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The Application of Automated Image Processing Technology in Industrial Inspection

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Abstract: In modern industrial production, quality inspection and control play a crucial role in enhancing production efficiency and ensuring product reliability. Traditional inspection methods primarily rely on manual labor, which not only results in low efficiency but also introduces human error, leading to unstable inspection outcomes. With the advancement of science and technology, automated image processing technology has emerged, revolutionizing industrial testing. By leveraging computer vision and image analysis algorithms, automated image processing technology can rapidly and accurately identify and analyze defects and anomalies in images, significantly improving inspection efficiency and accuracy. This technology not only enables real-time monitoring of product quality on production lines but also provides data support for process optimization, driving industrial production toward intelligent and automated development.

Keywords: automated image processing technology; industrial inspection; application

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1. Introduction

The application of automated image processing technology in the field of industrial inspection aims to utilize advanced image analysis algorithms and computer vision technology to achieve high-efficiency, high-precision inspection of industrial products. Its core involves using high-definition cameras to capture product images and employing complex image processing algorithms to analyze potential defects and quality issues within the images. Compared to traditional manual inspection methods, automated image processing technology offers the advantages of speed, accuracy, and stability. This system can not only process large volumes of image data but also complete complex inspection tasks in a short time, significantly improving production efficiency. Additionally, automated image processing technology can analyze data from the production process to optimize production, thereby reducing production costs and improving product quality.

2. Application Advantages of Automated Image Processing Technology in Industrial Inspection

2.1. High Efficiency and High Precision Inspection

Traditional manual inspection methods primarily rely on visual observation and manual operations, which are not only slow but also susceptible to subjective human factors, leading to inconsistent inspection results. In stark contrast, automated image processing technology utilizes high-speed cameras and advanced image analysis algorithms to process large volumes of image data in a short time, achieving rapid detection. This technology can precisely identify minute defects and anomalies, even those that are difficult to detect with the naked eye[1]. For example, in the manufacturing of electronic components, automated image processing technology can promptly identify defects such as small scratches on chip surfaces or solder joints, thereby ensuring product quality and reliability. Based on this, high-precision testing can significantly improve production efficiency, reduce defect rates, and enhance market competitiveness.

2.2. Stability and Reliability Assurance

In industrial testing, automatic image processing technology offers the advantages of stability and reliability. Manual testing is susceptible to fluctuations in results due to factors such as the tester's subjective emotions, fatigue, and experience. Automatic image processing technology is based on predefined algorithms and standards, enabling it to maintain consistent detection performance without being influenced by external factors. This stability ensures the reliability and reproducibility of test results, enabling enterprises to accurately control product quality. Additionally, through regular calibration and maintenance, the long-term stable operation of automatic image processing systems is further enhanced. This high-stability, high-reliability testing model reduces human error while enhancing the controllability and predictability of production processes, providing enterprises with more reliable production guarantees.

2.3. Data-driven production optimization

Another major advantage of applying automatic image processing technology to industrial inspection is that it can provide data support for the production process, thereby achieving production optimization. By analyzing the massive amounts of data collected by the image processing system, issues and bottlenecks in the production process can be deeply analyzed. This project proposes a machine learning-based equipment fault prediction method that not only monitors product quality in real time but also predicts equipment faults, optimizes process parameters, and improves production efficiency[2] . For example, by analyzing test data, high defect rates in the production process can be identified, enabling targeted adjustments to process parameters or equipment maintenance. This data-driven production optimization method can help enterprises reduce production costs and improve production efficiency while enhancing overall product quality.

2.4. Adapting to Complex Environments and Diverse Testing Requirements

In the complex and ever-changing industrial production environment, traditional testing methods are no longer sufficient to meet the demands of such dynamic conditions. By leveraging advanced sensors and image processing algorithms, automatic image processing technology can effectively adapt to challenging environments such as high temperatures, high pressures, and high humidity. Additionally, this technology can be customized to meet different testing needs, ensuring it can address the requirements of various testing tasks. For example, in the automotive manufacturing sector, automatic image processing technology can be applied to various scenarios, such as body appearance testing and component assembly testing, to ensure quality control at every stage. This adaptive and flexible nature enables automatic image processing technology to be widely adopted across industries, meeting enterprises' diverse production needs.

3. Application Strategies of Automated Image Processing Technology in Industrial Inspection

3.1. Scientific Construction of an Image Acquisition System Based on the Characteristics of the Inspection Object

It is essential to closely align with the intrinsic characteristics of the inspected object, optimize multiple parameters synergistically to obtain high-quality images, conduct a comprehensive investigation of the object's features, and clarify its geometric dimensions (length, width, height, curvature, etc.), surface condition (smoothness, roughness, reflectivity, etc.), material composition (metal, plastic, ceramic, etc.), and production environment (temperature, humidity, light intensity, vibration frequency, etc.), and use this as the basis for system construction.

Based on the investigation results, select imaging equipment. The camera resolution must match the required detection accuracy; for example, if 0.01 mm detection accuracy is required, an industrial camera with over one million pixels must be selected. The frame rate should be adjusted according to the production line's operating speed to ensure sufficient images are captured within a unit of time to cover the entire target. On a production line operating at 1 m/s, the camera frame rate should be no less than 50 frames. Additionally, based on the spectral characteristics of the measured object, appropriate coating materials should be selected to reduce stray light interference [3].

The lighting system design should adopt a multi-parameter coordinated control strategy. The type of lighting should be determined based on detection requirements. High-brightness LED ring lights should be used to detect surface defects, while near-infrared lights with strong penetration capability should be used to detect internal structures. To adapt to the reflective characteristics of different material surfaces, the intensity of the lighting should be continuously adjusted; The angle of light incidence must be adjusted from multiple angles to ensure that light reaches the target area without casting shadows. Three-dimensional modeling software can be used to simulate the movement trajectory of the target object on the production line, combined with the distribution of key inspection areas, to determine the number and spatial positions of cameras. In multi-camera layouts, effective overlap of image acquisition areas must be ensured to avoid detection blind spots.

After the system is set up, it needs to be calibrated, including geometric calibration and grayscale calibration. By shooting a standard grid plate, the mapping relationship between pixels and actual dimensions is calculated to eliminate errors caused by distortion. Gray-scale calibration is a new method that involves capturing a standard gray-scale card to establish a correspondence between gray-scale values and actual brightness in the image, ensuring that images captured at different times share a consistent gray-scale reference.

3.2. Optimization of image preprocessing techniques tailored to detection requirements

Conduct image quality evaluation studies by calculating parameters such as image signal-to-noise ratio, contrast, and edge gradient to identify primary interference factors (Gaussian noise, salt-and-pepper noise, Poisson noise, etc.), areas with insufficient contrast, and the extent of geometric distortion. This provides a basis for selecting appropriate preprocessing methods. Different filtering strategies are adopted for different types of noise: when the image primarily contains Gaussian noise, an adaptive Gaussian filter is used to filter the image. By analyzing the grayscale changes in local image regions, the standard deviation of the filter kernel is dynamically adjusted to suppress noise while preserving image details [4].

For salt-and-pepper noise, an improved median filtering algorithm is used in conjunction with a noise point detection mechanism. Only pixels identified as noise are replaced with the median value to minimize interference with normal pixels. For mixed noise, wavelet transform is used to filter the image, removing high-frequency noise while preserving low-frequency structural information.

For images with concentrated gray-scale distributions, a histogram equalization-based image enhancement method is employed. For images with concentrated gray-scale distributions, an adaptive histogram equalization method is used to divide the image into multiple subregions, each of which undergoes histogram equalization, thereby avoiding local detail loss caused by global equalization.

For images with strong reflective regions, the Retinex algorithm is used to separate the illumination components from the reflective components, correct the illumination components, eliminate the effects of uneven illumination on the image, enhance the reflective components in the image, and highlight image details. Standard scale plate images are acquired, feature points on the calibration plate are extracted, and distortion parameters are calculated using the least squares method to establish a mapping relationship between pixel coordinates. Geometric deformations are precisely corrected using methods such as bilinear interpolation and cubic spline interpolation.

During image segmentation, morphological characteristics of the detection object are considered, and a multi-strategy fusion approach is employed for segmentation: for regions with significant gray-level differences, adaptive thresholding is used for segmentation, with the optimal threshold determined through iteration to separate the target from the background. For targets with distinct edge features, Gaussian filtering is used for noise reduction, followed by gradient direction and amplitude calculation, extreme value removal, dual-threshold detection, and edge connection algorithms to form closed regions. For targets in complex backgrounds, a semantic segmentation model based on deep learning is studied. A pixel-level classification model is established using training samples to achieve precise segmentation of the target region. During preprocessing, a quality evaluation feedback mechanism is introduced. By calculating parameters such as the integrity of the segmentation region and edge continuity, preprocessing parameters are dynamically adjusted to ensure that the preprocessing results meet the requirements for subsequent feature extraction.

3.3. Precise extraction and analysis based on defect characteristics

For the object being tested (e.g., cracks, dents, scratches, deformations, discoloration, etc.), determine the geometric characteristics of the object to be tested (area, perimeter, width, roundness, rectangle, eccentricity, etc.), texture characteristics (grayscale co-occurrence matrix, local binary pattern, wavelet texture features, etc.), color characteristics (RGB component means, HSV color space parameters, color moments, etc.), and shape characteristics (Fourier descriptors, invariant moments, etc.)[5]. In terms of feature extraction, both the category of features and computational efficiency must be considered comprehensively. For geometric features, contour analysis is used to calculate relevant parameters of the target, and contour tracking algorithms are employed to obtain the boundary pixel coordinates of the target. Basic parameters such as area and perimeter are calculated from the pixel coordinates and converted into composite parameters such as roundness and rectangularity.

For texture features, the joint probability distribution of pixel grayscale values in different directions and distances is calculated using the grayscale co-occurrence matrix, and features such as energy, entropy, and contrast are extracted. The local binary pattern compares the gray values of each pixel and its neighboring pixels to obtain a binary encoding, which is used as a texture feature. Features should be standardized to eliminate scale differences between them. Numerical features are normalized using Z-score normalization, converting feature values into normalized data with a mean of 0 and a standard deviation of 1. For categorical features, unique codes are used to convert them into binary vectors.

Feature importance evaluation methods can be used to remove redundant and irrelevant features. Variance analysis, mutual information methods, and ReliefF algorithms can be used to calculate the correlation between features and defects, retaining highly correlated features, and reducing the dimensionality of the feature space to improve analysis efficiency. A multi-algorithm fusion strategy can be adopted to construct feature analysis and classification models. For simple defects, statistical analysis methods can be used to calculate the differences in feature distributions between normal and defective samples, set threshold ranges, and achieve defect identification. For complex defect identification, machine learning classification models need to be established, such as support vector machines to find the optimal classification surface, achieving linear or nonlinear classification. Decision trees construct tree structures for hierarchical classification of features, while random forests fuse multiple decision trees for learning to improve classification accuracy.

3.4. Detection result feedback and system continuous optimization mechanism

A closed-loop feedback-based detection method can be adopted, and detection results can be fed back and optimized to ensure the long-term stable operation of the industrial detection system. A detection result data management system should be constructed, including a structured database containing raw images, preprocessed images, extracted feature parameters, detection times, and other data, to enable effective querying and management of detection results. Combined with data backup strategies, this ensures the security and integrity of the data[6]. Real-time feedback of detection results should be seamlessly integrated with the production line control system. Defect judgment results should be transmitted to the production line PLC via industrial Ethernet or fieldbus. When non-conforming products are detected, the production line's automatic sorting mechanism should be activated to automatically remove non-conforming products.

Inspection results such as defect location, type, and severity can be displayed in real-time on monitoring terminals for operator reference. Based on this, statistical analysis of inspection data is conducted using data mining techniques to extract hidden information. Key performance indicators such as inspection accuracy, false negative rate, false positive rate, and detection rate are statistically analyzed, and the distribution patterns of defects across different periods and product categories are analyzed, with trends identified.

Based on the statistical analysis results, system parameters are dynamically optimized. For defect types with high false negative rates, image acquisition parameters are re-evaluated by adjusting camera focal length, light intensity, or shooting angle to ensure clear imaging of defect areas. For cases with extremely high false negative rates, optimize the preprocessing algorithm by adjusting filtering parameters or thresholds to reduce misjudgments caused by background interference. When feature extraction is insufficient, add new feature parameters or improve the algorithm during feature extraction to enhance the discriminative ability of features. Model iteration and updates require establishing a sample augmentation mechanism, regularly collecting new samples, retraining the original classification model, and using incremental learning methods to absorb new sample information while retaining existing knowledge, thereby avoiding significant model degradation.

Disclosure statement

The author declares no conflict of interest.

References

[1] Liu L, 2024, On the Application of Machine Vision Inspection Technology in Industrial Automation. Value Engineering, 43 (36): 128-130.

[2] Chen S, Chen Y, Chen Y, Jiang R, Chen Y, Zhang J, 2024, Algorithm Research on Automated Inspection of Precision Components in Industrial Production. Modern Information Technology, 8(22): 156-160.

[3] Liu Z, Kou S, 2024, Application of Machine Vision Inspection Technology in the Field of Industrial Automation. Paper Making Technology and Application, 52(03): 46-48.

[4] Chen Y, 2024, Application of Computer Vision in Industrial Automation Inspection. Paper Making Equipment and Materials, 53(07): 17-19.

[5] Wang D, 2022, Analysis of the Application of AI Intelligent Detection in Industrial Automation Control Systems. Information and Computers (Theoretical Edition), 34(01): 165-167.

[6] Sun J, Wang D, 2020, Research on Automated Control Methods for Industrial Temperature Detection Instruments Based on Artificial Intelligence. Automation and Instrumentation, 2020(10): 43-46.