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Literature Review on Autonomous Navigation of Drones

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Abstract

This paper reviews the research progress in the field of autonomous navigation of drones, with a particular focus on navigation and positioning issues in environments where satellite signals are limited. It begins by introducing the potential applications of drones in civilian, military, and scientific research fields, as well as the importance of drone navigation systems for the quality of task completion. The paper then discusses the current state of research both domestically and internationally on navigation based on multi-agent reinforcement learning for visual navigation, deep reinforcement learning navigation algorithms, and navigation using the fusion of multiple sensors. The application of Ultra-Wideband (UWB) technology in the field of drone autonomous navigation is also explored, including its positioning principles and potential in drone swarm intelligence. Additionally, the paper analyzes the current state of development of drone autonomous landing systems in both civilian and military fields. Finally, the paper discusses the research progress in drone detection and recognition technology based on deep learning, as well as radar detection and recognition technology for drones.

Keywords

Drones; Autonomous Navigation; Visual Navigation; Ultra-Wideband (UWB) Technology; Deep Learning.

1. Introduction

In recent years, drones, characterized by their small size, flexible movement, and ease of operation, have demonstrated significant potential in multiple domains such as civilian, military, and scientific research. For instance, they play crucial roles in power line inspection under harsh conditions, atmospheric environment monitoring, emergency rescue, and enemy situation reconnaissance. With the continuous advancement of drone technology, the feasible applications of drones have become increasingly powerful and extensive. Numerous industries have ventured into the field of drones, and the flight tasks of drones have exhibited a trend of diversification and complexity. As the foundation for drones to undertake various tasks, the accuracy and robustness of the drone navigation and positioning system are vital guarantees for the quality of task completion [1]. Currently, most drone navigation systems rely on the Global Positioning System (GPS) based on satellite positioning. However, under the influence of factors such as the occlusion of urban high-rise buildings, indoor environments, and the time-varying and dynamic nature of the wartime environment, satellite signals cannot always meet the real-time navigation requirements. In such circumstances, drones can only rely on onboard sensors or collaborative devices for scene perception and conduct navigation and positioning based on the obtained data [2].

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2. Research Status at Home and Abroad

Visual navigation based on multi-agent reinforcement learning is a research hotspot in the fields of artificial intelligence and robotics. This approach integrates the multi-agent reinforcement learning algorithm into collaborative visual navigation and directly generates the navigation strategies of each agent from the perception results through the joint training of each agent's network parameters [3]. As the basis of artificial intelligence navigation methods, it is prone to integration with other tasks to achieve a higher degree of intelligence. Therefore, an increasing number of researchers are dedicated to the study of visual navigation based on deep reinforcement learning. The autonomous navigation algorithm of drones is a constantly evolving research field involving various technologies and methods.

Mainly including:

The research background of the autonomous navigation system of drones based on visual navigation mainly focuses on enhancing the autonomy and navigation accuracy of drones in complex environments [4]. The visual navigation system acquires environmental images using cameras and realizes the precise positioning and navigation of drones through image processing techniques. With the development of computer vision and machine learning technologies, the visual-based navigation system has been extensively researched and applied in the field of drones. Firstly, the visual navigation system can provide drones with abundant environmental information, including terrain, obstacles, and targets, enabling drones to conduct autonomous flights and task executions in unknown or dynamically changing environments. For example, in environments with limited GPS signals such as indoors or urban canyons, visual navigation becomes an important means for drone positioning and navigation [5]. Secondly, the research of the visual navigation system involves multiple key technologies, including image preprocessing, feature extraction, pose estimation, Visual Odometry (VO), and Simultaneous Localization and Mapping (SLAM). The development of these technologies has enhanced the accuracy and robustness of drones in autonomous navigation.

A robust model can handle noise and outliers in the input data and maintain the accuracy of prediction or classification even when the data quality deteriorates or the data distribution changes [6].

Furthermore, to address the limitations of a single visual sensor in certain circumstances, such as changes in lighting and occlusion issues, researchers have begun to explore the fusion of the visual system with other sensors like Inertial Measurement Units (IMU) and Light Detection and Ranging (LiDAR) to achieve more stable and reliable navigation performance.

The research status of the autonomous navigation system of drones based on visual navigation encompasses multiple aspects, ranging from the application of deep learning in drone navigation, the research progress of visual landing technology, to the review of visual perception and pose estimation methods. Firstly, the application of deep learning technology in the field of drone navigation is advancing rapidly, and many studies focus on using deep learning methods to enhance the autonomous navigation ability of drones. For instance, in a review article published in the "Drones" magazine by Thomas Lee et al., it is pointed out that the rise of deep learning methods in computer vision applications has brought significant advancements to autonomous driving of vehicles. Similarly, in the field of drone navigation, deep learning is also being widely utilized to improve the performance of autonomous navigation. Secondly, visual navigation technology is an important research area in the autonomous navigation system of drones [7]. However, there are certain drawbacks to the autonomous navigation of drones based on visual navigation; Sensitivity to lighting and environmental changes: The visual system is relatively sensitive to lighting conditions and environmental variations. Image differences under different lighting, seasons, and angles may lead to the degradation of the performance of visual algorithms. Challenges in dynamic scenes: In dynamic scenarios, the visual system of drones needs to process a large amount of data in real-time, has high requirements for computing resources, and needs to identify and track targets quickly and accurately. Dependence on high-quality reference images: The accuracy of the visual navigation system depends to a certain extent on high-quality reference images or pre-made maps. The acquisition and update of

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these images may be costly and time-consuming. Real-time and computing resource limitations: To achieve real-time navigation, the visual system requires rapid image processing and matching calculations. However, limited by the computing capacity and energy supply of drones, it may be difficult to achieve real-time processing of complex algorithms. Limitations of sensors and algorithms: Although deep learning methods exhibit great potential in visual navigation, the robustness of existing algorithms under different viewpoints, scales, and occlusions still needs improvement. Complexity of multi-sensor fusion: To improve the robustness and accuracy of the system, the visual system is often fused with other sensors such as IMU and GPS. However, the design and implementation of multi-sensor data fusion algorithms present certain complexities [8]. Difficulty in creating high-precision maps: There are technical challenges in creating high-precision maps suitable for visual navigation, especially in areas with complex terrain or rapid changes. Issues of viewpoint and appearance invariance: At different flight altitudes and angles, the visual system of drones needs to be capable of accurately identifying and matching targets, which requires the algorithm to have good viewpoint and appearance invariance. However, existing technologies still have limitations in these aspects. Search problems in large-scale scenes: In large-scale scenes, the visual navigation system needs to quickly search and match a large number of images, which poses higher requirements for the efficiency and accuracy of the algorithm. Challenges in deployment on onboard platforms with limited computing resources: Deploying the visual navigation system on a drone platform with limited computing resources requires solving the lightweight and optimization issues of the model to meet real-time requirements.

For the navigation and positioning of drones in satellite-denied environments, numerous studies have been conducted both domestically and internationally. The main solutions can be divided into positioning based on wireless signal intersection, positioning based on environmental database matching, and track based on inertial measurement elements [9]. Wireless signal positioning mainly utilizes WiFi, Bluetooth, Radio Frequency Identification, and UWB for signal strength or distance measurement for position calculation. This method has a low implementation cost, and the positioning system is easy to establish. Among them, the UWB-based positioning technology possesses advantages such as strong penetration, high positioning accuracy, low power consumption, high transmission efficiency, and low implementation complexity, and has broad application prospects in local navigation and positioning of robots. The current positioning based on environmental database matching is mainly positioning based on visual image features and environmental perception positioning based on LiDAR data. This method can obtain more intuitive environmental features [10]. With the development of Simultaneous Localization And Mapping (SLAM) technology, this method can meet the dual requirements of positioning and mapping. However, this method has low adaptability to the positioning environment, complex sensors, and large data operation volume, and has high requirements for the load capacity and computing power of small drones. Since IMU devices can only provide high-precision positioning for a short period of time, with obvious long-term drift, the track based on inertial measurement elements mainly utilizes the fusion of IMU with other sensors to improve positioning accuracy. Currently, the navigation and positioning of drones in satellite-denied environments mainly rely on the fusion of multiple sensors and the introduction of new algorithms such as neural networks. Due to the low payload capacity of small drones, their load capacity cannot meet the usage conditions of high-power sensors, and to reduce costs, small drones mostly select low-precision MEMS devices. The improvement of a single algorithm cannot significantly enhance the navigation accuracy [11]. This article designs a UWB-based multi-sensor fusion positioning system for small drones in satellite-denied environments. Flight control development was carried out based on the open-source flight control Pixhawk. The feasibility of the system was verified through simulation, and a physical platform was built to achieve autonomous flight of drones in satellite-denied environments.

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3. Application of UWB Technology in the Field of Drone Autonomous Navigation

The application of UWB (Ultra-Wideband) technology in the autonomous navigation system of drones is mainly reflected in providing high-precision positioning capabilities. UWB technology transmits data by sending and receiving extremely narrow pulses at the nanosecond or sub-nanosecond level. These pulse signals have very high time resolution and are highly suitable for high-precision positioning. UWB positioning technology achieves positioning by measuring the signal propagation time difference, frequency difference, or phase difference between the object and the receiver. Among them, the method based on time difference measurement (TDOA) is the most common.

In the autonomous navigation system of drones, UWB technology can be used for precise positioning and flight control of drones, enhancing flight safety and autonomy [12]. For example, by carrying a UWB positioning tag on the drone and arranging UWB base stations reasonably in indoor or outdoor spaces, the drone can achieve precise positioning through communication with the base stations. This positioning method does not rely on GPS signals and is particularly suitable for indoor or GPS-signal-limited environments.

The application of UWB technology in the field of drone swarm intelligence also shows great potential. The collaborative operation of drone swarms can improve the overall working efficiency and achieve the upgrade from individual performance to group performance. In swarm collaboration, UWB technology can be used for precise position collaboration among drones, enabling them to perform effective information sharing and collaborative decision-making, thereby achieving swarm intelligence.

In addition, UWB technology also has advantages such as low power consumption, high security, and low cost. Its large bandwidth and low power consumption characteristics make UWB systems highly useful in Internet of Things devices, especially in scenarios that require high-precision positioning and low power consumption. The high-precision advantage of UWB technology makes it a key technology in multiple application scenarios such as smart cities, smart homes, and industrial automation.

In practical applications, UWB positioning systems typically include UWB positioning tags, UWB positioning base stations, IoT positioning platforms, and application platforms. The UWB tag on the drone sends pulse signals, the base stations receive and measure these signals, the IoT positioning platform completes the position calculation, and finally, the application platform utilizes this position information for business expansion [13].

To sum up, the application of UWB technology in the autonomous navigation system of drones provides a high-precision and anti-interference positioning solution, contributing to the improvement of the autonomy and swarm collaboration ability of drones. With the continuous development of technology, UWB technology is expected to play an even more significant role in the future of drone navigation and the Internet of Things.

4. UWB Ranging Principle

UWB positioning is accomplished through ranging. Based on different measurement parameters, UWB ranging methods can be classified into Received Signal Strength Indicator (RSSI), Angle-of-Arrival (AOA), Time-Of-Arrival (TOA), and Time-Difference Of-Arrival (TDOA), etc. Among them, the TOA method calculates the distance by measuring the flight time of the signal between the mobile target and the base station. It has the characteristics of small calculation amount and simplicity but requires strict time synchronization between the base station and the target. The Two Way-Time of Arrival (TW-TOA) based on the bidirectional ranging method can achieve high-precision ranging without the need for time synchronization between the base station and the target. Each module generates its independent timestamp from the start. The Poll packet, Response packet, and Final

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packet are all communication data packets between the base station and the mobile target. The error introduced by the clock deviation is compensated by recording the sending and receiving times of the data packets multiple times [14].

5. UWB Positioning Principle

The UWB positioning principle is based on the transmission characteristics of radio waves, and determines the position of an object by measuring the propagation time of the radio signal in the environment. UWB technology uses extremely narrow pulse signals, which have a very wide frequency band (usually above 500 MHz, and some even reach several GHz). Due to the extremely high time resolution of these signals, they are highly suitable for precise positioning. Time measurement: The UWB positioning system operates by measuring the time it takes for the radio pulse signal to travel from the transmitter (such as a UWB tag) to the receiver (such as a UWB base station). Since radio waves propagate at the speed of light, the distance can be calculated by measuring the time. Time Difference of Arrival (TDOA): This is one of the most commonly used methods in UWB positioning. In TDOA positioning, at least three base stations are required to determine the two-dimensional position of an object, and four base stations can determine the three-dimensional position. Each base station measures the time when the signal arrives and calculates the position difference of the object relative to each base station by comparing these times. Two-way ranging: In this method, there is two-way communication between the tag and the base station to measure the distance between them. First, the base station sends a signal to the tag, and the tag immediately replies after receiving it. After the base station receives the reply, it can calculate the round-trip time of the signal and thereby obtain the distance [15].

Through the UWB positioning principle, after the drone obtains the distances between the mobile target and multiple base stations, the position of the mobile target can be calculated using the spherical positioning model. At least four reference base stations are required for three-dimensional space positioning.

6. Research on Autonomous Landing of Drones

The current development status of autonomous landing systems for drones in the civilian field: It is mainly divided into instrument landing systems and radar landing systems.

Instrument landing system: In the initial stage of the civil aviation field, the Instrument Landing System (ILS) was installed around the ground airport runway and provided landing guidance information to pilots during the approach and landing phases of civil aircraft. This system passed the tests organized by the National Bureau of Standards of the United States in 1919 and played an important role during World War II, thus further being promoted and applied. In 1949, the instrument landing system was promoted to countries around the world as an international standard by the International Civil Aviation Organization (ICAO). This system can provide aircraft with azimuth, elevation, and distance information, and the calculation of the above information is completed through the cooperation of ground stations and onboard equipment. During the aircraft's approach process, the onboard receiver calculates the beams with different frequencies generated by the ground course beacon and glide slope beacon in real-time to obtain relative positioning information through the calculation of the horizontal and vertical beams [16]. The course beacon station generally works in the Ultra High Frequency (UHF) band and is responsible for providing the deviation of the aircraft from the centerline of the runway; the glide slope beacon station generally works in the Very High Frequency (VHF) band and is responsible for providing the deviation from the ideal glide path (2.5° - 3.5°). This system is currently the most widely used guidance system, with good robustness and adaptability. The navigation and positioning accuracy is between 5 - 20m. However, with the increasingly complex electromagnetic spectrum environment near airports in recent years, the calculation accuracy of this system has been interfered with to a certain extent, and the positioning accuracy and update frequency are difficult to meet the accuracy requirements of the drone control system.

Radar landing system: In 1943, the US military applied radar technology to the Ground Control Approach (GCA) system and gradually promoted it to the civil aviation field; in 1947, a DC-3 aircraft of Southwest Airlines in the United States, under the guidance of the radar landing system and the instrument landing system, achieved the world's first truly commercial flight blind landing. The information provided by this system mainly relies on radar equipment. After obtaining the relative position information, since the initial data link did not have the condition for return transmission, pilots usually communicate with the tower navigator through voice and obtain the deviation data of the glide path through voice reporting to compensate for the measurement error caused by their visual observation, and finally complete the safe landing process. In recent years, with the development and maturity of data links, flight controllers, and data fusion algorithms, this guided landing method has evolved into a "data link + radar" form. That is, after the ground or ship-based radar system calculates the deviation, the information is returned to the onboard equipment through a high-speed data link. The flight controller calculates and predicts the relative value position in real-time based on the kinematic and dynamic characteristics of the aircraft, and simultaneously updates the guidance rate and control strategy to finally achieve semi-autonomous or autonomous landing.

The current development status of autonomous landing systems for drones in the military field:

MagicCarpet landing system: The "MagicCarpet" landing system is a new type of advanced precision landing control and display technology developed by the US Navy in recent years. It completed its first sea trial in April 2015 and completed supporting tests in 2016. This system focuses on improving and enhancing the lift control technology in the flight controller algorithm, achieving decoupled control of the glide trajectory planning and landing stage attitude, and providing information such as glide track error, alignment error, and command amplitude to the pilot, further optimizing the landing process, simplifying the pilot's operational load, and significantly improving the landing success rate and safety. The JPALS system mainly provides the latitude and longitude coordinate information of the shore-based and aircraft carrier deck landing areas. The MagicCarpet landing system pays more attention to improving the smoothness of drones during the landing process.

Airborne visual guidance landing technology: The Aerospace Engineering Department of South Korea proposed an airborne visual guidance landing solution. In this solution, a red arched safety airbag is placed in the landing area, and the visual sensor on the small drone autonomously recognizes the red target and its scale to complete relative positioning and drone recovery. Kim proposed an image processing algorithm based on color segmentation and morphology, which recognizes the image features of the impact net area on the airborne visual equipment and completes the guided recovery of small fixed-wing drones. This visual algorithm focuses on the analysis of the predicted geometric shapes and reversely calculates the current orientation information of the drone. During the landing process, the guidance rate and control rate are corrected; the ground control system detects the flight status of the drone and intervenes manually when necessary to improve the safety and reliability of the landing process. Zhu Jianming modified the H-type cooperative target, closed the upper opening of the traditional H-type target, and enhanced the directional characteristics of the new shape. In the process of identifying the H-type target in the landing area from the air, a corner detection method based on gray-scale changes was adopted, and the relative position of the drone was obtained through the calculation of the feature points. Shakernia proposed a visual autonomous landing solution for the Yamaha R-50 rotorcraft drone in his doctoral thesis. The core idea of this solution is also to use the cooperative target to achieve relative position estimation. At the same time, Shakernia also studied the Linear/Non-linear Two-view Motion Estimation algorithm and the Multi-view Planar Algorithm. In addition to obtaining relative position information, it effectively estimates the attitude of the drone during the landing process and provides auxiliary information for the effective generation of control instructions by the drone flight control system. Through simulation and outdoor comprehensive tests, the position deviation of this solution is controlled within 0.05m, and the angle deviation is controlled within 0.5°, achieving accurate positioning and landing. However, since the cooperative identifier is not applicable to most drone scenarios, the migration of this algorithm to the identification and position and attitude estimation of non-cooperative targets has certain difficulties. The University of Southern California designed an H-type landing mark and performed landing positioning by calculating the Hu invariant moment. The current accuracy of this system is: the position error is less than 0.4m, and the angle error is less than 0.7° [17].

Guided landing technology based on vision: In terms of ground-based visual guidance, it is a new idea in recent years to deploy multiple fixed-focus cameras for relay measurement and zonal guidance of the drone landing process. The system solution proposed by the School of Aerospace Science and Technology of National University of Defense Technology: Images captured by the camera group are transmitted to the main control computer using sub-computers on both sides of the landing runway. The visual guidance part of this system consists of 6 industrial high-speed cameras with selected different focal lengths and field of view angles and servers. The 6 cameras are divided into 3 groups and are deployed on both sides of the runway respectively, and are calibrated and debugged according to the measurement requirements of the far field, middle field, and near field. Generally, the field of view range of each camera needs to have a certain overlap, and the overall field of view range formed covers the entire landing area. This solution has a simple design concept, and the combination of multiple focal lengths compensates for the limitation of the field of view angle of a single visual system. However, the overall architecture of this system is complex, the outdoor deployment position error has a great impact on the calculation accuracy, and the steps of the visual system in the calibration process are complex, and the deployment flexibility needs to be further enhanced.

7. Research on Detection and Recognition of Drones Based on Deep Learning

Traditional detection and recognition of drones usually design features using various traditional methods and then use classifiers for detection and recognition. Drone visual detection and recognition technology usually consists of two steps. Specifically, features are first extracted from drone images using techniques such as Histogram of Oriented Gradients and Scale-Invariant Feature Transform, and then the extracted features are classified using algorithms such as Support Vector Machine. Drone audio detection and recognition technology usually first extracts features such as Linear Prediction Coding, Fourier coefficients, and Mel Frequency Cepstral Coefficients of the drone audio signal, and then compares the extracted features with pre-saved labels to identify the drone. Drone radar detection and recognition often uses Frequency-Modulated Continuous Wave radar to send continuous waves and measure the frequency difference between the sent and received signals to determine the target drone and its distance. Early researchers used statistical features extracted from captured radio frequency signals to detect and recognize drones. For example, wireless packet sniffers were used to capture drone radio frequency signals and extract statistical features to identify drones. It can be seen that these traditional methods all require manual feature extraction, and this process is relatively complex and has poor performance [18]. In contrast, deep learning-based algorithms can simplify the feature extraction process and significantly improve the detection and recognition effect. Therefore, the application of deep learning in drone detection and recognition is particularly necessary.

Drone visual detection and recognition aims to use the visual sensor carried on the drone and image processing technology to achieve the task of automatic detection and recognition of the target. Different from the traditional drone visual detection and recognition methods that rely on manual extraction of drone image features, the deep learning-based method uses a deep neural network to train an end-to-end model, which can achieve high-precision detection and recognition. The core of deep learning is to extract features for detection and recognition from a large amount of data. However, in the field of drone vision, reliable datasets are relatively scarce. To solve this problem, ZHU Pengfei released a large-scale drone image dataset. This dataset was collected through various types of drones and contains 8,599 images covering various real-world scenarios. The Convolutional Neural Network (CNN), as an important model of neural networks, has attracted much attention because it can automatically learn and extract important features of the data. Especially in the aspect of target detection, CNN has achieved remarkable performance breakthroughs. The research on drone recognition methods based on deep convolutional neural networks proposed a drone recognition method based on deep convolutional neural networks. This method first uses the SSD algorithm for target detection on the video image dataset, and then obtains an efficient recognition model by training a learning network based on VGG16. Currently, common one-stage detection algorithms include YOLO, SSD, and RetinaNet [19].

Among them, the YOLO algorithm is a powerful multi-target detection algorithm that can transform complex recognition problems into regression problems and achieve high-precision and fast detection through a single end-to-end neural network. However, because the data used by YOLO in the training process has almost no intersection with the sample space of the newly input drone image data, there are problems in the process of spatial positioning bounding boxes in the drone image data by YOLO. To apply YOLO to drone images, researchers usually adopt various techniques to modify the hyperparameters of YOLO, such as fine-tuning, data augmentation, and optimization of hyperparameters. SAHINO proposed an improved YOLO algorithm "YOLO Drone" for the above problems to detect objects in drone images. This algorithm was evaluated on the VisDrone2019 dataset. Experimental results show that the performance of the YOLODrone algorithm is better compared to the YOLOv3 algorithm.

As drones tend to miniaturize, YOLO has efficiency problems in dealing with detection tasks. In contrast, SSD performs detection on feature maps of different scales, can capture targets of different sizes, and has a better detection effect on small-sized objects. For example, WANG Guangya proposed an improved target detection and tracking algorithm based on deep learning. This algorithm combines target detection and tracking technology based on the SSD one-stage detection algorithm to achieve more accurate dynamic target tracking. Experimental results show that the average accuracy of this algorithm reaches 91.5%, achieving good results. RetinaNet introduces Focal Loss, effectively solving the problem of imbalance between positive and negative samples in the target detection of the above algorithms, thereby helping to deal with the imbalance of drone categories. BISIO I proposed a method based on the RetinaNet framework in the 4th issue, etc.: A review of research on detection and recognition of drones based on deep learning 613 for detecting vehicles from drone aerial images. The performance of the detector in drone detection was evaluated on the Vis Drone2019 dataset. The results show that this method has high detection accuracy and stability on the used dataset.

Faster R-CNN is an improved version of the R-CNN series of target detection models, introducing a Region Proposal Network to achieve end-to-end target detection. LAN Meng introduced Faster R-CNN into the field of drone image detection for multi-class electrical equipment defect detection. This model consists of a deep fully convolutional network and a Fast R-CNN detector. The former is used to generate region proposals, and the latter passes the region proposals and image data as input to the training network. By sharing the features of the deep convolutional layer, the entire algorithm forms a unified two-stage target detection network. Experimental results show that this method is superior to traditional target detection algorithms on real electrical equipment image datasets. Compared to Faster R-CNN, Mask R-CNN adds a branch network and introduces ROI Align, which can not only detect the position of the target but also accurately segment the pixel-level region of the target. YAYLA R applied Mask R-CNN to vehicle detection in drone images. This method is not only applicable to static images but also to dynamic images and videos. To solve the problem of scale variation in low-altitude aerial images, MITTAL P introduced the Feature Pyramid Network in the two-stage detection framework, successfully achieving effective detection of objects of various scales, thereby significantly improving the performance of target detection in drone images.

Technical challenges and future directions of deep learning in drone visual detection and recognition:

In recent years, the development and application of deep learning technology have promoted the research on the detection and recognition of drone visual data. Deep learning methods automatically learn task-related features through end-to-end training, replacing the traditional method of manual

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feature extraction, thereby obtaining high-level abstract representations of image data. However, the current problem is the lack of large-scale and diverse datasets for drone detection and recognition. To solve this problem, researchers have adopted the idea of transfer learning. In addition, the current deep learning methods are not ideal in dealing with complex scenarios such as multi-target occlusion and small-sized targets. Although adding additional training data can improve the performance of the model, it cannot completely overcome these difficulties. Therefore, it is necessary to improve the model structure to further enhance the detection and recognition effect of drones. To this end, it is necessary to deeply explore deep learning theory and propose new model structures and training methods to accelerate model training and improve detection effects. Data augmentation and transfer learning are the most effective methods currently, and generative models such as Generative Adversarial Networks may become the future development direction. In addition, considering the practical application scenarios of drone visual detection and recognition, integrating multimedia information (such as audio, radar, radio frequency, etc.) into the deep learning model is also a direction worth exploring.

8. Drone Radar Detection and Recognition based on Deep Learning

In modern high-tech warfare, drones are widely used in electronic warfare due to their equipped radar sensors. As an active sensor, radar, unlike computer vision and acoustic sensor technologies, is not affected by factors such as lighting and audio and can operate all day. Therefore, drone radar detection and recognition have always played a key role in electronic warfare, and its core goal is to extract important information from the intercepted radar signals of enemy drones. The interception stage of drone radar signals forms the basis for subsequent signal detection and recognition; signal preprocessing is mainly used for noise reduction and alignment, and the main signal processing involves effective feature extraction methods to achieve the detection and recognition of drone radar signals, thereby determining the type and function of the drone, as well as threat assessment, etc. The introduction of deep learning technology can greatly simplify the process of drone radar signal detection and recognition and improve accuracy. Different from the methods of traditional signal processing systems, deep learning methods directly use neural networks to extract drone radar signal features after signal preprocessing, avoiding excessive reliance on manual processing and thus simplifying the signal processing process. In addition, deep neural networks can capture deeper features of drone radar signals, thereby significantly improving the accuracy of detection and recognition. The classification of drones and drones classifies different types of drones effectively by detecting and recognizing drone radar signals. Given the excellent performance of neural networks in the field of image processing, the collected drone radar signals are usually processed into image forms, such as spectrograms, and then classified using neural networks. By using CNN to process the short-time Fourier transform spectrograms of simulated radar signals, five different drones are classified, and the situation of noise false alarms is also considered. Experiments have confirmed the feasibility of using machine learning to classify drone radar signal data. On the other hand, PARK D proposed a deep learning-based drone classification model. This model achieves precise classification of drones by learning the micro-Doppler features on radar spectrum images, solving the problem that the above models cannot detect and recognize in real time. It was verified on a self-built radar spectrogram dataset, and it was proved that the proposed model has shorter training time and higher accuracy compared to the ResNet-18 model.

9. Conclusion

Autonomous navigation technology for drones is one of the key technologies in the field of unmanned aerial vehicles and is crucial for improving the autonomy and navigation accuracy of drones in complex environments. Although current GPS-based navigation systems perform well in a variety of environments, drones rely on onboard sensors or collaborative devices for scene perception and navigation positioning in environments where satellite signals are obstructed. UWB technology, as a high-precision positioning technology, shows great potential in drone autonomous navigation, especially in indoor or GPS signal-limited environments. Furthermore, deep learning technology has made significant progress in the detection and recognition of drone vision, improving the accuracy and efficiency of detection and recognition. Future research should continue to explore multi-sensor data fusion algorithms, the creation of high-precision maps, and the challenges of deploying visual navigation systems on drone platforms with limited computing resources. With the continuous development of technology, UWB technology and deep learning are expected to play an increasingly significant role in the future of drone navigation and the Internet of Things.

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