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Artificial Intelligence-Empowered Optimization of Industrial Welding Robots

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Abstract:
This paper provides a comprehensive review of the use of artificial intelligence in the optimization of industrial welding robots, with the goal of addressing major challenges that traditional welding robots face in complex scenarios, such as insufficient robustness, low defect detection efficiency, and difficulties with dynamic parameter adaptation. The research explores how AI utilizes deep learning, machine vision, digital twins, and adaptive control technologies to improve system integration, defect detection, and autonomous learning in welding robots. This document examines the utilization of an enhanced ResNet50 model for the advancement of dynamic tracking and high-precision localization of weld seams, alongside the notable enhancements realized by the lightweight YOLO-DEFW model integrated with data augmentation methods for real-time, efficient, and accurate detection of welding defects. This paper examines the application of artificial neural networks (ANN) and the Fuzzy ARTMAP framework in developing an autonomous learning and dynamic optimization system for welding parameters, thereby effectively mitigating the overdependence on expert experience inherent in traditional methods. The profound integration of AI technology may markedly improve the intelligence, welding quality, and production efficiency of industrial welding robots, offering unique technical avenues and extensive development opportunities for smart manufacturing.

Keywords: Artificial Intelligence, Industrial Welding Robots, Machine Vision, Artificial Neural Network

1. Introduction

Welding, a fundamental procedure in contemporary manufacturing, is extensively utilized in critical sectors such as aerospace, rail transit, and heavy machinery. The swift advancement of smart manufacturing technology presents numerous obstacles for classical welding robots regarding precision, efficiency, and consistent performance. Simultaneously, in intricate operating conditions, welding quality is compromised by ambient disturbances (such as reflections and smoke), and conventional algorithms and control systems are unable to address this issue. In recent years, the profound integration of artificial intelligence technologies with industrial applications has yielded new insights for tackling this difficulty. Using multi-modal awareness, real-time decision-making, and closed-loop control for synergistic optimization, this technique is driving the advancement of welding processes toward intelligent solutions. This is being accomplished by leveraging it.

Currently, existing welding automation technologies primarily rely on pre-set parameters and fixed path planning, with limitations manifesting in three key areas: weld seam recognition algorithms lack robustness in high-reflectivity and low-contrast environments, leading to issues during the welding process; weld defect detection relies on manual sampling, resulting in low efficiency and frequent missed defects; and process parameter adjustments heavily depend on expert experience, making it difficult to dynamically respond to the instantaneous changes in the molten pool's morphology and the varying process requirements across different welding scenarios. With the rise of artificial intelligence, convolutional neural networks (CNN) have effectively enhanced image analysis capabilities. However, issues such as limited model generalisation and low recognition accuracy continue to constrain practical application outcomes.

China began gradually developing industrial robots in the 1970s. Recent research has led to long-term development in industrial robot research and application technology, while the development of manufacturing has driven the development of the national economy. According to incomplete statistics, China's industrial robots have shown rapid growth in recent years, with an average annual growth rate of over 40% and a growth rate of over 60% for welding robots [1].

In response to the above issues, this paper aims to explore the application of artificial intelligence in the optimization of industrial welding robots. We will begin by analyzing the system integration optimization of robotic vision systems, examining how AI enhances the robustness and accuracy of weld seam recognition through image preprocessing and the ResNet50 image recognition algorithm. Subsequently, we will focus on the role of AI in optimizing weld defect recognition, including how data augmentation techniques, lightweight deep-learning models such as YOLO-DEFW, and intelligent loss function design improve the efficiency and accuracy of defect detection. Finally, this paper will explore in depth how AI can be combined with welding robots to achieve autonomous learning of soldering skills, reduce dependence on expert experience through intelligent parameter data analysis and online/offline learning frameworks (such as ANN and Fuzzy ARTMAP), and achieve adaptive optimization of soldering processes.

2. System Integration and Optimization

2.1 Image Preprocessing

Image pretreatment is key to improving target recognition accuracy and efficiency, and its technical implementation directly affects the robustness of subsequent algorithms. First, grayscale binarization processing is implemented, using a dynamic threshold segmentation algorithm to eliminate background color interference and effectively solve the problem of feature blurring caused by color differences on the target surface. This processing significantly reduces the dimensionality of image information, establishing a standardized data foundation for subsequent feature engineering. A noise detection mechanism based on connected component analysis has been developed to address discrete noise in binary images, effectively removing interference through morphological filtering algorithms. After image purification, a region marking algorithm is used to spatially locate the target object, followed by the extraction of a set of multidimensional feature parameters. A feature parameter matrix is constructed to achieve the digital representation of the target, which serves as the input vector for pattern recognition. A similarity matching algorithm is then used to compare and analyze the matrix against a predefined threshold. When the cosine similarity between the feature vector and the standard template exceeds the set threshold, the system completes the precise identification and spatial localization verification of the target [1-3].

2.2 Image Recognition Algorithm Optimization

The ResNet50 model, further enhanced for use in CNN models, employs skip connections as the primary technical means in its network architecture design. Skip connections establish direct channels across layers, enabling shallow-layer features to be directly transmitted to deeper layers of the network. This mechanism offers dual advantages: first, by constructing a shortcut path for gradient propagation, it significantly alleviates the vanishing gradient problem encountered during training of deep networks; second, the fusion of multi-level features enhances the network's feature representation capabilities. ResNet, as a typical example, features a residual structure that not only improves training stability but also endows the model with stronger noise tolerance and feature extraction capa-

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bilities. Compared to traditional CNN models, ResNet50 demonstrates significant performance advantages across various testing environments. During the training process of deep neural networks, as the number of network layers increases, gradients tend to gradually decrease or even disappear during backpropagation, leading to ineffective updates of network parameters and stagnation in model performance. The skip connections in ResNet50 act as a "fast track" for gradients, enabling information to be directly transmitted across multiple layers, significantly alleviating this issue and ensuring the stability and convergence of deep network training. By integrating features from different depths, ResNet50 can simultaneously utilize the detailed information from shallow layers and the abstract features from deep layers. This multi-level feature integration enhances the network's feature representation capabilities, enabling it to more comprehensively understand image content, particularly when dealing with complex backgrounds, lighting changes, or partially occluded weld seam images, allowing for more accurate target identification and localization. Although increasing network depth prolongs training time, the resulting improvement in accuracy fully validates the effectiveness of this architectural optimization. This explains why ResNet has become a landmark network architecture in the field of computer vision and continues to be applied and expanded in tasks such as image recognition and object detection [2].

3. Weld Defect Detection Optimization

3.1 Dataset Construction

In robotic welding processes, the number of defect samples is limited. Data augmentation methods are used to expand the dataset, thereby improving the model's generalization ability and reducing overfitting. At the same time, the types of data augmentation are controlled to balance the sample size and minimize biases caused by data imbalance. Experiments demonstrate that by applying 25 data augmentation techniques (geometric transformations, color transformations, noise addition, etc.), the original 460 images are expanded to 11,960 images, with balanced category distributions, followed by random sampling for testing, achieving a label consistency rate of 100% [4-7].

3.2 Model Optimization

Jianfeng Yue et al. further improve the YOLOv8 algorithm in 3 ways to reduce the model computation and number of parameters and improve the computational efficiency, refer to Table 1 [4]. DSConv (Distributed Shift Convolution) replaces the traditional convolutional layer, which significantly reduces the number of model parameters and computational cost, and the processing time of a single-frame image is only 3.9 ms, which meets the demand of real-time detection.EMA (Efficient Multiscale Attention Mechanism) enhances the model's ability to extract multiscale features, and especially improves the detection accuracy of small defects (e.g., cracks, air holes) [5].FWCE Loss Combined lossfunction, combining Focal Loss and weighted cross-entropy, alleviates the data imbalance problem by dynamically adjusting the weights, and improves the detection performance of rare defects (e.g., splash, incomplete melt-through) [6].

Table 1. Performance comparison between the YOLOv8 model and the YOLO-DEFW model

	YOLOv8	YOLO-DEFW
Parameter Quantity	3,007,00	2,601,00
Accuracy Rate	53.1%	60.2%
Recall Rate	60.4%	70.7%

4. AI autonomous Learning of Welding Skills

4.1 Intelligent Data Analysis and Learning

The application of AI in the autonomous learning of welding skills is first reflected in the intelligent analysis of parameter data. Enhanced image recognition algorithms enable AI to process and analyze image data in real time. AI can accurately calculate the geometric dimensions (width and height) of welds and estimate the penetration depth when combined with other sensor data. This high-precision geometric measurement capability forms the basis for AI's subsequent learning and optimization of welding parameters. Perhaps most importantly, AI can perform intelligent statistical pattern analysis using machine learning algorithms, such as regression analysis and decision trees, to automatically identify how key parameters, such as welding current, voltage, speed, and welding gun distance, influence the geometric shape and quality of welds. The system designs a large number of experiments and uses AI models to extract deep correlations from the resulting data. For example, it can analyze trends in weld penetration depth and width under different parameter combinations through neural networks. This establishes a parameter knowledge base that requires no human intervention [7].

Neural networks trained through deep learning can adaptively identify and remove discrete noise from images. AI models can learn complex noise patterns and perform more refined noise suppression based on contextual information. This is unlike traditional fixed morphological filtering. As a result, weld edge details are better preserved. After a region marking algorithm precisely locates the target object, AI can extract a set of multidimensional feature parameters and use convolutional neural networks to automatically learn and recognize high-dimensional features. Integrating .AI algorithms into modules such as OMRON FZ-PanDA[3] enables smart noise suppression and enhanced edge features, ensuring dynamic tracking and high-precision localization of weld seam trajectories in harsh environments with strong reflections and low contrast while maintaining robustness.

4.2 Online/Offline Learning

Grossberg S et al. proposed an automatic learning framework that does not require human intervention, using computer vision to capture weld geometry data in real time and training and predicting patterns using a Fuzzy ARTMAP neural network [8][9]. Using a high-speed CCD Basler camera, the system can feed back ANN and provide training patterns for online learning, enabling it to reproduce good geometric shapes in the future. This allows robotic welders to adapt to various materials and scenarios by adjusting parameters such as current/voltage, welding speed, and torch distance, thereby reducing reliance on human intervention [5]. During the offline learning phase, AI can utilize historical welding data and simulation data to train the Fuzzy ARTMAP neural network. The advantage of Fuzzy ARTMAP lies in its ability to handle uncertain information and fuzzy data, which is particularly important in complex welding processes, as it can better model the nonlinear, fuzzy relationship between parameters and welding results. The patterns learned by AI through the Fuzzy ARTMAP can predict the geometric shapes and potential defects that may form in welds under specific parameters, providing preliminary guidance and a knowledge framework for online learning.

True intelligence is reflected in AI's online learning capabilities. Through real-time capture of weld geometry data using visual systems such as high-speed CCD Basler cameras, AI feeds this real-time feedback into the ANN. As a powerful function approximator, the ANN compares the real-time observed weld seam state with the target weld seam geometry and dynamically adjusts welding parameters (such as current, voltage, speed, etc.). This closed-loop feedback mechanism is key to AI achieving adaptive control. For example, if AI identifies that the weld seam width is too narrow, the ANN will immediately adjust the current or wire feed speed to correct this deviation.

AI integrates these capabilities into an automated learning framework that enables welding robots to acquire welding skills autonomously, without human intervention. Through continuous AI learning and optimization, this framework allows robots to autonomously generate high-quality welds in diverse scenarios involving different materials, plate thicknesses, and joint types. The online learning system completes parameter training in 4.5 minutes and can successfully reproduce various specified geometric welds, such as 4 mm wide and 2 mm high, in half the time of traditional methods. The system's prediction accuracy for penetration depth is 93.2%, verifying its adaptability in complex nonlinear welding processes [10].

5. Conclusion

This paper provides a thorough review of the primary applications and recent developments in artificial intelligence (AI) technology for optimizing industrial welding robots. It explores how AI fundamentally addresses key challenges of traditional welding robots, such as poor weld seam recognition robustness, low defect detection efficiency, and difficulty achieving adaptive process parameter adjustment. System integration optimization, AI-driven intelligent image preprocessing, and the ResNet50 deep learning model have greatly improved weld recognition accuracy and adaptability to complex environments. This lays a solid foundation for precise welding operations. Regarding weld defect recognition, AI-based data augmentation technology, lightweight YOLO-DEFW models, and intelligent loss functions have significantly enhanced the real-time performance, accuracy, and recall rate of defect detection, enabling efficient and reliable quality control.

More importantly, AI builds an autonomous learning framework that requires no human intervention. When combined with intelligent parameter analysis and online/offline learning mechanisms, such as ANN and Fuzzy ARTMAP, welding robots can actively sense the welding process. They can also adaptively adjust process parameters and continuously optimize welding skills. This reduces reliance on expert experience and greatly improves

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production efficiency.

In summary, the deep integration of artificial intelligence (AI) technology is fundamentally transforming the landscape of industrial welding, driving it from traditional automation toward true intelligence. These AI-driven innovations significantly enhance welding quality and efficiency, reduce production costs, and provide robust technical support for diverse, high-precision, and highly flexible production requirements. As AI technology and computational capabilities continue to advance, industrial welding robots are expected to achieve higher levels of autonomous decision-making, multi-robot collaboration, and more precise quality prediction and control. Future research could optimize models further to better understand the influence of additional parameters on weld quality and improve AI learning to achieve fully automated manufacturing.

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