Monitoring of Crop Growth Status based on UAV Multi-Sensor

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Abstract. In recent years, the technology of remote sensing has achieved rapid development in UAV. In addition, the global reduction of arable land has led to increased food security challenges, and the demand for precision agriculture is increasing, and more and more drones are being used in this area.Compared with the traditional satellite remote sensing monitoring crops, UAV with remote sensing has the advantages of high flexibility, little influence by high altitude atmosphere, low cost and high quality of remote sensing images .In order to learn the working principle and shortcomings of UAV remote sensing, this paper mainly introduces and summarizes the types of UAV sensors and the acquisition of data,how to get information on crop growth status and farmland environment including diseases and insect pests, growth stage, weeds and soil environment, through large-scale processing of raw data. This paper also compares the remote sensing effects of different sensors and analyzes the application characteristics of different sensors. This paper also compares traditional algorithm with deep learning methods and list some potential problems. Then the author lists three possible solutions that include secondary analysis, the adoption of iot technologies, and the development of lightweight deep learning systems. Finally, the author analyzes the application prospects and challenges of the technology of UAV remote sensing in view of the current environment and development trend.

Keywords: Plant Protection UAV, Crop Growth Status Monitoring, Remote Sensing Monitoring, Precision Agriculture

1 Introduction

In recent years, due to the acceleration of urbanization, the number of cultivated land area has decreased, besides, frequent occurrence of extreme climate and resource shortage, the crisis of food security has become increasingly serious [1]. Efficient use of cultivated land resources and the cultivation of good crops have become important measures to alleviate food security. Both soil status and crop characteristics information are important indicators to assess the quality of cultivated land and harvest. Traditional information acquisition mostly adopts manual sampling survey method, which has low efficiency, high cost, and incomplete data, contingent problems. In recent years, UAV has developed rapidly in the past few years because it is not limited by the surface form

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and space, and is widely used in industry, national defense, military, agriculture and other aspects.

Remote sensing is used in precision agriculture and smart agriculture widely. For instance, Valentineet al. , in northeastern Germany ,they used satellite remote sensing data from six diverse optical sensors to estimate grain and rape production [2]. Luo Wei of Guangxi University of China, Zhang Muqing of Guangxi Academy of Agricultural Sciences, Jiang Zhuhui of Guangxi Sugar Group, proposed a sugarcane production prediction model based on Sentienl-2 and BiseNetV2 satellites [3]. However, satellite remote sensing usually has low resolution ratio and the undetailed detection level; and the satellite is susceptible to sunlight, weather, climate, ground conditions and other uncontrollable factors, its remote sensing quality is not stable [4]. By ncorporating the RGB sensor, multispectral sensor, thermal imaging sensor to the drones and monitoring at low altitude, people can obtain a variety of information of plants, and analysis of the current growth state by comparing it with normal spectral features. Thus people can carry out a variety of agricultural activities for large or part area even several plants , such as plant irrigation, soil management, pesticide spraying. For example, Zhao Lian et al. in China extracted the soil points in the maize plots through lidar and visible light band difference vegetation index (VDVI), and used the changes in the image spectrum and spatial spectral features after crop lodging to measure the difference in the height before and after the canopy and determine whether the maize plants were lodging [5]. Wu Qiang, Inner Mongolia Agricultural University, monitored and estimated the yield of wheat in Hetao irrigation area in China by using UAV remote sensing technology and machine learning [6]. Ma Shuying studied the spectral feature of chestnut leaves and found that the best spectral features to identify red spider diseases and insect pests on chestnut trees were low side, red edge, green peak and red valley. The chestnut trees in the experimental area were also monitored by aerial remote sensing [7].

The organization of this paper is presented as follows: Section 2 mainly introduces the application of remote sensing in precision agriculture and its working principle. Section 3 outlines the types of UAV and sensors they can carry. Section 4 and 5 introduce the characteristics of electromagnetic wave used by remote sensing technology. In the next section (the section 6), the phenotypic parameters of vegetation composed of different electromagnetic characteristics are introduced. Section 7 and 8 compare the two data processing methods of traditional machine learning and deep learning, and obtain the collocation scheme with the best performance, and then analyze the potential problems of the scheme and list a series of solutions. In the final section 9, a summary and reflection on the whole article is given.

2 Precision Agriculture and Remote Sensing

Global population growth poses a serious threat to the food system. Precision agriculture and smart agriculture can not only help farmers manage their farmland more efficiently, but also increase grain production per unit area. For example, by using sensors in the farm to obtain information and process them, farmers can obtain the real-time growth status of different crops, and carry out targeted agricultural activities such as chemical fertilization, irrigation, and branch and leaf pruning on certain plants, this way can save time and cost.

Precision agriculture has consistently relied on remote sensing as a crucial source of information.It obtains information about the target object by capturing the energy reflected or emitted by the target. Its main process is: (a) provide electromagnetic source. (b) interact between target and sensor. (c) record reflection energy. (d) transmit, receive and process energy into image. (e) analysis image, obtain target information [4].

3 Type of the UAV and Sensor

UAV is a type of aircraft that can be operated either via radio remote control equipment or through an autonomous program control system.In recent years, it has played an irreplaceable role in the aspects of aerial photography, military, national defense, transportation and rescue. The types of drones can be classified according to the following three aspects: (a) fixed wing, rotary wing (single rotor, multi-rotor), flapping wing, hybrid wing, parafoil-wing; (b) according to cruise capability: Hand-hold, Close, Tactical, MALE (low altitude long endurance), HALE (high altitude long endurance), Hypersonic.; (c) according to size: large, medium, small, very small, and micro [8].

In general, small size, light weight, multi-rotor and medium-range drones are suitable for precision agriculture. UAV has a limited load capacity due to the limitation of UAV's size and type. Therefore, the sensor it carries should meet the characteristics of small size, low weight and high precision. Here is an introduction to the different sensors.

3.1 The RGB Sensor

The RGB sensor is used to record the spectrum within the visible wavelength spectrum, and for this reason, using it alone is not enough to obtain some information related to crop health, so it is often used in conjunction with data obtained from other sensors. Currently, a single RGB spectrum is used to monitor and analyze crop diseases and pests and conduct plant classification. For example, Chun-Han Lee et al., by using a vectorized grayscale symbiosis matrix to process RGB data , make the accuracy increase by 3% [9].

3.2 Multispectral Sensor

Multispectral sensor is a sensor equipped with two or more spectral channels [10]. Compared with the visible spectrum, the multi-spectral sensors have a narrower frequency band and can be extracted more information. For example, Tiansheng Li et al., through the visible spectral vegetation index and the multispectral vegetation index,uses three methods to extract cotton seedlings from the soil to predict their emergence rate [11].

3.3 Hyper-spectral Sensor

Compared to multi-spectral sensors, hyper spectral sensors have higher resolution ratio from the narrow band of a crop and can capture more missed detailed information because of the broad band of multi-spectral sensors [12]. For example, Ma Shuying et al.predicted the pest and pest harm grade of red chestnut trees using hyper-spectral images and spectral curves measured by hyper-spectral camera and non-imaging spectrometers [7] .

The price of hyper spectral sensors is high, and the performance improvement of multi-spectral sensors is not proportional to the extra price, so how to apply hyper spectral technology to precision agriculture still needs to be studied and explored.

3.4 Thermal Imaging Sensor

Thermal imaging sensors estimate the degree of crop pests or growth environment based on the change in temperature. Because the working principle of thermosensor is to detect the infrared radiation emitted by an object's surface and translate it into temperature measurements, it is easily affected by the external environment, such as air humidity, wind and wind. Therefore, how to carry out the original image calibration to avoid the relevant impact needs further research and exploration.

3.5 Radar

There are many kinds of radar that have been widely used in agricultural investigation in recent years. For example, lidar sensors acquire the distance between the drone and the vegetation by using laser beams, which can create high-precision 3D maps. Millimeter-wave radar sensors measure the distance of the vegetation by using electromagnetic waves, which is making it an ideal choice for applications that require remote and all-weather monitoring and scanning. The working principle and characteristics of radar enable radar to penetrate vegetation and improve the efficiency of detection and modeling.

4 Spectral Characteristics and Vegetation Index

Electromagnetic wave is a form composed of wavelength and frequency, because of the different wavelength and frequency can constitute different electromagnetic wave. Spectral features can be extracted using the reflectance measured by the sensor in different electromagnetic ranges. The reflected light on the surface of an object is related to the object material. For example, water can absorb the electromagnetic Spectral data within the mid-infrared wavelength range, while the soil is more reflective of it [12]. Therefore, we can judge the distribution area of water and soil by the intensity of the electromagnetic spectrum in the mid-infrared wavelength range received by the sensor. Because the objects of different materials show different reflectivity, the spectral index can be obtained by making algebraic operation on a single optical spectral segment.

In remote sensing images, a spectral index used to quantify the crop vegetation trait index is called the Vegetation Index (VI). It mainly comes from the visible, near-infrared and mid-infrared spectra. Common vegetation indexes include the Normalized Difference Vegetation Index (NDVI), the Red, Green and Blue Vegetation Index (RGBVI), the Green Normalized Difference Vegetation Index (GNDVI) and the Normalized Difference Red Edge Index (NDRE), etc. Among them, for example, NDVI is a multi-spectral vegetation index, which can be acquired by calculating from near infrared and red band. Because chlorophyll absorbs red spectral [13], it can reflect the chlorophyll content of the plant, and then reflect the health status of the plant and predict the growth trend.

5 Texture Features

Image texture plays a great role in the spatial arrangement of the pixel intensity on an image. Edge detection and co-occurrence matrices are two common image texture measures. A feature called Grayscale Co-occurrence Matrix (GLCM) was first proposed by Haralicket [14]. The research extracted 14 texture measures from the GLCM, for example, variance, contrast.Furthermore, integrating texture features with spectral image characteristics or plant phenotypic parameters provides an enhanced approach to estimate the crop conditions. For example, Chun-Han Lee et al., processed RGB data by using vectorized gray symbiosis matrix (GLCMv) instead of GLMC, which improved the accuracy by 3% compared to before [9].

Texture features can complement else image features such as spectra for the estimation of crop traits.

6 Crop Phenotypic Parameters

6.1 Crop Plant Height

Plant height can reflect the structure of the crop population, and when the pixel is small enough, theoretically, it can reflect the structure of a single plant. The plant height is usually estimated by calculating the difference value between the top of the vegetation (Digital Surface Model (DSM)) and the bottom of the vegetation (Digital Terrain Model (DTM)) [12]. DTM stands for the natural ground surface altitude, while DSM contains other features such as vegetation. Two primary techniques exist for determining elevation information: motion structure analysis and multi-view stereo vision, and on-board laser scanning [15]. High plants are prone to lodging; low plants indicate poor health of crops. Therefore, the height of plant plants can effectively judge and predict the growth status and situation of plants. It is usually acquired through lidar and imaging technology. For example, Tao Liu et al., uses fused thermal infrared images and RGB images to extract the lodging area based on the developed model [16].

6.2 Crop Canopy Coverage

The canopy coverage can reflect the growth status of the crop, which is defined as the ratio of the vegetation pixels to the total pixel in each small area [12]. Non-vegetation and vegetation areas can be distinguished by setting the pixel threshold standard. For example, Tiansheng Li et al., vy analyzed the acquired images, proposed three analysis strategies including Otsu threshold analysisuallis, extract cotton seedlings, and predicted the emergence rate of cotton seedlings [11].

6.3 Crop Leaf Area Index

Crop leaf Area Index (LAI) refers to the sum of crop leaf area per unit area. It is mainly derived from its data integration and analysis, such as Songtao Yanget al., proposing a data set to estimate alfalfa's LAI based on information on integrated meteorological data, multiple soil depth, plant height, and plant leaf size [17]. LAI can well reflect the biological effects of various plants, which is also an important basis for evaluating the crop status and predicting the growth trend [13].

6.4 Crop Water Stress

Two important indicators of water stress are stomatal conductance and leaf water potential. The canopy temperature can reflect the stomatal conductivity, so the crop water stress index can be assessed according to the canopy temperature. For example, Zhang Zhitao et al. extracted the maize canopy temperature by using the multispectral features, and put it into the water stress formula to obtain the corresponding index [18].

6.5 Farmland Soil Moisture

Soil Water Content (SMC) defines the nutrient and structure status of soil aggregates, and the management of SMC in cultivated land through proper irrigation can improve the soil states in the key growth period of crops, and thus the crop yield and quality can be improved. It can be acquired at different soil depths through the thermal infrared images taken by the UAV, by calculating the water temperature composite index (including the sum of crop water stress index, canopy and surface relative temperature differences).

7 Data Processing Process and Methods

7.1 Traditional Algorithms

When applying the traditional algorithm to UAV images, three steps are often taken:(a) image acquisition (sections 3 and 4 of this paper). (b)feature extraction (sections 5, 6 and 7 of this paper). (c) model construction (as shown in the Figure 1).

Among them, the image should be processed between image acquisition and feature extraction. Image processing is the foundation of UAV remote sensing research. Because the atmospheric environment, sensor position, UAV flight position and other factors will affect the image imaging effect, the image must be processed before extracting the crop phenotype parameters. The main content of image processing is the post-processing of the images acquired by the UAV, including data quality inspection, image feature point extraction, image matching, aerial triangulation and regional network leveling, generating DEM, orthophoto correction generation of Digital Orthophoto Map (DOM), and image splicing [19].

After the feature extraction is completed, the appropriate model should be selected for the establishment, and then the model prediction and evaluation should be carried out. When constructing a model, the combination of multiple features can often improve the prediction performance of the model. This undoubtedly increases the workload of the researchers.

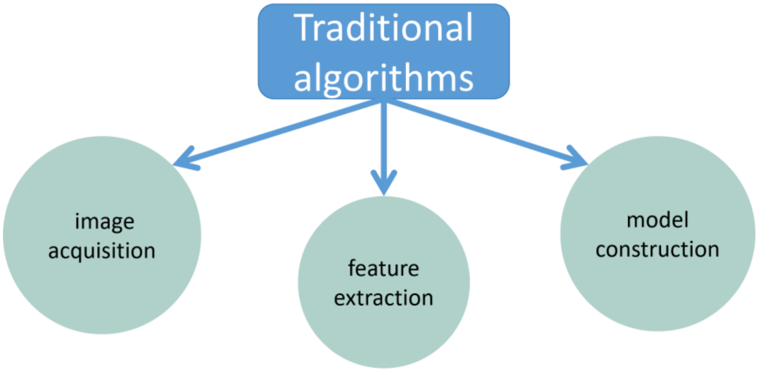

Fig. 1. Workflow diagram of traditional algorithm

7.2 New Remote Sensing Detection Algorithm

The so-called new remote sensing detection is embedded deep learning, replacing the traditional machine vision recognition method. CNN represents advanced deep learning methods for many computer vision-based applications and image processing (as shown in the Figure 2). At present, because the CNN architecture has the powerful ability to automatically extract features from the input images, the typical CNN architecture consists of three (or more) major types of layer groups CNN by convolution operation in each layer, so as to transfer the selective image features to the next layer, thus reducing the size of the image.

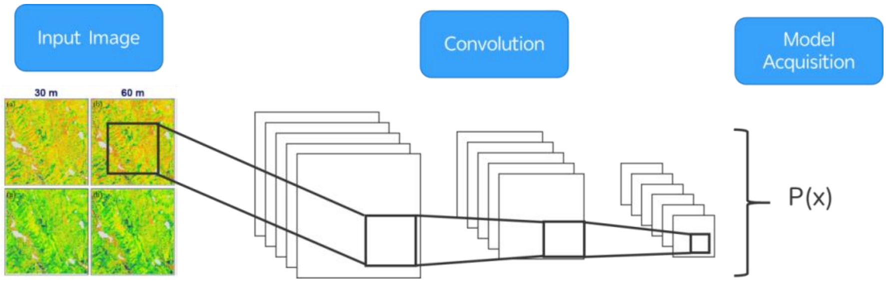

Fig. 2. CNN flow diagram

Therefore, deep learningusing convolutional neural networks allows for automatic feature extraction rather than manual feature screening. In other words, all we need to do is to annotate the data to generate the data set, and then let the system learn by itself and generate the corresponding model (as shown in the Figure 3) .

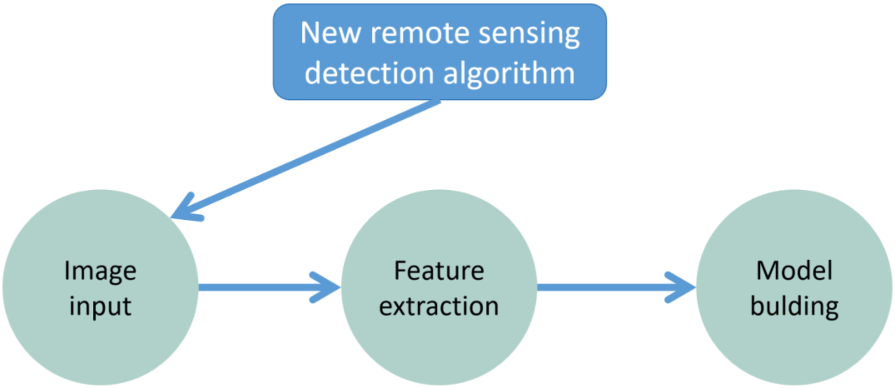

Fig. 3. Workflow diagram of new remote sensing detection algorithm

8 Discussion

1) Compared with a single sensor, the fusion use of multiple sensors can supplement the lack of spectral perception of a single sensor. For example, RGB sensors can be used to obtain visible light images of crops, and set the pixel threshold standard to obtain crop canopy coverage to judge the current crop growth state. However, combined with multi-spectral sensors, the leaf area index of crops (such as chlorophyll content) can be judged by infrared spectroscopy to judge the growth trend of crops.
2) To sum up, compared with traditional machine vision, deep learning algorithm (taking CNN as an example) can independently extract features of single pixels, find the relationship between different pixels and the growth state of crop plants, and build a model to save manpower and time cost.
3) The addition of deep learning has made new requirements for machine performance. Higher performance tends to represent greater mass and volume of hardware. Due to

the limited nature of UAV loading, the processing of data becomes a new obstacle. There are several possible solutions for this problem:(a) Secondary analysis. The real-time data obtained by the UAV is temporarily stored in the airborne processor, and the UAV returns to the base camp after the operation for analysis and processing. (b) The Internet of Things (IoT). By means of the Internet of Things, the real-time data obtained by the UAV is transmitted to the server through the network nodes, and then the data is processed and transmitted to other agricultural machinery and equipment, including the UAV, to realize collaborative operation. (c) Lightweight deep learning. That is to develop a powerful lightweight learning algorithm, so that it can reduce the demand as much as possible to ensure the hardware performance, reduce energy consumption and increase the endurance time of UAV.

9 Conclusion

The rapid development within the sphere has put forward new requirements for precision agriculture, and the new farming mode of UAV combined remote sensing has come into the public view. This study introduces a variety of types of sensors carried by UAV, compares the traditional machine vision algorithm and the visual deep learning algorithm, and finds that the scheme of UAV + multi-sensor + deep learning has the best effect. Compared with the traditional mechanical learning method, this combination method not only can saves people's energy and it has faster analysis speed, but is more conducive to the development of agricultural modernization as well .Compared with the same topic articles, this study also lists some potential problems of deep learning for UAV performance and the corresponding solutions, to provide a possible direction for future research.

The shortcomings of this study: (a) There are many architectures of deep learning. This paper only takes CNN as an example to introduce and compare. (b) In the sensor part, this paper focuses on the types, and does not summarize the data usage of each sensor. In the next step,the autuhor will research the available vegetation index types,and find the overlapping vegetation index of different sensors to optimize the sensor collocation scheme.

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