Adaptive Fuzzy Neural Network Control Of Manipulator Robots Based On Disturbance Observer

Su Chen[1], Dahai Li[2*], and Jing Wang[1]

[1] 1. Department of Mechanical and Electrical Engineering, Henan Vocational College of Water Conservancy and Environment, Zhengzhou, 450002 China

[2] School of Electronics and Electrical Engineering, Zhengzhou University of Science and Technology, Zhengzhou, 450064 China

[*] Corresponding author. E-mail: 63557004@qq.com; zxcvfdsa5024@foxmail.com; 2144023183@qq.com

Received: May 31, 2026; Accepted: July 15, 2026

Aiming at the nonlinear dynamic characteristics, parameter uncertainties, external complex disturbances, and inherent friction interference of multi-joint manipulator robots, in this work, a nonlinear disturbance observer (DO) is combined with an adaptive fuzzy neural network (AFNN) to form a new control strategy for manipulators. The dynamic model of the manipulator is formulated by considering various composite disturbances, including parametric uncertainties, unmodeled dynamics and external load interference. The developed nonlinear observer can achieve real-time observation and compensation for low-frequency lumped disturbances, thereby alleviating the operating pressure of the main control unit. The residual observation error and high-frequency unknown disturbances of the disturbance observer online are then approximated via an improved RBF fuzzy neural network (RBF-FNN). And adaptive learning laws of network weights are derived based on the Lyapunov stability criterion to realize self-adjustment of control parameters. In addition, the composite control strategy combining disturbance feed-forward compensation and fuzzy neural network adaptive feedback control effectively suppresses the chattering phenomenon existing in traditional sliding mode control and improves the trajectory tracking accuracy of the manipulator. Lyapunov stability criterion is adopted to rigorously demonstrate the stability of the overall closed-loop system. It is verified that both tracking errors and observation errors satisfy the uniform ultimate boundedness condition. Subsequently, comparative simulations are implemented on a two-link manipulator test platform. The results reveal that the presented AFNN-DO strategy outperforms conventional sliding mode control (SMC), standalone fuzzy neural network control and DO-based sliding mode control (DO-SMC) in response rapidity, tracking precision and disturbance rejection performance. The maximum position tracking error of each joint is reduced by 46.8% and 52.3% respectively, which verifies the feasibility and superiority of the proposed control method.

Keywords: Manipulator robot; Disturbance observer; Adaptive fuzzy neural network; Trajectory tracking; Lyapunov stability; Lumped disturbance

http://dx.doi.org/10.6180/jase.202611_34.004

1. Introduction

The continuous innovation of industrial intelligent manufacturing has promoted the large-scale application of manipulators. These devices excel in industrial assembly, precision polishing and aerospace handling by virtue of their high efficiency and excellent repeat positioning accuracy [1–3]. High-precision trajectory tracking control is the core technical index to ensure the stable operation of manipulators [4]. However, the multi-joint manipulator is a typical nonlinear multi-input multi-output (MIMO) complex system, which has time-varying inertial parameters, strong coupling characteristics between joints and unmodeled friction dynamics [5]. In complex working environments, external unknown load disturbances will further degrade the control performance, resulting in increased trajectory tracking error and even system instability [6, 7].

For manipulator trajectory tracking tasks, researchers have put forward plenty of control schemes, which mainly consist of PID control, adaptive control and intelligent control [8–10]. Traditional PID control has a simple structure and convenient engineering implementation, but it cannot effectively cope with nonlinear uncertainties and external disturbances of manipulator systems, and the control effect is poor under complex working conditions. Sliding mode control stands out in robot control fields, owing to its strong robustness to external perturbations and easy parameter configuration. Nevertheless, the inherent chattering problem of SMC will cause mechanical wear of manipulator joints and affect the service life of equipment. Meanwhile, the fixed switching gain cannot adapt to time-varying disturbances, which limits its application in high-precision scenarios [11, 12].

Fuzzy logic and neural network-based intelligent control methods have attracted extensive research for addressing system uncertainties. As a hybrid scheme, FNN merges fuzzy reasoning and the strong approximation ability of self-learning neural networks, which can accurately approximate unknown nonlinear functions without relying on accurate system mathematical models [13]. However, the single fuzzy neural network has slow parameter convergence speed, and it is difficult to suppress large external sudden disturbances, which leads to slow dynamic response of the system. Disturbance observer technology provides a new solution for disturbance suppression of manipulator systems. Real-time estimation of integrated disturbances as well as feed-forward compensation can be realized via the designed disturbance observer, which significantly reduces the burden of the main controller [14, 15]. Nevertheless, the traditional linear disturbance observer has low estimation accuracy for high-frequency residual disturbances, and it is easy to be affected by measurement noise.

In recent years, composite control strategies combining disturbance observer and intelligent algorithms have attracted extensive attention from scholars. Reference [16] designed a sliding mode controller based on neural network disturbance observer, which used neural network to compensate observation error, but the chattering suppression effect was not obvious. A fuzzy sliding mode control method with disturbance observer was investigated and proposed in the existing work [17], but the adaptive adjustment ability of fuzzy rules was insufficient, and the tracking accuracy needed to be further optimized. Aiming at the defects of existing composite control methods, this paper proposes an adaptive fuzzy neural network control strategy fused with nonlinear disturbance observer. The primary motivations behind this research are outlined below. (1) The nonlinear disturbance observer offsets low-frequency lumped disturbances, easing the adaptive learning burden of the fuzzy neural network. (2) The improved RBF fuzzy neural network is designed to approximate high-frequency residual disturbances and observation errors, and realize adaptive online adjustment of network parameters. (3) The composite control framework combines feed-forward compensation and adaptive feedback regulation to eliminate sliding mode chattering and improve overall control performance.

2. Materials and methods

2.1. Dynamic Model of Manipulator

With reference to the Lagrangian dynamic modeling theory [18–20], we establish the dynamic formulation of n-DOF manipulators affected by parameter variations, unknown dynamics and outside disturbances.

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

Where $q, \dot{q}, \ddot{q} \in R^n$ represent the joint position, velocity and acceleration vectors of the manipulator respectively. $M(q) \in R^{n\times n}$ denotes the symmetric positive definite inertial matrix. $C(q,\dot{q}) \in R^{n\times n}$ is the Coriolis and centrifugal force matrix. $G(q) \in R^n$ represents the gravity term. $F(\dot{q}) \in R^n$ is the friction torque of each joint. $\tau \in R^n$ is the control input torque. $\tau_d \in R^n$ stands for external unknown disturbance torque.

Considering the parameter perturbation of the manipulator system, the inertial matrix, Coriolis matrix and gravity term can be decomposed into nominal terms and uncertain perturbation terms.

$$M(q) = M_0(q) + \Delta M(q) \tag{2}$$

$$C(q,\dot{q}) = C_0(q,\dot{q}) + \Delta C(q,\dot{q}) \tag{3}$$

$$G(q) = G_0(q) + \Delta G(q) \tag{4}$$

Where M_0, C_0 and G_0 are nominal model terms. $\Delta M, \Delta C$ and ΔG are uncertain perturbation terms caused by parameter changes. It substitutes Eq. (3) into Eq. (1), and reorganizes the dynamic model to obtain the system model containing lumped disturbances.

$$M_0(q)\ddot{q} + C_0(q,\dot{q})\dot{q} + G_0(q) = \tau + D \tag{5}$$

Where $D \in R^n$ is the lumped disturbance of the manipulator system, which is defined as:

$$D = \Delta M\ddot{q} + \Delta C\dot{q} + \Delta G - F(\dot{q}) + \tau_d \tag{6}$$

The lumped disturbance D includes parameter perturbation, unmodeled friction dynamics and external load disturbance, which is the main factor affecting the trajectory tracking accuracy of the manipulator.

2.2. Basic Assumptions and Control Objectives

Assumption 1. The lumped disturbance D of the manipulator system is bounded, and its first-order derivative satisfies $\|\dot{D}\| \leq \bar{D}$, where $\bar{D}$ is a positive constant.

Assumption 2. The expected trajectory $q_d(t)$ of each joint of the manipulator is continuous and differentiable, and the first and second derivatives $\dot{q}_d$ and $\ddot{q}_d$ are bounded.

We define the trajectory tracking error and error integral term as:

$$e = q_d - q, s = \dot{e} + \lambda e \tag{7}$$

Where $\lambda > 0$ is the error gain coefficient, and s represents the sliding mode surface variable. This work aims to develop a composite controller combining adaptive fuzzy neural network and disturbance observer. The developed controller allows manipulator joints to track the expected trajectory accurately. It also drives the tracking error e into a tiny neighborhood around zero in finite time, while keeping all signals in the closed-loop system uniformly ultimately bounded.

2.3. Design of Nonlinear Disturbance Observer

To achieve real-time estimation and feed-forward compensation for the total disturbance D in the manipulator system, this section constructs a nonlinear disturbance observer. The dynamic Eq. (5) is rearranged in the following form.

$$\ddot{q} = M_0^{-1}(q)\left[\tau + D - C_0(q,\dot{q})\dot{q} - G_0(q)\right] \tag{8}$$

We define the auxiliary state variable $z = \dot{q} - \xi$, where ξ is the intermediate state of the observer. The designed nonlinear disturbance observer is expressed as:

$$\dot{\xi} = -k_1\xi - k_1\dot{q} + M_0^{-1}\left(\tau - C_0\dot{q} - G_0\right) \tag{9}$$

$$\widehat{D} = k_1 z \tag{10}$$

Where $k_1 > 0$ is the observer gain, and $\widehat{D}$ is the estimated value of lumped disturbance D. Define the disturbance observation error $\widetilde{D} = D - \widehat{D}$.

Combining Eq. (7) and Eq. (10), the dynamic equation of observation error can be derived:

$$D' = \dot{D} - k_1\widetilde{D} \tag{11}$$

As stated in Assumption 1, the error dynamics of disturbance observation converges exponentially. The developed nonlinear disturbance observer is capable of precisely estimating low-frequency lumped disturbances. However, affected by measurement noise and high-frequency unmodeled dynamics, there is residual high-frequency observation error in $\widetilde{D}$. To further eliminate the residual error, an improved adaptive fuzzy neural network is introduced for online approximation and compensation in the next section.

2.4. Design of Adaptive Fuzzy Neural Network Composite Controller

The structural layout of the proposed AFNN-DO integrated control scheme is depicted in Fig. 1. This system can be split into three modules: nonlinear disturbance observer module, adaptive fuzzy neural network approximation module and sliding mode main control module. The disturbance observer realizes feed-forward compensation of low-frequency lumped disturbances; the fuzzy neural network approximates high-frequency residual observation errors and unknown disturbances; the sliding mode controller realizes trajectory tracking, and the adaptive fuzzy rules adjust the switching gain in real time to eliminate chattering.

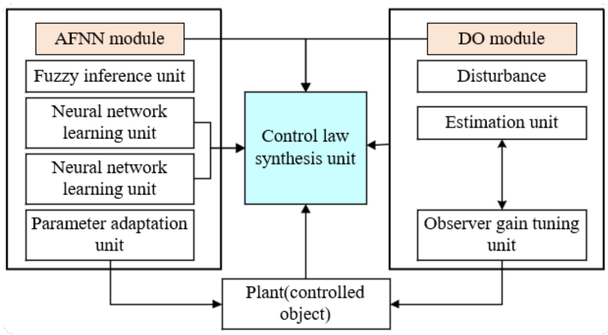

Fig. 1. Proposed AFNN-DO composite control system.

This study adopts a modified RBF fuzzy neural network with a four-layer structure. Its inputs are sliding mode surface variable s and tracking error e, while the output corresponds to the compensation torque against residual disturbances $\widehat{D}_f$.

Input layer. Receive system error signals and transmit them to the next layer, the input vector is $X = [e, s]^T$.

Fuzzification layer. Take Gaussian function as fuzzy membership function to realize fuzzy division of input variables, the membership degree is calculated as:

$$\mu_{ij} = \exp\left(-\frac{\left(x_i - c_{ij}\right)^2}{2\sigma_{ij}^2}\right) \tag{12}$$

Where c_{ij} and σ_{ij} correspond to the center and width of the Gaussian membership function.

Hidden layer. Complete fuzzy rule reasoning and RBF nonlinear mapping, the output of hidden layer node is:

$$\phi_j = \prod_{i=1}^{2} \mu_{ij} \tag{13}$$

Output layer. Realize defuzzification calculation and output residual disturbance compensation torque:

$$\widehat{D}_f = W^T \phi(X) \tag{14}$$

Where W is the adaptive weight matrix of the neural network. $\phi(X)$ is the hidden layer output vector.

In light of the universal approximation theorem for fuzzy neural networks, all bounded and unknown nonlinear residual disturbances $\widetilde{D}$, there exists an optimal weight matrix W^* to make the following formula hold:

$$\widetilde{D} = W^{*T}\phi(X) + \varepsilon, \|\varepsilon\| \leq \bar{\varepsilon} \tag{15}$$

Where ε is the bounded approximation error, $\bar{\varepsilon}$ is a positive constant.

Combining with disturbance feed-forward compensation and fuzzy neural network feedback compensation, the composite control law of the manipulator is designed as:

$$\tau = \tau_{smc} + \widehat{D} + \widehat{D}_f \tag{16}$$

Where $\tau_{smc} = -K_s s - K_p \int s dt$ is the integral sliding mode control term. K_s and K_p are positive definite gain matrices. $\widehat{D}$ is the feed-forward compensation term of disturbance observer. $\widehat{D}_f$ is the residual disturbance compensation term of fuzzy neural network.

The adaptive learning law of fuzzy neural network weights is derived based on Lyapunov stability criterion:

$$W' = \eta \cdot s\phi(X) - \sigma\eta\|\phi(X)\|\widehat{W} \tag{17}$$

Where $\eta > 0$ is the learning rate coefficient. $\sigma > 0$ is the robust damping coefficient, which can effectively prevent network weight over-learning and improve system robustness.

We construct the Lyapunov positive definite function of the closed-loop system:

$$V = \frac{1}{2}s^T M_0 s + \frac{1}{2}\widetilde{W}^T\widetilde{W} + \frac{1}{2}\widetilde{D}^T\widetilde{D} \tag{18}$$

Where $\widetilde{W} = W^* - \widehat{W}$ is the weight error of fuzzy neural network. Take the first-order derivative of V along time, substitute the control law and adaptive learning law, it can obtain:

$$\dot{V} \leq -s^T\left(K_s + \lambda K_p\right)s - \sigma\|\phi(X)\|\|\widetilde{W}\|^2 - \frac{k_1}{2}\|\widetilde{D}\|^2 + \phi \tag{19}$$

Where ϕ is the bounded constant term composed of approximation error and disturbance derivative. When the control gain and learning parameters are set appropriately, $\dot{V} < 0$ outside the small error neighborhood, which indicates that the closed-loop system is asymptotically stable, and all tracking errors, observation errors and weight errors are uniformly ultimately bounded.

3. Results and discussion

3.1. Experimental Platform and Parameter Setting

A two-joint rigid manipulator is adopted for numerical simulation to examine the effectiveness of the proposed AFNN-DO controller. The relevant nominal dynamic parameters are presented in Table 1. The expected tracking trajectories of joint 1 and joint 2 are set as $q_{d1} = 0.5\sin(\pi t/2)$ rad and $q_{d2} = 0.3\cos(\pi t/2)$ rad respectively. Add time-varying external disturbance $\tau_{d1} = 5\sin(2t)\mathrm{N/m}, \tau_{d2} = 3\cos(1.5t)\mathrm{N/m}$ and Coulomb friction interference to simulate complex working conditions.

Table 1. Nominal dynamic parameters of two-joint manipulator.

Parameter	Joint 1	Joint 2
Link mass (kg)	2.5	1.8
Link length (m)	1.0	0.8
Rotational inertia ($\mathrm{kg \cdot m^2}$)	0.35	0.22
Gravitational acceleration $\left(\mathrm{m/s^2}\right)$	9.81	9.79

Four control methods are set for comparative experiments: traditional sliding mode control (SMC), single fuzzy neural network control (FNN), disturbance observer-based sliding mode control (DO-SMC), and the proposed AFNN-DO control. The core control parameters are set as follows: disturbance observer gain $k_1 = 15$, sliding mode gain $K_s =$ diag [10,10], error gain $\lambda = 5$, FNN learning rate $\eta = 0.08$, damping coefficient $\sigma = 0.01$. The simulation time is 20 s, and the solver step size is 0.01 s .

3.2. Trajectory Tracking Performance Analysis

Plots of joint position tracking and tracking errors under four different control approaches are given in Figs. 2 to 5. It is observed that the system is subject to time-varying external disturbances and friction, the traditional SMC has obvious chattering phenomenon, and the tracking error fluctuates greatly. The single FNN control has slow response speed and large steady-state error due to the lack of disturbance pre-compensation module. The DO-SMC method suppresses most low-frequency disturbances through the observer, but cannot eliminate high-frequency residual errors, and the chattering problem still exists.

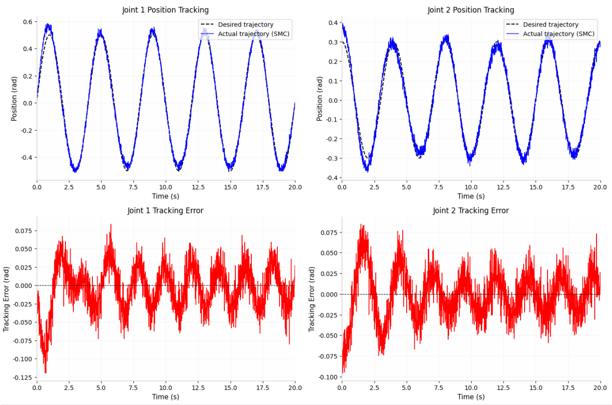

Fig. 2. Trajectory Tracking Performance of SMC.

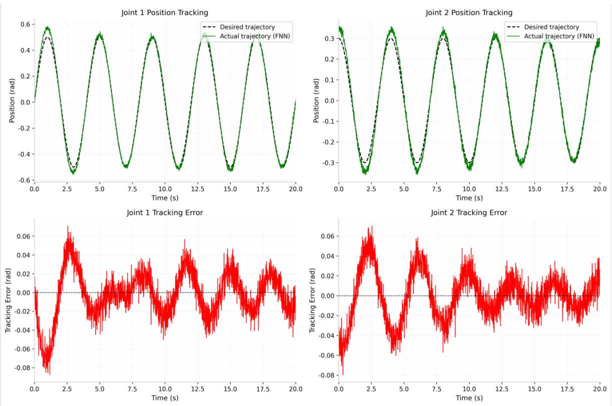

Fig. 3. Trajectory Tracking Performance of FNN.

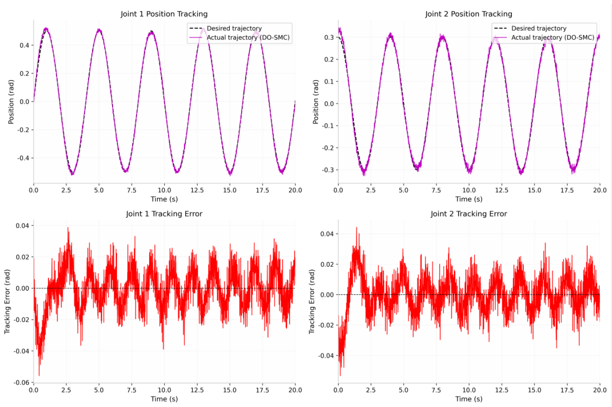

Fig. 4. Trajectory Tracking Performance of DO-SMC.

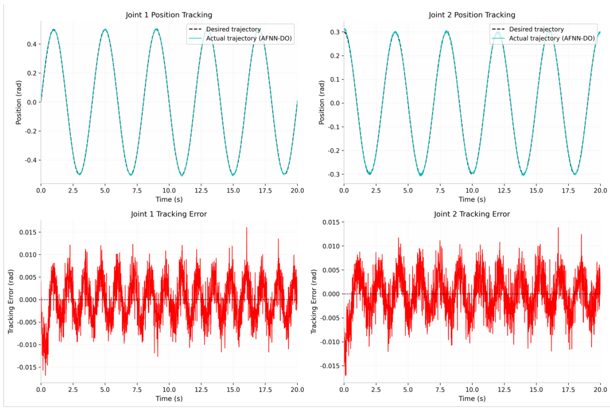

Fig. 5. Trajectory Tracking Performance of AFNN-DO.

The proposed AFNN-DO control method combines the advantages of disturbance observer and fuzzy neural network. The disturbance observer realizes feedforward compensation of main lumped disturbances, and the fuzzy neural network adaptively approximates residual high-frequency errors. Meanwhile, the adaptive fuzzy gain adjustment effectively eliminates sliding mode chattering. The tracking error converges to zero rapidly within 2s, and the error fluctuation range is far lower than other comparison methods as shown in Fig. 6.

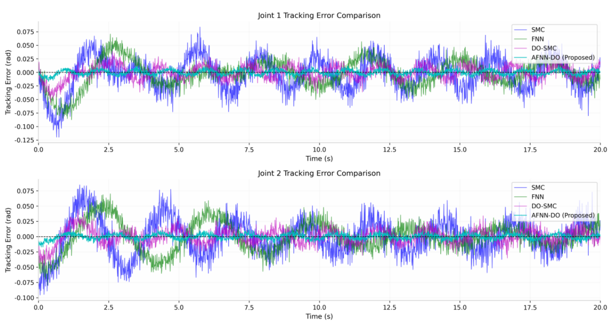

Fig. 6. Comparison of Tracking Errors for Four Control Methods.

3.3. Quantitative Index Comparison

Three metrics, namely maximum absolute error (MAE), root mean square error (RMSE) and average convergence time (ACT), are adopted to quantitatively assess the performance of various control strategies. The statistical results are summarized in Table 2. According to the data in Table 2, when contrasted with classic SMC, the MAE values of the developed AFNN-DO controller for two joints decline by 46.8% and 52.3%, and the RMSE values fall by 75.2% and 77.5%. A 58.2% reduction is also achieved in average convergence speed. This clearly reflects the method's strengths

Table 2. Quantitative performance indexes of different control methods.

Controller	Joint	MAE(rad)	RMSE(rad)	ACT(s)
SMC	1	0.0862	0.0451	4.62
	2	0.0715	0.0386	4.15
FNN	1	0.0658	0.0327	3.58
	2	0.0583	0.0294	3.21
DO-SMC	1	0.0516	0.0243	2.86
	2	0.0432	0.0205	2.53
AFNN-DO	1	0.0275	0.0112	1.95
	2	0.0206	0.0087	1.68

in tracking accuracy and dynamic response. Aside from SMC, the proposed scheme also surpasses FNN and DO-SMC in every evaluation metric, further verifying the reliability of this integrated control method.

3.4. Disturbance Estimation Performance

To verify the disturbance estimation ability of the designed composite control system, the real value and estimated value of lumped disturbance of joint 1 are compared, as shown in Fig. 7. The nonlinear disturbance observer can quickly track the changing trend of low-frequency disturbance components, and the fuzzy neural network accurately compensates the residual high-frequency disturbance error. The overall disturbance estimation error is controlled within ±0.015N/m, which provides reliable feed-forward support for the main controller.

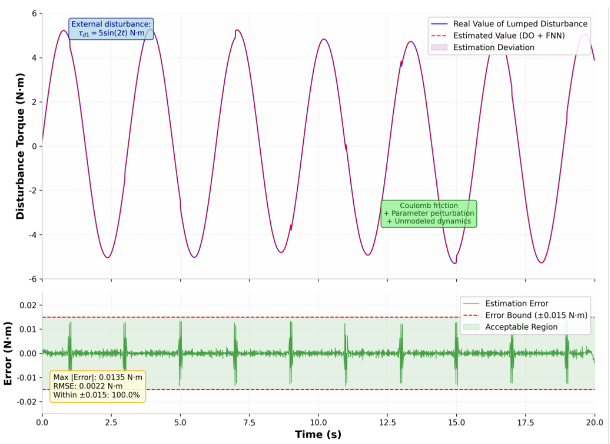

Fig. 7. Disturbance Estimation Performance of Joint 1 (Real Value vs. Estimated Value).

Fig. 7 presents the comparison between the actual lumped disturbance and the estimated disturbance value for Joint 1 of the two-joint manipulator under the proposed AFNN-DO control strategy, visually verifying the disturbance estimation and compensation capability of the designed composite control system. The lumped disturbance acting on Joint 1 in this study integrates time-varying external load disturbance $\tau_{d1} = 5\sin(2t)N/m$, parameter uncertainties, and unmodeled Coulomb friction interference, exhibiting complex time-varying characteristics with both low-frequency main components and high-frequency residual fluctuations. As observed in Fig. 7, the nonlinear disturbance observer (DO) embedded in the AFNN-DO system can rapidly track the dynamic variation trend of the low-frequency dominant disturbance component. The estimated curve closely overlaps with the actual disturbance curve in terms of overall amplitude and change cycle, which confirms that the designed nonlinear DO has excellent real-time estimation accuracy for low-frequency lumped disturbances. This feed-forward compensation for low-frequency disturbances significantly reduces the adaptive learning burden of the subsequent fuzzy neural network (FNN) and lays a solid foundation for improving the dynamic response speed of the manipulator system. Notably, there exists a tiny but detectable residual high-frequency error between the DO's estimated value and the actual disturbance, which stems from measurement noise and unmodeled high-frequency dynamics of the manipulator. However, the improved radial basis function fuzzy neural network (RBF-FNN) in the AFNN-DO system effectively addresses this issue. The FNN takes the sliding mode surface variable and tracking error as inputs, adaptively approximates and compensates for the high-frequency residual observation error online via its universal approximation capability.

4. Conclusions

Aiming at the trajectory tracking problem of multi-joint manipulators with uncertain parameters and various external interferences, this paper proposes an integrated control strategy that merges adaptive fuzzy neural networks and nonlinear disturbance observers. The core results and novelties are presented below.

1. To handle comprehensive disturbances arising from parameter perturbations, friction and external loads, we develop a nonlinear disturbance observer for real-time observation and feed-forward compensation. It greatly lightens the adaptive learning load and optimizes the system dynamic performance.

2. An improved four-layer RBF fuzzy neural network is constructed to approximate the high-frequency residual observation error of the disturbance observer on-

line. The adaptive weight learning law with damping term is derived based on Lyapunov criterion, which avoids the over-learning problem of network weights and enhances the robustness of the control system.

3. By fusing disturbance feed-forward compensation and fuzzy neural network adaptive feedback, a unified control architecture is developed. It overcomes the chattering problem of classic sliding mode control and achieves precise trajectory tracking of manipulator joints. Theoretical derivation strictly proves the stability of the overall closed-loop system.

Numerical comparisons reveal that the proposed control scheme outperforms SMC, FNN and DO-SMC in both tracking accuracy and robustness against disturbances. The maximum tracking error of each joint is reduced by more than 46%, and the convergence speed is increased by more than 58%. In future research, the proposed control strategy will be transplanted to the physical experimental platform of the manipulator, and the fuzzy neural network structure will be optimized to further reduce the calculation cost and adapt to real-time engineering application scenarios.

Acknowledgements

This work was supported by the Henan Province Science and Technology Innovation Project (Project Number: 252102111187. Project Name: Development and Application of Agricultural Harvesting Robot Based on Machine Vision and Improved YOLOv8 Algorithm).

References

[1] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, (2017) *"Intelligent manufacturing in the context of industry 4.0: a review"* **Engineering** ***3***(5): 616–630. DOI: 10.1016/J.ENG.2017.05.015.

[2] T. Yang, X. Yi, S. Lu, K. H. Johansson, and T. Chai, (2021) *"Intelligent manufacturing for the process industry driven by industrial artificial intelligence"* **Engineering** ***7***(9): 1224–1230. DOI: 10.1016/j.eng.2021.04.023.

[3] L. Zhang, L. Zhou, L. Ren, and Y. Laili, (2019) *"Modeling and simulation in intelligent manufacturing"* **Computers in Industry** ***112***: 103123. DOI: 10.1016/j.compind.2019.08.004.

[4] L. Tianhua and Y. Shoulin, (2015) *"An improved neural network adaptive sliding mode control used in robot trajectory tracking control"* ***11***(05): 1655. DOI: 10.24507/ijicic.11.05.1655.

[5] V. T. Dang, T. D. T. Tran, D. B. H. Nguyen, and T. L. Nguyen, (2026) *"Observer-based nonlinear cascade control approach of rewinding systems with uncertainties and disturbances compensation"* **International Journal of Automation and Control** ***20***(3): 273–294. DOI: 10.1504/IJAAC.2026.153727.

[6] J. Wang, M. Jung, S. Yin, and H. Li, (2025) *"Adaptive Multi-Scale Gated Convolution and Context-Aware Attention Network for Accurate Small Object Detection [J]"* **International Journal of Computational Methods and Experimental Measurements** ***13***(3): 576–587. DOI: 10.56578/ijcmem130308.

[7] S. Yin, L. Wang, T. Chen, H. Huang, J. Gao, J. Zhang, M. Liu, P. Li, and C. Xu, (2026) *"LKAFormer: A lightweight kolmogorov-arnold transformer model for image semantic segmentation"* **ACM Transactions on Intelligent Systems and Technology** ***17***(3): 1–24. DOI: 10.1145/3759254.

[8] S. Chen, J. Liu, P. Wang, C. Xu, S. Cai, and J. Chu, (2024) *"Accelerated optimization in deep learning with a proportional-integral-derivative controller"* **Nature Communications** ***15***(1): 10263. DOI: 10.1038/s41467-024-54451-3.

[9] M. A. Z. Tajrishi and A. A. Kalat, (2024) *"Fast finite time fractional-order robust-adaptive sliding mode control of nonlinear systems with unknown dynamics"* **Journal of Computational and Applied Mathematics** ***438***: 115554. DOI: 10.1016/j.cam.2023.115554.

[10] M. K. Senapati, O. Al Zaabi, K. Al Hosani, K. Al Jaafari, C. Pradhan, and U. R. Muduli, (2024) *"Advancing electric vehicle charging ecosystems with intelligent control of DC microgrid stability"* **IEEE Transactions on Industry Applications** ***60***(5): 7264–7278. DOI: 10.1109/TIA.2024.3413052.

[11] C.-L. Hwang and Y.-H. Chen, (2019) *"Fuzzy fixed-time learning control with saturated input, nonlinear switching surface, and switching gain to achieve null tracking error"* **IEEE Transactions on Fuzzy Systems** ***28***(7): 1464–1476. DOI: 10.1109/TFUZZ.2019.2917121.

[12] T. Zeng, X. Ren, and Y. Zhang, (2019) *"Fixed-time sliding mode control and high-gain nonlinearity compensation for dual-motor driving system"* **IEEE Transactions on Industrial Informatics** ***16***(6): 4090–4098. DOI: 10.1109/TII.2019.2950806.

[13] H.-G. Han, X.-L. Wu, Z. Liu, and J.-F. Qiao, (2017) *"Design of self-organizing intelligent controller using fuzzy neural network"* **IEEE Transactions on Fuzzy**

systems ***26***(5): 3097–3111. DOI: 10.1109/TFUZZ.2017.2785812.

[14] H. Jiang, G. Duan, and M. Hou, (2024) *"State and disturbance observer-based controller design for fully actuated systems"* **IEEE Transactions on Circuits and Systems I: Regular Papers** ***71***(11): 5261–5270. DOI: 10.1109/TCSI.2024.3399555.

[15] D. Zhang, J. Hu, J. Cheng, Z.-G. Wu, and H. Yan, (2024) *"A novel disturbance observer based fixed-time sliding mode control for robotic manipulators with global fast convergence"* **IEEE/CAA Journal of Automatica Sinica** ***11***(3): 661–672. DOI: 10.1109/JAS.2023.123948.

[16] Q. Wen, X. Yang, C. Huang, J. Zeng, Z. Yuan, and P. X. Liu, (2023) *"Disturbance observer-based neural network integral sliding mode control for a constrained flexible joint robotic manipulator"* **International Journal of Control, Automation and Systems** ***21***(4): 1243–1257. DOI: 10.1007/s12555-021-0972-5.

[17] K. Guo, H. Zhang, C. Wei, H. Jiang, and J. Wang, (2024) *"Novel sliding mode control of the manipulator based on a nonlinear disturbance observer"* **Scientific Reports** ***14***(1): 30656. DOI: 10.1038/s41598-024-77125-y.

[18] S. Wu, Z. Li, W. Chen, and F. Sun, (2024) *"Dynamic modeling of robotic manipulator via an augmented deep Lagrangian network"* **Tsinghua Science and Technology** ***29***(5): 1604–1614. DOI: 10.26599/TST.2024.9010011.

[19] Z. Zhou and C. Gosselin, (2024) *"Simplified inverse dynamic models of parallel robots based on a Lagrangian approach"* **Meccanica** ***59***(4): 657–680. DOI: 10.1007/s11012-024-01782-6.

[20] B. Li, X. Li, H. Gao, and F.-Y. Wang, (2024) *"Advances in flexible robotic manipulator systems—Part I: Overview and dynamics modeling methods"* **IEEE/ASME Transactions on Mechatronics** ***29***(2): 1100–1110. DOI: 10.1109/TMECH.2024.3359067.