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Stable Neural Adaptive Filters for Teleoperations with Uncertain Delays

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***Abstract*—Uncertainties in communication networks negatively affect the performance and usability of teleoperation systems, specially, in time-critical applications such as telesurgery. There already exist different methods to tackle this problem using filtering and learning approaches to smoothly estimate perturbed reference signals. Despite these efforts, the instability issue remains unsolved for such systems under random time-delay perturbations. This study employs and extends one of the best filtering techniques and proposes a new strategy based on learning capabilities of artificial neural networks to adaptively filter out delay-related disturbances and provides the most stable yet accurate estimations. To achieve this goal, an adaptive learning mechanism is proposed based on a Lyapunov-Krasovskii functional to not only analyse and guarantee the stability of the overall system, but also preventing the learning algorithm to get stuck in local optima. The proposed method is experimentally evaluated and compared with other closely similar methods in the recent literature. The results demonstrate the outstanding performance of the proposed solution in this study.**

***Index Terms*—Neural networks, adaptive filters, teleoperation, time-delay.**

I. Introduction

As a networked robotic system, teleoperation systems are critically vulnerable to uncertainties and time-delays. Researchers have been investigating solutions for these two major challenges [1], [2]. Offering several useful applications in health-care [3], [4], space explorations [5]–[7], and many more [8]–[10], teleoperation systems have gained a lot of attentions during recent years. There are a huge number of solutions devised for such systems ranging from purely deterministic and classic control theories [11]–[13] to more probabilistic and intelligent approaches [1], [14]. Those solutions based on artificial intelligence (AI) techniques have shown a better outcome, specially, in dealing with randomly time-varying delays [15].

Being one of the most popular AI-based approaches, neural-networks (NN) have proven their learning capabilities in various areas, including health-care [16], autonomous systems [17]–[19], finance [20], for instance. Researchers have utilised NN in teleoperation systems to predict network delays [21], dynamic interactions [9], and handling uncertainties [14]. Amongst different types of NN, radial-basis-functions (RBF) is well known for estimating unknown parameters in system dynamics, for example [1], [14]. Moreover, researchers have also developed control algorithms based on multilayer perceptron neural-networks (MLP) for estimating states of a teleoperation system to guarantee the stability and performance, simultaneously [22].

Communication networks are the main sources of uncertainty in a teleoperation process. Regardless of how fast and large the network's bandwidth is, extremely random drops and latencies in packets transmission will deteriorate the quality and performance of the teleoperation task [15]. Researchers have been investigating solutions to deal with these issues, especially using NN-based techniques. An adaptive NN approach developed in [23] to handle constrains on inputs. Another NN approach was proposed to deal with uncertainties in kinematics and dynamics in teleoperation actuators [24]. Researchers in [25] developed an NN adaptive solution for teleoperation under constant time-delays. A similar approach was also developed in [26], although for multilateral teleoperation under constant delays. Combining fuzzy and NN approaches for interval uncertainty estimations [27]–[29], researchers have also developed NN-based algorithms to deal with time-varying delays in teleoperation systems. Moreover, an adaptive scheme was proposed in [30] to guarantee the teleoperation performance under time-varying delays. The practicality and efficiency of most of those solutions is questionable, due to the data collection and learning processes of the NN-based models. Effectiveness of those models highly depends on the experimental data collection, and consequently, training procedures which involve a number of parameters and hyper-parameters that should be finely tuned.

Hence, this study concerns the aforementioned challenges and proposes an adaptive methodology to effectively filter out perturbations caused by network-induced latencies. Firstly, employing a neural-network for adjusting the filtering gains for the best possible results (compared to constant gains in [2] and others that does not necessarily provide the best performance). Those gains in the estimation filter can significantly affect the performance and stability of the system. Having them set by constant values do not guarantee a reliable performance for all cases. However, being able to adaptively adjust the gains according to system's errors is the key advantage of the current

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study which can provide a promising performance.

Secondly, the utilised neural-network does not require a huge effort on training, thanks to the proposed adaptive learning approach. This approach updates the neural-network's parameters (weights and biases) according to errors being observed during system's operation. Moreover, the learning (adaptation) approach is developed based on Lyapunov-Krasovskii stability theorem, which assesses the global convergence of the learning parameters. Therefore, the learning procedure will not get stuck in local optima since the theorem only applies on global solutions. This analysis is also detailed in section three of the paper. Furthermore, applications of neural-networks in robotic and teleoperation systems were mostly focused in radial-basis-functions neural-networks (RBF-NN), whose performance and effectiveness considerably depend on how the network has been trained. On the other side, RBF-NN was chiefly used for estimating unknown dynamics of teleoperation systems, such as contact forces in the remote workspace [1], [9], [14]. However, the present study proposes multilayer perceptron neural-networks (MLP) which offers a better performance with less training effort.

Therefore, the main contributions of the current study are:

- Developing an adaptive filtering algorithm to smoothly estimate teleoperation reference signals disturbed because of communication uncertainties. The filtering structure used in this study is already well-developed in the literature [2], [31]. However, this study for the first time introduces a stable adaptive scheme for fine-tuning the filtering parameters.
- A multilayer perceptron NN is devised based on an adaptive learning approach to fine-tune the filter's coefficients. Convergence and optimality of the adaptive learning approach is investigated and proven via Lyapunov-Krasovskii functional theorem.
- Mathematically verified, the proposed adaptive NN filtering scheme not only guarantees the performance and stability of the teleoperation task, but also avoids getting stuck in local optima.
- Moreover, assessed by Lyapunov-Krasovskii theorem, the proposed learning approach seeks for a solution alongside globally minimised system's errors. In other words, the learning process runs at the same time while the system is operating. Since the local stability of the system under the filtering mechanism is already demonstrated in previous studies [2], [31], the NN-based adaptation method in this study not only stabilise the system, but also it searches for the best coefficient values of the filter. Therefore, as demonstrated in the experiments, the teleoperation task proceeds smoothly.

Furthermore, a real-world teleoperation platform is set up to experimentally evaluate and confirm the practicality and effectiveness of the proposed neural adaptive filtering method. The proposed approach is also compared with two other similar approaches recently published in the literature [1], [2].

The paper is organised as follows. The next section states the teleoperation problem and time-delay challenges involved in the model. Section III explains the derivation of the proposed neural adaptive methodology in details. Experimental evaluations and results are discussed in Section IV, followed by Section V concluding the study.

II. Problem Statement

This section describes an uncertain robotic teleoperation system and the challenges being raised through a delayed teleoperation process. This study considers the generic equations of teleoperation dynamics and properties as below:

$$\begin{cases} M_{op}\ddot{q}_{op} + C_{op}(q_{op},\dot{q}_{op}) + g_{op} + \mu_{op}(\dot{q}_{op},q_{op}) \\ +\sigma_{op}(t) = \tau_{op} + J_{op}^T(f_h + \mathbf{f}_e^d) \\ M_{tel}\ddot{q}_{tel} + C_{tel}(q_{tel},\dot{q}_{tel}) + g_{tel} + \mu_{tel}(\dot{q}_{tel},q_{tel}) \\ +\sigma_{tel}(t) = \tau_{tel} - J_{tel}^T f_e \end{cases} \tag{1}$$

in which, $M_i,\ i \in \{op, tel\}$ are inertia and mass matrices, C_i are centripetal and Coriolis matrices, g_i are gravity vectors, μ_i are friction vectors, σ_i are unknown but bounded disturbances, τ_i are control torques, J_i are Jacobian matrices for operator interface and teleoperator subsystems, respectively. $f_j,\ j \in \{e,h\}$ are haptic forces h and environment reactions e.

After translating (1) to Cartesian workspaces and considering all the model uncertainties and delayed signals, eventually reformed into:

$$\begin{cases} \mathcal{M}_{op}(\ddot{\mathbf{x}}_{op}) + \mathcal{N}_{op}(\dot{\mathbf{x}}_{op},\mathbf{x}_{op}) + \mathcal{G}_{op}(\mathbf{x}_{op}) = \\ \mathcal{T}_{op} + \mathbf{f}_h - \vec{\delta}_{op} \\ \mathcal{M}_{tel}(\ddot{\mathbf{x}}_{tel}) + \mathcal{N}_{tel}(\dot{\mathbf{x}}_{tel},\mathbf{x}_{tel}) + \mathcal{G}_{tel}(\mathbf{x}_{tel}) = \\ \mathcal{T}_{tel} - \mathbf{f}_e - \vec{\delta}_{tel} \end{cases} \tag{2}$$

where, translation of $\mathcal{M}_i$, $\mathcal{N}_i$, $\mathcal{G}_i$, and $\mathcal{T}_i$ from their correspondents in joint space (1) is extensively explained in [2], [27], [32], therefore, will be avoided to repeat them here for saving space. $\vec{\delta}_{op}$ and $\vec{\delta}_{tel}$ contain all model uncertainties and disturbances augmented altogether. Notably, the subscripts h, m, s, and e stand for the human operator, operator interface, teleoperator robot, and remote environment, respectively. The delayed signals are the reference position for the teleoperator robot and the contact forces from interactions between the robot's end-effector and objects in the remote environment. Relations between these delayed reference signals and their corresponding signals on either operator interface or teleoperator sides are also expressed as:

$$\mathbf{x}_{op}^d(t) = \mathbf{x}_{op}(t - d_f(t)) \quad , \quad \mathbf{f}_e^d(t) = \mathbf{f}_e(t - d_b(t)) \tag{3}$$

with the same considerations and assumptions on the time-delay functions mentioned in [2], [31]:

1) The latency should be bounded ($|d(t)| < \infty$),
2) time-delay functions to be piecewise differentiable and $|d(t_2) - d(t_1)| \le \zeta|t_2 - t_1|,\ \forall t_1, t_2 \in \mathbb{R},$ for some $\zeta \ge 0$.

Remark 1. The assumption is that the time-delay function d(t) to be piecewise differentiable and its rate (changes in values) of the delay be slower than time (sampling rate of the system). Considering the relatively high sampling rates of the robot (125 Hz), haptic device (1kHz), network switches (~MHz), and hosting computers (~GHz), such an assumption is not practically restrictive. Moreover, these assumptions are commonly found and accepted in the literature [31]. According to the convergence proof for the proposed learning algorithm (in the next section), time-derivative of delays should be less than 1 to achieve the global convergence of the solution at all time during the teleoperation. However, if this condition is not met at any instances of sampling/transmissions, the learning solution (coefficient values obtained) will be only a local optima and will maintain the stability at that time instance. In other words, the results would be similar to the constant (non-adaptive) gains. Constant coefficients for the filter will be the case of studies [2] and [31], which have been already discussed in those studies.

Researchers in [2] proposed the control torques τ_{op} and τ_{tel} in such a way to guarantee a stable and robust performance of a teleoperation system in the presence of time-delays and model uncertainties. To achieve this goal the authors have employed a filtering algorithm for smoothly estimating the reference signals perturbed due to time-varying delays through communication networks. The filter used in that study:

$$\begin{cases} \dot{\eta}_{op1} = \eta_{op2} + |c_{op1}c_{op2}|(\mathbf{f}_e^d - \eta_{op1}) \\ \dot{\eta}_{op2} = c_{op1}^2|c_{op3}|(\mathbf{f}_e^d - \eta_{op1}) \end{cases} \tag{4}$$

for the force feedback signals, and:

$$\begin{cases} \dot{\eta}_{tel1} = \eta_{tel2} + |c_{tel1}c_{tel2}|(\mathbf{x}_{op}^d - \eta_{tel1}) \\ \dot{\eta}_{tel2} = c_{tel1}^2|c_{tel3}|(\mathbf{x}_{op}^d - \eta_{tel1}) \end{cases} \tag{5}$$

for the teleoperator position tracking. It should be noted that the superscript d indicates the delayed, perturbed signals to be smoothly estimated by the filter. Either filters have three parameters $c_{ij},\ i \in \{op, tel\},\ j \in \{1,2,3\}$ for each corresponding operator interface and teleoperator systems, respectively. The only constraint that these parameters have is to make the filter subsystem Routh-Hurwitz stable, which requires all the three parameters to be positive. Thence, this study modifies the filters by considering the absolute values of the coefficients. This is to relax the positivity constrains of them for design purposes explained in the next section. However, the performance of the filter critically depends on the actual value of the three coefficients. In other words, the proposed adaptive algorithm will be forced to estimate a set of coefficients that satisfies the condition above.

In other words, larger c_{i1} results in sharper responses and more accurate estimations, while smaller c_{i1} makes the filter more stable and smoother estimations. Increasing c_{i2} improves the transient response of the filter but its decrease worsens the filter's output with overshoot and chattering. Moreover, enlarging c_{i3} decreases steady state errors of the filter's output. The limitation on increasing c_{i2} and c_{i3} values will be the cost and effort of the resulted control signals. Referring to the control strategies proposed in Theorem 1 in [2], the cost of increasing c_{tel3} is directly observed in τ_{tel}, for example. c_{op3} will subsequently affect the control effort regarding the final Lyapunov stability condition. The proposed values implemented in [2] were $c_{i1} = 10$ and $c_{i2} = c_{i3} = 1,\ i \in \{op, tele\}$, which resulted in smooth control signals τ_{op} and τ_{tel} as reported in that study.

Notably, the filter's parameters can significantly affect the performance of the overall system in dealing with delays and

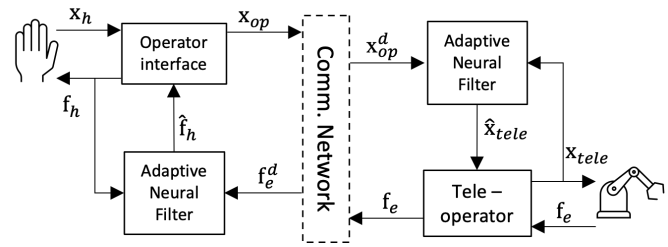

Fig. 1. The block diagram of the proposed filtering approach in a teleoperation structure.

Input parameters teleoperation errors e_i
Output parameters filters' coefficients c_{ij}
Cost functions Lyapunov-Krasovskii V_i
Begin:
while teleoperation in process **do**:
  Calculate V_i for the corresponding errors e_i
  Check Lyapunov-Krasovskii stability criteria
  if $\dot{V}_i > 0$ **then**
    update MLP parameters w_l^i , β_l^i
    estimate a new set of coefficients
  else if $\dot{V}_i \leq 0$ **then**
    continue with the current set of parameters
  end if
end while

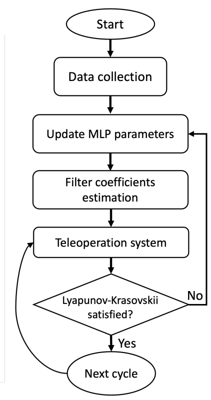

Fig. 2. Algorithmic representation of the proposed adaptive neural filter and the recursive procedure of a teleoperation with the adaptive neural filters.

perturbations during the teleoperation process. However, setting those coefficients to some constant values may not be the ideal case for all situations considering the extremely uncertain behaviour of network-induced delays. The next section of this paper will investigate and propose an adaptive algorithm to dynamically adjust these parameters utilising a feed-forward neural-network to achieve the best possible performance under most delay conditions.

III. Neural Adaptive Filtering

Following the observations explained in the previous section, this study investigates an algorithm to adaptively tune those coefficients to guarantee both stability and performance of the system under time-delay perturbations occurring on the reference signals in a teleoperation procedure. To achieve this goal, learning capability of artificial neural networks is utilised in dealing with uncertain nature of time-delays in signal transmissions through a teleoperation system.

The main goal is to minimise the teleoperation error criteria at either end of the system:

$$e_s = \mathbf{x}_{tel}^* - \hat{\mathbf{x}}_{tel} \quad , \quad e_m = \mathbf{f}_h^* - \hat{\mathbf{f}}_h \tag{6}$$

in which, e_s is the position tracking error of the teleoperator robot, and e_m is the haptic error at the operator interface side. Here, we consider the following cost function for minimising the errors in (6), and also developing the adaptive algorithm for the filtering parameters in (4) and (5):

$$E_{op} = \frac{1}{2}e_{op}^T e_{op} = \frac{1}{2}\|e_{op}\|^2 \quad , \quad E_{tel} = \frac{1}{2}e_{tel}^T e_{tel} = \frac{1}{2}\|e_{tel}\|^2 \tag{7}$$

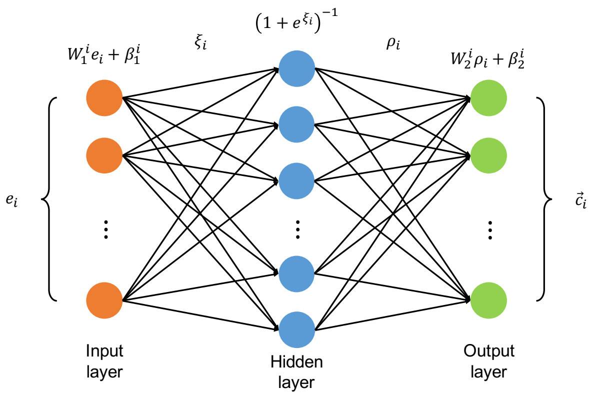

Fig. 3. Structure of the MLP neural network considered in this study.

Therefore, we derive a neural network (NN)-based adaptive algorithm for the filtering coefficients. The proposed NN-based adaptive algorithm is identical for both the operator interface and teleoperator systems. Hence, we replace the subscripts $\{op, tel\}$ with i for simplification and space reasons. The block diagram in Figure 1 illustrates that how the proposed adaptive neural filters incorporate into a teleoperation system. Moreover, Fig 2 shows the flowchart of the overall procedure that the adaptive neural filters proceed.

The neural network type considered in this study is a multi-layer perceptron (MLP) with n neurons in its hidden layer depicted in Figure 3. MLP networks are well known for their outstanding capabilities in estimations and forecasting stochastic trends. This MLP takes the teleoperation errors $e_i \in \mathbb{R}^6$ as its input and outputs a vector containing estimations of the corresponding filtering parameters $\vec{c}_i \in \mathbb{R}^3$. The relation between inputs and outputs of the MLP is considered as:

$$\xi_i = W_1^i e_i + \beta_1^i \quad , \quad \rho_i = \frac{1}{1+\mathbf{e}^{\xi_i}} \quad , \quad \vec{c}_i = W_2^i \rho_i + \beta_2^i \tag{8}$$

This MLP-based estimation process will get adaptively updated and improved according to time-delay perturbations and the system's performance. For this aim, weight matrices $W_1^i = [w_1^i] \in \mathbb{R}^{n\times 6}$, $W_2^i = [w_2^i] \in \mathbb{R}^{3\times n}$ and bias vectors $\beta_1^i \in \mathbb{R}^n$, $\beta_2^i \in \mathbb{R}^3$ parameters of the MLP network will be updated through a gradient-based approach by:

$$\begin{aligned} w_l^i(t+1) &= \alpha_i w_l^i(t) + \gamma_i(t)\frac{\partial E_i}{\partial w_l^i} \\ \beta_l^i(t+1) &= \alpha_i \beta_l^i(t) + \gamma_i(t)\frac{\partial E_i}{\partial \beta_l^i} \end{aligned} \tag{9}$$

where, $l \in \{1,2\}$ indicates the layer number, α_i is an arbitrarily small positive constant and $\gamma_i(t)$ is an adaptive learning rate which its adaptation law will be derived later in this section. Notably, (9) is considered for every element in the weight matrices and bias vectors of the MLP network (8). One-step derivative of each line in (9) obtains:

$$\begin{aligned} \dot{w}_l^i &= (\alpha_i - 1)w_l^i + \gamma_i\frac{\partial E_i}{\partial w_l^i} \\ \dot{\beta}_l^i &= (\alpha_i - 1)\beta_l^i + \gamma_i\frac{\partial E_i}{\partial \beta_l^i} \end{aligned} \tag{10}$$

Theorem 1. Considering the teleoperation system (2) under the time-delay assumptions discussed in [33], [34], and provided with the filters (4)-(5), in which, coefficients $c_{ij},\ i \in \{op, tel\},\ j \in \{1,2,3\}$ are being adaptively tuned by the MLP neural-network (8)-(10), the following gradient equation:

$$\begin{aligned} \frac{\partial E_i}{\partial w_l^i} &= \max(\Omega_{i,1}, \Omega_{i,2}) \\ \frac{\partial E_i}{\partial \beta_l^i} &= \max(\Lambda_{i,1}, \Lambda_{i,2}) \\ \Omega_{i,1} = \frac{(1-\alpha_i)w_{i,1}}{\gamma_i} \quad &, \quad \Omega_{i,2} = \frac{(1-\alpha_i)w_{i,2}}{\gamma_i} \\ \Lambda_{i,1} = \frac{(1-\alpha_i)\beta_{i,1}}{\gamma_i} \quad &, \quad \Lambda_{i,2} = \frac{(1-\alpha_i)\beta_{i,2}}{\gamma_i} \end{aligned} \tag{11}$$

minimises the cost functions (7), and therefore, guarantees stable performance of the teleoperation system (2).

Proof: Let's consider Lyapunov-Krasovskii theory to investigate the aforementioned theorem. The reason for this proposition is two-folded: not only analysing the stability of the teleoperation system under randomly varying delays by minimising the cost functions (7), but also preventing the adaptive learning strategy (9) from getting stuck in local minima. To achieve this goal, a Lyapunov-Krasovskii functional is considered for the cost functions and the adaptive learning rate as follows:

$$\begin{aligned} V_i =& E_i + \int_{t-d_\zeta(t)}^{t} E_i d\theta + \int_{t-d_\zeta(t)}^{t} \dot{e}_i^T \dot{e}_i d\theta \\ &+ \int_{-D_\zeta}^{0}\int_{t+\theta}^{t} E_i d\sigma d\theta + \frac{1}{2}\tilde{\gamma}_i^2 \end{aligned} \tag{12}$$

in which, $d_\zeta(t),\ \zeta \in \{f, b\}$ concerns time-varying delays through forward and backward communication channels, with $|d_\zeta(t)| \le D_\zeta < \infty$. $\tilde{\gamma}_i$ is the adaptation error of the learning rate γ_i for an arbitrarily optimal γ_i^*, $(\tilde{\gamma}_i = \gamma_i - \gamma_i^*)$. Now, by differentiating V_i along time we will investigate the stability of the system and update rules for the MLP:

$$\begin{aligned} \dot{V}_i =& \dot{E}_i + E_i - (1-\dot{d}_\zeta(t))E_i(t-d_\zeta(t)) \\ &+ \|\dot{e}_i\|^2 - (1-\dot{d}_\zeta(t))\dot{e}_i(t-d_\zeta(t)) + D_\zeta E_i \\ &- \int_{t+\theta}^{t} E_i d\sigma + \dot{\gamma}_i(\gamma_i - \gamma_i^*) \end{aligned} \tag{13}$$

considering the practically-validated assumptions on the time-delay functions [1], [2], [27], [31], [32] $|d_\zeta(t)| \le D_\zeta < \infty$ and $\dot{d}_\zeta(t) < 1$ (Figure 5),

$$\dot{V}_i < E_i(1+D_\zeta) + \dot{E}_i + \|\dot{e}_i\|^2 + \dot{\gamma}_i(\gamma_i - \gamma_i^*) \tag{14}$$

By proposing the adaptive learning law:

$$\dot{\gamma}_i = E_i \tag{15}$$

and choosing $\gamma_i^* > (1+D_\zeta)$:

$$\begin{aligned} \dot{V}_i <& \dot{E}_i + \|\dot{e}_i\|^2 + \gamma_i\|e_i\|^2 \\ =& \frac{\partial E_i}{\partial w_l^i}\dot{w}_l^i + \frac{\partial E_i}{\partial \beta_l^i}\dot{\beta}_l^i + \|\dot{e}_i\|^2 + \gamma_i\|e_i\|^2 \end{aligned} \tag{16}$$

which by recalling (10) becomes:

$$\dot{V}_i < -\Bigg(\underbrace{-\gamma_i}_{a_w}\|\frac{\partial E_i}{\partial w_l^i}\|^2 + \underbrace{(1-\alpha_i)w_l^i}_{b_w}\frac{\partial E_i}{\partial w_l^i}\underbrace{-\gamma_i\|e_i\|^2}_{c_w}\Bigg) - \Bigg(\underbrace{-\gamma_i}_{a_\beta}\|\frac{\partial E_i}{\partial \beta_l^i}\|^2 + \underbrace{(1-\alpha_i)\beta_l^i}_{b_\beta}\frac{\partial E_i}{\partial \beta_l^i}\underbrace{-\|\dot{e}_i\|^2}_{c_\beta}\Bigg) \tag{17}$$

which could be rewritten in a quadratic form as below:

$$\dot{V}_i < -\left(\frac{\partial E_i}{\partial w_l^i} + \Omega_i\right)^2 - \left(\frac{\partial E_i}{\partial \beta_l^i} + \Lambda_i\right)^2 \tag{18}$$

Thence, for making $\dot{V}_i$ negative, the complete square terms in (18) should have valid solutions meeting the criteria:

$$b_w^2 - 4a_w c_w = 0 \quad , \quad b_\beta^2 - 4a_\beta c_\beta = 0$$

which yields two solutions for each w_i and β_i:

$$(w_i)_{1,2} = \pm\sqrt{\frac{4\gamma_i^2\|e_i\|^2}{(1-\alpha_i)^2}} \quad , \quad (\beta_i)_{1,2} = \pm\sqrt{\frac{4\|\dot{e}_i\|^2}{(1-\alpha_i)^2}}$$

and therefore, according to (18):

$$\begin{aligned} \Omega_{i,1} &= \frac{(1-\alpha_i)w_{i,1}}{\gamma_i} \quad , \quad \Omega_{i,2} = \frac{(1-\alpha_i)w_{i,2}}{\gamma_i} \\ \Lambda_{i,1} &= \frac{(1-\alpha_i)\beta_{i,1}}{\gamma_i} \quad , \quad \Lambda_{i,2} = \frac{(1-\alpha_i)\beta_{i,2}}{\gamma_i} \end{aligned} \tag{19}$$

which make $\dot{V}_i$ negative and indicates the asymptotic stability of the teleoperation system with the errors (6). Moreover, this result shows that the adaptive updating laws (9) and (15) will globally minimise the cost functions (7), which avoids getting stuck in local minima during the learning process. Furthermore, considering the maximum among each Ω_i and Λ_i pairs in (19), as proposed in (11), makes the energy-like Lyapunov-Krasovskii functional (12) to shrink faster and tend to its global equilibrium or optimal point. Having said that, the proof is complete. ■

Remark 2. One main consideration in this study was real-world implementation of the proposed approach. Furthermore, updating law (15) may not be the fastest or best solution for the learning rate γ_i. It is only one simple solution that helps with negativity of $\dot{V}_i$. One obvious reason for proposing such a solution is to cancel out $E_i(I + D_\zeta)$ (as a positive multiplication of E_i) in (14). In fact, this study considered the worst case scenario for $\dot{V}_i$ by $\dot{\gamma}_i = E_i$, which implies less negativity in $\dot{V}_i$. However, considering that γ_i^* being an arbitrary value and only required to be greater than $(1 + D_\zeta)$, one could possibly consider $\dot{\gamma}_i = pE_i$ with $p > 1$ so that not only $E_i\gamma_i^*$ is still greater than $E_i(1+D_\zeta)$, but also making $\dot{\gamma}_i$ to converge faster by punishing the errors. In other words, having a coefficient $p > 1$ for E_i in (15) makes $\dot{V}_i$ more negative in (14) and (16). It is worth to note that $\dot{V}_i$ being negative along time and $V_i \geq 0$ means that it always tends towards its global minimum $V_i = 0$. Which also means $E_i = 0$, $\dot{e}_i = 0$, and $\tilde{\gamma}_i = 0$. And it is achieved through the adaptation laws derived in this section. In other words, considering the proposed adaptive filters (4)-(5) and updating their coefficients via the MLP network (8) with the learning strategies (11)-(15), stability and performance of the teleoperation system (2) under randomly time-varying delays. To further evaluate this proposition, the next section experimentally examines the proposed methodology, and also compares its performance with the two similar approaches in the literature, [1] and [2].

The main reason for choosing these two particular studies for comparison purposes is their similarities in concept and conditions taken into account in either of them. Additionally, the current study is partially based on the torque control design in [2] and shares the same filtering structure, and also both of the references are of the most recently-published articles in the literature. Thence, it should be worth appraising the performance of the proposed neural adaptive approach against those similar ones. Although, there might be several other studies also with quite similar methodologies, it is not possible to consider all of them in one single paper. Thus, the most related ones are only considered for the comparison goals in this paper.

IV. Experimental Results

This section presents and discusses the experimental validation and comparison made between the proposed neural adaptive approach in this article and those of [1] and [2]. Figure 4 illustrates the robotic teleoperation setup developed and considered as a testing platform in real-world. The teleoperation setup consists of a haptic device (Phantom Omni) as the operator interface, a UR10 robotic arm as the teleoperator system, and a host desktop computer that executes the control algorithm and emulates arbitrarily random delays through the Ethernet-based communication with UR10's controller. The delay functions in forward and backward communication routes have been experimentally measured and presented in Figure 5, which confirms the assumptions made on the time-delay characteristics. Noticeably, the nominal operational rate of the UR10 robot is 125 Hz, whereas, the Omni haptic device operates at about 1kHz (~8 times faster). On the other hand, physical dimensions and inertial properties of UR10 also limit the robot's velocity and agility compared to human's hand motion.

The experiment is designed in such a way to imitate a normal clinical practice, in which, the human operator needs to rub a sanitiser gel on a narrow surface of the dummy object shown in Figure 4. The object is slightly flexible that can bend under a limited force profile being applied by the robot. In a direct-contact operation, a human can easily execute this task without losing contact with the object's surface or applying too much force. Whilst, successful execution of the same procedure through the teleoperative robot critically depends on the effectiveness and performance of the teleoperation strategy. Therefore, it can be a good benchmark for comparing the algorithms[1].

All weights and bias parameters of the MLP network in this study are randomly initialised. Filters' coefficients are initially considered $c_{i1} = 10$, and $c_{i2} = c_{i3} = 1$ same as in [2]. Indeed, the MLP architecture in this study was considered

[1]Supplementary video files demonstrate the executed experiments.

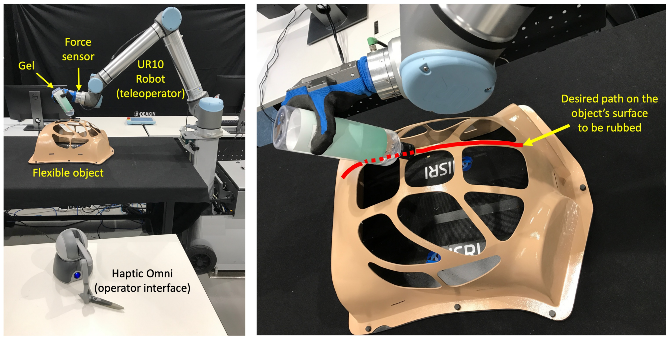

Fig. 4. The teleoperation setup considered as the experimental platform in this study, UR10 as the teleoperator robot, Omni Haptic device as the operator interface to the human operator, and a flexible dummy object. The teleoperation task is to rub the gel on the object's surface through the desired path highlighted in the picture.

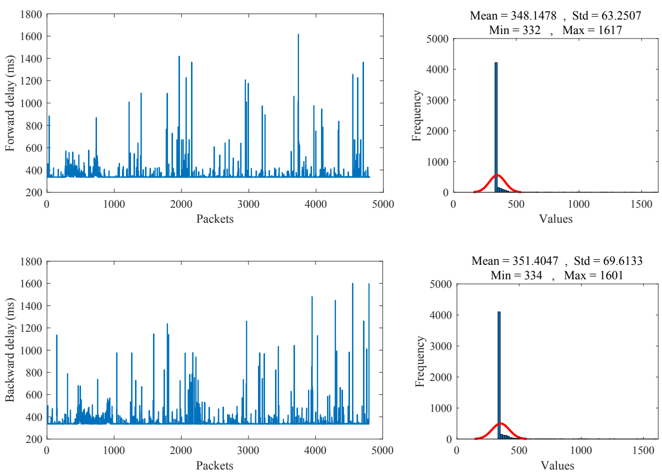

Fig. 5. Communication delays implemented between the two ends of the teleoperation setup (Figure 4). These delays were measured in real-time while the actual teleoperation was in progress.

with only one hidden layer and 13 nodes in its hidden layer. The reason for such a selection is the fact that each MLP at either side of the teleoperation system has an input vector of n=6 elements being either position (x) or force (f) errors. Moreover, the authors carried out some initial experiments to discover what works relatively best for the main goal of this study, considering its computation load, difficulties in implementation, and effectiveness in real-time operation of the proposed approach. Therefore, and according to [33], [34] (as two of the highly appreciated studies in the literature of MLP feed forward neural networks), 2n+1 number of nodes are considered in the hidden layer of the MLP architecture in the study. Of course, the considered architecture for the MLP in the current study may not be the best or optimal one. All other control design parameters are also considered identical to those in [2] for a fair comparison. Moreover, for the RBF-based approach, network parameters and controller gains are all considered as advised in [1], as were applicable in the current teleoperation setup.

Figures 6 to 9 illustrate the results obtained for the three control approaches; the RBF-based robust adaptive method in [1], the robust adaptive algorithm in [2], and the adaptive neural filtering (ANF) strategy in this paper, respectively. Figure 6 shows the position tracking of the three, where, method [1] struggled in z-direction (perpendicular to the object's surface). Comparing the tracking errors in terms of mean absolute error (MAE), root mean square error (RMSE), and normalised RMSE (NRMSE), Figure 7 provides a better observation on the three approaches. The reason for considering those error criteria is to better, fairly evaluating the approaches regardless of magnitudes of measured signals in every trial accomplished.

On the other hand, force reflection of the proposed ANF approach is also evaluated alongside that of [1] and [2]. Figure 8 illustrates the contact forces measured on the teleoperator robot's end-effector, and the haptic feedback provided to the human operator at the operator interface side. The proposed ANF scheme demonstrated a better and more accurate force-reflection compared to the other algorithms. Its outstanding performance can be quantitatively verified by the same error criteria reported in Figure 9. It is worth mentioning that the haptic quality in teleoperation tasks is extremely critical. In other words, haptic capabilities of teleoperation systems directly indicate their transparency for the human operator to be able to operate and accomplish tasks remotely.

Remark 3. Transparency is a key-role player in teleoperation processes, and reflects the quality and reliability of a teleoperation system. However, uncertainties in communication networks drastically impact haptics and transparency features in teleoperation tasks. The adaptive learning-based methodology developed in this study has demonstrated a great performance in tackling those issues, and significantly improved the transparency of teleoperation systems under random delays. More specifically, the capability of the three approaches in position tracking and force reflection (haptics transparency) affects the task accomplishment in terms of either time or successful completion of the task. In other words, poor performance of any of the control approaches would be observed by those terms. Therefore, if a controller fails to provide an accurate and reliable force reflection at the right time, the human operator will react to a wrong force, and therefore, deviates from the original path. Consequently, trying to correct the resulted deviation from the path, the human operator has to compensate for the missing sectors of the path that are not rubbed properly. As a result, this phenomenon causes the overall teleoperation task to take more time and effort to be completed.

In other words, the deviations or overshoots observed in the charts in Figure 6 are because of the improper and wrong force feedback generated by the controllers. Moreover, the reason that those deviations are mostly observed along z direction is that the teleoperation task requires applying force alongside z direction while moving along other directions (x and y). More precisely, the operator only needs to move their hand along x and y directions (forward and lateral) and feeling haptics along z direction (upward). There is no trajectory along z direction to be taken by the operator. Trajectories along z are basically generated by the controllers to maintain the contact force and provide the haptic. Poorer the performance of a controller, more deviations the operator will feel.

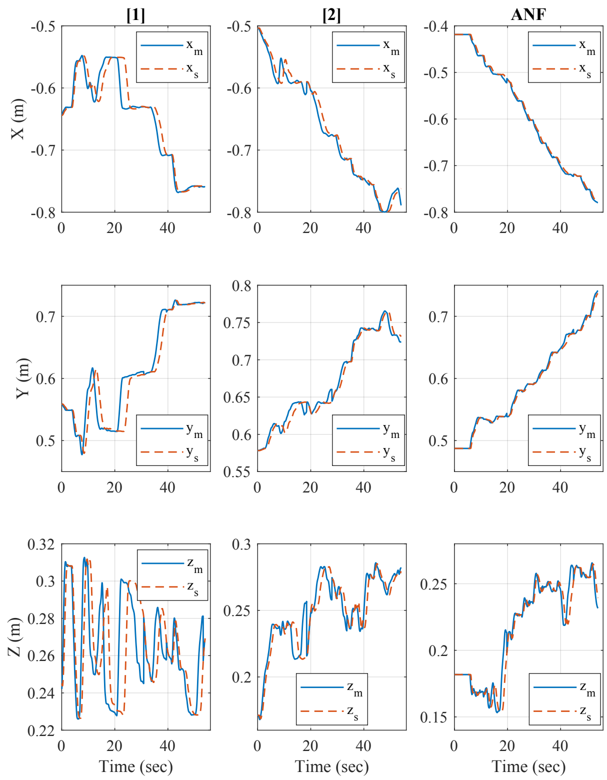

Fig. 6. Position tracking of the three teleoperation approaches.

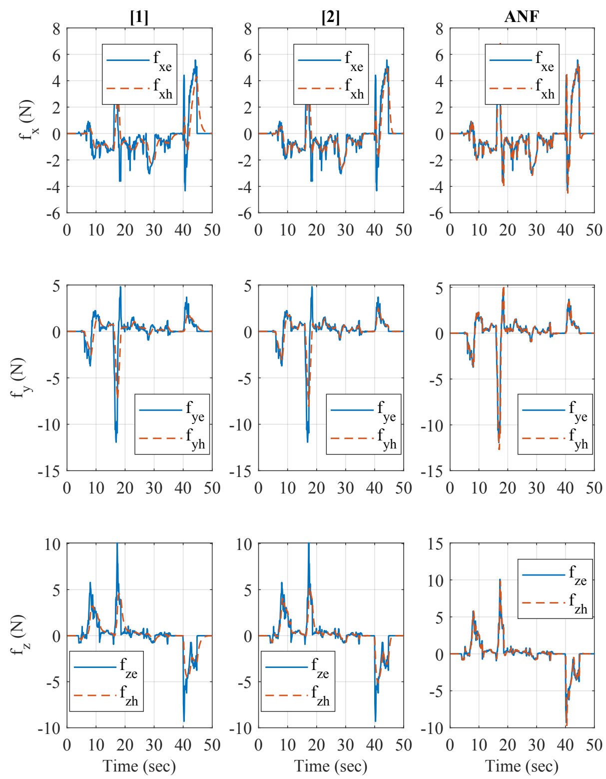

Fig. 8. Haptic/force reflection of the three teleoperation approaches.

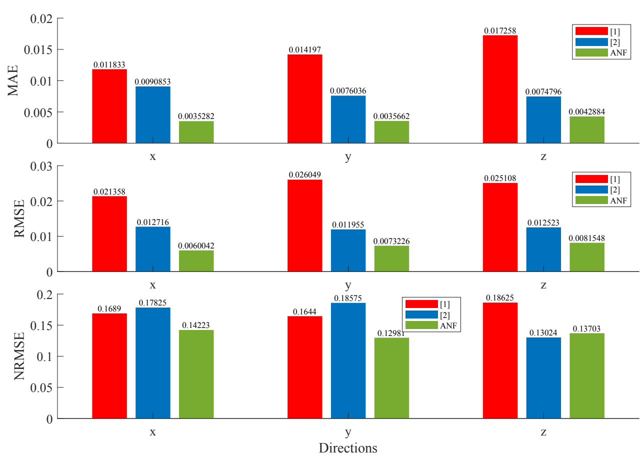

Fig. 7. Tracking errors of the three teleoperation approaches evaluated in three criteria; MAE, RMSE, and NRMSE.

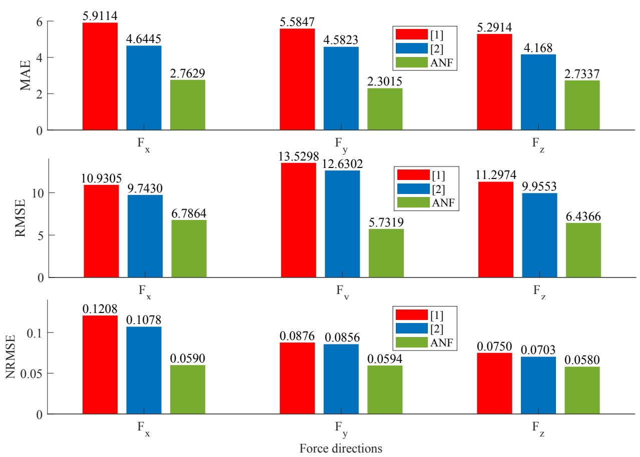

Fig. 9. Force/haptic errors of the three teleoperation approaches evaluated in three criteria; MAE, RMSE, and NRMSE.

V. Conclusions

This article concerned communication uncertainties, as the major bottleneck, in teleoperation systems. Many methods have been investigated in the literature to tackle the issue of time-delays in teleoperation processes. However, the practicality and applicability of them yet to be devised. Employing learning and forecasting capabilities of artificial neural networks, researchers could develop learning-based techniques for the mentioned problem of random latencies. Radial-basis functional is mainly used to resolve dynamics and parameter uncertainties in teleoperation systems. Another common approach to deal with time-delay challenges is using smoothing filters to approximate delayed reference signals.

This study proposed an adaptive algorithm to fine-tune a stable filtering technique with adjustable coefficients. A multilayer perceptron neural network is developed to learn the most efficient set of coefficients according to the random perturbations due to time-varying delays. Weights, biases, and learning rates of the MLP network were also stably fine-tuned via a Lyapunov-Krasovskii functional without getting stuck in local optima. The effectiveness and performance of the proposed neural adaptive filtering approach was demonstrated in a real-world teleoperation practice. In addition, experimentally compared with other two similar and recent

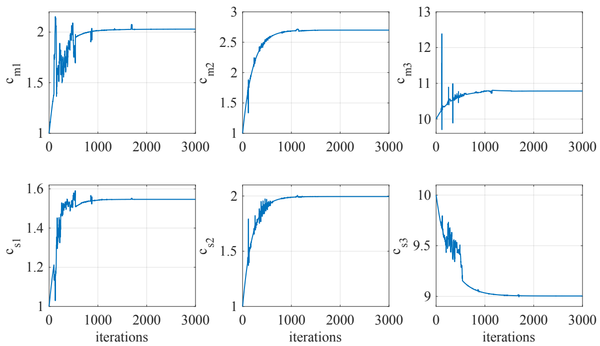

Fig. 10. The learning curves of the filtering coefficients in (4) and (5). The stable convergence of the coefficients indicates that the proposed adaptive learning approach efficiently estimates proper values in a limited number of iterations.

algorithms, the proposed solution in this article outperformed them, specifically, in terms of haptics and transparency.

In the future, optimising the MLP will be considered as a further continuation of this work. Additionally, investigation for more advanced training procedures is going to be another perspective of the current study.

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