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Neural Control of Bimanual Robots with Guaranteed Global Stability and Motion Precision

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***Abstract*—Robots with coordinated dual arms are able to perform more complicated tasks that a single manipulator could hardly achieve. However, more rigorous motion precision is required to guarantee effective cooperation between the dual arms, especially when they grasp a common object. In this case, the internal forces applied on the object must also be considered in addition to the external forces. Therefore, a prescribed tracking performance at both transient and steady states is first specified, and then a controller is synthesized to rigorously guarantee the specified motion performance. In the presence of unknown dynamics of both the robot arms and the manipulated object, the neural networks approximation technique is employed to compensate for uncertainties. In order to extend the semiglobal stability achieved by conventional neural control to global stability, a switching mechanism is integrated into the control design. Effectiveness of the proposed control design has been shown through experiments carried out on the Baxter Robot.**

***Index Terms*—Neural networks; Bimanual robots; Tailored tracking performance; Global uniformly ultimately boundedness (GUUB)**

I. Introduction

With bimanual cooperation, our humans are able to perform delicate and complicated manipulations. There has been a pronounced tendency in the robotics and automation community to shift focus of studies from single manipulators to coordinated dual-arm robots [1]–[6]. In comparison to a single arm robot, a dual-arm robot has prominent advantages in the handling capability, loading capability as well as manipulative skills. For example, in tool using tasks such as carving or screwing, distribution of motions and forces required by the tasks between the two robot arms greatly reduces the complexity and energy cost of manipulation, compared with that of a single robot arm. Therefore, the topics of dual arms robot control have attracted much research attention over the past decades [7]–[10]. The early studies of coordinative control schemes of two robotic arms were reported in [11] and [12], where the position tracking and force control were addressed. To deal with the unknown output hysteresis in the control of coordinate robot, an adaptive neural control was presented with computational efficiency [6]. In [7], a dual NN has been used to resolve the distribution problem of redundant coordination robot systems by using a multicriteria to minimize the global kinetic energy.

It should be emphasized that the motion precision is of great importance in the robot operation, especially for the dual arm manipulation [13]. A precise coordination of both arms can ensure that no excessive internal force would occur, and also reduce possible variation of the internal forces. In this regards, the rigorous requirement of motion precision implies that the transient performance in the operation must also be taken into account. Therefore, much effort in the control community has been made to achieve a desired transient performance [14]–[17]. For this purpose, an effective tracking algorithm was proposed to control a five-bar closed-chain robot based on transformation of tracking errors in [16]. In [17], a constraint on output was considered for control of a class of multi-input-multi-output (MIMO) systems. The above mentioned control approaches rely on purposely built transformations with appropriate inverses which increase the complexity of the control design.

In practice, usually the kinematics information of robots can be accurately known from the manufacturer, but there exist inevitable uncertainties of the dynamics of the robot [18]–[22]. Nevertheless, we can always access the input-output data of an robot system, thus it is desirable to use available input-output data to approximate the unknown robot dynamics, in order to design a controller with satisfactory performance. One of the most successful control approaches is the neural network (NN) based intelligent controller, which utilizes the powerful universal approximation ability of NN to compensate for unknown dynamics [23]–[34]. In [35], the NN was used to approximate the hypersonic flight vehicle dynamics in the tracking control of strict-feedback systems. In [15], the NN was used to compensate for the complicated nonlinearity in the closed-loop robot dynamics.

It should be noted that the above mentioned NN control methods only ensure stability in the sense of semiglobally uniformly ultimately boundedness (SGUUB) of the closed-loop signals, because the NN's approximation only holds over a certain compact set, so called NN's approximation domain. Therefore, the range of state variable must be within this ap-

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proximation domain during operation. However, such compact set is impossible to be identified precisely beforehand, especially for highly nonlinear complicated systems with multiple inputs and multiple outputs (MIMO). Therefore, it is important to develop an NN controller with guaranteed global stability. In [36], a robust adaptive neural controllers was developed to achieve global uniformly ultimately boundedness (GUUB) stability. An adaptive NN control for hypersonic flight vehicle systems was proposed to ensure GUUB stability in [35]. However, only single-input-single-output (SISO) systems were reported in most existing works, and few of them consider transient performance at the same time.

In this paper, we aim to achieve both tailored transient performance and guaranteed global stability at the same time, by exploiting the barrier Lyapunov functions (BLFs). The BLFs were originally developed in the nonlinear control community to deal with the state and output constrains [37]–[40]. A BLF-based controller was developed to control a robot manipulator with joint space constraints in [37]. In [40], an asymmetric time-varying BLF was presented for nonlinear systems in strict-feedback form.

It is noted that by posing constraints to the behavior of the states or outputs, tracking errors can be indirectly constrained using the technique of BLFs. Motivated by this, in this paper the BLFs technique was exploited to achieve the tailored tracking performance at both transient and steady states. Comparing with the regulation of steady state responses, the shaping of the transient control is much more difficult. By constructing a prescribed tracking performance requirement function, a proper BLF is proposed for controller synthesis of a dual-arm robot, such that both transient and steady state tracking performance can be ensured. Meanwhile, a switching mechanism is introduced into the NN controller design to ensure global stability. In comparison to the conventional NN controllers which only ensure the stability of SGUUB, our proposed NN controller guarantees global stability of the closed-loop system. This is practically much more useful as the requirement of the NN inputs is greatly relaxed.

II. Problem Formulation and Modelling Procedure

A. Problem Formulation

Consider a bimanual robot grasping a common object, our objective is to design a robot controller such that the manipulated object could track a desired trajectory x_d specified in the task space, as shown in Fig. 1, while simultaneously guarantee (i) the tracking errors fall into the predefined bounds to achieve tailored tracking performances; (ii) all the signals in the close-loop bimanual robot system remain GUUB; and (iii) the internal forces between the end-effectors and the object converge to a small neighborhood of specified values.

B. Modeling of the Bimanual Robot

The position and orientation of the manipulated object could be defined by a vector $x \in \mathbb{R}^{N_0}$, where N_0 is the object's degree of freedom (DOF). Assume that both arms grasp the object rigidly so that there is no relative motion in between the object and the end-effectors. Then, based on the forward kinematics of robot manipulator, the relations between task space and robot joint space can be calculated in the following manner:

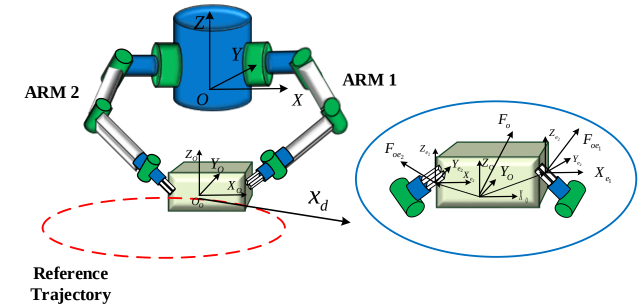

Fig. 1. An overwive of the dual arm robot manipulated a common object

$$x = p_i(q_i), \quad \dot{x} = \dot{p}_i(q_i) = J_i(q_i)\dot{q}_i \tag{1}$$

where $q_i \in \mathbb{R}^{N_i}$ and $\dot{q}_i \in \mathbb{R}^{N_i}$ are vectors of joint variable and joint velocity of the ith robotic arm, respectively, and N_i is the DOF of the ith robotic arm. p_i is a continues function, and $J_i(q_i)$ is the Jacobian matrix. The following assumptions are considered to facilitate the modeling procedure of the bimanual robot system:

Assumption 1: The dynamics of the robot manipulators are uncertain, while the kinematics is accurately available. The robotic arms are operating away from any singular configurations during the motion.

Assumption 2: The rigid object would not be deformed by the exerted forces.

Then, the dynamics of each robot arm are described in the following Lagrangian form:

$$M_i(q_i)\ddot{q}_i + C_i(q_i, \dot{q}_i)\dot{q}_i + G_i(q_i) = \tau_i + J_{e_i}^T(q_i)F_{e_i} \tag{2}$$

where $M_i(q_i) \in \mathbb{R}^{N_i \times N_i}$, $C_i(q_i, \dot{q}_i) \in \mathbb{R}^{N_i \times N_i}$, $G_i(q_i) \in \mathbb{R}^{N_i}$ are the inertial matrix, Coriolis and centrifugal matrix and gravity vector, respectively. $J_{e_i}^T(q_i)$ represents the robotic arm's Jacobian matrix, while $\tau_i \in \mathbb{R}^{N_i}$ is the joint torque, $F_{e_i} \in \mathbb{R}^{N_0}$ is the force vector exerted at end-effector. The dynamics of the object's motion can be described as:

$$M_o(x)\ddot{x} + C_o(x, \dot{x})\dot{x} + G_o(x) = F_o \tag{3}$$

where $M_o(x)$, $C_o(x, \dot{x})$ and $G_o(x)$ denote the inertial, Coriolis and centrifugal matrix, and the gravitational vector of manipulated object, respectively, while $F_o \in \mathbb{R}^{N_0}$ is the resulting force given as follows

$$F_o = -F_{oe_1} - F_{oe_2}, \quad F_{oe_i} = f_i + f_{o_i} \tag{4}$$

where F_{oe_i} is the interaction force applied on the end-effector of ith robotic arm. F_{oe_i} are decomposed into an external force f_{o_i} and an internal force f_i, where the external forces f_{oi} derive the motion of the object, and the internal forces f_i cancel with each other and satisfy the constraint $f_1 + f_2 = 0_{[n]}$. Combination of equation (3) and (4) yields

$$f_i = F_{oe_i} - D_i(t)(f_{o_1} + f_{o_2}) \tag{5}$$

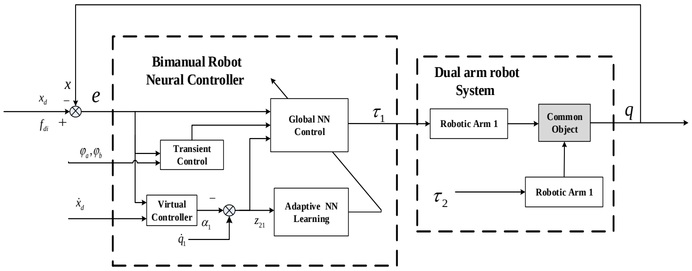

Fig. 2. The framework for the bimanual robot controller

where $D_i(t) \in \mathbb{R}^{N_0 \times N_0}$ is the object load distribution matrix satisfying $D_1(t) + D_2(t) = I_{N_0}$, where $I_{N_0} \in \mathbb{R}^{N_0 \times N_0}$ is an identity matrix.

Combination of (2), (3), (4), (5) and the kinematic equation (1) yields a compact form below:

$$\tau_i = \mathcal{M}_i(q_i)\ddot{q}_i + \mathcal{C}_i(q_i, \dot{q}_i)\dot{q}_i + \mathcal{G}_i(q_i) - J_i^T(q_i) f_i \tag{6}$$

where $\mathcal{M}_i = M_i + D_i \mathcal{M}_o,\ \mathcal{M}_o = J_i^T M_o J_i,\ \mathcal{C}_i = C_i + D_i(M_D + \mathcal{C}_o),\ \mathcal{C}_o = J_i^T C_o J_i,\ M_D = J_i^T \mathcal{M}_o \dot{J}_i,\ \mathcal{G}_i = G_i + D_i \mathcal{G}_o,\ \mathcal{G}_o = J_i^T G_o$. To be self-contained, the fundamental properties of robot manipulator dynamics, which will be used later for control design and analysis, are described below:

Property 1: [10] The skew-symmetric matrix $2\mathcal{C}_i(q_i, \dot{q}_i) - [\dot{\mathcal{M}}_i(q_i) - \dot{D}_i(t)\mathcal{M}_o(q_i, \dot{q}_i)]$ satisfies that:

$$\partial^T \Big\{ \big(2\mathcal{C}_i(q_i, \dot{q}_i) - \dot{\mathcal{M}}_i(q_i)\big) - \dot{D}_i(t)\mathcal{M}_o(q_i, \dot{q}_i) \Big\} \partial = 0,\ \forall \partial$$

Property 2: [10] The matrix $\dot{D}_i(t)\mathcal{M}_0(q_i)$ is bounded and uniformly continuous while satisfies the following inequality:

$$\|\dot{D}_i(t)\mathcal{M}_0(q_i)\| \leq 2\varrho, \quad \forall t \geq 0 \tag{7}$$

where ϱ is a positive constant.

III. Control design

Before proceeding to control design, let us introduce the following tracking error signals:

$$e = x - x_d, \quad z_i = \dot{q}_i - \alpha_i \quad i = 1, 2 \tag{8}$$

where $e = [e_1, e_2, \cdots, e_{N_0}] \in \mathbb{R}^{N_0}$ stands for the position tracking error of the manipulated object, $z_i = [z_{i1}, z_{i2}, \cdots, z_{iN_i}] \in \mathbb{R}^{N_i}$ stand for the velocity tracking error of each robotic arm in joint space, and α_i is a virtual controller to be specified in (19), x_d is the reference trajectory of the manipulated object. Our control strategy is illustrated in Fig. 2.

A. Specification on Requirement for Tracking Performance

To specify tracking performance, especially transient performance (e.g., overshoot, undershoot and coverage rate), we construct a series of smoothly decreasing functions $\phi(t) = [\phi_1, \phi_2, \cdots, \phi_{N_0}]$ to shape the motion of the object as

$$\phi_k(t) = (\rho_{0k} - \rho_{\infty k})e^{-a_k t} + \rho_{\infty k} \tag{9}$$

where ρ_{0k}, $\rho_{\infty k}$ and a_k $(k = 1, 2, \cdots, N_0)$ are properly chosen positive constants. Let us define $\varphi_{a,k}(t) = -\beta_{1k}\phi_k(t)$ and $\varphi_{b,k}(t) = \beta_{2k}\phi_k(t)$, with positive constants β_{1k} and β_{2k} to be specified by the designer.

Remark 1: The functions $\varphi_{a,k}(t)$ and $\varphi_{b,k}(t)$ specify the tracking transient response, i.e., the exponential term a_k regulates the required convergence rate of tracking errors, $\beta_{1k}\rho_{0k}$, $-\beta_{2k}\rho_{0k}$ define the maximum overshoot and undershoot, and $-\beta_{1k}\rho_{\infty k}$, $\beta_{2k}\rho_{\infty k}$ regulates the bounds of the steady errors, as shown in Fig. 3. This implies that we are able to regulate both transient and steady-state performance by properly choosing parameters β_{1k}, β_{2k}, ρ_{0k}, $\rho_{\infty k}$ and a_k.

The following coordinate transformation of tracking errors will be used in the later design.

$$\begin{aligned} \xi_a &= \left[\frac{e_1}{\varphi_{a,1}}, \cdots, \frac{e_{N_0}}{\varphi_{a,N_0}}\right]^T \xi_b = \left[\frac{e_1}{\varphi_{b,1}}, \cdots, \frac{e_{N_0}}{\varphi_{b,N_0}}\right]^T \\ \xi_k &= h_k(e_k)\xi_{b,k} + (1 - h_k(e_k))\xi_{a,k} \end{aligned} \tag{10}$$

where $\xi_{a,k}$, $\xi_{b,k}$ are the kth element of the vectors ξ_a, ξ_b, respectively, and $h_k(e_k)$ is defined as

$$h_k(e_k) = \begin{cases} 1 & e_k \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

B. Controller Design Using BLF and Backstepping

Inspired by the work [40], an asymmetric time-varying barrier function is constructed for the ith robotic arm as

$$V_{i1} = \sum_{k=1}^{N_0} \left(\frac{h_k}{2} \ln \frac{1}{1 - \xi_{b,k}^2} + \frac{1 - h_k}{2} \ln \frac{1}{1 - \xi_{a,k}^2} \right) \tag{12}$$

The differentiation of (12) with respect to time gives us

$$\dot{V}_{i1} = \sum_{k=1}^{N_0} \left(\frac{h_k}{1 - \xi_{b,k}^2} \xi_{b,k}\dot{\xi}_{b,k} + \frac{1 - h_k}{1 - \xi_{a,k}^2} \xi_{a,k}\dot{\xi}_{a,k} \right) \tag{13}$$

According to definitions of $\xi_{a,k}, \xi_{b,k}$, and substituting (8) into (13) we have

$$\begin{aligned} \dot{V}_{i1} = &\sum_{k=1}^{N_0} \left(\frac{\xi_k^2}{(1 - \xi_k^2)e_k} \dot{e}_k \right) \\ &+ \sum_{k=1}^{N_0} \left(\frac{(1 - h_k)\xi_{a,k}^2}{(1 - \xi_{a,k}^2)} \frac{\dot{\varphi}_{a,k}}{\varphi_{a,k}} + \frac{h_k \xi_{b,k}^2}{(1 - \xi_{b,k}^2)} \frac{\dot{\varphi}_{b,k}}{\varphi_{b,k}}) \right) \end{aligned} \tag{14}$$

Then, by defining a transient control vector

$$P = [\frac{\xi_1^2}{(1 - \xi_1^2)e_1}, \frac{\xi_2^2}{(1 - \xi_2^2)e_2}, \cdots, \frac{\xi_{N_0}^2}{(1 - \xi_{N_0}^2)e_{N_0}}]^T \tag{15}$$

and substituting it into (14), we rewrite V_{i1} as below:

$$\dot{V}_{i1} = P^T \dot{e} + \sum_{k=1}^{N_0} \left(\frac{(1 - h_k)\xi_{a,k}^2}{(1 - \xi_{a,k}^2)} \frac{\dot{\varphi}_{a,k}}{\varphi_{a,k}} + \frac{h_k \xi_{b,k}^2}{(1 - \xi_{b,k}^2)} \frac{\dot{\varphi}_{b,k}}{\varphi_{b,k}}) \right) \tag{16}$$

Note that the relation between $\dot{x}$ and $\dot{q}_i$ as specified in (1) always hold. According to the definitions of e and z_i in (8), we have

$$\dot{e} = J_i(q)(z_i + \alpha_i) - \dot{x}_d \quad i = 1, 2 \tag{17}$$

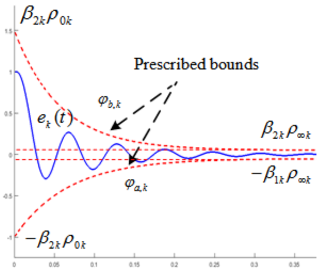

Fig. 3. Relationship between the tracking error $e_k(t)$ and the performance function

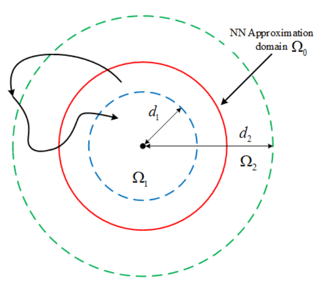

Fig. 4. Global tracking performance

Substituting (17) into (16) yields

$$\begin{aligned}\dot{V}_{i1} &= P^T(J_i(q)(z_i+\alpha_i)-\dot{x}_d)\\ &+\sum_{k=1}^{N_0}\left(\frac{(1-h_k)\xi_{a,k}^2}{(1-\xi_{a,k}^2)}\frac{\dot{\varphi}_{a,k}}{\varphi_{a,k}}+\frac{h_k\xi_{b,k}^2}{(1-\xi_{b,k}^2)}\frac{\dot{\varphi}_{b,k}}{\varphi_{b,k}})\right)\end{aligned}\tag{18}$$

Then, let us design a virtual controller α_i as

$$\alpha_i = J_i^{+}(q)\left(\dot{x}_d - K_1 e - \sigma(t)e\right)\tag{19}$$

where $J_i^{+}(q_i)$ is the Moore-Penrose inverse of $J_i(q_i)$, $K_1 = \mathrm{diag}\{k_{11}, k_{12}, \cdots, k_{1N_0}\}$ with k_{1_k} being positive constants. And $\sigma(t) = \mathrm{diag}\{\sigma_1(t), \sigma_2(t), \cdots, \sigma_{N_0}(t)\}$ with $\sigma_k(t) = \sqrt{(\frac{\dot{\varphi}_{a,k}}{\varphi_{a,k}})^2 + (\frac{\dot{\varphi}_{b,k}}{\varphi_{b,k}})^2 + k_a}$, where k_a selected as a positive parameter that ensures the boundedness of $\dot{\alpha}_i$ when $\dot{\varphi}_{a,k}(t)$, $\dot{\varphi}_{b,k}(t)$ are zero. Substituting (19) into (18) yields

$$\begin{aligned}\dot{V}_{i1} &= P^T J_i(q)z_i - P^T(K_1 e + \sigma(t)e)\\ &+\sum_{k=1}^{N_0}\left(\frac{h_k\xi_{b,k}^2}{(1-\xi_{b,k}^2)}(\frac{\dot{\varphi}_{b,k}}{\varphi_{b,k}})+\frac{(1-h_k)\xi_{a,k}^2}{(1-\xi_{a,k}^2)}(\frac{\dot{\varphi}_{a,k}}{\varphi_{a,k}})\right)\end{aligned}\tag{20}$$

Note that the following inequality holds

$$\sigma_k(t) - h_k\frac{\dot{\varphi}_{a,k}}{\varphi_{a,k}} - (1-h_k)\frac{\dot{\varphi}_{b,k}}{\varphi_{b,k}} \geq 0\tag{21}$$

Using the definition of P in (15) and in terms of (21), equation (20) can be rewritten as

$$\dot{V}_{i1} \leq -\sum_{k=1}^{N_0} k_{1_k}\frac{\xi_k^2}{(1-\xi_k^2)} + P^T J_i(q)z_i\tag{22}$$

C. Global Adaptive NN (GANN) Control

1) Radial basis function neural network (RBFNN) [41]: In this paper, the following RBFNNs are used to approximate a continuous vector function $F(Z) = [f_1(Z), f_2(Z), \cdots, f_n(Z)]^T \in \mathbb{R}^n$,

$$\hat{F}(Z) = \hat{W}^T S(Z)\tag{23}$$

where $\hat{F}(Z) \in \mathbb{R}^n$ is the estimate of $F(Z)$, $Z \in \Omega_Z \subset \mathbb{R}^q$ is NN inputs vector, and q denotes the demonstration of the input; $\hat{W} = [\hat{W}_1, \hat{W}_2, \cdots, \hat{W}_n] \in \mathbb{R}^{n\times l}$ is the estimation of NN optimal weight matrix W^*, and l is the number of NN nodes. $S(Z) = [s_1(Z), s_2(Z), \cdots, s_l(Z)]^T \in \mathbb{R}^l$ is the regressor vector with $s_i(\cdot)$ being a radial basis function. In general, the most commonly used Gaussian radial basis functions are employed as follows:

$$s_i(\|Z-\mu_i\|) = \exp\left[\frac{-(Z-\mu_i)^T(Z-\mu_i)}{\vartheta_i^2}\right]\tag{24}$$

where μ_i $(i = 1, \cdots, l)$ are distinct points in state space, $\mu_i = [\mu_{i1}, \mu_{i2}, \cdots, \mu_{iq}]^T$ is the center of the neural and ϑ_i is the Gaussian function's width. It has been established that, with sufficiently large node number, an arbitrary continuous function $F(Z)$ can be approximated by the RBFNN (23) over a compact set Ω_Z as

$$F(Z) = W^{*T}S(Z) + \varepsilon(Z), \quad \forall Z \in \Omega_Z\tag{25}$$

where W^* is an ideal constant weight vector, and $\varepsilon(Z) \in \mathbb{R}^n$ is the approximation error. There exist ideal weight vector W^* such that $|\varepsilon(Z)| < \varepsilon^*$ with constant $\varepsilon^* > 0$ for all $Z \in \Omega_Z$.

2) Global NN control design: Let us define a positive Lyapunov function as,

$$V_{i2} = V_{i1} + \frac{1}{2}z_i^T\mathcal{M}_i z_i\tag{26}$$

Substituting (6) and (8) into its derivative, and considering Properties 1 and 2, we can derive from (26) that

$$\begin{aligned}\dot{V}_{i2} &\leq \dot{V}_{i1} + \varrho_i z_i^T z_i\\ &+ z_i^T(\tau_i - \mathcal{M}\dot{\alpha}_i - \mathcal{C}_i\alpha_i - \mathcal{G}_i + J_i^T(q_i)f_i)\end{aligned}\tag{27}$$

where $\mathcal{M}_i$, $\mathcal{G}_i$ and $\mathcal{C}_i$ are abbreviations of $\mathcal{M}_i(q)$, $\mathcal{G}_i(q)$ and $\mathcal{C}_i(q,\dot{q})$, respectively, and ϱ_i is a positive constant specified in (7).

Considering the dynamics of robot in (6), we reformulate it by using a function vector $F_i(Z_i) \in \mathbb{R}^{N_i}$ as

$$F_i(Z_i) = -(\mathcal{M}\dot{\alpha}_i + \mathcal{C}_i\alpha_i + \mathcal{G}_i)\tag{28}$$

where $F_i(Z_i) = [f_{i,1}(Z_i), f_{i,2}(Z_i), \cdots, f_{i,N_i}(Z_i)]^T$, $Z_i = [q_i^T, \dot{q}_i^T, \alpha_i^T, \dot{\alpha}_i^T]^T \in \mathbb{R}^{\nu_i}$, with $\nu_i = 4N_i$. It should be noted that, for the functions $f_{i,j}(Z_i) \in \mathbb{R}$, $j = 1, 2, \cdots, N_i$, there exist known bounded nonnegative smooth functions $f_{i,j}^U(Z_i)$ such that $|f_{i,j}(Z_i)| \leq f_{i,j}^U(Z_i)$, $\forall Z \in \mathbb{R}^{\nu_i}$.

Applying RBFNN described in Section III.C, we see that over a compact set Ω_{i1},

$$\hat{F}_i(Z_i) = \hat{W}_i^T S_i(Z_i) + \varepsilon_i\tag{29}$$

where $\hat{W}_i = [\hat{W}_{i,1}, \hat{W}_{i,2}, \cdots, \hat{W}_{i,N_i}]^T \in \mathbb{R}^{l_i\times N_i}$ is the estimation of optimal neural weight matrix W_i^*, and $\hat{W}_{i,j} = [\hat{\omega}_{i,j1}, \hat{\omega}_{i,j1}, \cdots, \hat{\omega}_{i,jl_i}] \in \mathbb{R}^{l_i}$, $S_i(Z_i) \in \mathbb{R}^{l_i}$ is the basis vector function with l_i being the NN nodes number, and ε_i is the NN construction error satisfying $|\varepsilon_i| < \bar{\varepsilon}_i$.

Prior to proceed to control design, let us introduce a set of smooth switching functions $Q_i(Z_i) \in \mathbb{R}^{N_i\times N_i}$ as

$$Q_i(Z_i) = \mathrm{diag}\Big(M_{i1}(Z_i), M_{i2}(Z_i), \cdots, M_{iN_i}(Z_i)\Big)\tag{30}$$

where $M_{ij}(Z_i) = \prod_{c=1}^{\nu_i} m(z_{ic})$, and $m(z_{ic})$ is designed as

$$m(z_{ic}) = \begin{cases} 1 & |z_{ic}| < d_{1,ic} \\ \dfrac{d_{2,ic}^2 - z_{ic}^2}{d_{2,ic}^2 - d_{1,ic}^2} e^{\left(\frac{z_{ic}^2 - d_{1,ic}^2}{\omega_i(d_{2,ic}^2 - d_{1,ic}^2)}\right)^2} & \text{otherwise} \\ 0 & |z_{ic}| > d_{2,ic} \end{cases}\tag{31}$$

where $d_{1,ic}$ and $d_{2,ic}$ are positive constants satisfying $0 < d_{1,ic} < d_{2,ic}$, ω_i are positive constants with $\omega_i \geq 1$.

Remark 2: The switching function $m(\cdot)$ are scaled to $m(\cdot) = 1$ in the compact set Ω_1 and $m(\cdot) = 0$ outside the domain Ω_2 as show in Fig. 4. Therefore the adaptive NN control can be thoroughly disabled when the neural active region is no longer remain.

Then, the adaptive global NN robot control law is designed as

$$\begin{aligned}\tau_i = & - K_{2i}z_i - J_i^T(q_i)P - J_i^T(q_i)f_{d_i} - Q_i(Z_i)\Phi_i^a \\ & - (1 - Q_i(Z_i))\Phi_i^b\end{aligned} \tag{32}$$

where $K_{2i} = \text{diag}\{k_{2,i1}, k_{2,i2}, \cdots, k_{2,iN_i}\}$ is an designed positive definite diagonal matrix, f_{di} is the desired internal force, P is the transient controller specified in (15). Φ_i^a and Φ_i^b are designed as

$$\Phi_i^a = \hat{F}_i(Z_i), \quad \Phi_i^b = F_i^U(Z_i)\ \Gamma_i\left(\frac{F_i^U(Z_i)z_i}{\varpi}\right) \tag{33}$$

where $\hat{F}_i$ is the estimate of F_i, and $F_i^U = \text{diag}\{f_{i,1}^U(Z_i), f_{i,2}^U(Z_i), \cdots, f_{i,N_i}^U(Z_i)\}$, $\Gamma_i\left(\frac{F_i^U(Z_i)z_i}{\varpi}\right) = [\tanh(\frac{F_i(Z_i)z_{i1}}{\varpi}), \tanh(\frac{F_i(Z_i)z_{i2}}{\varpi}), \cdots, \tanh(\frac{F_i(Z_i)z_{iN_i}}{\varpi})]^T$ with ϖ being a positive parameter.

The NN weight adaptive law is designed as

$$\dot{\hat{W}}_i = \Theta_i(Q_i(Z_i)S(Z_i)z_i - \gamma_i\hat{W}_i) \tag{34}$$

where Θ_i is a positive definitive matrix, and γ_i is a positive constant.

Remark 3: The controller proposed in (32) consists of an adaptive NN controller Φ_i^a and an extra robust controller Φ_i^a. When the tracking runs in the NN active domain Ω_1, the term Φ_i^a plays a decisive role, once the the NN runs out of the Ω_2, the extra robust term Φ_i^b will pull the state back. If the NN runs in the domain between the Ω_2 and Ω_1, both terms work and will pull the state back to the compact set Ω_1.

Consider the following Lyapunov function

$$V_i = V_{i2} + \frac{1}{2}\sum_{j=1}^{N_i}\tilde{W}_{i,j}^T\Theta_i^{-1}\tilde{W}_{i,j} \tag{35}$$

where $\tilde{(*)} = \hat{(*)} - (*)$. Taking derivative of (35) along time, and considering the control law (32) and the adaptive law (34), yields

$$\begin{aligned}\dot{V}_i \quad = \quad & \dot{V}_{i1} + z_i^T\Big(- K_{2i}z_i + \varrho_i z_i - J_i^T(q_i)P + J_i^T(q_i)\tilde{f}_i\Big) \\ + \quad & z_i^T\Big(- Q_i(Z_i)\Phi_i^a - (I - Q_i(Z_i))\Phi_i^b + F_i(Z_i)\Big) \\ + \quad & \sum_{j=1}^{N_i}\tilde{W}_{i,j}^T\Theta_i^{-1}\dot{\hat{W}}_{i,j}\end{aligned} \tag{36}$$

where $\tilde{f}_i = f_i - f_{di}$. Substituting (29), (33) and (34) in (36), we have

$$\begin{aligned}\dot{V}_i \leq & \dot{V}_{i1} + z_i^T(-K_{2i}z_i - J_i^T(q_i)P + J_i^T(q_i)\tilde{f}_i + \varrho_i z_i) \\ & + \sum_{j=1}^{N_i}\Big(z_{ij}f_{i,j}^U - z_{ij}f_{i,j}^U\tanh(\frac{z_{ij}f_{i,j}^U}{\varpi})\Big) \\ & + \sum_{j=1}^{N_i}\Big(-\gamma_i\tilde{W}_{i,j}^T(W_{ij}^* + \tilde{W}_{i,j}) + z_{ij}\varepsilon_{ij}\Big)\end{aligned} \tag{37}$$

Notice that following inequalities hold in terms of the Young's inequality,

$$\begin{aligned}-\tilde{W}_{i,j}^T(W_{ij}^* + \tilde{W}_{i,j}) \quad & \leq \quad -\frac{1}{2}||\tilde{W}_{i,j}||^2 + \frac{1}{2}||W_{i,j}{}^*||^2 \\ z_{ij}\varepsilon_{ij} \quad & \leq \quad \frac{1}{2}z_{ij}^2 + \frac{1}{2}\varepsilon_{ij}^2\end{aligned} \tag{38}$$

And the following inequality holds for any $\varpi > 0$ and $z \in \mathbb{R}$:

$$0 \leq |z| - z\tanh\left(\frac{z}{\varpi}\right) \leq \kappa\varpi \tag{39}$$

where κ is a constant satisfying $\kappa = e^{-(\kappa+1)}$, i.e., $\kappa = 0.2785$.

Substituting (22), (38) and (39) into (37), we have

$$\begin{aligned}\dot{V}_i \leq & -\sum_{k=1}^{N_0}k_{1j}\frac{\xi_k^2}{(1-\xi_k^2)} + \Big(\dot{e} + (K_1 + \sigma)e\Big)^T\tilde{f}_i \\ & + \sum_{j=1}^{N_i}\Big(-(k_{2,ij} - \varrho_i - \frac{1}{2})z_{ij}^2 - \frac{1}{2}\gamma_i|||\tilde{W}_{i,j}||^2\Big) \\ & + \sum_{j=1}^{N_i}\Big(\frac{1}{2}\gamma_i||W_{i,j}{}^*||^2 + \frac{1}{2}\varepsilon_{ij}^2 + \kappa\varpi\Big)\end{aligned} \tag{40}$$

Then, taking the Lyapunov function $V = V_1 + V_2$ and considering the property of internal forces, we have

$$\begin{aligned}\dot{V} = \dot{V}_1 + \dot{V}_2 \leq & \sum_{k=1}^{N_0}\Big(-2k_{1_k}\ln\frac{1}{(1-\xi_k^2)}\Big) \\ & + \sum_{i=1}^{2}\sum_{j=1}^{N_i}\Big(-k_{c,ij}z_{ij}^2 - \frac{1}{2}\gamma_i|||\tilde{W}_{i,j}||^2\Big) \\ & + \sum_{i=1}^{2}\sum_{j=1}^{N_i}\Big(\frac{1}{2}\gamma_i||W_{i,j}{}^*||^2 + \frac{1}{2}\varepsilon_{ij}^2 + \kappa\varpi\Big)\end{aligned} \tag{41}$$

where $k_{c,ij} = k_{2,ij} - \varrho_i - \frac{1}{2}$, and the fact $\frac{\xi_k^2}{(1-\xi_k^2)} \geq \ln\frac{1}{(1-\xi_k^2)}, \forall|\xi_k| < 1$ has been used.

D. Stability Analysis

Theorem 1: Consider the bimanual robot system in (6), together with the virtual controllers α_i in (19), the control law (32), the adaptation law in (34), and the performance functions in (9). Given initial conditions e_k satisfy that $\varphi_{a,k}(0) < e_k(0) < \varphi_{b,k}(0)$, the proposed adaptive control scheme can guarantee that: (i) the tracking error e are bounded by the predefined function φ_{aj}, φ_{aj}, (ii) all the tracking signals in the close loop system are uniformly ultimately bounded; (iii) the tracking error e converge to a small neighbourhood of zero.

Proof: From (12), (26) and (35), we have

$$V = \sum_{k=1}^{N_0}\left(\ln\frac{1}{1-\xi_k^2}\right) + \frac{1}{2}\sum_{i=1}^{2} z_i^T\mathcal{M}_i(z_i)z_i + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{N_i}\tilde{W}_{i,j}^T\Theta_i^{-1}\tilde{W}_{i,j} \tag{42}$$

According to (42), the inequality (41) can be represented as

$$\dot{V}(t) = -\eta V(t) + \mu \tag{43}$$

where $\eta = \min\{2\lambda_{\min}(K_1), \frac{2\lambda_{\min}(K_{c_i})}{\lambda_{\max}(\mathcal{M}_i)}, \frac{\gamma_i}{\lambda\max(\Theta_i^{-1})}, |i = 1,2\}$, $\mu = \sum_{i=1}^{2}\sum_{j=1}^{N_i}\left(\frac{1}{2}\varepsilon_i^2 + \frac{1}{2}||W_{i,j}^*||^2 + \kappa\varpi\right)$, and $K_{c_i} = \mathrm{diag}\{k_{c,i1}, k_{c,i2}, \cdots, k_{c,iN_i}\}$.

Multiplying both sides by $e^{\eta t}$ in (43), and applying the integration over $[0,t]$, we have

$$V(t) \le (V(0) - \mu/\eta)Ee^{-\eta t} + \mu/\eta \le V(0) + \mu/\eta \tag{44}$$

From the above inequality, and in terms of (12), (26), (35), as well as the initial condition of $\xi_k(0)$, we can conclude that the terms $\ln(1/(1-\xi_k^2))$, z_i as well as the NN weight estimation errors $\tilde{W}_{i,j}$ are bounded. Thus we can conclude that $\varphi_a < e < \varphi_b$, which implies the transient performance are guaranteed. And since φ_a and φ_b are bounded function, e must be bounded. From (8), we can obtain that x is also bounded. therefore J_i is bounded. From the definition of α_i, we can know that α_i is also bounded. In terms of the boundness of z_i and α_i and according to $\dot{q}_i = z_i + \alpha_i$, $\dot{q}_i$ is also bounded. Hence, all the signals in the closed-loop dual arm robot system are bounded. This completes the proof. ■

Remark 4: The designed matrices K_1 and K_{c_i} in the controller can be chosen simply as positive definite diagonal matrices. The gains in the NN adaptive law Θ_i and γ_i should be positive. And in term of (44), if the gains K_1, K_{2_i} and γ_i are chosen to be relatively small, while Θ_i chosen relatively large, then the amplitude of tracking error could be made smaller.

Theorem 2: The proposed global adaptive NN controller (32) also guarantee the error of the internal force $\tilde{f}_i$ converge to a small neighborhood of the origin.

Proof: See the Appendix.

IV. Experimental studies

The Baxter bimanual robot, as shown in Fig. 5, is used in the experiment. It is of two 7-DOF arms and advanced sensing technologies, including position, force and torque sensors and control at every joint. The resolution for the joint sensors is 14 bits with 360 degrees (0.022 degrees per tick resolution), while the maximum joint torques that can be applied to the joints are 50 Nm (the first four joints) and 15Nm (the last 3 joints).

In the experiment, the Baxter robot is commanded to grasp an object by using its two robotics arms with grippers mounted on the end-effectors. For each robotic arm, we initialized the position of the joints to make the arm locating in a horizontal plane as shown in Fig. 5. For simplicity and without loss of generality, we use three parallel revolute joints (s_0, e_1, w_1) of each arm to derive the motion in the experiment. The grasped object is a cylinder made of plastic, with 0.1 kg in weight, 0.1m in length and 0.06m in diameter. The internal forces could be calculated by using torque sensors equipped with each joint together with gravity compensation model built in [42] and in terms of the equation (5).

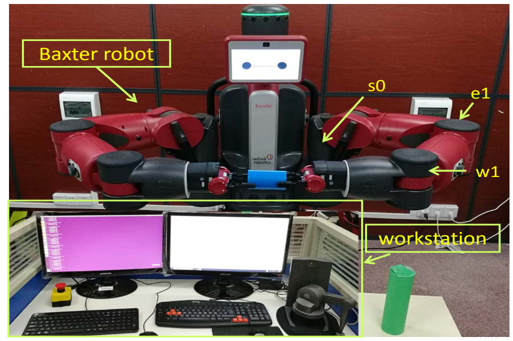

Fig. 5. Illustration of the setup of the experiment. [photo taken at South China University of Technology]

In order to well approximate the robot dynamics and considering both the accuracy and the computational efficiency, we divide the inputs of RBFNN into 2 groups, with one group contains $[q_i^T, \dot{\alpha}_i^T]^T \in R^6$ and another $[q_i^T, \dot{q}_i^T, \alpha_i^T]^T \in R^9$, and employ three centres for each input dimension of the NNs, and ended up with totally $l_1 = 20412$ NN nodes for each neural network. The centres of the neural networks nodes are evenly spaced between the upper and lower bound of the motion range and speed limits of each joint, in $[-1.7, 1.7] \times [-1.05, 2.61] \times [-1.57, 2.09] \times [-1.5, 1.5] \times [-1.5, 1.5] \times [-1.5, 1.5] \bigcup [-1.7, 1.7] \times [-1.05, 2.61] \times [-1.57, 2.09] \times [-1.5, 1.5] \times [-1.5, 1.5] \times [-1.5, 1.5] \times [-1.5, 1.5] \times [-1.5, 1.5] \times [-1.5, 1.5]$. And the NNs weight matrix are initialized as $\hat{W}_1(0) = \mathbf{0} \in \mathbb{R}^{3l_1\times 3}$ and $\hat{W}_2(0) = \mathbf{0} \in \mathbb{R}^{3l_2\times 3}$. And the gains of NN adaptive law are chosen as $\Theta_1 = \mathrm{diag}\{2\}$, $\Theta_2 = \mathrm{diag}\{2\}$. The designed parameters K_1 and K_{2i} of the controller are specified as $K_1 = \mathrm{diag}\{10, 9, 9\}$, $K_{21} = K_{22} = \mathrm{diag}\{9, 4.5, 1.2\}$. And the parameters ϖ in the controller (32) are selected as $\varpi = 0.1$.

In the experiment, the object is required to trace the following trajectory specified in the Cartesian space

$$\begin{pmatrix} x \\ y \\ \theta \end{pmatrix} = \begin{pmatrix} 0.65 + 0.1\sin(2\pi/5t) \\ 0.12\cos(2\pi/5t) \\ 0 \end{pmatrix} \tag{45}$$

The initial configuration of the object is $(0.55, 0.2, 0.2)$, and the initial velocity is set to $\dot{x}(0) = 0$, $\dot{y}(0) = 0$, $\dot{\theta}(0) = 0$. The desired internal force are chosen as $f_{d1} = [0, 3, 0]$, $f_{d2} = [0, -3, 0]$. The parameters of performance functions (9) are designed with $\rho_{01} = \rho_{02} = 0.2$, $\rho_{03} = 0.4$, $\rho_{\infty 1} = \rho_{\infty 2} = 0.012$, $\rho_{\infty 3} = 0.025$, and $a_k = 2.5$, $\beta_{1k} = \beta_{2k} = 1$, $k = 1, 2, 3$.

A. Experimental Results

The experimental results are presented in Figs. 6-9. The tracking performance of the manipulated object in task space

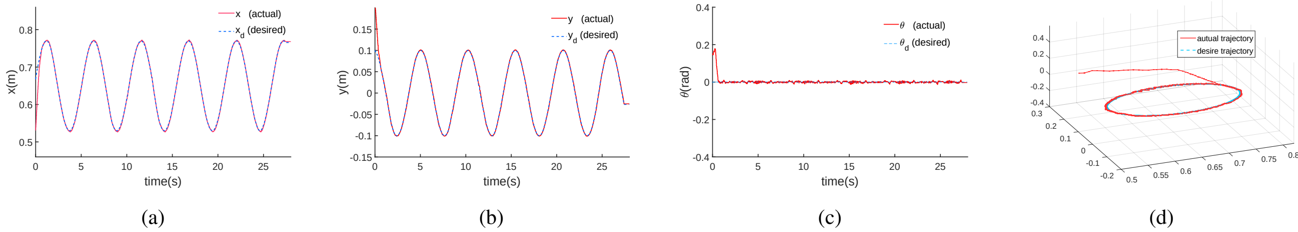

Fig. 6. Tracking performance of the manipulated object (a) x. (b) y. (c) θ (d) Task space tracjectory

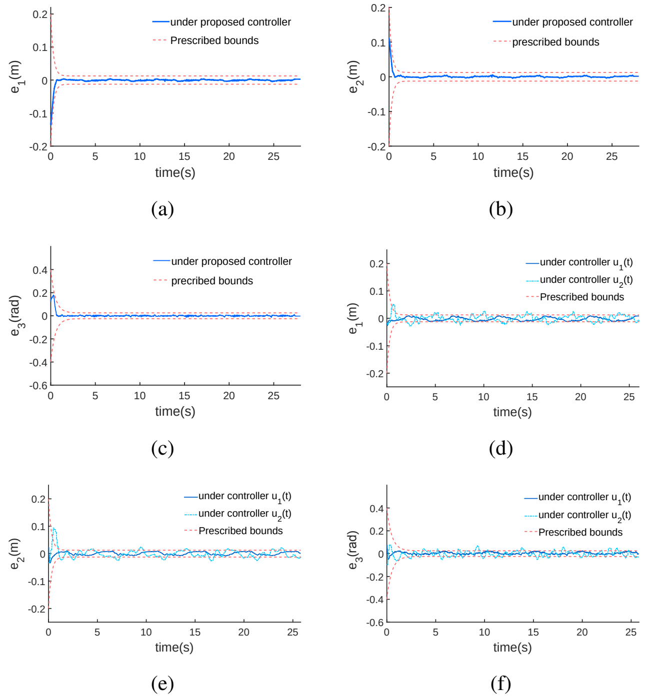

Fig. 7. Tracking error of the object manipulation. (a)(b)(c) tracking errors with the proposed controller. (d)(e)(f) tracking errors with the modified controllers $u_1(t)$ and $u_2(t)$.

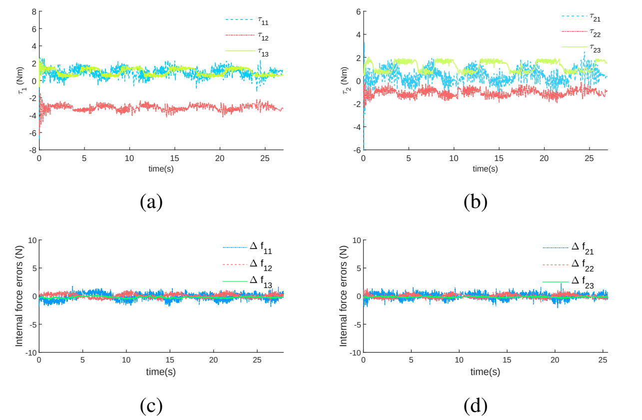

Fig. 8. Control inputs and internal force errors of each arm of the Baxter robot (a) τ_1. (b) τ_2. (c) $\tilde{f}_1 = f_1 - f_{d_1}$. (d) $\tilde{f}_2 = f_2 - f_{d_2}$.

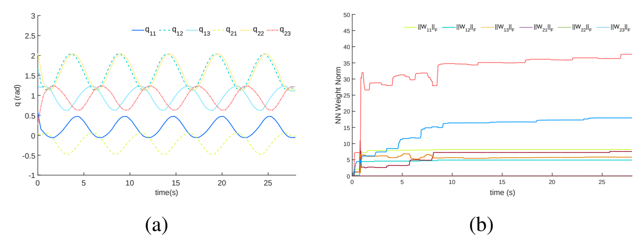

Fig. 9. Trajectory of joint position and the convergence of NN weight (a) joint angles q_{ij} (b) NN weight norm $||W_{ij}||$ $(i = 1, 2,\ j = 1, 2, 3)$.

is shown in Fig. 6(d) where the proposed controller is observed with a good performance when following a circular trajectory. The trajectories with respect to x, y and θ are depicted in the Figs. 6(a) - 6(c). The tracking errors of the manipulated object are shown in Figs. 7(a)-7(c). As shown in these figures, the grasped object follows the reference trajectories very well, the tracking errors converge to a neighborhood around zero without violation of the prescribed transient bound (red dash line '-'). The trajectories of control inputs, internal force errors, joint positions and NN weight norm are depicted as shown in Figs. 8 and 9. We can see from the figures that close-loop signals are bounded and the internal force errors converge to a neighborhood of zero. In addition, comparative experimental results based on two modified controllers are shown in Figs.7(d)-7(f) ($u_1(t)$ controller without NN adaptation; $u_2(t)$ controller without both transient and NN control). As shown in these figures, without using the NN control and transient control, the tracking errors violated the the prescribed transient bounds, while relatively larger steady-stage errors are observed without using the NN control. The experimental results illustrate that our proposed controller can successfully guarantee the tracking errors remaining in the predefined region and ensure the prescribed transient bounds to be never violated.

V. Conclusion

In this paper, we designed an adaptive neural control for general dual-arm robot systems, with prescribed tracking performance and guaranteed global stability. By introduction of a set of boundary functions and integration of them into the controller design, specified motion precision in both transient and steady states are achieved. The transient response such as overshoot, settling time, and final tracking RBFNNs are employed to approximate the unknown dynamics of both the robot arms and the manipulated object. Semi-global stability achieved by the conventional neural control has been extended to global stability by incorporation of a switching mechanism into the controller. The resulted neural control also ensures proper internal force applied on the object, as specified by the designer. Experiment studies have demonstrated the effectiveness of the proposed control scheme.

VI. Appendix

Proof of Theorem 2: Combining the equations (6) and (32), we can obtain the error dynamics equation as

$$\begin{aligned} &\mathcal{M}_i\dot{z}_i + \mathcal{C}_i z_i + \mathcal{G}_i + \varepsilon_i + (I-Q_i)(-\Phi_i^a - \Phi_i^b) + K_{2i}z_i \\ = \;& J^T(q_i)\tilde{f}_i - J_i^T(q_i)P \end{aligned} \tag{46}$$

Then, multiplying $J_i(q_i)\mathcal{M}_i^{-1}$ on both sides on the equation (46), we have

$$\begin{aligned} M_{c_i}\tilde{f}_i &= J_i(q_i)\mathcal{M}_i^{-1}(I-Q_i)(-\Phi_i^a - \Phi_i^b) + M_{c_i}P \\ &+ J_i(q_i)\mathcal{M}_i^{-1}\Big((\mathcal{C}_i + K_{2i})z_i + \mathcal{G}_i + \varepsilon_i\Big) + J_i(q_i)\dot{z}_i \end{aligned} \tag{47}$$

where $M_{c_i} = J_i(q_i)\mathcal{M}_i^{-1}J^T(q_i)$. And since $J_i(q_i)z_i = \dot{e} + (-K_1+\sigma)e$, we can obtain that

$$\dot{J}_i(q_i)z_i + J_i(q_i)\dot{z}_i = \ddot{e} + \Lambda\dot{e} \tag{48}$$

where $\Lambda = -K_1 + \sigma$. Substituting (48) into (46), we have $M_{c_i}\tilde{f}_i = \ddot{e} + \Lambda\dot{e} + \chi_i$, where $\chi_i = J_i(q_i)\mathcal{M}_i^{-1}(I-Q_i)(-\Phi_i^a - \Phi_i^b) + M_{c_i}P + J_i(q_i)\mathcal{M}_i^{-1}\Big((\mathcal{C}_i + K_{2i})z_i + \mathcal{G}_i + \varepsilon_i\Big) - \dot{J}_i(q_i)z_i$.

Then, let us compute the term and consider the following equality by using the property of internal forces, $U\tilde{f} = H$ where $\tilde{f} = [\tilde{f}_1^T, \tilde{f}_2^T]^T$, $H = [\chi_1^T - \chi_2^T, 0]^T$, and $U = \begin{bmatrix} M_{c_1} & -M_{c_2} \\ I & I \end{bmatrix}$. Since the terms M_{c_1} and M_{c_2} are positive definite, we can obtain that U is bounded and invertible. As analyzed in the proof of Theorem 1, q_i, $\dot{q}_i$, e and z_i are all bounded, we can deduce that χ_i is also bounded, hence H is bounded. Therefore, the vector of internal forces errors $\tilde{f}$ are bounded. This complete the proof. ■

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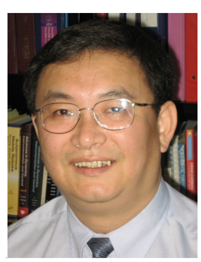

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