Application of UAV Remote Sensing in Crop Detection

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Abstract. Unmanned Aerial Vehicle (UAV) remote sensing has become an important means of accurate detection of crops because of its high spatial-temporal resolution, flexibility, and cost control. This paper systematically summarizes the research progress of UAV Remote Sensing Application in crop detection. Firstly, the principles of mainstream sensors such as multispectral, hyperspectral, thermal infrared, visible light, and lidar and their application characteristics in agricultural monitoring are summarized. Secondly, focusing on the main tasks of pest identification, lodging monitoring, weed detection, and soil moisture monitoring, the retrieval methods based on different sensors are sorted out. On this basis, the advantages, disadvantages, and application scope of physical model and machine learning inversion models are compared. Research shows that the combination of multi-source sensor fusion and machine learning models significantly improves detection accuracy, but it still faces challenges such as poor model generalization ability, high sensor cost, and complex data processing. In the future, it should promote the coordinated development of UAV remote sensing, satellite and aerial remote sensing, and build a multi-scale, all-weather agricultural monitoring system.

Keywords: UAV remote sensing, crop detection, multi-source sensors, precision agriculture, inversion model.

1. Introduction

With the continuous development of technology, agricultural crop detection requires more and more accuracy and real-time. The traditional satellite remote sensing and aerial remote sensing can not meet the hourly state detection of crops due to the impact of cloud cover and revisit cycle. However, due to the low efficiency and strong subjectivity of manual sampling on the ground, it is impossible to quickly obtain information on a large scale [1, 2]. The emergence of UAV remote sensing provides solutions to these problems. The UAV platform is equipped with remote sensing to obtain crop information, and UAV images can flexibly provide centimeter level or even higher resolution information, and it will not increase the revisit cycle due to the improvement of resolution, and its use cost is also lower. These crop information is helpful to summarize the current situation and laws in pest identification, lodging detection, soil moisture and weed detection.

In recent years, scholars have carried out a lot of research on the application of UAV Remote Sensing in agriculture. Dai et al used multispectral UAV images to analyze the spectral information of cotton lodging and establish a model, and found the best model for cotton lodging monitoring [3]. Gao Lin and others successfully monitored the dynamic changes of winter wheat leaf area index using hyperspectral UAV Remote Sensing Technology [4]. However, with in-depth research, various methods show the characteristics of fragmentation; the results of different sensors and different algorithm models are different, and there is still a lack of systematic induction and summary.

Therefore, this paper first summarizes the acquisition principle of mainstream UAV sensors and their application characteristics in crop monitoring. Secondly, the advantages, disadvantages, and application scope of physical models and machine learning inversion models are compared. Then, for the main detection objects such as soil moisture, lodging, diseases, and pests, etc., sort out the inversion methods based on different sensors. Finally, the future trend of cooperative development of UAV remote sensing, satellite remote sensing, and aerial remote sensing is prospected. It aims to provide readers with a systematic reference for UAV Remote Sensing in agricultural practice.

2. Research Progress of UAV Remote Sensing in Crop Detection

2.1. Research Progress of Different Sensors

2.1.1. Multispectral sensor

A multispectral sensor is an imaging device with about ten or fewer spectral channels. From the perspective of data acquisition, the biggest advantage of UAV multispectral technology is that it has fewer bands (usually 3-10 to meet monitoring requirements while maintaining centimeter resolution) and lower cost. From the perspective of application analysis, various vegetation indices including the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDV), and Soil Adjusted Vegetation Index (SAVI), which are calculated via band operations on multispectral data, have been widely adopted for monitoring various crop [5]. Due to the limited number of bands and the large band width, it is difficult for multispectral data to capture the continuous spectral changes of ground objects in the fine wavelength range.

2.1.2. Hyperspectral remote sensing

Hyperspectral remote sensing is a remote sensing technology that can obtain dozens or even hundreds of very narrow and continuous spectral band images. Its spectral resolution is higher (usually up to the nanometer level), and research shows that 458-830nm has better spectral quality [4]. Hyperspectral remote sensing can record the reflectance spectrum curve of ground objects almost continuously, and distinguish different ground objects or stress types with similar spectral characteristics (such as nitrogen deficiency and drought, stripe rust and powdery mildew). Secondly, hyperspectral remote sensing has a strong ability of quantitative inversion, which can accurately extract chlorophyll content, nitrogen, water, cellulose, and other biochemical components, and support crop nutrition diagnosis and precision fertilization. And hyperspectral remote sensing has a strong ability of early detection. When diseases and pests or stress have not appeared with visible symptoms, hyperspectral remote sensing can realize early warning through spectral anomalies [6]. The limitation of hyperspectral remote sensing is that it has large data redundancy, complex processing, high price, and high requirements for the UAV platform, which limits its popularity.

2.1.3. Thermal infrared Remote Sensing

Thermal infrared remote sensing is a remote sensing technology to retrieve the Land Surface Temperature (LST) of ground objects by detecting the spontaneous emission energy of ground objects in the thermal infrared band (usually 8-14 μ m). Thermal infrared remote sensing can directly respond to water stress and is not affected by light. It can also be imaged at night. When crop water deficit occurs, canopy temperature changes before the visible light near-infrared spectrum, which can realize early warning of stress. In the application, the thermal infrared sensor is often combined with the temperature data to calculate the Crop Water Stress Index (CWSI), which indirectly reflects the soil water status in the root zone [7, 8]. Its limitations lie in its low temporal and spatial resolution, which is far lower than that of visible light and multispectral cameras (usually decimeter to meter level), and it is greatly disturbed by natural environmental factors, so it needs to be corrected with the data of the weather station.

2.1.4. Visible light Sensor

The visible light (Red-Green-Blue,RGB) camera is the most basic and lowest-cost sensor; its advantage is that the image is intuitive, the spatial resolution is high (up to the centimeter level), and the data processing is relatively simple. By using the Structure from Motion (SfM) algorithm, the three-dimensional point cloud of crops can be reconstructed from the visible light image, so as to extract the plant height, canopy coverage, leaf area index, and other structural parameters [9]. In crop detection, visible light sensors are often used to calculate visible light vegetation indices such as the excess green index (ExG), visible light band difference vegetation index (VDVI), and to identify crops and background (soil, dead branches, weeds). At the same time, combined with deep learning, such as the U-shaped Convolutional Network(U-Net) and You Only Look Once (YOLO) series

algorithms), visible light images can realize pixel-level or target-level recognition of disease spots, lodging areas, and weeds. However, the visible light sensor lacks the red edge and near-infrared bands, and its sensitivity to crop physiological parameters is low, so it is difficult to distinguish early nutrient stress and mild disease.

2.1.5. Lidar sensor

Lidar can directly obtain the three-dimensional structure information of crops and generate high-precision point cloud data by transmitting laser pulses and receiving echoes. Cunhaneto et al. Found that the higher the point cloud density, the stronger the correlation of single tree overestimation, and the smaller the error. 100 points/m2 is the best point cloud density for a lidar UAV to estimate tree height [10]. In crop detection, lidar is mainly used for plant height measurement, canopy vertical structure analysis, leaf area vertical distribution inversion, lodging degree assessment, and biomass estimation [11]. Compared with SFM reconstruction based on visible light, lidar can penetrate part of the canopy and obtain information about internal leaves and the plant bottom. It is not affected by light conditions and can work at night or in weak light. It can clearly distinguish the tilt angle and distribution area of erect and lodging plants. Its disadvantages are high equipment cost, complex data post-processing algorithm, lack of spectral information, and the need to be fused with other sensors. The advantages, disadvantages, and applicable tasks of the above five sensors are shown in Table 1.

Table 1. Comparison of remote sensing sensors of different UAVs

Sensor type	Advantage	Shortcoming	Applicable tasks
Multispectral	Low cost and small amount of data	Low spectral resolution	Large area crop detection
Hyperspectral	High resolution/early diagnosis	Large data redundancy, expensive	Identification and detection of pests and diseases
Thermal infrared	Water stress sensitivity	Low spatial resolution and susceptible to interference	Soil temperature monitoring
Visible light (rgb)	Lowest cost, intuitive	Lack of red edge band	Disease spot, lodging identification
Lidar	Three-dimensional structure, penetrating canopy	Expensive equipment, no spectral information	Lodging monitoring, biomass estimation

2.2. Common Inversion Models

2.2.1. Physical model

Based on the radiation transmission mechanism, the physical model establishes the positive relationship between reflectance and physiological structure parameters by simulating the physical interaction between light and crop canopy; the most representative is the PROSPECT-SAIL coupled radiative transfer (PROSAIL) model [12]. Niuqinglin et al. Combined with UAV digital images and the PROSAIL model, used a look-up table method to retrieve the Leaf Area Index (LAI) of summer maize. The results showed that the estimation accuracy of the random forest regression method combined with PROSAIL was significantly improved (R^2 reached 0.98) [12].

2.2.2. Machine learning model

Machine learning models have developed rapidly in recent years, which can automatically learn the complex nonlinear mapping relationship between remote sensing features and target parameters. Common algorithms include Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and deep Convolutional Neural Network (CNN). Traditional models, such as random forest and support vector machine, essentially establish mathematical relationships through artificially designed vegetation indices (such as NDVI), which can solve some nonlinear problems. However, they cannot directly extract spatial information from the original image, and the upper limit of performance is limited. In contrast, the deep learning model is more powerful. An artificial neural network is composed of multi-layer computing units, which can automatically find rules from data. However, it has obvious defects in image processing. It must "straighten" the two-dimensional image into one-dimensional data, resulting in the loss of the spatial relationship between left and right, up

and down, between pixels, and the shape and lodging trend of crop disease spots depend on this location information.

Deep convolutional neural networks specifically solve this problem. This method introduces a "sliding window" (convolution kernel), which scans the image block by block like a flashlight, analyzes only a small local area at a time, and then combines this local information layer by layer to form a global judgment of the whole image. In this way, CNN can not only see the fine texture of the disease spot, but also combine the surrounding background for comprehensive recognition, showing much better accuracy than traditional methods in the segmentation of the lodging area, weed target detection, and disease grade judgment. For example, Bari et al. used Fast Regin-Convolutional Neural Network (Fast R-CNN) for real-time detection of rice leaf diseases, and the proposed algorithm achieved an accuracy rate of more than 99% in the detection tasks of rice diseases and pests (rice blast, brown spot, and rice planthopper) [13]. At present, specific network architectures such as u-net (for pixel-level fine segmentation) and Yolo (for fast target detection) have been widely used. However, the deep learning model also relies on a large number of labeled samples, and its internal decision-making process is difficult to explain intuitively, so it still needs to be carefully verified when applied across regions.

Machine learning models have significantly improved estimation accuracy, which is the current mainstream method, but it also faces challenges such as high sample size requirements, poor model interpretability, and easy overfitting.

2.3. Application Status Based on Detection Task

2.3.1. Pest identification

UAV remote sensing can identify diseases and pests by detecting the spectral, thermal radiation, and morphological changes of crop canopy. Hyperspectral sensors can detect subtle changes in reflectivity before disease symptoms appear, which is suitable for early diagnosis. The multispectral sensor can distinguish healthy, mild, and severe disease areas by calculating NDVI and other vegetation indices, which is suitable for large-scale investigation. The thermal infrared sensor can indirectly judge the weakening of transpiration caused by diseases by monitoring the increase of canopy temperature, such as the remote sensing monitoring of Cotton Verticillium Wilt and grape downy mildew [6]. A visible light sensor combined with a deep learning algorithm (such as CNN) can realize automatic detection and counting of disease spots. Nagasubramanian et al. Used a new three-dimensional deep convolutional neural network to classify and recognize soybean stem rot, and the accuracy rate reached 95.73% [14]. At present, the main challenges include weak spectral signals in the early stage of disease, overlapping spectral characteristics of different diseases, and insufficient generalization ability of models across regions and years.

2.3.2. Lodging monitoring

UAV lodging monitoring mainly uses remote sensing technology to record electromagnetic spectrum characteristics in real time, and uses different ground objects with different wavelengths or frequencies when transmitting, reflecting, or absorbing electromagnetic waves to distinguish ground objects [11].

Visible remote sensing obtains high-resolution RGB images by UAV, and extracts the lodging area by texture analysis. Lizongnan and others successfully distinguished the corn lodging and non-lodging regions by using the color and texture features of a UAV equipped with an RGB camera, and the error was only 4.7% [12]. The multispectral camera is developed from the visible light camera. Yang and other UAV multispectral images based on the deep learning algorithm resnet-50 have an accuracy of 96% for lodging classification [15]. Lidar can quantitatively assess the lodging area and severity by analyzing the inclination angle of plants and the decrease of canopy height [11]. At present, the research is developing from the simple classification of "lodging and not lodging" to the refined direction of lodging rate estimation and lodging angle classification. However, the versatility of the model under different crop types and different lodging forms still needs to be improved.

2.3.3. Weed detection

UAV weed detection mainly uses the spectral differences, morphological differences, and spatial distribution differences between crops and weeds [16].

Multispectral sensors can distinguish row-sown crops from broad-leaved weeds through the red edge and near-infrared bands. Visible light sensors combined with deep learning, such as YOLO and Mask Region-Convolutional Neural Network (Mask R-CNN), can detect and classify individual weeds in complex backgrounds. Lidar can extract three-dimensional structural features such as plant height and leaf inclination to assist in identifying weeds close to the height of crops [17]. Pengmingxia et al. Introduced the deep learning model of Fast R-CNN convolutional neural network into cotton weed image recognition, with an accuracy of 95.5% [15]. The limitations are that the morphology of weeds and crop seedlings is similar, and the robustness of the model is poor under different light and growth stages [8].

2.3.4. Soil moisture monitoring

There are two ways to monitor soil moisture by UAV Remote Sensing: the canopy temperature index method based on thermal infrared and the soil moisture retrieval model based on thermal infrared [7, 16].

The canopy temperature can be obtained by a thermal infrared sensor, and the crop water stress index (CWSI) can be calculated by combining it with the air temperature to indirectly reflect the soil water status in the root zone. Or the soil moisture can be retrieved by measuring the thermal radiation emitted from the ground surface to achieve a wide range of soil moisture measurement, Wang Fajing et al. Proposed the thermal inertia model of evapotranspiration based on thermal infrared remote sensing technology, and retrieved it by a Back Propagation (BP) neural network. The experimental results showed that Root Mean Square Error (RMSE) was 0.037, and the Unbiased Root Mean Square Error (UBRMSE) was 0.036, and the correlation coefficient was 0.72, which were higher than the commonly used thermal inertia model [15]. At present, the main limitations include that thermal infrared measurement is susceptible to solar radiation, wind speed, humidity, and other meteorological factors, which need to be corrected.

3. Conclusion

This paper systematically summarizes the sensor selection, inversion model, and detection task of UAV Remote Sensing in crop detection. At the sensor level, multispectral technology is mature, cost-controllable, and suitable for large-scale crop monitoring. Hyperspectral resolution is very high, which can realize early stress diagnosis, but the data redundancy is large, and the cost is high. Thermal infrared is sensitive to water stress and can realize early warning, but it is vulnerable to environmental interference. Visible light has the lowest cost, high spatial resolution, and can complete the identification of disease spots and lodging areas combined with deep learning. Lidar can penetrate the canopy to obtain three-dimensional structure, which is a powerful tool for lodging monitoring, but the equipment is expensive, and the data processing is complex. A single sensor is difficult to meet all requirements, and multi-source data fusion is the key direction to improve the detection accuracy.

Secondly, at the level of the inversion model, the physical model mechanism is clear, but the parameter calibration is complex. Machine learning models can automatically learn the nonlinear relationship and significantly improve the estimation accuracy, which is the mainstream method at present. The development direction of the future model is the integration of physical mechanism and data driven. Third, at the level of detection tasks, lodging monitoring is developing from secondary classification to refinement of lodging rate and angle classification. Early diagnosis of diseases and pests still faces challenges such as weak spectral signal and overlapping characteristics of different diseases and pests. The morphological differentiation ability of weed detection at the seedling stage needs to be strengthened.

In view of the above bottlenecks, the following breakthroughs can be made in the future. First, promote the miniaturization and multiple fusion of sensors to achieve one flight and multi-source acquisition. Secondly, build a satellite-space-ground collaborative monitoring network, and promote the deep integration of physical mechanism and data-driven model, so as to truly realize the automation and intelligent closed-loop application of UAV Remote Sensing in precision agriculture.

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