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Research on Intelligent Traffic Inspection Applications Based on Unmanned Aerial Vehicle Imaging

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Abstract: *This paper explores the applications of intelligent traffic inspection based on unmanned aerial vehicle (UAV) imaging. Addressing the issues of low efficiency, high safety risks, and limited coverage in traditional traffic inspection methods, it proposes an automated inspection solution that integrates UAV technology with image recognition technology. The study employs a DJI M300 RTK UAV equipped with visual sensors for data collection, utilizing the YOLO 11 algorithm to achieve efficient and precise recognition of vehicles and traffic anomalies. Imaging optimization of the visual sensors has been carried out to ensure image quality under varying weather and lighting conditions. Compared to its predecessors, the YOLO 11 algorithm demonstrates significant improvements in inference speed, recognition accuracy, occlusion tolerance, and model lightweightness, making it particularly suitable for small object recognition tasks in traffic inspection. Through the design of a standardized UAV traffic inspection process, full-chain automated processing is realized, covering video collection, quality verification, object detection and tracking, to result output and data archiving. Experimental results indicate that the proposed solution can effectively identify and track different types of vehicles in port traffic management scenarios, validating its accuracy and reliability in practical applications and providing a new solution for intelligent traffic inspection.*

Keywords: *Unmanned aerial vehicle; Traffic inspection; Image recognition technology; Route planning; Low altitude*

1. Introduction

Traditional traffic inspection primarily relies on manual efforts and traffic control as its main management modes. In manual inspection, traffic police or road administration personnel drive patrol vehicles to conduct on-site inspections, identifying traffic congestion, violating vehicles, and accident scenes through visual observation. This approach is not only inefficient but also exposes personnel to safety risks posed by road conditions. Regarding traffic control, cameras are mainly installed at fixed locations to capture traffic violations, resulting in limited coverage and slow response times to remote road sections and unexpected incidents [1]. Therefore, it is urgent to explore a new type of intelligent traffic inspection method.

UAV imaging efficiently integrates UAV technology with image recognition technology, leveraging the superior aerial perspective to enable real-time, efficient, and accurate automated inspection methods that capture road surface information, including congested road sections, vehicle violations, and traffic accident scenes [2]. Currently, UAVs can process raw data with a single click through simple software. By importing deeply customized algorithm modules, they can automatically plan inspection routes without requiring operators to possess specialized knowledge [3]. Image recognition technology boasts a variety of mature AI model databases that facilitate seamless image recognition and processing, enabling effective tracking and identification of vehicles [4]. The integration of these two technologies has been widely applied in high-voltage power line inspection [5], bridge damage detection [6], and natural gas pipeline inspection [7]. However, there remains a significant deficiency in the ability to identify dynamic small targets such as vehicles and personnel, with relatively poor precision and accuracy [8], which restricts the application and promotion of UAV imaging in traffic inspection scenarios.

To enhance the application capabilities of UAV imaging in traffic inspection scenarios, this paper employs UAVs equipped with visual sensors for data and image collection. By utilizing the YOLOv11 training model for training, a closed-loop inspection system is achieved that enables "efficient collection-

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precise recognition-real time response". This approach improves the automation level of UAV-based vehicle inspection and facilitates the digital delivery of vehicle inspection results conducted by UAVs.

2. Hardware Configuration

2.1. Configuration and Performance Parameters of Unmanned Aerial Vehicles

The flight platform utilizes the DJI M300 RTK UAV (Figure 1), which has a maximum takeoff weight of 15.8 kg, a maximum payload capacity of 6 kg, and a maximum flight time of approximately 60 minutes. The UAV supports the mounting of multiple sensors, making it well-suited for long-distance highway inspections. These sensors include an omnidirectional binocular vision system (with panoramic color fisheye views), a horizontally rotating LiDAR, a LiDAR, a downward three-dimensional infrared ranging sensor, and a six-directional millimeter-wave radar. This perception system features high ranging accuracy and a wide detection range. Its forward-looking ranging range is 0.4m to 21m, and the overall detection range can reach 0.4m to 200m. Both the horizontal and vertical detection field of view are 90°. It can identify small targets such as vehicles on the road and road defects at close range, and also obtain environmental and dynamic object information in the inspection area at long range. It can meet the requirements of short-range identification and long-range monitoring in traffic inspection. It can provide multi-source perception data for unmanned aerial vehicle (UAV) autonomous obstacle avoidance and inspection target recognition, enhancing the environmental adaptability and target detection efficiency of UAVs in complex traffic inspection scenarios.

Figure 1. DJI M300 RTK UAV

2.2. Multi-scenario Configuration and Imaging Optimization of Visual Sensors

Environmental factors play a significant role in determining the accuracy of visual inspection. Under different weather conditions, the parameters and functions of the visual sensor vary accordingly. For clear weather, the primary requirement is to capture high-definition details and avoid overexposure. The sensor configuration can include a 1080P/60fps high-definition CCD camera with an aperture of F2.0-F4.0, supporting automatic exposure adjustment, and paired with a 10x optical zoom, enabling clear distant shooting of small targets such as road cracks and debris. For weather conditions such as rainy or foggy days where there is insufficient light and poor visibility, the core requirement is to enhance the transparency of the image and reduce noise. The sensor configuration needs to be a CCD camera with image enhancement algorithms (supporting HDR mode), and an 8-14μm infrared camera can be optionally equipped. The lens is equipped with a fog-proof coating, and the working temperature range is -10 to 50℃ (able to withstand humid environments). For night or situations without natural light and complex lighting conditions, the core requirement is to overcome the limitation of low light and avoid light interference. The sensor configuration is an infrared thermal imaging camera (with a detection distance of ≥ 100 meters) combined with a visible light illuminator (with adjustable brightness to avoid glare). In strong wind conditions, attention is paid to issues such as image jitter and lens contamination. The core requirement is to stabilize the image, protect the lens, and the sensor configuration is a dustproof and waterproof CCD camera (with protection level IP65+) equipped with a three-axis stabilized gimbal (accuracy ±0.02°). The Zenith P1 camera supports fast autofocus and mitigates the effects of vibration during flight. In summary, the visual sensor of this study uses the Zenith P1 camera (1080P/60fps), along with an optional infrared camera and visible light camera, to handle daily anomaly identification. The infrared camera is suitable for special scenarios such as night and rainy foggy days. The onboard computing unit needs to support GPU acceleration (such as NVIDIA Jetson Orin NX) to meet the real-time inference requirements of the YOLO 11 model at 60+ FPS, and the lightweight design can reduce

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the power consumption of the equipment. The communication system adopts a 4G/5G + video transmission scheme, which needs to achieve a transmission distance of at least 5 kilometers and a delay of less than 200ms to ensure the stable and real-time transmission of high-definition images and recognition results in areas without signal obstruction. In addition, the positioning system adopts GPS + Beidou dual-mode, with a positioning accuracy of ≤ 1 meter. It can precisely mark the positions of abnormal targets, and at the same time supports automatic flight path planning and fixed-point hovering functions. The pan-tilt component is equipped with a three-axis stabilized pan-tilt, with an elevation angle of ±90° and an accuracy of ±0.02°. It can effectively counteract flight vibrations and ensure clear imaging, suitable for multi-angle inspection scenarios such as road surfaces and bridge bottoms.

3. Image Recognition

3.1. YOLO 11 Algorithm

This paper adopts the YOLO 11 (You Only Look Once version 11) model developed by Ultralytics for the recognition of small target images. Test results from traffic inspection tasks show that the overall performance of YOLO 11 is superior to the widely used YOLO 8 model. When the onboard camera captures 1080P resolution images, the inference speed of YOLO 11 can reach over 60 FPS, which is about 20% faster than the 45-50 FPS of YOLO 8, meeting the computing power requirements for real-time inspections. For small targets such as fine cracks on the road surface and small scattered objects, the recognition accuracy of YOLO 11 exceeds 85%, a 10-percentage-point increase from the approximately 75% of YOLO 8, effectively reducing the rate of missed detections. In occlusion scenario tests, YOLO 11 can tolerate up to 30% target occlusion, while the recognition performance of YOLO 8 significantly drops when the occlusion rate exceeds 20%. Therefore, YOLO 11 is more suitable for inspection needs in complex scenarios such as traffic congestion and cluttered environments..

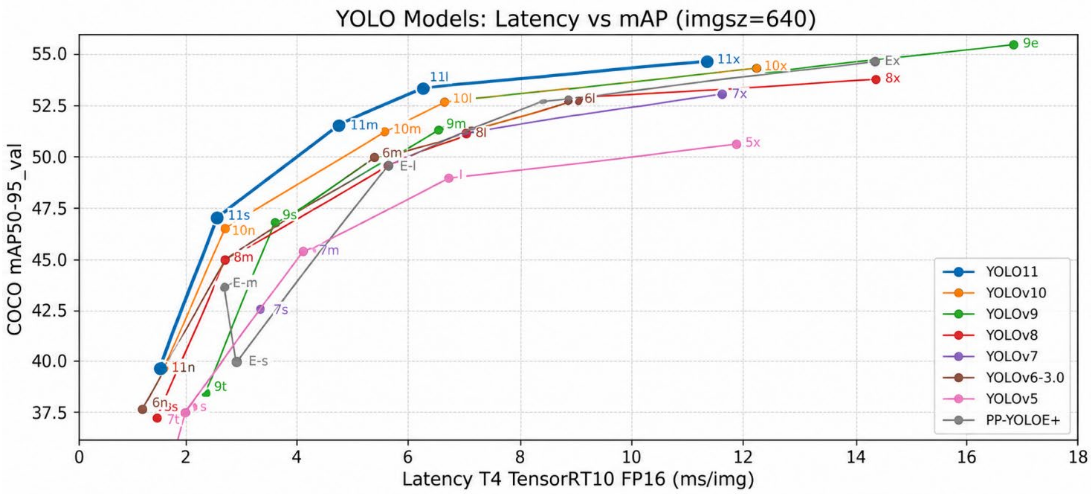

Figure 2. Performance data of YOLO series models

The model is lightweighted in dimensions. After compression, the storage size of YOLO 11 is 80 MB, which is nearly 30% less than that of YOLO 8 (110 MB). This significantly reduces the storage requirements and operational power consumption of the onboard inspection equipment. In terms of transfer learning efficiency, the data demand for YOLO 11 when adapting to new scenarios is reduced by approximately 40%. Without the need for large-scale re-training, it can cover various operation scenarios such as urban roads and tunnels, effectively reducing the model's iteration cost. In terms of functionality, YOLO 11 has an added ability to quantitatively output abnormal targets, which can automatically calculate parameters such as the length of road cracks and the area of debris. YOLO 8 only supports target classification and cannot directly provide the numerical indicators required for inspection evaluation. In environmental adaptability tests, the detection accuracy of YOLO 11 under conditions such as sudden changes in lighting and rain and fog interference fluctuates within 5%, which is lower than the 12% fluctuation range of YOLO 8. The detection stability in adverse weather conditions is also better. Combined with the performance test data of the YOLO series models (Figure 2), YOLO 11 has better average accuracy while maintaining low inference latency. Its comprehensive performance is superior to the existing mainstream YOLO models and can be selected as the preferred option for target detection algorithms in traffic inspection scenarios.

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3.2. Vehicle Model Recognition Based on YOLO 11 Model Training

During the dataset preprocessing stage, first, vehicle samples that match the perspective of unmanned aerial vehicle traffic inspection are selected from the BIT-Vehicle Dataset. The samples cover different vehicle models, lighting conditions, and occlusion scenarios. Subsequently, data augmentation processing such as random cropping, brightness adjustment, adding rain and fog effects, and reverse light effects is performed on the samples to simulate the actual complex working conditions of traffic inspection and enhance the model's robustness.

A total of 50 vehicle sample images that have been enhanced were used in this experiment. They were divided into training set, validation set and test set in a ratio of 7:2:1. The division process ensured that the sample distribution of the three data sets was consistent. The annotation work was completed using the LabelImg software. During annotation, a fixed category order was set, with the first target category numbered 0, the second category numbered 1, and so on in sequence. Subsequently, the YOLO 11 model training was carried out in the Visual Studio Code environment, and the recognition and validation results are shown in Figure 3.

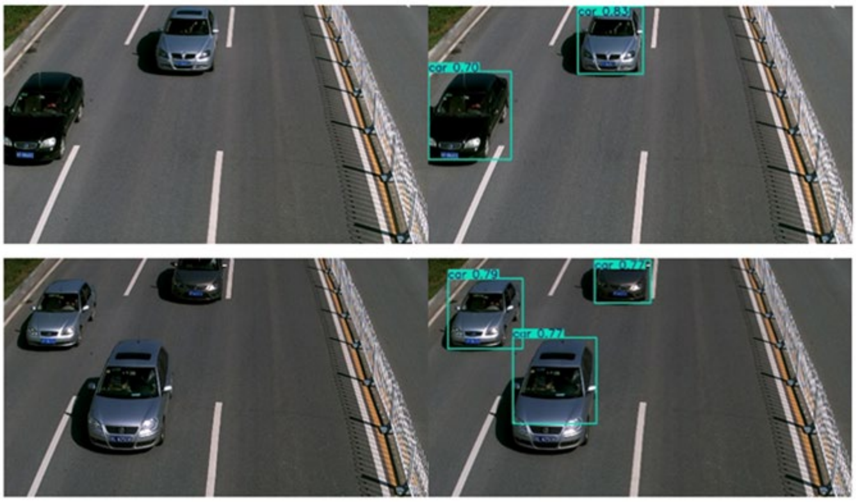

Figure 3. Vehicle recognition

4. Design of a Standardized UAV Traffic Inspection Process

To secure accurate recognition and uninterrupted monitoring of vehicular targets during traffic inspection operations, a vehicle detection-and-tracking sub-process was designed within the broader task-planning framework. Using real-time video streams acquired by UAVs as its input, this sub-process produces traceable inspection data through sequential frame-quality verification, target detection, and persistent target tracking, as shown in Figure 4. At the initial stage, video acquisition and quality verification are performed. Once airborne, the UAV employs its onboard vision sensors to capture real-time roadway video, after which frame clarity is automatically checked by the system. Should blurring, noise, or related degradation arise from flight-induced vibration, illumination shifts, or comparable disturbances, the UAV flight state is automatically adjusted (for example, altitude or gimbal orientation) until the frames satisfy detection requirements. Where frame quality is adequate, the workflow moves directly to vehicle detection.

At the detection stage, vehicle identification and subsequent tracking are executed in sequence—though, operationally, the handoff is effectively immediate. Within clear video frames, the YOLO 11 model performs real-time detection of vehicle targets, extracting vehicle category, spatial position, and movement direction. Once a vehicle has been detected, a tracking algorithm is automatically triggered so that the target vehicle remains continuously locked and followed, with positional information and motion state updated in real time to reduce the risk of target loss. On completion of detection and tracking, the system produces and outputs integrated results covering vehicle type, total count, exact location, and movement trajectory. At the same time, the captublue video, detection outputs, and tracking paths are archived in the traffic inspection database, thereby forming detailed, traceable digital inspection records. In practical terms, this process addresses the previously pronounced limitations associated with the recognition of dynamic small targets, including vehicles and personnel.

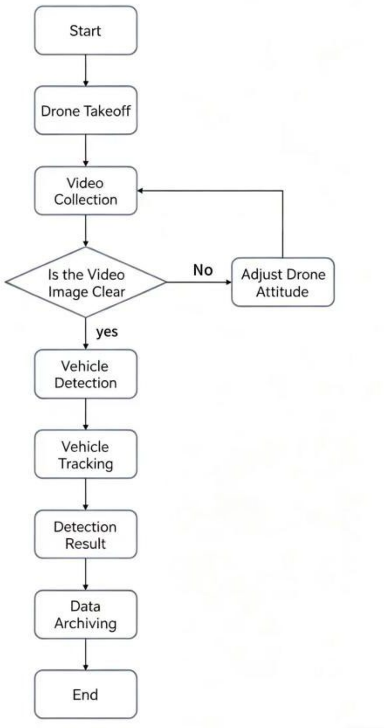

Figure 4. Flowchart of UAV traffic inspection process

5. Inspection Testing Experiment

Figure 5. Validation of Vehicle Recognition Results

To validate the overall performance and the accuracy of UAV-based traffic inspections, this study conducted verification through a traffic management scenario within a port area, enhancing environmental complexity by performing vehicle detection and tracking under conditions where containers and trucks exhibited low distinguishability. The flight process remained stable, with precise GPS positioning. As shown in Figure 5, the system accurately identified truck information within the container environment and effectively differentiated between large trucks and small cars.

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6. Conclusion

This research integrates unmanned aerial vehicle (UAV) technology with the YOLO 11 image recognition algorithm to develop a traffic intelligent inspection system. This system leverages the high-altitude perspective and mobility characteristics of UAVs, along with multiple sensor configurations and imaging optimization schemes, to address the limitations of traditional traffic inspection in terms of limited coverage and high risks in dangerous sections, thereby enhancing inspection efficiency and operational safety. The introduction of the YOLO 11 algorithm optimizes the recognition performance of small targets in complex traffic scenarios, balancing inference speed and recognition accuracy, and provides good recognition stability for scenarios where vehicles and signs are obscured. The research has designed a standardized inspection process, enabling the automation of the entire inspection process and digital storage of data, providing traffic management departments with traceable full-scale inspection data support. The research conducted field tests in a mixed traffic scenario at the port, and the results showed that the system could operate stably and effectively identify and track different types of operation vehicles and social vehicles, meeting the inspection requirements of actual scenarios. This research only verified the application effect in the port scenario and did not cover scenarios with severe signal obstructions such as mountain roads and areas with dense super-high-rise buildings in cities. In the future, the communication mechanism of the UAV and the algorithm recognition accuracy can be optimized for such scenarios to expand the application scope of the system and provide technical references for the implementation of the intelligent traffic inspection system.

Acknowledgment

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