Adaptive Neural Control for Robotic Manipulators Under Constrained Task Space

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Abstract. A fundamental requirement in human-robot interaction is the capability for motion in the constrained task space. The control design for robotic manipulators is investigated in this paper, subject to uncertainties and constrained task space. The neural networks (NN) are employed to estimate the uncertainty of robotic dynamics, while the integral barrier Lyapunov Functional (iBLF) is used to handle the effect of constraint. With the proposed control strategy, the system output can converge to an adjustable constrained space without violating the predefined constrained region. Semi-globally uniformly ultimate boundedness of the closed-loop system is guaranteed via Lyapunov's stability theory. Simulation examples are provided to illustrate the performance of the proposed strategy.

Keywords: Constrained task space · Robots · Neural networks (NN) Integral barrier Lyapunov functionals

1 Introduction

Due to the increasing demands on robots and humans to share the same workspace or task, research on the safe control for robotic manipulators, in interaction with humans, is gaining importance [4,6,7]. In recent years, similar research works have been developed to handle the safety issue for robotic tasks [1,14]. In particular, when the robotic applications are related to human-robot interaction, robots must be subject to certain motion constraints, which typically include constraints of position and velocity [33]. Therefore, it is essential for robotic manipulators to be able to perform safe control under constrained task space.

There is a remarkable increasing attention on robotic control [19], and it is a fact that there exist constraints in actual robotic systems, especially in the human-robot cooperation [18]. Great system performance degradation may

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result from the violation of constraints. Therefore, it is significant and necessary to solve the effect of constraints in the control design for robot manipulators. In [12], Hongan introduces the impedance control strategy for robot-environment interactions. The impedance control is firstly proposed, that not to track the desired position, but rather to regulate the robot-environment interaction dynamics. During the decades, impedance control has been widely studied. In [20], a decentralized fuzzy control approach is applied to a practical robotic platform with impedance interaction, where two cooperating robotic manipulators are carrying out more complicated tasks which may not be accomplished by a single manipulator, and fuzzy logic systems are developed to tackle the uncertain robotic model. Impedance control design has been used to solve for robot control in [3,17,24,32].

Recently, the use of barrier Lyapunov Functional (BLF) for solving the control problem with constraint has been an active area [21]. A survey paper on model predictive control about constraint-handling methods is established in [23]. Then, the BLF control strategy have been extended to the control for nonlinear systems in [22,25,30,31] and the application in robot [8], flexible marine riser [10] and flexible crane system [11]. Next, the integral barrier Lyapunov functionals (iBLFs) are developed in [13,16,29]. The advantage of iBLFs-based control strategy is that the state constraint is directly mixed with the error terms. Although previous research works have addressed the constraint effect by using iBLFs, there is an urgent requirement to apply the iBLF technology to solve challenging problems, that is improving the safe human-robot interaction. Moreover, another important motivation of this paper is that, it is difficult to push the iBLFs technology to the robotic control due to the highly coupled nonlinear dynamics and great capability in performing complex and complicated tasks, especially some operational requirements under real-world working conditions. Therefore, the problem for robotic control with constraints needs to be further developed.

An adaptive neural network control technique is studied for robotic manipulators under constrained task space. The main contributions of the proposed approach are given as follows:

(i) Different from the conventional barrier Lyapunov functions, in this paper, integral barrier Lyapunov functions are developed to handle the motion control of robotic manipulators under constrained task space, without carrying out an additional mapping to the error space. The proposed control strategy generates the constrained output, and guarantees the stability of the whole system.

(ii) Unknown packaged functions are estimated by constructing appropriate neural networks, and adapting parameters are utilized to approximate the unknown bounds of NNs approximation error. All signals in the closed-loop system are bounded.

The outline of the paper is given as follows. Section 2 shows the problem formulation, followed by the control design and stability analysis in Sect. 3. Section 4 offers simulation examples. The last part contains the conclusion.

2 Preliminaries and Problem Formulation

Consider the following robotic in joint space [5,15]

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau \tag{1}$$

where $q = [q_1, \cdots, q_n]^T \in \mathbb{R}^n$ is the position; $M(q) \in \mathbb{R}^{n\times n}$, $G(q) \in \mathbb{R}^n$, and $C(q,\dot{q}) \in \mathbb{R}^n$, is the inertia matrix, gravitational force, and Centripetal and Coriolis force, respectively; $\tau = [\tau_1, \cdots, \tau_n]^T \in \mathbb{R}^n$ is the control input. In this paper, $M(q)$, $C(q,\dot{q})$ and $G(q)$ are unknown.

Assume $x = [x_1, \cdots, x_n]^T \in \mathbb{R}^n$ is the position vector in task space, using the transformation between the joint space and task space: $\dot{x} = J(q)\dot{q}$, where $J(q) \in \mathbb{R}^n$ is the Jacobian matrix. The dynamics in task space is considered as

$$M_x(q)\ddot{x} + C_x(q,\dot{q})\dot{x} + G_x(q) = \tau_x \tag{2}$$

where $G_x(q) = J^{-T}(q)G(q)$, $M_x(q) = J^{-T}(q)M(q)J^{-1}(q)$, $\tau_x = J^{-T}(q)\tau$, and $C_x(q,\dot{q}) = J^{-T}(q)(C(q,\dot{q}) - M(q)J^{-1}(q)\dot{J}(q))J^{-1}(q)$. Several basic properties of above dynamics are listed as follows [2,26,27].

Property 1: $M_x(q)$ is bounded positive definite and symmetric.
Property 2: The matrix $\dot{M}_x(q) - 2C_x(q,\dot{q})$ is skew symmetric, such that $y^T(\dot{M}_x(q) - 2C_x(q,\dot{q}))y = 0, \forall y \in \mathbb{R}^n$.

The following result is recalled for stability analysis.

Lemma 1 [28]. *The following inequality holds for* $\forall\delta > 0, \forall x_i \in \mathbb{R}$

$$0 \le |x_i| - x_i \tanh(\frac{x_i}{\delta}) \le 0.2785\delta. \tag{3}$$

The control objective is to design an adaptive NN controller to ensure the constraint is not violated such that $|x_i| < k_{c_i}$, $t > 0$, where k_{c_i} is the bound of x_i, while the output y is driven to track the desired trajectory $x_d = [x_{d_1}, \cdots, x_{d_n}]^T \in \mathbb{R}^n$ to a bounded compact set.

3 Control Design and Stability Analysis

Under the condition that the system states x and $\dot{x}$ in system (2) are all available for feedback, the adaptive NN control is proposed in this section. Assume the error signals as

$$z = [z_1, \ldots, z_n]^T = x - x_d \tag{4}$$

$$\omega = [\omega_1, \ldots, \omega_n]^T = \dot{x} - \alpha \tag{5}$$

where $\alpha = [\alpha_1, \ldots, \alpha_n]^T$ is the virtual control. The iBLF is proposed as follows

$$V_{x_i}(z_i, x_{d_i}) = \int_0^{z_i} \frac{\sigma k_{c_i}^2}{k_{c_i}^2 - (\sigma + x_{d_i})^2} d\sigma \tag{6}$$

Let $\sigma = \theta z_i$, based on the analysis in [28], there is

$$\frac{z_i^2}{2} \leq V_{x_i} \leq z_i^2 \int_0^1 \frac{\theta k_{c_i}^2}{k_{c_i}^2 - (\theta z_i + x_{d_i})^2} d\theta. \tag{7}$$

The Lyapunov functional candidate is

$$V_1 = \sum_{i=1}^{n} V_{x_i} \tag{8}$$

The time derivative of (8) is

$$\dot{V}_1 = \sum_{i=1}^{n} \left(\frac{k_{c_i}^2 z_i}{k_{c_i}^2 - x_i^2} (\omega_i + \alpha_i - \dot{x}_{d_i}) + \frac{\partial V_{x_i}}{\partial x_{d_i}} \dot{x}_{d_i} \right) \tag{9}$$

where

$$\frac{\partial V_{x_i}}{\partial x_{d_i}} = z_i \left(\frac{k_{c_i}^2}{k_{c_i}^2 - x_i^2} - \rho_i(z_i, x_{d_i}) \right) \tag{10}$$

and

$$\rho_i(z_i, x_{d_i}) = \frac{k_{c_i}}{2z_i} \ln \frac{(k_{c_i} + z_i + x_{d_i})(k_{c_i} - x_{d_i})}{(k_{c_i} - z_i - x_{d_i})(k_{c_i} + x_{d_i})} \tag{11}$$

with

$$\lim_{z_i \to 0} \rho_i(z_i, x_{d_i}) = \frac{k_{c_i}^2}{k_{c_i}^2 - x_{d_i}^2} \tag{12}$$

The virtual control $\alpha = [\alpha_1, \ldots, \alpha_n]$ is designed as

$$\alpha_i = -\kappa_{z_i} z_i + \frac{(k_{c_i}^2 - x_i^2)\dot{x}_{d_i} \rho_i}{k_{c_i}^2}, \quad i = 1, \ldots, n \tag{13}$$

where $\kappa_{z_i} > 0$. Substituting (13) into (9), it yields

$$\dot{V}_1 = -\sum_{i=1}^{n} \frac{\kappa_i k_{c_i}^2 z_i^2}{k_{c_i}^2 - x_i^2} + \sum_{i=1}^{n} \frac{k_{c_i}^2 z_i \omega_i}{k_{c_i}^2 - x_i^2} \tag{14}$$

Then, the following Lyapunov candidate functional is chosen as

$$V_2 = V_1 + \frac{1}{2} \omega^T M_x \omega \tag{15}$$

The time derivative of V_2 is

$$\dot{V}_2 = -\sum_{i=1}^{n} \frac{\kappa_{z_i} k_{c_i}^2 z_i^2}{k_{c_i}^2 - x_i^2} + \sum_{i=1}^{n} \frac{k_{c_i}^2 z_i \omega_i}{k_{c_i}^2 - x_i^2} + \omega^T [\tau_x - C_x \dot{x} - G_x - \tau_x - M_x \dot{\alpha}] \tag{16}$$

The ideal control τ_x^* is designed as

$$\tau_x^* = -K_\omega \omega - \phi + C_x \dot{x} + G_x + M_x \dot{\alpha} \tag{17}$$

where $K_\omega = \mathrm{diag}[\kappa_{\omega_1}, \ldots, \kappa_{\omega_n}] > 0$, and $\phi = [\phi_1, \ldots, \phi_n]^T$, with

$$\phi_i := \frac{k_{c_i}^2 z_i}{k_{c_i}^2 - x_i^2}. \tag{18}$$

However, due to the unknown robot dynamics, i.e., the terms M_x, C_x and G_x are all unknown, which results in the fact that τ_x^* is not available. Thus, the NN is used to estimate the uncertainty, and then the adaptive NN control τ is proposed as

$$\begin{aligned} \tau &= J^T \tau_x \\ \tau_x &= -K_\omega \omega - \phi + \hat{W}^T S(Z) - \hat{p} \circledast \tanh(\frac{\omega}{\delta}) \end{aligned} \tag{19}$$

where $\hat{W} = [\hat{W}_1, \ldots, \hat{W}_n]^T \in \mathbb{R}^{n \times l}$ are the NN estimation weights of ideal weight W^* with estimation errors $\tilde{W} = \hat{W} - W^*, \|\tilde{W}\| \le s_w^*$, and input vector $Z = [x^T, \dot{x}^T, \alpha^T, \dot{\alpha}^T]$. $\hat{p} = [\hat{p}_1, \ldots, \hat{p}_n]^T \in \mathbb{R}^n$ are the estimation of unknown parameters $p^* = s^* s_w^* + \epsilon^*$ with $\delta > 0$. τ_{x_i} could represent as

$$\tau_{x_i} = -\kappa_{\omega_i} \omega_i - \phi_i + \hat{W}_i^T S_i(Z) - \hat{p}_i \tanh(\frac{\omega_i}{\delta_i}) \tag{20}$$

The term $W^{*T} S(Z)$ is used to estimate the uncertainty in τ_x^* as

$$C_x \dot{x} + G_x + M_x \dot{\alpha} = W^{*T} S(Z) + \epsilon \tag{21}$$

where $\| \epsilon \| \le \| \epsilon^* \|$ is the estimation error. We design the adaptive law as

$$\dot{\hat{W}}_i = -\Gamma_i [S_i(Z) \omega_i + \sigma_i \hat{W}_i] \tag{22}$$

$$\dot{\hat{p}}_i = \omega_i \tanh(\frac{\omega_i}{\delta_i}) - \sigma_{p_i} \hat{p}_i \tag{23}$$

where $\hat{p}_i(0) > 0, \tilde{p}_i = \hat{p}_i - p_i^*$ is the estimation error; $\Gamma_i > 0$, $\delta_i > 0$; $\sigma_i > 0$ and $\sigma_{p_i} > 0$. The stability analysis of the system is given by the following theorem.

Theorem 1. *For robotic manipulators (2), under the proposed control (13) and (19) with the NN weights updated by (22) and adapting parameter updated by (23), provided that the initial conditions $x(0) \in \Omega_x$ and $\hat{W}_1(0)$, $\hat{p}_1(0)$ are bounded, all signals in the closed-loop system are semi-global uniformly ultimately bounded, the task space constraints are guaranteed and particularly the tracking error $z \in \mathbb{R}^n$ converge to a small neighborhood of origin as $\lim_{t \to \infty} \|z(t)\| \le \sqrt{\frac{2C}{K}}$, with the constants $K \in \mathbb{R}^+$ and $C \in \mathbb{R}^+$ are defined in (31) and (32), respectively.*

Proof. Consider the following Lyapunov function as

$$V = V_2 + \frac{1}{2}\sum_{i=1}^{n} \tilde{W}_i^T \varGamma^{-1} \tilde{W}_i + \frac{1}{2}\sum_{i=1}^{n} \tilde{p}_i^2. \tag{24}$$

Taking the time derivative of V is

$$\begin{aligned}\dot{V} = &-\sum_{i=1}^{n} \frac{\kappa_{z_i} k_{c_i}^2 z_i^2}{k_{c_i}^2 - x_i^2} + \omega^T(\tilde{W}^T S - \epsilon - \hat{p} \circledast \tanh(\frac{\omega}{\delta})) - \omega^T K_\omega \omega \\ &- \sum_{i=1}^{n} \tilde{W}_i^T [S_i \omega_i + \sigma_i \hat{W}_i] + \sum_{i=1}^{n} \tilde{p}_i[\omega_i \tanh(\frac{\omega_i}{\delta_i}) - \sigma_{p_i} \hat{p}_i].\end{aligned} \tag{25}$$

By using the Young Inequalities to obtain

$$-\tilde{W}_i^T \sigma_i \hat{W}_i \leq \frac{\sigma_i}{2}(\| W_i^* \|^2 - \| \tilde{W}_i \|^2) \tag{26}$$

$$-\sigma_{p_i} \tilde{p}_i \hat{p} \leq -\frac{\sigma_{p_i}}{2} \tilde{p}_i^2 + \frac{\sigma_{p_i}}{2} p_i^{*2} \tag{27}$$

Since $\| -\epsilon \| \leq \| \epsilon^* \| \leq \| p^* \|$ and utilizing Lemma 1, it yields

$$\begin{aligned}&-\omega^T \epsilon - \omega^T[\hat{p} \circledast \tanh(\frac{\omega}{\delta})] + \sum_{i=1}^{n} \omega_i \tilde{p}_i \tanh(\frac{\omega_i}{\delta_i}) \\ &\leq p^*[\| \omega \| - \omega^T \tanh(\frac{\omega}{\delta})] \leq \sum_{i=1}^{n} 0.2785 \delta_i p_i^*\end{aligned} \tag{28}$$

Substituting (26)–(28) into (25), results in

$$\begin{aligned}\dot{V} \leq &-\sum_{i=1}^{n} \frac{\kappa_i k_{c_i}^2 z_i^2}{k_{c_i}^2 - x_i^2} - \omega^T K_\omega \omega + 0.2785 \sum_{i=1}^{n} \delta_i p_i^* \\ &- \sum_{i=1}^{n} \frac{\sigma_i}{2} \| \tilde{W}_i \|^2 + \sum_{i=1}^{n} \frac{\sigma_i}{2} \| W_i^* \|^2 - \sum_{i=1}^{n} \frac{\sigma_{p_i}}{2} \tilde{p}_i^2 + \sum_{i=1}^{n} \frac{\sigma_{p_i}}{2} p_i^{*2}.\end{aligned} \tag{29}$$

which implies

$$\dot{V} \leq -KV + C \tag{30}$$

with the positive constants as

$$K = \min\left(2\lambda_{\min}(K_z), \min_{i=1,2,\cdots,n}(\sigma_{p_i}), \frac{2\lambda_{\min}(K_\omega)}{\lambda_{\max}(M_x)}, \min_{i=1,2,\cdots,n}\left(\frac{\sigma_i}{\lambda_{\max}(\varGamma_i^{-1})}\right)\right) \tag{31}$$

$$C = 0.2785 \sum_{i=1}^{n} \delta_i p_i^* + \sum_{i=1x}^{n} \frac{\sigma_{p_i}}{2} \| W_i^* \|^2 + \sum_{i=1}^{n} \frac{\sigma_{p_i}}{2} p_i^{*2} \tag{32}$$

Integrating the above inequality, it yields

$$V \leq (V(0) - \frac{C}{K})e^{-Kt} + \frac{C}{K} \leq V(0)e^{-Kt} + \frac{C}{K} \tag{33}$$

For any bounded initial conditions, when $t \to \infty$, V is bounded. Using $\frac{1}{2}\sum_{i=1}^{n} z_i^2 \leq V$, $\frac{1}{2}\sum_{i=1}^{n} \tilde{W}_i^T \Gamma^{-1} \tilde{W}_i \leq V$ and $\frac{1}{2}\sum_{i=1}^{n} p_i^2(t) \leq V$, the errors signals $z_i, \tilde{W}_i, \tilde{p}_i, i = 1, \ldots, n, \forall t \geq 0$, are uniformly bounded as

$$|z_i| \leq \sqrt{2(V(0) + \frac{C}{K})}, \quad |\tilde{p}_i| \leq \sqrt{2(V(0) + \frac{C}{K})} \tag{34}$$

which also means ultimately bounded as $\lim_{t\to\infty} |z_i(t)| \leq \sqrt{\frac{2C}{K}}$, $\lim_{t\to\infty} \| \tilde{W}_i \| \leq \sqrt{\frac{2C}{K}}$ and $\lim_{t\to\infty} |\tilde{p}_i(t)| \leq \sqrt{\frac{2C}{K}}$. Since V is bounded, there is $V \to \infty$, as $|x_i| \to k_{c_i}$, $i = 1, \ldots, n$, which implies the constrained region in task space is guaranteed. This completes the proof.

4 Simulation

In this section, we consider a robotic manipulator with two rotary degrees and one prismatic degree of freedom. The matrices $M_x(q)$, $C_x(q, \dot{q})$, $F_x(q, \dot{q})$, $G_x(q)$ and J, and the robotic parameters are defined in [9]. In simulation studies, the desired trajectory is defined as

$$x_d = [0.2, -\cos(\pi t), \sin(\pi t)]^T \tag{35}$$

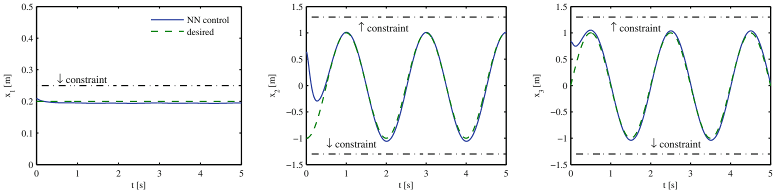
The end-effector x_1, x_2 and x_3 are subject to the task space constraints simultaneously

$$-k_{c1} < x_1 < k_{c1}, \quad -k_{c2} < x_2 < k_{c2}, \quad -k_{c3} < x_3 < k_{c3}, \forall t \leq 0 \tag{36}$$

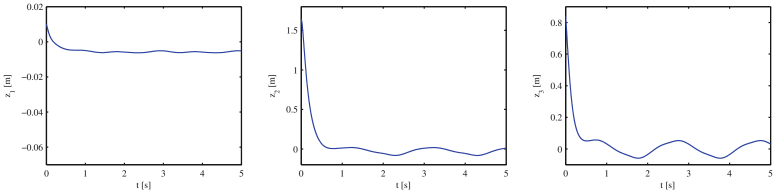
where $k_{c1} = 0.25$, $k_{c2} = 1.3$ and $k_{c3} = 1.3$. In order to be more practical, we consider the initial positions of the end-effector as $x = [0.21, 0.64, 0.84]^T$ and $x = [0, 0, 0]^T$.

In this simulation, the control parameters are set as $\kappa_{z1} = 5$, $\kappa_{z2} = 5$, $\kappa_{z3} = 5$ and $K_W = \mathrm{diag}[100, 10, 10]$. A number of $2^9(512)$ nodes with centers $\mu_i = 0.0$ are used for each $S_i(Z)$. The parameters Γ_1, Γ_2, Γ_3, σ_1, σ_2 and σ_3 are chosen the same value as $\Gamma_1 = \Gamma_2 = \Gamma_3 = 100$, $\sigma_1 = 1$, $\sigma_2 = 1$ and $\sigma_3 = 1$. The variances of centers are both set as $\eta^2 = 25$. The initial weight $\hat{W}_{1,i} = \hat{W}_{2,i} = \hat{W}_{3,i} = 0$ $(i = 1, 2, \cdots, 512)$.

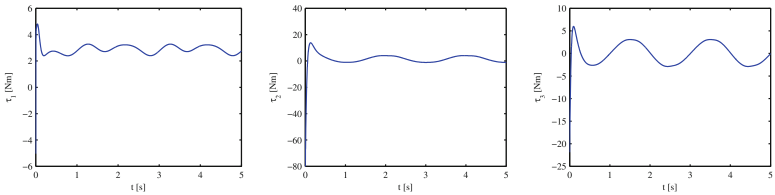
Figure 1(a) illustrates the tracking performance of the closed-loop system for the end-effector x_1, x_2 and x_3. From the figure, we can clearly learn that the proposed control (19) can track the desired trajectory successfully and the end-effector are both bounded in $\pm k_{c1}$, $\pm k_{c2}$ and $\pm k_{c3}$, respectively. From Fig. 1(b), it can be observed that the tracking error will eventually converge to a small value near zero. Figure 1(c) represents the corresponding control signal. The norms of



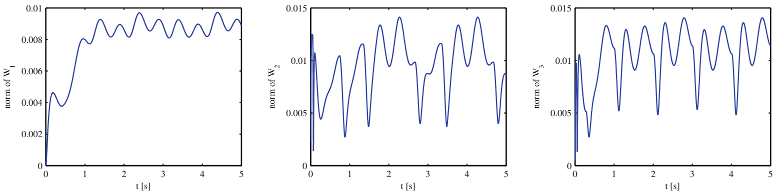
(a) System output x



(b) Tracking error z_1



(c) Control signal τ



(d) Weights W

Fig. 1. Simulation results

$\| \hat{W}_1 \|$, $\| \hat{W}_2 \|$ and $\| \hat{W}_3 \|$ are shown on Fig. 1(d). By the learning abilities of NNs, the proposed control can achieve control under the robot with unknown system dynamics. From Fig. 1(d), the boundedness of NN estimation weights are guaranteed. All in all, the proposed control can successful ensure the end-effector the desired trajectory while always remaind in constrained task space.

5 Conclusions

Adaptive NN control for motion control of robotic manipulators with uncertainty in constrained task space has been proposed in this paper, where the iBLF is used to handle the constraint, and neural networks are employed to estimate the uncertainty. Through Lyapunov synthesis, task space vector of end-effector have been proved coverage to an adjustable small neighborhood around a desired trajectory, and all signals in the closed system are bounded. The performance and effectiveness of the proposed control have been illustrated through simulation.

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