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Force Control in Flexible Object Grasping Based on Position Predictor

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***Abstract*— A novel manipulation method for grasping flexible objects with a simple rigid robot hand is proposed in this study. Based on a position predictor, it mainly focuses on force control during the object grasping. A desired force for grasping is given at first, then during the process of grasping it is converted to a predicted displacement. An online linear approximator for solving the predicted displacement iteratively is proposed. Here Model Predictive Control (MPC) is adopted to achieve accurate position control. Meanwhile a flexible model is designed for the simulation and verification. This method is verified in a flexible object contact situation and the result indicates that it can control the force precisely in flexible object grasping and achieve better performance compared with admittance control.**

***Index Terms*— Flexible object, Predictor-based control, Grasping, Contact**

I. Introduction

As more and more robots have been applied in a variety of scenarios of human life, including family services and industrial environment, robotic grasping has become an emergent issue to be solved [1]. In fact, objects grasping has been studied for a long period and numerous methods have been developed for different applications. In some circumstances, specific objects, especially rigid items, can be grasped well with an end-effector. However, compared with common rigid items, other objects like Doufu can be very flexible and light. That makes it much harder to be grasped and manipulated because the force between the end-effector and target is difficult to be controlled precisely, which has been a valuable and challenging issue for researchers [2].

Various studies about objects grasping and manipulation have been performed recently. Those studies concentrate on novel end-effector design, position/force control, grasp stability analysis and tactile sensing [3]–[5]. In many tasks like unknown objects grasping, it is important to conduct accurate force control. In this case, Zhang designed an underactuated hand which can achieve force control by controlling the motor shaft's angle [6]. It focuses on the structure of the finger and changes the force for different objects. A soft gripper based on an automatic grasp system with several sensors was also devised by Wu to grasp objects with a wide range of sizes and shapes [7]. Different gestures based on the novel gripper is defined and information including pressure and tactus was applied in the training.

Unknown objects grasping is an important but difficult issue for researchers. It is easy for humans to find nearly the best gesture and force to grasp a new target whereas it is difficult for robots. Unstructured shapes of diverse objects and unknown properties of them require different grasping gestures and forces. Herzog developed a method called template learning to find suitable grasp poses based on previously demonstrated grasps [8]. Different finger configurations can be achieved in that study for unknown targets. Besides, in order to solve another crucial problem of grasp stability, Cornella proposed an algorithm focusing on force-closure determination [9]. Due to the complexity of targets and unstructured environment, Hsiao gave an approach to find a set of suitable gestures and then executed a compliant robust grasp, taking the contact information into consideration [10].

To some extent, flexible objects, especially those which may deform significantly like Doufu and animals, are more arduous to be grasped. Precise force control is necessary in these cases because a deficient force may cause slippage when an excessive force can lead to damage. Additionally, unlike humans, lots of robotic systems are based on position control. Although there are various motors that can achieve force control, the robotic system can't output precise force due to the dynamics modelling uncertainties of the system such as the friction inside the reducer. Hence, researchers have developed various position-based algorithms for force control. Lange presented a position-based force control for industrial tasks [11]. The desired pose of the tool center point is computed by the force control error, which is instructive for flexible objects grasping. Seraji devised an adaptive admittance control to conduct explicit force control in compliant motion while in contact with an environment having an unknown stiffness [12]. Actually, admittance control plays an important role in force control. In many scenarios, it tracks the specified force setpoint very well. But when the robot contacts with the environment, the admittance control sometimes may lead to undesired overshoot which can cause damage to the object.

Actually, unknown stiffness of the object is very chal-

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lenging for force control. Inspired by the position-based force control, a method based on position predictor, named predictor-based control, is proposed to calculate the predicted desired displacement with force feedback. This method focuses on the contact force control during flexible object grasping. In this research, the force overshoot, which may cause damage to the object, of the control method is selected as the most important criterion during experiments. To observe the effectiveness, the proposed method is tested by a contacting simulation of flexible object grasping and compared with admittance control.

The rest of the paper is organized as follows. Section II presents the methods related to flexible object grasping modeling and control. Section III introduces the contact simulation conducted in this study. The results and discussion including a comparison between predictor-based control and admittance control are reported in Section IV. Finally, Section V gives the conclusion.

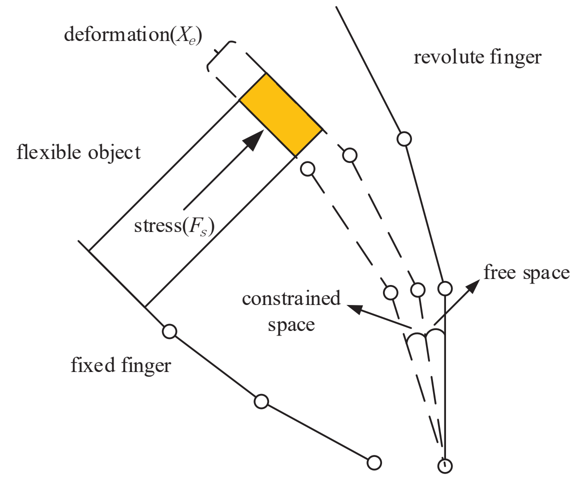

Fig. 1. Grasping analysis for flexible objects

II. METHOD

The process of grasping a flexible object is illustrated in Fig. 1. There is a space between the revolute finger and the flexible item at the very beginning and another finger is assumed to be fixed. Firstly, the finger rotates towards the object, which is a normal task of position control in the free space. After the revolute finger touches the surface of the target for the first time, how to impose the desired force on the object is the main problem of grasping a flexible object. Different items may have various strain-stress characteristics, leading to a large uncertainty in position control. In this case, a novel method based on an online position predictor is proposed to address the problem of analyzing contacting process during grasping.

The key point of the method developed in this work is the position predictor, which consists of a linear iterative approximator. This function calculates the predicted displacement using the force feedback. Then the controller for grasping conducts specific motion control according to the predicted displacement. To verify this method, a virtual flexible object is designed in the simulation. In addition, a human-like finger for detecting the contact force and position is constructed. What's more, force overshoot is limited strictly, so an precise control algorithm is desired during the grasping. Here MPC is adopted for precise position control. The framework of flexible objects grasping is presented in Fig. 2.

A. Flexible object model

There are a wide variety of flexible objects in human environments such as animals. Those have different characteristics, containing diverse mathematical contact models inside. And a large percentage of flexible or soft objects like towel and tomato are too intricate to be modeled well. In this study, two kinds of model are designed for the grasp verification. The first is a model similar to rubber. The relationship between force and deformation of rubber can be seen in [13]. Here the approximate mathematical model is given by

$$F_e = f_1 = 10(0.03\sin(96\pi X_e) + 3.36\pi X_e), \tag{1}$$

where F_e represents the force arising from the surface of the object when it contacts the finger while X_e stands for the deformation of object. As can be seen, the relationship between deformation and force is nonlinear.

In addition, to verify the performance on generalization of the proposed method, another parabolic contact model is given as

$$F_e = f_2 = 10000X_e^2. \tag{2}$$

B. Position predictor

The critical of position predictor is an online linear iterative approximator. Since there are heaps of kinds of mathematical models for different flexible objects, it is difficult to model every kind of flexible objects for grasping. Furthermore, even modeling for many objects can be achieved, robots may still conduct some wrong behavior when they are faced with new flexible targets.

Supposing the first contact point and the last two contact points are $(0,X_{e0})$, (F_{e1},X_{e1}) and (F_{e2},X_{e2}), the force and deformation generated by the object can be noted as (F_{e1},X_e1-X_{e0}) and $(F_{e2},X_{e2}-X_{e0})$. Here F_{e1} and F_{e2} are the forces generated by the object while X_{e0}, X_{e1} and X_{e2} are the rotation angles of motor instead of the displacements of fingertip's surface. In the simulation or experiment, the force and deformation can be detected by force sensor and velocity sensor such as the encoder attached to the motor. Thus, two different approximate linear mathematical models of the object can be given respectively by

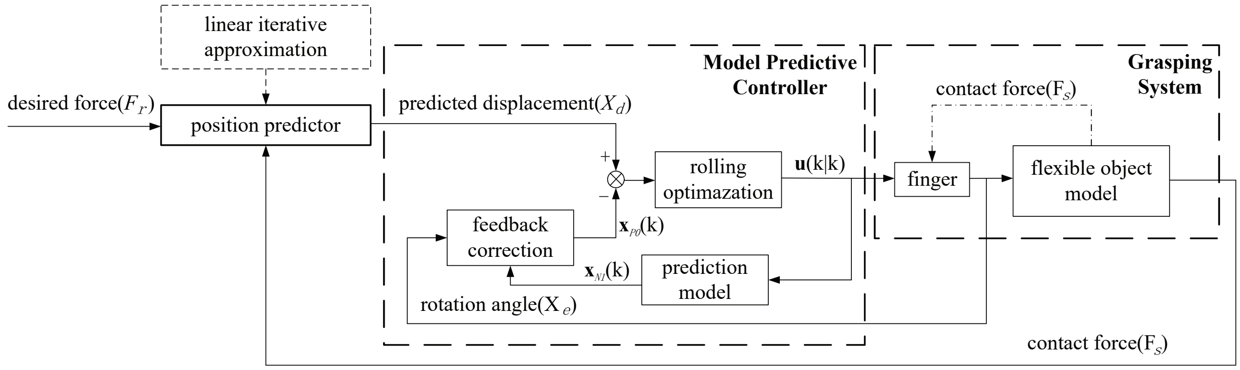

Fig. 2. Framework of flexible objects grasping

$$X_{d1} = \frac{X_{e2} - X_{e0}}{F_{e2}} \cdot F_r + X_{e0}, \tag{3}$$

$$X_{d2} = \frac{X_{e2} - X_{e1}}{F_{e2} - F_{e1}} \cdot (F_r - F_{e2}) + X_{e2}. \tag{4}$$

Here X_{d1} and X_{d2} represent two different kinds of predicted desired displacements while F_r is the desired force. With X_{d1} and X_{d2}, the weighted predicted displacement X_r can be calculated by

$$X_d = X_{d1} \cdot k_1 + X_{d2} \cdot (1 - k_1), \tag{5}$$

where k_1 is a weight factor. When the next moment is coming, (F_{e1}, X_{e1}) will be replaced by (F_{e2}, X_{e2}) while (F_{e2}, X_{e2}) is going to be replaced by (F_c, X_c). Here F_c and X_c are the latest force generated by the target and the latest rotation angle of the motor. After that, a new equation and a new predicted displacement for the motor will be calculated for the next control cycle.

C. Finger for verification

The basic element for grasping objects is the manipulator which may vary in shape during different tasks. In the previous researches, the multi-fingered hand is one of the most popular manipulator with the superior ability to grasp objects which may have various shapes and other physical properties [14]. Deriving from the natural environment, especially humans, that structure has been studied by many researchers and has shown a superior performance to other kinds of manipulators. In this study, a finger has been designed for verifying the effectiveness of the grasping strategy. Here a single finger rather than a multi-fingered hand is chosen to conduct the simulation for two purposes. First, the verification is designed to analyze the force and deformation generated by the flexible object instead of observing whether or not the object can be grasped well. Second, there should be an easy way of analyzing the stability and astringency of the force control scheme in addition to the motion process of the finger's surface.

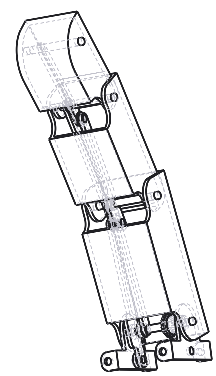

Fig. 3. Finger for verification

Specifically, a finger with one degree of freedom(DOF) is designed in this investigation. Inside there is a six-bar mechanism whose position is more convenient to be controlled precisely than a wire-driven finger. The structure of the finger is presented in Fig. 3.

There are two assumptions in this study.

(1) The touch point of the finger is at the surface of the fingertip.
(2) The force appeared on the fingertip is all at the touch point instead of a part of or whole surface.

These two assumptions will help us simulate the deformation process of the object and change of force and motion more conveniently. In this case, the key point of the grasping is to control the force appeared at the touch point on the surface of the finger, which is crucial to avoid slippage or damage during grasping.

D. Model predictive controller

In Fig. 2, predicted displacement is the output of the position predictor and the input of the position controller. As described before, to control the rotation angle of the finger precisely, MPC has been selected as the position control method in this study since it has several advantages when compared with other control algorithms. Those superiorities are listed in the following.

- Engineers can model the system easily by multiple ways such as the step response experiment. They don't have to analyze the internal principle of the system which may have very sophisticated mathematical model.
- Since MPC is a kind of optimal control algorithm, it can find the optimum controlled quantity for the system with the desired position, thus making for a quick response and a small overshoot. Furthermore, it is an incremental algorithm with a digital integral function, so there is no static error in the process of control in spite of model mismatch.
- The algorithm's dependence on parameters is less than other algorithms like PID, so it is easy for researchers to achieve a satisfying result with little effort to optimize these parameters.

Specifically, Dynamic Matrix Control(DMC) has been chosen in this work. Before the contacting simulation of object grasping, the dynamics of the finger is detected and described by its step response

$$\mathbf{a} = a_1, a_2, ..., a_p.$$

With the step response parameter $\mathbf{a}$, the next predicted rotation angle of the finger $\mathbf{x}_{N1}(k)$ can be calculated by

$$\mathbf{x}_{N1}(k) = \mathbf{x}_{N0}(k) + \mathbf{a}\Delta u(k|k)), \tag{6}$$

where $\mathbf{x}_{N0}(k)$ is the predicted rotation angle without the excitation increment $\Delta u(k|k)$. In fact, the mathematical parameter $\mathbf{a}$ can't describe the robotic system precisely and thus it's necessary to conduct a closed-loop control instead of an open-loop control. DMC uses the position feedback $x(k)$ with the predicted rotation angle $x_{N1}(k|k)$ to calculate the error of prediction by

$$e(k) = x(k) - x_{N1}(k|k). \tag{7}$$

The predicted value $\mathbf{x}_{cor}(k+1)$ is corrected as

$$\mathbf{x}_{cor}(k+1) = \mathbf{x}_{N1}(k+1) + \mathbf{h} \cdot e(k), \tag{8}$$

where $\mathbf{h}$ is the error correction weighting matrix. At last, The discrete control law of the controller uses the following formula

$$\Delta \mathbf{u}(k+1) = (\mathbf{A}^T\mathbf{Q}\mathbf{A} + \mathbf{R})^{-1}\mathbf{A}^T\mathbf{Q}(\mathbf{w}_P(k+1) - \mathbf{x}_{P0}(k+1)). \tag{9}$$

Here $\mathbf{Q} = \mathbf{diag}(q_1, q_2, ..., q_p)$ is the error weighting matrix and $\mathbf{R} = \mathbf{diag}(r_1, r_2, ..., r_p)$ represents the control weighting matrix. $\mathbf{A}$ is the dynamic matrix calculated by $\mathbf{a}$ while $\mathbf{w}_P$ is the expected position. And $\mathbf{x}_{P0}(K)$ is the predicted rotation angle matrix.

E. Admittance control

In order to verify the effectiveness of the method proposed in this work, an admittance controller is adopted as a comparison. Given the desired force F_r, the designed position X_d and a reference position X_{r0}, a control law based on the linear second-order relationship is considered as follows while the contact force is F_e,

$$M_d(\ddot{X}_d - \ddot{X}_{r0}) + D_d(\dot{X}_d - \dot{X}_{r0}) + K_d(X_d - X_{r0}) = F_r - F_e. \tag{10}$$

Here the positive constants M_d, D_d and K_d are the desired inertia, damping and stiffness separately [15]. The reference position is assumed as a constant, which means $\ddot{X}_{r0} = \dot{X}_{r0} = 0$. The parameters are $M_d = 0.5$, $D_d = 2.9$, $K_d = 0$, which has been tuned.

III. SIMULATION

The predictor-based control presented in this work is designed to minimize the force overshoot, thus guarantee the safety of the object. The effectiveness of the method is validated and compared with the admittance control in contact simulations of object grasping. The whole contacting tasks are divided into two parts shown in Fig. 1. The first is performed in the free space where the finger can move without any external force until it touches the target. The reference position in both of the controllers, i.e., the initial desired rotation angle of the finger is preset as $X_{r0} = 0.5rad$. After the finger touches the object and the object begins to deform, the controllers will work in the constrained space in which they have to track the desired force and minimize the force overshoot. In these simulations, two nonlinear contact models, which have been described in Section II, instead of the linear spring are adopted to emulate the contact environment with complex unknown stiffness. In this study, three different experiments with different desired force have been carried out.

IV. RESULTS AND DISCUSSION

Figure 4–7 and Table I present the performance on force control as well as position control and some key criteria. The actual displacement represents the current actual rotation angle of the finger while the predicted displacement is the desired displacement predicted by the predictor-based controller. In Table I, the settling time is measured in terms of the steady state error of 2%. The PID parameters of admittance controller have been optimized to decrease the force overshoot. In Table I, controller A represents the predictor-based controller when controller B is based on admittance control.

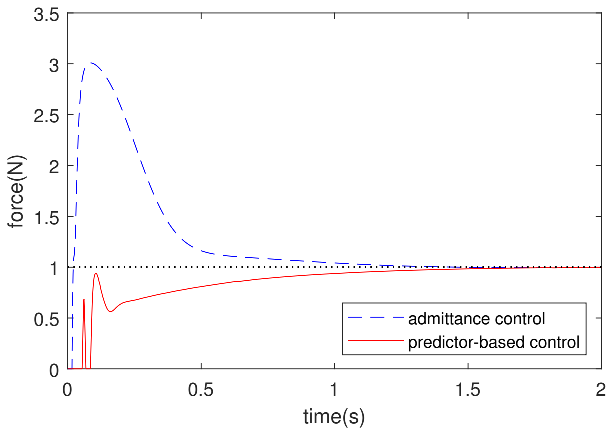

Fig. 4. Force control, $F_r = 1N, F_e = f_1 = 10(0.03\sin(96\pi X_e) + 3.36\pi X_e)$

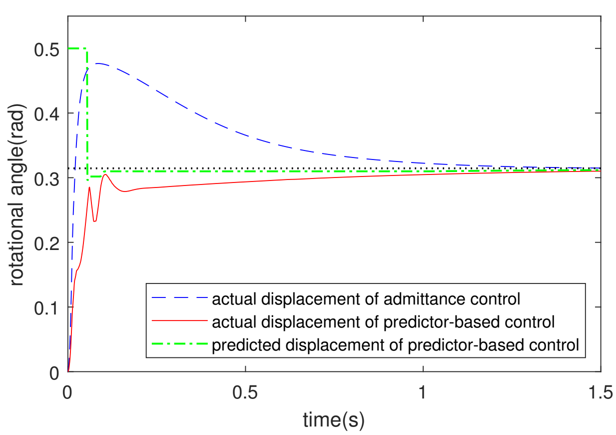

Fig. 5. Position control, $F_r = 1N, F_e = f_1 = 10(0.03\sin(96\pi X_e) + 3.36\pi X_e)$

A. *Performance of predictor-based control*

Taking $F_r = 1N$ and $F_e = f_1$ as an example, Figure 4–5 show the results of the two controllers. It is clear that both of them can make the force and position converge to the desired value but predictor-based controller shows a better performance on minimizing the force overshoot.

From Fig. 4, it can be seen that there are two different kinds of workspace separated clearly. Before $t = 0.055s$, the finger rotates in the free space and the external force is zero. But after the finger touches the flexible object for the first time, the predictor starts to work and calculates the predicted displacement. When the finger works in the constrained space, there is a force and displacement fluctuation happening to the finger between $0.055s$ and $0.16s$. Actually, that is caused by the force generated by the object. The force imposed on the surface of the finger brings a large uncertainty to the controller. In this circumstance, the output of MPC is not the optimal value anymore, leading to the force and displacement fluctuation. But in the process of contacting,

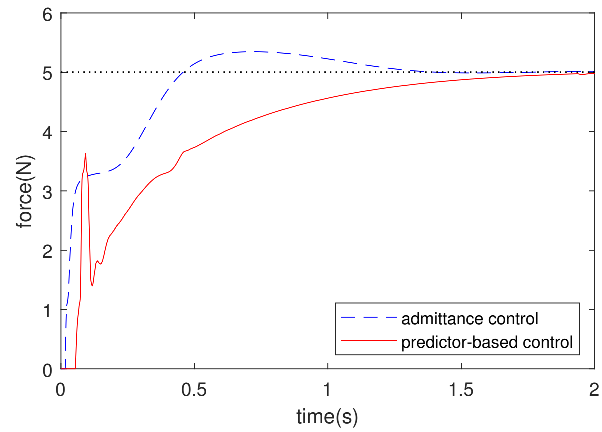

Fig. 6. Force control, $F_r = 5N, F_e = f_1 = 10(0.03\sin(96\pi X_e) + 3.36\pi X_e)$

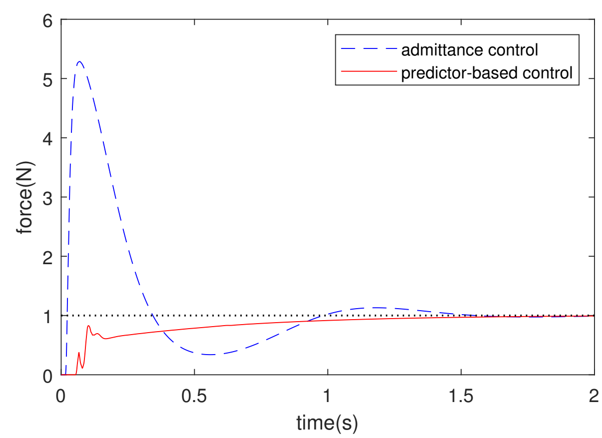

Fig. 7. Force control, $F_r = 1N, F_e = f_2 = 10000X_e^2$

TABLE I

PARAMETERS AND RESULTS IN SIMULATION

	$F_r = 1N$		$F_r = 5N$	
	controller A	controller B	control A	control B
control period (ms)	6	1	6	1
simulation time (s)	2	2	2	2
reference position (rad)	0.5	0.5	0.5	0.5
settling time (s)	1.439	1.171	1.582	1.177
force overshoot	0	200.87%	0	6.94%

the embedded model is corrected with the displacement feedback gradually and the force converges to $1N$ at about $t = 1.439s$. It also can be seen that the predicted displacement gets closer to the desired displacement when the actual displacement increases. What's more, the generalization of the proposed method is also validated by changing the contact model to a parabolic function, presented in Fig. 7. The force overshoot of the proposed method remains zero while the overshoot of admittance control gets bigger, fully showing the effectiveness of predictor-based control.

B. Comparison between predictor-based control and admittance control

In the case of $F_e = f_1$, the comparison of force control and position control is shown in Fig. 4–6. Although the force in admittance control simulation also converges to the desired value, there is a big force and displacement overshoot. While $F_r = 1N$, the force in admittance control hits the peak of approximate $3N$, about three times as big as the desired force and that may cause damage to the target in grasping.

From the comparison between $F_r = 5N$ and $F_r = 1N$ it also can be seen that the force and displacement overshoot increase with a decreased desired force. In fact, a series of simulations in which the desired force varies from $1N$ to $5N$ reveals that the overshoot depends heavily on the parameters of PID controller and X_{r0} while M_d, D_d, K_d are fixed.

Here the parameters of PID and admittance controller are all optimized to balance the results of overshoot and settling time. It should be noted that the effectiveness of admittance control with PID is highly affected by the tuning of its parameters while the dependence of predictor-based control with MPC on parameters is very small. In this study, predictor-based control with little efforts on tuning outperforms optimized admittance control.

V. Conclusion

In this paper, a novel flexible object grasping method concentrating on force control during the contact process is proposed. Due to the complex structures and properties of various flexible items, it is quite difficult to model every kind of objects and difficult to conduct the contact force control in the process of grasping. To address this problem, an online linear iteration approximator called position predictor is designed for predicting the desired displacement, which is helpful to conduct force control in turn.

A specific contact case focusing on the flexible item contacting is also built for the validation. The process of contacting between the finger and object has been implemented in this study with two different kinds of flexible models. The simulation indicates that the online linear iterative approximator achieves precise force control successfully during the first grasping, which means this method can be applied in a single grasp without any training. Astringency is verified in this simulation as well and no displacement and force overshoot happens. For the future work, it will be very interesting to verify the work with an experiment, which is currently under investigation.

VI. Acknowledgement

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