Industrial Robot Control Based on Deep Learning

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Abstract. The concept of Industry 4.0 originated in Germany, with its core being a highly digitalized factory interior that enables an efficient manufacturing system and even autonomous control of production. In the era of Industry 4.0, with the application of neural network learning, industrial robots can complete a large amount of production work with greater control. However, the control of industrial robots has not yet fully achieved intelligence. Deep learning does not require artificial features and can be used to further improve its ability to handle complex environments and generalization ability. This paper first introduces industrial robots and robot control. It then discusses the research on deep learning in robot motion control from three perspectives: robot motion control stability, position prediction and compensation, and robot crawling. This paper aims to provide a reference for the development of industrial robot control technology and promote the integration of deep learning and robot motion control in the field of industry, then improving the operational capabilities along with the intelligence of industrial robots.

Keywords: Industrial Robots, Robot Control, Deep Learning.

1 Introduction

Industry 4.0 represents a visionary project synonymous with the "Fourth Industrial Revolution." Originating in Germany, it seeks to initiate a fundamental shift in industrial production by integrating Internet technology with advanced technologies related to "smart" objects, such as machines and products. At its core is the highly digitalized factory interior, enabling a modular and efficient manufacturing system, and even allowing products to autonomously control their own production processes. The goal is to achieve the manufacturing of personalized products with a batch size of 1 while maintaining the economic efficiency of mass production [1].

During the process of implementing Industry 4.0, industrial robots play a very important role. As an indispensable part of industrial automation, they are widely used in today's industrial production, mainly undertaking tasks that are highly repetitive, labor-intensive, or potentially dangerous to humans. In the era of Industry 4.0, with the promotion of intelligent factories and the establishment of digital twin systems, industrial robots are crucial in industrial production because they can complete most of the repetitive production work. However, the uncertainties in the industrial production environment and the limitations of shallow learning make it impossible for robot

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control to fully achieve production intelligence: many monitoring and robot control tasks still cannot do without human regulation; it is difficult for machines to have generalization ability for tasks with a small sample size. In the future, with the intelligent upgrade of machine control and factories, industrial production will gradually achieve intelligence and move forward to the era of Industry 5.0, realizing intelligent human-machine collaboration and green production.

Deep learning emulates the brain's learning process, enabling the analysis of complex and unstructured data, which is highly significant in the research of industrial robot control.

This paper first introduces the research status of industrial robots and robot control in Section 2. Then, in Section 3, it reviews the applications of deep learning in industrial robot motion control stability, pose prediction and compensation, and robot crawling. Then, in Section 4, it summarizes the full text and looks forward to the future.

2 Industrial Robots and Robot Control

2.1 Industrial Robots

Industrial robots are the core automated equipment in modern factories. They possess the versatility of mechanical structures and can perform manufacturing tasks with much flexibility, reconfiguration, and little defection, such as material handling, pick-and-place, assembly, processing, inspection, etc. [2]. In the Industry 4.0 era, intelligent industrial robots are the core of digital and flexible manufacturing. Control methods based on artificial intelligence have shown potential, but there are still breakthroughs needed in terms of generalization ability, sample efficiency, and real-world adaptability. In the future, it is necessary to address the "reality gap", enhance human-robot collaboration, and integrate multiple learning strategies to promote efficient and flexible production in future factories [3].

2.2 Robot Control

Robot control is a field that focuses on how to make robots move and behave as intended. It is one of the fundamental areas of robotics and draws on knowledge from various disciplines, including control theory, mechanical and electrical engineering, artificial intelligence, and computer science. The primary goal is to design and implement robot systems that can perceive their environment, make decisions, and carry out actions effectively.

To make robot control intelligent, its core objectives include the following: trajectory tracking, pose control, force control, adaptive control, and intelligent control. For industrial robots, not only the above-mentioned core objectives need to be considered, but also more attention should be paid to the efficiency, stability, and safety of control. Motion control needs to focus on all the above-mentioned core objectives and is fundamental in robot control.

3 Motion Control of Industrial Robots Based on Deep Learning

3.1 Deep Learning

Deep learning is a branch of machine learning, a subset of AI, based on deep neural networks [4]. Without the need for manual feature design, deep learning automatically learns multilevel abstract features from raw data; at the same time, based on data-driven distributed representations, it has stronger generalization ability [5].

Many uncertainties in the industrial production environment limit traditional shallow machine learning. Many monitoring and robot control tasks still require human adjustment. However, with the application of deep neural networks, industrial robot control will reach a new level, improving the efficiency and stability of traditional industrial production. The following discussion will explore the application of deep learning in industrial robot control.

Robotic motion control can be mainly divided into two aspects: moving along a specific path and moving to grasp objects according to specific requirements. The former emphasizes precise movement along a programmed path, which is reflected in kinematic control, pose prediction and compensation, etc. The latter emphasizes the efficiency of identifying and grasping objects. Both control methods have been optimized in deep learning applications. This paper will proceed to examine the research status of deep-learning-based approaches from three perspectives: kinematic control, pose prediction and compensation, and robot grasping.

3.2 Control Stability

In the calibration process of industrial robots, the traditional kinematic model analysis has disadvantages such as strict conditions and long processing time. To solve this problem, deep learning is introduced to help optimize the kinematic model.

The team led by Toquica proposed an optimization scheme based on deep learning to address the inverse kinematics problem of industrial parallel robots. They trained the model using a dataset generated by the robot controller within the TensorFlow environment. Among the three training models, the Gated Recurrent Unit (GRU, an improved recurrent neural network) model is shorter in training time, faster in inference speed, and higher in accuracy. The GRU consists of 2 GRU layers (120 to 60 output) and one convolutional layer, using Xavier uniform initialization of weights to minimize the number of parameters. The output layer adopts linear activation to directly predict joint angles, resulting in higher training efficiency [6]. The team led by Wang Xiaoqi proposed a Damping Least Squares optimization method based on deep learning. On this basis, an "optimal enhancement coefficient" K is introduced, and this coefficient is predicted through a deep neural network to achieve a fast and high-precision solution of inverse kinematics and improve the computational efficiency under complex configurations. This method significantly reduces the number of iterations required for convergence by introducing the coefficient K determined by analyzing spatial data. During training, the selected samples can ensure the generalization of the network, and the Levenberg-Marquardt algorithm is used, combined with the Bayesian rule to optimize the weights. At the same time, the stability of the algorithm near the singular configuration is enhanced to avoid sudden changes in joint velocity [7].

For the structural and non-structural uncertainties in the robotic arm dynamics system, the team led by Wang Shou Jun proposed a method for dynamic parameter identification and error compensation of a six-degree-of-freedom (DOF) robot that combines the physical dynamic model and deep learning. This method solves the structural and non-structural uncertainties in the dynamics system, improves the torque prediction accuracy, and provides support for high-precision robot control. This method first constructs a physical model through parameter identification to obtain more accurate torque prediction, and then uses Uncertainty Compensation Model based on attention mechanism and Long Short-Term Memory network to compensate for errors [8].

3.3 Pose Prediction and Compensation

In industrial production, pose prediction and compensation play a decisive role in production accuracy. Numerous studies have been conducted extensively on pose prediction and compensation using deep learning. To achieve a higher level of pose accuracy, research team optimizes existing models to achieve better results.

To enhance the accuracy pose compensation and ensure the smooth operation of models with a limited number of samples, research teams, including Wei Wang, have proposed an industrial robot error compensation method using Deep Belief Network (DBN) and error similarity. The Particle Swarm Optimization algorithm was employed to optimize the model parameters, and an offline feed-forward compensation method was implemented to improve accuracy in industrial robots, significantly increasing assembly precision. As a feature extractor, the DBN enhances non-linear mapping capabilities, while the similarity of robot errors helps expand the sample size and extract error-related features from the samples [9].

Traditional stereo vision pose estimation requires precise calibration of camera intrinsic and extrinsic parameters. The process is cumbersome and vulnerable to environmental interference. Research teams such as Abdelaal have proposed a 6-DOF pose estimation algorithm based on uncalibrated stereo vision and the model of a deep neural network. Images are collected through a stereo vision system, and it detects the four corner points of the object. The deep learning model predicts object pose without intrinsic and extrinsic camera calibration. This algorithm enables the provision of 6-DOF pose estimation for industrial robotic arms, which is used for grasping and placing tasks. High-precision pose prediction is achieved on an uncalibrated low-cost stereo vision system, outperforming traditional calibration methods [10].

3.4 Robot Crawling

Nowadays, in automated production, most robot grasping systems are based on traditional automation systems and utilize artificial vision and shallow machine learning technologies. Although they can accurately identify specific targets, there are still some problems, including the need for long-term training and manual tuning, difficulty in handling complex environments, and challenges in grasping overlapping objects. The following will briefly describe the research progress of deep learning from the perspectives of algorithm improvement, generalization optimization, and system optimization.

Teams like Sekkat have proposed a visual-guided robotic arm grasping control algorithm that utilizes deep reinforcement learning to enhance existing visual detection methods. This approach does not depend on known action models. Instead, it integrates You Only Look Once version 5 for target detection, inverse projection for 3D positioning, inverse kinematics calculations, and the algorithm of Deep Deterministic Policy Gradient. As a result, the system can autonomously compute the robot's joint angles and control the end effector to accurately reach the target position based on the classification of the target object and the specific task requirements, thereby achieving high-precision grasping [11].

To solve the problem that machine grasping depends on long-term training and manual tuning, the team led by Bergamin proposed a framework, which is based on Deep Convolutional Neural Network. This framework can calculate multiple grasping poses for an object from a single red, green, blue image, achieving real-time prediction of stable grasping poses of unknown objects without pre-building object models or manually annotating features. The framework proposed a novel loss function, adopting a smaller network structure while maintaining the accuracy level of the most advanced methods at present, and it can be trained on a smaller dataset from scratch [12]. To address the interference, such as low light and occlusion in the real environment, the team led by Liu Yongkui proposed a simulation-to-reality transfer method based on digital twin deep reinforcement learning, which improves the grasping success rate and environmental adaptability. This method adopts a virtual-physical system parallel and synchronous correction mechanism; designs two parallel fully convolutional networks and introduces a "reliability" decay mechanism; and uses a deep Q network, combined with experience replay and Huber loss function to improve its robustness [13].

To achieve the transformation from automation systems in the past to those based on deep learning, teams such as Solowjow use a dual-network-controlled robot that is controlled by Programmable Logic Controller and applied with deep learning. In practical situations, it can complete up to 350 grabs per hour, with a high success rate and low total system power consumption. The object detection network in this model adopts the MobileNet Single Shot Multibox Detection model. It reduces the parameter scale through depth-separable convolutions, adapts to embedded hardware, and supports real-time object detection. Another grasping calculation network is based on Fully Convolutional Grasp Quality Convolutional Neural Network of Dex-Net 4.0. It optimizes the gripper, inputs the cropped depth image, outputs the grasping position and quality score, and realizes generalized grasping of unknown objects through synthetic data training [14].

4 Conclusions

This article mainly analyzes the research on deep learning of the motion control of industrial robots from three aspects. Although there are some limitations in the existing research, some studies only remain at the laboratory stage and face factors such as few experimental variables and little field testing. At the same time, there is more noise interference in the actual production environment, and the direct application of the model constructed from the existing data may bring problems such as insufficient accuracy. Nevertheless, deep learning algorithms have still made progress in the motion control of robots in industry: optimizing traditional algorithms in the two major directions of pose and grasping, reducing errors in work, and having advantages such as more stability and better robustness compared with traditional motion control algorithms. Evidently, the motion control of industrial robots based on deep learning has broad application prospects.

In addition, to pursue accuracy and choose to use large models, when they are widely used, it is necessary to consider the cost issues brought about by the large amount of computations required by deep learning algorithms, as well as issues such as whether there is a possibility of model simplification, which can be explored. There is still much room for exploration in the field of industrial robot control based on deep learning.

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