



Bilateral Teleoperation Systems Using Backtracking Search optimization Algorithm Based Iterative Learning Control

A. Alfi*

Faculty of Electrical and Robotic Engineering, Shahrood University of Technology, Shahrood 36199-95161, Iran

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ABSTRACT

This paper deals with the application of iterative learning control (ILC) to further improve performance of bilateral telerobotic systems based on Smith predictor. The aim is to achieve robust stability and optimal transparency for these systems simultaneously. The proposed control structure makes the slave manipulator follow the master in spite of uncertainties in time delays appeared in communication channel and model parameters of master-slave robots, called model mismatch. The time delays are considered to be large, unknown and asymmetric, but the upper bound of the delay is assumed to be known. The main aspect of the proposed controller is that a designer can use the classical controller like proportional-integrator-derivative (PID). However, one of its main difficulties is how to assign proper parameter values for the controller. In other words, the parameters of the controller are not unique and are chosen only to satisfy the stability condition. To solve this problem, in this paper, the local controller is also optimized by backtracking search optimization algorithm (BSA), which is a novel heuristic algorithm with a simple construction. Simulation results illustrate the appropriate performance of the proposed controller.

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1. INTRODUCTION

The remote control of telerobotic systems has gained considerable attention during two past decades. Telerobotic systems are widely utilized to perform complex tasks in hazardous environments [1].

A telerobotic system is generally composed of the following interconnected parts: a human operator, a dual robot allocated in local and remote sites namely master and slave robots, an environment and a communication channel. In a bilateral telerobotic system, the master robot is directly handled by a human operator in order to manipulate the slave robot in a task environment. It has been shown that the performance improvement is accomplished by providing feedback of the interaction force of the slave robot with the environment to the human operator, which is called force reflection [2].

The communication channel and interactions between the task environment and the slave are of important matters. When the distance between the

master and slave is too long, a time delay in communication channel appears that cannot be ignored. Small value of the time delay can cause system instability [3, 4]. Several techniques have been introduced in literature to address this problem [5-11]. Transparency is a major criterion for the performance of telerobotic systems in presence of time delay uncertainties. If the slave accurately reproduces the master's commands and the master correctly feels the slave forces, the human operator experiences the ideal situation of direct action on the task environment. This is called complete transparency in telerobotic system. Iterative Learning Control (ILC) is an efficient methodology for improving the performance of the system specially tracking aspect. The key difference between conventional feedback control and ILC is that the system operated under the ILC can be treated a two-dimensional system where one dimension is time and other one is iteration. The systems with ILC framework act repetitively by nature like robot manipulators [12-14]. In ILC, as increase the number of iterations, tracking error would decrease in the definite time interval.

*Corresponding Author's Email: a_alfi@shahroodut.ac.ir (A. Alfi)

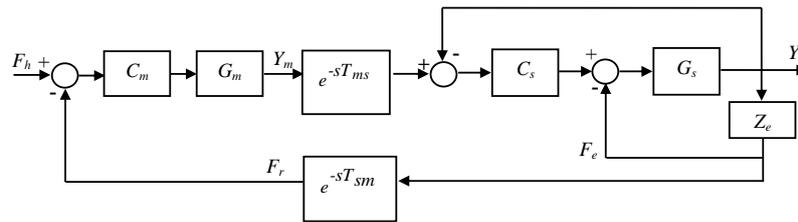


Figure 1. The general framework for bilateral telerobotic system

Due to existence of model uncertainty, obtaining the good performance is normally challenging [15]. In telerobotic systems, the model of master and slave robots and time delay in communication channel usually are uncertain, which is called model mismatch. These problems conduce to instability and bad performance.

Based on aforementioned researches, this paper addresses issues of stability and transparency in bilateral telerobotic systems against model mismatch using ILC based on smith predictor. It is assumed that the time delay in communication channel be unknown and asymmetric, but the upper bound of delay is supposed to be known. Since the time delay of the practical systems are often bounded, it is reasonable to assume the upper bound on the time delay. In the core of controller structure, Smith predictor is employed to improve the closed-loop stability for the system. According to our knowledge, this is the first application of Smith predictor-based ILC for controlling of telerobotic systems.

In addition, when applying the local controller into the system, we face with choosing an arbitrary set of the gains for the controller. It is unclear how the parameters of the controller are properly chosen, since these parameters are directly related to the controller performance. That is, the parameters of the local controller values are not unique and are opted only to satisfy the stability condition. The manual tuning is a time-consuming task and depends considerably on knowledge of the plant and experience of an operator. From this viewpoint, it is required to develop an optimal tuning strategy of the controllers, which can determine a set of controller gains simultaneously by solving an optimization problem. To this reason, the problem in hand can be considered as an optimization problem. Thus, in the proposed strategy, a novel heuristic algorithm, namely Backtracking Search Optimization Algorithm (BSA), is also used to achieve optimal performance of the system.

The rest of this paper is organized as follows. Section 2 describes a general framework of telerobotic systems. In Section 3, the design of the controllers is discussed in detail. Stability analysis is given Section 4. Section 5 represents the explanation of BSA. Section 6 illustrates simulation results. Finally, Section 7 draws conclusions and future works.

2. GENERAL FRAMEWORK

The control framework for telerobotic systems used in this paper is adopted from [6], as shown in Figure 1. In this figure, G_m and C_m are the transfer function of the master robot and the corresponding controller namely local controller, respectively, G_s and C_s the transfer function of the slave robot and corresponding controller namely remote controller, T_{ms} and T_{sm} are the forward and backward time delays in communication channel, respectively, f_h is the force exerted on the master by human operator, f_e is the environmental reaction force which is measurable, f_r the reflection force after being passed through a backward delay, and Z_e the impedance of the task environment. In the control structure, the compliance control and direct-force measurement-force reflecting control has been combined.

Stability and transparency are two main purposes of the control structure shown in Figure 1. To achieve these goals, the local and remote controllers (i.e. C_m and C_s) are designed. The aim of designing C_s is to guarantee the motion tracking, whereas C_m is designed to ensure the stability of the closed-loop system as well as force tracking simultaneously. In the following, we explain the designing of the local and remote controllers in detail.

3. DESIGN OF CONTROLLERS

3. 1. Remote Controller Consider the output of master and slave robots is position, then from Figure 1, we have

$$\frac{X_s(s)}{X_m(s)} = \frac{C_s(s)G_s(s)}{1 + Z_e G_s(s) + C_s(s)G_s(s)} e^{-sT_{ms}} \quad (1)$$

Since the denominator of the transfer function given in Equation (1) is free of the time delay, the design of remote controller is then independent of the time delay. Accordingly, we can use the classical control methods

like proportional-derivative (PD) to design a local controller C_s for the remote site such that system in Equation (1) is stable. This means that the poles of the transfer function are in the left-hand side of the S -Plane. Based on this, the position of the slave robot will follow the position of the master robot in such a way that the tracking error for position is satisfactory.

3. 2. Local Controller For simplicity, we define the following new variables.

$$\hat{G}_s(s) = \frac{Z_e C_s(s) G_s(s)}{1 + Z_e G_s(s) + C_s(s) G_s(s)} \quad (2)$$

$$G(s) = \hat{G}_s(s) G_m(s) \quad (3)$$

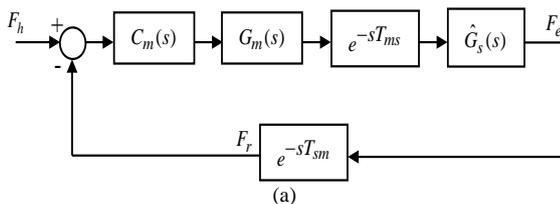
$$T = T_{ms} + T_{sm} \quad (4)$$

$$F_r(s) = F_e(s) e^{-sT_{sm}} \quad (5)$$

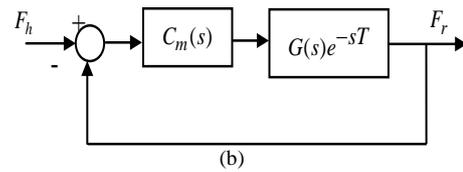
Using these variables, the control scheme shown in Figure 1 can be simplified as Figure 2(a). Considering the force tracking, a new output F_r can be defined in Figure 2(a). As a result, the system shown in Figure 2(a) can be simplified as the system in Figure 2(b). From Figure 2(b), the transfer function of the closed-loop system can be written as

$$M(s) = \frac{C_m(s)G(s)e^{-Ts}}{1 + C_m(s)G(s)e^{-Ts}} \quad (6)$$

Form Equation (6), the roles of $M(s)$ are the stability of the overall system as well as force tracking. It can be seen that the time delay can make system unstable and degrade the performance of the whole system. To solve this problem, different approaches have been introduced. Smith predictor is an effective method to eliminate the time delay from the characteristic equation [16]. Figure 3 represents the structure of Smith predictor. In this Figure, $P(s) = G(s)e^{-sT}$ is the transfer function of the real model, in which G is the model delay-free part transfer function and $T > 0$ is the time delay. Also, $P_m(s) = \tilde{G}(s)e^{-s\tilde{T}}$ is the transfer function of the nominal model.



(a)



(b)

Figure 2. The simplified schematic of general framework

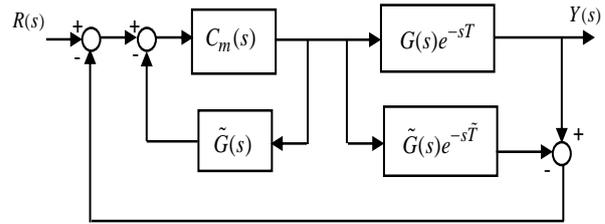


Figure 3. Smith predictor scheme

Referring to Figure 3, the closed-loop transfer function is

$$\tilde{M}(s) = \frac{C_m(s) G(s) e^{-sT}}{1 + C_m(s) G(s) + C_m(s) G(s) [e^{-sT} - e^{-s\tilde{T}}]} \quad (7)$$

If there is no model mismatch, then the closed-loop system is stable. In other words, if $G(s) = \tilde{G}(s)$ and $T = \tilde{T}$, then Equation (7) can be rewritten as:

$$M(s) = \frac{C_m(s) G(s)}{1 + C_m(s) G(s)} e^{-sT} \quad (8)$$

Here, the stability of the closed-loop becomes delay-independent and the local controller C_m is designed somehow for the delay-free system. Thus, one can use the classical control methods for designing local controller C_m like Proportional-Integrator-Derivative (PID). Unfortunately, the main problems is that: (1) it is hard to get the precise model of master and slave robots, and (2) the time delay is not constant. These will lead to instability of the system.

To handle this problem, in this paper, ILC strategy is applied in the closed-loop system. Figure 4 represents the general schematic ILC-based Smith predictor for controlling bilateral telerobotic system [17]. The goal of this structure is to achieve progressively force tracking as:

$$\lim_{t \rightarrow \infty} |e_f(t)| = \lim_{t \rightarrow \infty} |f_h(t - T) - f_r(t)| \rightarrow 0 \quad (9)$$

where T is the summarizing time delay defined in Equation (4). Assuming knowledge of the upper bound of time delay ($T \leq T_{max}$), Figure 4 should be modified as Figure 5 [18]. In the next part, we provide conditions for stability of the overall closed-loop system.

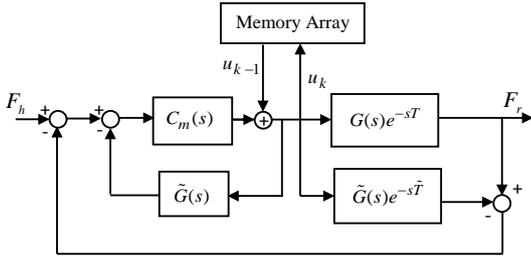


Figure 4. General schematic of ILC-based Smith predictor

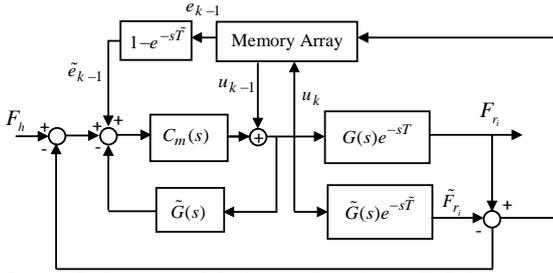


Figure 5. Structure of Smith predictor-based ILC for designing local controller

4. STABILITY ANALYSIS

Assuming the worst case for the time delay (i.e., $\tilde{T} = T_{\max}$), from Figure 5, the updating law of the control signal can be obtained as:

$$U_{i+1} = U_i + C \left[R - \left(G(s)e^{-sT} - \tilde{G}(s)e^{-s\tilde{T}} + \tilde{G}(s) \right) \right] U_{i+1} + \tilde{E}_i \quad (10)$$

where

$$\tilde{E}_i = \left(F_{r_i} - \tilde{F}_{r_i} \right) \left(1 - e^{-sT} \right) \quad (11)$$

Substituting Equation (11) into Equation (10) and further simplifications, it yields

$$\tilde{F}_{r_{i+1}} = \frac{1 + C_m \left(G(s)e^{-sT} - \tilde{G}(s)e^{-s\tilde{T}} + \tilde{G}(s) - G(s)e^{-s(T-T_{\max})} \right)}{1 + C_m \left(G(s)e^{-sT} - \tilde{G}(s)e^{-s\tilde{T}} + \tilde{G}(s) \right)} \times \tilde{F}_{r_i} + \frac{1 + C_m G(s)e^{-sT}}{1 + C_m \left(G(s)e^{-sT} - \tilde{G}(s)e^{-s\tilde{T}} + \tilde{G}(s) \right)} F_h \quad (12)$$

By defining

$$E_i = R e^{-s\tilde{T}} - F_{r_i} \quad (13)$$

the recursion equation with respect to force tracking error can be written as:

$$E_{i+1} = Q(s)E_i \quad (14)$$

where

$$Q(s) = \frac{1 + C_m \left(G(s)e^{-s\tilde{T}} - \tilde{G}(s)e^{-s\tilde{T}} + \tilde{G}(s) - G(s)e^{-s(T-T_{\max})} \right)}{1 + C_m \left(G(s)e^{-sT} - \tilde{G}(s)e^{-s\tilde{T}} + \tilde{G}(s) \right)} \quad (15)$$

The sensitivity (S) and complementary sensitivity (H) functions associated with the nominal model are as follows:

$$S = \frac{1}{1 + C(s)\tilde{G}(s)} \quad (16)$$

$$H(s) = \frac{C(s)\tilde{G}(s)}{1 + C(s)\tilde{G}(s)} \quad (17)$$

Using Equation (16) and Equation (17), we obtain

$$Q(s) = \frac{S + WH \left(e^{-s\tilde{T}} - 1 \right)}{1 + WH e^{-s\tilde{T}}} \quad (18)$$

in which

$$W(s) = \frac{G}{\tilde{G}} e^{-s(T-\tilde{T})} - 1 \quad (19)$$

$W(s)$ is a bounded function including all the uncertainties called the ignorance function [19].

$$\|W(j\omega)\| \leq \Delta(j\omega) \quad (20)$$

Theorem [17]: A sufficient condition for the convergence of the force tracking error is

$$\|S\| + 3\|\Delta H\|_{\infty} < 1 \quad (21)$$

5. BSA

As mentioned in section 3.2, a designer can utilize the classical controller like PID for the local controller. The problem is that appropriate values are assigned to the parameters of the controller. Then, an arbitrary set of gains can be chosen by the designer for the controller. One of its main difficulties is how to select suitable parameter values for the controller. The manual tuning is a time-consuming task. So, we need to develop an optimal tuning strategy of the controller, which can determine a set of controller gains simultaneously by solving an optimization problem. To this end, the problem in hand can be considered as an optimization problem. Traditional methods like gradient descents and dynamic programming often fail or trapped at local optima depending on the initial guess of solution while solving multimodal problems having large number of variables and non-linear objective functions. To overcome this shortage, various heuristic algorithms have been successfully applied in different areas [20-28]. To achieve the optimal performance of the system, BSA [29] is employed, which is a novel heuristic algorithm. Figure 6 illustrates the structure of the Smith-based ILC using BSA. BSA has a simple

construction that is effective, fast and capable of solving multimodal optimization problems. Furthermore, the performance of BSA is not over sensitive to the initial value of this parameter. Unlike many population-based algorithms, BSA requires only one parameter that affects the performance of the algorithm [29]. Here, this optimization algorithm will be discussed briefly.

BSA's strategy for generating a trial population includes two new crossover and mutation operators.

BSA's strategies for generating trial populations and controlling the amplitude of the search-direction matrix and search-space boundaries give it very powerful exploration and exploitation capabilities. In particular, BSA possesses a memory in which it stores a population from a randomly chosen previous generation for use in generating the search-direction matrix. Thus, BSA's memory allows it to take advantage of experiences gained from previous generations when it generates a trial preparation. BSA can be explained by dividing its functions into five processes as is done in other EAs: initialization, selection-I, mutation, crossover and selection-II.

5.1. Initialization BSA initializes the population P as:

$$P_{i,j} \approx U(\text{low}_j, \text{up}_j) \tag{22}$$

for $i = 1, 2, 3, \dots, N$ and $j = 1, 2, 3, \dots, D$, where N and D are the population size and the problem dimension, respectively, U is the uniform distribution and each P_i is a target individual in the population P .

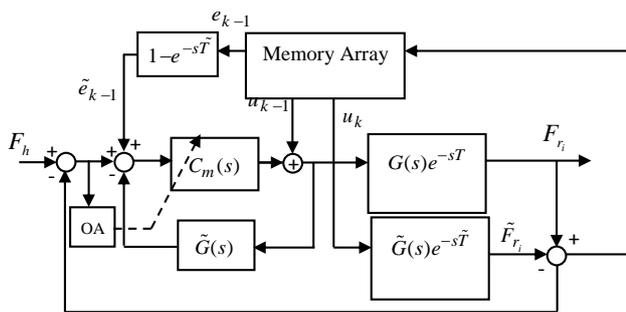


Figure 6. The structure of Smith-based ILC using BSA

5.2. Selection-I BSA's Selection-I stage determines the historical population $oldP$ to be used for calculating the search direction. The initial historical population is determined using Equation (23).

$$oldP_{i,j} \approx U(\text{low}_j, \text{up}_j) \tag{23}$$

BSA has the option of redefining $oldP$ at the beginning of each iteration through the 'if-then' rule given in Equation (24).

$$\text{if } a < b \text{ then } oldP := P|_{a,b} \approx U(0,1) \tag{24}$$

where $:=$ is the update operation.

Equation (24) ensures that BSA designates a population belonging to a randomly selected previous generation and remembers this historical population until it is changed. After $oldP$ is determined, Equation (25) is used to randomly change the order of the individuals in $oldP$:

$$oldP := \text{permuting}(oldP) \tag{25}$$

The *permuting* function used in Equation (25) is a random shuffling function.

5.3. Mutation BSA's mutation process generates the initial form of the trial population $Mutant$ using Equation (26).

$$Mutant = P + F \cdot (oldP - P) \tag{26}$$

In Equation (26), F controls the amplitude of the search-direction matrix $(oldP - P)$. Because the historical population is used in the calculation of the search-direction matrix, BSA generates a trial population, taking partial advantage of its experiences from previous generations. Here, we use the value $F = 3 \cdot \text{rand}$, where $\text{rand} \approx N(0,1)$ (N is the standard normal distribution).

5.4. Crossover BSA's crossover process generates the final form of the trial population T . BSA's crossover process has two steps. The first step calculates a binary integer-valued matrix (map) of size $N \cdot D$ that indicates the individuals of T to be manipulated by using the relevant individuals of P . If $map_{n,m} = 1$, where $n \in \{1, 2, 3, \dots, N\}$ and $m \in \{1, 2, 3, \dots, D\}$, T is updated with $T_{n,m} := P_{n,m}$.

6. SIMULATION

6.1. Modeling of Master and Slave Robots In this paper, similar to many papers in this field, a one-degree-of-freedom robot is used for the master and slave systems [5-7, 30].

The system dynamics will be then represented by the following equations.

$$\begin{aligned} s(M_m s + B_m)x_m &= \tau_m + \tau_h, \\ s(M_s s + B_s)x_s &= \tau_s - \tau_e \end{aligned} \tag{27}$$

where B is the viscose friction coefficient, M the manipulators inertia, x the position and τ the input force; indices m and s are for the master and the slave

systems, respectively; τ_h the force applied to the master by human operator and τ_e the force exerted on the slave from the environment. The nominal models of master and slave robots are $\tilde{G}_m(s) = \frac{0.5}{s(0.4s+3)}$, $\tilde{G}_s(s) = \frac{10}{s(0.5s+0.2)}$, respectively and the nominal values of the time delays existed in backward and forward, i.e., $T = 1$. The real models of master and slave robots are $G_m(s) = \frac{1}{s(0.4s+3)}$, $G_s(s) = \frac{1}{s(s+0.2)}$, respectively. Furthermore, the maximum values of the time delays are considered $2sec$. It is worth to mention that to assess the performance of the proposed control method, we consider the worst case by choosing $\tilde{T} = T_{max}$.

6. 2. Results Simulation results are carried out in two cases: (1) Smith predictor-based ILC, and (2) optimal Smith predictor-based ILC. In each case, two different conventional controllers are designed. The first one is the remote controller C_s and the second one the local controller C_m . Here, the classical PD and PID controllers are designed for the remote and local sites, respectively. To obtain optimal performance in case 2, the BSA is employed to obtain the parameters of PID local controller. Before proceeding with the optimization operations, a performance criterion should be first defined. In this paper, the following cost function J is considered.

$$J = \int_0^\infty e_f^2(t)dt \tag{28}$$

where $e_f(t)$ is given in Equation (9).

To minimize the above cost function, BSA is applied to this problem 12 independent times. These results are compared in terms of cost value over 15 runs independently. The corresponding search spaces for the control gains are chosen as $k_p, k_d, k_i \in [0 \ 2]$. The obtained controllers are listed in Table 1. The dashed line in the former Figure shows the right-hand side of Equation (21) (i.e., $20\log(1)=0$ db). Referring to Figure 8, it can be seen that the convergence condition is satisfied. The upper bound of ignorance function $W(s)$ is also obtained as $\Delta(s) = \frac{2.1s+1}{0.75s+2}$. For BSA, the control parameter *mixrate* is set to 1 [29].

Figure 9 illustrates the human force. Figures 10-18 demonstrate the transparency response for both two cases. The results show that the system is robust stable whereas the slave robot can track the master effectively.

As these figures show, the proposed method has effectively controlled the system by considering transient and steady-state responses, in order to achieve transparency and stability of telerobotic system. In addition, it is evident that the performance of the system obtained in case 2 is better than case 1 as shown Figure 18.

TABLE 1. Type of local and remote controllers

Controller	Case	Type	K_P	K_D	K_I
Remote	Case I	PD	34.8	30	0
	Case II	PD	34.8	30	0
Local	Case I	PID	0.25	0.1	0.15
	Case II	PID	0.5	0.05	0.1

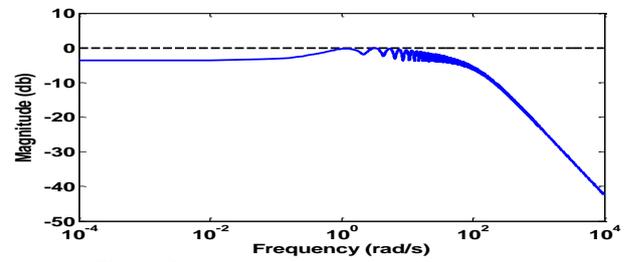


Figure 8. Stability condition given in Eq. (26)

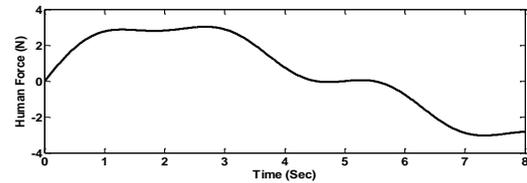


Figure 9. Human force

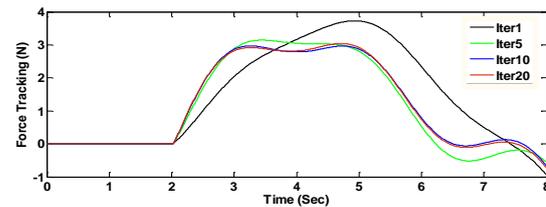


Figure 10. Force tracking for iteration 1, 5, 10 and 20 (case 1)

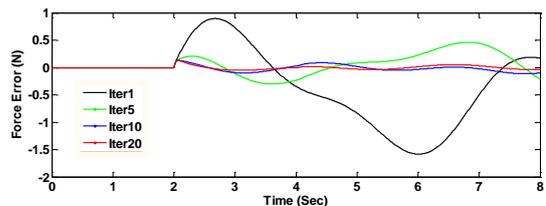


Figure 11. Force error for iteration 1,5,10 and 20 (case 1)

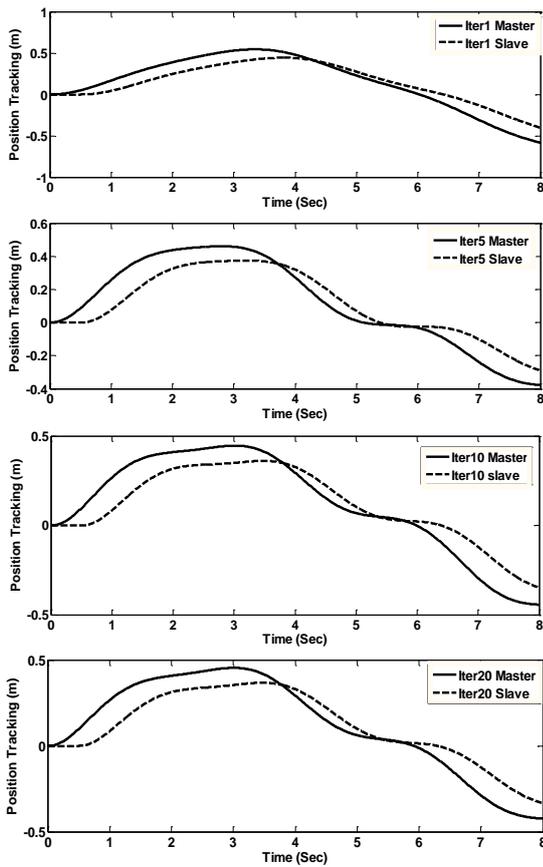


Figure 12. Position tracking for iteration 1, 5, 10 and 20 (case 1)

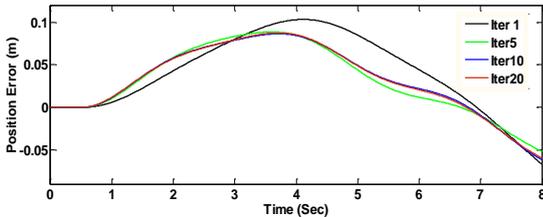


Figure 13. Position error for iteration 1,5,10 and 20 (case 1)

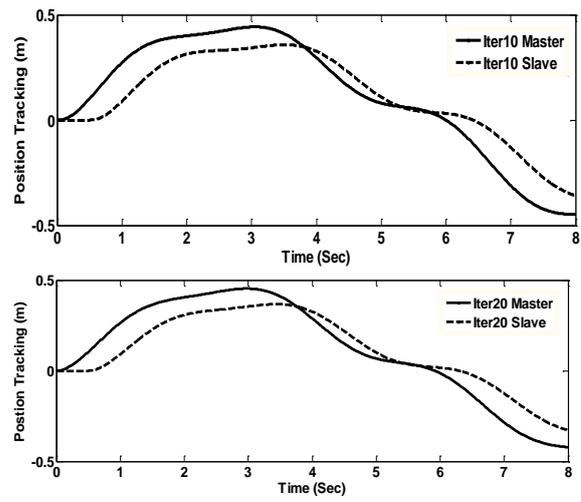
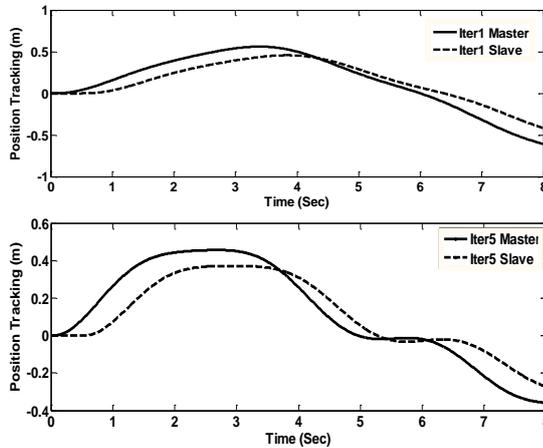


Figure 14. Position tracking for iteration 1,5,10 and 20 (case 2)

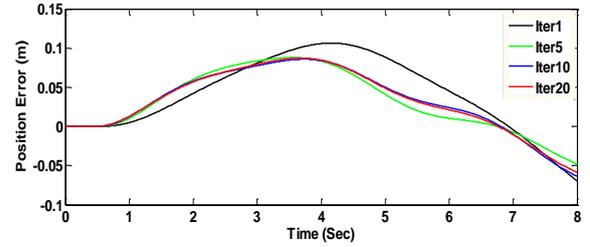


Figure 15. Position error for iteration 1,5,10 and 20 (case 2)

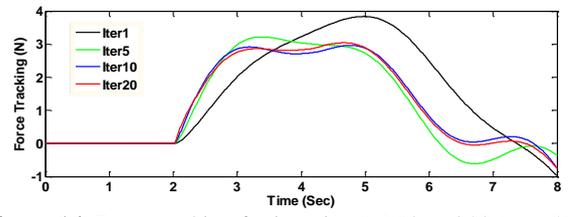


Figure 16. Force tracking for iteration 1,5,10 and 20 (case 2)

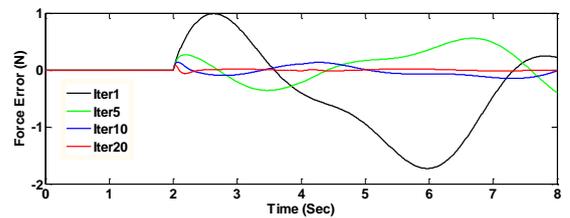


Figure 17. Force error for iteration 1,5,10 and 20 (case 2)

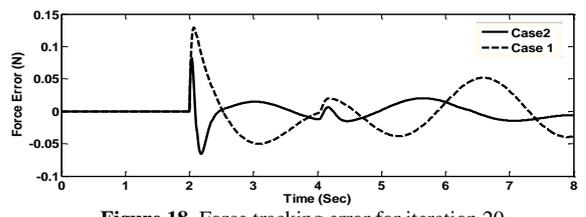


Figure 18. Force tracking error for iteration 20

7. CONCLUSION

To obtain transparency and robust stability, a novel control structure of bilateral telerobotic systems was proposed using ILC-based smith predictor, in presence of model mismatch. To this end, two controllers, namely local and remote controllers, were designed. The main advantage of the structure is the simplicity of the controllers design such that one can use classical controllers such as PD, PI or PID controller. In addition, to acquire optimal performance of the system, BSA was utilized. Simulation results indicated that the proposed control scheme is a viable choice for telerobotic systems with model mismatch. Future works in this area is to consider practical experiments.

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Bilateral Teleoperation Systems Using Backtracking Search optimization Algorithm Based Iterative Learning Control

A. Alfi

Faculty of Electrical and Robotic Engineering Shahrood University of Technology, Shahrood 36199-95161, Iran

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این مقاله به کاربرد کنترل یادگیری تکراری برای بهبود بیشتر عملکرد سیستم‌های حرکتی از راه دور دوطرفه بر اساس پیش‌بین اسمیث می‌پردازد. هدف دستیابی همزمان به پایداری مقاوم و عملکرد بهینه است. ساختار کنترلی پیشنهادی سبب می‌گردد که سیستم فرمان‌بر از سیستم فرمانده در حضور نامعینی در زمان تاخیر کانال ارتباطی و پارامترهای مدل سیستم‌های فرمانده و فرمانبر تبعیت کند. زمان‌های تاخیر در کانال ارتباطی بزرگ، نامشخص و نابرابر با حد بالایی محدود فرض می‌شود. ویژگی اصلی کنترل‌کننده پیشنهادی آن است که طراح می‌تواند از کنترل‌کننده‌های کلاسیک مانند تناسبی-انتگرالی‌گیر- مشتق‌گیر استفاده کند. هرچند مشکل اساسی تعیین مقادیر مناسب پارامترهای کنترل‌کننده است. به بیانی دیگر، پارامترهای کنترل‌کننده منحصر به فرد نبوده و تنها بایستی شرط پایداری را برآورده سازند. برای حل این مساله، در این مقاله کنترل‌کننده محلی توسط الگوریتم بهینه‌سازی جستجوی بازگشتی که یک الگوریتم اکتشافی جدید و ساده است نیز بهینه می‌شود. نتایج شبیه‌سازی عملکرد مناسب کنترل‌کننده پیشنهادی را نشان می‌دهد.

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