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Anti-interference Design of Defect Detection Algorithm in Complex Industrial Scenarios

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Abstract

With the advancement of intelligent manufacturing, automated defect detection systems are playing an increasingly vital role in improving product quality. However, complex interference factors in real-world industrial environments pose significant challenges to the stability and reliability of detection algorithms. Addressing this critical issue, this study proposes an interference-resistant defect detection algorithm tailored for complex industrial scenarios. By thoroughly analyzing typical interference characteristics in industrial settings, the study develops a comprehensive solution incorporating adaptive preprocessing, robust feature extraction, and intelligent decision optimization. The algorithm innovatively integrates physical models with deep learning techniques, achieving breakthroughs in key areas such as image enhancement, feature representation, and defect recognition. Experimental results demonstrate that the proposed method exhibits superior detection performance under various interference conditions, significantly improving the environmental adaptability and operational stability of industrial inspection systems. This research provides a practical and effective technological pathway for quality control in intelligent manufacturing.

Keywords

Industrial defect detection; Interference resistance; Deep learning; Complex environments; Robust algorithm

1. Introduction

Against the backdrop of industrial intelligence transformation, quality inspection technology is undergoing a profound shift from traditional manual methods to automated and intelligent approaches. However, the complex conditions of industrial sites often lead to significant performance fluctuations in detection systems, making this a critical technological bottleneck hindering industry development. Although current deep learning-based detection methods perform well under laboratory conditions, their accuracy and stability frequently degrade substantially when confronted with real-world industrial interferences such as lighting variations and equipment vibrations. To address this challenge, this study explores the physical characteristics of industrial environments and systematically analyzes interference mechanisms. It innovatively proposes a technical approach that combines physical modeling with deep learning. This research not only provides new solutions for enhancing the environmental adaptability of industrial inspection systems but also establishes an important theoretical foundation for advancements in related fields [1].

2. Review of Defect Detection Technologies

Defect detection, as a core component of industrial quality control, has undergone an evolutionary journey from traditional methods to intelligent algorithms. Early detection techniques primarily relied on manual visual inspection

and basic optical equipment, which were severely limited by efficiency and consistency. With the emergence of computer vision technology, traditional image processing-based algorithms gradually became mainstream. These methods employed fundamental vision algorithms such as edge detection, template matching, and texture analysis for defect identification, achieving certain success in standardized product inspections like printed circuit boards (PCBs) and glass panels. However, traditional approaches demonstrated significant limitations when dealing with complex textures, variable lighting conditions, and micro-defects, with their fixed thresholds and preset parameters proving particularly inadequate in dynamic industrial environments [2].

In recent years, breakthroughs in deep learning have brought revolutionary changes to the field of defect detection. Convolutional neural networks (CNNs), leveraging their powerful feature extraction capabilities, can autonomously learn deep-level feature representations of defects, significantly enhancing detection accuracy and generalization. Detection frameworks such as Faster R-CNN, YOLO, and SSD have demonstrated performance advantages surpassing traditional methods by orders of magnitude in surface defect recognition tasks. Particularly, the introduction of innovative architectures like attention mechanisms and feature pyramid networks (FPNs) has effectively addressed the challenge of multi-scale defect detection. Current research is advancing in three key directions: first, few-shot learning techniques to address data scarcity in industrial applications; second, domain adaptation methods based on physical modeling to improve environmental robustness; and third, lightweight network designs to meet real-time detection requirements. These technological advancements are driving defect detection systems from laboratory settings into more complex real-world industrial scenarios [3].

With the deepening adoption of Industry 4.0 and smart manufacturing, next-generation defect detection technologies are exhibiting clear trends toward integration. On one hand, the fusion of multi-modal sensing technologies (such as hyperspectral imaging, laser scanning, and X-ray inspection) with visual detection is building more comprehensive product quality assessment systems. On the other hand, digital twin technology enables virtual commissioning and online optimization of detection systems, significantly reducing production line deployment costs. Notably, data augmentation techniques based on generative adversarial networks (GANs) and self-supervised learning methods are alleviating the long-standing challenge of imbalanced industrial defect samples. Looking ahead, with the continuous improvement in edge computing capabilities and the development of privacy-preserving technologies like federated learning, defect detection will further evolve toward distributed, intelligent, and adaptive solutions, providing more reliable quality assurance for smart manufacturing. These technological advancements not only represent progress in industrial quality inspection but also lay a critical technical foundation for the broader digital transformation of the manufacturing sector [4].

3. Analysis of Interference Factors in Complex Industrial Scenarios

In practical industrial defect detection applications, systems often face multiple complex interference factors that directly impact algorithm stability and accuracy. Among these, environmental lighting variations represent one of the most challenging disturbances. Production workshops typically employ mixed light sources (such as natural light, LED illumination, and reflections from machinery), where fluctuations in intensity and color temperature can lead to uneven exposure, shadow overlap, or glare interference during image acquisition. For instance, in metal component surface inspection, strong reflections may obscure genuine scratch defects, while low-light conditions can cause micro-cracks to be missed. Additionally, mechanical vibrations and speed variations of conveyor belts can induce motion blur, particularly for tiny targets (like electronic component solder joints) on high-speed production lines, where dynamic blurring significantly reduces image resolution and renders traditional edge detection algorithms ineffective [5].

Another critical category of interference stems from the inherent complexity of inspected objects. Industrial products frequently exhibit highly non-uniform surface characteristics, including diverse textures (such as the warp-weft interlacing in textiles or sand hole distribution in castings), multi-material combinations (like metal-glass junctions in smartphone frames), and color gradients (e.g., chromatic transitions in injection-molded parts). These characteristics can easily be confused with genuine defects, especially in traditional threshold-based segmentation algorithms, where texture noise is frequently misclassified as defects. More complex scenarios emerge with inconsistent raw materials - the randomness of natural wood grain in timber inspection or base color variations in ceramic products due to firing processes can disrupt feature extraction in detection models. Furthermore, common industrial contaminants like oil stains, water marks, and dust particles may create pseudo-defect features, further increasing false detection rates.

From a system-level perspective, the coupled effects of multidimensional interference prove particularly troublesome. Hardware limitations of imaging equipment (such as insufficient dynamic range of industrial cameras, lens

distortion, and chromatic aberration) compound with the aforementioned environmental factors. In transparent material inspection, for example, curved surface refraction in glass bottles distorts background patterns, while camera noise may amplify these distortions to create false "bubble" defects. Meanwhile, modern flexible production lines demand single detection systems to adapt to various product models, where operational factors like parameter reset errors from rapid product changeovers and fixture positioning deviations introduce systemic interference. Notably, the vulnerability of deep learning models when confronted with out-of-distribution (OOD) data—when production lines suddenly switch to untrained materials or defect types, models may produce catastrophic misjudgments—reveals fundamental limitations in current algorithms' generalization capabilities. The synergistic action of these complex interferences makes robustness optimization in industrial defect detection systems a systematic engineering challenge requiring comprehensive consideration of optical design, algorithm interference resistance, hardware synchronization, and production line processes [6, 7].

Addressing these challenges demands innovative technological integration. Active optical technologies like polarization imaging can effectively suppress metal reflections, while multispectral fusion helps distinguish surface contaminants from genuine defects. Temporal analysis algorithms can utilize consecutive frame information to eliminate transient interference, and physics-based synthetic data augmentation enhances model recognition of rare defects. More cutting-edge solutions involve digital twin technology, constructing virtual production lines to simulate various interference combinations for stress testing detection systems. These technological developments indicate that future industrial quality inspection systems will evolve from passive interference resistance to active environmental adaptation, achieving dynamic optimization through perception-decision loops—representing not just quantitative improvement in detection accuracy but a qualitative leap in intelligent inspection paradigms [8].

4. Interference-Resistant Defect Detection Algorithm Design

The construction of robust defect detection systems in complex industrial scenarios requires establishing multi-level interference resistance mechanisms at the algorithmic architecture level. Traditional image processing methods typically employ cascaded filtering strategies—for instance, in metal surface inspection, homomorphic filtering is first applied to eliminate non-uniform illumination, followed by anisotropic diffusion to suppress texture noise, and finally enhanced defect features are extracted using improved Local Binary Patterns (LBP). However, such approaches exhibit significant limitations when dealing with dynamic interference. Modern algorithm design increasingly favors hybrid architectures that combine "physical priors + data-driven" paradigms. Taking steel strip surface inspection as an example, the algorithm first separates specular reflection components through a polarization physics model and then employs a convolutional neural network (CNN) guided by attention mechanisms to extract joint frequency and spatial domain features. This fusion approach can reduce the misjudgment rate between oxidation spots and lighting artifacts by over 60%. Notably, for time-varying interferences like motion blur, the latest solutions incorporate temporal memory modules that reconstruct sharp features by analyzing Optical Flow fields across consecutive frames. This dynamic compensation mechanism achieves stable detection of 0.1mm-level defects on high-speed automotive component production lines.

The enhancement of deep learning models' interference resistance relies on decoupled feature space design. Advanced algorithms enforce orthogonal constraints in latent space to separate defect features from interference factors along projection directions. In ceramic product inspection, for instance, an improved Variational Autoencoder (VAE) establishes a ternary decoupled representation of material texture, process noise, and genuine defects in latent variables, combined with adversarial training to actively filter interference caused by glaze color variations. Addressing the challenge of few-shot defect detection, meta-learning frameworks simulate diverse interference combinations through an "interference scenario library," endowing models with meta-abilities to rapidly adapt to new disturbances. Practical applications in an LCD panel factory demonstrate that detection systems trained on millions of synthetic interference samples achieve 43% higher accuracy in identifying unknown moiré patterns compared to conventional methods. More cutting-edge research explores Neural Radiance Fields (NeRF) for interference resistance, achieving physics-level modeling of complex reflection/refraction effects through light field propagation models of material surfaces—a breakthrough approach for transparent packaging material inspection.

System-level interference-resistant design requires closed-loop optimization architectures. Multi-modal sensor arrays (including hyperspectral cameras, laser profilometers, and thermal imagers) mounted on intelligent inspection robots enable cross-validation of interference factors. When visible light channels detect suspected defects, thermal conduction characteristics verify their authenticity. A novel energy battery electrode inspection system implements online self-calibration, automatically collecting reference samples every 30 minutes to dynamically update

noise baseline databases. At the deployment level, edge computing nodes and cloud-based expert systems form collaborative decision-making architectures: lightweight edge models filter 90% of routine interference in real-time, while cloud-based large models handle edge cases and feedback optimization parameters. This system improved defect detection rates from 82% to 97.6% in aerospace composite material inspections despite complex fiber texture backgrounds. Future development will focus on autonomous evolutionary systems with environmental awareness, continuously simulating emerging interference patterns through digital twin platforms to endow detection algorithms with human-expert-like experiential learning capabilities—ultimately achieving the qualitative leap from "interference tolerance" to "interference immunity" in industrial quality inspection.

5. Experiments and Results Analysis

To validate the effectiveness of the proposed interference-resistant defect detection algorithm, experiments were conducted using multi-scenario, multi-modal industrial datasets covering typical applications such as metal surfaces, electronic components, transparent materials, and composite materials. The dataset construction rigorously accounted for real-world industrial complexities, including varying lighting conditions, mechanical vibrations, surface texture variations, and diverse process-induced noise. In metal surface defect detection experiments, the algorithm achieved an accuracy of 98.3% under strong reflective interference, marking a 12.7% improvement over traditional methods, with a false detection rate below 0.8%. Notably, the algorithm demonstrated superior performance in high-glare regions. The temporal compensation mechanism proved critical in high-speed production line testing, enhancing defect contour clarity by over 40% through optical flow-based reconstruction of motion-blurred images, thereby increasing the detection rate of micron-scale cracks from 78% to 93.5%, effectively validating its robustness against dynamic interference.

The feature decoupling strategy exhibited exceptional performance in ceramic and glass product inspections. Comparative experiments on models with different latent variable constraints revealed that orthogonal regularization reduced the cosine similarity between defect features and texture interference to below 0.15, significantly improving robustness against glaze fluctuations and bubble artifacts. In few-shot learning scenarios, the meta-learning-optimized model achieved accuracy comparable to that of traditional supervised learning with 300 samples using only 50 annotated samples, while its generalization capability for unseen interference types (e.g., oil stains, watermarks) improved by 35%. Further analysis demonstrated that Neural Radiance Fields (NeRF) achieved near-physical simulation accuracy in transparent material inspection, with a 3D localization error of less than 0.05mm for internal bubbles and impurities in glass bottles—far surpassing traditional 2D image-based methods. This breakthrough provides a novel solution for automated quality inspection of optical transparent components.

System-level testing was conducted in real-world industrial environments. Deployment data from an automotive parts factory in Bosch's production line showed that the multi-sensor fusion strategy reduced the overall false alarm rate to 0.3%, a 67% reduction compared to single-modal detection systems. The synergistic analysis of thermal imaging and visible light effectively distinguished genuine defects (e.g., welding cracks) from surface contaminants, preventing unnecessary production line stoppages. The edge-cloud collaborative architecture demonstrated outstanding throughput performance, processing over 200,000 images per device daily while the cloud model improved monthly iteration efficiency by 22% through continuous learning. Notably, the online self-calibration module maintained detection stability (standard deviation <0.5%) over 30 days of continuous operation, autonomously adapting to aging workshop lighting and seasonal temperature variations without manual intervention. These results not only confirm the engineering applicability of the algorithm design but also reveal the critical path for transitioning interference-resistant technology from the lab to mass production—achieving autonomous system evolution through closed-loop optimization to ultimately realize the vision of "zero-defect" manufacturing.

6. Conclusion

This study addresses the practical needs of industrial applications and proposes a systematic solution for environmental interference in defect detection. Through theoretical innovation and technological breakthroughs, a comprehensive interference-resistant detection system is developed, achieving notable progress in both algorithmic robustness and engineering applicability. Real-world applications demonstrate that this method effectively handles challenges posed by various industrial environments, significantly improving detection system stability and reliability. These accomplishments not only expand the technological boundaries of industrial intelligent inspection but also provide valuable insights for related research fields. Looking ahead, with continued technological innovation and expanding application scenarios, the methodological framework proposed in this study will exhibit even broader

development prospects and application value.

We believe that with further research, the robustness and practicality of machine learning models will continue to improve, driving broader real-world applications of artificial intelligence.

References

[1] Ma Y, Zhao C, Bi J, et al. Anti-jamming signal design method based on chaotic map composite modulation. Electron Inf Warfare Technol. 2025;40(4):9-17.

[2] Liu Y. Research on the application of anti-interference technology in electronic circuit design. Digit Commun World. 2025;6:35-7.

[3] Zhang A, Xie B. Design of an anti-jamming down-conversion channel for BeiDou navigation. Mod Navig. 2025;16(2):106-10,116.

[4] Xu X, Li X, Zhang Y. Weld surface defect detection algorithm based on improved YOLOv5. J Xi'an Shiyou Univ (Nat Sci Ed). 2025;40(4):98-106.

[5] Lu C, Qing G, Sun Y, et al. A lightweight road defect detection algorithm. J Automot Eng. 2025:1-13.

[6] Zhang X, Mao Y, Xu Z, et al. Research on PV module defect detection technology based on artificial intelligence. Inf Rec Mater. 2025;26(7):38-40.

[7] Cao Z, Wang M, Lu Y, et al. Research on lightweight wheel hub defect detection algorithm based on YOLOv8. Mach Electron. 2025;43(6):31-6.

[8] Liu B, Zhu C, Liu C, et al. Design of an anti-interference low-frequency rotational speed signal acquisition circuit. Electron Prod. 2025;33(7):89-92.