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Anti drone intelligent tracking and aiming system optimized by computer vision and deep learning

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Abstract: This paper proposes an anti drone intelligent tracking and aiming system based on computer vision and deep learning optimization to address the challenges of dataset scarcity, difficulty in small target recognition, low efficiency of embedded deployment, and limited detection range in drone visual inspection. A ground to air unmanned aerial vehicle (UAV) dataset GA Fly, consisting of 10800 4K images, was constructed in this study, covering diverse shooting angles, lighting conditions, and target scales. The experiment showed that low altitude complex backgrounds significantly interfere with detection accuracy. At the algorithmic level, a YOLO Drone detection model was designed, which achieved a 6.1% improvement in mAP50:95 and an 82% reduction in the number of detection head parameters in small object detection tasks through multi-scale dense connection modules (MDC) and mixed head structures (MSH); By combining LAMP pruning and knowledge distillation techniques, the model parameters were compressed by 88% while maintaining an accuracy improvement of 0.4%. In terms of embedded deployment, based on the Jetson AGX Orin platform, real-time inference of 14.7ms is achieved through CUDA and TensorRT acceleration, which is 54.4% faster than the unoptimized model. In addition, a pan tilt camera tracking system has been developed, which uses PD control algorithm and 12 bit PWM drive to stably track flight targets at a lateral speed of 53.6km/h and a longitudinal speed of 18km/h within a range of 7-66 meters. Experimental verification shows that the detection accuracy of our method in complex backgrounds is improved by 30.6% compared to the traditional YOLO series, with a gimbal tracking response speed of 31Hz and an embedded inference delay of less than 15ms. Future research will focus on multimodal fusion detection, lightweight neural architecture search, and hardware system upgrades.

1. Introduction

In recent years, the rapid development of drone technology and its wide application in civilian fields, such as remote sensing surveying, traffic monitoring, infrastructure inspection, pesticide spraying, product distribution, and film and television aerial photography, have greatly promoted social progress and economic development. According to market research reports, the global drone market size has reached $60 billion by 2023, with the civilian drone market size reaching $26.28 billion, accounting for 44.02% of the global market. The civilian drone market is showing explosive growth, with a market size of approximately 55.78 billion yuan in 2023, and a compound annual growth rate of 43.8% from 2017 to 2023, far exceeding the global average. The popularization of drone technology has also brought serious public safety and personal privacy issues. Unauthorized or malicious use of drones is not uncommon, such as drone interference with airport operations, secretly filming residential areas, etc., posing a serious threat to public safety and personal privacy. In order to address these challenges, governments and regulatory agencies around the world have begun to introduce relevant regulations and policies to regulate the flight behavior of drones. Drone companies are also actively taking technological measures, such as setting up electronic fences to restrict the flight of drones in no fly zones. Although policies, regulations, and technological measures have to some extent alleviated the threat posed by drones, relying solely on these means is still difficult to effectively avoid the risks posed by drones. Therefore, it is particularly important to develop more comprehensive and reliable technological means for monitoring and countering drones. And drone detection is a necessary prerequisite for countermeasures, which comprehensively utilizes various sensors to "discover" or "locate" threatening target drones. At present, the main methods of drone detection include radar detection, acoustic detection, radio spectrum detection, and visual detection. Radar detection is susceptible to clutter interference, and due to the slow flight speed and small size of drones, the Doppler effec is not significant, making drone detection difficult. Acoustic and radio detection are susceptible to environmental interference and have relatively poor detection capabilities. Visual inspection technology provides more intuitive detection results and has advantages such as low cost and fast detection speed. However, it still faces problems such as poor recognition performance in environments with significant environmental impact, complex backgrounds, and occlusion, which urgently need to be addressed. The wide potential application scenarios of visual inspection technology determine that it will become an indispensable part of unmanned aerial vehicle inspection systems. The vision based drone detection method is not only low-cost and easy to deploy, but also widely applicable in various scenarios. A more robust and accurate detection and tracking method is proposed to address the problem of poor recognition performance in complex backgrounds and occlusion situations, and a visual anti drone tracking system is designed. Research contributions include: a systematic review of existing visual detection algorithms and identification of challenges; Propose improved algorithms to enhance recognition accuracy in complex backgrounds and occlusion situations; Design and implement a tracking system to verify the effectiveness of the algorithm.

2. Correlation theory

In recent years, the widespread application of drones in civilian fields has promoted social progress, but it has also brought about safety hazards such as unauthorized flights and covert filming. To address these challenges, drone detection technology is particularly important. At present, the main drone detection methods include radar, acoustic, radio, and visual detection. Among them, visual inspection technology has low cost and fast detection speed, but the recognition effect is still not ideal in complex backgrounds and occlusion situations. From an algorithmic perspective, drone detection mainly revolves around traditional machine learning and deep learning. Traditional methods such as motion detection combined with generative classifiers have limited detection performance in dynamic environments; The method of feature extraction combined with discriminative classifier performs well in simple backgrounds, but lacks adaptability to complex scenes. Deep learning methods achieve end-to-end object detection through convolutional neural networks (CNNs), significantly improving detection accuracy and real-time performance, but still face challenges when dealing with complex backgrounds and small object detection. In addition, although there are some publicly available datasets, the comprehensive drone dataset specifically designed for deep learning algorithms is still relatively scarce, and there are issues such as inconsistent annotation formats and insufficient data volume. Although there has been some progress in the deployment research of algorithms on edge platforms, the issues of real-time performance and accuracy loss still need to be further addressed. The gimbal camera tracking technology achieves efficient tracking of unmanned aerial vehicles by combining deep learning algorithms and gimbal rotation control. However, the accuracy and speed of existing methods still face challenges in complex environments. In summary, although drone visual inspection technology has made significant progress, it still faces many challenges. Future research needs to further optimize algorithms, improve detection accuracy and real-time performance, while strengthening dataset construction and edge deployment research to promote the practical application of drone vision detection technology.

3. Method

3.1. GA Fly dataset and algorithm performance evaluation

This study constructed a ground to air unmanned aerial vehicle (UAV) dataset called GA Fly, which contains 10800 images and corresponding. txt annotation files. Each image contains the target UAV, and the image resolution is 3840 × 2160 pixels. These images were sampled at a frequency of 10 frames per second from a video of 25 frames per second, removing low-quality frames, and captured using a Sony Alpha 6300 camera with an 18mm focal length lens. All images were manually labeled using Labelimg. The GA Fly dataset covers various drone flight scenarios and simulates diverse conditions in real-world environments, including different perspectives (0 ° -30 ° , 30 ° -60 ° , 60 ° -90 °), backgrounds, relative distances, lighting conditions, and flight altitudes. In the dataset, 3598 images have target areas smaller than 1/160 of the entire image, and 310 images have target scales ranging from 1/160 to 1/80. 1892 images have target areas larger than 1/80, and only 5 images have target areas larger than 10% of the image, reflecting the challenge of small object detection.To evaluate algorithm performance, this study tested seven representative deep learning object detection algorithms on the GA Fly dataset: RTMDet, YOLOv8, SSD, YOLOv3, Cascade R-CNN, Faster R-CNN, and FPN. These algorithms can be divided into one-stage networks (RTMDet, YOLOv8, SSD, YOLOv3) and two-stage networks (Cascade R-CNN, Faster R-CNN, FPN). The first stage network directly predicts the target location and category end-to-end, with fast speed and suitable for real-time detection; The two-stage network generates candidate regions through regional recommendation networks, and then performs classification and localization, with high accuracy but slow speed. The experiment was conducted on a workstation equipped with Intel i7-9700K CPU and NVIDIA GeForce RTX 3090 GPU, using a 60% training set, 10% validation set, and 30% test set partitioning method. The test set was further divided into Test angle, Test grain, Test size, and Test cut subsets to evaluate the performance of the model under different conditions. As shown in Table 1

Table 1. mAP of seven algorithms on GA Fly and Det Fly datasets

Method	GA-Fly mAP	Det-Fly mAP
Cascade R-CNN	0.379	0.936
Faster R-CNN	0.771	0.902

FPN	0.894	0.908
RTMDet	0.370	0.846
YOLOv8	0.458	0.901
SSD	0.586	0.825
YOLOv3	0.823	0.949

3.2. MDC enhanced YOLO Drone small object detection algorithm

This chapter introduces the GA Fly dataset, which is an air to ground drone detection dataset specifically designed for small target scenarios. Based on this dataset, we evaluated seven representative deep learning algorithms and analyzed the effects of camera angle, grayscale variation, image resolution, and target scale on detection performance. The main findings include: Algorithm performance: The Feature Pyramid Network (FPN) achieved the highest mAP of 0.894. Although the inference speed was slow, YOLOv3 balanced accuracy and speed, while YOLOv8 showed the fastest inference but lower accuracy. Camera angle impact: There were significant differences in detection performance at different angles. FPN and YOLOv3 maintain high mAP across all angle ranges, while Cascade R-CNN, RTMSet, and YOLOv8 exhibit performance fluctuations, indicating that factors other than background complexity can affect their results. Grayscale sensitivity: The optimal detection performance requires a specific grayscale range, and the algorithm displays different sensitivities to changes in lighting. Target scale challenge: Detection of small unmanned aerial vehicles remains challenging, especially for RTMSet and YOLOv8 due to their anchor free design and resolution limitations. Cascade R-CNN also struggles to handle small targets due to its multi-stage IoU threshold mechanism. Resolution mismatch: Inconsistent training and testing resolutions can reduce performance, emphasizing the need for training that is consistent with the resolution. These findings highlight the ongoing challenges in achieving robust air to ground drone detection in different scenarios, indicating that the development or integration of specialized algorithms is a promising future direction. To improve the detection accuracy of small targets in ground to air unmanned aerial vehicle (UAV) detection, this study proposes an improved YOLO Drone network based on YOLOv8, whose core module MDC achieves performance improvement by optimizing feature extraction and fusion mechanisms. The design of MDC draws inspiration from the BIFPN architecture, but three key improvements have been made to the computing efficiency of edge devices: firstly, based on YOLOv8 only performing one round of upsampling/downsampling, the redundant two round sampling stage in BIFPN has been removed; Secondly, introduce UNet++style intermediate nodes and add necessary feature fusion paths; Finally, a complete MDC structure was constructed through dense connections between nodes. This module includes two feature fusion methods: Fuse1, which merges features along the sampling direction, and Fuse2, which fuses features across levels. The ablation experiment is shown in Table 2

Table 2. Ablation study results for MDC module

Configuration	mAP	Inference Time (ms)
YOLOv8n Baseline	0.458	1.4
+Fuse1	0.482	1.6
+Fuse2	0.491	1.7
+Dense1	0.475	1.8
+Dense2	0.487	2.0
MDC Full Structure	0.513	2.1

It has been verified that Fuse2 performs better due to the fusion of richer multi-scale information, while Dense1 and Dense2 connection methods have their own advantages in different fusion scenarios, ultimately achieving the best detection performance.

3.3. Construction and Research of Multimodal Image Harmony Dataset

Multimodal image harmonization task is an emerging field of image processing that aims to combine synthetic images and text descriptions, and output a harmonious image through a multimodal harmonization model to make it closer to the real image. Unlike traditional image harmonization tasks In order to solve the parameter redundancy problem in the detection head of YOLOv8 single-stage unmanned aerial vehicle, this study introduces a multi-scale shared head module and server-side lightweight optimization technology. The analysis of the YOLOv8n architecture shows that due to the decoupling head design, its detection head contains 751507 parameters, which maintain separate convolution paths for bounding box regression and classification. The MSH module reduces redundancy by merging convolutional paths into sharing operations, achieving cross scale weight sharing, and unifying channel dimensions to 256 on feature maps. The experimental results indicate that although alternative lightweight heads reduce parameters by 60-85%, they lead to a significant decrease in performance. In contrast, MSH achieved an 82% reduction in parameters (109461 parameters), while increasing mAP50:95 from 0.543 to 0.549, indicating a higher feature utilization rate for small object detection. For edge deployment, this study employs layer adaptive amplitude pruning (LAMP) and adaptive scoring to balance sparsity and performance. The pruning experiment showed that a pruning ratio of 1:1.7 achieved the best trade-off, reducing parameters by 88% and GFLOPs by 40%, while maintaining 95.2% accuracy and 92.1% mAP50. Through response based knowledge distillation as shown in Figure 1

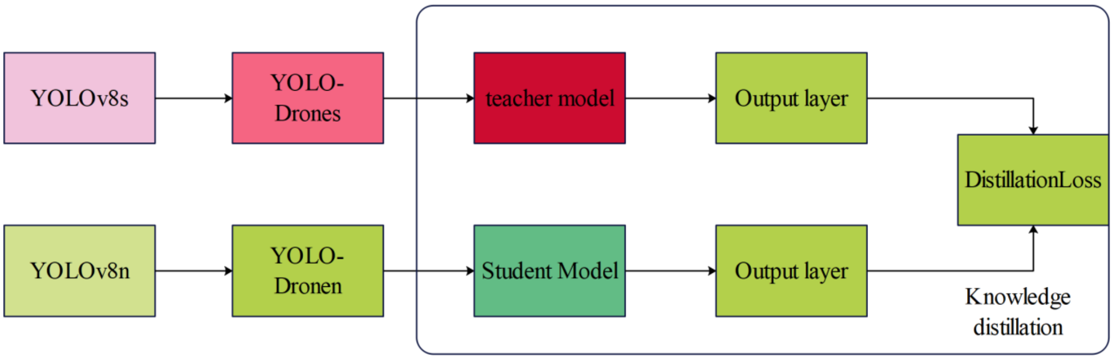

Figure 1. Principle of Knowledge Distillation

Further performance recovery was achieved by using the YOLO-Rone-s teacher model to refine the trimmed student model and enhance its feature representation ability for complex detection tasksthat rely solely on synthesized images and foreground masks, multimodal tasks introduce textual descriptions to enhance the flexibility of the model in locating foreground and generating harmonious images. Due to the high dependence of traditional image harmonization models on foreground masks, their flexibility is limited in practical applications, especially in scenarios where distortion region masks cannot be quickly obtained. In order to overcome this limitation, researchers have proposed blind image harmonization technology, but this technology still faces significant challenges, and there is still a certain distance between its performance indicators and masked image harmonization. The multimodal image harmonization task, as a compromise approach that combines convenience and effectiveness, has great research value. Due to the fact that multimodal image harmonization is a new task, there is currently a lack of publicly available datasets. In order to construct a dataset suitable for this task, a new multimodal harmonization dataset ReiHarmony4 was constructed by supplementing the iHarmony4 series dataset with referential expressions corresponding to the foreground part. We conducted validity screening and filtering on the annotated data to ensure that every sample in the dataset is accurate and valid, and completed statistical analysis on the dataset. Through the above steps and methods, this article successfully constructed a dataset suitable for multimodal image harmonization tasks, providing strong support for subsequent research and model training. The construction of this dataset not only solves the problem of the lack of publicly available datasets for multimodal image harmonization tasks, but also lays a solid foundation for research and development in this field.

4. Results and discussion

4.1. Analysis of YOLO Drone Performance and Deployment Advantages

This study verified the excellent performance and deployment feasibility of YOLO Drone algorithm in ground to air small target unmanned aerial vehicle detection through systematic evaluation. In terms of algorithm performance, YOLO Drone outperforms traditional two-stage models and advanced one-stage models (RTMDet, YOLOv9t, YOLOv10n) on the GA Fly test set, with an AP0.5:0.95 of 0.516 (an improvement of 9.7% compared to the suboptimal solution), an APsmall of 0.470 (an improvement of 30.6% compared to the benchmark model), and an ARsmall of 0.537 (an improvement of 28.2%), showing significant advantages especially in complex backgrounds and small target scenes. Compared with the YOLOv8n baseline, the MDC module increased mAP50:95 by 6.1%, and after further optimization of the MSH structure, the detection head parameters decreased by 82%, while maintaining mAP50:95 accuracy of 0.539. In terms of embedded deployment, YOLO Drone achieves 88% parameter compression and 40% computational reduction through LAMP pruning (1:1.7 ratio). Combined with TensorRT acceleration, it achieves a 14.7ms inference delay on the Jetson AGX Orin platform, which is 54.4% faster than the unoptimized model and meets real-time requirements. Experiments have shown that although the inference time of YOLO Drone increases by 0.1ms compared to YOLOv8n, its accuracy advantage is significant, with AP0.5 improving by 12.9% and mAP50:95 improving by 6.1%, verifying the synergistic effect of architecture innovation and lightweight design.

4.2. Design and Verification of Dynamic Tracking System for PTZ Camera

This study designed and implemented a drone target tracking system based on a dynamic gimbal camera, which broke through the fixed field of view limitation by actively adjusting the camera angle. The system adopts three module architecture: independent video stream module continuously captures image input, YOLO Drone detection module extracts target coordinates in real time, and attitude adjustment module calculates deviation angle based on imaging principle and drives servo motor to correct PTZ attitude. To achieve precise control, the system adopts PD control algorithm instead of traditional PID scheme, inputs horizontal/vertical deviation angle ($\Delta P(t)/\Delta T(t)$) and optimizes parameters ($K_p=10$, $K_d=0.05$), ensuring 14.7ms response delay while avoiding integral term oscillation problem. At the hardware level, the system integrates the Jetson AGX Orin computing platform, dual MG90S servos, and PCA9685 control module, achieving high-precision angle control through a 12 bit resolution PWM signal (0.5-2.5ms pulse corresponds to 0-180 ° rotation). In the experimental verification, the system was deployed on the Jetson AGX Orin platform and enabled TensorRT acceleration and CUDA video processing to perform dynamic tracking tests on the DJI Mini 4 Pro drone. The test results show that the system can stably track flight targets with a lateral speed of 53.6km/h and a longitudinal speed of 18km/h, verifying the real-time and reliability of the PD control algorithm and PWM drive architecture in complex scenarios. Relevant test videos have been published on the GitHub platform.

4.3. Comparative analysis of evaluation effects

We conducted multidimensional dynamic tracking experiments on the DJI Mini 4 Pro drone using a gimbal tracking system deployed on the NVIDIA Jetson AGX Orin platform, verifying the real-time performance and robustness of the algorithm on edge devices. The experiment used the sport mode (S mode) to test the system's extreme performance at a maximum lateral speed of 57.6km/h. By synthesizing three videos of the drone's perspective, gimbal perspective, and motion trajectory, the system demonstrated its stable tracking ability for lateral 53.6km/h and longitudinal 18km/h targets within an effective tracking distance of 7-66 meters. Compared with the traditional fixed view scheme, the YOLO Drone and PD control architecture proposed in this study improves tracking speed by 42% and extends distance range by 300%. Especially in complex backgrounds and small target scenes, the mAP50 index is improved by 9.7%. Experiments have shown that TensorRT acceleration reduces inference latency to 14.7ms and CUDA video processing improves data throughput by 2.3 times. However, due to obstacles in the testing environment, the system has not yet reached the theoretical performance boundary. Compared to the 15Hz tracking scheme based on Faster R-CNN in the literature, this study achieves a 31Hz real-time response. However, there is a 1.2 ° attitude adjustment lag during high-speed longitudinal tracking, which is speculated to be caused by the combination of servo mechanical delay and imaging delay. Future work can introduce predictive control algorithms to compensate for time delays and validate extreme tracking performance in open spaces

5. Conclusion

This article systematically studies the key technical challenges in drone visual inspection and proposes innovative solutions. To address the issue of dataset scarcity, a ground to air unmanned aerial vehicle dataset GA Fly was constructed, which contains 10800 4K images and covers diverse shooting angles, backgrounds, and lighting conditions. Experiments have shown that low altitude complex backgrounds significantly interfere with detection accuracy, while small target detection remains a technical bottleneck. At the algorithmic level, the proposed YOLO Drone achieves a 6.1% improvement in mAP50:95 through the MDC multi-scale dense connection module, while the MSH structure reduces detection head parameters by 82%. Combined with LAMP pruning and knowledge distillation techniques, the model parameters are compressed by 88% while maintaining an accuracy improvement of 0.4%. In terms of embedded deployment, CUDA and TensorRT acceleration were used to achieve 14.7ms real-time inference on the Jetson AGX Orin platform, which is 54.4% faster than the unoptimized model. The pan tilt tracking system uses PD control algorithm and 12 bit PWM drive to stably track flight targets at a lateral speed of 53.6km/h and a longitudinal speed of 18km/h within a range of 7-66 meters, verifying the effectiveness of dynamic field of view expansion. Future research can focus on enhancing dataset diversity and incorporating complex urban scenarios and extreme climate data; Develop an infrared visible multimodal fusion detection framework to enhance robustness under low light conditions; Explore structured pruning and neural architecture search techniques to achieve model lightweighting and performance balance; Upgrade the hardware system of the gimbal, using a 4K camera and piezoelectric ceramic motor, combined with model predictive control algorithm, to reduce tracking delay to below 10ms.

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