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Model-free Fault-tolerant Control of Robotic Manipulator Subject to Actuator Fault: A Robust Control Approach Based on Function Approximation Technique with Considering its Accuracy

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Abstract

This paper introduces a novel robust fault-tolerant control (FTC) framework for electrically-driven robot manipulators subject to simultaneous actuator faults and time-varying external disturbances. To address the inherent uncertainties in both the manipulator and motor dynamics, a model-free approach is developed using function approximation technique (FAT) as universal approximators, eliminating dependence on precise system modeling. A core contribution is the formulation and incorporation of an approximation quality index into the adaptive update laws in the framework of FTC. This error-driven refinement mechanism, which quantifies the instantaneous fidelity of the identifier, markedly accelerates parameter convergence and enhances the accuracy of online uncertainty estimation. The learning-based design is further fortified to actively estimate and compensate for lumped perturbations, including fault-induced effects and exogenous disturbances. Within a voltage-based control structure, the proposed scheme ensures that all closed-loop signals remain uniformly ultimately bounded, as rigorously proven through Lyapunov stability analysis. Comprehensive simulations on a two-link robotic manipulator under fault effects demonstrate the superior performance of the proposed controller in maintaining trajectory tracking, uncertainty estimation and disturbance attenuation compared to existing related methods.

Keywords: Robust Control, Robot Manipulator, Actuator Fault, FAT, Stability, Approximation Accuracy, Adaptation Mechanism, Model-free Control.

1. Introduction

Robotic manipulators serve as the backbone of industrial automation, playing a vital role in executing complex and sensitive operations. Due to the highly nonlinear nature, dynamic coupling between joints, and uncertain parameters such as payload mass and friction, achieving precise trajectory tracking remains a significant challenge in control engineering [1]. In real operational environments, the system not only grapples with modeling uncertainties but is also affected by time-varying external disturbances. Therefore, designing control strategies that guarantee both stability and high robustness is essential to ensure the safety and efficiency of robots in various scenarios [2].

Among nonlinear control methods, the backstepping approach has received considerable attention for its ability to manage systems with cascade structures and ensure global stability using Lyapunov functions. However, a fundamental drawback of classical backstepping is the explosion of complexity in the control signal, caused by repeated differentiation of virtual control functions [3]. Techniques such as command-filtered control have been introduced to address this issue [4]. Yet, these filters alone cannot overcome unstructured system uncertainties.

Given that accurate mathematical models of robots are often unavailable, intelligent approximators such as neural networks or fuzzy systems have gained prominence as model-free strategies. These systems estimate unknown dynamic functions based on universal approximation theorems [5]. However, a major limitation is that neural and fuzzy approximators impose high computational loads, complicating real-time implementation. To overcome this, function approximation techniques (FAT) have emerged as computationally efficient universal approximators [6]. Nevertheless, in most adaptive laws based on universal approximators, the focus is solely on reducing tracking error without considering approximation accuracy. Rarely has a mechanism been designed to monitor the instantaneous approximation quality and adjust learning steps accordingly. The absence of such an index leads to parameter fluctuations and reduced convergence accuracy when facing sudden system changes.

Beyond modeling challenges, actuator faults pose a serious threat to the continuity of robotic operations. In industrial robots, actuator faults can manifest as sudden efficiency loss, bias faults, complete phase loss, or gradual drift. Most existing research employs torque-control strategies where motor dynamics are neglected. In practice, robotic arms are driven by motors whose actual inputs are voltage. Therefore, voltage-control frameworks that integrate both motor and manipulator dynamics offer superior physical fidelity [7,8].

This paper addresses these research gaps with the following contributions: (1) A voltage-based control framework incorporating complete electromechanical dynamics is presented; (2) An approximation quality index is defined and integrated into adaptive laws to enhance estimation accuracy and convergence speed; (3) The approach employs command-filtered control with FAT, simultaneously reducing complexity while eliminating the need for separate disturbance observers; (4) Voltage control, fault tolerant control (FTC), FAT, and complexity reduction are unified into a single architecture; and (5) Rigorous Lyapunov-based proof of uniform ultimate boundedness is provided.

2. Methodology

2.1 System Modeling

Consider an n-link electrically-driven robotic manipulator. The dynamic equations of the manipulator are expressed as:

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

in which q, $\dot{q}$, $\ddot{q}$ represent joint positions, velocities, and accelerations, respectively. $D(q)$, $C(q,\dot{q})$, and $G(q)$ denote inertia, Coriolis/centrifugal, and gravitational torque matrices. The torque τ is generated by DC motors as:

$$J_m\ddot{\theta}_m + B_m\dot{\theta}_m + r\tau = \tau_m \tag{2}$$

where J_m and B_m are motor inertia and damping matrices, and $\tau_m = K_m I_a$ represents motor torque. The electrical equations are:

$$V = RI_a + L\dot{I}_a + k_b\dot{\theta}_m \tag{3}$$

With the gear ratio $q = r\theta_m$, the state-space representation is:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= f_1 + ax_3 + d_1(t) \\ \dot{x}_3 &= f_2 + bu + d_2(t) \end{aligned} \tag{4}$$

where $x = [q, \dot{q}, I_a]^T$, $a = rJ_m^{-1}K_m$, $b = L^{-1}$, and $u = V$. The functions f_1 and f_2 encapsulate all complex, unknown, time-varying dynamics of both the manipulator and motors.

2.2 Actuator Fault Modeling

The actuator fault is modeled as:

$$u_i(t) = k_i(t)s_i(t) + g_i(t) \tag{5}$$

where $s_i(t)$ is the desired control voltage under normal conditions, $0 < \bar{k}_i \le k_i(t) \le 1$ represents efficiency loss, and $g_i(t)$ denotes bias faults. Various fault types are covered: bias faults ($g_i(t_f) \neq 0$), drift faults ($g_i(t) = \lambda_i t$), and loss of efficiency ($k_i(t) < 1$).

2.3 Function Approximation Technique

This paper employs the Szász-Mirakyan operator as a universal approximator:

$$S_\mu(f,t) = \sum_{k=0}^{\infty} f\left(\frac{k}{\mu}\right) p_k(\mu t) \tag{6}$$

The truncated form is:

$$S_{\mu m}(f,t) = \sum_{k=0}^{m} f\left(\frac{k}{\mu}\right) p_k(\mu t) = \Gamma^T\phi \tag{7}$$

where $\Gamma \in \mathbb{R}^{(2m+1)\times 1}$ is the parameter vector and $\phi = [e^{-\mu t}, te^{-\mu t}, \ldots, t^m e^{-\mu t}]^T$ is the regressor vector. Since f is unknown, Γ is estimated online through adaptive update laws.

2.4 Control Design

The command-filtered backstepping approach is employed with approximation quality monitoring. The tracking errors are defined as $\omega_{1i} = x_{1i} - x_{1di}$. The compensated tracking errors are $\nu_{1i} = \omega_{1i} - z_{1i}$, where z_{1i} are compensation signals for filter errors.

Step 1: The virtual control is designed as $x_{2i}^d = -k_{1i}\omega_{1i} + \dot{x}_{1di}$, where $k_{1i} > 0$. The command filter produces x_{2i}^c from x_{2i}^d via $\alpha_{2i}\dot{x}_{2i}^c + x_{2i}^c = x_{2i}^d$. The compensation signal dynamics are $\dot{z}_{1i} = -k_{1i}z_{1i} + z_{2i} + (x_{2i}^c - x_{2i}^d)$. The Lyapunov function candidate is $V_1 = \frac{1}{2}\sum_{i=1}^{n}\nu_{1i}^2$, yielding $\dot{V}_1 = \sum_{i=1}^{n}(-k_{1i}\nu_{1i}^2 + \nu_{1i}\nu_{2i})$.

Step 2: For the second subsystem, with $\omega_{2i} = x_{2i} - x_{2i}^c$, the virtual control is:

$$x_{3i}^d = \frac{-\hat{\Gamma}_{1i}^T\phi_{1i} - k_{2i}\omega_{2i} - \omega_{1i} + \dot{x}^c{}_{2i}}{a_i} \tag{8}$$

where $k_{2i} > 0$. The compensation dynamics are $\dot{z}_{2i} = -k_{2i}z_{2i} - z_{1i} + a_i z_{3i} + a_i(x_{3i}^c - x_{3i}^d)$. To incorporate approximation accuracy, the identifier error is defined as $Z_{2i_{PE}} = x_{2i} - \hat{x}_{2i}$ such that:

$$\hat{\dot{x}}_{2i} = \hat{\Gamma}_{1i}^T\phi_{1i} + a_i x_{3i} + \beta_{1i}Z_{2i_{PE}} \tag{9}$$

The adaptive law for $\hat{\Gamma}_{1i}$ is:

$$\dot{\hat{\Gamma}}_{1i} = \gamma_{1i}\left(\left(\nu_{2i} + \gamma_{Z_{2i}}Z_{2i_{PE}}\right)\phi_{1i} - \delta_{1i}\hat{\Gamma}_{1i}\right) \tag{10}$$

where $\gamma_{1i} > 0, \gamma_{Z2i} > 0, \delta_{1i} > 0$. The combined term $\left(\nu_{2i}+\gamma_{Z2i}Z_{2i_{PE}}\right)$ is the key innovation: ν_{2i} drives tracking performance while $Z_{2i_{PE}}$ monitors and corrects approximation quality. The composite Lyapunov function is:

$$V_2 = V_1 + \frac{1}{2}\sum_{i=1}^{n}\nu_{2i}^2 + \frac{1}{2}\sum_{i=1}^{n}\tilde{\Gamma}_{1i}{}^T\gamma_{1i}^{-1}\tilde{\Gamma}_{1i} + \frac{1}{2}\sum_{i=1}^{n}\gamma_{Z_{2i}}Z_{2i_{PE}}^2 \tag{11}$$

Its derivative yields:

$$\begin{aligned}\dot{V}_2 \le &-\sum_{i=1}^{n} k_{1i}\nu_{1i}^2-\sum_{i=1}^{n}\left(k_{2i}-\frac{1}{2}\right)\nu_{2i}^2\\ &+\sum_{i=1}^{n} a_i\nu_{2i}\nu_{3i}-\sum_{i=1}^{n}\frac{\delta_{1i}}{2}\tilde{\Gamma}_{1i}^T\tilde{\Gamma}_{1i}\\ &-\sum_{i=1}^{n}\gamma_{Z2i}\left(\beta_{1i}-\frac{1}{2}\right)Z_{2i_{PE}}^2\\ &+\sum_{i=1}^{n}\left(\bar{\epsilon}_{1i}^2+\frac{\delta_{1i}}{2}\|\Gamma_{1i}^*\|^2\right)\end{aligned} \tag{12}$$

Step 3: For the third subsystem, the actual control law is:

$$s_i=\frac{-\hat{\Gamma}_{2i}^T\Phi_{2i}-k_{3i}\omega_{3i}-a_i\omega_{2i}+\dot{x}_{3i}^c}{b_i} \tag{13}$$

The identifier error is defined as $Z_{3i_{PE}}=x_{3i}-\hat{x}_{3i}$ such that:

$$\dot{\hat{x}}_{3i}=\hat{\Gamma}_{2i}^T\phi_{2i}+b_i s_i+\beta_{2i}Z_{3i_{PE}} \tag{14}$$

The adaptive law for $\hat{\Gamma}_{2i}$ is:

$$\dot{\hat{\Gamma}}_{2i}=\gamma_{2i}\left(\left(\nu_{3i}+\gamma_{Z_{3i}}Z_{3i_{PE}}\right)\phi_{2i}-\delta_{2i}\hat{\Gamma}_{2i}\right) \tag{15}$$

where $\gamma_{2i}>0$, $\gamma_{Z3i}>0$, $\delta_{2i}>0$. By defining the final Lyapunov function as $V_3=V_2++\frac{1}{2}\sum_{i=1}^{n}\nu_{3i}^2+\frac{1}{2}\sum_{i=1}^{n}\tilde{\Gamma}_{2i}{}^T\gamma_{2i}^{-1}\tilde{\Gamma}_{2i}+\frac{1}{2}\sum_{i=1}^{n}\gamma_{Z_{3i}}Z_{3i_{PE}}^2$, its derivative yields $\dot{V}_3\le -AV_3+B$, where A and B are positive constants. Therefore, all signals remain uniformly ultimately bounded.

3. Discussion and Results

Numerical simulations were conducted on a two-link robotic manipulator equipped with electric motors. The reference trajectory was $2\sin(t/4)$ for both joints. The external disturbance was $3\sin(3t)e^{-0.2t}$. The IAE performance index was defined as $J=\int_0^T \parallel \omega_1(\kappa) \parallel d\kappa$. Actuator faults were applied from $t=14s$ with $k_i(t)=0.5e^{-0.4(t-14)}$ and $g_i=0.5$.

The proposed method was compared with the disturbance observer-based FTC from [9]. Fig. 1 shows the reference trajectory tracking, demonstrating satisfactory performance for both joints despite actuator faults. Fig. 2 displays the IAE index with values of 1.04 and 1.08 for joints 1 and 2, compared to 5.82 and 8.56 for the comparative method. Fig. 3 displays the control voltage signals within acceptable limits. The proposed FAT-based approach was also compared with a fuzzy approximator. Fig. 4 demonstrates that the proposed method achieves better estimation accuracy.

4. Conclusions

This paper presented a novel model-free robust fault-tolerant controller for electrically-driven robotic manipulators using function approximation technique with approximation quality monitoring. The key contributions are: (1) a voltage-based control framework incorporating full electromechanical dynamics; (2) integration of approximation quality indexes into adaptive laws to enhance estimation accuracy and convergence speed; (3) elimination of explosion of complexity via command-filtered control while avoiding separate disturbance observers; (4) unified integration of voltage control, fault tolerance, FAT, and complexity reduction; and (5) rigorous Lyapunov-based stability analysis proving uniform ultimate boundedness. Simulation results validated the effectiveness, achieving IAE values of 1.04 and 1.08 for joints 1 and 2, significantly outperforming the disturbance observer-based method and fuzzy-based method. Computational efficiency improved from 34s to 21s. Future work includes investigating measurement noise effects and extending the framework to flexible-joint robots.

5. References

[1] C. Yang, Y. Jiang, W. He, J. Na, Z. Li, B. Xu, Adaptive parameter estimation and control design for robot manipulators with finite-time convergence, *IEEE Trans. Ind. Electron.* 65 (10) (2018) 8112–8123.

[2] M. Mirzaee, R. Kazemi, Type-II fuzzy inference system-based fractional terminal sliding mode control for zero-force exoskeleton robots, *Iranian. J. Fuzzy. Sys.* 21 (6) (2025) 147–171.

[3] S.A. Saadat, M. M. Fateh, J. Keighobadi, Adaptive state augmented clustering-based fuzzy learning control of a passive torque simulator., *Int. J. Dyn. Cont.*, 10(3) (2022) 917-929.

[4] J. Keighobadi, A. Mehrjouyan, A. Alfi, Efficient learning control of uncertain nonlinear systems with input constraints: a disturbance observer-based neural network approach, *Int. J. Dyn. Cont.*, 12(9) (2024) 3392-3406.

[5] G. Li, J. Yu, X. Chen, Adaptive fuzzy neural network command filtered impedance control of constrained robotic manipulators with disturbance observer, *IEEE Trans. Neural Netw. Learn. Syst.* (2021) 1–10.

[6] A. Izadbakhsh, S. Khorashadizadeh, S. Ghandali, Robust adaptive impedance control of robot manipulators using Szasz–Mirakyan operator as universal approximator, *ISA Trans.* 106 (2020) 1–11.

[7] J. Keighobadi, B. Xu, A. Alfi, A. Arabkoohsar, G. Nazmara, Compound FAT-based prespecified performance learning control of robotic manipulators with actuator dynamics, *ISA Trans.* (2022), doi:10.1016/j.isatra.2022.04.027.

[8] F. Piltan, A. Prosvirin, M. Sohaib, B. Saldivar, J. Kim, An SVM-Based Neural Adaptive Variable Structure Observer for Fault Diagnosis and Fault-Tolerant Control of a Robot Manipulator, *Appl. Sci.* 10 (1344) (2020), 1–26.

[9] H. Huang, W. He, J. Li, B. Xu, C. Yang, W. Zhang, Disturbance Observer-Based Fault-Tolerant Control for Robotic Systems with Guaranteed Prescribed Performance, *IEEE Trans. Cybern.*, 53(2), (2022) 1–12.

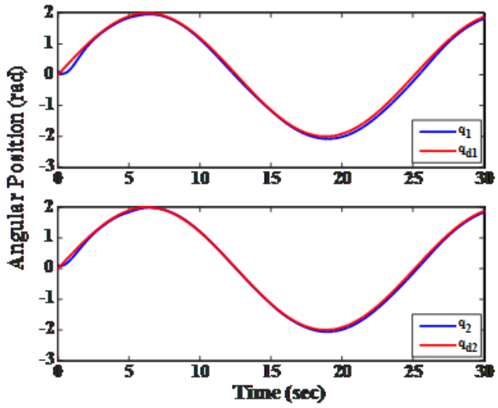

Fig. 1. Tracking response of the proposed method

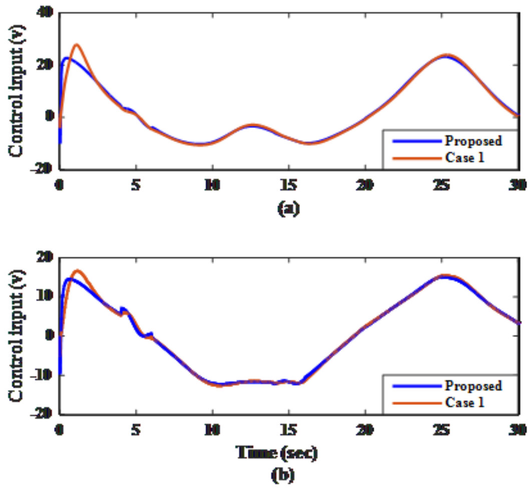

Fig. 3. Control signals compared with [9]

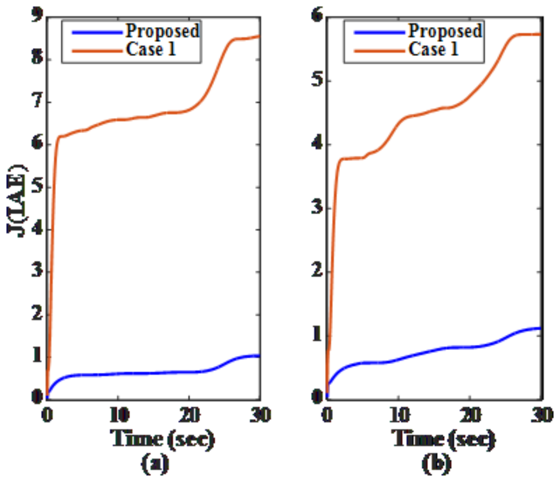

Fig. 2. Performance index compared with [9]

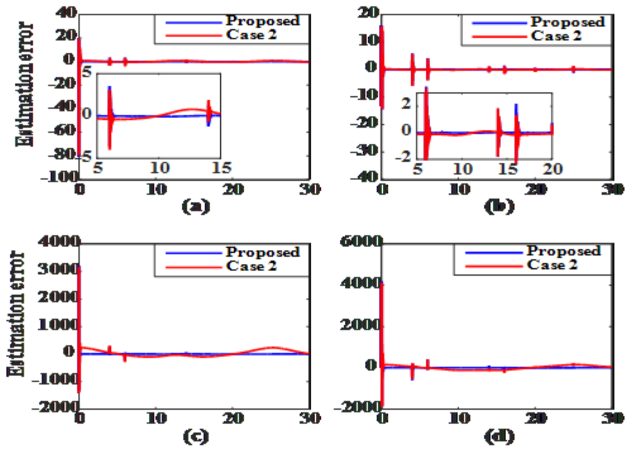

Fig. 4. Comparison with fuzzy-based design