Adaptive Neural Control for Bilateral Teleoperation System using External Force Approach

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Abstract: The paper deals with external force control approach based on four channel scheme, that is reported in previous paper (Outayeb et al., 2016). The problem of controlling bilateral teleoperation system under disturbances due mainly to unknown environment, dynamic robot uncertainties and in presence of noisy measurement of force sensors is considered. The Control Algorithms are obtained on two control strategies, the first one consists on a force/Impedance control approach applied to the master robot, whereas the second one consists on external force control loop combined with position control loop applied to the 3-DOF nonlinear slave robot. A neural network (NN) compensator and online environment estimation based on forgetting factor recursive least squares method (FFRLS) are integrated, to eliminate the effects of uncertainties in dynamic model of the slave robot, as well as, to estimate the unknown time varying characteristics of the environment under noisy measurements of force sensors. Numerical simulations using Labview show the efficacy of proposed scheme to guarantee system stability and acceptable transparency performance.

1 INTRODUCTION

Teleoperation is sometimes associated with manipulation of environments that are too distant or inaccessible to man, but also to interact with small area like human body cavity to improve surgical performances in terms of less invasive operations and more confortable positions.

A teleoperation system consists of a teleoperated robot (slave device) controlled by a local control station equipped with haptic interface for the reproduction of the effort applied at the remote site (master device) via a telecommunication channel.

The two major issues in teleoperation are stability robustness which may constitute a problem especially in presence of time delays in the communication and transparency performance which mean that operator should feel as he is directly acting in the remote site (Lawrence, 1993).

There exist various kinds of control schemes for teleoperation systems. In theory and under ideal conditions, four-channel and even three-channel control architectures offer perfect transparency with linear model of master and slave robots (Lawrence, 1993; Zaad and Salcudean, 1999). However in some of these structure both position and force signals are transmitted from one site to another. Therefore, measurement of force in both sides is inevitable to ensure full transparency. By consequence mounting force sensors on robots causes some limitations such as high expense, increasing noise and soft structure (Ohnishi et al., 1994; Dehghan et al., 2014).

Unfortunately, an ideal transparent bilateral teleoperation system cannot be conceived without compromising stability, which highly depends on the robustness of the control scheme implemented under disturbances due mainly to unknown characteristics of the environment, the dynamics of robots and delays in communications (Park and Cho, 1999; Ye et al., 2013; Artigas et al., 2011).

For this reason, in the literature a number of control schemes have been developed based on different criteria including the passivity, compliance, predictive and adaptive control considering either linear or nonlinear models of manipulators. A comparative study based on several approaches can be found in (Arcara and Melchiorri, 2002).

This paper is organized as follows: section 2

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presents the formulation of dynamical models of constrained robots used in master and slave sites respectively, specified in task space. In Section 3, we demonstrate a control algorithms laws designed for both master and slave stations. Moreover, neural compensator is developed in this section, followed by Section 4 which discusses an online estimation of environment based on FFRLS algorithm. Finally, simulation results are shown in Section 5 and conclusion is drawn in section 6.

2 DYNAMIC MODELS

In this section, we consider a bilaterally controlled teleoperator system where both the master and the slave are 3-DOF with revolute joints, that dynamic models are described as follows.

2.1 Dynamic Model of Slave Robot

Consider a nonlinear teleoperated manipulator system consisting of 3-DOF with dynamics given by:

$$M_s(q)\ddot{q}_s + V_s(q,\dot{q})\dot{q}_s + G_s(q) = \tau_{sc} \quad (1)$$

Where $M_s(q)$ is the inertia matrix, $V_s(q,\dot{q})$ is the vector of Coriolis and centrifugal forces, $G_s(q)$ is the gravity term and τ_{sc} is the generalized torque acting on q. Defining the Jacobian $J(q)$ as:

$$\dot{X} = J(q_s)\dot{q}_s \quad (2)$$

With $\dot{X}$ *is* the Cartesian velocity, and the acceleration is given by

$$\ddot{q}_s = J^{-1}(\ddot{X}_s - \dot{J}\dot{q}_s) \quad (3)$$

Substituting (2) and (3) in (1), and applying the relation between the joint torque τ_{sc} and the Cartesian force F_{sc} at the end-effector, $\tau_{sc} = J^T F_{sc}$, the dynamic robot in contact with environment can be written in Cartesian coordinates as

$$M_x(q_s)\ddot{X}_s + V_x(q_s,\dot{q}_s)\dot{X}_s + G_x(q_s) + F_f = F_{sc} - F_e \quad (4)$$

With

$$M_x = J^{-T} M_s(q_s) J^{-1} \quad (5)$$

$$V_x = J^{-T}\left[V_s(q_s,\dot{q}_s) - M_s J^{-1}\dot{J}\right]J^{-1} \quad (6)$$

$$G_x = J^{-T} G_s(q_s) \quad (7)$$

Where F_e is the vector of external forces appears at the end-effector when the robot is in contact, F_{sc} and F_f are respectively the forces due to the controlled torque and friction.

2.2 Dynamic Model of Master Robot

The geometric form of master robot is identical to the slave robot. Unless it is characterized by known linear dynamic model which is represented by the following equation:

$$A_m\ddot{q}_m + B_m\dot{q}_m + g_m = \tau_{mc} \quad (8)$$

Where A_m, B_m and g_m refers the impedance characteristic of this robot in the joint space.Reformulating this end into Cartesian space and applying the same manner as below, the model equation is given as :

$$A_x\ddot{X}_m + B_x\dot{X}_m + g_x = F_{mc} + F_h \quad (9)$$

Where F_h is the force applied by the operator on end-effector master interface.

3 CONTROLLER DESIGN

This section is carried out to present a proposed control scheme based on the Force/Impedance controller applied at the master, and the Force/Position control loop using external force approach developed to the slave device.

3.1 Master Controller

The block diagram of proposed controller is shown in (Fig. 1), The force/impedance control is designed to obtain desired behavior of the manipulator described by the following relationship between end-effector motion and applied force exerted by the operator

$$A_d\ddot{X}_m + B_d\dot{X}_m = F_h - \hat{F}_e \quad (10)$$

Where A_d, B_d represent the desired inertia and damping respectively, $\hat{F}_e$ is the force recovered from noisy force sensors measured in the remote site.

Given the manipulator dynamics and in order to achieve the desired impedance behavior, an inverse dynamics control law can be proposed as

$$F_{mc} = \left(\hat{B}_x - \frac{\hat{A}_x}{A_d}B_d\right)\dot{X}_m + \left(\frac{\hat{A}_x}{A_d} - 1\right)F_h - \frac{\hat{A}_x}{A_d}\hat{F}_e - \frac{\hat{A}_x}{A_d}K_d(X_s - X_m) - \hat{g}_x \quad (11)$$

Where the hats denote the available estimates of the corresponding dynamic terms, this controller is operational in either free or constrained space, by taking account the correction of the error occurred in the positioning of the local robot when the slave robot is constrained by the environment.

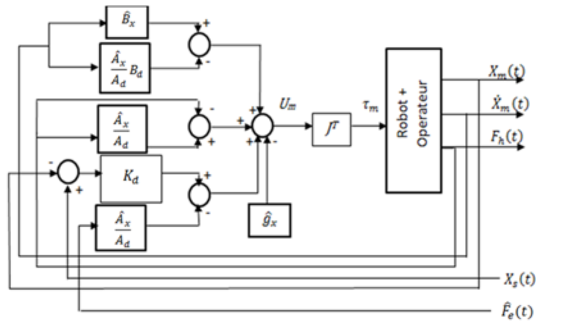

Figure 1: Force/Impedance control structure for the master interface.

3.2 Slave Controller

An adaptive force/position control scheme is developed in this section according to the external force control concept proposed in literature (Schutter and Van Berussel, 1988), where we take into account the uncertainty dynamics of slave robot, unknown location of the object, variable stiffness of the environment and noisy quality of force sensor. For this end, we have integrated two complementary techniques based on a neural compensator and a FFRLS method described later.

$$F_{sc} = \widehat{M}_x(U + U_a) + \widehat{V}_x\dot{X}_s + \widehat{G}_x X_s + \widehat{F}_e \qquad (12)$$

Where the hats denote the available uncertain estimates of the dynamic terms M_x, V_x, G_x and $\widehat{F}_e$ is the signal force recovered from noisy measured force sensor, by applying the online environment estimation method that will be discussed in section 4.

By following the external force control approach, U is designed to assure a compliant motion by feeding the error between desired force F_h and actual force $\widehat{F}_e$ into the force controller, this contact force acts as correction which will modify the desired trajectory applied to the position control loop, so:

$$U = \ddot{X}_s + K_v\dot{E}_p + K_p E \qquad (13)$$

With

$$E = X_m + \Delta X_c - X_s = E_p + \Delta X_c$$

Where ΔX_c presents the correction of desired position

Namely, as (Chiaverini and Sciavesco, 1999) the dynamic model of the slave represents a highly nonlinear and strongly coupled system for which the nonlinear dynamic decoupling approach can be adopted. The closed loop dynamic equation can be rewritten as

$$M_x\ddot{X}_s + K_v\dot{E}_p + K_p E_p + \Delta X_c = \qquad (14)$$

$$\left(\Delta\widehat{M}_x\ddot{X}_s + \Delta\widehat{V}_x\dot{X}_s + \Delta\widehat{G}_x X_s + F_f + \Delta F_e\right) - U_a$$

With

$$\Delta X_c = K_p\,\widehat{K_e}^{-1}\left(K_{fi}\int\left(F_h - \widehat{F}_e\right) + K_{fv}\left(\dot{F}_h - \dot{\widehat{F}}_e\right) + K_{fp}\left(F_h - \widehat{F}_e\right)\right)$$

When Δ denotes the uncertainty terms.

The Neural compensator output U_a, described later, is trained to minimize the uncertainty terms in (14).

$$\text{let } v = M_x\ddot{X}_s + K_v\dot{E}_p + K_p E_p + K_p\widehat{K}_e^{-1}\left(K_{fi}\int E_f + K_{fv}\dot{E}_f + K_{fp}E_f\right) \qquad (15)$$

Since the control objective is to generate U_a to reduce v to zero. We propose here to use v as the error signal for training the neural network.

In the ideal case $(v = 0)$ the output of the neural compensator is required to be

$$U_a = \left(\Delta\widehat{M}_x\ddot{X}_s + \Delta\widehat{V}_x\dot{X}_s + \Delta\widehat{G}_x X_s + F_f + \Delta F_e\right) \qquad (16)$$

The slave controller is schematized by the following diagram

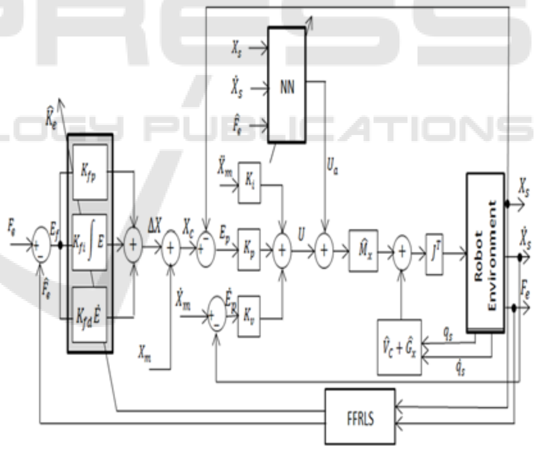

Figure 2: Adaptive structure of external Force controller loop combined with FFRLS estimator and NN compensator for the Slave manipulator.

3.3 Neural Network Compensator Design

The network model selected in this paper in order to implement the proposed artificial neural network compensator is a three layer network structure (see Fig.3) which is composed of a linear input layer $I = [X_m^T(t)\ \dot{X}_m^T(t)\ F_e^T(t)]$, a non-linear hidden layer of sigmoid type expressed by the following equation:

$$f(u_j) = \frac{2}{(1 + exp^{-u_j})} - 1 \tag{17}$$

And an output layer of linear processing unit. Therefore, the input-output relationship of the network is

$$U_a = \sum_{j=1}^{Nc} W_{jk}^2 \left(\frac{2}{\left(1 + exp^{-\left(\sum_{i=1}^{Ne} x_i W_{ij}^1 + b_j^1\right)}\right)} - 1 \right) + b_k^2 \tag{18}$$

Where, W_{ij}^1 are the weights between the input layer and the hidden layer, W_{jk}^2 are the weights between the hidden layer and the output layer, b_j^1 is the bias of the j-th neuron in the hidden layer and b_k^2 is the bias of the k-th neuron in the output layer.

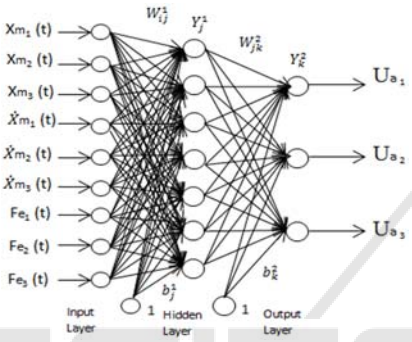

Figure 3: Structure of Neural Network Compensator

The goal is to generate an auxiliary computed torque U_a altering the training signal v to be zero as either v_{free} or $v_{contact}$, and that is based on the minimization of a quadratic function J, where J is given by:

$$J = \frac{1}{2} v^T v \tag{19}$$

The weight updating law is obtained by using the back-propagation algorithm of the gradient (Ferguene and Toumi, 2005). This algorithm consists of modifying a variable U_a in the opposite direction to the derivative function of the error, yields the gradient of J as:

$$\frac{\delta J}{\delta w} = \frac{\delta v^T}{\delta w} v = -\frac{\delta {U_a}^T}{\delta w} v \tag{20}$$

Where the weight adaptation law with a momentum term is:

$$\Delta W(t) = \eta \frac{\delta {U_a}^T}{\delta w} v + \mu \Delta W(t-1) \tag{21}$$

With η is the update rate and μ is the momentum coefficient. Explicitly, the resulting algorithm can be derived by making use of (20).

$$\begin{aligned} \Delta W_{ij}^1(t) &= \eta 0.5 \left(1 - Y_j^1\right)^2 x_{d_i} \left[\sum_{k=1}^{n} v_k W_{jk}^2\right] \\ &\quad + \mu \Delta W_{ij}^1(t-1) \\ \Delta W_{jk}^2(t) &= \eta v_k Y_j^1 + \mu \Delta W_{jk}^2(t-1) \\ \Delta b_j^1(t) &= \eta 0.5 \left(1 - Y_j^1\right)^2 \left[\sum_{k=1}^{n} v_k W_{jk}^2\right] \\ &\quad + \mu \Delta b_j^1(t-1) \\ \Delta b_k^2(t) &= \eta v_k + \mu \Delta b_k^2(t-1) \end{aligned} \tag{22}$$

4 ENVIRONMENT DYNAMIC

In this paper, we propose a good online estimation algorithm that have objective to track and identify the location and dynamic characteristics of any constraints in a robot's workspace.

The model considered is not homogeneous in the sense that it is manifested by a time varying stiffness K_e. More specifically, this environment has the following dynamics:

$$F_e = (K_e + (0.25 * K_e * \sin(t)) * (x_e - x_{ec})) \tag{23}$$

Where x_{ec} is the position of the object at rest, and K_e is a (3×3) constant diagonal stiffness matrix. In discrete domain, the environment dynamics can be written as (Ljung, 1987):

$$F_k = \phi_k^T \theta_k + n_k \, , x_k > 0 \tag{24}$$

Where the subscript k denotes the time instant, $\phi_k^T = [x_k, x_{k-1,\dots,} x_{k-m}]$ is the measurement vector, $\theta_k = [K_k]^T$ the vector of parameters, n_k the modeling error and measurement noise, x_k the penetration at sample time $= k.T$, the parameter T is the sample time.

4.1 Estimation Method of Unknown Time Varying Parameter

For abruptly parameter identification, the use of RLS method with periodic initialization of estimated value can highly capture the new values of the parameter. However for real time varying parameter estimation, it is necessary to apply forgetting factor to RLS algorithm. The concept of FFRLS algorithm has the tracking ability as the covariance ceases to exist gradually to zero with time, Hence this method can be viewed as giving less weight to older data and more weight to recent data. Smaller forgetting factors will improve the tracking ability and can affect the stability of the algorithm (Vahidi et al., 2005). The "loss-function" is then defined as :

$$J(\hat{\theta},k) = \frac{1}{2}\sum_{i=1}^{k} \lambda^{k-i}\left(f(i) - \phi^T(i)\hat{\theta}(k)\right)^2 \quad (25)$$

Where λ is called forgetting factor and $0 < \lambda \leq 1$. Obviously, small values for λ puts greater emphasis on recent data and θ can be calculated recursively using the update equations derived as follows:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + L(k)\varepsilon(k) \quad (26)$$

$$\varepsilon(k) = f(k) - \phi^T(k)\hat{\theta}(k-1) \quad (27)$$

With

$$L(k) = P(k)\phi(k) = \frac{p(k-1)\phi(k)}{\lambda + \phi^T(k)p(k-1)\phi(k)} \quad (28)$$

$$p(k) = \lambda^{-1}p(k-1)\left(I - L(k)\phi^T(k)\right) \quad (29)$$

$P(k)$ is normally referred to as the covariance matrix of parameters $\hat{\theta}(k)$. More detailed derivation can be found in books on parameter estimation such as (Astrom and Wittenmark, 1994).

5 SIMULATION

To check out the efficiency of the proposed approach, two geometric identical 3-DOF rotary manipulators are simulated, a slave robot whose parameters are taken from the first three links of Puma 560 arm (Armstrong and Khatib, 1986), whereas a linear master robot whose parameters are assumed to be known accurately. Model uncertainties included a 5 Kg Mechanical tool attached to the third link, Coulomb friction and viscous friction torques $\tau_f(\dot{q})$ added to each joint where $\tau_f = 0.8\dot{q} + 0.5sign(\dot{q})$. For the NN compensator we have chosen nine input neurons $(n_I = 9)$ and seven hidden neurons $(n_H = 10)$. The back propagation algorithm parameters are: $\eta = 0.001$, $\mu = 0.9$. Weights are initially randomly selected and adjusted every sampling time in online fashion.

On the assumption of unknown geometric proprieties of manipulated object and in order to calculate an online estimation of their stiffness from poor quality force sensors measurements, we apply a FFRLS method with $P(0) > 0$, $\hat{\theta}(0) = 15000N/m$, $\lambda = 0.975$, The gains of controller law and the desired Impedance are fixed experimentally by

$$A_d = I,\ B_d = 40\times I, K_d = 800\times I$$

$$M_d = I\ (kg), K_v = 40(Ns/m)\times I,$$

$$K_p = 40(Ns/m)\times I\ , K_{fi} = 0.15,$$

$$K_{fv} = 400,\ K_{fp} = 8000$$

Task space has object with flat surface and variable stiffness which depends on time with:

$$K_e = \begin{pmatrix} K_{ex} \\ K_{ey} \\ K_{ez} \end{pmatrix} = \begin{pmatrix} 2200+(550*\sin(t)) \\ 15000+(3750*\sin(t)) \\ 7000+(1750*\sin(t)) \end{pmatrix} \quad (30)$$

The test bed consists of master and slave robots situated at positions

$$P_{m,s} = (0.4115m, 0.150m, 0.4331m)$$

of different sites. Initially, the operator applies constant force F_h through 3 directions on the end-effector interface to move it with respect to the desired impedance calculated above (10), while the slave robot starts tracking the trajectory generated by master interface until it crashes the object situated at unknown position (supposed in our simulation at $P_m = (0.45m, 0.21m, 0.55m)$). At this time, the operator pushes the interface with sinusoidal force as given by equation (31). The slave robot is being in constrained space, so it moves with master's position and controls the force of interaction on the surface of the object according to the force applied by the operator, in this case, the slave robot will dominate a force action over position action. By consequence, different positions will generated and transmitted to the master station in order to move it with respect to slave robot position. The input signal of force applied by operator is given by

$$(t) = \begin{cases} 0\ 0 \leq t < 1 \\ 8\ 1 \leq t < 3 \\ 8 + 2 * \sin(6.28 * t)\ 3 \leq t < 5 \\ -8\ 5 \leq t < 7 \\ 0\ t \geq 7 \end{cases} \quad (31)$$

In Figure 4, it's obviously marked the quality of recovered signal from noisy force sensors measurements over 3 directions, and when interacting with environment characterized by time varying stiffness.

In Figures (5.1) and (5.2), the responses illustrates that the whole system is stable and guarantees equality between the force applied by the operator and that applied to the environment. Moreover, it presents a good tracking of both master and slave trajectory either in free or constrained space.

Considering fair results obtained compared with those obtained in previous work. We conclude the ability to investigate with complex methods proposed for controlling a local manipulator, to deals with more complicated problems in teleoperation system.

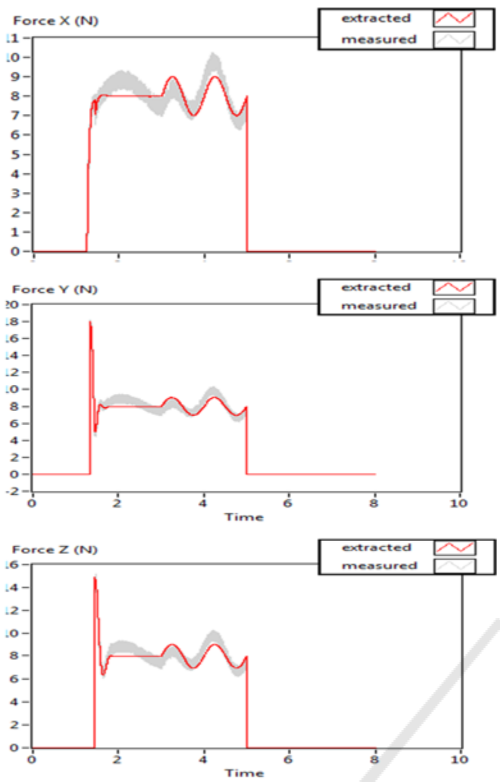

Figure 4: The recovered force signal and noise rejected along X, Y and Z axis.

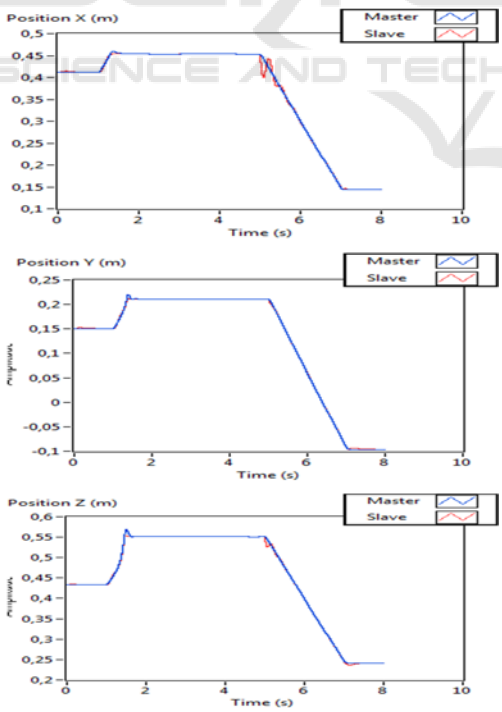

Figure 5.1: Position Tracking along X, Y and Z axis for teleoperation system.

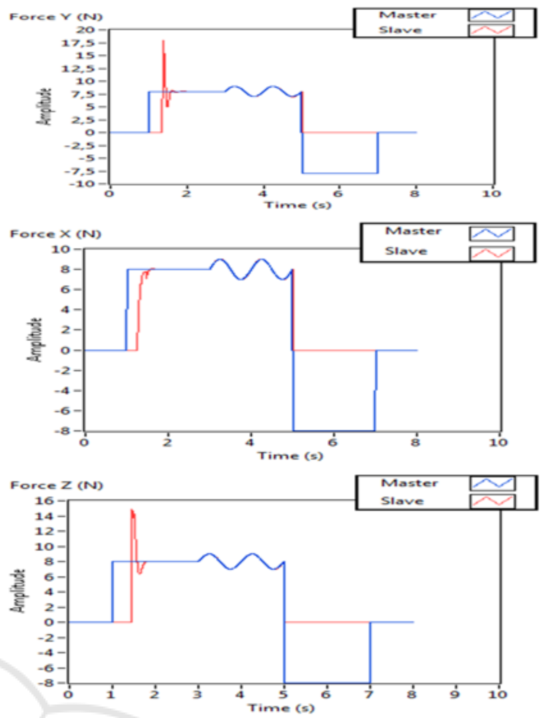

Figure 5.2: Force applied along X, Y and Z axis for teleoperation system.

6 CONCLUSION

In this work, an adaptive force/position control algorithm in bilateral teleoperation system is developed, using an external force control approach, taking advantage of four channel structure that we have presented in previous work. Our approach is based on force/impedance controller at the master and external force control loop, combined with a neural compensator and forgetting factor recursive least square estimator at the slave.

The results of simulations obtained with our proposed scheme are convincing and similar to those reported in (Outayeb et al., 2016). Whole teleoperator system stability is guaranteed with acceptable transparency performances, even when there are the slave robot dynamic uncertainties, unknown and variable environment stiffness, and poor measurements of force sensors.

Studies are remained as a proposed future work going along with designing more robust controller, by considering a full unknown dynamic of slave robot and environment.

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