Journal of Electronic Research and Application, 2026, Volume 10, Issue 4
http://ojs.bbwpublisher.com/index.php/JERA
Online ISSN: 2208-3510
Print ISSN: 2208-3502

Design and Optimization of Visual Algorithms for Inspection Robots

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Abstract: As an important equipment for intelligent operation and maintenance, inspection robots have been widely used in high-risk and complex scenarios such as power, mining, and chemical industries. The visual system, as the "eyes" of inspection robots, undertakes tasks including image enhancement, navigation and positioning, target recognition, and error correction, and its performance directly affects the robots' autonomous operation capabilities. Currently, the visual algorithms of inspection robots still face several problems, such as poor adaptability to complex environments, insufficient navigation accuracy, difficulty in balancing target recognition accuracy and real-time performance, and weak adaptability of error correction. Combined with the current application status of inspection robots, this paper elaborates on the design ideas of the four major modules of visual algorithms and proposes optimization strategies for existing problems, providing references for improving the autonomous inspection capabilities of inspection robots and promoting the upgrading of intelligent inspection technology.

Keywords: Inspection robot; Visual algorithm; Design; Optimization

Online publication: May 21, 2026

1. Introduction

With the upgrading of industrial intelligence, traditional manual inspection can no longer meet the needs of scenarios such as power substations, thermal power plants, and mines, due to its high labor intensity, low efficiency, high risk, and susceptibility to missed and false inspections. Relying on advantages such as autonomous movement and intelligent perception, inspection robots have gradually replaced manual labor as intelligent operation and maintenance equipment, and are widely used in industries such as power and mining.

The visual system is the core for inspection robots to achieve autonomous navigation, target detection, and environmental perception. As the "brain", visual algorithms run through the entire inspection process, mainly including four modules: image enhancement, navigation and positioning, target recognition, and error correction, which are responsible for image quality improvement, path planning and positioning, accurate target recognition, and error correction respectively.

Existing studies have proposed various methods such as UM-HE image enhancement, lidar-vision fusion navigation, and YOLO-V5 target recognition. However, current algorithms still have some shortcomings, mainly manifested as poor image enhancement effects in complex environments, low navigation accuracy in unknown environments, imbalance between real-time performance and accuracy of target recognition, and weak adaptability of error correction [1–3]. Therefore, exploring the design and optimization paths of algorithms is of great significance for promoting the performance improvement of visual algorithms and facilitating the development and application of intelligent inspection technology.

2. Design of visual algorithms for inspection robots

The design of visual algorithms for inspection robots needs to be based on scenario requirements and carried out around four modules to ensure practicality, real-time performance, and reliability, providing support for autonomous operation. The structure of the experimental platform of the inspection robot to be adopted in this paper is shown in **Figure 1**.

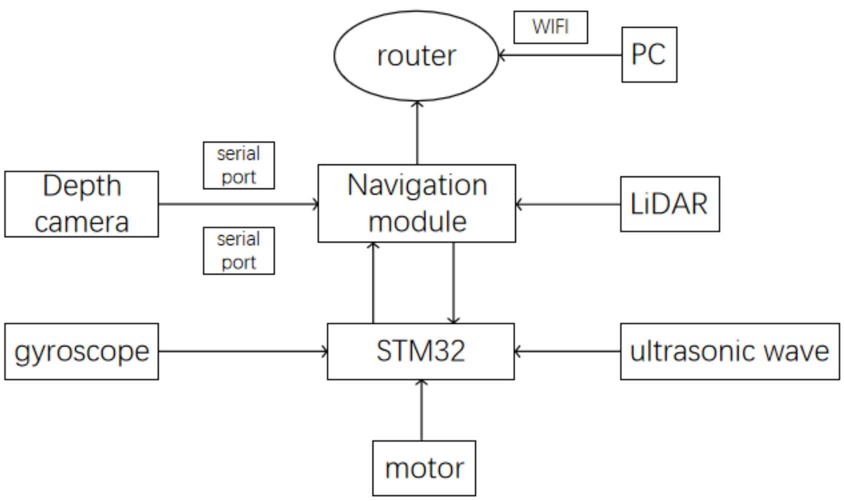

Figure 1. Experimental module composition of inspection robot.

2.1. Design of image enhancement algorithm

Inspection robots mostly work in complex environments such as uneven lighting, heavy dust, and foggy weather. The collected images are prone to problems such as blurriness, noise, and low contrast. The image enhancement algorithm aims to improve image quality and provide effective data for subsequent processing. The design are as follows:

(1) Basic image preprocessing design: Denoise, normalize the size, and grayscale the original image. For Gaussian noise and salt-and-pepper noise in inspection scenarios, a combination of median filtering and Gaussian filtering is adopted to denoise while retaining details; unify the resolution through size normalization to avoid the impact of size differences on processing efficiency; convert color images to grayscale images to reduce data volume and improve real-time performance [1,4];

(2) Adaptive contrast enhancement design: Aiming at the problems of low image contrast and blurred details under complex lighting, based on the adaptive histogram equalization (HE) algorithm, optimize

parameters combined with inspection scenarios, and use the UM-HE algorithm to process images in blocks, calculate the equalization parameters of each block, avoid over-enhancement and detail loss caused by the traditional HE algorithm, and apply it to complex lighting scenarios such as relay rooms of thermal power plants;

(3) Foggy image enhancement design: Aiming at the problem of blurred foggy images in outdoor inspection, the dark channel prior algorithm is used for defogging, restoring clear images by estimating atmospheric light and transmittance, and adjusting saturation to avoid color distortion, ensuring the clarity of foggy images and providing reliable support for subsequent processing [4].

2.2. Design of target recognition algorithm

Target recognition is an important function to complete inspection tasks, requiring accurate recognition of equipment, defects, and obstacles. The idea of combining deep learning with traditional image processing is adopted.

For the design of inspection target feature extraction, corresponding features for different types of targets are extracted. For structured targets, a combination of HOG and SIFT features is used to extract shape and texture features to ensure uniqueness; for unstructured defect targets, combine image segmentation and semantic segmentation technologies to segment defect areas and extract feature parameters to provide support for recognition [5].

For the design of deep learning target recognition model, a model was constructed using the YOLO-V5 algorithm, the network structure was optimized to reduce parameters and improve real-time performance; expand the training dataset to cover target images under different scenarios, angles, and lighting conditions, improve the generalization ability of the model, and ensure accurate recognition of equipment, defects, and obstacles [6]. Leveraging the YOLO-V5 algorithm's advantages in both detection accuracy and speed, we propose adopting the lightweight YOLOv5s object recognition model tailored for embedded hardware applications in inspection robots. This enables the robots to rapidly deliver high-precision detection results in complex environments, providing intelligent support for equipment operation and maintenance. The network architecture of YOLOv5s consists of four components, as illustrated in **Figure 2**.

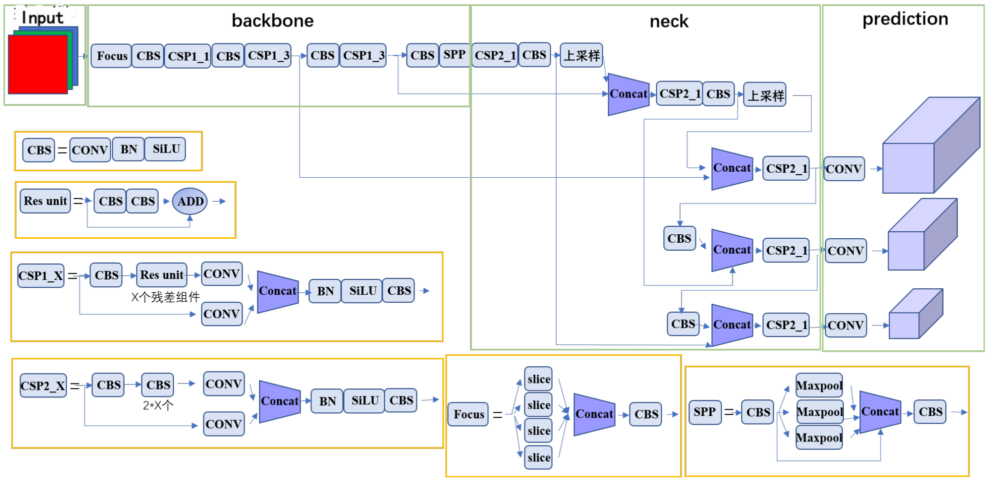

Figure 2. YOLOv5s network structure diagram.

For the design of post-processing for target recognition, deduplicate, filter, and verify the recognition results to remove falsely recognized and repeatedly recognized targets; compare the current and background images using the background subtraction method to confirm the authenticity of targets and reduce the false detection rate; locate and label targets, record information such as position, type, and size, and provide support for inspection reports [7].

2.3. Design of error correction algorithm

The visual system is prone to visual errors due to lens distortion, sensor errors, etc. The goal of the error correction algorithm is to correct errors and improve measurement accuracy and reliability [8].

For the design of lens distortion error correction, Zhang Zhengyou's calibration method was used to obtain distortion parameters, correct images through the inverse mapping algorithm, restore the real geometric shape, and avoid positioning and navigation deviations for radial and tangential lens distortion [9].

For the design of visual measurement error correction, a correction method was adopted based on the Elman neural network, construct a model and train it with measurement data and real data under different scenarios, and combine least squares fitting optimization to improve correction accuracy, which is suitable for power inspection robots [10].

3. Optimization strategies for visual algorithms of inspection robots

Aiming at the shortcomings of current algorithms, optimization strategies are proposed for each module to improve algorithm performance and adapt to complex scenario requirements.

3.1. Optimization of image enhancement algorithm

The optimization strategies are as follows:

(1) Improved optimization based on UM-HE: Aiming at the poor enhancement effect in high-noise scenarios, add noise detection and suppression links before block equalization, perform targeted denoising on high-noise blocks before equalization, and adapt to multi-noise scenarios;

(2) Multi-scenario adaptive optimization: Construct a multi-scenario enhancement model, automatically identify scenarios through image features and select corresponding algorithm parameters, and train an adaptive model combined with GAN to solve the problem of poor adaptability of a single algorithm;

(3) Real-time optimization: Simplify the calculation process, use GPU acceleration for parallel computing of key links, optimize parameter settings to avoid excessive computation, and improve real-time performance while ensuring effects.

3.2. Optimization of target recognition algorithm

The optimization approaches were performed as follows:

(1) Lightweight optimization of deep learning models: Adopt pruning and quantization technologies to remove redundant parameters, and reconstruct the model combined with MobileNet to improve computing speed while ensuring accuracy;

(2) Optimization of target recognition accuracy: Expand the training dataset and adopt data augmentation technology, introduce the Focal Loss function to solve the problem of imbalance between positive and negative samples, and reduce the missed detection rate of small targets;

(3) Multi-target collaborative recognition optimization: Adopt the improved NMS algorithm to reduce overlap and false detection in multi-target recognition, and integrate semantic segmentation and target detection technologies to achieve collaborative recognition of equipment, defects, and obstacles [11].

3.3. Optimization of error correction algorithm

The optimization actions were used as outlined:

(1) Optimization of lens distortion error correction: Design a dynamic calibration mechanism to update distortion parameters regularly, and train an automatic correction model combined with deep learning to improve correction efficiency and accuracy;

(2) Adaptive optimization of visual error correction: Optimize the Elman neural network model, add an environmental feature input layer, and integrate the complementary advantages of multiple correction methods to improve adaptability and accuracy;

(3) Optimization of cumulative error: Optimize the frequency and accuracy of loop closure detection, construct a 3D map combined with SLAM technology, and correct positioning errors through map matching to ensure long-term inspection accuracy.

4. Experimental verification and analysis

An indoor multi-obstacle scenario was selected to build an experimental platform, and the performance of the optimized algorithm in this paper was compared with that of traditional algorithms to verify its effectiveness. A visible light camera and lidar sensor were mounted on the experimental robot equipment. The experimental platform is shown in **Figures 3** and **4**.

Figure 3. Experimental platform based on LEO car.

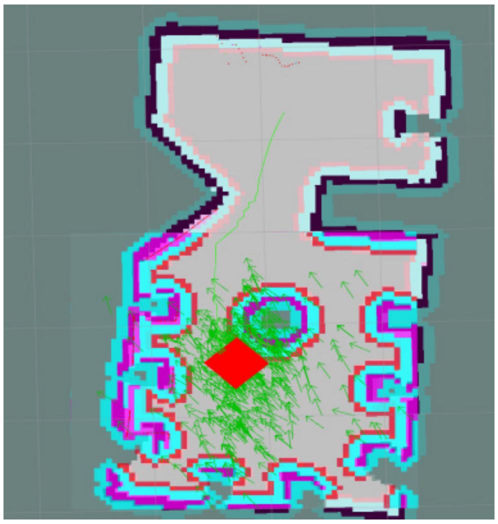

Figure 4. Lidar mapping.

By comparing the test data of the experimental scenario, the results show that the image contrast of the optimized algorithm is increased by 35%, the noise suppression rate is increased by more than 28%, significantly improving image quality; the navigation accuracy is increased by more than 40%, the path extraction accuracy reaches more than 98%, and the obstacle avoidance response time is ≤ 0.3s; the target recognition accuracy reaches more than 95%, the false detection rate is ≤ 3%, and the computing speed is increased by more than 50%. The experimental results prove that the optimized visual algorithm makes up for the shortcomings of traditional algorithms, has the ability of real-time recognition and high-precision recognition, and meets the intelligent inspection needs of multiple complex scenarios.

5. Conclusion

In summary, visual algorithms are the key support for the autonomous operation of inspection robots, and their performance directly affects inspection efficiency and accuracy. This study focuses on four aspects: image recognition, navigation and positioning, target recognition, and error correction, designs and proposes algorithm optimization schemes. Experimental verification shows that the optimized algorithm significantly improves the image display effect, navigation and positioning accuracy, target recognition performance, and error correction ability of inspection robots, and can be applied to complex and diverse inspection scenarios. In future applications, combined with the operation and maintenance needs of specific scenarios, technologies such as scenario understanding based on image matching, equipment fault detection, and equipment pattern recognition can be continuously improved to enhance the visual recognition efficiency of inspection robots and guarantee for the safe and stable operation of equipment.

Funding

School-Level Scientific Research Fund Project of Chongqing University of Technology in the Second Half of 2024 (Project No.: 2024XZKY006); School-Level Scientific Research Fund Project of Chongqing University of Technology in 2025 (Project No.: 2025XZKY007)

Disclosure statement

The authors declare no conflict of interest.

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