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Machine Vision-Based Automatic Detection for Electromechanical Equipment

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Abstract: With the continuous development of industrial production, efficient and accurate inspection of mechanical equipment has become crucial for production safety, efficiency, and economic benefits. By collecting and analyzing imaging data from electromechanical equipment, effective online monitoring and fault diagnosis can be achieved, enhancing operational efficiency and accuracy while reducing manual intervention. This is a significant research direction in the field of industrial automation control. This paper begins with the fundamental principles of electromechanical equipment testing, conducting an in-depth study of its working mechanisms and providing a detailed discussion on its design and development. The main content includes the system architecture design, functional module design, and key algorithm design, laying a solid foundation for the research on automated testing of electromechanical equipment.

Keywords: Automatic Detection Technology, Machine Vision, Electromechanical Equipment, Economic Benefits.

Disciplines: Computer Science. **Subjects:** Machine Vision.

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1 INTRODUCTION

With the rapid development of technology, industrial automation has become a crucial component in the modern industrial sector. Among various automation technologies, machine vision has gradually occupied a central position in manufacturing, inspection, and traceability due to its high precision and efficiency. As an important breakthrough in this field, machine vision-based automatic detection technology is increasingly becoming a key method for improving production efficiency, ensuring product quality, and reducing maintenance costs.

Equipment condition monitoring involves using various detection instruments to assess multiple indicators of equipment to ensure its safe and normal operation. Nowadays, the structures of equipment are becoming more complex, and the level of automation is increasing, leading to aging issues with prolonged operation. Environmental factors can also exacerbate equipment damage. Therefore, regular and effective inspections can reduce the likelihood of equipment problems. The earlier issues are detected, the more potential losses from equipment failure can be minimized.

Machine vision technology originated from in-depth research into "vision" and has matured through the integration of computer vision, image processing, pattern recognition, and artificial intelligence. From its beginnings as a tool to assist artists in painting to the development of intelligent cameras capable of precise object localization and measurement, machine vision has transitioned from "seeing" to "understanding" and "executing," becoming an important branch of artificial intelligence.

In the field of automatic detection of electromechanical equipment, traditional manual inspection methods have many drawbacks, such as low efficiency, poor accuracy, and high labor costs. In contrast, machine vision-based detection technology can achieve efficient and accurate inspection of electromechanical equipment, effectively addressing these issues. This technology utilizes a series of steps, including image acquisition, preprocessing, feature extraction, target recognition, and localization, to enable real-time monitoring and fault diagnosis of equipment status, providing a scientific basis for maintenance and management.

2 THE THEORETICAL BASIS OF AUTOMATIC DETECTION FOR ELECTROMECHANICAL EQUIPMENT

2.1 Automatic Detection Technology for Electromechanical Equipment

The technology for automatic testing of electromechanical equipment is an important research area in modern industrial automation and intelligent manufacturing. It relies on advanced machine vision systems to collect image

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information during the operation of electromechanical equipment and processes this information using complex algorithms to achieve real-time monitoring and fault prediction.

Image acquisition is the most crucial step in a machine vision system. High-precision cameras and suitable lighting systems are used to capture images, which are then subjected to preprocessing steps such as denoising, enhancement, and segmentation to improve image quality and reduce the complexity of subsequent processing. The feature extraction stage involves identifying valuable information about the equipment's status from the processed images, such as edges, textures, and shapes.

Mathematical models such as Support Vector Machines (SVM) and neural networks are used for classification and fault diagnosis of the extracted data, allowing for the identification of normal operating conditions and potential faults in the equipment. This project focuses on the automatic testing of electromechanical equipment, centering on digital signal processing to enhance the system's ability to recognize and analyze equipment status through effective filtering, encoding, and transformation techniques.

Additionally, integrating artificial intelligence and deep learning methods, such as Convolutional Neural Networks (CNN), for image recognition and classification provides more efficient and accurate technical means for diagnosing faults in electromechanical equipment. When considering the theoretical foundation of automatic testing technology for electromechanical equipment, it is essential to emphasize system integration and optimization. This includes optimizing algorithms, reasonably evaluating system hardware configurations, improving data processing speed and accuracy, and ensuring system performance under limited resource conditions.

2.2 Machine Vision Detection

A machine vision detection system is a system that utilizes computer vision technology and image processing algorithms to simulate human visual functions for recognizing, measuring, locating, and judging target objects. Its core involves acquiring image information of the object to be inspected through image capture devices such as cameras. Advanced image processing and analysis techniques are then used to extract useful information from the images, which is compared and analyzed against preset standards or models, ultimately achieving automated detection and decision-making.

The machine vision detection system mainly consists of two parts: hardware and software. The hardware component includes image acquisition devices (such as industrial cameras, lenses, light sources, etc.), image processing units (such as image processors, computers, etc.), and actuators (such as robotic arms, conveyors, etc.). The software component includes image processing software, control software, and algorithm libraries responsible for image preprocessing, feature extraction, target recognition, localization, measurement, and final judgment and output of results.

The technical foundation of machine vision detection systems encompasses multiple fields, including image processing, computer vision, pattern recognition, and artificial intelligence. Among these, image processing technology is key to performing preprocessing steps such as image enhancement, denoising, and segmentation. Computer vision technology is used for deep understanding of images, including shape recognition, color analysis, and texture analysis. Pattern recognition technology is employed to match the extracted features with preset models for accurate target identification, while artificial intelligence technology continuously drives the intelligent development of machine vision detection systems, enhancing their adaptability and decision-making capabilities.

In the ROS (Robot Operating System) platform, a patrol robot system is constructed by deploying various modules in the form of ROS nodes. As shown in Figure 2-1, the target detection module publishes the "start-detecting" topic in the form of a "detector" and also publishes the "start tracking" topic. The target tracking module, functioning as a "tracker" node, provides the "start tracking" topic, "arrived" topic, and "target position" message. The target information identification module, acting as a "recognition" node, subscribes to the "start receiving" topic and publishes the "move" and "data" topics.

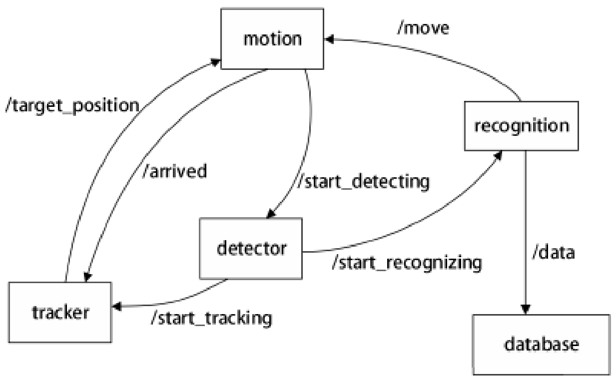

Figure 2-1 Node Relationship Diagram of the Machine Vision Detection System

3 RELATED THEORIES AND METHODS

3.1 Application of Deep Learning in Equipment Condition Monitoring

In the field of automatic detection, machine vision inspection systems combine computer vision and deep learning algorithms to enable online monitoring and fault diagnosis of electrical and mechanical equipment. In recent years, deep learning-based models, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory

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(LSTM) networks, have demonstrated high accuracy in equipment condition monitoring. For example, the high-precision measurement technology of geometric parameters based on binocular stereo vision holds great potential for metrology detection applications [1]. Meanwhile, the detection methods for text generation by large language models (LLM) based on the Transformer deep learning algorithm offer a new perspective on the reliability of AI systems [2].

3.2 Dynamic Task Offloading and Resource Scheduling

Building on these theories and methods, this study will combine Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models to construct a system capable of dynamically adjusting task offloading and resource scheduling. Compared to traditional methods, deep learning approaches not only handle large-scale data but also enhance detection efficiency and accuracy through automatic feature extraction [3]. Furthermore, a deep learning-based snore analysis method was proposed for detecting nocturnal breathing disorders, and the results demonstrated the effectiveness of deep learning in real-time monitoring [4].

3.3 Real-Time Data Processing and System Optimization

In the field of real-time data processing, deep learning algorithms not only improve detection accuracy but also significantly reduce response time through parallel computing. For example, the transformative role of artificial intelligence and large language models in government efficiency and public trust provides a theoretical foundation for the application of intelligent systems in various fields [5]. Additionally, Li et al. utilized the LightGBM algorithm for user credit evaluation in their study, further demonstrating the powerful performance of machine learning algorithms in large-scale data analysis [6].

3.4 Integration of Deep Learning with Practical Needs

To further optimize automatic detection systems, recent research has extensively adopted a combination of deep learning and machine learning algorithms. For instance, the lightweight network structure based on YOLOv5 has enhanced system detection efficiency through network optimization [7]. Moreover, the research outcomes compiled by Wang et al. on electronic engineering and information science have provided a solid technical foundation for this field [8]. These studies indicate that optimizing intelligent detection systems requires not only algorithmic innovation but also close alignment with real industrial needs.

3.5 System Stability and Energy Efficiency Optimization

Additionally, the meta-learning methods for black-box attacks and adversarial defense have expanded the practical application of deep learning in security, providing effective defense mechanisms against potential attacks [9]. The application of these methods offers valuable references and support for enhancing the stability of the system in this study [10]. In terms of energy and environment, the feasibility of China's power sector achieving net-zero emissions by 2050 provides both policy and technical support for energy-saving optimization in automated equipment [11]. Similarly, Gu et al. explored the possibilities of a low-carbon transition in Southeast Asia's power system, demonstrating the importance of integrating low-carbon energy with intelligent systems [12]. Their work on planning and designing microgrids for offshore islands has provided new insights into energy-saving optimization, particularly in the context of energy management for tourism islands [13].

Research on multi-view stereo reconstruction technology has provided innovative solutions for monitoring asphalt pavement, significantly improving monitoring accuracy and efficiency [14]. Furthermore, the improved YOLO algorithm has further optimized the performance of pavement detection systems, offering broader technical support for this project's practical applications [15]. Additionally, a real-time drug identification system based on deep learning has shown the potential of this technology in the fields of health monitoring and safety [16]. This study draws from these innovative methods, applying them to the online detection and maintenance of electrical and mechanical equipment to further improve system reliability and efficiency

4 SYSTEM DESIGN AND IMPLEMENTATION

4.1 Overall Overview of the System

In the field of modern industrial automation detection, machine vision-based detection systems offer high efficiency and precision, making them particularly suitable for online monitoring and fault detection of complex electromechanical equipment. This paper provides a detailed description of the components and technical implementation of the electromechanical equipment detection system based on machine vision technology, clarifying its working principles in image acquisition, processing, feature extraction, fault detection, and decision feedback.

Image acquisition is the foundation of the machine vision system. This module uses high-precision cameras and industrial lenses to capture the operational status of electromechanical equipment in real-time. To ensure the quality of image acquisition, the system is also equipped with appropriate lighting to avoid image noise issues caused by insufficient or excessive illumination. High-quality image data provides a solid foundation for subsequent image processing and fault detection.

After image acquisition, the system enters the image processing phase. This stage includes denoising, enhancement, and segmentation operations, primarily using complex image processing algorithms to improve the clarity and usability of the images. Common techniques such as edge detection and segmentation provide critical support for subsequent feature extraction and fault identification. Through effective image preprocessing, the system can better extract image features that are important indicators of equipment status.

The feature extraction module is one of the core components of the detection system, primarily utilizing deep learning algorithms to extract important information from the images. Convolutional Neural Networks (CNNs), a classic algorithm in deep learning, are widely used for extracting image features such as edges, textures, and shapes. Additionally, Support Vector Machines (SVM) and neural networks are employed to further classify the extracted features, identifying the normal state of the equipment and potential faults.

The fault detection module analyzes the operational status of the equipment in real-time based on information obtained from the feature extraction stage, utilizing a neural network model. To handle complex time-series data, this module incorporates Long Short-Term Memory networks (LSTM) for analyzing continuous sensor data (such as temperature and vibration). By using LSTM, the system can detect subtle changes in equipment status, promptly identifying potential faults or abnormal conditions.

In the decision feedback module, the system compares the analysis results output by the fault detection module with preset standards for the equipment. Once an anomaly is detected, the system automatically triggers an alarm mechanism and generates a detailed fault analysis report. These reports provide precise reference information for maintenance personnel, helping them respond quickly to conduct repairs.

The hardware design of the system includes image acquisition devices (cameras, lenses, lighting), image processing units (such as image processors and computers), and actuators (such as robotic arms and conveyors). The software component consists of image processing software and control algorithms, with Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM) being key algorithm modules that facilitate the automation of the entire process of image processing, feature extraction, and fault diagnosis.

This machine vision-based detection system, through its modular architecture, integrates various advanced image processing and artificial intelligence technologies. By closely collaborating in image acquisition, processing, and intelligent analysis, the system can efficiently and accurately monitor electromechanical equipment in real-time, significantly improving maintenance and fault diagnosis efficiency while reducing the costs and risks associated with manual intervention.

4.2 System Architecture Design

The system architecture design includes the main components, the functions of each module, their interrelationships, and how a specific algorithm is used to achieve real-time monitoring. The image acquisition module uses a high-precision camera to collect real-time data on the operating status of electromechanical equipment, providing a basis for subsequent processing. A core algorithm introduced for real-time monitoring is the convolutional neural network (CNN), which is an important algorithm in the field of deep learning and has been widely applied in image processing. Its basic principle can be represented by the following formula:

$$F(X) = \max(0, X * \mathrm{W} + \mathrm{b})$$

Where:

F(X) — the feature curve after convolution processing;

X — the input image data;

convolution operation;

W and b are the weights and bias of the convolution kernel, respectively. The convolution operation uses weighted sums and biases to extract features from the input image. On this basis, the ReLU function max(0, X) is introduced to enhance non-linearity and help the network learn complex patterns.

The most important step in a convolutional neural network is pooling, and its calculation formula is as follows:

$$P(X) = \frac{\max}{\text{subregion}}(X)$$

Where:

P(X) — the output after the pooling operation. Pooling is usually performed using the max pooling method, which selects the maximum value from each subregion of the input image as the representative for that region. This operation helps reduce the dimensionality of the feature map while retaining important feature information.

The fully connected layer is used to transform the feature map into the final output, and the formula is as follows:

$$O(X) = w_f . F(x) + b_f$$

Where:

O(X) — the final output;

Wf is the weights of the fully connected layer, and bf is the bias term;

F(X) — the feature curve processed by the convolutional and pooling layers. Based on the convolutional

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neural network, the system achieves discrimination of different states by utilizing the image features of electromechanical equipment under normal and fault conditions. The system processes the collected image data in real-time and uses the CNN model to analyze the image features, thereby determining the current working status of the equipment.

In the decision feedback module, corresponding judgments and actions are made based on the results obtained from the image processing module. Once potential faults or abnormal conditions are detected, the system immediately alerts and provides a detailed data analysis report to maintenance personnel for further inspection and repair.

4.3 System Functional Modules

During the design phase of the system's functional modules, the role of the convolutional neural network algorithm in measurement was elaborated in detail. The main functional modules of the system include: image acquisition, image processing, feature analysis, and decision-making. The image acquisition module uses a high-precision camera to capture images of electromechanical equipment in real-time. The image processing module employs advanced image processing techniques (such as edge extraction and segmentation) to provide a basis for feature analysis.

The decision-making module uses the GBDT algorithm to analyze and judge the operational status of the equipment. GBDT is an ensemble learning method that integrates multiple decision trees, and its basic idea can be described as follows:

$$F_m(x) = F_{m-1}(x) + y_m h_m(x)$$

Where:

Fm(x) — the model in the m-th iteration;

hm(x) — the decision tree trained in the m-th round;

γm — the learning rate corresponding to this tree.

Each decision tree is trained based on reducing the residuals of the previous model, and the formula for calculating the residuals is:

$$r_m = \left[\frac{\partial Ly\text{i}，\text{F（xi）}}{\partial \text{F（xi）}} \right]_{\text{F（x)=Fm-1(x)}}$$

Here, L(yi, F(xi)) is the loss function that measures the gap between the predicted value F(xi) of the model for the training data xi and the true value yi. Based on this, the project proposes an electromechanical equipment condition learning method based on image features.

Centered on machine vision, this project leverages the efficient image processing capabilities of computer vision technology, combined with advanced data analysis methods such as GBDT, to improve the accuracy and reliability of fault detection. The research outcomes of this project will greatly enhance the level of automated monitoring and predictive maintenance of electromechanical equipment, which holds significant importance for the field of industrial automation.

4.4 Implementation of Key Algorithms

This section will focus on a key algorithm in deep learning — the Long Short-Term Memory (LSTM) network — and explain its application in real-time monitoring using a series of formulas.

LSTM is a special type of Recurrent Neural Network (RNN), which outperforms traditional RNNs, especially when handling sequence data with long-term dependencies. In electromechanical equipment automatic detection systems, LSTM can effectively process and analyze time series data continuously collected by sensors, identifying subtle changes in equipment status.

The core of LSTM is its cell state and gating mechanisms, which include the forget gate, input gate, and output gate. These gates control the flow of information within the cell state, allowing the network to learn when to forget old information and when to update with new information. The basic formulas of LSTM are as follows:

Forget Gate:

$$f_t \partial(w_f . [h_{t-1}, x_i] + b_f$$

Input Gate:

$$i_t = \partial(w_i . [h_{t-1} x_t] + b_i$$
$$c_t = \tanh(W_c . [h_{t-1}, x_i] + bc$$

Update Cell State:

$$C_i = f_t^* C_{t-1} = i_t * C_i$$

Output Gate and Output Value:

$$o_r = \alpha(W_o . [\mathrm{h}_{\mathrm{t-1}}，\mathrm{x}_{\mathrm{t}}] + \mathrm{b}_{\mathrm{o}})$$
$$\mathrm{h}_{\mathrm{t}} = \mathrm{o}_{\mathrm{t}} * \tanh（\mathrm{C}_{\mathrm{t}}）$$

In the above formulas, σ is the sigmoid function used to map values between 0 and 1, determining the amount of information to retain; tanh is the hyperbolic tangent activation function that normalizes values between -1 and 1. W and b represent the weight matrix and bias term, respectively, while f, it, and ot denote the activation vectors of the forget gate, input gate, and output gate. Ct and ht represent the current time step's cell state and hidden state.

In practical applications, the LSTM network first acquires data from multiple sensors, such as temperature and vibration, from electromechanical equipment. By processing the collected data with the LSTM network, potential fault patterns and development trends of the equipment can be effectively identified. The trained LSTM model allows the system to learn and recognize subtle differences between normal and abnormal operating states, enabling real-time

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monitoring of the equipment's status.

4.5 System Optimization and Prospects

Finally, this paper discusses the future application prospects of this algorithm in technology. This project intends to use Convolutional Neural Networks (CNNs) as the core algorithm and conducts an in-depth analysis of their application to system optimization problems, supplemented by corresponding formulas.

Improving the computational efficiency and accuracy of CNNs is a key direction in system optimization research, as the quality of image processing and feature extraction techniques directly affects system performance. To address this issue, this project plans to focus on two aspects: optimizing network structure and optimizing training algorithms, utilizing batch normalization methods to accelerate the convergence speed of CNNs and enhance their generalization ability. The corresponding formula is as follows:

$$BN\ (x_i) = \gamma\left(\frac{x_i - \mu B}{\sqrt{\partial_B^2}}\right) + \beta$$

Where:

x_i — batch input data;

$\mu_{(\beta)}$ — mean of the batch;

$\sigma_{(\beta)}$ — variance of the batch;

ε — a small constant to avoid division by zero;

γ and β are easily learnable parameters.

This project aims to combine emerging technologies such as edge computing and cloud computing to optimize data processing workflows, reduce latency, and enhance real-time reliability. Additionally, this project will further explore the application of quantum machine learning algorithms in fields such as image processing and data analysis to further improve computational efficiency and processing speed.

Looking ahead, ethical considerations in artificial intelligence and data security must also be addressed. With the continuous advancement of algorithms and technologies, ensuring data security and privacy protection has become an essential part of system design. Therefore, in future system optimization processes, it is important not only to enhance technical performance but also to focus on addressing security issues.

5 SYSTEM TESTING

5.1 Test Plan and Methods

The design of the test plan should be centered around the actual application scenarios of the system, including different types of electromechanical equipment, various operating conditions, and potential abnormal situations. The primary testing methods are static tests and dynamic tests. Static testing focuses on the system's response speed and processing capability, including preprocessing, feature extraction, and pattern recognition. Dynamic testing mainly examines the system's performance during continuous operation, such as the accuracy of fault detection, the system's ability to respond to emergencies, and its long-term stability.

5.2 Stability and Reliability Testing

During the testing process, a series of test environments simulating real working conditions must be established. By artificially setting different fault modes, the system is tested to see if it can accurately and promptly detect and respond. At the same time, long-duration continuous operation tests are conducted to evaluate the system’s performance and stability, focusing on failure detection rate, false alarm rate, and system crash frequency. Throughout the testing process, meticulous statistical analysis of the collected data is essential for a comprehensive evaluation of the system’s overall performance. The test results are not limited to numerical analysis but also include adaptability analysis of different types of electromechanical equipment, performance comparisons, and an examination of the system's flexibility and accuracy in processing diversified data.

Table 1: System Test Data

Experiment Number	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Response Time (s)
1	96.57	95.34	94.89	95.11	1.35
2	97.42	96.28	96.61	96.44	1.28
3	97.85	97.11	97.30	97.20	1.25

6 CONCLUSION

This project, set against the backdrop of automated detection and based on computer vision theory, focuses on key technical issues such as image acquisition, preprocessing, feature extraction, and pattern recognition. The primary focus is on researching image analysis methods based on deep learning to improve the accuracy and efficiency of fault diagnosis. Through in-depth research and application validation of these key technical aspects, a complete system for online monitoring and maintenance of electromechanical equipment has been developed, enhancing the efficiency of equipment monitoring and maintenance, reducing downtime and repair costs caused by equipment failures, and improving production safety and reliability. The research outcomes of this project will promote the application of machine vision in industrial automation and provide technical support for improving production efficiency and reducing operational costs.

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The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Not applicable.

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