Unmanned Aerial Vehicle Uses Multiple Sensors for Target Recognition and Classification

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Abstract. Based on the gradual popularization of UAV and the development trend of UAV application, the application of UAV sensors for target recognition and information fusion analysis has become one of the key topics of today's research. Researchers have made progress in UAV target recognition by adopting wireless sensor networks and distributed beamforming methods, as well as using YOLO detection method, constructing detection data sets, and extracting target multi-receptive field features by using res2net.By synthesizing the existing literature, this study identifies the strengths and weaknesses of the method, thereby facilitating advancements in science and technology related to UAV application sensors for target recognition and information fusion analysis. Unmanned aerial vehicles (UAVs) use distributed beamforming technology as a result of their integration with wireless sensor networks (WSNs). As a result, it is imperative to enhance data collecting and monitoring, as well as optimize UAV data collection efficiency. However, data synchronization issues remain, such as the quantization of random errors such as wireless channel distortion and noise. The YOLO approach to object detection is incredibly quick.To enhance the features' ability to represent many scales, a novel hybrid feature pyramid structure is built using the pyramid model as a foundation.Res2net is utilized in this process to extract multi-receptive field features.

Keywords: UAV, Sensor, Target Recognition, Classification, Information Fusion

1 Introduction

Background of UAV application of sensors for target recognition and information fusion analysis. Unmanned technology has been widely used for development and technological progress at any time. In the field of environmental monitoring, agricultural management, disaster relief and military reconnaissance, there is a wide range of applications, accurate and rapid identification of drones, and real-time transmission and processing of various information. With the continuous development of UAV technology, the requirements for autonomous navigation and intelligent control of UAV are constantly improving. Through multi-sensor fusion technology, UAV can obtain environmental information from multiple angles more

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comprehensively, which provides important support for achieving more accurate navigation.To give an overview of the current stage of progress, the methods for information fusion analysis and UAV target recognition are evaluated, along with the advantages and disadvantages of each approach.

By providing theoretical support for studies aiming at improving UAVs' capacity to expand information collection and boost the effectiveness of information fusion analysis and processing, this work aims to advance related research.The following article mainly describes the UAV application of multi-sensor information collection method and information fusion method. The method of combining UAV and wireless sensor system can effectively improve the efficiency of UAV data collection. There are also drones that use distributed beamforming, although they still face difficulties in data synchronization. The YOLO detection method of UAV can reduce the computational effort and simplify the network structure.A new pyramid with mixed feature structure is built based on the pyramid concept, a probe data set is created, and multi-receptive field features are extracted using Res2net.

2 Target Recognition, Information Fusion Analysis Method

2.1 Uav Uses Multi-sensors to Collect Target-related Information

Uav Target Recognition, information Fusion Analysis Method. The use of Uavs in conjunction with wireless sensor networks can enhance the collection and monitoring of data [1]. The drone can collect data through sensor nodes in a controlled area.Uav has the characteristics of air mobility, flexibility and so on, so UAV is suitable for air BS.In large-scale operation,RN or relay nodes are an important part of WSN. RN is in charge of the data collected from SN. The drone collects data from the RN and then uploads the obtained information to the base station. Figure 1 showed the relationship between UAVs and RN and BS.

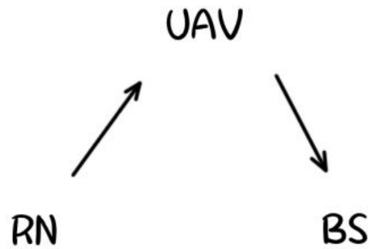

Fig. 1. Relationship between Uavs and RN and BS

In a fixed sensor environment, the drone collects data from sensor nodes on the ground [2]. Describes wireless data transmission to a drone. Figure 2 showed the data collection in WSN utilizes a variety of UAV-based solutions.

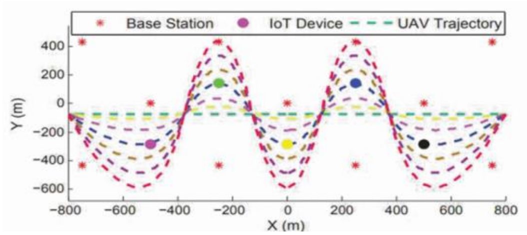

Fig. 2. Data collection in WSN utilizes a variety of UAV-based solutions

The collaborative use of Uavs and WSNS can enhance data collection and improve WSN structure. Furthermore, the primary driving force behind extending the lifespan of sensors in the process of integrating UAVs with wireless sensor networks is the development of a novel network design to efficiently gather sensing data in sensor networks.Additionally, it can increase the effectiveness of UAV data collection [3]. The transmission priority of each frame is determined by the UAV coverage area.The sensor frame or region with the lowest transmission priority is the one situated in the most frontal (less relevant) portion of the UAV coverage area. However, the highest transmission priority is assigned to the frames in the emergency area, which is the last side of the UAV coverage area. By employing this framework, the number of sensors in this task may be minimized and the cost can be saved. Figure 3 showed the sensors in various areas (the transmission priority is greatest in the urgent region and lowest in the less essential area.

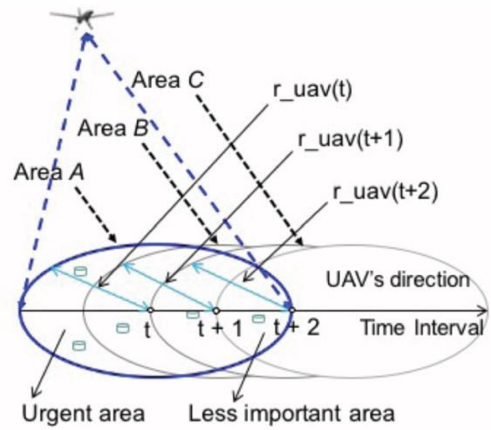

Fig. 3. Sensors in various areas (the transmission priority is greatest in the urgent region and lowest in the less essential area

To manage the order of data transmission from sensor nodes to UAVs, a priority-based data access policy is provided. This policy can be built up depending on the priority of each frame and each individual node contained inside the frame.This framework provides an effective way to collect data by combining UAVs with WSNS. It can greatly improve the efficiency of collecting data.

The Uavs Use Distributed Beamforming Techniques. Distributed beamforming is thought to be the most promising communication method, in contrast to independent communication. As technology advances, unmanned aerial vehicles (Uavs) can deliver identical messages to all single-antenna ground nodes (GNS) by utilizing distributed beamforming techniques to obtain data from numerous GNSs. This is accomplished through a sensor data synchronization mechanism [4]. When the speed of the UAV is unrestricted, the system has essentially already reached its maximum potential.Distributed beamforming collects data from many single-antenna ground nodes (GNS).When deployed within a swarm and interacting with other devices, the GN can function as both a computing and communication header, as well as the sensor itself (D2D).Because random flaws like as quantization noise and wireless channel distortion occur, a sensing data synchronization mechanism is provided in each cluster to ensure that all GNS broadcast consistent messages. Fundamental performance upper boundaries are revealed by well-structured optimal solutions offered by the Lagrangian dual technique.It first considers the ideal relaxation problem without considering the flight speed limit of the UAV.We propose an efficient algorithm that uses convex optimization and approximation techniques to obtain high-quality solutions to solve the common problem of UAV flight speed constraints [5]. Consideration is given to data gathered by dispersed beamforming from several GNS.By adjusting the UAV's trajectory and the GN's power distribution, we can increase the average data rate throughput and reduce the likelihood of a transmission interruption.Data synchronization techniques and the quantification of random faults like noise and wireless channel distortion remain challenging issues that are being researched.Lastly, for dependable and quick data gathering, receive beamforming with numerous UAVs and multi-antenna UAVs might be taken into consideration.

3 Target Information for Fusion Analysis

3.1 The YOLO Detection Method Has Excellent Speed

YOLO-UAV, a target detection technique for UAV photos, is suggested by improving YOLOv5.YOLO-UAV reduces the computational effort and streamlines the network architecture in order to first recreate the feature fusion network and backbone network [6]. Consisting of dense connections, the Dense_CSPDarknet53 backbone network continuously leverages features to assist in extracting latent picture information [7]. Removing the 20x20 large target detecting head lowers the number of unnecessary calculations and model parameters. To improve the model's small item recognition performance.A 160x160 compact object detection head is integrated.It is possible to efficiently fuse features at different scales by using the BiFPN architecture.By reducing the detrimental effects of poor samples on the model's performance, this optimization helps the model to converge more quickly. The experimental results with the VisDrone2019 public dataset show that Yolo-UAV outperforms other cutting edge techniques for object detection.The mAP0.5 of YOLO-UAV is improved from 35.1% to 46.7%, and the MAP0.5:0.95 is improved from 19.1% to 27.4%,in contrast to the

YOLOv5s baseline model. AP increased from 10.2% to 17.3% for small-scale targets. Tests have shown that YOLO-UAV improves the accuracy of target detection.
Figure 4 showed the YOLO-UAV network model architecture.

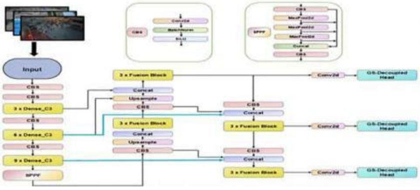

Fig. 4. YOLO-UAV Network Model Architecture

An object detection model for UAV imagery using deep learning. To achieve high accuracy, the model blends the efficiency of YOLOv5 with the particular visual problems faced by UAVs [6].

Object detection techniques are classified into two types of detection algorithms: single-stage and two-stage.Detectors with two stages comprise algorithms like R-CNN [7], Faster R-CNN and Libra R-CNN [8]. These algorithms generally perform more accurately than single-stage methods, especially when it comes to managing complex backdrops and identifying small objects, which leads to more accurate object detection.Conversely, single-stage detectors like theYOLO series, SSD, RetinaNet, and CenterNet have real-time performance and processing speed.Nevertheless [9], these techniques typically show poor accuracy, particularly when handling complicated backdrops and recognizing small objects, which can result in false positives or missing detections. Furthermore, class imbalance issues may arise from one-stage algorithms' requirement for the classification and regression of every possible location.

3.2 A Probe Dataset is Created, and Multi-receptive Field Features

After building the UAV detection dataset, res2net is used to extract the target's multi-receptive field features.A new hybrid feature pyramid structure is presented to improve the network's performance in two domains: hierarchical multi-scale feature fusion and fine-grained multi-scale feature extraction.A UAV target identification network based on multi-scale feature fusion is feasible [10]. Features were extracted using the convolutional layer network in the Faster R-CNN technique.After the region candidate frame network generates the candidate regions, the region of interest pooling layer converts the feature map into a uniform size.Regression and classification are carried out in four stages by candidate regions.It is suggested to use a novel hybrid feature pyramid structure to avoid unnecessary processing. Through two processes, it can improve the multi-scale representation capabilities of features by fusing feature maps of non-adjacent resolutions. It is a universal module that can be used with any detection network because it also keeps the original architecture of the network structure [11]. Figure 5 showed the Faster R-CNN flow chart.

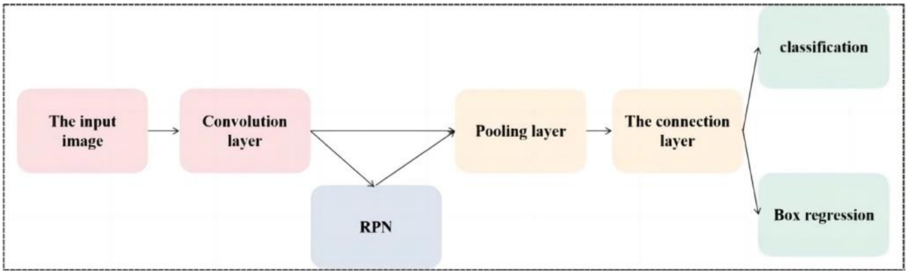

Fig. 5. Faster R-CNN flow chart

4 Discussion

The method of combining wireless sensor network with UAV and distributed beamforming can be used for target recognition and classification of UAV. The first method will increase the cost of UAV to transmit and collect information.Quantizing random defects, like noise and wireless channel distortion, and data synchronization remain challenging issues that require ongoing investigation and research.The second approach, which has essentially reached the maximum limit and has difficult conditions, is the best scenario if the UAV's speed is unrestricted.Energy harvesting has been recommended as a critical push factor to extend the lifespan of WSNS, since combining UAVs with WSNS may increase usage costs due to the lifetime problem of WSNS nodes and the efficiency of battery energy, which is costly and labor-intensive for sensor batteries.

The YOLOv5 model is optimized as the initial step in the UAV information fusion process.This optimization speeds up the convergence of the model and reduces the impact of low sample quality on the model's performance.The second technique comprises creating a new hybrid feature pyramid structure and deploying a multi-scale feature fusion-based UAV target detection network.The Faster R-CNN algorithm is used.The UAV's image data is trustworthy and sufficient, and it is frequently the primary source of evaluation. However, due of the incredibly small number of pixels in its digital image, the severely deteriorated target features, the subtle contour features, and the ease with which it is impacted by external variables, the identification of low and slow small targets may not be precise enough. As a result, some objects are challenging to differentiate, and it is simple to misinterpret comparable objects, leading to poor judgment.

5 Conclusion

After reading the paper, you will gain a better understanding of how multi-sensor UAV target information extraction and fusion is applied to improve UAV data collection efficiency and information fusion processing capabilities, as well as to enhance the effectiveness of traditional data collection frameworks, increase the precision of UAV information fusion algorithms, and address current issues with partial UAV information recognition extraction and information fusion processing.The combination of UAV and wireless sensor network needs to strengthen the data collection and monitoring, improve the efficiency of UAV data collection, but it needs to be carried out under the ideal condition that the flight speed of UAV is not constrained. Distributed beamforming technology is used by unmanned aerial vehicles (UAVs).However, quantization of random mistakes like noise and distorted wireless channels remains a challenge for data synchronization. The YOLO UAV target detection method is particularly fastRes2net is used to extract multi-receptive field features, and a new hybrid feature pyramid structure based on the pyramid concept is constructed to increase the features' capacity for multi-scale representation.The research findings can serve as valuable references and guidelines for future research and practice in related domains, and they will play a major role in advancing the development of UAV image capture and processing.

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