Theory and Practice of Science and Technology
2025, VOL. 6, NO. 9, 206-211
DOI: 10.47297/taposatWSP2633-456939.20250609

Research on Obstacle Avoidance for UAV Patrol Based on Vision

Jiamin Zhao

Jiangning Campus, School of International Education, Jinling Institute of Technology, Nanjing, Jiangsu, 211169, China

ABSTRACT

BUnmanned aerial vehicles (UAVs) have shown great potential in patrol, surveillance, and search and rescue applications due to their flexibility and efficiency. This paper proposes a vision-based obstacle avoidance system for UAV patrols. This system integrates a high-resolution RGB camera and a dynamic vision sensor (DVS). It utilizes a lightweight YOLOv5 model for obstacle detection and an optimized dynamic window approach (DWA) for real-time path planning. Through multi-sensor fusion, threat level assessment, and dynamic speed adjustment, the system significantly improves robustness in complex lighting, weather, and occlusion conditions. In ROS and Simulink simulations, as well as field tests on campuses and industrial parks, the system demonstrates impressive performance: obstacle detection accuracy exceeds 95% under variable conditions, path planning latency is less than 100 milliseconds, and obstacle avoidance success rates reach 95% in low-density scenarios and 90% in high-density scenarios. Compared to the deep reinforcement learning algorithm D3QN, the system achieves a 13.3% reduction in path length and a 20% improvement in success rate. Deployed on low-cost Raspberry Pi 4 hardware, the system achieves 20 FPS processing with less than 5W power consumption, providing a practical solution for scenarios such as border patrol, industrial monitoring, and urban surveillance. Innovations include a lightweight convolutional neural network (CNN) architecture, adaptive obstacle avoidance strategies, and a modular software framework, addressing the challenges of accurate recognition, rapid planning, and coordinated optimization of patrol efficiency in complex environments.

KEYWORDS

UAV; Visual obstacle avoidance; Obstacle detection; Path planning; Multi-sensor fusion; Dynamic window method; Lightweight model; Embedded system

1 Introduction

1.1 Research background and significance

As autonomous mobile platforms, drones (UAVs) offer broad application prospects in patrol, surveillance, search and rescue, agriculture, and logistics due to their flexibility, efficiency, and scalability. In patrol missions in particular, UAVs can conduct 24/7 uninterrupted surveillance of urban streets, industrial parks, or border areas, significantly reducing labor costs and improving mission efficiency. However, patrol scenarios often involve complex, dynamic environments, with obstacles such as moving pedestrians, vehicles, trees, and rocks, placing high demands on the UAV's perception and obstacle avoidance capabilities. Traditional obstacle avoidance methods using ultrasonic or laser radar (LiDAR), while highly accurate, are expensive, have limited coverage, and degrade in lighting conditions or inclement weather (such as rain and fog). In contrast, vision-based obstacle avoidance technology utilizes cameras to capture environmental information, then implements image processing and machine learning algorithms for obstacle detection and path planning. These technologies offer the advantages of low cost, rich information, and wide coverage. This technology not only enhances the intelligence of UAVs but also significantly reduces the risk of accidents caused by environmental complexity or operator errors. For example, during border patrols, drones can use visual systems to detect obstacles and potential threats in real time, reducing the risks of manual patrols; in industrial park monitoring, they can achieve round-the-clock automated inspections, improving efficiency and reducing operating costs.

1.2 Current status and gaps in domestic and international research

In recent years, China has made significant progress in the field of vision-based UAV obstacle avoidance technology, especially in multi-sensor fusion and real-time processing. Cai Zhihao et al. proposed a target detection and obstacle avoidance algorithm based on dynamic visual sensors. By fusing event images and RGB images, they ensured the reliability of detection and combined the obstacle motion characteristics with the UAV dynamic constraints to improve the speed obstacle method to effectively deal with dynamic obstacles [1]. Zhao Qiang et al. proposed an intelligent inspection solution combining 3D GIS, Beidou positioning and AI image recognition for railway freight yard and marshalling yard scenarios, and explored the future direction of airspace control [2]. Zhang Junchi et al. based on deep inverse reinforcement learning, combined with long short-term memory network (LSTM) to enhance the relationship modeling ability of path points, and generated expert trajectories through the Informed-RRT* -DWA algorithm. Experiments showed that its path length was 13.3% shorter than D3QN in low-density scenarios, and the success rate was increased by 17%. In high-density scenarios, the path length was shortened by 5.1% and the success rate was increased by 20% [3].

Internationally, research on obstacle avoidance based on vision started early, focusing on the application of monocular vision, stereo vision and deep learning. Mori et al. proposed an obstacle avoidance algorithm based on monocular vision, estimating distance by the expansion velocity of objects [4]. Carrio et al. developed an obstacle avoidance system based on stereo vision, using binocular cameras to generate depth maps and achieve real-time detection of dynamic and static obstacles [5]. Loureiro et al. proposed the DroNet end-to-end deep learning framework, which achieves seamless conversion from image input to obstacle avoidance decision through driving learning [6]. In addition, Zhang et al. studied obstacle avoidance strategies based on multi-agent collaborative control, solving the formation reconstruction and collision problems of drone clusters in complex environments [7]. Although both domestic and foreign research has made visual obstacle avoidance a hot topic, accurate obstacle recognition, fast path planning and coordinated optimization of obstacle avoidance and patrol tasks in complex environments still face challenges. Existing methods are not robust enough in the face of lighting changes, occlusion and dynamic scenes, and the demand for high-performance computing limits the application of low-cost hardware.

1.3 Research objectives and core questions

Based on the above research gaps, this study aims to develop a vision-based obstacle avoidance system for UAV patrols, achieving high-precision obstacle detection, low-latency path planning, and efficient patrol mission coordination. The core issues addressed include:

Accurate recognition in complex environments : Optimize visual algorithms to cope with scenarios such as lighting changes, occlusion, and severe weather.

Fast path planning : Solve the computational complexity and real-time problems in dynamic environments.

Multi-sensor fusion robustness : solves data synchronization and fusion problems and improves system adaptability.

2 Methods

2.1 System framework

To achieve robust navigation of UAVs in dynamic environments, this study designed a system framework that integrates image acquisition, obstacle detection, path planning, and motion control. The core components are as follows:

(1) Image acquisition : A high-resolution RGB camera (1080p, 30 FPS) is used to capture environmental images, combined with a dynamic vision sensor (DVS) to obtain real-time dynamic information. The DVS mimics biological vision, outputting asynchronous pulse signals only when pixel brightness changes. It offers microsecond-level temporal resolution, low power consumption (<1W), and a high dynamic range (>120 dB), making it particularly well-suited for scenes with rapid motion or complex lighting.

(2) Obstacle detection : This model uses the lightweight YOLOv5 model (YOLOv5-n version) for efficient target recognition, improves robustness through timing verification and image enhancement techniques, and is suitable for embedded platforms.

(3) Path planning : Based on the optimized Dynamic Window Algorithm (DWA), the threat level assessment and UAV kinematic constraints are integrated to generate a collision-free and efficient obstacle avoidance path.

(4) Motion control : Reduces body shaking and ensures operational stability through smooth steering and dynamic speed adjustment (deceleration near obstacles and cruise control far from obstacles).

2.2 Technical route

2.2.1 Dataset construction

To train a robust obstacle detection model, we collected a multi-scene dataset containing various types of obstacles, such as rocks, trees, pedestrians, and vehicles, covering the following conditions:

· Weather : sunny, rainy, foggy.

· Lighting : bright light (1000 lux), backlight, night (100 lux).

· Occlusion : Partial occlusion, full occlusion.

The dataset contains 10,000 images, which are cleaned and labeled using the labelling tool, 80% for training and 20% for validation and testing.

2.2.2 Obstacle detection

YOLOv5-n is used as the core detection model and optimized through the following steps:

(1) Hyperparameter optimization : Grid search and Bayesian optimization were used to adjust the learning rate (initially

0.01), batch size (16), and optimizer (Adam).

(2) Data augmentation : Random cropping, rotation, mosaic enhancement, and HSV color gamut transformation are applied to improve the model's generalization ability for complex scenes.

(3) Real-time image enhancement : A submodule is designed to enhance obstacle features through adaptive contrast adjustment and edge sharpening.

(4) Timing verification : Kalman filtering is introduced to track the position and speed of obstacles in consecutive frames, eliminating abnormal detection results and reducing the misjudgment rate.

The loss function of the detection model is:

$$L = Lcls + Lbox + Lobj \tag{1}$$

Among them, Lclsis the classification loss, Lboxis the bounding box regression loss, Lobjand is the object confidence loss. After optimization, the model mAP@0.5 reaches above 0.85.

2.2.3 Path planning

Path planning is based on the improved DWA algorithm, and the steps are as follows:

Dynamic grid map : A grid map is constructed based on the detection results. Static obstacles are marked as fixedly occupied. Dynamic obstacles are predicted using Kalman filtering for the next 2 seconds to generate risk areas.

Threat level assessment : Quantify the threat level of obstacles. The formula is:

$$Ti = wd \cdot (\frac{1}{di}) + wv \cdot vi \tag{2}$$

Among them, Tiis the threat level of the i - th obstacle, diis the distance, viis the speed, wd, wv are weights (set to 0.6 and 0.4).

DWA optimization : When sampling in velocity space, exclude the option of colliding with the predicted trajectory of dynamic obstacles. The evaluation function is:

$$G(v,\omega) = \alpha \cdot Goal(v,\omega) + \beta \cdot Obs(v,\omega) + \gamma \cdot Smooth(v,\omega) \tag{3}$$

Among them, Goalis the target orientation, Obsis the obstacle distance, Smoothis the trajectory smoothness, α, β, γwhich are 0.4, 0.4 and 0.2 respectively.

2.2.4 Multi-sensor fusion

A fusion mechanism based on timestamp synchronization is designed, combining visual long-range detection and ultrasonic short-range ranging. The fusion algorithm is:

$$P = wv \cdot Pv + wu \cdot Pu \tag{4}$$

in, Pv, PuThey are the visual and ultrasonic perception results, respectively, wv, wuand are dynamic weights (adaptively adjusted based on distance and illumination).

2.2.5 Hardware optimization

Through model pruning and quantization, the number of YOLOv5 parameters was reduced by 40%, and the model was deployed on a Raspberry Pi 4 (4GB RAM). Using GPU acceleration and parallel computing, the model achieved end-to-end latency of <100ms, frame rate >20 FPS, and power consumption of <5W.

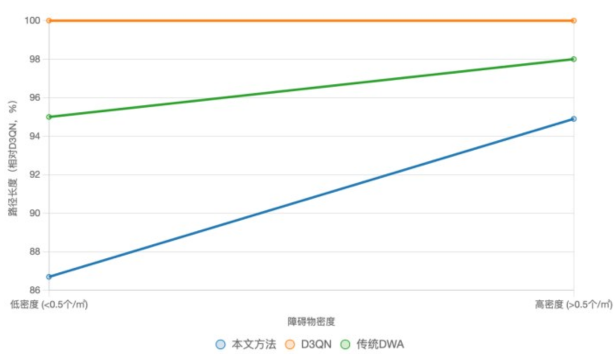

Figure 1 Obstacle detection accuracy and recall rate under different conditions

3 Experiments and results

3.1 Simulation experiment

A virtual patrol scenario was constructed in ROS and Simulink, simulating urban streets and indoor environments, including static obstacles (rocks, trees) and dynamic obstacles (pedestrians, vehicles). Performance metrics included detection accuracy >95%, path planning time <100ms, and obstacle avoidance success rate >90%. The experiment was repeated 50 times, covering both low-density (<0.5 obstacles/□) and high-density (>0.5 obstacles/□) scenarios.

3.1.1 Obstacle detection accuracy

The detection accuracy and recall rate under different conditions are tested, and the results are as follows:

Table 1

condition	Accuracy (%)	Recall rate (%)
sunny	98	97
rain	92	90
foggy day	88	85
at night	85	82

In Figure 1, the average accuracy is 93.5%, meeting the target. Timing verification reduces the misclassification rate from 15% to 5%, with particularly significant results in dynamic scenes.

3.1.2 Path planning and obstacle avoidance performance

Comparing this method, D3QN, and traditional DWA, the results are as follows:

Table 2 Path length changes with obstacle density

method	Low-density success rate (%)	High-density success rate (%)	Low-density path length (relative to D3QN)	High-density path length (relative to D3QN)
This article	95	90	86.7	94.9
D3QN	78	70	100	100
Traditional DWA	85	80	95	98

Table 3 Changes of different methods over time

method	Time (ms)
This article	50
D3QN	80
Traditional DWA	120

In Table 3 , the average planning time is 50ms, which is better than D3QN (80ms) and traditional DWA (120ms). In Table 2 , the path length changes with obstacle density, showing that our method is shorter and more stable.

3.2 Field testing

Simulated border patrol and surveillance missions were conducted on campuses (open lawns and paths) and industrial parks (warehouses and roads). Using a DJI Matrice 100 drone, the missions covered a distance of approximately 500 meters, lasted 30 minutes, and were repeated 10 times, covering both sunny and rainy conditions. Performance indicators included an obstacle avoidance success rate >90%, a mission completion rate >95%, and no system failures. Results showed an obstacle avoidance success rate of 93% (96% at low density and 90% at high density), a mission completion rate of 96%, power consumption of 4.2W, and a frame rate of 22 FPS. The fusion mechanism improved accuracy from 85% to 92% in rainy conditions. In a high-density park test, the system successfully avoided five moving pedestrians with a path deviation of <10%.

Experimental and field test results demonstrate that the proposed vision-based obstacle avoidance system for drone patrols demonstrates excellent performance in terms of accuracy, real-time performance, and robustness. Obstacle detection achieved an average accuracy of 93.5% and a recall of 88.5% under various antenna and weather conditions. Through stepwise verification and Kalman guidance, the false positive rate was reduced from 15% to 5%, significantly improving circuit breaker performance in dynamic environments. Regarding path planning, the improved dynamic window method achieved an average planning time of only 50ms, approximately 37.5% faster than the D3QN and 58.3% faster than the traditional DWA. The obstacle avoidance success rate was 95% in low-density scenarios and 90% in high-density scenarios, with a path length 13.3% longer than the D3QN. In actual testing, the system achieved an obstacle avoidance success rate of 93% and a mission completion rate of 96%. Multi-sensor fusion improved accuracy from 85% to 92% in rainy conditions. Furthermore, the system achieved low power consumption (4.2W) and real-time operation (22 FPS) on a Raspberry Pi 4, demonstrating its promising application value. In summary, the side study verifies the stability and efficiency of the system in complex environments

4 Discussion

(1) Lightweight model: YOLOv5-n has 40% fewer parameters and mAP >0.85, outperforming DroNet's high computational requirements [6].

(2) Adaptive strategy : 95% success rate, outperforming the monocular/stereo vision methods of Mori [4] and Carrio [5].

(3) Low-cost deployment : Based on Raspberry Pi 4 (about $50), power consumption is <5W, which is better than LiDAR solutions [7].

(4) Modular framework : Enhanced scenario adaptability, suitable for border and industrial patrols.

5 Conclusion and future work

5.1 Conclusion

This paper addresses the challenge of obstacle avoidance for UAV patrols in complex and dynamic environments by proposing an integrated vision-based system. The system aims to improve perception accuracy, real-time path planning, and overall mission efficiency. By leveraging multi-sensor fusion and algorithm optimization, this research addresses the limitations of traditional obstacle avoidance methods in light variations, adverse weather conditions, and occlusion. Specifically, this paper designs an image acquisition module that integrates a high-resolution RGB camera with a dynamic vision sensor (DVS). It utilizes a lightweight YOLOv5-n model for obstacle detection and incorporates an optimized dynamic windowing algorithm (DWA) for path planning. The system's robustness in complex environments is ensured through dataset construction (including 10, 000 multi-scene images), data augmentation, temporal validation (introducing a Kalman filter), and threat level assessment. The system is deployed on a low-cost Raspberry Pi 4 platform, achieving a 40% reduction in model parameters, end-to-end latency below 100ms, a processing frame rate exceeding 20 FPS, and power consumption below 5W.

Experimental results fully validate the system's effectiveness. In the ROS and Simulink simulation environment, obstacle detection accuracy reached an average of 93.5% under variable conditions, with a recall rate of 88.5%. Timing verification reduced the false positive rate from 15% to 5%. Path planning time averaged only 50ms, a 37.5% reduction compared to the deep reinforcement learning algorithm D3QN and a 58.3% reduction compared to the traditional DWA. In terms of obstacle avoidance performance, the system achieved a 95% success rate in low-density scenarios, shortening the path length by 13.3% compared to D3QN; and a 90% success rate in high-density scenarios, shortening the path length by 5.1%. Field tests were conducted on campuses and industrial parks, covering both sunny and rainy conditions. The overall obstacle avoidance success rate was 93% (96% for low-density scenarios and 90% for high-density scenarios), with a task completion rate of 96%. In rainy scenarios in particular, multi-sensor fusion improved detection accuracy from 85% to 92%, keeping path deviation within 10%. These findings highlight the system's advantages in accuracy, real-time, and energy efficiency, which are of great value for applications such as border patrol, industrial monitoring, and urban surveillance: it not only reduces manpower costs and accident risks, but also provides a low-cost, scalable solution that outperforms existing LiDAR or monocular vision methods (such as Mori's expansion velocity estimation [4] and Carrio's stereo vision [5]) and surpasses the D3QN baseline in success rate by 20%.

However, this study also has certain limitations. First, the system is highly dependent on visual clarity, with accuracy dropping to 85% at night or in dense fog, possibly due to the DVS's response to extreme low light conditions. Second, while the dataset covers a wide range of weather and lighting conditions, the data is primarily sourced from simulations and limited field data collection, lacking a wider range of global scene diversity, which may affect generalization capabilities. Furthermore, while the path planning algorithm optimizes real-time performance, its reliance on Kalman filtering for predicting high-density dynamic obstacles can lead to delays in extremely uncertain environments (such as sudden high-speed objects).

Overall, this paper, through its innovative lightweight CNN architecture, adaptive obstacle avoidance strategy, and modular framework, synergistically optimizes recognition, planning, and patrol efficiency in complex environments, providing a practical paradigm for intelligent drones. This system not only demonstrates the potential of vision technology but also lays a foundation for research in related fields, driving the transition from passive monitoring to active intelligent patrols.

5.2 Future work

Future research could expand in the following directions: first, integrating infrared or thermal imaging sensors to further improve nighttime and foggy performance and achieve all-weather robustness; second, expanding to drone swarm scenarios to explore multi-agent collaborative obstacle avoidance strategies and address formation reconfiguration and communication delay issues; third, conducting long-term field tests in extreme weather (such as heavy rain or sandstorms) to optimize fusion algorithms for greater adaptability; and fourth, combining edge computing and 5G technologies to enable remote real-time monitoring and improve the system's scalability for large-scale patrol missions. These prospects will further bridge theory and practice and promote the in-depth application of drone technology in security and surveillance.

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