Trajectory On-line Adaption based on Human Motion Prediction for Teleoperation

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***Abstract*—In this work, a human motion intention prediction method based on an autoregressive (AR) model for teleoperation is developed. Based on this method, the robot's motion trajectory can be updated in real time through updating the parameters of the AR model. In the teleoperated robot's control loop, a virtual force model is defined to describe the interaction profile and to correct the robot's motion trajectory in real time. The proposed human motion prediction algorithm acts a feedforward model to update the robot's motion and to revise this motion in the process of human-robot interaction. The convergence of this method is analysed theoretically. Comparative studies demonstrate the enhanced performance of the proposed approach.**

***Note to Practitioners*— In general, the robot trajectory is predetermined and it does not consider the influence of the interaction profiles in terms of position and interaction force between the human and the robot. In addition, it is hard to quantify the influence of interaction profile for the robot trajectory. For teleoperation, an AR-based model is proposed to predict the trajectory of the human and then to update the trajectory of the robot. The developed method includes the following aspects: 1) the robot trajectory can be regulated based on the interaction profiles; 2) the feedforward model can estimate the trajectory of the human to achieve the purpose of human intention recognition in advance for the robot; 3) the proposed method can be potentially utilized for telerehabilitation and microsurgery, etc.**

***Index Terms*—Teleoperation system, human motion estimation, virtual force, prediction model, physical human-robot interaction**

I. Introduction

Teleoperation is an important type of human-robot interface [1] [2] [3] as it allows humans to complete a task by combining the human perception and robot's capabilities in two separate spaces [4] [5] [6] [7]. Dünser *et al*. proposed a visual and manual control algorithm [8] to explore the suitability of teleoperation. Electromyography (EMG) based methods were developed to improve the human-robot interaction (HRI) in teleoperation [9] [10] [11]. Improving ecological interfaces and mixed-initiative haptic strategy were proposed to enhance the performance of mobile robot teleoperation [12] [13] [14]. Haptic interface is an effective interface for teleoperation [15]. In [16], a haptic feedback algorithm based on psychophysical signals and motor learning was developed to guide the teleoperated aerial robots to perform a task. In [17], a haptic feedback approach was proposed to conduct the microinjection task for the teleoperated robotic system. In [18], Stefanov *et al*. designed a haptic computer-assistant to improve the task performance of the system through action recognition unit and an assistive unit. In addition, assisted control methods are the solution to simplify the remote manipulation. For example, Munoz *et al*. developed an adaptive multispace transformation to improve the precision and ergonomics and to reduce the task execution time [19].

Since the teleoperated robots represent typical human-in-the-loop systems, human intention may impact on the performance of teleoperation. Therefore, it is essential to know how to utilize the human intention in order to enhance the performance of teleoperation. In [20], an intention recognition framework was proposed to enhance the task performance through exchanging the dynamic role of partners in haptic collaboration. A control method based on haptic intention augmentation with force feedback was developed in a collaborative task [21]. Narayanan *et al*. introduced a framework of human-ware control to achieve a safe and compliant motion interaction for a teleoperated wheelchair system [22]. In addition, shared control algorithms were widely used to recognize the humans' intent for the teleoperated system [23] [24]. For instance, in [25], a recognition framework involving shared control was developed for teleoperation. Gao *et al*. proposed a shared autonomy strategy to recognize human intention and to provide a motion assistance [26]. An assistive grasping strategy [27] and a task planing approach based on projection [28] were developed to detect human intention in an interaction task. Furthermore, programming by demonstration was often used to encode human motion in the applications of teleoperation [29] [30] [31].

It is demonstrated that human motion prediction can enhance the quality of the experience and performance in teleoperation [32]. In [33], a trajectory prediction algorithm based on contextual information and sharing autonomy was proposed to infer the human trajectory. Wang *et al*. presented a virutal reality method involving a hidden Markov model and K-means clustering to predict human welder's operation [34]. A Kalman filter method was presented to predict human motion in real time and applied on a haptic device in teleoperation [35]. These methods used the human motion profile but not the force information in teleoperation.

In this paper, we develop a novel prediction method based

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on autoregressive (AR) model to estimate the human motion intention for the teleoperated system. In the proposed method, the human motion prediction can be adapted on-line through updating the parameters of AR. In addition, we use the interaction force of HRI to adjust the predicted motion intention. For this purpose, we propose a virtual force model. Theoretical analysis based on Lyapunov theory indicates the convergence of the this method. Experimental results demonstrated the effectiveness and feasibility of proposed method.

Section II elaborates the problem formulation and preliminaries about teleoperated system and AR model. The prediction model of human motion and the virtual force model are presented in Section III. Section IV presents the theoretical analysis of the proposed method. The comparative experimental results are given in Section V. Finally, conclusion and discussion are given in Section VI.

II. Problem formulation and preliminaries

A. Problem formulation

In the teleoperated system, a human partner holds the joystick of the haptic device to control the slave robot. We consider the interaction between the haptic device and the human partner in the teleoperated system and the applied force of human partner f_h is an input of the system, therefore the dynamics of the human partner with the haptic device can be defined as

$$M_m(x_d)\ddot{x}_d + C_m(x_d,\dot{x}_d)\dot{x}_d + G_m(x_d) = u_m + f_h \quad (1)$$

where M_m and C_m are the inertia matrix and Coriolis and centrifugal matrix of the haptic device, respectively. G_m denotes the gravitational force matrix. x_d is the position in the process of interaction. u_m denotes the control input of the haptic device.

Impedance control is usually used for human-robot interaction, which can be achieved by designing a control input as below

$$\begin{aligned} u_m = {} & C_m(x_d,\dot{x}_d)\dot{x}_d + G_m(x_d) - f_h \\ & + M_m(x_d)(\ddot{x}_m - M_{md}^{-1}(D_{md}(\dot{x}_d - \dot{x}_m) \\ & + K_{md}(x_d - x_m) - f_h)) \end{aligned} \quad (2)$$

where M_{md} denotes the desired inertia matrix of the haptic device. D_{md} and K_{md} are the desired damping and stiffness matrices of the haptic device, respectively. x_m denotes the reference trajectory of the haptic device.

Based on (1) and (2), one has

$$M_{md}(\ddot{x}_d - \ddot{x}_m) + D_{md}(\dot{x}_d - \dot{x}_m) + K_{md}(x_d - x_m) = f_h \quad (3)$$

which is the impedance model for the haptic device. By setting $x_m = 0$ and $K_{md} = 0$, the haptic device can passively follow the movement of the human partner. In this case, the haptic device cannot cooperate with the human parter actively, which requires a force from the human parter to compensate for the dynamics of the haptic device. This can be observed from the following equation:

$$M_{md}\ddot{x}_d + D_{md}\dot{x}_d = f_h \quad (4)$$

On the contrary, if $K_{md} \neq 0$ and x_m can be designed correctly based on the motion intention of the human partner, the haptic device can move to x_m actively, so it can reduce effort of the human partner.

Therefore, the aim of this paper is to design the reference motion of the haptic device according to the prediction of the motion intention of the human partner.

B. Preliminaries

1) Dynamic model of teleoperation system: The dynamics of master side in the joint space can be presented as

$$M_m(q_m)\ddot{q}_m + C_m(q_m,\dot{q}_m) + G_m(q_m) = F_m(t) + J_m^T F_h(t) - \tau_m \quad (5)$$

where $q_m \in \mathbb{R}^m, \dot{q}_m \in \mathbb{R}^m, \ddot{q}_m \in \mathbb{R}^m$ represent the joint variables in terms of joint angle, velocity, and acceleration, respectively. $M_m \in \mathbb{R}^{m\times m}, C_m(q_m,\dot{q}_m) \in \mathbb{R}^m, G_m(q_m) \in \mathbb{R}^m$ are the inertia matrix, Coriolis and centripetal matrix, and gravity matrix, respectively. It is noted that $M_m(q_m)$ is a symmetric and positive definite matrix. $F_m(t) \in \mathbb{R}^m$ denotes the disturbance. $F_h(t) \in \mathbb{R}^h$ is the human applied force. $J_m \in \mathbb{R}^{h\times m}$ represents the Jacobian matrix. $\tau_m \in \mathbb{R}^m$ denotes the control input of the master.

Similarly, the dynamic model of slave side can be described as

$$M_s(q_s)\ddot{q}_s + C_s(q_s,\dot{q}_s) + G_s(q_s) = F_s(t) - J_s^T F_e(t) + \tau_s \quad (6)$$

where $q_s \in \mathbb{R}^n, \dot{q}_s \in \mathbb{R}^n, \ddot{q}_s \in \mathbb{R}^s$ are the joint angle, velocity, and acceleration, respectively. $M_s \in \mathbb{R}^{n\times n}$ is the inertia matrix. $C_s(q_s,\dot{q}_s) \in \mathbb{R}^n$ denotes Coriolis and centripetal matrix. $G_s(q_s) \in \mathbb{R}^n$ is the gravity matrix. $F_s(t) \in \mathbb{R}^n, J_s \in \mathbb{R}^{h1\times n}, \tau_s \in \mathbb{R}^m$ are the disturbance, Jacobian matrix, and control input of the slave, respectively. $F_e(t) \in \mathbb{R}^{h1}$ indicates the interaction force between the environment and the slave robot.

There are four properties for the teleoperation system [36], which will be used for the controller design.

Theorem 1. *For the master, it satisfies* $z^T(M_m(q_m) - 2C_m(q_m,\dot{q}_m))z = 0, \forall z \in \mathbb{R}^m$.

Theorem 2. *For the master,* $M_m(q_m), G_m(q_m)$ *are bounded. It satisfies* $\forall q_m \in \mathbb{R}^m, \dot{q}_m) \in \mathbb{R}^m, \exists K_{cm} \in \mathbb{R} > 0 \; based \; on \; C_m(q_m,\dot{q}_m), thus \; \|C_m(q_m,\dot{q}_m)\| \leq K_{cm} \mid \dot{q}_m \mid$.

Theorem 3. *For the slave, it satisfies* $z^T(M_s(q_s) - 2C_s(q_s,\dot{q}_s))z = 0, \forall z \in \mathbb{R}^n$.

Theorem 4. *For the slave,* $M_s(q_s), G_s(q_s)$ *are bounded. It satisfies* $\forall q_s \in \mathbb{R}^n, \dot{q}_s) \in \mathbb{R}^m, \exists K_{cs} \in \mathbb{R} > 0 \; based \; on \; C_m(q_s,\dot{q}_s), thus \; \|C_s(q_s,\dot{q}_s)\| \leq K_{cs} \mid \dot{q}_s \mid$.

With the forward kinematics between the joint space and the Cartesian space $\dot{x}_m = J_m\dot{q}_m$ and $\dot{x}_s = J_s\dot{q}_s$, one has

$$\begin{cases} \dot{q}_m = J_m^{-1}\dot{x}_m \\ \ddot{q}_m = \dot{J}_m^{-1}\dot{x}_m + J_m^{-1}\ddot{x}_m \\ \dot{q}_s = J_s^{-1}\dot{x}_s \\ \ddot{q}_s = \dot{J}_s^{-1}\dot{x}_s + J_s^{-1}\ddot{x}_s \end{cases} \quad (7)$$

where J_m^{-1}, J_s^{-1} are the inverses of J_m, J_s. $x_i, \dot{x}_i, \ddot{x}_i$ denote the position, velocity, and acceleration variables, respectively with $i = m,\ s$.

Based on (5)-(7), we can obtain the dynamics of teleoperation system in Cartesian space.

2) Autoregressive model: In this paper, we aim to predict the human motion to enhance the teleoperation performance. It has been verified that human motion can be described using a time series model [37]. Among different methods, the AR method is widely used in many areas such as generalized predictive control [38], gait analysis [39], and elbow joint angle estimation [40] etc. In general, a time series can be described using an AR model as

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + e_t \tag{8}$$

where $\phi_0, \phi_1, \phi_1, ..., \phi_p$ are the parameters that need to be determined. e_t denotes the white noise with mean value 0 and variance σ.

Eq. (8) can be rewritten in the form of state space as

$$\mathbf{Y}_t = \mathbf{H}_t \mathbf{A}_t + \mathbf{V}_t \tag{9}$$

where $\mathbf{A}_t = (\phi_0, \phi_1, \phi_2, ..., \phi_p)$. $\mathbf{H}_t = (y_{t-1}, y_{t-2}, ..., y_{t-p})$. $\mathbf{V}_t = \mathbf{0}$. The AR method can be solved by using Yule-Walker equation [41].

III. Method

In this paper, we propose a method to adapt the robot's trajectory in Fig. 1. It can be seen that the robot trajectory is adapted based on the human motion prediction, which utilizes the interaction profiles between the robot and the human.

A. Prediction model of human motion

The framework of the proposed method for the teleoperated system is presented in Fig. 2. It can be seen that there are two parts: master part and slave part. On the master side, the human partner moves the haptic device, whose position is predicted based on the proposed prediction model. The predicted position is used as the reference position for the slave robot, whose actual position is fedback to the master side to close the loop.

We suppose that the hand motion of the human partner is a continuous trajectory defined as below

$$\begin{aligned} \dot{x}_{human}(t) = a_0 + a_1 x(t) + a_2 x(t-T) + ... \\ + a_i x(t-(i-1)T) + ... + a_p x(t-(p-1)T) \end{aligned} \tag{10}$$

where T denotes a time step. $a_i, i = 0, 1, 2, ..., p$ represents the weight. The value of p is determined by the types of human hand motion. $x(t - iT)$ denotes the ith time step information.

For convenience, (10) can be rewritten as below

$$\dot{x}_{human}(t) = A^{\mathrm{T}} L(t) \tag{11}$$

with

$$A^{\mathrm{T}} = [a_0,\ a_1,\ a_2,\ ...,\ a_p] \tag{12}$$

$$L(t) = [1,\ x(t),\ x(t-T), ...,\ x(t-(p-1)T)] \tag{13}$$

In order to obtain $\dot{x}_{human}(t)$, we can make an approximation as below

$$\dot{\hat{x}}_{human} = \hat{A}^{\mathrm{T}} L(t) - \alpha_1 \tilde{x}_{human}(t-T) \tag{14}$$

with

$$\begin{aligned} \tilde{x}_{human}(t-T) &= \hat{x}_{human}(t-T) - x_{human}(t-T) \\ &= \hat{x}_{human}(t-T) - x_d(t) \end{aligned} \tag{15}$$

where $\hat{A}$ denotes the estimated value of A. α_1 represents a positive scalar.

In order to capture motion intention of human hand accurately, we propose an update law

$$\dot{\hat{A}} = -\tilde{x}_{human}(t-T) L(t) - \alpha_2 \tilde{f} L(t) \tag{16}$$

where $\alpha_2 > 0$.

The reference trajectory of the haptic device can be defined as below

$$\dot{x}_m = \hat{x}_{human} - \alpha_3 \tilde{f} + \alpha_1 \tilde{x}_{human}(t-T) \tag{17}$$

where α_3 denotes a positive scalar.

B. Virtual force model

As shown in Fig. 3, it can be seen that the interaction force is a virtual force generated by the motion tracking error between the haptic device and the slave robot. The virtual force can be represented using an admittance model as below:

$$\tilde{f} = M_{virtual}(\ddot{x}_d - \ddot{x}_s) + B_{virtual}(\dot{x}_d - \dot{x}_s) + K_{virtual}(x_d - x_s) \tag{18}$$

where $M_{virtual}$ is a virtual mass. $B_{virtual}$ and $K_{virtual}$ are the virtual damping and the virtual stiffness, respectively.

The virtual force provides a haptic feedback in the process of interaction between the teleoperated system and the human partner. In addition, the human hand model can be presented as

$$f_h = K_{human}(x_d - x_{human}) \tag{19}$$

where K_{human} is the control gain of the human partner. It is noted that x_{human} is unknown to the haptic device. In the teleoperated system, the human force is an input of system, so the system of haptic device can be written as below

$$f_h = m(t)\ddot{x}_d + b(t)\dot{x}_d + \tilde{f} \tag{20}$$

where $m(t)$ and $b(t)$ denote the inertia matrix and Coriolis and centrifugal matrix of the haptic device.

When the motion of the teleoperation system is slow, acceleration $\ddot{x}_d$ and velocity $\dot{x}_d$ of haptic device can be ignored. Therefore, (19) can be rewritten as

$$f_h = \tilde{f} \tag{21}$$

which indicates that we can obtain the human applied force f_h without a force sensor through the virtual model.

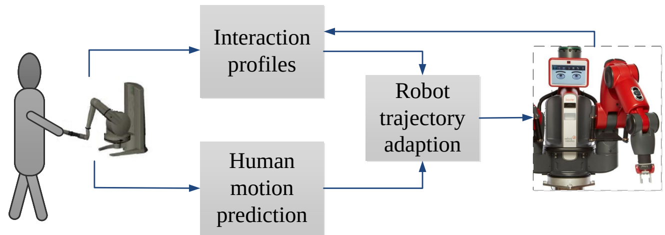


Fig. 1. A schematic diagram of relationship between human motion prediction and robot trajectory adaptation.

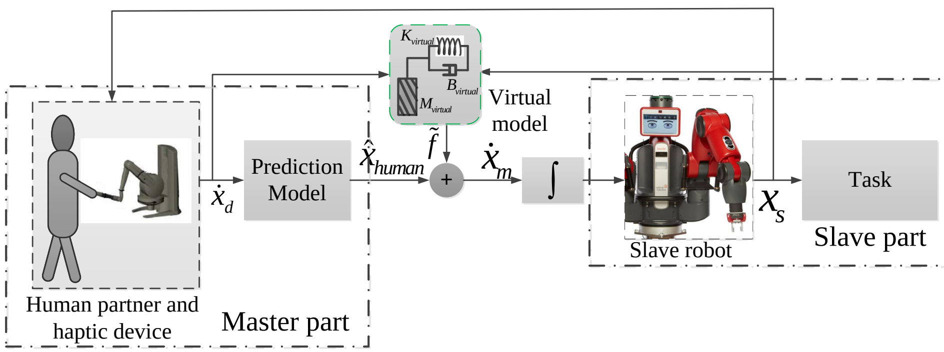


Fig. 2. Framework of human motion estimation for the teleoperated system.

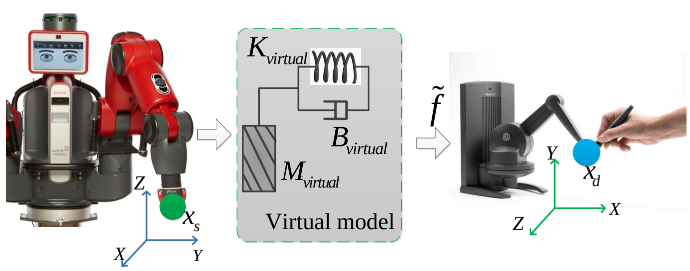


Fig. 3. An illustration of virtual model.

IV. Convergence Analysis

In this section, we aim to establish the convergence of the human motion estimation approach.

Considering the Lyapunov function candidate as below

$$V = V_1 + V_2 + V_3 + V_4 \tag{22}$$

where

$$V_1 = \frac{1}{2\alpha_2}\text{trace}(\tilde{A}^{\mathrm{T}}\tilde{A}) \tag{23}$$

$$V_2 = \frac{1}{2\alpha_2}\tilde{x}_{human}^{\mathrm{T}}\tilde{x}_{human} \tag{24}$$

$$V_3 = \frac{1}{2}(\dot{e}^{\mathrm{T}}M_{md}\dot{e} + e^{\mathrm{T}}K_{md}e) \tag{25}$$

where $e = x_d - x_m$.

$$V_4 = \frac{1}{2}(x_d - x_{human})^{\mathrm{T}}K_{human}^{\mathrm{T}}(x_d - x_{human}) \tag{26}$$

For V_1, by taking the derivative with respect to time, one has

$$\begin{aligned}\dot{V}_1 &= \frac{1}{\alpha_2}\text{trace}(\tilde{A}^{\mathrm{T}}\dot{\tilde{A}}) \\ &= \frac{1}{\alpha_2}\text{trace}(\tilde{A}^{\mathrm{T}}\dot{\hat{A}})\end{aligned} \tag{27}$$

where $\dot{A} = 0$.

Based on (16) and (27), one has

$$\dot{V}_1 = -\text{trace}(\tilde{A}^{\mathrm{T}}(\frac{1}{\alpha_2}\tilde{x}_{human}^{\mathrm{T}}(t-T)L(t) + \tilde{f}^{\mathrm{T}}L(t))) \tag{28}$$

Differentiating V_2 with respect to time, one has

$$\dot{V}_2 = -\frac{1}{\alpha_2}\tilde{x}_{human}^{\mathrm{T}}\dot{\tilde{x}}_{human} \tag{29}$$

Based on (11) and (14), one has

$$\dot{\tilde{x}}_{human}(t) = \tilde{A}^{\mathrm{T}}L(t) - \alpha_1\tilde{x}_{human}(t-T) \tag{30}$$

Therefore, (29) can be rewritten as

$$\dot{V}_2 = -\frac{1}{\alpha_2}\tilde{x}_{human}^{\mathrm{T}}(\tilde{A}^{\mathrm{T}}L(t) - \alpha_1\tilde{x}_{human}(t-T)) \tag{31}$$

We assume that the time step T is small and combine (28) and (31), so we have

$$\dot{V}_1 + \dot{V}_2 = -\tilde{f}^{\mathrm{T}}\tilde{A}^{\mathrm{T}}L(t) - \frac{1}{\alpha_2}\tilde{x}_{human}^{\mathrm{T}}\alpha_1\tilde{x}_{human} \tag{32}$$

Differentiating V_3 with respect to time, one has

$$\dot{V}_3 = \dot{e}^{\mathrm{T}}(M_{md}\ddot{e} + K_{md}e) \tag{33}$$

Based on the impedance model (3), we have

$$\begin{aligned}\dot{V}_3 &= \dot{e}^{\mathrm{T}}(-D_{md}\dot{e} + \tilde{f}) \\ &= -\dot{e}^{\mathrm{T}}D_{md}\dot{e} + \dot{e}^{\mathrm{T}}\tilde{f}\end{aligned} \tag{34}$$

Differentiating V_4 with respect to time, one has

$$\dot{V}_4 = (x_d - x_s)^{\mathrm{T}}K_{human}^{\mathrm{T}}(\dot{x}_d - \dot{x}_{human}) \tag{35}$$

Based on (17) and (21), (35) can be rewritten as

$$\begin{aligned}\dot{V}_4 &= \tilde{f}^{\mathrm{T}}(\dot{x}_d - \dot{x}_{human} + \dot{\tilde{x}}_{human}) \\ &= \tilde{f}^{\mathrm{T}}(\dot{x}_d - \dot{x}_m - \alpha_3\tilde{f} + \alpha_1\tilde{x}_{human} + \dot{\tilde{x}}_{human}) \\ &= -\alpha_3\tilde{f}^{\mathrm{T}}\tilde{f} + \tilde{f}^{\mathrm{T}}\dot{e} + \tilde{f}^{\mathrm{T}}(\alpha_1\tilde{x}_{human} + \dot{\tilde{x}}_{human})\end{aligned} \tag{36}$$

Based on (30), one has

$$\dot{V}_4 = -\alpha_3\tilde{f}^{\mathrm{T}}\tilde{f} + \tilde{f}^{\mathrm{T}}\dot{e} + \tilde{f}^{\mathrm{T}}\tilde{A}^{\mathrm{T}}L(t) \tag{37}$$

Differentiating V with respect to time, we have

$$\begin{aligned}\dot{V} &= \dot{V}_1 + \dot{V}_2 + \dot{V}_3 + \dot{V}_4 \\ &= -\frac{1}{\alpha_2}\tilde{x}_{human}^{\mathrm{T}}\alpha_1\tilde{x}_{human} - \dot{e}^{\mathrm{T}}D_{md}\dot{e} - \alpha_3\tilde{f}^{\mathrm{T}}\tilde{f} \\ &\leq 0\end{aligned} \tag{38}$$

Therefore, when $t \longrightarrow \infty$, $\tilde{x}_{human} \longrightarrow 0$, $\dot{e} \longrightarrow 0$, and $\tilde{f} \longrightarrow 0$. In this sense, the desired motion of human hand can be obtained, and the haptic device can track the reference motion x_d.

V. Experiments and Results

In this section, the performance of the proposed method is demonstrated by comparative experiments.

A. Experiment setup

The experimental platform is built to validate the effectiveness of the developed approach. A Touch X joystick is used as the haptic device, and a Baxter robot with seven joints is utilized as a slave device. The human moves the Touch X to manipulate the slave Baxter. All devices are controlled using robot operating system (ROS). A proportional-differential (PD) controller with $K_p = diag[150, 80, 25, 10, 3, 3, 2.5]$ and $K_d = diag[7, 6, 5, 2, 0.8, 0.8, 0.015]$ is utilized to control the Baxter robot. $\alpha_1 = 0.0001$, $\alpha_2 = 0.00001$, and $\alpha_3 = 0.2$.

Mean absolute error (MAE) is used to quantify the performance of the developed method.

B. Experiment 1

In Experiment 1, three different motions are performed. Fig. 4 shows the results of tracking performance in the condition of time delay 20ms.

Fig. 4(a) indicates that when the teleoperation is performed without prediction, the slave cannot track the master accurately in the whole process. In comparison, the teleoperation achieves a better performance of trajectory tracking in the case of prediction. Fig. 4(b) shows the tracking errors with and without prediction. It can be seen that the slave robot achieves a smaller tracking error by predicting the human motion intention.

In order to verify the robustness of the proposed method, another two different motions are performed in the experiments. Figs. 4(c)-4(f) show the tracking results of trajectories 2 and 3, respectively. Compared with the tracking performance of trajectory 1, there is a similar result for trajectories 2 and 3. It can be concluded that the slave can update its trajectory online based on prediction of human motion and tracks the master accurately in the presence of time delay.

TABLE I
Comparisons (MAE) in the condition of time delay 20ms for trajectories 1, 2, 3 in Experiment 1.

Parameters	Without prediction (m)	With prediction (m)
Trajectory 1	0.0017	$8.0279e^{-4}$
Trajectory 2	0.0027	0.0020
Trajectory 3	0.0022	0.0012

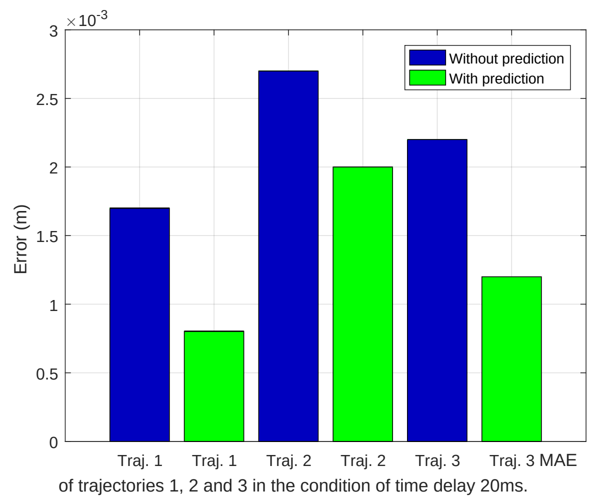
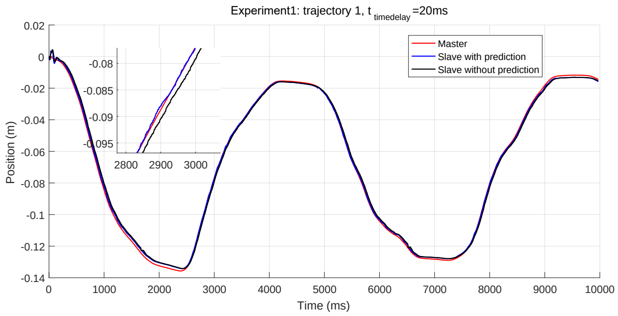


Fig. 5. Comparison of MAE with/without prediction in Experiment 1.

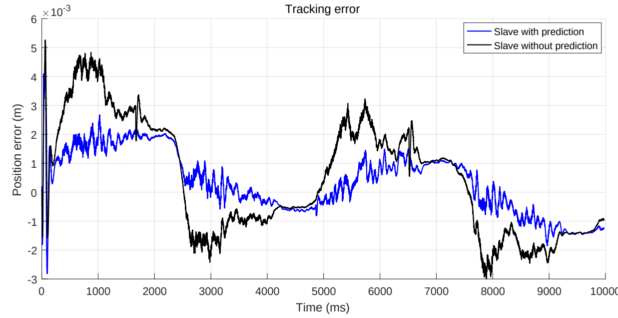
Table I and Fig. 5 show the MAE of tracking performance for trajectories 1, 2, 3 in the condition of time delay 20ms. It can be concluded that the proposed method based on prediction can achieve smaller tracking error than that without prediction.

C. Experiment 2

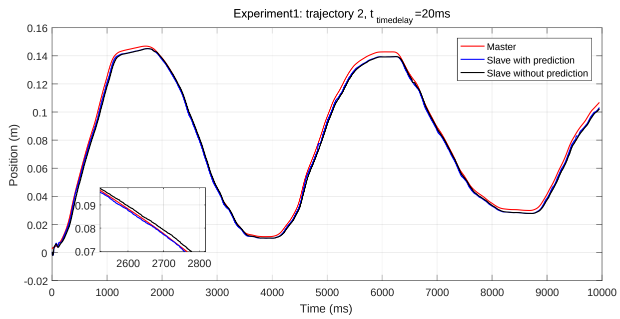
In this section, we demonstrate the performance of the proposed method in the conditions of different time delays.



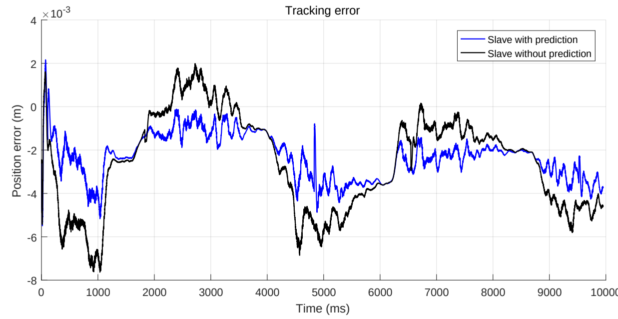
(a) Tracking performance of trajectory 1.



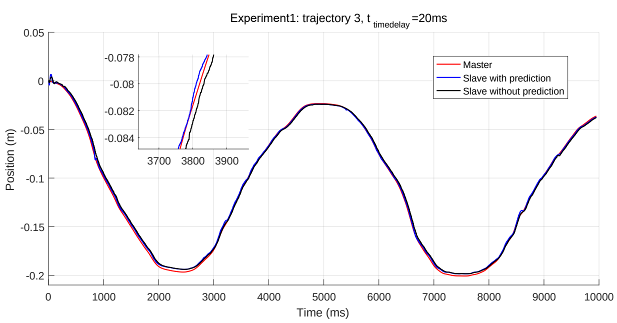
(b) Tracking error of trajectory 1.



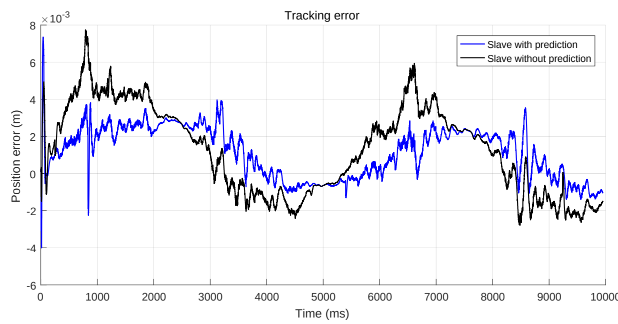
(c) Tracking performance of trajectory 2.



(d) Tracking error of trajectory 2.



(e) Tracking performance of trajectory 3.



(f) Tracking error of trajectory 3.

Fig. 4. Performance comparison with/without prediction in Experiment 1.

Fig. 6(a) illustrates the tracking performance under time delay 20ms. In comparison, there are relatively large errors when the slave (the black line) tracks the master (the red line) without prediction for time delays of 50ms and 80ms in Figs. 6(c) and 6(e). Additionally, the tracking error increases with the increase of time delay. In this sense, the teleoperation system cannot work without human motion prediction.

As presented in Figs. 6(b)-6(f), the trajectory of the slave stays close to the master's by using the proposed method with prediction. Figs. 6(b), 6(d), and 6(f) illustrate that the proposed method can achieve similar performance in the condition of time delay 80ms in comparison with that of time delays 20ms and 50ms. It indicates that the performance of the proposed method is independent of the time delay's increment.

Table II and Fig. 7 present the performance comparison of the teleoperation system in terms of MAE. It can be seen that the MAE without prediction is larger than that with prediction.

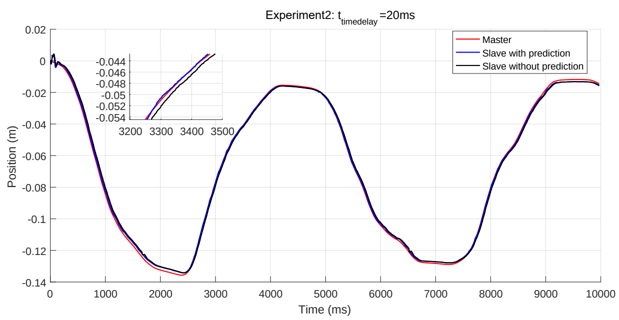
In summary, the proposed method is tested by different human motion trajectories and different time delay conditions. In this sense, the effectiveness and robustness of the proposed approach are verified.

TABLE II
COMPARISONS (MAE) IN THE CONDITIONS OF TIME DELAYS 20MS, 50MS AND 80MS IN EXPERIMENT 2.

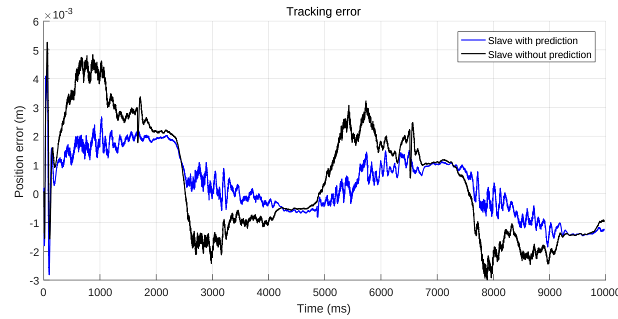
Parameters	Without prediction (m)	With prediction (m)
20ms	0.0017	$8.0279e^{-4}$
50ms	0.0031	$7.4042e^{-4}$
80ms	0.0045	$7.9180e^{-4}$

VI. CONCLUSION AND DISCUSSION

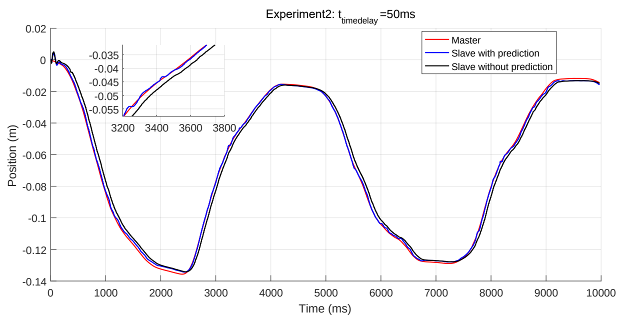
In this paper, a robot motion updating strategy based on human motion prediction is developed for teleoperation. In order to utilize the interaction profile, we propose a virtual force model to correct the robot's motion trajectory. The human motion prediction can provide a feedforward model to the robots, and the virtual force provides a feedback to adapt



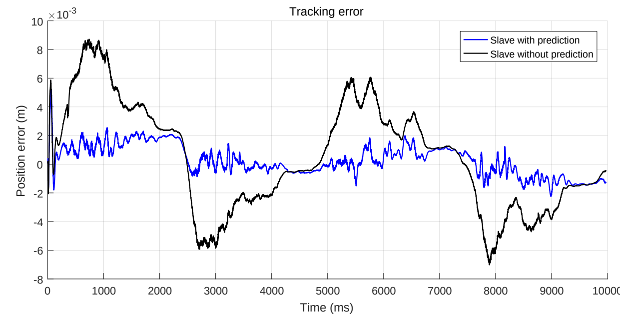
(a) Tracking performance in the condition of time delay 20ms.



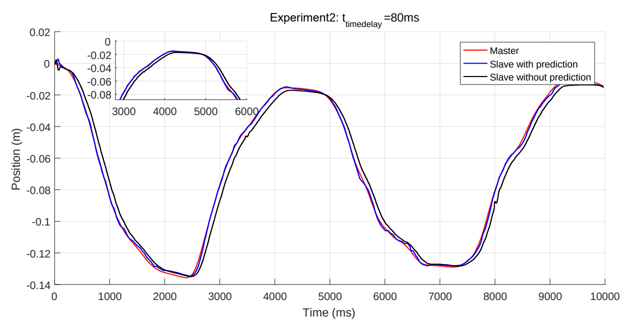
(b) Tracking error in the condition of time delay 20ms.



(c) Tracking performance in the condition of time delay 50ms.



(d) Tracking error in the condition of time delay 50m.



(e) Tracking performance in the condition of time delay 80ms.

(f) Tracking error in the condition of time delay 50ms.

Fig. 6. Performance comparison with/without prediction in Experiment 2.

the robot motion. The comparative experimental results verify the effectiveness of the developed approach. It is noted that there are many methods to deal with the time delay problem for teleoperation such as neural network and wave variable method. Compared to these methods, ours uses not only prediction of human movement as a feedforward component, but also a virtual force as a feedback. Other control methods will be used to enhance the active interaction performance of the robot in future work [42].

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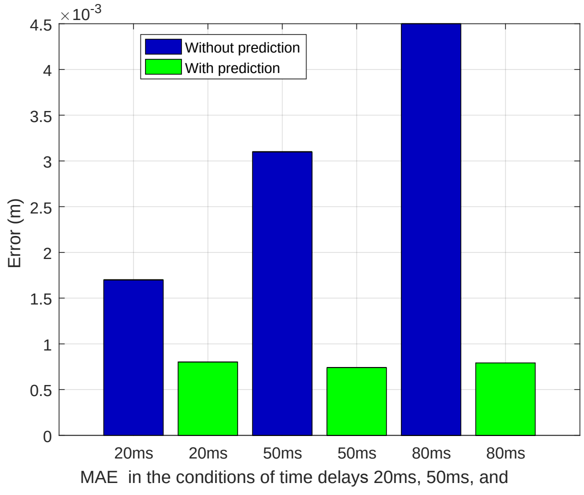

Fig. 7. Comparison of MAE with/without prediction in Experiment 2.

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