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Retraction

Retracted: Motion Trajectory Error of Robotic Arm Based on Neural Network Algorithm

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] B. Xu and C. Sem-Lin, "Motion Trajectory Error of Robotic Arm Based on Neural Network Algorithm," *Journal of Control Science and Engineering*, vol. 2023, Article ID 3958434, 6 pages, 2023.

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Research Article

Motion Trajectory Error of Robotic Arm Based on Neural Network Algorithm

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In order to solve the problems of unstable motion and large trajectory tracking error of the manipulator when it is disturbed by the outside world, the author proposes an adaptive neural network manipulator motion trajectory error method. The author gives the dynamic equation of the manipulator and uses the positive feedback neural network to study the dynamic characteristics of the manipulator. An adaptive neural network control system is designed, and the stability and convergence of the closed-loop system are proved by the Lyapunov function. A schematic diagram of the manipulator model is established, and MATLAB/Simulink software is used to simulate the dynamic parameters of the manipulator. At the same time, it is compared and analyzed with the simulation results of the PID control system. Simulation results show that in robot arm 3, the expected motion trajectory is $\theta_3 = 0.4\cos(2\pi t)$, the initial condition $\theta(0) = [000]^{\tau}$, the control parameter $K = \mathrm{diag}(40,40),40)$, the disturbance parameter $\tau' = 20\cos(\pi t)$, robot arm link parameters $l_1 = 0.62$ m, $l_2 = 0.41$ m, $l_3 = 0.34$ m, $m_1 = 3.5$, $m_2 = 2.5$ kg, $m_3 = 2$ kg, $g = 9.82$ m/s^2, under $t = 2_{s,}$ the motion trajectory of the robotic arm is disturbed by the outside world, and the adaptive neural network is used to control the motion trajectory with a small tracking error, input torque ripple is small. *Conclusion*. The manipulator adopts the adaptive neural network control method, which can improve the control accuracy of the motion trajectory and weaken the jitter phenomenon of the manipulator motion.

1. Introduction

From the founding of New China to the construction of a powerful modern socialist country, China's manufacturing industry has been continuously improved and developed, forming a manufacturing system with Chinese characteristics, which has effectively promoted the process of industrial modernization. However, compared with many developed countries, China's manufacturing industry is still in a state of lack of innovation, the "Made in China 2025" strategic plan promulgated by the State Council in May 2015; it provided support and pointed out the direction for the advancement of China's manufacturing industry. "Made in China 2025" aims to target new materials and new information technologies, lead the gathering of resources, and promote the development of high-tech industries. Among them, the robotic arm, as an indispensable part of modern manufacturing, has been widely used in industrial production, cargo transportation, and other fields [1]. The use of industrial robotic arms can not only improve production efficiency, ensure product quality, and reduce the cost of production materials, but also improve the working environment, reduce the work intensity of workers, and ensure the personal safety of workers. Nowadays, under the innovative requirements of China's manufacturing industry, robotic arms are no longer limited to industrial production lines; it has a wider range of uses in aerospace, medical rehabilitation, fire and disaster relief, intelligent manufacturing, and other fields as well as in daily life. For example, the robotic arm of the core cabin of the space station, the lower limb rehabilitation robot that helps humans rebuild, the polishing robot, the coffee latte robot, etc. With the interdisciplinary development with various disciplines, the future robotic arm will have greater

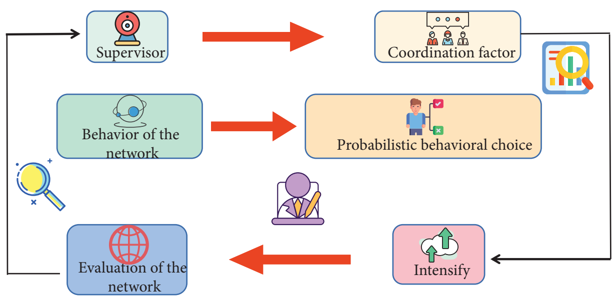

Figure 1: A neural network-based robotic arm control method and process.

innovation and development in high-tech industries such as high-performance medical equipment, aerospace equipment, and high-end CNC machine tools, and become more efficient and intelligent, it will drive the transformation and upgrading of the manufacturing industry in the development planned by "Made in China 2025," provide convenience for human production and life, and bring greater economic benefits to human society.

In their respective fields, industrial robotic arms replace humans to complete some single boring, complex, high-risk, and tiring tasks. Usually, we divide the tasks of industrial robotic arms into two types, one is contact work and the other is noncontact work. With the deepening of intelligence, robotic arms are no longer limited to simple noncontact operations (such as painting, handling, etc.), and more and more robotic arms will interact with the external environment during the work process, for example, industrial robotic arms perform assembly, grinding, and cutting tasks; Rehabilitation robots perform rehabilitation therapy on human lower limbs; Robotic arms replace doctors to perform high-precision tumor removal tasks in surgical operations. According to statistics, the proportion of contact tasks of robotic arms is about 70%, which is far greater than the application of noncontact tasks [2]. In the contact operation of the manipulator, the manipulator interacts with the external environment, at this time, the position tracking control of the manipulator cannot be simply performed, and the contact force of the external environment of the manipulator must be considered because the excessive contact force will cause damage to the robot arm or the operator; If the contact force is too small, it will be difficult for the robotic arm to achieve the set control requirements. The reason for this is that the robotic arm is a rigid body without haptics and lacks compliance. Improving the flexibility of the robotic arm is an important proposition for the tracking control of the robotic arm. Figure 1 is a mechanical arm control method and process based on a neural network.

The research of trajectory control algorithm of manipulator has experienced the development process from traditional control algorithm to modern control algorithm. The representative of the traditional control system is the PID control algorithm. The algorithm is simple and easy to understand, and the parameters can be easily adjusted to ensure the stability and accuracy of the motion, which is ready for the continued competition of all joints. For the manipulator, this method will cause large errors, and if the PID is not well adjusted, it will make the method deviate from the correct one [3]. Modern control algorithms mainly include a sliding mode control (SMC) algorithm, adaptive control algorithm, neural network, fuzzy control, and genetic algorithm.

2. Literature Review

Luo et al. Aiming at the nonlinearity and uncertainty of the manipulator system, a fuzzy sliding mode control method based on the RBF (Radial Basis Function) neural network is proposed, which enables the manipulator to control the dynamics of a given trajectory well. Using RBF neural network to estimate the balance of the sliding mode controller, do not need to build a data model, the researchers developed the fuzzy controller to the change of the sliding mode control type and the current motor points and the change of the sliding mode surface, so it is good to solve the communication problem, and the system response and control performance has improved, modify the control strategy of reducing the vibration time, The simulation results show that the proposed algorithm has a good effect on three degrees of freedom control. A manipulator of freedom [4]. Askarian et al. A model-free adaptive control method is used to control the control system. In this method, the controller is created according to the input and data of the manipulator process without model data specification. The simulation results show that the error convergence is zero, and the convergence effect is better [5]. A feedforward dynamic position feedback controller, a variable matrix nonlinear controller, and a first-order closed-loop linear dynamic compensator are studied for the control of a speed-sensitive manipulator. It makes the derivation of the closed-loop system uniformly asymptotically stable, and the controller is robust to unknown parameters. The effectiveness of this method is verified by the simulation of the two-link manipulator [6]. In the fuzzy sliding mode control based on radial basis function neural network (RBFNN), the Lyapunov function is selected in the sliding mode control design, the weight of RBFNN is adjusted according to the calculation of the governing equation, and the adjustment algorithm, so as to meet the requirements of RBFNN. Finally, the control method and PID controller are tested on the ManuTEC-R15 industrial manipulator. The test results show that the proposed method can be applied in practical operations. The control program of manipulator tracking [7]. Jin et al. An adaptive neural network control method with hidden node number and a low computational burden is proposed to estimate the uncertainty of the system and track the path of the robot arm. The tracking error is large, and the tracking scheme avoids the problem of overfitting and underfitting and provides better control. Simulation results show that the scheme has better performance [8]. Hu et al. aim at the control operation under complex disturbance, and a new model-free trajectory tracking control method is proposed. The method takes time delay as the control basis, provides model-free control, and uses the adaptive nonsingular terminal sliding mode (ANTSM) to achieve high control and fast response. This method not only achieves accurate and effective control of noise and performance but also ensures the quality of the new control strategy. It has been confirmed by many comparative simulation studies [9]. Chen et al. proposed a novel sliding mode controller (PD-ESO-SMC) based on Extended State Observer (ESO) to achieve high-precision trajectory tracking of manipulators. The sliding mode surface of the controller is designed for PD form, using ESO to estimate and compensate for unknown external disturbances, parameter perturbations, and unmodeled dynamics in real time, and the introduction of the sal function is defined to suppress the chattering phenomenon. The simulation results show that the proposed control scheme can achieve high-precision trajectory tracking and has strong robustness to external disturbances [7].

The author uses the modified neural network to control the end of the controller and uses the Lyapunov function to prove the stability and integrity of the neural network closed-loop system. Trajectory control error and input torque of neural network control method were simulated in MATLAB/Simulink environment. Meanwhile, compared to the PID control method, as can be seen from the simulation curve, when the robot arm is broken by the outside world, the adaptive feedforward neural network control method has high trajectory tracking accuracy, which weakens the shaking phenomenon of the manipulator, and the motion of the system is relatively stable, which can meet the trajectory tracking task of the manipulator with high-precision requirements.

3. Research Methods

3.1. Dynamic Characteristics of the Robotic Arm. For a manipulator with N degrees of freedom, its coupling position difference is denoted as follows: $q = [q_1, q_2, \ldots, q_n]^T$. It is assumed that the research object can be represented by m variables $x = [x_1, x_2, \ldots, x_m]^T$ $(m < n)$, and at the same time, $x = f(q)$, f are the positive solution equations of kinematics. The following formula can be obtained after taking the second derivative of x:

$$x'' = J'(q)q' + J(q)q''. \tag{1}$$

In the formula, $J(q) = \partial f(q)/\partial q$, $J(q) \in R^{m\times n}$ represents the Jacobian matrix of the manipulator.

The pseudoinverse matrix (represented by $\overset{+}{J}(q)$) of the manipulator Jacobian matrix $J(q)$ is defined as the following formula:

$$J^+ = J^T\left(JJ^T\right)^{-1}. \tag{2}$$

In the formula $JJ^+ = I_m$, $I_m \in R^{m\times m}$—identity matrix.

For a manipulator with N connection pairs, the rotational direct drive can be expressed by the following relation:

$$M(q)q'' + V_m(q, q') + G(q) + F(q') = \tau. \tag{3}$$

In the formula, $M(q) \in R^{n\times n}$—inertia matrix;
$V_m(q, q')$—centripetal Coriolis force matrix;

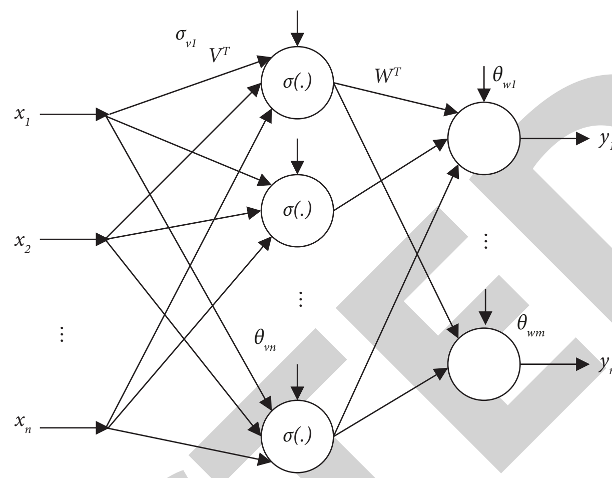

Figure 2: Feedforward neural network.

$G(q) \in R^n$—gravity matrix;
$F(q')$—friction matrix;
$\tau \in R^n$—torque input vector.

3.2. Feedforward Neural Networks. A two-layer feedforward neural network includes n input units, m output units, and N hidden level units as shown in Figure 2.

$$z_i = \sum_{j=1}^{N} \omega_{ij}\sigma\left(\sum_{k=1}^{n} v_{jk}y_k + \theta_{vj}\right) + \theta_{\omega i}, \quad i = 1, 2, \ldots, m. \tag{4}$$

In the formula $\sigma(.)$—the hidden layer neuron activation function, $\sigma(y) = 1/(1 + e^{-y})$;

v_{jk}—The weight of the interconnection from the input layer to the hidden layer;

ω_{ij}—The interconnection weight from the hidden layer to the output layer;

θ_{vj}, $\theta_{\omega i}$—Bias weights [10, 11].

Substituting the neural network weight values v_{jk} and ω_{ij} into the weight matrices V^T and V^T, respectively, the corresponding vector of the neural network equation can be obtained as shown in the following formula:

$$z = W^T\boldsymbol{\sigma}\left(V^T y\right). \tag{5}$$

where $\sigma(x) = [\sigma(x_1), \sigma(x_2), \cdots, \sigma(x_n)]^T$—activation function vector, $x \in R^n$.

3.3. Adaptive Neural Network Controller

3.3.1. Error Analysis. By studying the input value parameter $\tau(t)$ of the control torque, the actual operation trajectory of the robot end manipulator can be as consistent as possible with the expected operation trajectory. Therefore, the controller input value should effectively utilize the degree of freedom redundancy of the robot arm to achieve effective tracking of program subtasks. The operation space tracking error $e(t) \in R^m$ can be expressed as the following formula:

$$e(t) = x_d - x, \tag{6}$$

where $x_d \in R^m$—the expected operating trajectory in the operating space.

The defined subtask tracking error $e_N(t) \in R^n$ is expressed by the following formula:

$$e_N(t) = \left(I_n - J^+ D\right)\left(g - q'\right). \tag{7}$$

In the formula, $g(.) \in R^n$ is established according to the subtask control objective.

In order to provide incentives for the determination of the control objectives of the program subtasks, the time derivative is taken from Equation (6), after simplification, the closed-loop operation space trajectory tracking error system can be finally written as the following form:

$$e' = -\alpha e + Jr, \tag{8}$$

where $\alpha \in R^n$- Positive definite gain diagonal matrix, $r(t) \in R^n$; r—the filtered tracking error signal, and $r = J^+ (x_d' + \alpha e) + (I_n - J^+ Jg - q'$ is satisfied.

Use formula (7) to set the control input parameter value to ensure that the error of the operating space and the tracking error after screening are adjusted within the specified range. Then the properties of the inverse matrix can be used to achieve the above requirements, and the following equation can be obtained:

$$e_N = \left(I_n - J^+ J\right)r. \tag{9}$$

It can be seen from formula (9) that $e_N(t)$ can be adjusted by adjusting $r(t)$, so that the subtask control of the program can be realized.

3.3.2. Neural Network Control. The design of the controller based on the adaptive feedforward neural network is based on the following assumptions:

Assumption 1: Both $x_d, x_d, x_d, g(t)$ and $g'(t)$ are bounded functions of time

Assumption 2: All kinetic and kinematic function parameters (e.g., $g'(t), V_m(qq'), G(q), J(q)$ and $J^+(q)$) are bounded under all conditions of D [12, 13]

For the convenience of notation, the weight matrix of the neural network is specified as $Z \equiv diag\{W, V\}$, at the same time, the weight estimation errors are denoted as $\widetilde{W} = W - \widehat{W}, \widetilde{V} = V - \widehat{V}$, and $\widetilde{Z} = Z - \widehat{Z}$. The ideal neural network weight value is bounded and satisfies $Z||_F \leqslant Z_M$ and $Z_F^2 = tr(Z^T Z)$ under the condition of known Z_M [14]. At the same time, under the condition of given y, the hidden layer output value error $\widetilde{\sigma} = \sigma(V^T y) - \sigma(\widehat{V}^T y)$.

Regarding the tracking error of the robotic arm after the screening, its dynamic characteristics can be written as the following formula :

$$Mr' = -V_m r - Kr + \widehat{W}^T \widehat{\sigma} \widetilde{V}^T y + \widetilde{W}^T \widehat{\sigma} + \omega - J^T e. \tag{10}$$

In the formula $\omega = \widetilde{W}^T \widehat{\sigma}' \widetilde{V}^T y + W^T O(\widetilde{V}^T y)2 + \varepsilon$, K—positive definite gain matrix.

Then the boundary value $w(t)$ of the interference term can be determined by the constants c_0, c_1 and c_2. The weight estimates $\widehat{W}$ and $\widehat{V}$ are bounded, and the operation space and subtask tracking errors can be adjusted to be arbitrarily small [15].

Proof. For the Lyapunov function candidates of the following equation:

$$L = \frac{1}{2} e^T e + \frac{1}{2} r^T M r + \frac{1}{2} \mathrm{tr}\left(\widetilde{W}^T F_\omega^{-1} \widetilde{W}\right) + \frac{1}{2} \mathrm{tr}\left(\widetilde{V}^T G_v^{-1} \widetilde{V}\right). \tag{11}$$

Taking the time derivative of the Lyapunov function, combining equations $\widetilde{W}' = -\widehat{W}', \widetilde{V}' = -\widehat{V}'$, and the adaptive learning rule, the following equation can be obtained:

$$L' = -e^T \alpha e - r^T K r. \tag{12}$$

The stability of the Lyapunov function is determined by $L' \leq 0$ and $L' \leq 0$, thereby ensuring that $r(t)$, $\widetilde{W}$, and $\widetilde{W}$ (and corresponding $\widehat{W}$, $\widehat{V}$) are all bounded.

The boundedness of the $r(t)$ function ensures the boundedness of the functions $e(t)$ and $e'(t)$, the reason is that the boundedness of x, x' and y is reflected by the boundedness of the expected trajectory. The boundedness of the signal represented on the right side of equation (10) verifies the boundedness of r and L and the consistent continuity of L. Since the change of L with time tends to zero value t, $e(t)$ and $r(t)$ also tend to zero value, so it can be concluded from formula (9) that $e_N = (t)$ also tends to zero value [16]. □

4. Results Analysis

4.1. Simulation and Analysis. In order to evaluate the tracking effect of the motion controller controlled by the adaptive neural network, a round of simulations on the tracking error of the motion controller was carried out in MATLAB/Simulink. The tracking error of robot arm 3 is simulated and analyzed. The simulation results of robot arm 1 and robot arm 2 are similar to the simulation results of robot arm 3, and the simulation proof is not done here. The simulation parameters are set as follows: the required manipulator 3 is $\theta_3 = 0.4\cos(2\pi t)$, initial condition $\theta(0) = [0\,0\,0]^T$, control parameter $K = diag(40, 40), 40\}$, interference parameter $\tau' = 20\cos(\pi t)$, manipulator link parameters $l_1 = 0.62$m, $l_2 = 0.41$m, $l_3 = 0.34$m, $m_1 = 3.5$, $m_2 = 2.5$kg, $m3 = 2.0$kg, $g = 9.82\text{m/s}^2$, $t = 2_8$ [17–20]. Figures 3 and 4 show the simulation results of the tracking path of robot arm 3 when there is no external interference, the simulation results of the tracking of robot arm 3 are shown in Figure 5 [21]. The practical torque simulation result of robot arm 3 is shown in Figure 6 [22].

It can be seen from Figures 3 and 4 that in the absence of external interference, adaptive neural network control and PID control can control the user's demand, and the input torque of PID control has a large change and vibration. Therefore, the adaptive neural network control method should be adopted [23]. It can be seen from Figures 5 and 6 that in the presence of external interference, the adaptive neural network control can better control the expected

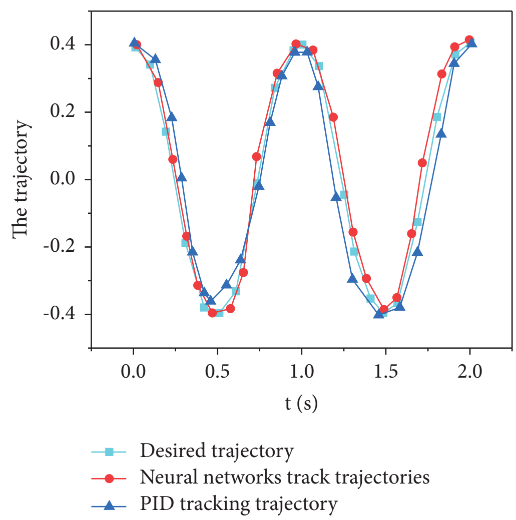

Figure 3: Movement trajectory of robotic arm 3 (no external interference).

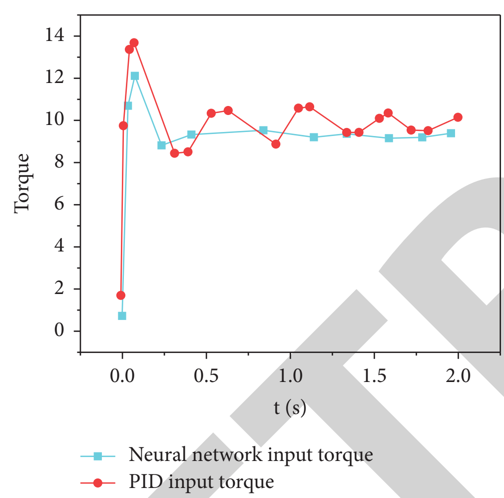

Figure 4: Torque control of robot arm 3 (no external interference).

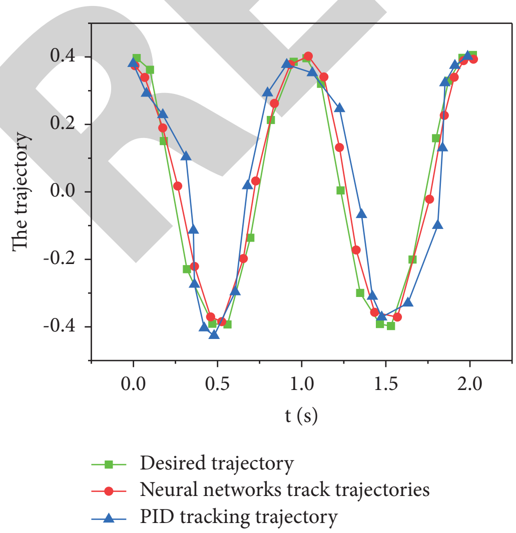

Figure 5: Movement trajectory of robotic arm 3 (with external interference).

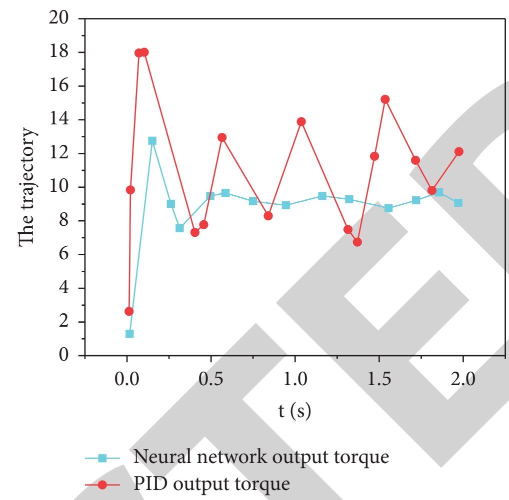

Figure 6: Torque control of robot arm 3 (with external interference).

trajectory of the manipulator, and the input torque range is small. However, PID control has a large error in controlling user demand and a large torque input, and the result is more serious. Advanced comparison and control neural networks can be used to track and control performance [24].

5. Conclusion

In this paper, the neural network control of robot arm motion is studied. The neural network controller can use the trajectory control and control function of the end-effector. If no prior training is required, the neural network feed can be used to complete the task of exploring the unknown power of the robot arm. The Lyapunov function obtained from the weight matrix ensures the stability of the system. The trajectory control error of the manipulator is verified by simulation in MATLAB/Simulink environment. Simulation results show that the adaptive neural network control method can not only accurately track the path of the robot in the presence of external disturbances. It also reduces the probability of a robotic arm.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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