Stiffness Perception, Dexterous hand teleoperation, Motion Mapping

1. Introduction

In dexterous hand teleoperation, controlling slave robot hand to accurately grasp a wide variety of previously unidentified objects is always a challenging task for an operator since these objects have various properties, from soft to hard, light to heavy, fragile to solid. A teleoperation system should be transparent enough so that the operator can manipulate the slave robotic hand to grasp objects efficiently and safely without dropping or destroying them [1][2]. There is no doubt that visual feedback is essential for operators to acquire the position and shape information of an object so as to plan a correct posture of the robot hand. However, when the robot hand contacts with objects, haptic feedback becomes the dominant information for the operator to perceive the interaction between the robot hand and the objects [3][4]. The operator relies on the precise haptic feedback to manipulate the robot hand to finish tasks.

High performance force sensors are used in slave robot hand to measure the contact forces in remote environment accurately. Accordingly, haptic devices should also be able to provide accurate feedback force and stiffness to users. However, it is really a problem to reproduce the Hi-Fi force signals measured from slave side and output them to a user through the master haptic device. That is also why, for most robot hand teleoperation systems, force feedback is just the auxiliary information to partly enhance the transparency of teleoperation systems to improve the task performance [5]-[7]. These teleoperation systems are more suitable for applications that interact with objects which are hard enough not to be easily damaged. An operator without accurate haptic feeling would find it impossible to control a robot hand to precisely grasp all types of objects. Therefore, a more refined force feedback for operator is required so that he/she can distinguish the different objects, which widens the applications of haptic-based teleoperation systems.

In this paper, an object-based motion mapping method is presented to provide more identifiable output stiffness to users and benefit them in completing robot hand teleoperation. The motion mapping coefficient between the master device and the slave robot hand is regulated based on real time estimation of the properties of different objects. An automatic pre-estimation is conducted to evaluate the objects' dynamical properties to guarantee a refined feedback stiffness with high fidelity to represent the being grasped object. The slave hand is a Barrett three-fingered robot hand. The master force feedback device should be capable of controlling this robot hand conveniently and output the grasp force stably at the same time. Haptic gloves are the most commonly used master devices in robot hand teleoperation [8]-[12]; however, the motion mapping is complicated because of the different kinematic structures between the robot hand and haptic glove. In order to have a stable force feedback and to simplify the robot hand teleoperation system, a commercial desktop haptic device Falcon is used as an alternative for the master device. With the buttons on its handle, its motion is easy to be mapped to that of the robot hand.

Extensive experiments are conducted to evaluate the grasp performance based on the proposed method. The following section introduces the proposed object-based haptic control scheme. Section 3 describes the BarrettHand teleoperation system used in this paper. According to the robot hand and the master device, motion mapping and force feedback methods are developed for the system. Section 4 describes the experiments for the system and section 5 presents the results and discussion. Section 6 presents the conclusion and future work.

2. Object-based motion mapping method

2.1. The Effect of Different Grasp Force Perception on Grasping

For a robot hand operation, proper grasp force is critical for a safe and stable grasping (Figure 1). Insufficient grasp force causes repeated grasps and the object is easy to slip from the hand. While excessive grasp force may deform and even damage the object. For objects of different materials, the trajectories of grasp force change are varied. The grasp force changes with the deformation of the object. In order to grasp unknown objects in safety-critical teleoperation applications, the different variation of grasp force trajectories should be precisely perceived by the operator so that they can distinguish objects of different material properties.

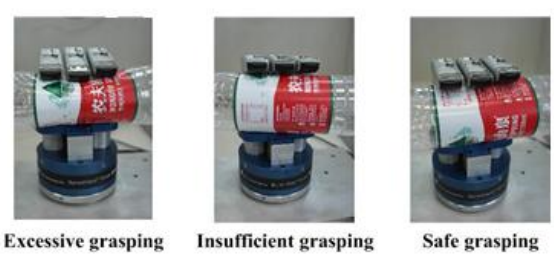

Figure 1. The effect of grasping by feeling inaccurate force feedback.

Although the resolution of feedback force is difficult to be improved, the output stiffness of a haptic device can be improved by regulating the trajectory of the device. Simulating high-resolution stiffness is able to enable users to distinguish objects of different materials and properties, and people can make the difference of all being grasped objects by feeling their different stiffness.

2.2. Real-time Motion Mapping based on Contact Impedance Estimation

Motion mapping between master and slave in a teleoperation system can be defined as:

$$P_s = f(k_p, P_m) \quad (1)$$

Where P_m and P_s represent master and slave motion (position, velocity) respectively. k_p is the motion mapping coefficient. We propose to adjust the motion mapping coefficient according to the object to be grasped. For instance, human hand moves slowly when grasp a soft object. Accordingly the motion of robot hand should be slow. The feedback force is relatively small and changes gently. In contrast, for a stiff object, the hand motion should be relatively fast. Otherwise, the operator will feel like contacting a soft object. Therefore, for different objects, the motion mapping should be different so that the subtle change of feedback force can be perceived and the difference in stiffness of objects can be recognized.

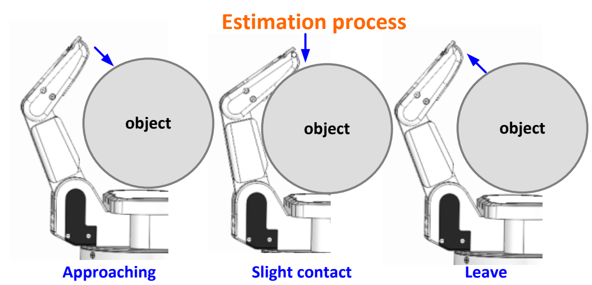

Figure 2. Pre-estimation step: object parameters estimation before real grasp.

A pre-estimation step is defined to estimate the stiffness of the object. The robot hand is first controlled to contact the object slightly for a while and then leave it (Figure 2). When the robot hand contacts the object again, the motion mapping coefficient is changed according to the parameters estimated in the pre-estimation step. To obtain the characteristics parameters of different materials in real time during the pre-estimation process, a contact model is required. There are several models [13]-[15] proposed to describe the dynamics of the contact between robotic device and the environment. In these models, the relationship for the penetration between the contacting bodies and the contact force is represented by a spring and a viscous damper. We use Hunt-Crossley model [16] to estimate the contact impedance, which has been proved to be suitable to describe the contact dynamics of both stiff and soft objects. The model is formulated as,

$$F_i(t) = \begin{cases} k_i x_i^n(t) + \lambda_i x_i^n(t)\dot{x}_i(t), & x_i \geq 0 \\ 0, & x_i < 0 \end{cases} \qquad (2)$$

where i = 1,2,3… represents the fingers of the robot hand. x_i is the penetration depth of the finger *i* and the object, which is calculated by the distance the finger moves after it contacts with the object. k_i and λ_i are the elastic and viscous parameters of the contact which change with the stiffness properties of grasped objects. The stiffness of different objects can be distinguished by these parameters. *n* is a constant number which relates to the geometry of contact surfaces. The online estimation algorithm in [16] is used to calculate the parameters k_i and λ_i in equation (2) with the following recursive equations:

$$\begin{cases} \theta(t+1) = \theta(t) + Q(t+1)[\varphi(t+1) - \mu^T(t+1)\theta(t)] \\ Q(t+1) = R(t)\mu(t+1)[\beta + \mu^T(t+1)R(t)\mu(t+1)]^{-1} \\ R(t+1) = \frac{1}{\beta}[I - Q(t+1)\mu^T(t+1)]R(t) \end{cases} \qquad (3)$$

where

$\theta(t) = [k(t), \lambda(t)]^T \quad \mu(t) = [x^n(t), x^n(t)\dot{x}(t)]^T \quad \varphi(t) = F(t)$,

t represents the discrete time variable where the step size is 10ms. β represents the forgetting factor limiting the estimation to more recent measure which is set to 1 in this paper.

Each finger of the robot hand has separate estimation processes. The final parameters are calculated by averaging the values of the fingers. The motion mapping coefficient k_p is proportional to the elastic parameter k_i of the object as follows:

$$k_p = k_e \frac{1}{n}\sum_{i=1}^{n} k_i \qquad (4)$$

where *n* represents the fingers of the robot hand. k_e is a scaling factor which converts the elastic parameters to the motion mapping coefficient.

3. BarrettHand Teleoperation System

3.1 System construction

A BarrettHand teleoperation system [17] is developed previously to study the grasping control in Three-fingered Robot Hand Teleoperation using Desktop Haptic Device. The motion control of different fingers is realized by using the four buttons on the ball handle of Falcon.

Figure 3 shows the control architecture of the robot hand teleoperation system. The BarrettHand and Falcon are connected to networked computers respectively. Communication between the master and the slave sides is realized by a UDP/IP connection in a local area network where time delay is negligible. The position and grasp force information of BarrettHand and the position commands of Falcon are exchanged between the two sides. A USB webcam is installed in slave side and the video information is transmitted to master side. The real-time simulation of the robot hand and the video feedback are displayed in the virtual environment for operator. BarrettHand is under velocity control mode using BarrettHand API. The frequencies of the haptic rendering of Falcon and network transmission are both 1 KHz. The virtual environment in the system is developed using VC++ and OpenGL library. The visual feedback provides approximate position information, and the force feedback provides more precise information about the contact between the hand and environment.

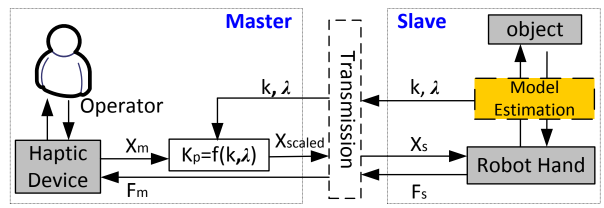

Figure 3. System control architecture.

3.2 Motion mapping and force feedback

The BarrettHand has two modes of motion: 1) fingers close and open, and 2) spread motion. In the first mode, the F1, F2, F3 fingers can close or open independently. In the spread motion, the F1 and F2 fingers can move around the hand palm synchronously. We map the motion between the two sides in joint space to avoid solving inverse kinematic problem. Figure 4 shows the motion mapping relationship in our system. The forward and backward motions (z-motion) of Falcon device are mapped to the fingers' close and open respectively. The spread motion of BarrettHand is controlled by the left and right side motion (x-motion) of Falcon device.

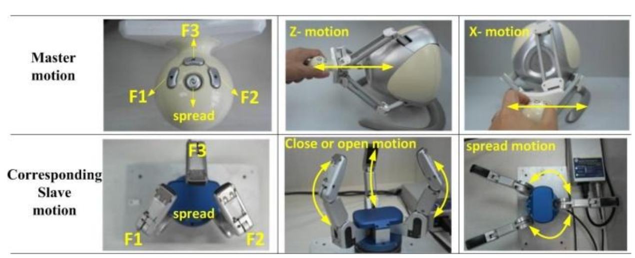

Figure 4.Motion mapping between Falcon and BarrettHand

The motion control of different fingers is realized by using the four buttons on the ball handle of Falcon. The operator can take control of each finger by pressing the corresponding button and release the control by pressing the button again. The F1, F2, F3 and spread buttons can be selected independently. So the three fingers can move individually or together depending on which button is selected. Repeated calibration [18] is used in the motion mapping method to solve the mapping problem of different workspaces between BarrettHand and Falcon device.

The position mapping between the haptic device and the robot hand is defined as:

$$P_{Fi}(t) = k_p \sum_{t=0}^{k} \Delta P_{Hz}(t) + P_{Fi}(0) \quad (5)$$

where $P_{Fi}(t)$ is the current joint angle of the finger i (i = 1,2,3,spread) at t moment and $P_{Fi}(0)$ is the initial joint angle of the finger. $\Delta P_{Hz}(t)$ is the z position difference of the haptic device between t moment and t-1 moment.

The grasp force on the fingertip F_{fi} (i = 1,2,3) is calculated using the strain gage value S_{sgi}, assuming the contact point is exactly at the fingertip.

$$F_{fi} = k_f S_{sgi} \quad (6)$$

The unit of strain gage value is counted from 0 to 4000 and the initial value for each finger without load is about 2000. k_f is a coefficient which converts the measured value of strain gage to grasping force. The feedback force F_Z at master side is calculated by averaging the grasp forces of the three fingers:

$$F_z = \frac{1}{3} \sum_i F_{fi} \quad (7)$$

The direction of the feedback force is in the z axis of the Falcon device.

4. Experiment Protocol

As described in section 2, the motion mapping in the system is determined by the mapping coefficient k_p. Experiments were conducted to evaluate the effectiveness of the proposed object-based motion mapping method through comparing it with constant motion mapping method.

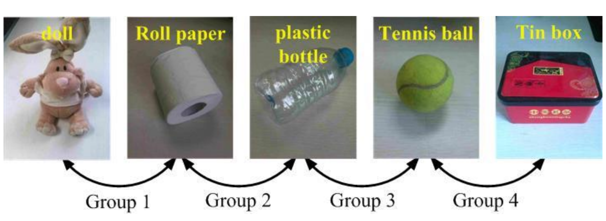

Figure 5. Objects and comparison groups in the experiment.

Five objects were chosen for the experiments (Figure 5). These objects are common things in our daily life. So the participants can distinguish them based on their knowledge. The objects were divided into four groups for comparison. The experimental task is to grasp the objects in each group and tell which object is stiffer than the other one. There is no visual feedback during the whole process. All the grasps are fingertip grasp where the objects could not contact with the palm of the hand.

Ten students, 7 male and 3 female, aged from 21 to 30, were invited to participant in the experiment. They were all right handed and familiar with the haptic device. All the participants had no experience in controlling a robot hand to grasp objects by using haptic device before. This study was approved by the Beihang university IRB and all participants signed an approved IRB consent form.

Before experiment, participants were given an introduction about the experiment and several pre-trails for them to get familiar with the experimental environment. The objects in pre-trials were different from the objects in Figure 5 to avoid any training effects on the experimental results. During the pre-trials, participants were taught about how to recalibrate the haptic device when it moves out of the workspace.

5. Results and Discussion

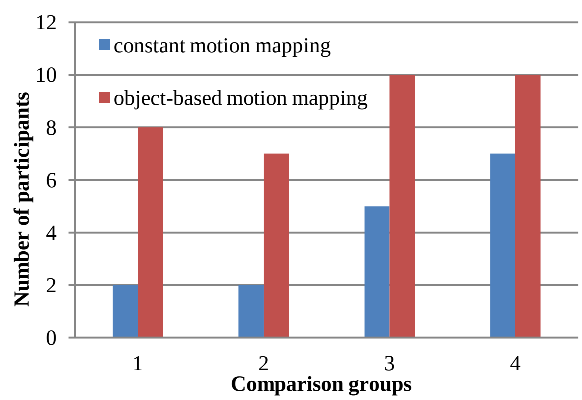

Figure 6. The number of participants who successfully distinguished the stiffness difference for the 4 comparison groups with two motion mapping methods.

Figure 6 shows the number of participants who successfully distinguished the stiffness difference of the objects in the 4 comparison groups with the two motion mapping methods. In object-based motion mapping mode, more participants could successfully distinguish the stiffness of objects as compared to the constant motion mapping mode. In constant motion mapping mode, the participants can only distinguish objects whose stiffness difference is large such as tennis ball and tin box in Group 4. The number of groups being successfully distinguished in two methods were also calculated and shown in Figure 7. The red dash, the upper and lower values of the boxes is the median, the first quartile and the third quartile respectively. The dot out of the box is the outlier. The results also show that most groups could be successfully distinguished with object-based motion mapping method. The success number of groups with constant motion mapping method is scattered because the stiffness difference between objects in each group is varied.

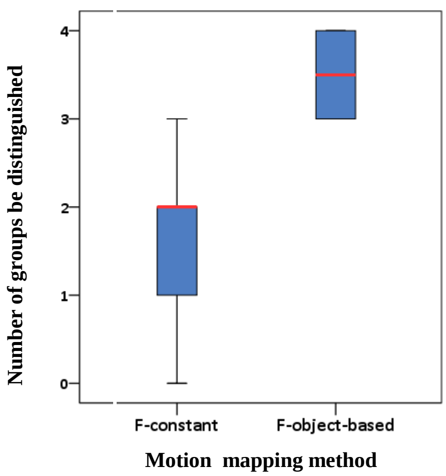

Figure 7. The box plots for the number of groups being successfully distinguished with two motion mapping methods.

6. Conclusion

In safety-critical teleoperation applications, safely grasping the objects in a remote environment without dropping and crushing is important. This paper proposed an object-based motion mapping method for identifiable stiffness perception in a robot hand teleoperation. The properties of the object are represented by the stiffness and damping parameters obtained by the contact impedance estimation of the robot hand system before each grasp. The motion mapping coefficient is proportional to the stiffness of the object. Based on this method, for stiff object grasping, the grasp force changes quickly with the deformation so the operator perceives stiff. While for soft object, the force change is relatively slow so the motion is slowed down. So that operators can distinguish the objects of different stiffness by perceiving the different grasp force changes. A comparison experiment is conducted between constant motion mapping and object-based motion mapping method. The results show that, by using object-based motion mapping method, the operator can distinguish more objects and the grasp force the operator used to safely hold an object is lower than the other two methods. We will further check the effectiveness of this approach in the environment with unknown objects in our future work.

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