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Neural Network based Passivity Control of Teleoperation System under Time-Varying Delays

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Abstract- In this paper, a novel neural network-based four-channel wave-based Time Domain Passivity approach (TDPA) is proposed for a teleoperation system with time-varying delays. The designed wave-based TDPA aims to robustly guarantee the channels passivity and provide higher transparency than the previous power-based TDPA. The applied neural network is used to estimate and eliminate the system's dynamic uncertainties. The system stability with linearity assumption on human and environment has been analyzed using Lyapunov method. The proposed algorithm is validated through experimental work based on a 3-DOF bilateral teleoperation platform in the presence of different time delays.

Index Terms-Bilateral teleoperation, Neural network, Wave variable, TDPA, Passivity, Time-varying delays.

1. Introduction

In the last five decades, teleoperation technologies have been widely applied and developed all around the world. Teleoperation system is defined as electromechanical mechanism that extends human's sensing, decision making and manipulation capability to the remote environment. A conventional teleoperation system consists of the human operator, the master robot, the communication networks, the slave robot and the environmental tasks. Teleoperation systems have numerous applications ranging from space exploration [1], underwater operation [2], mining [3], nuclear reactor [4] where human operators are protected from dangerous situations, to medical training [5], rehabilitation [6] and minimally invasive surgery [7] where a patient suffers less trauma through key-hole surgery. A teleoperation system is called unilateral if only the master's control signals are transmitted to the slave side. If there exists the motion or force feedback from the slave side to the master, this system can be called bilateral. Bilateral teleoperation is assessed through the two critical indices of stability and transparency. Stability requires the closed loop system to be stable under different environmental conditions. Ideal transparency means that the medium between the operator and the environment is not felt and the dynamics of the master and the slave are canceled out.

With the network technologies advancing at a staggering rate, teleoperation can be conducted by using commercially available communication networks. When the local and remote platforms are connected via commercial networks, the forward and feedback control signals between the master and the slave will be inevitably associated with time delays. In remote control and manipulation, without proper control algorithms, even a small time delay may destabilize and degrade the tracking performance of a teleoperation system. Numerous methods have been proposed to balance the trade-off between the system stability and transparency in the presence of time delays. A system designed by Lee and Spong uses direct position feedback to eliminate position drift [8]. Nunõ et al. deploy P-like, PD-like and scattering controllers to analyze the stability of the nonlinear

teleoperation systems with the classic assumptions of passivity [9]. Later, they introduce a general Lyapunov-like function to unify stability analysis on the passivity-based control for the nonlinear teleoperation systems [10]. An adaptive coordination control law based on the scattering approach is introduced by Chopra et al. to ensure position synchronization in the nonlinear teleoperation systems [11]. Yang et al. design a new fuzzy PD-like controller to deal with uncertainties of system dynamics [12]. However, all of the P-like and PD-like systems require pre-set dampers with constant gains associated with the value of time delays to guarantee the system stability by reducing transparency. Due to different types of time delays, these methods may be over-conservative in some situations.

In recent times, the neural networks (NN) have attracted much attention due to their prominent properties such as learning capability mapping and parallel processing. NNs have been deployed in the control of the robotic systems and have significantly improved their performance [13]-[14]. In bilateral teleoperation research, a control system with acceleration measurement is designed in [15] using NN to estimate nonlinear uncertainties. In [16], the NN is applied in a Prescribed Performance Control (PPC) system. A terminal sliding mode control system with NN is also designed in [17]. These systems, however, perform only under extremely restricting assumptions that the time delay is constant and the external force is zero, both of which are against the reality of these systems. In [18] NN is deployed for systems with time-varying delays, but the approach requires precise knowledge of the external force as well as the coefficients of mass and damper of the external force. [19] and [20] extend the application of NN to multilateral teleoperation. The major drawbacks of these studies are some of the assumptions underlying them. For example, the positive constraints including disturbances are assumed to be restricted by large velocity signals, and the rate of time delays must be less than one. In [21], the state-of-art neural network control systems is reviewed.

The idea of passivity characterized by mechanical energy, which uses force and velocity as efforts and flow variables, is an effective tool for establishing stability of bilateral teleoperation interaction under time delays. Compared with the methods based on absolute stability, most passivity-based methods are more conservative and sacrifice system transparency, but can easily accommodate communication time delays. Among the numerous passivity-based approaches, the wave variable method, introduced by Niemeyer and Slotine, is a classic approach to guarantee the time delayed channel passivity. However, the traditional wave variable transformation has many drawbacks. For example, it can hardly guarantee the system stability when time delay varies. In addition, the two intrinsic problems in a wave variable system, position drift and wave reflections can cause inaccurate position tracking and large signal variations, respectively. Numerous approaches have been proposed to overcome one or some of these shortcomings [22]-[30]. Nevertheless, according to the literature, none of the previous work addresses all the problems associated with the wave

variable transformation. Specially, the time-varying delay issue is still the main drawback of the previous work on wave-based systems.

Another classic passivity-based approach is Time Domain Passivity Approach (TDPA) that was first introduced by Hannaford et al., consisting of passivity observers and passivity controllers, to adaptively dissipate energy [31]. The passivity observers are used to monitor the channel passivity and the passivity controllers are used to dissipate the active energy. This method is later extended in [32] to deal with the time-varying delay issues. In [33] and [34], the energy-based TDPA is extended to the power-based TDPA, which can dissipates energy as soon as any active energy is produced. The power-based TDPA proposed in [34] is further extended in [35] to tackle the position drift issue. However, although the above TDPA-based system are capable to guarantee channels passivity under time-varying delays, transparency degradation is still their main drawback, especially in the presence of small constant or no time delay where high transparency can be easily derived by many non-passivity based schemes. In [36], we proposed a wave-based TDPA system to more accurately observe the power flow during different time delay scenarios. However, assumption of the rate of time delays less than one and degraded position and torque tracking owing to passivity controllers in the presence of sharply-varying delays were two major weaknesses of that method.

In this paper, a new wave-based TDPA system is proposed to guarantee the communication channels' passivity and achieve high tracking performance in the presence of time-varying delays without rate restrictions. Compared with the previous power-based TDPA, the proposed wave-based TDPA can more efficiently monitor the power flows under the condition of arbitrary time delays. The proposed passivity controllers do not influence position and force tracking. NN is applied to the proposed system to estimate and eliminate the dynamic uncertainties. The proposed control algorithm is deployed in the absence of the knowledge of the upper bound of the NN approximation error and external disturbance. Lyapunov functions are used to prove the system stability. Finally, the experimental work is performed to show the effectiveness of proposed control system in comparison with other systems in different scenarios.

The remainder of the paper is structured as follows: After providing a background in Section 2 on the dynamics of teleoperation system and its related properties, and the knowledge of the Radial Basis Function (RBF) NN, the proposed four-channel (4-CH) wave-based TDPA is described in Section 3. In Section 4, the NN-based controller design is introduced and the delay-based stability is also studied. Results of the experimental work are presented in Section 5. Section 6 draws some conclusions.

2. Background

2.1. Model of a teleoperation system

In this paper, the local (master) and the remote (slave) robots are modeled as a pair of n -DOF serial links with revolute joints. Their corresponding nonlinear dynamics are modelled as:

$$M_m(q_m)\ddot{q}_m + C_m(q_m, \dot{q}_m)\dot{q}_m + F_m\dot{q}_m + f_{cm}(\dot{q}_m) + g_m(q_m) - F_m^* = \tau_m + \tau_h \quad (1)$$

$$M_s(q_s)\ddot{q}_s + C_s(q_s, \dot{q}_s)\dot{q}_s + F_s\dot{q}_s + f_{cs}(\dot{q}_s) + g_s(q_s) - F_s^* = \tau_s - \tau_e \quad (2)$$

where $i = m, s$ for the master and slave. $\ddot{q}_i(t)$, $\dot{q}_i(t)$, $q_i(t) \in R^{n \times 1}$ are the joint acceleration, velocity and position, respectively. $M_i(q_i(t)) \in R^{n \times n}$ are the inertia matrices, $C_i(q_i(t), \dot{q}_i(t)) \in R^{n \times n}$ are Coriolis/centrifugal effects. $g_i(q_i(t)) \in R^n$ are the vectors of gravitational forces and τ_i are the control signals. $\tau_h(t)$ and $\tau_e(t)$ are the actual human and environmental torques applied to the robots. $F_i\dot{q}_i(t)$ denote the viscous friction and $f_{ci}(\dot{q}_i(t))$ denote the Coulomb friction. $F_i^*(t) \in R^{n \times 1}$ are the bounded unknown disturbances. In the paper, the Coulomb friction function $f_{ci}(\dot{q}_i(t))$ on the master and slave sides are bounded and piecewise continuous functions. Important properties of the above nonlinear dynamic model, which are used in this paper, are as follows:

P1: The inertia matrix $M_i(q_i)$ for a manipulator is symmetric positive-definite as: $0 < \sigma_{\min}(M_i(q_i(t)))I \leq M_i(q_i(t)) \leq \sigma_{\max}(M_i(q_i(t)))I < \infty$, where $I \in R^{n \times n}$ is the identity matrix. $\sigma_{\min}$ and $\sigma_{\max}$ denote the strictly positive minimum (maximum) eigenvalue of M_i for all configurations q_i .

P2: Under an appropriate definition of the Coriolis/centrifugal matrix, the matrix $\dot{M}_i - 2C_i$ is skew symmetric, which can also be expressed as:

$$\dot{M}_i(q_m(t)) = C_i(q_i(t), \dot{q}_i(t)) + C_i^T(q_i(t), \dot{q}_i(t)) \quad (3)$$

P3: For a manipulator with revolute joints, there exists a positive constant Z bounding the Coriolis/centrifugal matrix as:

$$\|C_i(q_i(t), x(t))y(t)\|_2 \leq Z\|x(t)\|_2\|y(t)\|_2 \quad (4)$$

P4: The time derivative of $C_i(q_i(t), \dot{q}_i(t))$ is bounded if $q_i(t)$ and $\dot{q}_i(t)$ are bounded.

In this paper, the external human and environmental torques are modelled as (5) and (6), where $\tau_{h,e}^*(t)$ stand for, respectively, the positive and bounded human operator and the environment exogenous input. $K_{h,e}$, $B_{h,e}$ and $M_{h,e}$ represent the non-negative constant scalars corresponding to the mass, damping and stiffness of human and environment. $\Delta K_{h,e}$, $\Delta B_{h,e}$, $\Delta M_{h,e}$ are the unknown bounded variables relating to $K_{h,e}$, $B_{h,e}$ and $M_{h,e}$. Moreover, we use the extended active observer (EAOB) to measure the human and environmental torques as well as acceleration signals [26]. Compared with other force observers, EAOB possesses the advantage of external noise suppression by deploying Kalman filter, and is suitable for nonlinear systems.

$$\tau_h(t) = \tau_h^*(t) - (K_h + \Delta K_h)q_m(t) - (B_h + \Delta B_h)\dot{q}_m(t) - (M_h + \Delta M_h)\ddot{q}_m(t) \quad (5)$$

$$\tau_e(t) = \tau_e^*(t) + (K_e + \Delta K_e)q_s(t) + (B_e + \Delta B_e)\dot{q}_s(t) + (M_e + \Delta M_e)\ddot{q}_s(t) \quad (6)$$

2.2. Neural networks (NN)

The main advantage of the NNs is its ability to approximate any smooth nonlinear function with arbitrary precision due to its inherent approximate capabilities [15], [38]. In this paper, the Radial Basis Function (RBF) NN is applied to approximate a continuous function $f(X): R^q \rightarrow R^p$ expressed as:

$$f(X) = W^T \Phi(X) + \xi(X) \quad (7)$$

where $X \in \Omega_x \subset R^q$ is the input vector. $W \in R^{n \times p}$ is the weight matrix. n is the number of the neurons. $\xi(X)$ is the approximation errors.

$\Phi(X) = [\Phi_1(X), \Phi_2(X), \dots, \Phi_k(X), \dots, \Phi_n(X)]$, where $\Phi_k(X)$ is

the RBF Gaussian function:

$$\Phi_k(X) = \exp(-\frac{1}{2H_k^2}\|X - C_k\|^2) \quad (8)$$

Where C_k and H_k are the center and the width of the k -th neuron, respectively. According to the universal approximation property of NNs, for any continuous function $f(X)$, there exists an NN such that

$$f(X) = W^{*T}\Phi(X) + \xi^*(X), \|\xi^*(X)\| \leq \xi_{up}^* \quad (9)$$

where W^* and $\xi^*(X)$ are the ideal weight and error in the approximation, respectively. ξ_{up}^* is $\xi^*(X)$'s upper bound. The dynamic functions of the manipulators can be considered to be piecewise continuous functions due to the existing friction and backlash. Assume that $f(X)$ is a piecewise function which can be written as: $f(X) = f_1(X) + f_2(X)$, where $f_1(X)$ is the continuous part and $f_2(X)$ is the bounded piecewise term, respectively. Therefore:

$$f(X) = W^{*T}\Phi(X) + \xi^*(X) + f_2(X) = W^{*T}\Phi(X) + \bar{\xi}^*(X) \quad (10)$$

where $\bar{\xi}^*(X) = \xi^*(X) + f_2(X)$, $\bar{\xi}^*(X) \leq \bar{\xi}_{up}^*$. $\bar{\xi}_{up}^*$ is the upper bound of the approximation error.

3. Wave-based TDPA

The system passivity in a traditional power-based TDPA system can be defined as [34], [35]:

$$P(t) = \tau_m(t)\dot{q}_m(t) - \tau_s(t)\dot{q}_s(t) = \frac{1}{2b}\tau_m^T(t)\tau_m(t) - \frac{1}{2b}(\tau_m(t) - b\dot{q}_m(t))^2 + b\dot{q}_s^T(t)\dot{q}_s(t) - \frac{1}{2b}(\tau_s(t) + b\dot{q}_s(t))^2 - \frac{1}{2b}\dot{T}_2(t)\tau_m^T(t)\tau_m(t) - \frac{b}{2}\dot{T}_1(t)\dot{q}_s^T(t)\dot{q}_s(t) + \frac{dE}{dt} = P_{diss} + \frac{dE}{dt} \quad (11)$$

$$E(t) = \frac{1}{2b}\int_{t-T_2(t)}^t \tau_s^T(\eta)\tau_s(\eta) d\eta + \frac{b}{2}\int_{t-T_1(t)}^t \dot{q}_m^T(\eta)\dot{q}_m(\eta) d\eta \quad (12)$$

where b is a positive constant that relates to the unit of torque and velocity. $T_1(t)$ and $T_2(t)$ are the forward and backward time delays, respectively. Since P_{diss} is not observable at any single port of the 2-port network, in order to facilitate real-time monitoring of the network's passivity, P_{diss} can be written as:

$$P_{diss}(t) = P_{diss}^m(t) + P_{diss}^s(t) \quad (13)$$

where $P_{diss}^m(t)$ and $P_{diss}^s(t)$ are the power dissipation components which are observable at the master and slave ports, respectively.

$$P_{diss}^m(t) = \frac{1}{b}\tau_m^T(t)\tau_m(t) - \frac{1}{2b}(\tau_m(t) - b\dot{q}_m(t))^2 - \frac{1}{2b}\dot{T}_2(t)\tau_m^T(t)\tau_m(t) \quad (14)$$

$$P_{diss}^s(t) = b\dot{q}_s^T(t)\dot{q}_s(t) - \frac{1}{2b}(\tau_s(t) + b\dot{q}_s(t))^2 - \frac{b}{2}\dot{T}_1(t)\dot{q}_s^T(t)\dot{q}_s(t) \quad (15)$$

$\bar{T}_{1,2}$ is replaced by constant parameters $\bar{\mu}_{1,2}$ in [34]-[35]. Their values are set to be the upper bound of $\bar{T}_{1,2}$. The passivity observers on the master and the slave side can be written as:

$$P_{obs}^m(t) = \frac{1}{b}\tau_m^T(t)\tau_m(t) - \frac{1}{2b}(\tau_m(t) - b\dot{q}_m(t))^2 - \frac{1}{2b}\bar{\mu}_2\tau_m^T(t)\tau_m(t) \quad (16)$$

$$P_{obs}^s(t) = b\dot{q}_s^T(t)\dot{q}_s(t) - \frac{1}{2b}(\tau_s(t) + b\dot{q}_s(t))^2 - \frac{b}{2}\bar{\mu}_1\dot{q}_s^T(t)\dot{q}_s(t) \quad (17)$$

By applying the passivity observers, the power flows can be detected in each port. Two passivity controllers attached at each port are activated when P_{obs}^m and P_{obs}^s are negative so that $P_{ctr}^m = -P_{obs}^m$ and $P_{ctr}^s = -P_{obs}^s$ where P_{ctr}^m and P_{ctr}^s are the dissipated power from the passivity controllers. By using the two passivity controllers, the torque perceived by the operator $\tau_m'(t)$ and the command velocity of slave $\dot{q}_s'(t)$ can be derived as [34]:

$$\tau_m'(t) = \tau_s(t - T_2(t)) + \tau_{PC}(t) \quad (18)$$

$$\dot{q}_s'(t) = \dot{q}_m(t - T_1(t)) - \dot{q}_{PC}(t) \quad (19)$$

where $\tau_{PC}(t)$ is the output of the master side passivity controller and $\dot{q}_{PC}(t)$ is the output of the slave side passivity controller. The power-based TDPA using the passivity observers and passivity controllers can robustly guarantee the passivity of the communication channels in the presence of time varying delays. However, as a conservative method for system passivity, this method can largely degrade the system's transparency in the presence of the constant time delays or even no delay ($\bar{\mu}_2 = 0$). During the free space movement ($\tau_{m,s} = 0$), (16) can be simplified as $P_{obs}^m(t) = -\frac{b}{2}\dot{q}_m^2(t)$, and during the hard environmental contact ($\dot{q}_{m,s} = 0$), (17) can be simplified as $P_{obs}^s(t) = -\frac{1}{2b}\tau_s^2(t)$. Under these conditions, $P_{obs}^m(t)$ and $P_{obs}^s(t)$ are negative to the extent that accurate torque and trajectory tracking performances cannot be achieved due to the adverse effect of the passivity controllers.

Remark. In this paper, the differentials of unsymmetrical time delays $T_1(t)$ and $T_2(t)$ are bounded by $\bar{\mu}_{1,2}$. That is, $|\dot{T}_{1,2}(t)| \leq \bar{\mu}_{1,2}$. $\bar{\mu}_{1,2}$ are arbitrary positive constants. Moreover, the time-varying delays $T_{1,2}(t)$ are considered to be the sum of the constant time delays $\bar{T}_{1,2}$ with their bounded perturbations $\Delta T_{1,2}(t)$. That is, $T_{1,2}(t) = \bar{T}_{1,2} + \Delta T_{1,2}(t) \leq \bar{T}_{1,2} + \bar{\epsilon}_{1,2} = T_{1,2}^{max}$, where $\bar{\epsilon}_{1,2}$ are the upper bounds of the perturbations and $T_{1,2}^{max}$ are the upper bounds of the $T_{1,2}(t)$.

Fig.1 shows the proposed 4-CH wave variable transformation which contains two wave transformation schemes.

Fig.1. 4-CH wave variable transformation

The two wave transformation schemes are applied to encode the feed-forward signals V_{A1} and V_{B1} with the feedback signals I_{A2} and I_{B2} , where $V_{A1}(t) = \beta\delta\dot{q}_m(t) + \alpha\delta\ddot{q}_m(t) + \gamma\delta\ddot{q}_s(t)$, $V_{B1}(t) = \alpha_1\delta\dot{q}_m(t) + \gamma_1\delta\ddot{q}_m(t)$, $I_{A2}(t) = \alpha_1\delta\dot{q}_s(t) + \gamma_1\delta\ddot{q}_m(t)$, $I_{B2}(t) = -\beta\delta\dot{q}_s(t) - \alpha\delta\ddot{q}_s(t) - \gamma\delta\ddot{q}_s(t)$. α , α_1 , γ , γ_1 and β , are diagonal positive-definite matrices. δ is a positive constant. In this system, position, velocity and

acceleration are transmitted between the two robots.
The wave variables in the two schemes are defined as follows:

$$u_{m1}(t) = \frac{b_1 V_{A1}(t) + \frac{1}{\lambda_1} I_{A2}(t - T_2(t))}{\sqrt{2b_1}}, u_{s1}(t) = \frac{b_1 V_{A2}(t) + \frac{1}{\lambda_1} I_{A2}(t)}{\sqrt{2b_1}} \quad (20)$$

$$v_{m1}(t) = \frac{I_{A2}(t - T_2(t))}{\sqrt{2b_1}}, v_{s1}(t) = \frac{I_{A2}(t)}{\sqrt{2b_1}} \quad (21)$$

$$u_{m2}(t) = \frac{b_2 V_{B1}(t)}{\sqrt{2b_2}}, u_{s2}(t) = \frac{b_2 V_{B1}(t - T_1(t))}{\sqrt{2b_2}} \quad (22)$$

$$v_{m2}(t) = \frac{\frac{b_2}{\lambda_2} V_{B1}(t) - I_{B1}(t)}{\sqrt{2b_2}}, v_{s2}(t) = \frac{\frac{b_2}{\lambda_2} V_{B1}(t - T_1(t)) - I_{B2}(t)}{\sqrt{2b_2}} \quad (23)$$

where $b_{1,2}$ and $\lambda_{1,2}$ are the positive characteristic impedances. The traditional wave variable transformation is written as

$$u_m(t) = -v_m(t) + \sqrt{2/b} \dot{q}_m(t), v_s(t) = -u_s(t) + \sqrt{2/b} F_e(t)$$

in [11], where the incoming wave variables v_m and u_s in this relationship are reflected and returned as the outgoing wave variable u_m and v_s . This phenomenon is called wave reflection. Wave reflections can last several cycles in the communication channels and then gradually disappear, which can easily produce unpredictable interference and disturbances that significantly influence transparency. Unlike the conventional wave variable, the outgoing wave variables v_{s1} and u_{m2} do not contain any unnecessary information from the incoming wave variables u_{s1} and v_{m2} as shown in (21)-(22). Therefore, the signal variations caused by wave-reflections can be efficiently reduced. In addition, direct position information is transmitted between the master and the slave, and position drift does not occur in this system. The control signals after transmission in Fig.1 can be derived as

$$I_{A1} = \alpha_1 \delta \dot{q}_s(t - T_2(t)) + \gamma_1 \delta \ddot{q}_s(t - T_2(t)) + b_1 \lambda_1 (\beta \delta \dot{q}_m(t) + \alpha \delta \dot{q}_m(t) + \gamma \delta \ddot{q}_m(t)) \quad (24)$$

$$I_{B1} = -\beta \delta \dot{q}_s(t - T_2(t)) - \alpha \delta \dot{q}_s(t - T_2(t)) - \gamma \delta \ddot{q}_s(t - T_2(t)) + \frac{b_2 \alpha_1}{\lambda_2} (\delta \dot{q}_m(t) - \delta \dot{q}_m(t - T_1(t) - T_2(t - T_1(t)))) \quad (25)$$

$$V_{A2}(t) = \beta \delta \dot{q}_m(t - T_1(t)) + \alpha \delta \dot{q}_m(t - T_1(t)) + \gamma \delta \ddot{q}_m(t - T_1(t)) - \frac{\alpha_1}{b_1 \lambda_1} (\delta \dot{q}_s(t) - \delta \dot{q}_s(t - T_2(t) - T_1(t - T_2(t)))) \quad (26)$$

$$V_{B2}(t) = \alpha_1 \delta \dot{q}_m(t - T_1(t)) + \gamma_1 \delta \ddot{q}_m(t - T_1(t)) + \frac{\lambda_2}{b_2} (\beta \delta \dot{q}_s(t) + \alpha \delta \dot{q}_s(t) + \gamma \delta \ddot{q}_s(t)) \quad (27)$$

In order to simplify this expression, we define $T_{l1}(t) = T_2(t) + T_1(t - T_2(t))$ and $T_{l2}(t) = T_1(t) + T_2(t - T_1(t))$. We also have the constraints $\dot{T}_{l1}(t) \leq \bar{\mu}_1$, $\dot{T}_{l2}(t) \leq \bar{\mu}_2$. The proposed 4-CH wave variable transformation can actually be seen as the combination of two 2-port networks. Therefore, the power flow in the 4-CH wave variable transformation can be defined as:

$$P_{4CH}(t) = P_1(t)[scheme1] + P_2(t)[scheme2]$$

$$\begin{aligned} P_1(t) &= V_{A1}(t)I_{A1}(t) - V_{A2}(t)I_{A2}(t) \\ &= 2\lambda_1 u_{m1}^T(t)u_{m1}(t) + \frac{2}{\lambda_1} v_{s1}^T(t)v_{s1}(t) - 2(u_{m1}^T(t)v_{m1}(t) + u_{s1}^T(t)v_{s1}(t)) \\ &= \lambda_1(u_{m1}^T(t)u_{m1}(t) - u_{s1}^T(t)u_{s1}(t)) + \frac{1}{\lambda_1}(v_{s1}^T(t)v_{s1}(t) - v_{m1}^T(t)v_{m1}(t)) + \frac{1}{\lambda_1}(v_{m1}(t) - \lambda_1 u_{m1}(t))^T(v_{m1}(t) - \end{aligned}$$

$$\begin{aligned} &\lambda_1 u_{m1}(t)) + \frac{1}{\lambda_1}(v_{s1}(t) - \lambda_1 u_{s1}(t))^T(v_{s1}(t) - \lambda_1 u_{s1}(t)) \\ &= \frac{d}{dt} \int_{t-T_1(t)}^t \lambda_1 u_{m1}^T(\eta)u_{m1}(\eta)d\eta + \frac{d}{dt} \int_{t-T_2(t)}^t \frac{1}{\lambda_1} v_{s1}^T(\eta)v_{s1}(\eta)d\eta + \frac{1}{\lambda_1}(v_{m1}(t) - \lambda_1 u_{m1}(t))^T(v_{m1}(t) - \lambda_1 u_{m1}(t)) + \frac{1}{\lambda_1}(v_{s1}(t) - \lambda_1 u_{s1}(t))^T(v_{s1}(t) - \lambda_1 u_{s1}(t)) - \lambda_1 \dot{T}_1(t)u_{s1}^T(t)u_{s1}(t) - \frac{1}{\lambda_1} \dot{T}_2(t)v_{m1}^T(t)v_{m1}(t) \\ &= \frac{dE_1(t)}{dt} + P_1^{diss}(t) \end{aligned} \quad (28)$$

$$E_1(t) = \int_{t-T_1(t)}^t \lambda_1 u_{m1}^T(\eta)u_{m1}(\eta)d\eta + \int_{t-T_2(t)}^t \frac{1}{\lambda_1} v_{s1}^T(\eta)v_{s1}(\eta)d\eta \quad (29)$$

$$\begin{aligned} P_1^{diss}(t) &= \frac{1}{\lambda_1}(v_{m1}(t) - \lambda_1 u_{m1}(t))^T(v_{m1}(t) - \lambda_1 u_{m1}(t)) + \frac{1}{\lambda_1}(v_{s1}(t) - \lambda_1 u_{s1}(t))^T(v_{s1}(t) - \lambda_1 u_{s1}(t)) - \lambda_1 \dot{T}_1(t)u_{s1}^T(t)u_{s1}(t) - \frac{1}{\lambda_1} \dot{T}_2(t)v_{m1}^T(t)v_{m1}(t) \end{aligned} \quad (30)$$

$$\begin{aligned} P_2(t) &= V_{B1}(t)I_{B1}(t) - V_{B2}(t)I_{B2}(t) \\ &= \frac{2}{\lambda_2} u_{m2}^T(t)u_{m2}(t) + 2\lambda_2 v_{s2}^T(t)v_{s2}(t) - 2(u_{m2}^T(t)v_{m2}(t) + u_{s2}^T(t)v_{s2}(t)) \\ &= \frac{1}{\lambda_2}(u_{m2}^T(t)u_{m2}(t) - u_{s2}^T(t)u_{s2}(t)) + \lambda_2(v_{s2}^T(t)v_{s2}(t) - v_{m2}^T(t)v_{m2}(t)) + \lambda_2 \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right)^T \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right) + \lambda_2 \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right)^T \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right) \\ &= \frac{d}{dt} \int_{t-T_1(t)}^t \frac{1}{\lambda_2} u_{m2}^T(\eta)u_{m2}(\eta)d\eta + \frac{d}{dt} \int_{t-T_2(t)}^t \lambda_2 v_{s2}^T(\eta)v_{s2}(\eta)d\eta + \lambda_2 \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right)^T \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right) + \lambda_2 \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right)^T \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right) - \frac{1}{\lambda_2} \dot{T}_1(t)u_{s2}^T(t)u_{s2}(t) - \lambda_2 \dot{T}_2(t)v_{m2}^T(t)v_{m2}(t) \\ &= \frac{dE_2(t)}{dt} + P_2^{diss}(t) \end{aligned} \quad (31)$$

$$E_2(t) = \int_{t-T_1(t)}^t \frac{1}{\lambda_2} u_{m2}^T(\eta)u_{m2}(\eta)d\eta + \int_{t-T_2(t)}^t \lambda_2 v_{s2}^T(\eta)v_{s2}(\eta)d\eta \quad (32)$$

$$\begin{aligned} P_2^{diss}(t) &= \lambda_2 \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right)^T \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right) + \lambda_2 \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right)^T \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right) - \frac{1}{\lambda_2} \dot{T}_1(t)u_{s2}^T(t)u_{s2}(t) - \lambda_2 \dot{T}_2(t)v_{m2}^T(t)v_{m2}(t) \end{aligned} \quad (33)$$

According to (29) and (32), the net energy flows are absolutely positive to guarantee passivity of the communication network. Based on the definition of passivity and assuming $E_1(0) = E_2(0) = 0$, the energy flow is derived as:

$$\begin{aligned} E_{flow}(t) &= \int_0^t P_{4CH}(\eta)d\eta = \int_0^t (P_1^{diss}(\eta) + P_2^{diss}(\eta) + \frac{dE_1}{dt}(\eta) + \frac{dE_2}{dt}(\eta))d\eta = E_1(t) + E_2(t) - E_1(0) - E_2(0) + \int_0^t P_1^{diss}(\eta) + P_2^{diss}(\eta)d\eta \geq \int_0^t P_1^{diss}(\eta) + P_2^{diss}(\eta)d\eta \end{aligned} \quad (34)$$

Therefore, in the situation that $P_1^{diss}(t) + P_2^{diss}(t) \geq 0$, according to (34), the energy flow $E_{flow}(t)$ is no less than zero and the passivity of the time delayed network can be guaranteed. Similar with (11), $P_1^{diss}(t) + P_2^{diss}(t)$ can also be defined as the sum of master power dissipation components $P_{diss}^m(t)$ and slave power dissipation components $P_{diss}^s(t)$ based on (30) and (33).

$$P_{diss}^m(t) = \frac{1}{\lambda_1} (v_{m1}(t) - \lambda_1 u_{m1}(t))^T (v_{m1}(t) - \lambda_1 u_{m1}(t)) + \lambda_2 \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right)^T \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right) - \frac{1}{\lambda_1} \hat{T}_2(t) v_{m1}^T(t) v_{m1}(t) - \lambda_2 \hat{T}_2(t) v_{m2}^T(t) v_{m2}(t) \quad (35)$$

$$P_{diss}^s(t) = \frac{1}{\lambda_1} (v_{s1}(t) - \lambda_1 u_{s1}(t))^T (v_{s1}(t) - \lambda_1 u_{s1}(t)) + \lambda_2 \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right)^T \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right) - \lambda_1 \hat{T}_1(t) u_{s1}^T(t) u_{s1}(t) - \frac{1}{\lambda_2} \hat{T}_1(t) u_{s2}^T(t) u_{s2}(t) \quad (36)$$

According to (35) and (36), the proposed passivity observers can observe the power dissipation components in real time, as $P_{diss}^m(t)$ and $P_{diss}^s(t)$ only contain the signals observed at the master and slave ports, respectively. The proposed 4-CH wave transformation is proposed to guarantee the passivity of the communication channels in the presence of constant delays so that the $P_{diss}^m(t)$ and $P_{diss}^s(t)$ are required to be positive when $\hat{T}_1(t) = \hat{T}_2(t) = 0$. Therefore, for constant time delays, the final two terms in (35) and (36) can be treated as zero and then (35) and (36) are definitely non-negative. Therefore, the communication channels' passivity can be guaranteed by the proposed 4-CH wave transformation and the passivity controllers will not be launched to degrade the system transparency.

The value of $\hat{T}_{1,2}$ can be measured by using the time delay differential estimator in Fig.2. When this estimator is used, the integral of $u_{m1}(t)$ and $v_{s1}(t)$ should be sent outside the wave transformation. The passivity observers are designed as:

$$P_{obs}^m(t) = \frac{1}{\lambda_1} (v_{m1}(t) - \lambda_1 u_{m1}(t))^T (v_{m1}(t) - \lambda_1 u_{m1}(t)) + \lambda_2 \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right)^T \left(v_{m2}(t) - \frac{1}{\lambda_2} u_{m2}(t) \right) - \frac{\hat{T}_2}{\lambda_1} v_{m1}^T(t) v_{m1}(t) - \lambda_2 \hat{T}_2 v_{m2}^T(t) v_{m2}(t) \quad (37)$$

$$P_{obs}^s(t) = \frac{1}{\lambda_1} (v_{s1}(t) - \lambda_1 u_{s1}(t))^T (v_{s1}(t) - \lambda_1 u_{s1}(t)) + \lambda_2 \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right)^T \left(v_{s2}(t) - \frac{1}{\lambda_2} u_{s2}(t) \right) - \lambda_1 \hat{T}_1 u_{s1}^T(t) u_{s1}(t) - \frac{\hat{T}_1}{\lambda_2} u_{s2}^T(t) u_{s2}(t) \quad (38)$$

$$\hat{T}_{1,2} = \begin{cases} \hat{T}_{1,2}^{estimate}, & \text{if } \hat{T}_{1,2}^{estimate} < \bar{M}_{1,2} \\ \bar{M}_{1,2}, & \text{else, if } \hat{T}_{1,2}^{estimate} \geq \bar{M}_{1,2} \\ \bar{M}_{1,2}, & \text{else, if } u_{m1}(t - T_1(t)) = 0 \text{ or } v_{s1}(t - T_1(t)) = 0 \end{cases} \quad (39)$$

where $\bar{M}_{1,2}$ are the estimated constant upper bound that satisfy $\bar{M}_{1,2} > \hat{T}_{1,2}$.

Fig.2. Time delay differential estimator

By using the passivity observer, we design the passivity controller to be:

$$\hat{V}_s(t) = V_{A2}(t) - V_{B2}(t) - \Gamma_2(t) \quad (40)$$

$$\hat{I}_m(t) = -I_{A1} - I_{B1} - \Gamma_1(t) \quad (41)$$

where $\hat{V}_s(t)$ and $\hat{I}_m(t)$ are the output control signals from the passivity controllers on the slave and master sides, respectively. $\Gamma_1(t)$ and $\Gamma_2(t)$ are designed as (42)-(43), where $\sigma_{1,2}, \varrho$ are positive constants.

$$\Gamma_1(t) = \begin{cases} 0, & \text{if } P_{obs}^m(t) \geq 0 \\ \frac{(\alpha - \alpha_1) \bar{\mu}_2 \delta \dot{q}_s^T(t - T_2(t)) \dot{q}_s(t - T_2(t))}{2(\dot{q}_m(t) + e^{-\varrho t})} + \frac{(\gamma - \gamma_1) \bar{\mu}_2 \delta \dot{q}_s^T(t - T_2(t)) \dot{q}_s(t - T_2(t))}{2(\dot{q}_m(t) + e^{-\varrho t})} \\ + \frac{b_2 \alpha_1 \bar{\mu}_2 \delta (\dot{q}_m^T(t) \dot{q}_m(t) + \sigma_1)}{2\lambda_2(\dot{q}_m(t) + e^{-\varrho t})}, & \text{if } P_{obs}^m(t) < 0 \end{cases} \quad (42)$$

$$\Gamma_2(t) = \begin{cases} 0, & \text{if } P_{obs}^s(t) \geq 0 \\ \frac{(\alpha - \alpha_1) \bar{\mu}_1 \delta \dot{q}_m^T(t - T_1(t)) \dot{q}_m(t - T_1(t))}{2(\dot{q}_s(t) + e^{-\varrho t})} + \frac{(\gamma - \gamma_1) \bar{\mu}_1 \delta \dot{q}_m^T(t - T_1(t)) \dot{q}_m(t - T_1(t))}{2(\dot{q}_s(t) + e^{-\varrho t})} \\ + \frac{\alpha_1 \bar{\mu}_1 \sigma_2 \delta (\dot{q}_s^T(t) \dot{q}_s(t) + \sigma_2)}{2b_1 \lambda_1(\dot{q}_s(t) + e^{-\varrho t})}, & \text{if } P_{obs}^s(t) < 0 \end{cases} \quad (43)$$

4. Design and analysis of the proposed teleoperation system

Based on the external force models (5)-(6), the teleoperation dynamics can be rewritten as the following form:

$$M_m(q_m) \delta \ddot{q}_m + C_m(q_m, \dot{q}_m) \delta \dot{q}_m = \tau_m + \tau_h^*(t) - B_h \delta \dot{q}_m(t) - M_h \delta \ddot{q}_m(t) + F_m^* - f_m(X_m) \quad (44)$$

$$M_s(q_s) \delta \ddot{q}_s + C_s(q_s, \dot{q}_s) \delta \dot{q}_s = \tau_s - \tau_e^*(t) - B_e \delta \dot{q}_s(t) - M_e \delta \ddot{q}_s(t) + F_s^* - f_s(X_s) \quad (45)$$

where $X_i(t) = [\ddot{q}_i^T(t), \dot{q}_i^T(t), q_i^T(t)]^T$. $f_i(X_i)$ are defined as:

$$f_i(X_i) = F_i \dot{q}_i + f_{ci}(\dot{q}_i) + g_i(q_i) + M_i(q_i)(1 - \delta) \ddot{q}_i + C_i(q_i, \dot{q}_i)(1 - \delta) \dot{q}_i + (K_{h,e} + \Delta k_{h,e}) q_i + \Delta b_{h,e} \dot{q}_i + \Delta m_{h,e} \ddot{q}_i \quad (46)$$

According to NNs approximation property, the functions $\hat{f}_i(X_i)$ are applied in this paper to approximate $f_i(X_i)$ with

$$\hat{f}_i(X_i) = \hat{W}_i^T \Phi_i(X_i) \quad (47)$$

Fig.3. Total block diagram

where $\hat{W}_i$ are the NN adaption parameters and $\Phi_i(X_i)$ are the NN basis functions. We define

$$\tilde{f}_i(X_i) = \hat{f}_i(X_i) - f_i(X_i) = (\hat{W}_i^T - W_i^{*T})\Phi_i(X_i) = \tilde{W}_i^T \Phi_i(X_i) + \tilde{\xi}_i^*(X_i) \quad (48)$$

Due to the piecewise continuous function $f_{ci}(\dot{q}_i)$, we assume that $\tilde{\xi}_i^*(X)$ are made up of ξ_i^* and $f_{ci}(\dot{q}_i)$.

Combine the proposed wave-based TDPA control method and the NN control method, the control laws of the overall teleoperation systems are given as follows:

$$\begin{aligned} \tau_m(t) &= \hat{f}_m(X_m) + \hat{I}_m(t) - (\alpha - \alpha_1)\delta\dot{q}_m(t) - (1 - b_1\lambda_1)\beta\delta q_m(t) - (1 - b_1\lambda_1)(\gamma - \gamma_1)\delta\ddot{q}_m(t) - G_m(t) - Y_m(t) \\ &= \hat{f}_m(X_m) - I_{A1} - I_{B1} - F_1(t) - (\alpha - \alpha_1)\delta\dot{q}_m(t) - (1 - b_1\lambda_1)\beta\delta q_m(t) - (1 - b_1\lambda_1)(\gamma - \gamma_1)\delta\ddot{q}_m(t) - G_m(t) - Y_m(t) \\ &= \hat{f}_m(X_m) + \beta(\delta q_s(t - T_2(t)) - \delta q_m(t)) + (\alpha - \alpha_1)(\delta\dot{q}_s(t - T_2(t)) - \delta\dot{q}_m(t)) + (\gamma - \gamma_1)(\delta\ddot{q}_s(t - T_2(t)) - \delta\ddot{q}_m(t)) \\ &\quad - \frac{b_2\alpha_1}{\lambda_2}(\delta\dot{q}_m(t) - \delta\dot{q}_m(t - T_{l2}(t))) - b_1\lambda_1\alpha\delta\dot{q}_m(t) - F_1(t) - G_m(t) - Y_m(t) \end{aligned} \quad (49)$$

$$\begin{aligned} \tau_s(t) &= \hat{f}_s(X_s) + \hat{V}_s(t) - (\alpha - \alpha_1)\delta\dot{q}_s(t) - (1 - \frac{\lambda_2}{b_2})\beta\delta q_s(t) - (1 - \frac{\lambda_2}{b_2})(\gamma - \gamma_1)\delta\ddot{q}_s(t) - G_s(t) - Y_s(t) \\ &= \hat{f}_s(X_s) + V_{A2}(t) - V_{B2}(t) - F_2(t) - (\alpha - \alpha_1)\delta\dot{q}_s(t) - (1 - \frac{\lambda_2}{b_2})\beta\delta q_m(t) - (1 - \frac{\lambda_2}{b_2})(\gamma - \gamma_1)\delta\ddot{q}_s(t) - G_s(t) - Y_s(t) \\ &= \hat{f}_s(X_s) + \beta(\delta q_m(t - T_1(t)) - \delta q_s(t)) + (\alpha - \alpha_1)(\delta\dot{q}_m(t - T_1(t)) - \delta\dot{q}_s(t)) + (\gamma - \gamma_1)(\delta\ddot{q}_m(t - T_1(t)) - \delta\ddot{q}_s(t)) \\ &\quad - \frac{\alpha_1}{b_1\lambda_1}(\delta\dot{q}_s(t) - \delta\dot{q}_s(t - T_{l1}(t))) - \frac{\lambda_2\alpha}{b_2}\delta\dot{q}_s(t) - F_2(t) - G_s(t) - Y_s(t) \end{aligned} \quad (50)$$

$Y_i(t)$ and $G_i(t)$ are the designed adaptive control laws as:

$$Y_i(t) = \begin{cases} \frac{\delta\dot{q}_i(t)}{\|\delta\dot{q}_i(t)\|} \hat{\Theta}_i(t), & \text{if } \|\dot{q}_i(t)\| \neq 0 \\ 0, & \text{if } \|\dot{q}_i(t)\| = 0 \end{cases}, \quad \hat{\Theta}_i(t) = \|\delta\dot{q}_i(t)\| \quad (51)$$

$$\begin{cases} G_i(t) = kh_i(t) \\ \dot{h}_i(t) = -\frac{\gamma - \gamma_1}{2} \frac{\|\delta\ddot{q}_i(t)\|^2 + \|\delta\dot{q}_i(t)\|^2}{\|h_i(t)\|^2} h_i(t) + k\delta\dot{q}_i(t) \end{cases} \quad (52)$$

The adaptive control laws $Y_i(t)$ are mainly used to deal with the approximation error, external positive input and unknown disturbance. $\hat{\Theta}_i(t)$ are applied to estimate the upper bounds Θ_i the sum of NN approximate error, the bounded external disturbance F_i^* and the exogenous input $\tau_{h,e}(t)$. That is, $\Theta_i \geq \|\tilde{\xi}_i^*(X) + F_i^* \pm \tau_{h,e}\|$. In the ideal situation where $\tilde{f}_i(X_i) = 0$, the adaptive controllers can be considered as damping terms which may influence transparency. However, by setting $0 < \delta < 1$, the adverse influence can be effectively reduced. The adaptive control laws $G_i(t)$ are applied to guarantee the stability of acceleration transmission. $h_i(t)$ are the states of the auxiliary system in (58) ($h_i(t) \neq 0$). k is a positive constant. setting $k < 1$ can efficiently reduce the influence of (52) on transparency.

Based on the control laws (49)-(50), $\hat{f}_i(X_i)$ and $Y_i(t)$ are deployed to diminish the side effects of system uncertainties as well as the external disturbance and input. The two terms of $-b_1\lambda_1\alpha\delta\dot{q}_m(t)$ and $-\frac{\lambda_2\alpha}{b_2}\delta\dot{q}_s(t)$ are applied to guarantee the system's stability and the two relationships of $-\frac{b_2\alpha_1}{\lambda_2}(\delta\dot{q}_m(t) - \delta\dot{q}_m(t - T_{l1}(t)))$ and $-\frac{\alpha_1}{b_1\lambda_1}(\delta\dot{q}_s(t) - \delta\dot{q}_s(t - T_{l2}(t)))$ can strengthen tracking performance and system stability. Under small time delays, these two terms are close to zero. For large time delays, they can be treated as dampers that can enhance the system stability. Also setting small value of α_1 can efficiently reduce the value of the two terms. The remaining parts produce accurate position, velocity and acceleration signals tracking. The proposed control laws allow the operator to feel the position, velocity and acceleration information of the remote environment, thus, highly accurate torque tracking is expected to achieve. When large and sharply varying delays occur, $F_{1,2}(t)$ will be immediately launched to guarantee the whole system's stability. More details on setting control parameters will be introduced later. The total block diagram of the proposed teleoperation system is

shown in Fig.3.

Theorem 1. Consider the teleoperation system (1)-(2). If the control laws are constructed by (49) and (50), the NN adaptive laws are

$$\dot{\hat{W}}_i = \Omega_i \Phi_i(X_i) \delta \dot{q}_i \quad (53)$$

where Ω_i are the positive definite matrices. The position and velocity tracking errors will asymmetrically converge to zero in the presence of arbitrary time delays.

Proof. Consider a positive semi-definite function $V(t)$ for the system as $V(t) = V_1(t) + V_2(t) + V_3(t) + V_4(t) + V_5(t)$ where

$$V_1(t) = \frac{1}{2} \delta \dot{q}_m^T(t) M_m(q_m(t)) \delta \dot{q}_m(t) + \frac{1}{2} \delta \dot{q}_s^T(t) M_s(q_s(t)) \delta \dot{q}_s(t) + \frac{1}{2} \text{tr}(\tilde{W}_m^T \Omega_m^{-1} \tilde{W}_m) + \frac{1}{2} \text{tr}(\tilde{W}_s^T \Omega_s^{-1} \tilde{W}_s) \quad (54)$$

$$V_2(t) = \frac{\beta}{2} (\delta q_m(t) - \delta q_s(t))^T (\delta q_m(t) - \delta q_s(t)) + \frac{1}{2} (\theta_m - \hat{\theta}_m(t))^2 + \frac{1}{2} (\theta_s - \hat{\theta}_s(t))^2 + \frac{1}{2} h_m^T(t) h_m(t) + \frac{1}{2} h_s^T(t) h_s(t) \quad (55)$$

$$V_3(t) = \frac{\beta}{2} \int_{-T_1(t)}^0 \int_{t+\pi}^t \delta^2 \dot{q}_m^T(\eta) \dot{q}_m(\eta) d\eta d\pi + \frac{\beta}{2} \int_{-T_2(t)}^0 \int_{t+\pi}^t \delta^2 \dot{q}_s^T(\eta) \dot{q}_s(\eta) d\eta d\pi \quad (56)$$

$$V_4(t) = \frac{\alpha - \alpha_1}{2} \int_{t-T_1(t)}^t \delta^2 \dot{q}_m^T(\eta) \dot{q}_m(\eta) d\eta + \frac{\alpha - \alpha_1}{2} \int_{t-T_2(t)}^t \delta^2 \dot{q}_s^T(\eta) \dot{q}_s(\eta) d\eta + \frac{\gamma - \gamma_1}{2} \int_{t-T_1(t)}^t \delta^2 \ddot{q}_m^T(\eta) \ddot{q}_m(\eta) d\eta + \frac{\gamma - \gamma_1}{2} \int_{t-T_2(t)}^t \delta^2 \ddot{q}_s^T(\eta) \ddot{q}_s(\eta) d\eta + \frac{b_2 \alpha_1}{2 \lambda_2} \int_{t-T_{l2}(t)}^t \delta^2 \dot{q}_m^T(\eta) \dot{q}_m(\eta) d\eta + \frac{\alpha_1}{2 b_1 \lambda_1} \int_{t-T_{l1}(t)}^t \delta^2 \dot{q}_s^T(\eta) \dot{q}_s(\eta) d\eta \quad (57)$$

$$V_5(t) = \delta^2 \dot{q}_m^T(t) \frac{M_h / \delta + \gamma - \gamma_1}{2} \dot{q}_m(t) + \delta^2 \dot{q}_s^T(t) \frac{M_e / \delta + \gamma - \gamma_1}{2} \dot{q}_s(t) \quad (58)$$

Using property 2 in Section 2, the control laws (49) and (50), the modelled human and environmental torques (5) and (6), and the NNs adaptive laws (53), the time derivative of $V_1(t)$ can be written as:

$$\begin{aligned} \dot{V}_1(t) = & \delta \dot{q}_m^T(t) \left(\hat{f}_m(X_m) - f_m(X_m) - B_h \dot{q}_m(t) - M_h \ddot{q}_m(t) + \tau_h^*(t) + F_m^* + \beta (\delta q_s(t - T_2(t)) - \delta q_m(t)) + (\alpha - \alpha_1) (\delta \dot{q}_s(t - T_2(t)) - \delta \dot{q}_m(t)) + (\gamma - \gamma_1) (\delta \ddot{q}_s(t - T_2(t)) - \delta \ddot{q}_m(t)) - 2b_1 \lambda_1 \alpha \delta \dot{q}_m(t) - \frac{b_2 \alpha_1}{\lambda_2} (\delta \dot{q}_m(t) - \delta \dot{q}_m(t - T_{l2}(t))) - \Gamma_1(t) - \frac{\delta \dot{q}_m(t)}{\|\delta \dot{q}_m(t)\|} \hat{\theta}_m(t) - G_m(t) \right) + \\ & \delta \dot{q}_s^T(t) \left(\hat{f}_s(X_s) - f_s(X_s) - B_e \dot{q}_s(t) - M_e \ddot{q}_s(t) + F_s^* - \tau_e^*(t) + \beta (\delta q_m(t - T_1(t)) - \delta q_s(t)) + (\alpha - \alpha_1) (\delta \dot{q}_m(t - T_1(t)) - \delta \dot{q}_s(t)) + (\gamma - \gamma_1) (\delta \ddot{q}_m(t - T_1(t)) - \delta \ddot{q}_s(t)) - \frac{2\lambda_2 \alpha}{b_2} \delta \dot{q}_s(t) - \frac{\alpha_1}{b_1 \lambda_1} (\delta \dot{q}_s(t) - \delta \dot{q}_s(t - T_{l1}(t))) - \Gamma_2(t) - \frac{\delta \dot{q}_s(t)}{\|\delta \dot{q}_s(t)\|} \hat{\theta}_s(t) - G_s(t) \right) - \text{tr}(\tilde{W}_m^T \Phi_m(X_m) \delta \dot{q}_m(t)) - \text{tr}(\tilde{W}_s^T \Phi_s(X_s) \delta \dot{q}_s(t)) \end{aligned} \quad (59)$$

Also, the time derivative of $V_2(t)$ is given by

$$\begin{aligned} \dot{V}_2(t) = & \beta \delta \dot{q}_m^T(t) (\delta q_m(t) - \delta q_s(t - T_2(t))) + \beta \delta \dot{q}_s^T(t) (\delta q_s(t) - \delta q_m(t - T_1(t))) - \\ & \beta \delta \dot{q}_m^T(t) \int_{t-T_2(t)}^t \delta \dot{q}_s(\eta) d\eta - \beta \delta \dot{q}_s^T(t) \int_{t-T_1(t)}^t \dot{q}_m(\eta) d\eta + \\ & (\hat{\theta}_m(t) - \theta_m) \hat{\theta}_m(t) + (\hat{\theta}_s(t) - \theta_s) \hat{\theta}_s(t) + h_m(t) \dot{h}_m(t) + h_s(t) \dot{h}_s(t) \end{aligned} \quad (60)$$

After algebraic manipulations, time derivative of $V_3(t)$ is found to satisfy

$$\dot{V}_3(t) \leq T_1^{\max} \dot{q}_m^T(t) \frac{\beta \delta^2}{2} \dot{q}_m(t) - \frac{\beta}{2} \int_{t-T_1(t)}^t \delta^2 \dot{q}_m^T(\eta) \dot{q}_m(\eta) d\eta + T_2^{\max} \dot{q}_s^T(t) \frac{\beta \delta^2}{2} \dot{q}_s(t) - \frac{\beta}{2} \int_{t-T_2(t)}^t \delta^2 \dot{q}_s^T(\eta) \dot{q}_s(\eta) d\eta \quad (61)$$

The time derivative of $V_4(t)$ can also be written as

$$\begin{aligned} \dot{V}_4(t) = & \frac{\alpha - \alpha_1}{2} (\delta^2 \dot{q}_m^T(t) \dot{q}_m(t) - \delta^2 \dot{q}_m^T(t - T_1(t)) \dot{q}_m(t - T_1(t))) + \dot{T}_1(t) \delta^2 \dot{q}_m^T(t - T_1(t)) \dot{q}_m(t - T_1(t)) + \\ & \frac{\alpha - \alpha_1}{2} (\delta^2 \dot{q}_s^T(t) \dot{q}_s(t) - \delta^2 \dot{q}_s^T(t - T_2(t)) \dot{q}_s(t - T_2(t))) + \dot{T}_2(t) \delta^2 \dot{q}_s^T(t - T_2(t)) \dot{q}_s(t - T_2(t)) + \frac{\gamma - \gamma_1}{2} (\delta^2 \ddot{q}_m^T(t) \ddot{q}_m(t) - \delta^2 \ddot{q}_m^T(t - T_1(t)) \ddot{q}_m(t - T_1(t))) + \dot{T}_1(t) \delta^2 \ddot{q}_m^T(t - T_1(t)) \ddot{q}_m(t - T_1(t)) + \\ & \frac{\gamma - \gamma_1}{2} (\delta^2 \ddot{q}_s^T(t) \ddot{q}_s(t) - \delta^2 \ddot{q}_s^T(t - T_2(t)) \ddot{q}_s(t - T_2(t))) + \dot{T}_2(t) \delta^2 \ddot{q}_s^T(t - T_2(t)) \ddot{q}_s(t - T_2(t)) + \frac{b_2 \alpha_1}{2 \lambda_2} (\delta^2 \dot{q}_m^T(t) \dot{q}_m(t) - \delta^2 \dot{q}_m^T(t - T_{l2}(t)) \dot{q}_m(t - T_{l2}(t))) + \dot{T}_{l2}(t) \delta^2 \dot{q}_m^T(t - T_{l2}(t)) \dot{q}_m(t - T_{l2}(t)) + \\ & \frac{\alpha_1}{2 b_1 \lambda_1} (\delta^2 \dot{q}_s^T(t) \dot{q}_s(t) - \delta^2 \dot{q}_s^T(t - T_{l1}(t)) \dot{q}_s(t - T_{l1}(t))) + \dot{T}_{l1}(t) \delta^2 \dot{q}_s^T(t - T_{l1}(t)) \dot{q}_s(t - T_{l1}(t)) \end{aligned} \quad (62)$$

The differential of $V_5(t)$ is

$$\dot{V}_5(t) = \dot{q}_m^T(t) \delta M_h \ddot{q}_m(t) + \dot{q}_s^T(t) \delta M_e \ddot{q}_s(t) + \dot{q}_m^T(t) \delta^2 (\gamma - \gamma_1) \ddot{q}_m(t) + \dot{q}_s^T(t) \delta^2 (\gamma - \gamma_1) \ddot{q}_s(t) \quad (63)$$

By setting σ_{1-2} large enough to make sure

$$\dot{q}_m^T(t) \dot{q}_m(t) + \sigma_1 > \dot{q}_m^T(t - T_{l2}(t)) \dot{q}_m(t - T_{l2}(t)) \quad (64)$$

$$\dot{q}_s^T(t) \dot{q}_s(t) + \sigma_2 > \dot{q}_s^T(t - T_{l1}(t)) \dot{q}_s(t - T_{l1}(t)) \quad (65)$$

using the following inequalities from Lemma 1 in [37]

$$-2 \dot{q}_m^T(t) \int_{t-T_2(t)}^t \dot{q}_s(\eta) d\eta - \int_{t-T_2(t)}^t \dot{q}_s^T(\eta) \dot{q}_s(\eta) d\eta \leq T_2^{\max} \dot{q}_m^T(t) \dot{q}_m(t) \quad (66)$$

$$-2 \dot{q}_s^T(t) \int_{t-T_1(t)}^t \dot{q}_m(\eta) d\eta - \int_{t-T_1(t)}^t \dot{q}_m^T(\eta) \dot{q}_m(\eta) d\eta \leq T_1^{\max} \dot{q}_s^T(t) \dot{q}_s(t) \quad (67)$$

and with the adaptive laws (51)-(52), it can be derived that

$$\begin{aligned} \dot{V}(t) < & -\delta \dot{q}_m^T(t) \left(b_1 \lambda_1 \alpha - \frac{\beta}{2} (\bar{T}_1 + \bar{T}_2 + \bar{\varepsilon}_1 + \bar{\varepsilon}_2) \right) \delta \dot{q}_m(t) - \\ & \delta \dot{q}_s^T(t) \left(\frac{\lambda_2 \alpha}{b_2} - \frac{\beta}{2} (\bar{T}_1 + \bar{T}_2 + \bar{\varepsilon}_1 + \bar{\varepsilon}_2) \right) \delta \dot{q}_s(t) - \\ & \frac{\alpha - \alpha_1}{2} (\delta \dot{q}_m(t) - \delta \dot{q}_s(t - T_2(t)))^T (\delta \dot{q}_m(t) - \delta \dot{q}_s(t - T_2(t))) - \frac{\alpha - \alpha_1}{2} (\delta \dot{q}_s(t) - \delta \dot{q}_m(t - T_1(t)))^T (\delta \dot{q}_s(t) - \delta \dot{q}_m(t - T_1(t))) - \frac{\gamma - \gamma_1}{2} (\delta \dot{q}_m(t) - \delta \dot{q}_s(t - T_2(t)))^T (\delta \dot{q}_m(t) - \delta \dot{q}_s(t - T_2(t))) \end{aligned}$$

$$\begin{aligned}
& T_2(t)) \Big)^T \left(\delta \dot{q}_m(t) - \delta \ddot{q}_s(t - T_2(t)) \right) - \frac{\gamma - \gamma_1}{2} \left(\delta \dot{q}_s(t) - \right. \\
& \left. \delta \ddot{q}_m(t - T_1(t)) \right)^T \left(\delta \dot{q}_s(t) - \delta \ddot{q}_m(t - T_2(t)) \right) - \\
& \frac{b_2 \alpha_1}{2 \lambda_2} \left(\delta \dot{q}_m(t) - \delta \dot{q}_m(t - T_{l2}(t)) \right)^T \left(\delta \dot{q}_m(t) - \delta \dot{q}_m(t - \right. \\
& \left. T_{l2}(t)) \right) - \frac{\alpha_1}{2 b_1 \lambda_1} \left(\delta \dot{q}_s(t) - \delta \dot{q}_s(t - T_{l1}(t)) \right)^T \left(\delta \dot{q}_s(t) - \right. \\
& \left. \delta \ddot{q}_s(t - T_{l1}(t)) \right) + \frac{(\alpha - \alpha_1) \bar{T}_1(t) \delta^2}{2} \dot{q}_m^T(t - T_1(t)) \dot{q}_m(t - \\
& T_1(t)) + \frac{(\alpha - \alpha_1) \bar{T}_2(t) \delta^2}{2} \dot{q}_s^T(t - T_2(t)) \dot{q}_s(t - T_2(t)) + \\
& \frac{(\gamma - \gamma_1) \bar{T}_1(t) \delta^2}{2} \ddot{q}_m^T(t - T_1(t)) \ddot{q}_m(t - T_1(t)) + \frac{(\gamma - \gamma_1) \bar{T}_2(t) \delta^2}{2} \ddot{q}_s^T(t - \\
& T_2(t)) \ddot{q}_s(t - T_2(t)) + \frac{b_2 \alpha_1 \bar{T}_{l2}(t) \delta^2}{2 \lambda_2} (\dot{q}_m^T(t) \dot{q}_m(t) + \sigma_1) + \\
& \frac{\alpha_1 \bar{T}_{l1}(t) \delta^2}{2 b_1 \lambda_1} (\dot{q}_s^T(t) \dot{q}_s(t) + \sigma_2) - \delta \dot{q}_m^T(t) \Gamma_1(t) - \delta \dot{q}_s^T(t) \Gamma_2(t) - \\
& \delta \dot{q}_m^T(t) B_h \dot{q}_m(t) - \delta \dot{q}_s^T(t) B_e \dot{q}_s(t) + \delta \dot{q}_m^T(t) \left(\bar{\xi}_m^*(X) + \right. \\
& \left. \tau_h^*(t) + F_m^* - \frac{\dot{q}_m(t)}{\|\dot{q}_m(t)\|} \hat{\theta}_m(t) \right) + \delta \dot{q}_s^T(t) \left(\bar{\xi}_s^*(X) - \tau_e^*(t) + F_s^* - \right. \\
& \left. \frac{\delta \dot{q}_s(t)}{\|\delta \dot{q}_s(t)\|} \hat{\theta}_s(t) \right) + (\hat{\theta}_m(t) - \theta_m) \|\delta \dot{q}_m(t)\| + (\hat{\theta}_s(t) - \\
& \theta_s) \|\delta \dot{q}_m(t)\| \quad (68)
\end{aligned}$$

Substituting the upper bounds θ_i of $\|\bar{\xi}_i^*(X) + F_i^* \pm \tau_{h,e}^*\|$ into (68), the final four terms in (68) can be removed. The Lyapunov approach requires $\dot{V}(t)$ to be negative semi-definite. In the presence of constant time delays, $\bar{T}_{1,2}(t)$ and $\bar{\varepsilon}_{1,2}$ are zero. Also, the passivity controllers do not take effect so that $\Gamma_1(t)$ and $\Gamma_2(t)$ are zero. $-\frac{b_2 \alpha_1}{2 \lambda_2} \left(\delta \dot{q}_m(t) - \delta \dot{q}_m(t - T_{l2}(t)) \right)^T \left(\delta \dot{q}_m(t) - \delta \dot{q}_m(t - T_{l2}(t)) \right)$ and $-\frac{\alpha_1}{2 b_1 \lambda_1} \left(\delta \dot{q}_s(t) - \delta \ddot{q}_s(t - T_{l1}(t)) \right)^T \left(\delta \dot{q}_s(t) - \delta \ddot{q}_s(t - T_{l1}(t)) \right)$ can be seen as $-\frac{b_2 \alpha_1}{2 \lambda_2} \zeta_a \delta^2 \dot{q}_m^T(t) \dot{q}_m(t)$ and $-\frac{\alpha_1}{2 b_1 \lambda_1} \zeta_b \delta^2 \dot{q}_s^T(t) \dot{q}_s(t)$ with $\zeta_{a,b} \geq 0$. Under small time delays, $\zeta_{a,b} \rightarrow 0$. $\dot{V}(t)$ can be guaranteed to be negative semi-definite by properly tuning $b_{1,2}$, $\lambda_{1,2}$, α , α_1 and β to make sure

$$b_1 \lambda_1 \alpha + \frac{b_2 \alpha_1}{2 \lambda_2} \zeta_a \geq \frac{\beta}{2} (\bar{T}_1 + \bar{T}_2) \quad (69)$$

$$\frac{\lambda_2 \alpha}{b_2} + \frac{\alpha_1}{2 b_1 \lambda_1} \zeta_b \geq \frac{\beta}{2} (\bar{T}_1 + \bar{T}_2) \quad (70)$$

When the time delay is varying, the passivity controllers are launched by the passivity observers, substituting (42)-(43) in to (68), the biased terms $\frac{(\alpha - \alpha_1) \bar{T}_1(t) \delta^2}{2} \dot{q}_m^T(t - T_1(t)) \dot{q}_m(t - T_1(t)) + \frac{(\alpha - \alpha_1) \bar{T}_2(t) \delta^2}{2} \dot{q}_s^T(t - T_2(t)) \dot{q}_s(t - T_2(t)) + \frac{(\gamma - \gamma_1) \bar{T}_1(t) \delta^2}{2} \ddot{q}_m^T(t - T_1(t)) \ddot{q}_m(t - T_1(t)) + \frac{(\gamma - \gamma_1) \bar{T}_2(t) \delta^2}{2} \ddot{q}_s^T(t - T_2(t)) \ddot{q}_s(t - T_2(t)) + \frac{b_2 \alpha_1 \bar{T}_{l2}(t) \delta^2}{2 \lambda_2} (\dot{q}_m^T(t) \dot{q}_m(t) + \sigma_1) + \frac{\alpha_1 \bar{T}_{l1}(t) \delta^2}{2 b_1 \lambda_1} (\dot{q}_s^T(t) \dot{q}_s(t) + \sigma_2)$ caused by the time varying delays in (68) are directly compensated by $-\delta \dot{q}_m^T(t) \Gamma_1(t) - \delta \dot{q}_s^T(t) \Gamma_2(t)$. No extra parameters need to be tuned when the time delays vary and $\dot{V}(t)$ is still negative semi-definite. Integrating both sides of (68), we get:

$$+\infty > V(0) \geq V(t) > \int_0^t \left(\frac{\alpha - \alpha_1}{2} \left(\delta \dot{q}_m(t) - \delta \dot{q}_s(t) - \right. \right.$$

$$\begin{aligned}
& T_2(t)) \Big)^T \left(\delta \dot{q}_m(t) - \delta \dot{q}_s(t - T_2(t)) \right) + \frac{\alpha - \alpha_1}{2} \left(\delta \dot{q}_s(t) - \right. \\
& \left. \delta \dot{q}_m(t - T_1(t)) \right)^T \left(\delta \dot{q}_s(t) - \delta \dot{q}_m(t - T_2(t)) \right) + \\
& \frac{\gamma - \gamma_1}{2} \left(\delta \dot{q}_m(t) - \delta \ddot{q}_s(t - T_2(t)) \right)^T \left(\delta \dot{q}_m(t) - \delta \ddot{q}_s(t - \right. \\
& \left. T_2(t)) \right) + \frac{\gamma - \gamma_1}{2} \left(\delta \dot{q}_s(t) - \delta \ddot{q}_m(t - T_1(t)) \right)^T \left(\delta \dot{q}_s(t) - \right. \\
& \left. \delta \ddot{q}_m(t - T_2(t)) \right) + \frac{b_2 \alpha_1}{2 \lambda_2} \left(\delta \dot{q}_m(t) - \delta \dot{q}_m(t - \right. \\
& \left. T_{l2}(t)) \right)^T \left(\delta \dot{q}_m(t) - \delta \dot{q}_m(t - T_{l2}(t)) \right) + \frac{\alpha_1}{2 b_1 \lambda_1} \left(\delta \dot{q}_s(t) - \right. \\
& \left. \delta \dot{q}_s(t - T_{l1}(t)) \right)^T \left(\delta \dot{q}_s(t) - \delta \dot{q}_s(t - T_{l1}(t)) \right) + \\
& \delta \dot{q}_m^T(t) B_h \dot{q}_m(t) + \delta \dot{q}_s^T(t) B_e \dot{q}_s(t) \Big) dt \quad (71)
\end{aligned}$$

Therefore, from $V(t) \geq 0$ and $\dot{V}(t) \leq 0$, it is true that $\tilde{W}_m$ and $\tilde{W}_s \in L_\infty$, $\dot{q}_m(t)$ and $\dot{q}_s(t) \in L_2$. $\left(\dot{q}_m(t) - \dot{q}_s(t - T_2(t)) \right)$, $\left(\dot{q}_s(t) - \dot{q}_m(t - T_2(t)) \right)$, $\left(\delta \dot{q}_m(t) - \delta \dot{q}_s(t - T_2(t)) \right)$, $\left(\delta \dot{q}_s(t) - \delta \dot{q}_m(t - T_2(t)) \right)$, $\left(\dot{q}_m(t) - \dot{q}_m(t - T_{l2}(t)) \right)$, $\left(\dot{q}_s(t) - \dot{q}_s(t - T_{l1}(t)) \right) \in L_2$. Using the fact that $q_m(t) - q_s(t - T_2(t)) = q_m(t) - q_s(t) + \int_{t-T_2(t)}^t \dot{q}_s(t) dt$, $q_s(t) - q_m(t - T_1(t)) = q_s(t) - q_m(t) + \int_{t-T_1(t)}^t \dot{q}_1(t) dt$ and using Cauchy-Schwarz inequality $\int_{t-T_2(t)}^t \dot{q}_s(t) dt \leq \sqrt{T_2(t)} \dot{q}_s(t)$ and $\int_{t-T_1(t)}^t \dot{q}_m(t) dt \leq \sqrt{T_1(t)} \dot{q}_m(t)$, we can get $q_m(t) - q_s(t - T_2(t))$, $q_s(t) - q_m(t - T_1(t)) \in L_\infty$.

The system's dynamic model can also be written as:

$$\delta \ddot{q}_i = M_i^{-1}(q_i) [\tau_i \pm \tau_{h,e}^*(t) - B_{h,e} \dot{q}_i(t) - M_{h,e} \ddot{q}_i(t) + F_i^* - f_i(X_i) - C_i(q_i, \dot{q}_i) \delta \dot{q}_i] \quad (72)$$

Differentiating both sides of (72):

$$\begin{aligned}
\frac{d}{dt} \delta \ddot{q}_i &= \frac{d}{dt} \left(M_i^{-1}(q_i) \right) [\tau_i \pm \tau_{h,e}^*(t) - B_{h,e} \dot{q}_i(t) - M_{h,e} \ddot{q}_i(t) + \\
& F_i^* - f_i(X_i) - C_i(q_i, \dot{q}_i) \delta \dot{q}_i] + M_i^{-1}(q_i) \frac{d}{dt} [\tau_i \pm \tau_{h,e}^*(t) - \\
& B_{h,e} \dot{q}_i(t) - M_{h,e} \ddot{q}_i(t) + F_i^* - f_i(X_i) - C_i(q_i, \dot{q}_i) \delta \dot{q}_i] \quad (73)
\end{aligned}$$

For the first term of the right side of (73), we have

$$\frac{d}{dt} (M_i^{-1}) = -M_i^{-1} \dot{M}_i M_i^{-1} = -M_i^{-1} (C_i + C_i^T) M_i^{-1} \quad (74)$$

According to Properties 1 and 3, $\frac{d}{dt} (M_i^{-1})$ is bounded. Based on Property 4, the terms in bracket of (74) are also bounded. Therefore, $\frac{d}{dt} \ddot{q}_i(t) \in L_\infty$ and $\ddot{q}_i(t)$ are uniformly continuous ($\int_0^t \ddot{q}_i(\eta) d\eta = \dot{q}_i(t) - \dot{q}_i(0)$). Since $\dot{q}_i(t) \rightarrow 0$, it can be concluded that $\ddot{q}_i(t) \rightarrow 0$ based on Barbalat's Lemma.

5. Experimental work

The teleoperation system used to validate the proposed algorithm consists of two 3-DOF Phantom manipulators: Phantom Omni and Phantom Desktop (Sensible Technologies, Inc., Wilmington, MA) as shown in Fig.3. The two haptic device are connected by two computers that are directly connected via a network cable and network cards. The Matlab software is applied to establish the proposed control system. To further enlarge and tune the value of the time delays, Simulink time delay blocks are also applied. During the experimental process, the control loop is configured

as a 1 kHz sampling rate. The general control parameters are configured as: $b_1 = b_2 = 2$, $\alpha = [15, 15, 15]^T$, $\beta = [15, 15, 15]^T$, $\alpha_1 = [2.5, 2.5, 2.5]^T$, $\gamma = [60, 60, 60]^T$, $\gamma_1 = [10, 10, 10]^T$, $\delta = 0.2$, $\Omega_s = \Omega_m = [25, 25, 25]^T$, $\sigma_1 = \sigma_2 = 0.25$, $\varrho = 4$, $k = 0.1$. We set the number of the neuron $\kappa = 7$. The center of the RBF is set as $C = 0.5 \times \text{ones}(9, 7)$ and the width of the RBF is set as $H = 0.1 \times \text{ones}(7, 1)$. The parameters relating to the time delays will be introduced in each experiment.

Fig.4. Experimental setup

5.1. Innovative passivity observers

The experiments conducted clearly demonstrate the novelty and contribution of the proposed passivity observers. The proposed system is compared with a TDPA-based system in [35]. The time delays are constant and T_1 is 200 ms, T_2 is 100 ms. According to (69) and (70), we set $\lambda_1 = 0.075$, $\lambda_2 = 0.3$, $\bar{\mu}_1 = \bar{\mu}_2 = \bar{\varepsilon}_1 = \bar{\varepsilon}_2 = 0$. In the system in [35], the slave PD controllers are chosen

as $K_p = 10$ and $K_d = 5$, and b in the passivity observers is set to 2.5.

Fig.5 shows the position tracking, torque tracking and observed power of the two systems during free motion. Even under small constant time delays whilst the rate of the time delays are zero, based on (16), the power observed in the master side is still non-positive so that the passivity controllers are still launched to reduce tracking performance. The launched passivity controllers regrade the position tracking and make the system over-damped so that the human operator can feel large feedback forces during free motion. As shown in Fig.5, the slave cannot quickly and closely track the master in the presence of such small delays in the system in [35]. Unlike [35], the power signals observed on the master and the slave sides of the proposed system are positive owing to the designed wave-based passivity observer, and the passivity controllers are not launched. Therefore, the slave can closely track the master and the human operator can hardly feel the feedback force.

On the other hand, Fig.6 displays the position tracking, torque tracking, and observed power signals of the two systems during hard contact. Based on (17), the power observed on the slave side in the system in [35] is definitely non-positive. Therefore, large torque tracking errors are caused by the passivity controllers. By contrast, the power signals observed in the proposed system are non-negative resulting in accurate torque tracking during hard contact. From these two diagrams, it can be observed that the proposed wave-based passivity observers makes the proposed system less conservative compared the conventional power-based systems and guarantees the system high tracking performance in the presence of constant time delays.

Fig.5. Free motion under constant time delays (Comparison between [35] and our system)

Fig.6. Hard contact under constant time delays (Comparison between [35] and our system)

Fig.7. Contact to a reverse wall under slowly varying delays (wave-based system in [11])

Fig.8. Contact to a reverse wall under slowly varying delays (our system)

5.2. Eliminating wave reflection

In this experiment, the proposed system is compared against the wave-based system proposed in [11] in order to show its effectiveness in eliminating wave reflection. Figs.7 and 8 show the position and torque tracking and their relating tracking errors when the slave is in contact with a reverse wall. The time delay in this experiment is around 900 ms with 100 variations, and its rate is around 0.2. According to (69) and (70), we set $\lambda_1 = 0.45$, $\lambda_2 = 1.8$, $\bar{\mu}_1 = \bar{\mu}_2 = 0.2$, $\bar{\varepsilon}_1 = \bar{\varepsilon}_2 = 0.2$. The wave-based system in [11] uses a traditional wave transformation with impedance matching to encode the velocity and position signals. Based on recommended values, we set $K_m = K_s = b = 4$. The extra energy caused by time-varying delays in their system is eliminated by applying the scaling gain $\sqrt{1 - \bar{\mu}_{1,2}}$.

At first, the slave robots in both systems are in free motion and both have accurate position tracking. Then the slave robots come in contacts with the reverse wall, in which both systems achieve accurate torque tracking. Therefore, it can be stated that both systems have good steady state performance. After about 2 seconds, the wall is suddenly removed, causing a sudden change in the environment. As a result, the impedances-matching approach of the system in [11] fails to work at the transient state to the extent that the wave-reflections are restored causing large perturbations that adversely affect the position and torque tracking performances of the system in [11] as shown in Fig.7. By contrast, based on the designed wave variables in (20)-(23), the outgoing signals do not contain necessary signals and the wave reflections are eliminated. Therefore, the proposed system has better performance on the transient state and the position error directly returned to zero after removing the wall as shown in Fig.8.

5.3. Performance in the presence of time-varying delays

In this subsection, we compare our system against classic PD+d system proposed in [10] in order to show its unique performance in dealing with the time-varying delays. The time delays in this experiment are approximately 1 s with 500 ms variations, and the rate is around 0.5. We set $\lambda_1 = 0.5$, $\lambda_2 = 2$, $\bar{\mu}_1 = \bar{\mu}_2 = 0.5$, $\bar{\varepsilon}_1 = \bar{\varepsilon}_2 = 0.5$. In order to guarantee stability, the parameters in the system in [10] are required to satisfy $4B_r B_l > (T_1^{max^2} + T_2^{max^2})K_l K_r$, $B_r \geq B_l$ and $K_r \geq K_l$. Therefore, we set the differential gain $K_d = 3$, and the proportional gains $K_r = K_l = 3$. Hence, $B_r = B_l = 3.5$. The PD+d system in [10] also uses the scaling gain $\sqrt{1 - \bar{\mu}_{1,2}}$ for velocity transmission. It is noticeable that when $\bar{\mu}_{1,2} \geq 1$, this approach is too conservative and velocities cannot be transmitted. Figs. 9 and 10 demonstrate position tracking, position errors and torque tracking of the two systems. The key element in a PD+d system is the velocity damper that can guarantee the system's stability but, instead, degrade the system's transparency.

As shown in Fig.9, with large time delays, the velocity damper B_r and B_l in the system in [10] have to be set large enough to guarantee stability, and $\sqrt{1 - \bar{\mu}_{1,2}}$ also affect the velocity transmission to the extent that the position tracking is affected and large position errors occur. Also, the operator feels the system over-damped and achieves large feedback forces even under free motion.

By contrast, passivity controllers in our system vary based on the observed power signals at each port. Based on Fig.10, the observed power signals are not definitely negative, so that the passivity controllers keep varying between activation and deactivation modes. Therefore, the proposed system is not as conservative as the classical PD+d system in [10] and can achieve more accurate position tracking performance under large time-varying delays. In addition, since the proposed system is not over-damped, the feedback force felt by the operator is not as large as that in the system in [10].

5.4. Performance in the presence of fast-varying delays

The novelty of the proposed system is also reflected by its ability to deal with fast-varying delays. In this section, we compare the new system with the performance of a system we developed previously [36]. The time delays for the experiment of are set to be very large (around 2s with 1s variations) and with a large rate (around 1.5). We set $\lambda_1 = 1$, $\lambda_2 = 4$, $\bar{\mu}_1 = \bar{\mu}_2 = 1.5$, $\bar{\varepsilon}_1 = \bar{\varepsilon}_2 = 1$. The slave robots in these two systems are controlled to have a free motion first and then to come in contact with a solid wall in the reverse direction. Figs.11 and 12 show the position and torque tracking as well as the related tracking errors of the two systems. The previous system [36] primarily has two deficiencies. First, the parameters of this system are seriously restricted by the assumption that $\dot{T}_{1,2}(t) \leq 1$. If $\dot{T}_{1,2}(t) > 1$, and the stability of the whole system cannot be guaranteed. The time delay for system in [36] is set to 2s with 1s variation but at

a rate of 0.9. The related parameters are set as recommended in [36]. The second drawback of system in [36] is how it guarantees system stability by largely reducing the position and torque signals. As shown in Fig.11, the slave robot cannot closely and rapidly track the master robot during free motion, and large torque tracking errors exist during hard contact with the environment.

In contrast, the passivity controllers in the new system are actually velocity dampers with the value varying according to the observed powers. Therefore, according to Fig.12, even with the higher rate of time delays, the position tracking in free motion and torque tracking in hard contact are still better than those of the system in [36]. The experimental results illustrate that our new system is more suited to practical application than the system proposed in [36] for the worst-case scenario

Fig.9. Free motion under time varying delays (PD+d system in [10])

Fig.10. Free motion under time varying delays (our system)

Fig.11. Free motion and hard contact under sharply-varying delays (system in [36])

Fig.12. Free motion and hard contact under sharply-varying delays (our system)

6. Conclusion

A new 4-CH wave-based TDPA teleoperation system with new passivity observers and controllers was proposed in this paper. RBF NN was also deployed to eliminate the nonlinear uncertainties in the dynamic models. Compared with conventional observer, the new observer can more efficiently and accurately monitor the power flow to guarantee that the system is not affected by the passivity controllers under constant time delays. Also, unlike the conventional passivity controllers, the new passivity controllers guarantee the system stability by

damping velocity but not reducing position and torque signals. Therefore in the worst case scenario where the rate of time delay is larger than one, the proposed system can still have fine position and torque tracking performances. The system stability with external human and environment inputs was also analyzed using Lyapunov functions. The proposed algorithm was validated using a 3-DOF teleoperation system under different time delay situations, and was shown to be superior over previous algorithm we proposed reported earlier.

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