A Systematic Review of UAV Structure and Monitoring Models for Forest Fire Detection

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Abstract. Forest fires pose a significant threat to ecosystems and economic development. In recent years, unmanned aerial vehicles (UAVs) have emerged as a critical technology for forest fire monitoring due to their high mobility, low cost, and real-time surveillance capabilities. This paper provides a systematic review of research progress on UAV-based forest fire monitoring, focusing on three key aspects: hardware design, fire detection algorithm improvement, and multi-sensor data fusion technologies. First, it summarizes optimization strategies for UAV hardware, including sensor configurations, wing design, and power supply improvements, aimed at enhancing flight stability and environmental adaptability. Second, it analyzes advancements in fire detection algorithms, particularly the performance enhancement and lightweight modifications of deep learning models, and explores their applicability in high-noise environments. Finally, it evaluates the potential of multi-sensor data fusion techniques to improve fire detection accuracy by integrating temperature, smoke, and image data. Despite the significant advantages of UAVs in fire monitoring, challenges remain, such as hardware performance limitations, the trade-off between algorithm accuracy and real-time processing, and the complexity of multi-sensor coordination. Future research should focus on flight stability optimization, the development of novel detection algorithms, and the refinement of sensor integration techniques to further advance UAV applications in forest fire monitoring.

Keywords: Unmanned Aerial Vehicle; Fire Detection; Monitoring Models; Forest Fire.

1. Introduction

Forests are an indispensable component of Earth's ecosystems, providing oxygen, regulating climate, and serving as essential resources for humans and other living organisms. However, forest fires, as a highly destructive natural disaster, not only result in significant economic losses but also cause long-term negative impacts on biodiversity and the environment. It is estimated that forest fires cause economic damages amounting to billions of dollars annually worldwide, while releasing substantial amounts of carbon dioxide, thereby exacerbating climate change. Consequently, the timely and accurate monitoring and detection of forest fires have become critical challenges requiring urgent attention.

In recent years, unmanned aerial vehicles (UAVs) have gradually become an essential tool for forest fire monitoring due to their high mobility, low cost, and capability to cover extensive areas. Compared with traditional ground-based monitoring systems or satellite-based systems, UAVs can flexibly navigate complex terrains and provide real-time, high-resolution fire information. However, UAVs face numerous challenges in practical applications, including susceptibility to environmental factors affecting flight stability, limited computational resources, and the immature application of multi-sensor fusion technologies. Therefore, optimizing UAV monitoring capabilities and improving the efficiency of fire detection algorithms are of great significance.

Existing studies primarily focus on UAV hardware optimization, the enhancement of target detection algorithms, and the application of multi-sensor data fusion technologies. Some representative research in these areas includes:

Chen et al., who explored UAV fire monitoring systems based on infrared sensors and proposed a fire detection method combining image texture features and temperature distribution, significantly improving detection accuracy, although monitoring speed remains constrained by hardware performance [1]. Wang et al. addressed the issue of UAV flight instability by developing an environment-adaptive flight path planning algorithm that improves UAV monitoring capabilities in complex terrains through real-time route adjustments, albeit at a higher cost [2]. Li et al. applied the YOLOv5 deep learning model for fire detection, incorporating lightweight modifications to the model structure, which enhanced both the real-time performance and accuracy of target detection. However, the model's stability in high-noise environments still requires further optimization [3].

These studies have laid a solid foundation for the application of UAV technology in forest fire monitoring, but numerous limitations persist. To address these issues, this paper seeks to analyze the constraints of existing methods and propose improvement directions, focusing on three key aspects: flight stability optimization, enhancement of target detection algorithms, and advancements in multi-sensor data fusion.

The structure of this paper is as follows:

Chapter 2: A detailed introduction to the technical components of UAVs for forest fire monitoring, including sensor configurations, wing design, and optimization strategies for power supply systems.

Chapter 3: A focused discussion on the application of target detection algorithms in fire monitoring, with an analysis of the performance of the YOLO model and its improvement schemes, as well as a comparison of the advantages and disadvantages of other traditional algorithms.

Chapter 4: An exploration of the potential of multi-sensor data fusion technologies, discussing how temperature, smoke concentration, and image data can be integrated to enhance the accuracy of fire detection and assessment.

Chapter 5: A summary of the limitations of existing research and proposals for potential future research directions and applications.

This paper systematically reviews the application of UAV technologies in forest fire monitoring, analyzing the current state of research and challenges in UAV hardware design, fire detection algorithms, and multi-sensor data fusion technologies. The literature reveals that while UAVs exhibit significant advantages in fire monitoring, issues such as flight stability, environmental adaptability, the trade-off between algorithm accuracy and real-time performance, and the complexity of multi-sensor data fusion remain unresolved. These challenges continue to hinder the broader adoption and advancement of UAV technologies in forest fire monitoring.

2. UAV Structure

2.1. Sensors

2.1.1 Infrared Sensors

Current fire detection methods include four primary types: smoke-based, temperature-based, light-based, and image-based. Among these, smoke-based sensors and remote sensing satellite sensors are often affected by environmental factors, resulting in poor real-time performance and relatively high false alarm rates. In contrast, light-based sensors, characterized by their rapid response and high sensitivity, have been widely used. Light-based sensors primarily include ultraviolet (UV) sensors and infrared (IR) sensors. However, UV sensors are more susceptible to external interference, making infrared sensors the preferred choice for fire detection applications [4].

Single-band infrared flame detectors, however, are prone to interference from other heat sources. A triple-band infrared detection system effectively eliminates these issues [5]. Therefore, UAV-based forest fire detection systems commonly utilize triple-band infrared detection sensors to improve accuracy and reliability.

2.1.2 Vision Sensors

Vision sensors consist of cameras and image processing systems. These sensors typically employ optical components to capture image and video data of the surrounding environment. Leveraging computer vision technology, UAVs can perform tasks such as target recognition, obstacle detection and avoidance, and image-based mapping.

Notably, conventional fire detection UAVs are often equipped with either visible light cameras or infrared cameras, without combining their capabilities or fusing the acquired images [6]. By integrating and analyzing data from both camera types, fire detection efficiency can be significantly enhanced.

2.2. UAV Wings

The design of UAV wings for forest fire monitoring is critical to their flight performance, balancing lift, stability, and flexibility. To navigate complex forest environments, UAV wings are constructed from lightweight, high-strength materials such as carbon fiber and aluminum alloy, ensuring structural integrity while reducing weight and enhancing endurance [7]. The use of carbon fiber composite materials reduces weight, improves fuel efficiency, and enhances flight stability.

The wings are designed with a foldable structure, enabling convenient transportation and deployment, especially for rapid response in remote areas. Additionally, aerodynamic optimization—achieved through wing shape design and extended wingspan—minimizes drag, increases lift, and ensures stable flight under varying wind conditions [8]. Modular designs further facilitate wing replacement and maintenance, making the UAV adaptable to different mission requirements.

In summary, lightweight construction, foldable designs, aerodynamic optimization, and modularity enable UAVs to perform fire monitoring tasks with flexibility and efficiency, while also enhancing system operability and maintenance convenience.

2.3. UAV Power Supply System

To meet the requirements for prolonged fire monitoring, tethered power systems can be utilized to supply energy to UAVs. These systems deliver continuous electrical power from a ground-based supply to ensure UAVs can hover stably for extended periods while providing uninterrupted illumination.

The working principle of tethered UAV power systems is relatively straightforward: high-voltage direct current (DC) generated by the ground power supply is transmitted to the UAV via tethered cables. An onboard power module in the UAV converts this high-voltage DC into the low-voltage DC required for operation. With this power supply, UAVs can sustain extended hovering durations and perform various tasks, including providing continuous lighting. Tethered UAVs integrate UAV technology with advanced lighting systems [9].

UAVs achieve flight control through built-in flight control systems, navigation systems, and propulsion systems, while lighting equipment is responsible for emitting light to illuminate specific areas. The integration of UAVs with lighting technology enables light to be projected freely from the air, achieving multi-angle and all-encompassing illumination.

3. Fire Monitoring Models

3.1. Traditional Video Monitoring Algorithms

Traditional video-based detection methods are still widely used in fields such as fire monitoring and traffic surveillance, but their robustness and generalization capabilities remain limited. With the continuous development of computer vision and deep learning technologies, modern algorithms like YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector) have gradually replaced traditional methods to become the mainstream approaches for object detection.

Traditional video monitoring algorithms primarily rely on three feature extraction techniques: color features, texture features, and motion features. For static observers, where the background image remains relatively stable, motion feature extraction algorithms can effectively identify moving targets, such as flames or smoke. However, when the observer is in motion, as in the case of UAVs capturing footage during flight, the background image continuously changes, making motion feature extraction significantly more challenging. As a result, motion-based algorithms are less effective for fire monitoring when UAVs are involved.

This section focuses on introducing two traditional fire detection models based on video monitoring.

3.1.1 Fire Detection Algorithms Based on Texture Feature Extraction

In forest fires, the internal texture of interfering objects significantly differs from that of fire, making texture features an effective tool for fire detection. Additionally, analyzing the texture features of smoke images reveals substantial differences from clear images, highlighting the unique characteristics of smoke textures. Common texture analysis methods include the gray-level difference statistical method and the gray-level co-occurrence matrix (GLCM).

Jingjing Wang et al. proposed a Texture Fusion Module (TFM) that integrates Fully Connected Attention (FCA) and Spatial Texture Attention (STA) during the final encoding stage [10]. This module effectively reconstructs missing spatial information in smoke features, significantly reducing redundant information while retaining features critical for fire monitoring. This innovation provides a novel approach for texture-based fire detection.

In summary, algorithms based on texture feature extraction play a vital role in flame detection. However, further integration with other feature detection methods can enhance their accuracy.

3.1.2 Fire Detection Algorithms Based on Color Feature Extraction

Fire detection is a critical component of fire warning systems. Traditional video-based detection methods often rely on the extraction of color, motion, and texture features. Among these, color feature extraction is particularly significant because flames exhibit distinct characteristics in various color spaces, making them easier to identify.

In the RGB color space, flames are typically characterized by a high red (R) component compared to green (G) and blue (B) components. Utilizing this trait, researchers have developed various color models to identify flame regions. For instance, Wu Xiayin et al. proposed a detection algorithm that combines circularity, rectangularity, and centroid height coefficients [11]. By enhancing the color feature model using both RGB and HSI color spaces, the method effectively extracts potential flame regions.

The YCbCr color space is also widely applied in flame detection. Zhang Dandan et al. developed a flame foreground extraction algorithm combining RGB, YCbCr, and region-growing techniques [12]. This approach reduces excessive noise in reflective and non-reflective regions, improving detection accuracy.

However, solely relying on color features may result in false detections due to variations in environmental lighting and background colors. To address this issue, researchers have combined color features with other attributes. For example, Maedeh Jamali introduced a video flame detection method based on saliency, integrating both color and texture features to significantly enhance detection accuracy and robustness [13].

In conclusion, fire detection algorithms based on color features play a crucial role in identifying flames. However, to improve their precision and robustness, these methods are often combined with other feature extraction techniques.

3.2. Deep Learning and Feature Extraction Algorithms

Traditional video-based fire detection methods rely on prior analysis of visual information, extracting visible features such as flame, smoke color, and motion characteristics for identification. However, these methods struggle to capture abstract feature representations, resulting in limited generalization. They often fail to effectively distinguish fire-like objects, such as car tail lights or mist. In contrast, deep learning-based object detection leverages powerful feature extraction and data modeling capabilities to identify abstract semantic features of smoke and fire. This section introduces the widely-used YOLOv5 and YOLOv8 object detection models in fire monitoring applications.

3.2.1 Fire Monitoring Algorithms Based on YOLOv5

The YOLOv5 model family includes versions such as YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, with YOLOv5s being the smallest and most lightweight version, serving as the foundation for the other variants. Balancing detection speed and accuracy, YOLOv5s is frequently employed for fire monitoring tasks. Several researchers have utilized or improved YOLOv5s for fire detection, achieving remarkable results:Furkat Safarov et al. replaced the CSPDarknet53 backbone in YOLOv5s with a Vision Transformer (ViT), enabling the model to capture both local and global dependencies within images [14]. This improvement allows accurate monitoring of occluded fire scenarios, making the model particularly effective in forest environments where fires are often obscured by trees. Yixin Chen et al. addressed the problem of missed and false detections in existing fire detection models by proposing the lightweight GS-YOLOv5s [15]. This model incorporates a multi-scale feature fusion and knowledge distillation architecture into the YOLOv5s baseline. It enhances the detection of small fire targets, which are prone to being overlooked in forests, while maintaining high accuracy. Its lightweight design makes it well-suited for deployment on UAV systems.

3.2.2 Fire Monitoring Algorithms Based on YOLOv8

The YOLOv8 model is a state-of-the-art one-stage object detection framework. Among its versions, YOLOv8n is the most basic, characterized by high precision and fast detection speed. These traits make it highly suitable for fire monitoring applications. Researchers have conducted various studies on adapting YOLOv8 for fire detection: Md. Waliul Hasan et al. added a custom neural network layer to YOLOv8, enhancing its ability to focus on fine-grained details and subtle variations [16]. This modification significantly improved the model’s capability to detect fire and smoke, making it more effective in capturing fire-related information. Yangyang Zheng et al. improved the YOLOv8n model by reconstructing the Bottleneck module with Group Shuffle Convolution (GSConv) and refining the residual structure [17]. These changes reduced network parameters while improving detection accuracy, particularly for small targets and in complex environments. Such advancements are instrumental in identifying early-stage fires in challenging forest settings.

In summary, improved YOLOv5s and YOLOv8n models demonstrate significant advantages in terms of monitoring speed and model compactness, making them well-suited for forest fire detection when deployed on UAV platforms. Their widespread application and promising potential indicate a bright future for deep learning-based fire monitoring technologies.

3.3. Improved and Innovative Algorithms

3.3.1 Multi-Sensor Hybrid Detection

Single sensor output can be highly fluctuating, and its values often overlap between fire and non-fire environments. For instance, video image-based detection demands high-quality images, especially in low-light conditions at night, where weak visible light makes it difficult to obtain clear images. Moreover, adverse weather conditions further limit the effectiveness of image-based methods [18]. To address these challenges, multi-sensor hybrid detection is increasingly utilized to improve fire monitoring accuracy and reduce the high false alarm rates associated with single-sensor methods.

Fire’s basic characteristics include flames, combustion products, and sound. Researchers have worked on developing multi-sensor models that can simultaneously detect flame, smoke, and temperature, significantly reducing the errors associated with single sensor-based detection. For example, Qiu Qimin et al. developed a multi-sensor monitoring model that effectively detected fire, smoke, and temperature, reducing the detection errors of individual sensors. Lai Xiaolong et al. collected multi-sensor data on CO_2, CO, smoke concentration, and environmental temperature and humidity, using a support vector machine algorithm for early forest fire detection [19]. Similarly, Qian Su et al. proposed a multi-sensor data fusion-based fire detection method, employing improved adaptive filtering and fuzzy Bayesian logic reasoning algorithms for data integration [20]. This model analyzes multi-dimensional data, ensuring robustness and enhancing fire monitoring capabilities in complex environments like forests.

By utilizing advanced algorithms for multi-sensor data fusion, systems can more accurately detect fire signals, reduce false alarms, and issue early warnings, thus providing critical time for fire suppression measures to be implemented.

3.3.2 Lightweight Algorithms for UAV-Based Detection

While UAVs offer the advantage of ease of aerial patrol, their onboard computing power is often limited. Therefore, when designing UAV algorithms, it is crucial to balance detection accuracy and speed with the constraints of the UAV’s computational resources. Lightweight algorithm models are thus necessary for effective deployment in such resource-limited environments.

He Yang proposed a forest fire detection method based on Re-yolo, which improves fire detection accuracy while maintaining detection speed [21]. Additionally, a lightweight version of this model, Re-yolo-tiny, was introduced to effectively monitor fires under low computational power conditions. Yin Bo introduced a lightweight fire detection algorithm based on an improved YOLOv8 model. The algorithm replaces the C2f module in YOLOv8 with a FasterC2f module and proposes a lightweight detection head architecture [22]. This method not only reduces the model size and computational load but also maintains, or even exceeds, the detection accuracy of the original YOLOv8 model. Many of the improvements discussed earlier also focus on model lightweighting.

In summary, the lightweighting of algorithm models is crucial for saving computational resources and is highly feasible. However, it should be noted that while lightweight models offer significant benefits, they may slightly impact detection accuracy.

4. Conclusion

This paper thoroughly explores the application of UAVs in forest fire monitoring, focusing on the UAV’s structure (particularly the infrared and visual sensors, lightweight and high-strength wing design), power supply system (tethering system for prolonged power supply), and fire detection models (comparing traditional algorithms with deep learning algorithms). Several solutions to challenges faced when using UAVs for fire monitoring are proposed: Endurance Issues: To address the issue of UAV flight time, solutions such as tethering systems for continuous power supply and lightweighting the monitoring models are recommended. False Alarm Issues: To reduce false positives, improvements to existing monitoring models and multi-feature hybrid monitoring approaches are suggested.Flight Stability: Using lightweight, high-strength wings designed according to aerodynamic principles can address UAV flight stability concerns.Environmental Impact: The use of tri-band infrared sensors and multi-sensor hybrid monitoring can significantly mitigate the environmental impact, particularly in forest fire monitoring.

In conclusion, UAVs show great potential in fire monitoring. By optimizing UAV structure, improving fire detection models, and innovating algorithms, the accuracy and efficiency of fire monitoring can be further enhanced, providing robust support for timely firefighting actions.

Future research directions include optimizing multi-sensor fusion technologies, innovating lightweight algorithms, improving deep learning algorithms, enhancing UAV autonomous flight and obstacle avoidance capabilities, and refining real-time monitoring and early warning systems. These advancements will further improve the precision and efficiency of fire detection and monitoring systems.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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