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Robust Control Approaches and Trajectory Planning Strategies for Industrial Robotic Manipulators in the Era of Industry 4.0: A Comprehensive Review †

Ammar Mazhar , Ahsan Tanveer *, Muhammad Izhan and Mohammad Zayan Tariq Khan

Department of Mechanical & Aerospace Engineering, Institute of Avionics & Aeronautics, Air University, Islamabad 44000, Pakistan; ammarmazhar9701@gmail.com (A.M.); 200555@students.au.edu.pk (M.I.); zayantariq007@gmail.com (M.Z.T.K.)

* Correspondence: ahsantanveer3883@gmail.com

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Abstract: This article presents a comprehensive review of control approaches for industrial robotic manipulators, focusing on research conducted from 2020 onwards. The efficient functioning of robotic arms and successful task completion necessitate effective control strategies. Addressing real-world challenges, such as dynamic system variations due to environmental changes and unknown disturbances, remains crucial. To tackle these challenges, robust control strategies, including PID, H∞ and Model Predictive Control, are thoroughly surveyed. Commercially employed trajectory-planning techniques for manipulators are also extensively discussed. This paper concludes by providing valuable insights into prospective areas for future research, with the aim of enhancing the capabilities and performance of control strategies for industrial robotic manipulators. This study offers valuable knowledge to advance the field of robotic automation in Industry 4.0, fostering the development of efficient and intelligent manufacturing processes.

Keywords: industrial robots; collaborative robots; trajectory planning; robust control; Industry 4.0

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1. Introduction

Robotic arms play a pivotal role in the modern industrial landscape. Being an important component of Industry 4.0, they are of great importance in various industries, and their integration is necessary to realize the concept of a smart factory. The significance of robotic arms is paramount, and their control strategies hold even greater importance as they ensure their proper functioning. There are many studies that have focused on the control of industrial robotic arms in the past. Some delved into the control strategies for a specific industrial application such as welding [1], assembly [2] or material handling [3], while others classified control strategies based on different criteria, such as kinematic configuration, end-effector type and payload capacity. Additionally, there are studies which extensively discussed one aspect of control in robotic arms, such as trajectory control [4]. In recent years, there has been a rapid increase in the use of intelligent control strategies for industrial robotic arms [5] driven by the need for adaptability to dynamic environments, increased flexibility to perform various tasks, the ability to handle unknown disturbances and ensuring safety. This review explores control strategies for industrial robotic manipulators, focusing on research published from 2020 onwards. This review discusses robust control strategies and highlights different aspects of control, including trajectory planning, trajectory tracking, convergence and stability, while considering the need for adaptability and flexibility in facing challenges like environmental changes and unknown disturbances. This study offers valuable knowledge to advance the field of robotic automation in Industry 4.0, fostering the development of efficient and intelligent control strategies for manufacturing processes.

Different control strategies can be used for robotic manipulators; this choice depends on the intended application, operating conditions and other application specific requirements. For instance, classical PID and a linear MPC controller are compared in [6] using a five-DOF RV-2AJ Mitsubishi robotic arm for three distinctively defined reference trajectories. The study argues that MPC is faster and requires less control effort, whereas PID has greater precision. It is also worth mentioning that the choice of controller, to some extent, is dictated by the dynamics of the system. In real-world scenarios, system dynamics can vary due to changes in the environment and unknown disturbances. Therefore, robust controllers are needed to handle uncertainties, parameter variations, external disturbances and unmodeled dynamics.

Following the Introduction, the second section of this article highlights some robust control strategies. Afterwards, this article explores trajectory-planning techniques for robotic manipulators. Section 4 discusses trajectory-tracking methods, whereas convergence and stability in controlling robotic manipulators is discussed in Section 5. Finally, valuable insights into prospective areas for future research, with the aim of enhancing the capabilities and performance of control strategies for industrial robotic manipulators, are provided in Section 6. Section 7 concludes the article.

2. Robust Control

Robust controllers are designed to effectively maintain performance by handling model uncertainties, parameter variations, external disturbances and unmodeled dynamics. Control strategies lacking robustness often rely on accurate knowledge of system parameters. However, in real-world scenarios, system dynamics can vary due to factors such as environmental changes or unknown disturbances. As Ulusoy et al. [7] and Liu et al. [8] used linear PID, ignoring coupled dynamics, their control strategy lacked robustness. The authors in [9], on the other hand, proposed an adaptive neural control based on a simple structured PID-like control. The authors used radial basis function neural networks to estimate uncertainties and determine PID gains through a direct Lyapunov method. The proposed method can deal with the nonlinear dynamics of robotic systems and model uncertainty. Furthermore, the proposed methodology demonstrates robustness against external disturbances with the ability to achieve auto-tuning of the PID gains. Another application of robust algorithms can be found in [10], in which an $H\infty$ controller and a fuzzy logic (FL) compensator work together to achieve robustness. This strategy can handle unmodeled dynamics and resolve parametric uncertainty but requires a high level of mathematical ability due to its computational complexity. Similarly, Parkash et al. [11] proposed an adaptive backstepping neural controller for a robot manipulator with dynamic uncertainties and demonstrated the controller performance using a four-DOF Barrett WAM Arm. Carlucho et al. [12] developed an adaptive controller based on data-driven MPC, which utilizes a model derived using an NN, considering environmental disturbances while controlling a manipulator working with unknown payloads. Similarly, Kang et al. [13] worked on NN-based MPC of a two-DOF robotic manipulator with unknown dynamics and input constraints to improve the model estimation accuracy. Taken together, these studies suggest that robust controllers offer effective solutions to the challenges posed by uncertainties, disturbances and unmodeled dynamics and overall improve control performance in real-world scenarios.

3. Trajectory Planning

Trajectory planning is a crucial aspect of robotic systems which involves determining the optimal path and motion profiles to be followed in order to accomplish a specific task. The need for trajectory planning arises from the complexity of robotic tasks and the desire for precise and efficient execution. By planning a well-defined trajectory, robots can navigate through their workspace with improved accuracy, safety and optimized motion.

In this regard, Song [14] proposed a manipulator trajectory-planning method based on a radial basis function (RBF) neural network and implemented it in a six-DOF robotic arm, showing that the proposed method can improve trajectory tracking accuracy and motion efficiency. However, ref. [15] proposed a soft actor–critic (SAC)-based deep reinforcement learning path-planning algorithm for multi-arm manipulators with periodically moving obstacles. Neural networks estimate the future location of moving obstacles in SAC. Further, to improve estimation for periodic signals, Prianto et al. [15] suggested other deep learning algorithms like RNN, whereas for optimized trajectory, Zhu [16] used a combination of a simulated annealing algorithm and neural network learning while employing the PID control algorithm to reduce errors. A neural network and PLC control system were combined to optimize the servo motor.

As far as collision avoidance is concerned, Tamizi [17] developed a Path-Planning and Collision-Checking Network (PPCNet) framework based on end-to-end learning that uses deep neural networks to find a real-time solution for path planning and collision checking. The Kinova Gen3 robot was used to examine the proposed framework. The neural network and PLC control system were combined to optimize the servo motor. However, challenges are posed by slowness and complexity in path planning. To address this issue, Abdi [18] proposed an approach based on Q-learning and neural networks. This is a hybrid path-planning method which uses KNN to determine the location of the starting point, obstacle and target. Then, the Q-learning algorithm is used to reach the target cell and avoid obstacles. Finally, a trained neural network is used to obtain the joint angles of the robotic arms. These diverse trajectory-planning methods are important for the intelligent operation of autonomous robotic arms. Overall, it can be inferred that the ongoing evolution of this field, in which intelligent algorithms and autonomous decision making are incorporated for path planning, is revolutionizing various industries and enabling robots to complete complex tasks with greater precision, efficiency and speed without any human intervention.

4. Trajectory Tracking

After the trajectory is planned, next comes trajectory tracking. Trajectory tracking focuses on controlling the robot's motion in real time to closely follow the predefined or planned trajectory. Not all control systems have both trajectory planning and trajectory tracking. It depends on the requirements and application. However, both can be incorporated to achieve robust, safe, optimized and accurate motion control. Nubert et al. [19] combined robust MPC and NN control to achieve safe and fast tracking of a KUKA LBR4+ robotic arm, whereas Sun [20] achieved an excellent position tracking performance under nonlinear interference by developing a Friction Compensation Controller (FCC) that integrated Time Delay Estimation (TDE) and an Adaptive Fuzzy Logic System (AFLS). Wang et al. [21], on the other hand, used a Baxter robot to validate whether an RBF-NN-based controller could track the reproduced motion accurately. Similarly, for a satisfactory tracking performance with superior anti-disturbance capability, Cheng et al. [22] proposed a generalized saturated adaptive controller based on backstepping control, singular perturbation decoupling and neural networks. The proposed method was successfully tested on a two-DOF flexible-joint robot with bounded torque inputs.

For position control, ref. [23] investigated four different control strategies for a two-DOF robotic arm and successfully applied them using an Alternating Current Brushless Permanent Magnet Motor (ACBPMM) and a three-phase multilevel inverter with 27 levels of voltage per phase to drive the first link. This study provided a base for position control of the robotic arm with multiple DOFs using AC motors and multilevel inverters. Nonetheless, the challenge of tracking error arises when there are discrepancies between the desired trajectory and the actual trajectory followed by a system. To that end, Hu et al. [24] proposed dynamic surface control (DSC) based on a nonlinear disturbance observer (NDO) with an interval type 2 fuzzy neural network (IT2FNN), which performed better than the adaptive DSC with a neural network (NN) approximator and type 1 fuzzy (T1F) approximator in converging the tracking error to a sufficiently small value. Furthermore, in order to improve trajectory tracking accuracy, an adaptive fuzzy sliding mode control (AFSMC) was used in [25], which allowed the researchers to compensate for parametric uncertainties, bounded external disturbances and constraint uncertainties. Meanwhile, Quynh [26] investigated using a Wavelet Neural Network (WNN) with adaptive fuzzy sliding model control and the Lyapunov method to train a two-DOF robotic arm with high tracking accuracy. In light of these advances, it is evident that trajectory tracking is crucial for industrial robotic arms, where precise and accurate task execution is required while ensuring high-quality output and reducing errors in manufacturing processes.

5. Convergence and Stability

Stability in control systems refers to the property of a system to remain bounded and achieve a balanced state over time, even in the presence of disturbances or uncertainties. Convergence, on the other hand, is the behavior of a system in which certain variables or parameters tend to approach a specific value or reach a desired goal. In this context, Trans et al. [27] used the radial basis function neural network (RBSFNN) along with sliding mode control using a neural network (SMC-NN) and the Lyapunov training method for a two-joint robotic manipulator which can guarantee finite-time convergence and stability. Similarly, ref. [28] used radial basis function neural network (RBFNN) control for three-link industrial robot manipulators under various environments to guarantee the stability of the system and the convergence of the weight adaptation. These studies point to the fact that advanced techniques like neural networks and sliding mode control contribute to stability and convergence, enhancing performance, reliability, efficiency and safety in intelligent industrial operations under diverse environments.

6. Future Directions

In light of recent research, it is evident that these approaches provide robust control and can deal with model uncertainties, environmental changes and unknown disturbances. However, future research is still required to continually advance control systems for industrial robotic manipulators with regard to robustness, intelligence and automation. This section discusses different areas which can be explored in future research to contribute to enhancing the field:

- Current robust control strategies often rely on offline tuning of control parameters or the assumption of known system dynamics. Future research could focus on developing online adaptive control algorithms that can continuously adapt the control parameters and adjust the control strategy based on real-time measurements and system feedback.
- Development of advanced prognosis health management systems for industrial robotic arms based on real-time monitoring and adaptive control techniques [29].
- The use of multiple robots in collaborative tasks is increasing to enhance productivity and flexibility [30]. Thus, a need for effective coordination strategies has arisen. Future research could explore techniques that consider the coordination and cooperation of multiple robots. This could involve developing control algorithms for collision-free motion and communication protocols.
- Soft robotics is another emerging area. Future research could focus on integrating robust control, trajectory-planning and trajectory-tracking algorithms for soft robotics to achieve more adaptive and compliant robot behavior. This could lead to advances in fields such as robot-assisted surgery, human–robot collaboration and assistive robotics.

7. Conclusions

In this article, the significance of control strategies for industrial robotic manipulators in the context of the modern industrial landscape was discussed. The importance of using robust control methods to handle uncertainties, parameter variations, external disturbances and unmodeled dynamics was highlighted. Additionally, works on trajectory-planning techniques to ensure accurate and efficient execution of robotic tasks, including neural networks, deep reinforcement learning and optimization algorithms, were reviewed.

Trajectory-tracking methods, such as robust MPC, adaptive control and neural-network-based controllers, were also mentioned in relation to achieving precise motion control and position tracking. This review also touched upon the topics of convergence and stability and concluded by providing valuable insights into prospective areas for future research.

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