

# Adaptive Type-2 Fuzzy Neural-Network Control for Teleoperation Systems With Delay and Uncertainties

Parham Mohsenzadeh Kebria<sup>1</sup>, Student Member, IEEE, Abbas Khosravi<sup>2</sup>, Member, IEEE, Saeid Nahavandi<sup>3</sup>, Senior Member, IEEE, Dongrui Wu<sup>4</sup>, Senior Member, IEEE, and Fernando Bello<sup>5</sup>

**Abstract**—Interacting with human operators, remote environment, and communication networks, teleoperation systems are considerably suffering from complexities and uncertainties. Managing these is of paramount importance for safe and smooth performance of teleoperation systems. Among the countless solutions developed by researchers, type-2 fuzzy (T2F) algorithms have shown an outstanding performance in modeling complex systems and tackling uncertainties. Moreover, artificial neural networks (NNs) are well known for their adaptive learning potentials. This article proposes an adaptive interval type-2 fuzzy neural-network control scheme for teleoperation systems with time-varying delays and uncertainties. The T2F models are developed based on the experimental data collected from a teleoperation setup over a local computer network. However, the resulted controller is evaluated on an intercontinental communication network through the Internet between Australia and Scotland. Moreover, the slave robot and the remote workspace are completely different and unforeseen. Stability and performance of the proposed control is analyzed by Lyapunov–Krasovskii method. Comprehensive comparative studies demonstrate that the proposed controller outperforms traditional techniques in experimental evaluations.

**Index Terms**—Adaptive control, neural network (NN), time delay, teleoperation systems, type-2 fuzzy (T2F) models, uncertainties.

## I. INTRODUCTION

TELEOPERATION systems have provided the humankind with a variety of great applications, especially in space explorations and medicine [1]–[5]. Involving various complex technologies, teleoperation systems severely suffer from uncertainties and nonlinearities [6]. Particularly, uncertainties in communication networks, human operators' and robots' dynamics, and remote environment are the major concerns in teleoperation applications. Therefore, controller design for such systems has

become a problematic task that a large amount of research has been committed to address these issues [7]. Among the proposed solutions for control of teleoperation systems, control methods based on computational intelligence have outperformed the traditional methodologies, in terms of dealing with complexities and uncertainties [8].

Introduced by Lotfi Zadeh [9]–[12], fuzzy computation approaches have undoubtedly shown a strong capability in the modeling of complex systems. Based on their universal approximations, fuzzy models are extremely useful in controller design for complex and nonlinear systems [13]–[22], decision making and forecasting [23]–[26], and disturbance rejection [27]–[30]. Basically, fuzzy models describe a considered system's dynamical behavior as a composition of several IF–THEN rules. Among the fuzzy modeling approaches, Takagi–Sugeno (T–S) [27] and Mamdani [31] are the most popular methods. Traditional fuzzy models, also known as type-1, assign crisp fuzzy membership functions on their variables [32]. Consequently, the system's model and performance of the controller designed based on this model will be vulnerable and sensitive to uncertainties [33]. In contrast, type-2 fuzzy (T2F) methodologies [34]–[36] have demonstrated a promising effectiveness in dealing with uncertainties [37]–[41]. T2F models may have type-2 membership functions for either antecedents or consequents [38], [39], [42].

In the field of teleoperation systems, researchers have proposed a two-layer fuzzy strategy on a remote mobile robot to tackle the communications failures [43]. In this approach, outputs of each fuzzy rule are input of the immediately next rule and are called the intermediate fuzzy variables. Hence, the resulted fuzzy controller has a network structure with a robust performance [44]. Reference [45] has considered a multirobot teleoperation system and proposed an adaptive fuzzy control strategy to compensate for the communication delay modeled by Markov process. They have considered the master and slave robots dynamically decoupled, which reduces the applicability of the proposed control algorithm. Combining with traditional sliding-mode control approaches, [46] has proposed a finite-time fuzzy controller for a teleoperation system, however, under constant time delay. T–S fuzzy controller proposed in [47] is based on the systems' parameters, and therefore, does not cope with model uncertainties. Researchers in [48] have developed an adaptive fuzzy solution, in which a switching algorithm is proposed for delay considerations. However, no uncertainty is taken into account and the resulted control torque signals are chattering, which degrades the practicality. The state convergent

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P. M. Kebria, A. Khosravi, and S. Nahavandi are with the Institute for Intelligent Systems Research and Innovations, Deakin University, Waurn Ponds, VIC 3216, Australia (e-mail: kebria@deakin.edu.au; abbas.khosravi@deakin.edu.au; saeid.nahavandi@deakin.edu.au).

D. Wu is with the Key Laboratory of the Ministry of Education for Image Processing and Intelligent Control, School of Automation, Huazhong University of Science and Technology, Wuhan 430074, China (e-mail: drwu@hust.edu.cn).

F. Bello is with the Centre for Engagement and Simulation Science, Imperial College London, SW7 2AZ London, U.K., and also with Chelsea and Westminster Hospital (Academic Surgery), SW10 9NH London, U.K. (e-mail: f.bello@imperial.ac.uk).

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fuzzy controller in [49] is designed based on the linear model of the teleoperation system and constant time delay. Although the fuzzy controller proposed in [50] and [51] have reduced the chattering in torque signals, it is applicable only for constant delays and no uncertainty is considered. Lu *et al.*[52] has recently proposed a fuzzy observer-based control for teleoperation systems with time delay.

Meanwhile, control solutions developed based on T2F models are more reliable and effective. For example, [53] has proposed a T2F controller combined with a wavelet neural-network (NN). However, they have considered T2F membership functions only for the antecedents, but crisp functions for the consequents, which decreases the robustness of the controller when facing uncertainties and time delays. Researchers in [54] proposed a controller based on a data-driven T2F model of a teleoperation system to deal with time delay and uncertainties. They have also applied Markov technique to model the network delay. Although closed-loop stability of the proposed control is proved by Lyapunov–Krasovskii and linear matrix inequality, its performance and error convergence depends on the systems' parameters and time derivatives of the delay functions, which are not necessarily available. A similar methodology has also been applied in [55]. Moreover, the experimental evaluation carried out in [53] and [54] was on two simple and similar devices. However, in real-world applications, the master and slave robots are generally dissimilar with completely different workspace and dynamics. This dissimilarity introduces additional uncertainties to teleoperation systems, and complicates the control design for each robot. Additionally, they have not considered human operator's and environment's dynamics that involve many uncertainties in the teleoperation dynamic analyses and performance [56]–[58].

On the other side, learning capabilities of NNs further empowers type-2 fuzzy neural network (T2FNN) based controllers to adaptively deal with external disturbances and internal uncertainties [59]–[67]. Many research studies have validated the functionality of adaptive NN-based control algorithms in complex real-world applications, including teleoperation systems [68]–[71]. Unknown remote workspace and communication characteristics are treated as the main sources of uncertainties in teleoperation systems. Hence, an adaptive control strategy with the ability of learning unknown dynamics, and also, dealing with uncertainties is required to protect the stability and performance of a teleoperation system. Therefore, investigation for an effective controller ensuring a teleoperation performance while confronting uncertainties and latencies is the main motivation for the current article. Considering difficulties encountered in teleoperation systems, this article aims to develop an efficient control solution applicable to real-world applications.

This article proposes a control methodology for teleoperation systems that not only accomplishes the desired task in the remote workspace, it also prevents instability and failures. The proposed controller takes the advantages of T2F techniques to deal with time-varying delays and uncertainties. Moreover, an NN-based online adaptation algorithm is developed to simultaneously tune the T2F models. Chiefly, main contributions of this article are as follows.

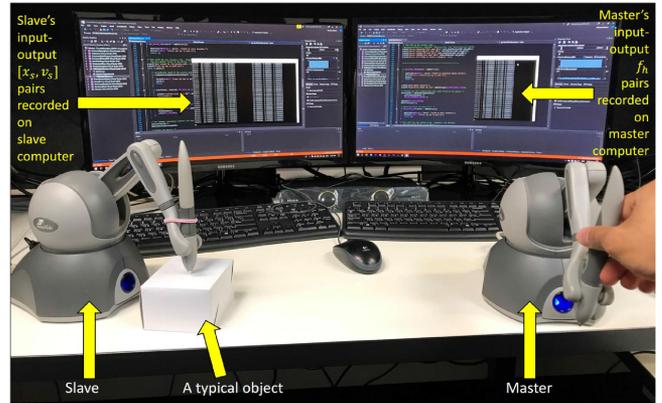


Fig. 1. Teleoperation setup with two Phantom Omni Haptic devices used for data collection. It should be mentioned that the sampling time of the whole experiment, including data collection and control implementation is 0.001 s (1 kHz). A very similar setup has been used in [54] for both modeling and evaluations. In this article, experimental evaluations are implemented and executed on a different and more complicated setup with a real-intercontinental communication (see Fig. 7).

- 1) Interval type-2 fuzzy (IT2F) modeling for Internet-based teleoperation systems. A real-world experimental teleoperation system has been considered for data collection. The collected data are then used for derivation of T2F models for increasing the fuzziness in antecedents and consequents. This way enables the controller to handle further uncertainties.
- 2) It is worth to mention that this study considers two different teleoperation configurations for each data collection and validation purposes. The main reason for this consideration is two folded: first, for an efficient way for collecting experimental data and second, validation of the proposed controller in a more realistic application that involves an intercontinental Internet communication and unforeseen workspace. This incurs uncertainties and time-delays that a real-world teleoperation experiences. Furthermore, the results demonstrate the effectiveness and practicality of the proposed control in real-world applications.
- 3) The considered teleoperation system for experimental data collection consists of two Phantom Omni Haptic devices on two different desktop computers connected through a local area network, Fig. 1. Notably, this teleoperation setup is only used in the data collection phase for T2F modeling purposes. But the proposed control algorithm is then evaluated on a different teleoperation configuration. Slave robot of the target teleoperation system is a virtual dynamic model of the UR5 manipulator. The slave system is located in Scotland receiving commands from the master system in Australia (see Fig.7). The master system communicates over a 4G mobile network, while the slave system is connected to the cable Internet.
- 4) The proposed controller is empowered by an adaptive NN that concurrently updates the parameters of the T2F model. To not getting stuck in local optima, the online adaptation

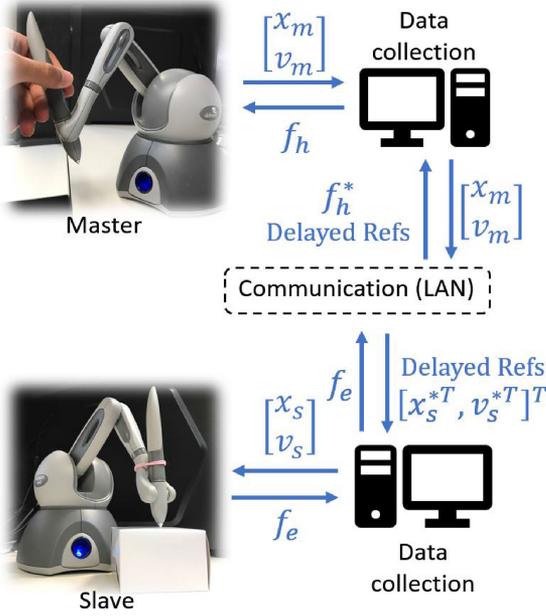


Fig. 2. Considered teleoperation configuration for data collection.

laws are derived by Lyapunov–Krasovskii approach. This also justifies the performance of the proposed T2FNN controller under time-varying delays and uncertainties.

Furthermore, to illustrate the superiority of the proposed control solution over the previous similar studies, experimental evaluations are also executed and compared with the control algorithms developed in [53] and [54].

The rest of this article is organized as follows. Section II describes the T2F modeling process of the Internet-based teleoperation system. Section III explains the derivation of the proposed adaptive T2FNN control algorithm for the teleoperation system. Performance of the proposed control methodology is experimentally evaluated in Section IV. Section V concludes this article.

## II. T2F MODELING OF INTERNET-BASED TELEOPERATION SYSTEMS

Dynamics of a master/slave robotic teleoperation system has the following general form (see Fig. 2).

$$\begin{aligned} M_i(q_i)\ddot{q}_i + C_i(q_i, \dot{q}_i) + g_i(q_i) + \mu_i(\dot{q}_i, q_i) \\ = t\tau_i + J_i^T(q_i)(f_j) + \sigma_j(t) \end{aligned} \quad (1)$$

where  $i \in \{m, s\}$  indicates the master and slave systems, respectively.  $j \in \{h, e\}$  refers to the human operator and remote environment.  $q_i \in \mathbb{R}^n$ ,  $\dot{q}_i$ , and  $\ddot{q}_i$  denote the joints' angular position, velocity, and acceleration of the corresponding robot, respectively.  $M_i \in \mathbb{R}^{n \times n}$  is the inertia matrix,  $C_i \in \mathbb{R}^{n \times n}$  the coriolis and centripetal terms, and  $g_i \in \mathbb{R}^n$  the gravitational vector of the corresponding robot, respectively.  $\mu_i \in \mathbb{R}^n$  stands for the unknown viscous and Coulomb friction vector.  $\tau_i \in \mathbb{R}^n$  is the input torques of the robots.  $f_j \in \mathbb{R}^6$  is the force imposed by either the human operator or remote environment.  $\sigma_j \in \mathbb{R}^n$

is the external disturbances. Noticeably,  $n \in \mathbb{N}$  indicates the corresponding robot's degree of freedom.  $J_i$  is the Jacobian matrix of the robots that relates the Cartesian and joint space variables of each robot [72], [73]. Jacobian calculations are one of the major uncertain and challenging concerns in robots' dynamic modeling. Moreover, dissimilarity between the master and slave robots introduces further difficulties [74]. However, in [54], the master and slave robots are identical. In this article, we considered the similar teleoperation setup as [54] for data collection (see Fig. 1). But the outcome will be evaluated on a more realistic teleoperation configuration (see Fig. 7). Moreover, the human operator and remote workspace are generally modeled as nonhomogeneous mass-spring-damper forces [56]

$$f_j = f_{j0} + M_j\ddot{x}_i + B_j\dot{x}_i + K_jx_i \quad (2)$$

in which,  $j = h$  when  $i = m$ , and  $j = e$  when  $i = s$ .  $f_{j0} \in \mathbb{R}^6$  is the nonhomogeneous term, and  $M_j$ ,  $B_j$ , and  $K_j$  are inertia, damping, and stiffness coefficient matrices, respectively. It should be mentioned that all the matrices, vectors, and coefficients in (1) and (2) are unknown and uncertain. Moreover,  $x_i = p_i(q_i)$ ,  $p_i(\cdot) : \mathbb{R}^n \rightarrow \mathbb{R}^6$ ,  $\dot{x}_i = J_i(q_i)\dot{q}_i$ , and  $\ddot{x}_i = \dot{J}_i(q_i)\dot{q}_i + J_i(q_i)\ddot{q}_i$  are the Cartesian position ( $p_i(q_i)$  is forward kinematics), velocity, and acceleration of each robot in its workspace, respectively. More details of the totally uncertain dynamics of the teleoperation system (1) coupled with (2) is found in [56]. Here, the coupled dynamics of (1) and (2) for each sides of the teleoperation system is being expressed as follows:

$$\mathcal{M}_i\ddot{x}_i + \mathcal{C}_i(x_i, \dot{x}_i) + \mathcal{G}_i(x_i) = \tau_i + f_j + \sigma_j(t) \quad (3)$$

in which

$$\begin{aligned} \mathcal{M}_i &= M_i J_i^\dagger - J_i^T M_j \\ \mathcal{C}_i(x_i, \dot{x}_i) &= C_i + \mu_i - (M_i J_i^\dagger \dot{J}_i J_i^\dagger + J_i^T B_j)\dot{x}_i \\ \mathcal{G}_i(x_i) &= g_i - J_i^T K_j x_i \\ f_j &= J_i^T f_j \\ J_i^\dagger &= (J_i^T J_i)^{-1} J_i^T y. \end{aligned} \quad (4)$$

It should be noted that all the matrices and coefficients above are uncertain and partially unknown. However, due to physical limitations and structures, there are upper and lower bounds for every unknown parameter considered as uncertainty intervals, including  $[\underline{M}_i, \overline{M}_i]$ ,  $[\underline{C}_i, \overline{C}_i]$ ,  $[\underline{G}_i, \overline{G}_i]$ , and  $[\underline{\sigma}_j, \overline{\sigma}_j]$ .

In most of the real-world teleoperation applications, the slave robot is desired to track the master's position ( $x_m$ ) and velocity ( $v_m$ ), and the master device should reflect the force imposed on the slave robot while interacting with the remote environment ( $f_e$ ). To this end, the required Cartesian and haptic information are being transmitted through the communication channel during the teleoperation process. Consequently, latencies and uncertainties induced by the communication network will delay the transmission procedure. In other words, desired signals  $x_s^*$ ,

$\mathbf{v}_s^*$ , and  $\mathbf{f}_h^*$  are considered as follows:

$$\begin{aligned}\mathbf{x}_s^*(t) &= \mathbf{x}_m(t - d_f(t)) \\ \mathbf{v}_s^*(t) &= \mathbf{v}_m(t - d_f(t)) \\ \mathbf{f}_h^*(t) &= \mathbf{f}_e(t - d_b(t))\end{aligned}$$

where,  $d_f(t)$  and  $d_b(t)$  are time-varying delays through the forward and backward communication channels, respectively.

To tackle these uncertainties, we utilize IT2F modeling approach. A sufficiently large number of input–output pairs are collected from the teleoperation setup in Fig. 1. At the master side,  $\mathbf{f}_h^*(kT)$  is considered as the input and  $\mathbf{f}_h(kT)$  as the output. Whereas,  $\mathbf{x}_s^*(kT)$  and  $\mathbf{v}_s^*(kT) = \dot{\mathbf{x}}_s^*(kT)$  are treated as the inputs, and  $\mathbf{x}_s(kT)$  and  $\mathbf{v}_s(kT) = \dot{\mathbf{x}}_s(kT)$  as the outputs of the slave system, with the sampling period  $T = 1$  ms and  $k \in \mathbb{N}$ . Hereafter, we drop the sampling argument ( $kT$ ) and denote the input–output pairs by  $\chi_s = [\mathbf{x}_s^T, \mathbf{v}_s^T]^T$  and  $\chi_s^* = [\mathbf{x}_s^{*T}, \mathbf{v}_s^{*T}]^T$ , for simplicity and saving space. IT2F approach is applied on every input–output pair to derive the mapping model between the position-velocity/force reference and output signals.

Considering the delayed reference signal  $\mathbf{f}_h^*$  and the haptic output  $\mathbf{f}_h$  for the master system, the desired and actual position-velocity  $\chi_s^*$  and  $\chi_s$  for the slave system, IT2F model describes the teleoperation system in the form of several IF–THEN rules like

$$\begin{aligned}\text{Rule } r_s : & \text{ IF } \mathbf{x}_s^* \in S_x^r, \text{ and } \mathbf{v}_s^* \in S_v^r \\ \text{ THEN : } & \hat{\chi}_s^r = \hat{a}_{s0}^r + \hat{A}_x^r \mathbf{x}_s^* + \hat{A}_v^r \mathbf{v}_s^*\end{aligned}\quad (5)$$

for the slave system, and

$$\begin{aligned}\text{Rule } r_m : & \text{ IF } \mathbf{f}_h^* \in S_f^r \\ \text{ THEN : } & \hat{\mathbf{f}}_h^r = \hat{a}_{m0}^r + \hat{A}_f^r \mathbf{f}_h^*\end{aligned}\quad (6)$$

for the master system, where  $r_i = 1, \dots, R_i$ ,  $R_i$  is the total number of rules for each system.  $\hat{A}_\xi^r$ ,  $\xi \in \{x, v, f\}$  are diagonal matrices of  $[\hat{a}_{\xi 1}^r, \dots, \hat{a}_{\xi 6}^r]^T$  and  $\hat{a}_{\xi n}^r \subseteq [\underline{a}_{\xi n}^r, \bar{a}_{\xi n}^r]$ ,  $n = 1, \dots, 6$  and  $\hat{a}_{i0}^r \subseteq [\underline{a}_{i0}^r, \bar{a}_{i0}^r]$  are uncertain interval coefficients. These parameters are basically related to the dynamics characteristics of the robots. The upper and lower bounds of these parameters indicates the range of the uncertainties in the dynamics of the systems. In this article, we applied the mathematical modeling tools and knowledges developed in [72] and [73] to derive numerical estimations of those parameters. Accordingly,  $\hat{\chi}_s^r \subseteq [\underline{\chi}_s^r, \bar{\chi}_s^r]$  and  $\hat{\mathbf{f}}_h^r \subseteq [\underline{\mathbf{f}}_h^r, \bar{\mathbf{f}}_h^r]$  in which

$$\begin{aligned}\underline{\chi}_s^r &= \underline{a}_{s0}^r + \underline{A}_x^r \mathbf{x}_s^* \quad , \quad \bar{\chi}_s^r = \bar{a}_{s0}^r + \bar{A}_x^r \mathbf{x}_s^* \\ \underline{\mathbf{f}}_h^r &= \underline{a}_{m0}^r + \underline{A}_f^r \mathbf{f}_h^* \quad , \quad \bar{\mathbf{f}}_h^r = \bar{a}_{m0}^r + \bar{A}_f^r \mathbf{f}_h^*\end{aligned}\quad (7)$$

$S_x^r$ ,  $S_v^r$ , and  $S_f^r$  are the IT2F sets with IT2F membership functions, respectively, denoted by  $\hat{\nu}_x^r(\mathbf{x}_s) = [\underline{\nu}_x^r(\mathbf{x}_s), \bar{\nu}_x^r(\mathbf{x}_s)]$ ,  $\hat{\nu}_v^r(\mathbf{v}_s) = [\underline{\nu}_v^r(\mathbf{v}_s), \bar{\nu}_v^r(\mathbf{v}_s)]$  and  $\hat{\nu}_f^r(\mathbf{f}_h) = [\underline{\nu}_f^r(\mathbf{f}_h), \bar{\nu}_f^r(\mathbf{f}_h)]$ . Illustrated in Fig. 3, Gaussian functions with uncertain standard deviation and mean are considered for every IT2F membership function  $0 \leq \underline{\nu}_{\xi_i}^r(\xi_i) \leq \bar{\nu}_{\xi_i}^r(\xi_i) \leq 1, \xi_i \in$

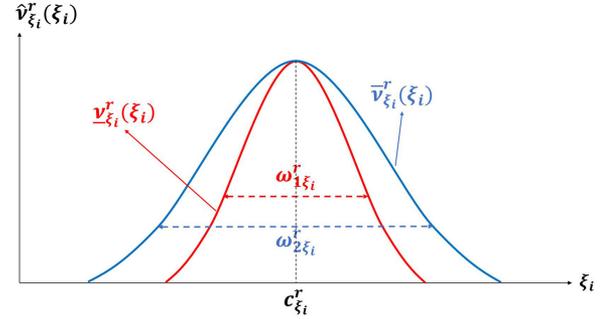


Fig. 3. Uncertain Gaussian function considered for every T2F membership function.

$\{\mathbf{x}_s, \mathbf{v}_s, \mathbf{f}_h\}$

$$\underline{\nu}_{\xi_i}^r(\xi_i) = \exp\left(-\frac{1}{2}\left(\frac{\xi_i - c_{\xi_i}^r}{\omega_{1\xi_i}^r}\right)^2\right)\quad (8a)$$

$$\bar{\nu}_{\xi_i}^r(\xi_i) = \exp\left(-\frac{1}{2}\left(\frac{\xi_i - c_{\xi_i}^r}{\omega_{2\xi_i}^r}\right)^2\right).\quad (8b)$$

As depicted in Fig. 3,  $\omega_{1\xi_i}^r$  and  $\omega_{2\xi_i}^r$  are the uncertain standard deviations of the lower and upper Gaussian membership functions  $\underline{\nu}_{\xi_i}^r(\xi_i)$  and  $\bar{\nu}_{\xi_i}^r(\xi_i)$ , respectively, with the uncertain means  $c_{\xi_i}^r$ . Noticeably, these parameters are being updated by the adaptive NN-based algorithm that will be developed in the next section.

Applying the product operator, the lower and upper functions of each rule in (5) are derived

$$\begin{aligned}\eta_s^r(\chi_s) &= \underline{\nu}_x^r(\mathbf{x}_s) \times \underline{\nu}_v^r(\mathbf{v}_s) \\ \bar{\eta}_s^r(\chi_s) &= \bar{\nu}_x^r(\mathbf{x}_s) \times \bar{\nu}_v^r(\mathbf{v}_s).\end{aligned}\quad (9)$$

Combining the  $R_i$  IT2F rules and applying the type reduction method proposed in [75], outputs of the rules are derived as

$$\hat{\chi}_s = \frac{1}{2} \left( \frac{\sum_{r=1}^{R_s} \eta_s^r(\chi_s) \underline{\chi}_s^r}{\sum_{r=1}^{R_s} \eta_s^r(\chi_s)} + \frac{\sum_{r=1}^{R_s} \bar{\eta}_s^r(\chi_s) \bar{\chi}_s^r}{\sum_{r=1}^{R_s} \bar{\eta}_s^r(\chi_s)} \right)\quad (10a)$$

$$\hat{\mathbf{f}}_h = \frac{1}{2} \left( \frac{\sum_{r=1}^{R_m} \underline{\nu}_f^r(\mathbf{f}_h) \underline{\mathbf{f}}_h^r}{\sum_{r=1}^{R_m} \underline{\nu}_f^r(\mathbf{f}_h)} + \frac{\sum_{r=1}^{R_m} \bar{\nu}_f^r(\mathbf{f}_h) \bar{\mathbf{f}}_h^r}{\sum_{r=1}^{R_m} \bar{\nu}_f^r(\mathbf{f}_h)} \right).\quad (10b)$$

Structure of the resulted IT2FNN is shown in Fig. 4. The initial values for the parameters and above, especially the mean of the Gaussian membership function, have been set by the previous calculations and tools developed in [72]. Moreover, in the next section, an adaptive algorithm is proposed for updating the network parameters of the IT2FNN model, including uncertain standard deviations and means of the IT2F membership functions. The adaptation laws are based on gradient descent method, however, to prevent from getting stuck in local optima, the updating rules are derived by Lyapunov–Krasovskii functional. In addition, this derivation also guarantees the stability and convergent performance of the proposed controller in the presence of time delays.

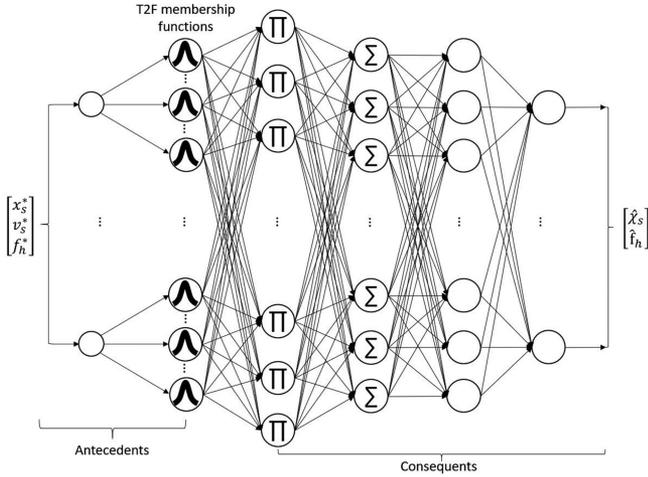


Fig. 4. Structure of the IT2FNN models.

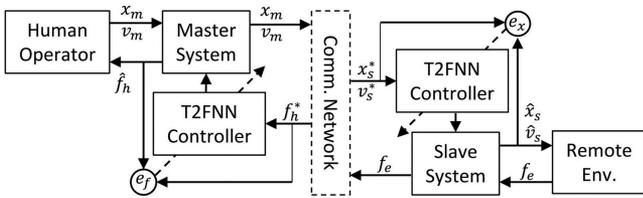


Fig. 5. Considered teleoperation configuration for development and evaluation of the adaptive T2FNN controller.

### III. ADAPTIVE T2FNN CONTROLLER

The teleoperation configuration for development and evaluation of the adaptive T2FNN controller is shown in Fig. 5. Illustrating the overall design process, Fig. 6 also depicts the flowchart of the proposed adaptive T2FNN control algorithm.

The main goal of this article is to develop a control strategy that robustly minimises the teleoperation errors

$$e_x = \mathbf{x}_s^* - \hat{\mathbf{x}}_s, e_f = \mathbf{f}_h^* - \hat{\mathbf{f}}_h. \quad (11)$$

To achieve this goal, a cost function is considered for each the master and slave subsystems

$$E_m = \frac{1}{2} e_f^T e_f = \frac{1}{2} \|e_f\|^2, E_s = \frac{1}{2} e_x^T e_x = \frac{1}{2} \|e_x\|^2. \quad (12)$$

Adaptation laws for adjustable parameters of the T2FNN controllers should be derived in order to minimize these objective functions. This section explains online learning algorithms for the T2FNN controllers for the master and slave systems. We use the subscription  $i \in \{m, s\}$  and the notations  $\xi \in \{\mathbf{x}_s, \mathbf{f}_h\}$  for simplification. Update laws are proposed as follows:

$$\begin{aligned} c_\xi^r(k+1) &= \alpha_i c_\xi^r(k) + \gamma_i(k) \frac{\partial E_i(k)}{\partial c_\xi^r(k)} \\ \omega_{1\xi}^r(k+1) &= \alpha_i \omega_{1\xi}^r(k) + \gamma_i(k) \frac{\partial E_i(k)}{\partial \omega_{1\xi}^r(k)} \\ \omega_{2\xi}^r(k+1) &= \alpha_i \omega_{2\xi}^r(k) + \gamma_i(k) \frac{\partial E_i(k)}{\partial \omega_{2\xi}^r(k)} \end{aligned} \quad (13)$$

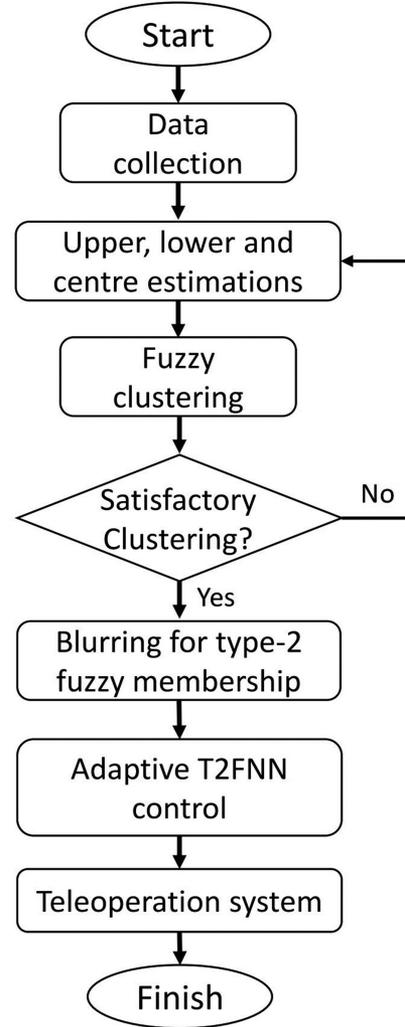


Fig. 6. Flowchart of the proposed adaptive T2FNN controller.

$\alpha_i$  and  $\gamma_i$  are learning rates. To avoid getting stuck in local minima and to increase the efficiency in adaptation [76], the learning rate  $\gamma_i$  is also considered adaptive

$$\dot{\gamma}_i = (1 + \|e_\xi\|) \|e_\xi\|. \quad (14)$$

Considering  $\Delta kT \rightarrow T$  as the one step ahead, time-derivative of the adaptive parameters are derived as

$$\begin{aligned} \dot{c}_\xi^r &= (\alpha_i - 1) c_\xi^r + \gamma_i \frac{\partial E_i}{\partial c_\xi^r} \\ \dot{\omega}_{1\xi}^r &= (\alpha_i - 1) \omega_{1\xi}^r + \gamma_i \frac{\partial E_i}{\partial \omega_{1\xi}^r} \\ \dot{\omega}_{2\xi}^r &= (\alpha_i - 1) \omega_{2\xi}^r + \gamma_i \frac{\partial E_i}{\partial \omega_{2\xi}^r}. \end{aligned} \quad (15)$$

Moreover, applying the chain rules

$$\begin{aligned}\frac{\partial E_i}{\partial c_\xi^r} &= \frac{\partial E_i}{\partial e_\xi} \cdot \frac{\partial e_\xi}{\partial \hat{\xi}} \cdot \frac{\partial \hat{\xi}}{\partial c_\xi^r} = (e_\xi^T)(-1) \frac{\partial \hat{\xi}}{\partial c_\xi^r} = -e_\xi^T \frac{\partial \hat{\xi}}{\partial c_\xi^r} \\ \frac{\partial E_i}{\partial \omega_{1\xi}^r} &= \frac{\partial E_i}{\partial e_\xi} \cdot \frac{\partial e_\xi}{\partial \hat{\xi}} \cdot \frac{\partial \hat{\xi}}{\partial \omega_{1\xi}^r} = -e_\xi^T \frac{\partial \hat{\xi}}{\partial \omega_{1\xi}^r} \\ \frac{\partial E_i}{\partial \omega_{2\xi}^r} &= \frac{\partial E_i}{\partial e_\xi} \cdot \frac{\partial e_\xi}{\partial \hat{\xi}} \cdot \frac{\partial \hat{\xi}}{\partial \omega_{2\xi}^r} = -e_\xi^T \frac{\partial \hat{\xi}}{\partial \omega_{2\xi}^r}\end{aligned}\quad (16)$$

and

$$\dot{\hat{\xi}} = \frac{\partial \hat{\xi}}{\partial c_\xi^r} \dot{c}_\xi^r + \frac{\partial \hat{\xi}}{\partial \omega_{1\xi}^r} \dot{\omega}_{1\xi}^r + \frac{\partial \hat{\xi}}{\partial \omega_{2\xi}^r} \dot{\omega}_{2\xi}^r + \frac{\partial \hat{\xi}}{\partial \xi^*} \dot{\xi}^*. \quad (17)$$

It should be noted that although the derivative term  $\dot{\xi}^* = \dot{\mathbf{f}}_h^*$  in (17) is not practically available for the master system, it could be calculated by  $\dot{\xi}^* = (\xi^*(kT) - \xi^*((k-1)T))/T$ . It is also known that every force profile should be physically limited and cannot vary much fast due to safety considerations and mechanical limitations [6]–[8]. Hence

$$\|\dot{\xi}^*\| \leq \bar{\Xi}, \bar{\Xi} : \text{a positive constant.} \quad (18)$$

However,  $\dot{\xi}^* = \dot{\mathbf{x}}_s^* = \mathbf{v}_s^*$  is feasible. Additionally, these time-derivative terms are not used in the design procedure, and appear only in theoretical analyses.

*Theorem:* The T2FNN controller (10) with the adaptation laws (14) and (15), where

$$\begin{aligned}\frac{\partial E_i}{\partial c_\xi^r} &= \max(P_{i1}, P_{i2}) \\ \frac{\partial E_i}{\partial \omega_{1\xi}^r} &= \max(N_{i1}, N_{i2}) \\ \frac{\partial E_i}{\partial \omega_{2\xi}^r} &= \max(Q_{i1}, Q_{i2})\end{aligned}\quad (19)$$

in which  $P_{i1,2}$ ,  $N_{i1,2}$ , and  $Q_{i1,2}$  are derived in the *Proof* below, minimizes the cost functions (12).

*Proof:* Considering the Lyapunov–Krasovskii functional

$$\begin{aligned}V_i(t) &= \frac{1}{2} e_\xi^T e_\xi + \int_{t-d_\delta(t)}^t e_\xi^T e_\xi d\theta + \int_{t-d_\delta(t)}^t \dot{e}_\xi^T \dot{e}_\xi d\theta \\ &+ \int_{-D_\delta}^0 \int_{t+\theta}^t e_\xi^T e_\xi d\zeta d\theta + \frac{1}{2} (\gamma_i - \gamma_i^*)^2\end{aligned}\quad (20)$$

where  $|d_\delta(t)|$  is the corresponding communication delay for  $\delta \in \{f, b\}$ .  $\gamma_i^*$  is an arbitrary design parameter. We show that a proper solution of (19) makes  $\dot{V}_i$  negative-definite, and therefore, the online learning algorithm (15) guarantees the asymptotic performance of the T2FNN controllers (10a) and (10b). Taking time-derivatives of  $V_i$

$$\begin{aligned}\dot{V}_i &= e_\xi^T \dot{e}_\xi + \|e_\xi\|^2 - (1 - \dot{d}_\delta(t)) \|e_\xi(t - d_\delta(t))\|^2 \\ &+ \|\dot{e}_\xi\|^2 - (1 - \dot{d}_\delta(t)) \|\dot{e}_\xi(t - d_\delta(t))\|^2 + D_\delta \|e_\xi\|^2 \\ &- \int_{t+\theta}^t e_\xi^T(\xi) e_\xi(\xi) d\xi + \dot{\gamma}_i (\gamma_i - \gamma_i^*)\end{aligned}\quad (21)$$

where  $|d_\delta(t)| \leq D_\delta$  and  $\dot{d}_\delta(t) < 1$  are practical assumptions that are experimentally verified (see Fig. 8). Therefore

$$\dot{V}_i < e_\xi^T \dot{e}_\xi + \|e_\xi\|^2 (1 + D_\delta) + \|\dot{e}_\xi\|^2 + \dot{\gamma}_i (\gamma_i - \gamma_i^*) \quad (22)$$

from (18) and knowing that  $\dot{e}_\xi = \dot{\xi}^* - \dot{\xi} \leq \bar{\Xi} - \dot{\xi}$ , then

$$\dot{V}_i < \bar{\Xi} \|e_\xi\| - e_\xi^T \dot{\xi} + \|e_\xi\|^2 (1 + D_\delta) + \|\dot{e}_\xi\|^2 + \dot{\gamma}_i (\gamma_i - \gamma_i^*). \quad (23)$$

Substituting (17) in (23) results in

$$\begin{aligned}\dot{V}_i &< \bar{\Xi} \|e_\xi\| + \|e_\xi\|^2 (1 + D_\delta) + \|\dot{e}_\xi\|^2 + \dot{\gamma}_i (\gamma_i - \gamma_i^*) \\ &- e_\xi^T \left( \frac{\partial \hat{\xi}}{\partial c_\xi^r} \dot{c}_\xi^r + \frac{\partial \hat{\xi}}{\partial \omega_{1\xi}^r} \dot{\omega}_{1\xi}^r + \frac{\partial \hat{\xi}}{\partial \omega_{2\xi}^r} \dot{\omega}_{2\xi}^r + \frac{\partial \hat{\xi}}{\partial \xi^*} \dot{\xi}^* \right).\end{aligned}\quad (24)$$

Now comparing (16) and (24) gives

$$\begin{aligned}\dot{V}_i &< \bar{\Xi} \|e_\xi\| + \|e_\xi\|^2 (1 + D_\delta) + \|\dot{e}_\xi\|^2 + \dot{\gamma}_i (\gamma_i - \gamma_i^*) \\ &+ \frac{\partial E_i}{\partial c_\xi^r} \dot{c}_\xi^r + \frac{\partial E_i}{\partial \omega_{1\xi}^r} \dot{\omega}_{1\xi}^r + \frac{\partial E_i}{\partial \omega_{2\xi}^r} \dot{\omega}_{2\xi}^r - e_\xi^T \frac{\partial \hat{\xi}}{\partial \xi^*} \dot{\xi}^*.\end{aligned}\quad (25)$$

Substituting the proposed adaptive laws (14) and (15) in (25) and setting  $\gamma_i^* > \max\{\bar{\Xi}, (1 + D_\delta)\}$

$\dot{V}_i <$

$$\begin{aligned}&- \left( \underbrace{-\gamma_i}_{a_c} \left( \frac{\partial E_i}{\partial c_\xi^r} \right)^2 + \underbrace{(1 - \alpha_i) \frac{\partial E_i}{\partial c_\xi^r}}_{b_c} \underbrace{\frac{\partial E_i}{\partial c_\xi^r} - \|e_\xi\|^2 + e_\xi^T \frac{\partial \hat{\xi}}{\partial \xi^*} \dot{\xi}^*}_{c_c} \right) \\ &- \left( \underbrace{-\gamma_i}_{a_{\omega 1}} \left( \frac{\partial E_i}{\partial \omega_{1\xi}^r} \right)^2 + \underbrace{(1 - \alpha_i) \omega_{1\xi}^r}_{b_{\omega 1}} \underbrace{\frac{\partial E_i}{\partial \omega_{1\xi}^r} - \gamma_i \|e_\xi\|^2}_{c_{\omega 1}} \right) \\ &- \left( \underbrace{-\gamma_i}_{a_{\omega 2}} \left( \frac{\partial E_i}{\partial \omega_{2\xi}^r} \right)^2 + \underbrace{(1 - \alpha_i) \omega_{2\xi}^r}_{b_{\omega 2}} \underbrace{\frac{\partial E_i}{\partial \omega_{2\xi}^r} - \gamma_i \|e_\xi\|^2}_{c_{\omega 2}} \right)\end{aligned}$$

which includes three quadratic equations

$$\dot{V}_i < - \left( \frac{\partial E_i}{\partial c_\xi^r} + P_i \right)^2 - \left( \frac{\partial E_i}{\partial \omega_{1\xi}^r} + N_i \right)^2 - \left( \frac{\partial E_i}{\partial \omega_{2\xi}^r} + Q_i \right)^2 \quad (26)$$

and makes the time-derivative of the Lyapunov–Krasovskii functional negative ( $\dot{V}_i < 0$ ).  $P_i$ ,  $N_i$ , and  $Q_i$  are solutions of the quadratic equations that requires

$$\begin{aligned}b_c^2 - 4a_c c_c &= 0 \\ b_{\omega 1}^2 - 4a_{\omega 1} c_{\omega 1} &= 0 \\ b_{\omega 2}^2 - 4a_{\omega 2} c_{\omega 2} &= 0\end{aligned}\quad (27)$$

TABLE I  
 RMSE, MAE, AND NRMSE VALUES OF THE THREE T2F-BASED CONTROLLERS

Metrics:		RMSE			MAE			NRMSE		
Methods:		AT2FNN	[53]	[54]	AT2FNN	[53]	[54]	AT2FNN	[53]	[54]
Position	$x$	<b>0.2682</b>	0.3681	0.4864	<b>16.0387</b>	25.7914	34.6060	<b>0.1299</b>	0.1746	0.1809
	$y$	<b>0.2855</b>	0.5572	0.5946	<b>17.5992</b>	35.5523	33.9617	<b>0.1557</b>	0.1569	0.1767
	$z$	<b>0.5158</b>	0.6737	0.8219	<b>23.7641</b>	30.8428	44.6107	<b>0.0878</b>	0.0908	0.1047
Orientation	$\alpha$	<b>0.44</b>	0.45	0.490	<b>0.1160</b>	0.1410	0.1963	<b>0.1015</b>	0.1100	0.1216
	$\beta$	<b>0.10</b>	0.27	0.210	<b>0.0649</b>	0.1064	0.1413	<b>0.1037</b>	0.1242	0.1387
	$\gamma$	<b>0.12</b>	0.26	0.260	<b>0.0758</b>	0.1014	0.1632	0.1328	<b>0.1197</b>	0.1685
Velocity	$v_x$	<b>2.560</b>	3.552	5.414	<b>16.9884</b>	23.0686	36.6404	0.1114	<b>0.1037</b>	0.1107
	$v_y$	<b>2.875</b>	4.942	5.910	<b>16.3634</b>	28.4500	32.2861	<b>0.1071</b>	0.1116	0.1208
	$v_z$	<b>4.60</b>	5.00	6.965	<b>20.1007</b>	22.4033	37.5394	<b>0.0706</b>	0.0821	0.0904
Force	$f_z$	<b>0.2624</b>	0.563	0.5029	<b>0.0903</b>	0.2767	0.2445	<b>0.0992</b>	0.1215	0.1349

The proposed adaptive T2FNN control algorithm has outperformed the other two approaches [53] and [54].

Comparing the error related metrics, the smallest values are bold faced to highlight the best performance out of the three controllers.

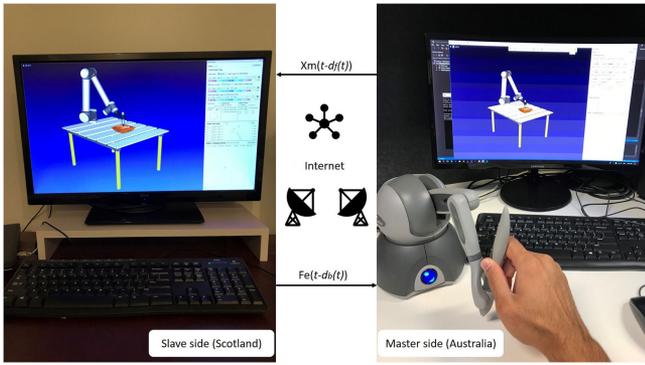


Fig. 7. Target teleoperation consisting of a virtual dynamic model of UR5 [73] as its slave teleoperator. Notably, the sampling rate of the simulation and control implementation is 1 kHz. This setup is used for evaluating the proposed adaptive T2FNN controller between Australia and Scotland [56].

Solving (27) obtains two solutions for each parameter

$$(c_{\xi}^r)_{1,2} = \pm \sqrt{\frac{4\gamma_i (e_{\xi}^T \frac{\partial \xi}{\partial \xi^*} \dot{\xi}^* - \|\dot{e}_{\xi}\|^2)}{(1 - \alpha_i)^2}}$$

$$(\omega_{1\xi}^r)_{1,2} = \pm \sqrt{\frac{4\gamma_i^2 \|e_{\xi}\|^2}{(1 - \alpha_i)^2}}, (\omega_{2\xi}^r)_{1,2} = \pm \sqrt{\frac{4\gamma_i^2 \|e_{\xi}\|}{(1 - \alpha_i)^2}} \quad (28)$$

and therefore, calculating  $(-b \pm \sqrt{b^2 - 4ac})/2a$  for each  $P_i$ ,  $N_i$ , and  $Q_i$  results in

$$P_{i1} = \frac{(1 - \alpha_i)(c_{\xi}^r)_1}{\gamma_i}, \quad P_{i2} = \frac{(1 - \alpha_i)(c_{\xi}^r)_2}{\gamma_i}$$

$$N_{i1} = \frac{(1 - \alpha_i)(\omega_{1\xi}^r)_1}{\gamma_i}, \quad N_{i2} = \frac{(1 - \alpha_i)(\omega_{1\xi}^r)_2}{\gamma_i}$$

$$Q_{i1} = \frac{(1 - \alpha_i)(\omega_{2\xi}^r)_1}{\gamma_i}, \quad Q_{i2} = \frac{(1 - \alpha_i)(\omega_{2\xi}^r)_2}{\gamma_i} \quad (29)$$

and finally, (19) makes  $\dot{V}_i$  much negative that guarantees the asymptotic convergence of the learning algorithms, and subsequently, stability of the proposed T2FNN controller for the both master and slave systems. ■

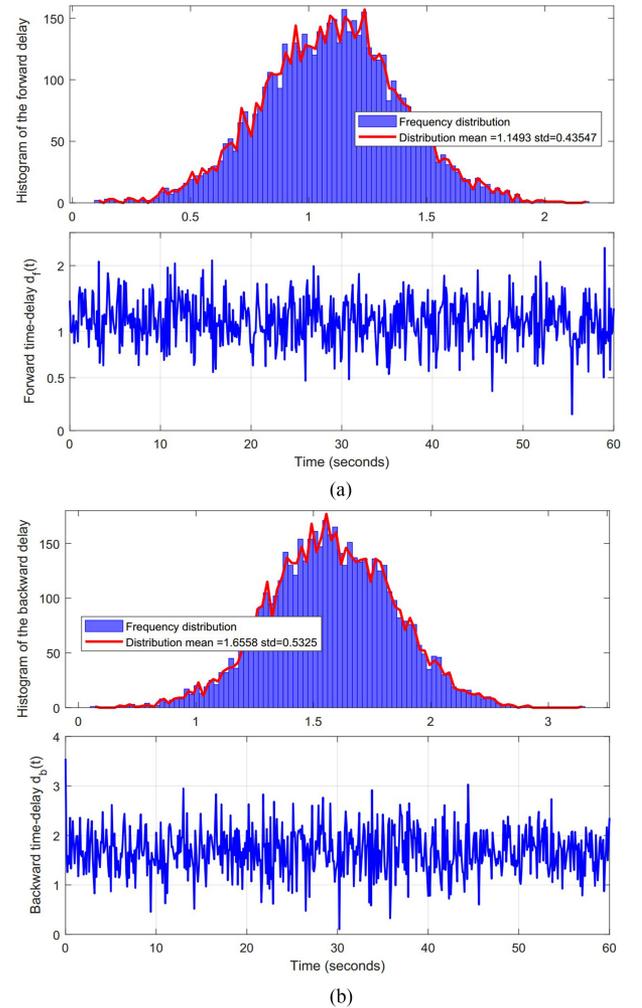


Fig. 8. Average forward and backward time-delays experimentally measured between Australia and Scotland. (a) Forward time-delay  $d_f(t)$ . (b) Backward time-delay  $d_b(t)$ .

*Remark 1:* It should be noted that the considered control signals are the desired position and velocity  $\chi_s$  for the slave robot, and the desired haptic signal  $f_h$  for the master system, respectively. This is because the considered haptic device is

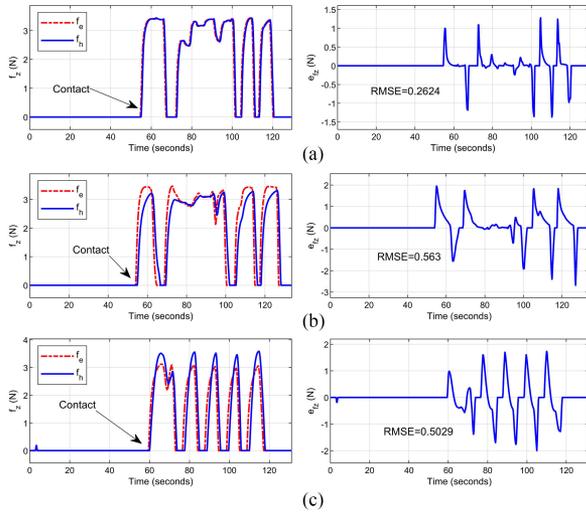


Fig. 9. Force reflection of the T2F-based controllers. (a) Our proposed adaptive T2FNN controller. (b) Proposed controller in [53]. (c) Proposed controller in [54].

capable to expose any demanded force to the human operator. On the other side, the slave robot is able to reach any desired, nonsingular, configuration. Therefore, the teleoperation problem is providing the either systems with their corresponding desired references.

#### IV. EXPERIMENTAL COMPARISON STUDY

This section evaluates the performance of the proposed adaptive T2FNN control strategy on the intercontinental teleoperation setup, Fig. 7. The main focus of this article is to experimentally assess and compare the performance of the proposed control method in this article and those of [53] and [54] under a realistic teleoperation configuration. To this end, the master device is located in Australia while the slave robot is a full-scale SimMechanics model of the UR5 manipulator in Scotland. This model is developed based on the dynamical parameters and features reported by the manufacturer and previously developed in [73]. Moreover, the learning parameters  $\alpha_i$  are identically considered as  $10^{-4}$  for both the master and slave controllers. However, the adaptive learning rates  $\gamma_i$  are shown in Fig. 14. The communication between the master and slave sites is established through the Internet. Delays between the two sites of the teleoperation has been experimentally measured and the average experiences are depicted in Fig. 8. Fig. 8(a) illustrates the average of experienced delay through the forward channel and mean and standard deviation values of its distribution are also shown. Fig. 8(b) presents the same information for the backward channel.

The teleoperation task is considered in two phases, including free motion and contact modes indicated in force reflection of the controllers [see Fig. 9(a)–(c)]. In the free motion genre, the human operator freely manoeuvres the master device in its workspace. While, in the second phase, the slave robot is desired to vertically interact with an object that introduces contact forces to the robot end-effector. As can be observed in those figures,

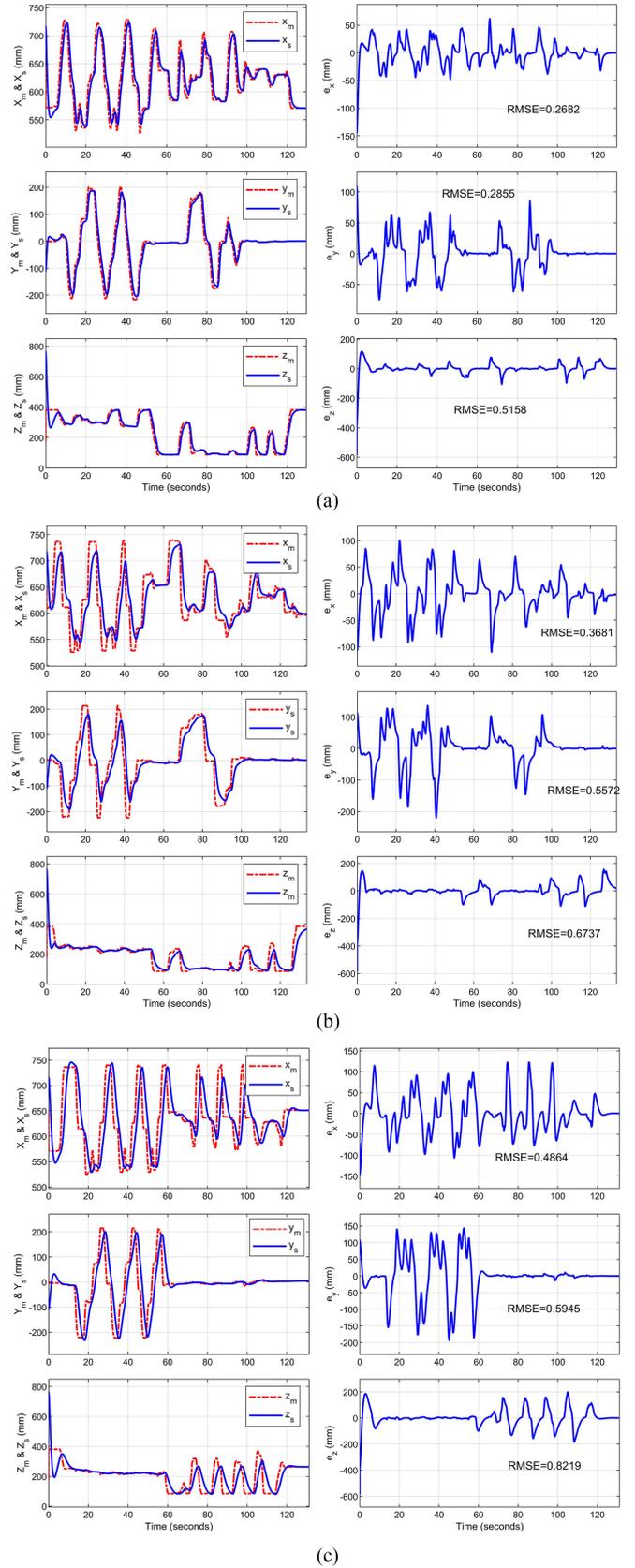
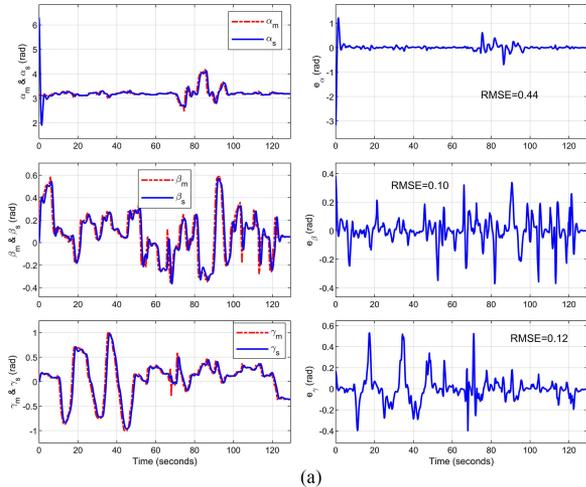
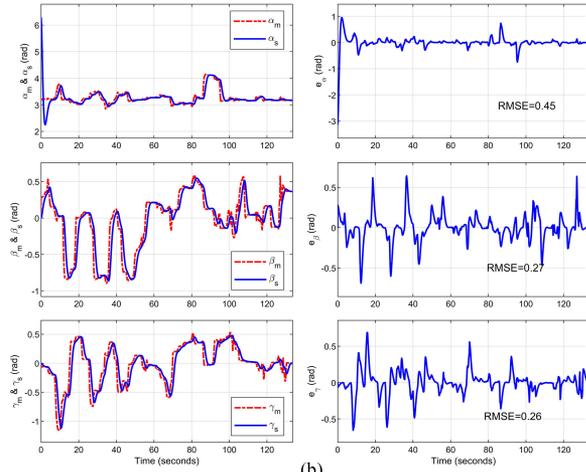


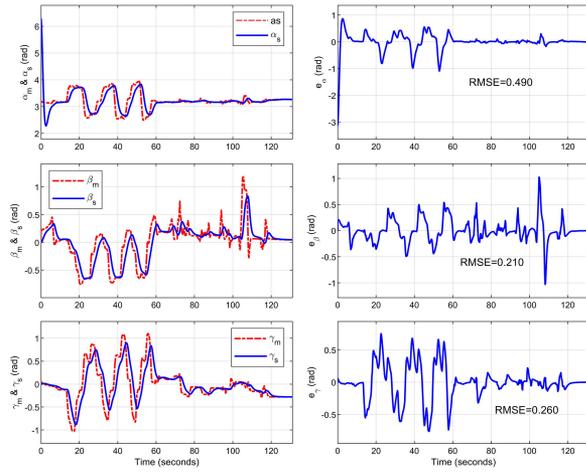
Fig. 10. Position tracking of the T2F-based controllers. (a) Our proposed adaptive T2FNN controller. (b) Proposed controller in [53]. (c) Proposed controller in [54].



(a)



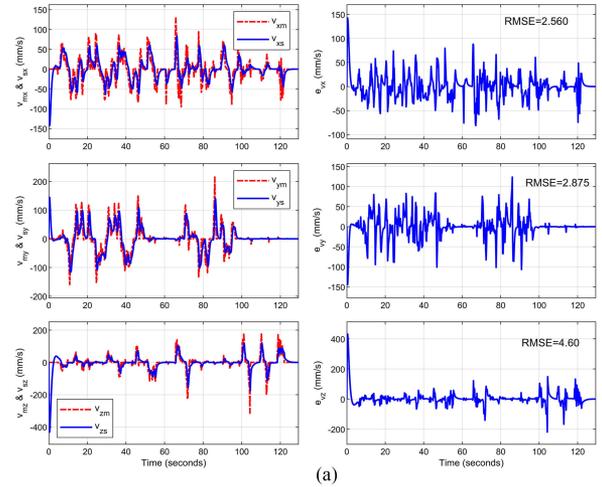
(b)



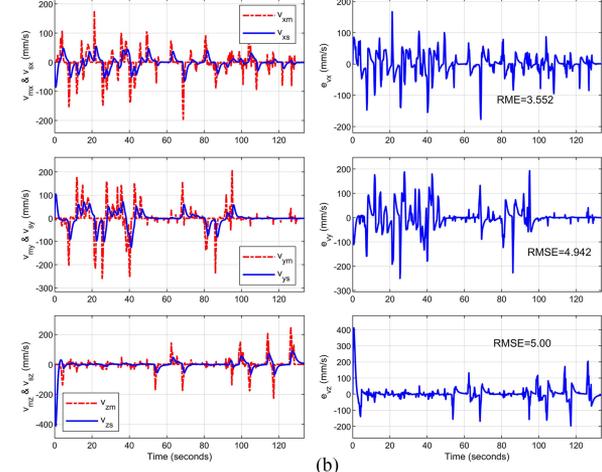
(c)

Fig. 11. Orientation tracking of the T2F-based controllers. (a) Our proposed adaptive T2FNN controller. (b) Proposed controller in [53]. (c) Proposed controller in [54].

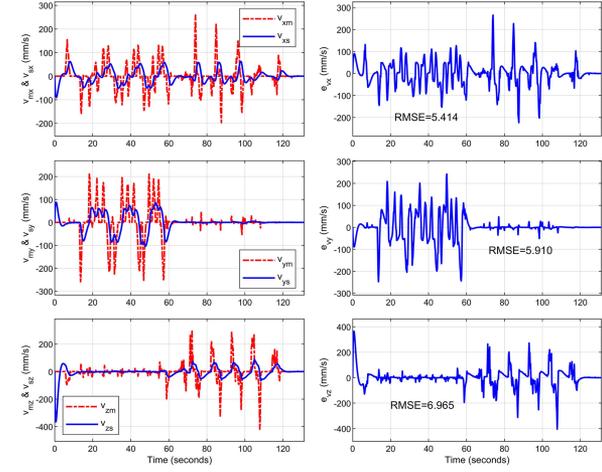
the haptic signal provided by the adaptive T2FNN technique is much accurate than the other controllers. Comparing the tracking performance of the controllers in Fig. 10(a)–(c) for position, Fig. 11(a)–(c) for orientation, and Fig. 12(a)–(c) for velocity, the proposed adaptive T2FNN control methodology



(a)



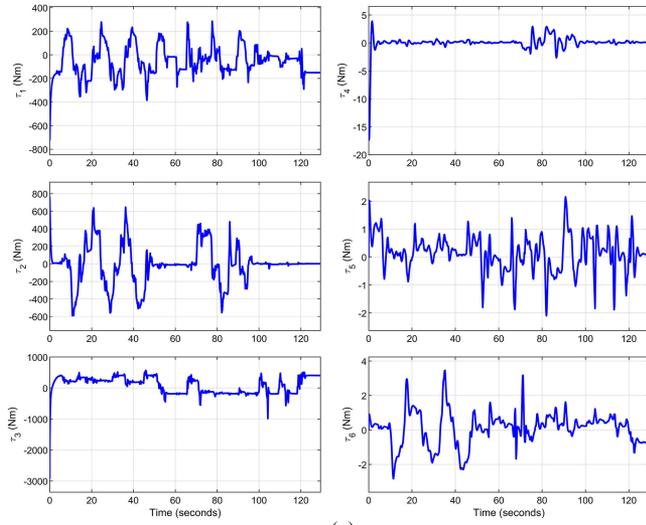
(b)



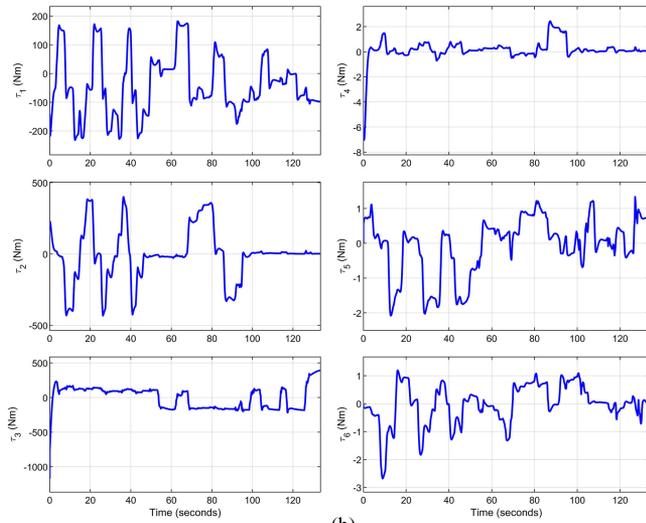
(c)

Fig. 12. Velocity tracking of the T2F-based controllers. (a) Our proposed adaptive T2FNN controller. (b) Proposed controller in [53]. (c) Proposed controller in [54].

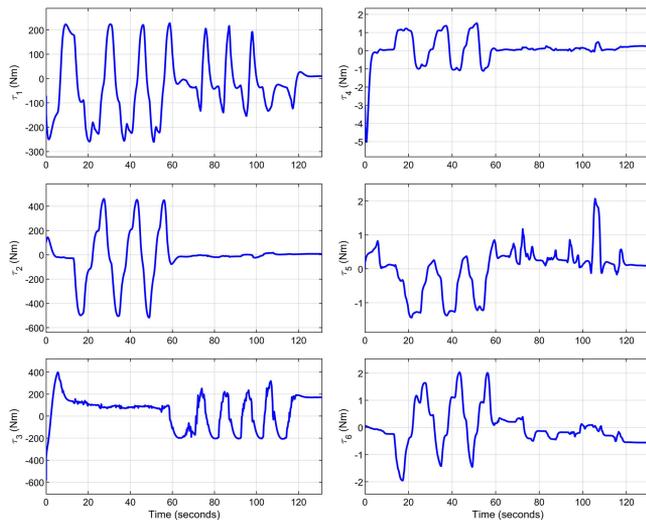
outperforms the other T2F-based controllers. Torque signals generated by the slave robot under the three controllers are shown in Fig. 13(a)–(c). Reported in Table I, values of root mean square error (RMSE), mean absolute error (MAE), and normalized RMSE (NRMSE) of the tracking errors of the



(a)



(b)



(c)

Fig. 13. Slave's torques of the T2F-based controllers. (a) Our proposed adaptive T2FNN controller. (b) Proposed controller in [53]. (c) Proposed controller in [54].

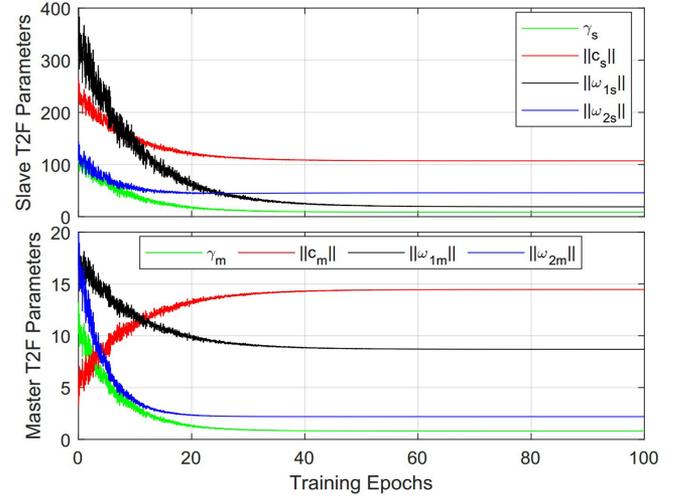


Fig. 14. Norm value of T2F parameters of the master and slave controllers.

proposed adaptive T2FNN controller are significantly smaller than those of the other T2F control algorithms. Considering NRMSE values, the proposed adaptive T2FNN controller has chiefly resulted in less numbers except in few cases, where the difference is ignorable. Additionally, to the best knowledge of the authors based on the literature, precise force reflection and practical haptic is one of the most critical challenges and objectives in teleoperation applications. On the other hand, it should be noted that the physical interaction between the slave robot and not-fully-known objects in the remote workspace is one of the major sources of uncertainties in teleoperation processes. Therefore, the superiority of the proposed approach in accurate force tracking is critically advantageous that is not achieved by many other solutions. Finally, Fig. 14 illustrates the learning trend of the T2F parameters of both the master and slave controllers over 100 epochs considered for the training process. It should be noted that the training time is not reported, since all the three methods took almost the same time.

## V. CONCLUSION

This article addressed the problem of teleoperation under time-varying delays and uncertainties. Known as one of the strongest tools in dealing with uncertainties, T2F approach is utilized to handle this issue in teleoperation applications. Moreover, artificial NNs are employed to further strengthen the nonlinear modeling capabilities of the proposed algorithm. Additionally, error-based adaptive laws are developed for tuning parameters of the T2FNN controller to improve the overall performance of the teleoperation system. Proven by Lyapunov–Krasovskii methodology, the proposed online updating algorithm does not get trapped in local minima. Notably, the T2FNN has learned on the training data collected by a simple teleoperation setup shown in Fig. 1. However, the resulted control technique is then applied and verified on a completely different and more complicated teleoperation configuration. Demonstrated in the comparative experimental simulations, the proposed adaptive T2FNN control

strategy outperformed the most recent T2F-based controllers in the literature. The RMSE, MAE, and NRMSE values of the three T2F-based controllers have been also reported to better compare the performance the three controllers.

In the future, further investigations on the T2FNN structures are being considered for semi/autonomous teleoperative assistance to the human operator. Moreover, considering adjustable parameters in fuzzy rules, including  $a_{in}^*$ ,  $i \in \{m, s\}$  is a future direction to further improve the performance of the system. Another strategy might be considered as development of nonlinear functions for the consequent parts of T2F rules. Chiefly, intelligent predictive models of the teleoperation system will be developed that autonomously executes secondary tasks alongside the main teleoperation process.

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