

The Fusion of Satellite and Unmanned Aerial Vehicle (UAV) Imagery for Improving Classification Performance

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Abstract - In recent years, Unmanned Aerial Vehicle (UAV) technology has made rapid progress, and it is becoming an important way to obtain regional vegetation types due to its characteristics of being flexible, comprehensive and dynamic. UAV-based data recognition technology can make full use of geometry and texture information in images, which is benefit to interpret the attribute characteristics of ground objects. Compared to satellite data, spectral information in UAV data is less detailed. This paper aims to increase the spectral information of UAV data, which helps to improve the accuracy of classification and recognition. For such purpose, data fusion of UAV images and satellite multispectral images is performed. In order to verify the effectiveness of the fused data, three classification algorithms are tested for comparison, which include Support Vector Machine (SVM), Artificial Neural Network (ANN) and Maximum Likelihood (ML). The accuracy of the classification result is evaluated by real ground sampling data. The result shows that, compared to the original UAV data, the classification accuracy of the fused data is significantly improved.

Index Terms - *image fusion; classification; satellite; Unmanned Aerial Vehicle (UAV); vegetation types*

I. INTRODUCTION

The rapid acquisition and analysis of ground vegetation information can provide basic data sources for precision agriculture, and has guiding significance for the monitoring of growing vegetation, disasters and other related information [1]. In terms of obtaining vegetation-related information, the traditional way are mainly based on statistical inquiry and sampling surveys. However, there are obvious drawbacks of those methods, such as strong subjectivity, large errors, laborious and time-consuming [2]. With the development of remote sensing technology, remote sensing ground vegetation recognition methods represented by satellites are widely used [3]. Wardlow et al. [4] used multiple time-series satellite data to analyze the crop planting pattern, growth phenology and crop planting areas. Badhwar et al. [5] combined satellite data with elevation information and other auxiliary features to carry out vegetation classification, and the classification accuracy was improved. Shackelford et al. [6] used object-oriented classification methods to identify crops and reduced fragmentation. Compared with traditional ground survey methods, the above mentioned satellite-based vegetation recognition methods have been improved significantly in effects and efficiency. However, satellites are highly

susceptible to external factors like cloud and fog. In addition, the orbits of the satellites are very high, so it is still difficult to achieve ideal accuracy for ground vegetation recognition.

Due to its flexibility, high-efficiency, economical and centimeter-level high spatial resolution, Unmanned Aerial Vehicles (UAVs) make up for the disadvantages of satellites. UAVs have been used successfully for estimating shrub utilization [7], mapping invasive species [8], measuring plant biomass and nitrogen [9], documenting water stress in crops [10], and mapping rangeland vegetation [11]. Classification and recognition technology based on UAV data provides a new way for vegetation type identification with high efficiency and high precision [12]. Marcaccio et al. [13] used high-resolution, seasonally-related images generated by UAV to classify the main vegetation types of wetlands. It was of great significance to the widespread use of UAVs in civilian use. J.Torres-Sánchez et al. [14] got image data of three different herbs through two cameras mounted on UAVs. Segmented and classified the vegetation cover with an automatic threshold based on object-oriented algorithm, and achieved a certain classification effect. Malek et al. [15] utilized UAV imagery for a given palm farm, applied learning machine classifier to analyse the texture of palm trees from other plants. Based on this, they proposed an effective palm detection framework.

At present, there is no single approach that can generally solve the problem of vegetation identification based on Unmanned Aerial Vehicle (UAV) data. According to the characteristics of high spatial resolution of data, the current study have made full use of spatial information, such as rich texture, shape, and geometry in images [16]. While the majority of UAV data only contain three bands of red, green, and blue, especially missing near-infrared (NIR) band. In this band, different plant types have distinct red reflectance spectra. That is, the information in NIR band plays an important role in vegetation identification. For the foregoing reason, in the existing identification methods, the spatial information of the UAV data is highly utilized but the use of spectral information is insufficient.

The satellite multispectral data have good NIR spectral information, but these data have low spatial resolution. Thus it is difficult to identify the species of vegetation in the image. Based on the characteristics of the above two kinds of remote sensing data, this article proposes to use data fusion

technology, fusing the spatial information of the UAV image and the spectral information of the satellite image to form a new image. Furthermore, Support Vector Machine (SVM), Artificial Neural Network (ANN) and Maximum Likelihood (ML) classification methods are used to compare the performance of the original data and the fused data.

The rest of this paper is organized as follows. Section II starts with a brief review of the study data, and then the overall design is described. The image fusion methods and results are presented in Section III. Section IV describes classification results and analysis for different situations. Conclusions and remarks on possible further work are given finally in Section V.

II. INTRODUCTION OF STUDY DATA AND OVERALL DESIGN

A. General Situations of Study Area

This article chose Pingyi county of Shandong province as the research area, which is at $35^{\circ}07' \sim 35^{\circ}43' \text{ N}$, $117^{\circ}25' \sim 117^{\circ}56' \text{ E}$, located in the south-central part of Shandong province, the west of LinYi City. It belongs to temperate monsoon region continental climate, and has rich natural resources. The research area includes buildings, roads, crops and other land types. The main crop type is honeysuckle. Pingyi is the hometown of China's honeysuckle named by the country. Besides honeysuckle, this study also selected maize, peanut and tree as the main vegetation target. The spatial location of the study area is shown in Fig. 1.

B. Data Source

There are two basic data sources used in this study: UAV imagery and satellite imagery. UAV RGB imagery was obtained with camera ZENMUSE X5s, which is mounted on the UAV system Inspire2. The UAV flew over the study area on May 25th, 2017, with a relative height of 100m, the spatial resolution of the obtained data is 0.02m per pixel.

The satellite imagery selected was multispectral data collected by the GF-1 satellite PMS camera. The GF-1 satellite is the first star of China's high-resolution earth observation system. The PMS camera can obtain panchromatic and multispectral data simultaneously. The acquisition date of satellite data is May 20th, 2017. The data have spatial resolution of 8m per pixel, and coverage period is 41 days. They include 4 bands of red, green, blue and NIR, and the spectral ranges are $0.45 \sim 0.52 \mu\text{m}$, $0.52 \sim 0.59 \mu\text{m}$, $0.63 \sim 0.69 \mu\text{m}$, $0.77 \sim 0.89 \mu\text{m}$. There are some differences in the acquisition time of the UAV and satellite data, but it does not affect the processing effect.

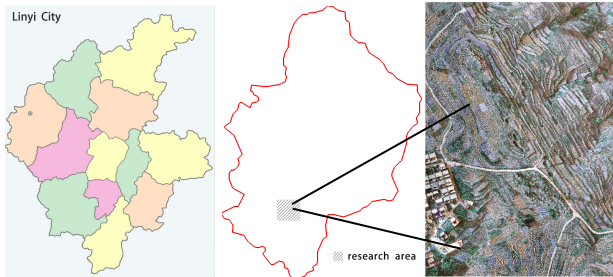


Fig. 1 Location of the study area

C. Overall Design

The overall design flow chart for this study is shown in Fig. 2. Due to the inevitable error in the data collection process, these errors influence the quality of the images. As a result, the images should be proper preprocessed firstly. After preprocessing, the UAV image becomes a single band grayscale image. Then UAV single band image and satellite image are fused to generate a composite image, which preserves the spatial information in UAV image while has the same spectral information in satellite multispectral image. The same classification methods are used to classify the fused image and original UAV image respectively. Then in order to objectively illustrate the effectiveness of this method, the confusion matrix is adopted to validate the accuracy.

The preprocess of satellite multispectral image mainly includes radiation calibration, atmospheric correction and orthorectification. The purpose of radiation calibration is to eliminate the error caused by the sensor itself, so as to determine the accurate radiation value of the good sensor entrance position. In order to correct the errors caused by atmospheric scattering, absorption and reflection, atmospheric correction processing is performed on the radiometric calibration data. Orthorectification is mainly to eliminate the influence of the terrain or the distortion caused by the camera orientation.

The preprocess of UAV RGB image is orthorectification and single-band extraction. The aim of orthorectification of UAV image is the same as that of satellite image. Single-band extraction of UAV image is to turn the UAV RGB image into a grayscale image. This step aims to preserve high spatial resolution of 0.02m per pixel of the original UAV image, preparing for fusion with satellite multispectral data.

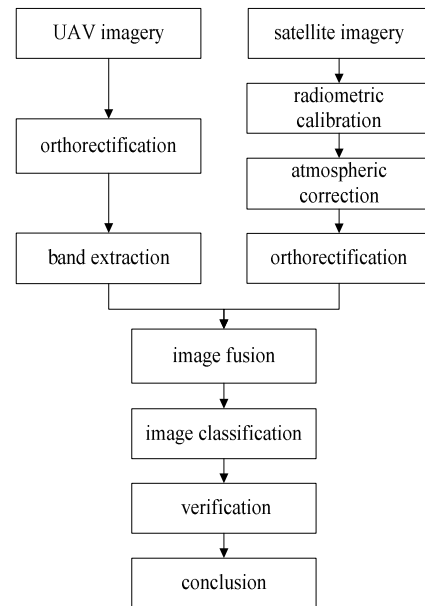


Fig. 2 Overall design flow chart

This paper is based on Orfeo ToolBox (OTB), implemented in C++ programming language under linux environment. OTB is an open source, object-oriented software system, built on the open source geospatial community. It provides a high resolution remote sensing image processing platform with multiple algorithm components. This paper selected the fusion algorithm and three different classification methods integrated in OTB to perform preprocess, fusion and classification.

III. IMAGE FUSION METHOD AND RESULTS

A. Method

The fusion process brings the information from different sensors with different characteristics together to get the best of both worlds. Image fusion can be roughly divided into three levels: pixel level image fusion, feature level image fusion and decision level image fusion. Pixel level image fusion method is chosen in this paper, which uses some algorithm to fuse two or more images of the same area into a composite image that meets some requirements.

After the preprocess, we can proceed to the data fusion. The fusion combines the images from UAV RGB camera and GF-1 satellite PMS sensor to generate images with high spatial resolution and several spectral bands. The implementation of the fusion process is to apply a low pass filter to the UAV single band image to give it a spectral content equivalent to the satellite multispectral image. Then we normalize the multispectral image with this low-pass UAV single band image and multiply the result with the original UAV single band image. The process is described, as shown in Fig. 3.

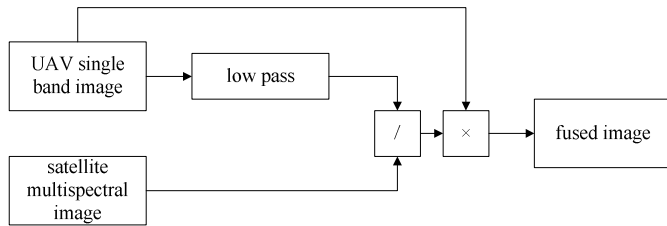


Fig. 3 Fusion procedure

The fusion operation on the two kinds of data is defined as:

$$Fused = \frac{Satellite}{Filtered(UAV)} UAV \quad (1)$$

where $Fused$ represents fusion image, UAV represents UAV single band image, $Filtered(UAV)$ represents low-pass filtered UAV single band image.

The specific operation on the pixel is defined as:

$$DN_{fusedXS(i)} = DN_{UAV} \frac{DN_{XS(i)}}{DN_{filUAV}} \quad (2)$$

The values of each pixel in the fused image can be calculated through the above equation (2). $DN_{fusedXS(i)}$ represents corresponding pixel in the i th band of the fused image. DN_{UAV} represents corresponding pixel in UAV image.

$DN_{XS(i)}$ represents corresponding pixel in the i th band of multispectral image. DN_{filUAV} represents corresponding pixel in low resolution UAV single band image. It also can be said DN_{filUAV} created from low resolution multispectral bands that roughly overlap the spectral response of the input high resolution UAV image [17].

B. Results

There are 24 kinds of false color combinations of the data with 4 bands. Three of them are chosen for display. The RGB 3:2:1 band combination is shown in Fig. 4. Which means the red component of a pixel in the result image is from the value of pixel at the same position in band 3, the green component of a pixel is from the value of pixel at the same position in band 2, the blue component of a pixel is from the value of pixel at the same position in band 1. In this way of band combination, the color of the fused data is very close to the real ground surface color. The RGB 4:3:2 band combination is shown in Fig. 5. The RGB 2:4:3 band combination is shown in Fig. 6. Under these circumstances, NIR spectral information of the data is better reflected. The characteristics of some ground vegetation are more obvious.

As can be observed in these images, the extracted UAV single band image (a) have more abundant spatial information. The boundaries of different vegetation types can be clearly seen. In satellite data (b), images are blurred and details are not enough. But the spectral information in satellite images are better. With different combinations of bands, different spectral characteristics can be presented. After fusing the two kinds of data, this article validated 24 kinds of different band combinations. No matter which band combination method is used, the spectral information of the fusion results is highly consistent with the original multispectral data, while simultaneously preserving excellent spatial information in the UAV data.

The fused data contains red, green, blue, and NIR bands and the spatial resolution is 0.02m per pixel. Through visual interpretation, the NIR spectral information of UAV image is increased after fusion. The image of UAV has been optimized. The visual effect of the fused data is soft, and the features of the ground and landform information are obvious. The fused image can be better used for calculating vegetation indices or for the ground vegetation classification purposes.

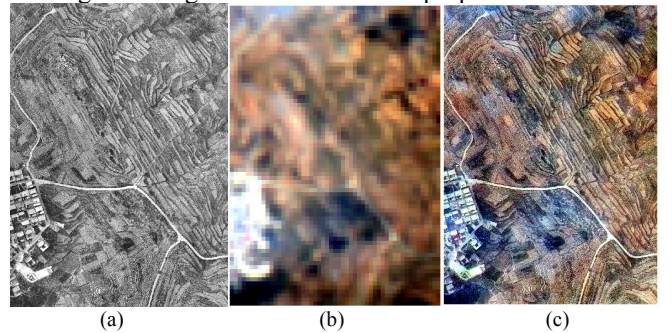


Fig. 4 Images of RGB 3:2:1 band combination. (a) UAV single-band image (b) satellite multispectral image (c) fusion image

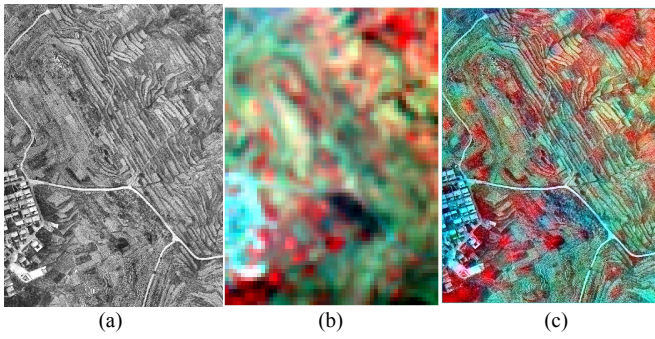


Fig. 5 Images of RGB 4:3:2 band combination. (a) UAV single-band image (b) satellite multispectral image (c) fusion image

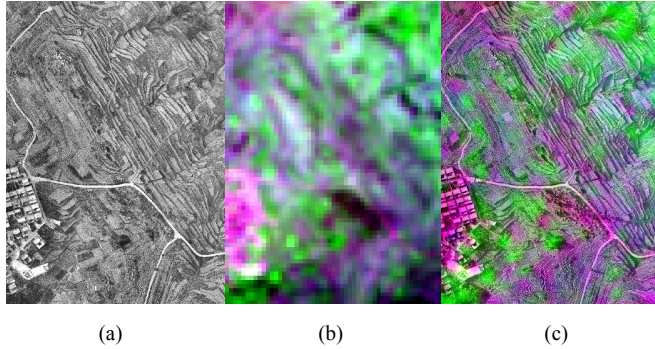


Fig. 6 Images of RGB 2:4:3 band combination. (a) UAV single-band image (b) satellite multispectral image (c) fusion image

IV. CLASSIFICATION ACCURACY AND ANALYSIS

A. Classification Accuracy Verification

SVM, ANN, and ML methods are used to classify and identify peanut, honeysuckle, corn, tree, and other species in the study area. In order to make the experimental results objective, this paper used the same training samples and validation samples under three different classification methods. The number of training samples and verification samples for each class is shown in Table. I.

TABLE I
NUMBER OF SAMPLES IN EACH CLASS

Class	Training Samples	Validation Samples
peanut	7190129	36941
maize	9196570	71267
honeysuckle	18582194	121863
tree	3324558	114882
others	4256114	379559

Confusion matrix was used to evaluate the image classification results. The confusion matrix report of ANN, SVM and ML is shown in Table. II, Table. III and Table. IV respectively.

In the tables, number 1 represents the UAV original image. Number 2 represents the fused image. Prod.Acc and User.Acc refer to the Producer's Accuracy and User's Accuracy respectively. The fifth class of others refers to the synthesis of non vegetation types such as road, bare land and building.

TABLE II
ANN CONFUSION MATRIX REPORT

Class	Prod.Acc1 (percent)	User.Acc1 (percent)	Prod.Acc2 (percent)	User.Acc2 (percent)
peanut	68.98	73.53	83.06	60.55
maize	69.23	58.04	71.89	57.02
honeysuckle	73.81	61.9	72.33	78
tree	76.26	72.14	87.77	91.2
others	83.08	91.43	84.92	87.81
overall accuracy1= 78.53 Kappa coefficient1= 0.73				
overall accuracy2= 85.72 Kappa coefficient2= 0.81				

TABLE III
SVM CONFUSION MATRIX REPORT

Class	Prod.Acc1 (percent)	User.Acc1 (percent)	Prod.Acc2 (percent)	User.Acc2 (percent)
peanut	71.86	64.69	75.45	69.22
maize	70.76	58.95	81.39	68.08
honeysuckle	55.33	63.73	59.07	43.62
tree	66.63	78.75	84.37	96.99
others	83.54	88.26	80.35	50.69
overall accuracy1= 78.59 Kappa coefficient1= 0.73				
overall accuracy2= 82.42 Kappa coefficient2= 0.75				

TABLE IV
ML CONFUSION MATRIX REPORT

Class	Prod.Acc1 (percent)	User.Acc1 (percent)	Prod.Acc2 (percent)	User.Acc2 (percent)
peanut	60.01	58.29	66.49	81.78
maize	62.43	51.72	79.41	79.43
honeysuckle	60.72	71.11	78.39	70.94
tree	74.17	83.69	80	85.31
others	72.34	68.1	83.8	76.35
overall accuracy1= 72.29 Kappa coefficient1= 0.65				
overall accuracy2= 80.65 Kappa coefficient2= 0.76				

As can be seen in the tables, using ANN classification method, the overall classification accuracy of data 1 is 78.53%, and Kappa coefficient is 0.73. The overall classification accuracy of data 2 is increased by 7.19%, and Kappa coefficient is increased by 0.08; Using SVM classification method, the overall classification accuracy of data 1 is 78.59%, and Kappa coefficient is 0.73. The overall classification accuracy of data 2 is increased by 3.83%, and Kappa coefficient is increased by 0.02; Using ML classification method, the overall classification accuracy of data 1 is 72.29%, and Kappa coefficient is 0.65. The overall classification accuracy of data 2 is increased by 8.36%, and Kappa coefficient is increased by 0.11. Under three different classification methods, the classification accuracy of the fused image is improved compared to the original UAV image. After data optimization, the overall classification accuracy are all over 80%, the Kappa coefficient is greater than or equal to

0.75. It shows that the validation samples are in good agreement with the real classification results.

In the 5 classes used in this study, the three methods generally have higher recognition accuracy for the fifth class. The reason is that the spectral characteristics of vegetation are significantly different from those of non vegetation types. In several vegetation types, the classification performance of trees is better. Peanuts are covered with plastic film in the data obtained, thus the classification accuracy of peanuts with thin film is poor in original UAV data. After fusion, the classification accuracy of peanuts increased greatly. Honeysuckle and trees are similar in shape and color, and the probability of misclassification between these two classes is higher.

Among the three classification methods adopted in this study, the ANN method has the highest classification accuracy for the two data, followed by SVM and the worst is ML. In the process of classification, ANN can be more convenient to add auxiliary data provided by GIS, so as to improve classification accuracy of the data. Compared to ML, the SVM method has advantages in adaptive ability, learning speed, high-dimensional feature space and expressiveness, so a better classification performance is shown in this study.

B. Analysis

Green plants have a strong response to electromagnetic waves. The spectral response characteristics of green plants is shown in Fig. 7.

As shown below, in the visible light spectrum, various pigments of the leaves play a dominant role in the spectral properties of the plant, of which the most important one is the chlorophyll. Because the pigment causes strong absorption, the leaves in the plant show very low reflection and transmission. For that reason, in the visible light band, green plants often appear darker features.

In the range of $0.74\sim1.3\mu\text{m}$, high reflectance occurs in the NIR spectral. In the NIR, the complex cell structure inside the ground vegetation leaves determines the strong red light reflectance characteristics of the plant. Since the internal structure of the leaves varies greatly between plant species, different plant species can be distinguished by measuring the reflectance in the NIR spectrum. This is the theoretical basis for improving the accuracy of classification by fusing data from UAV images and satellite multispectral images.

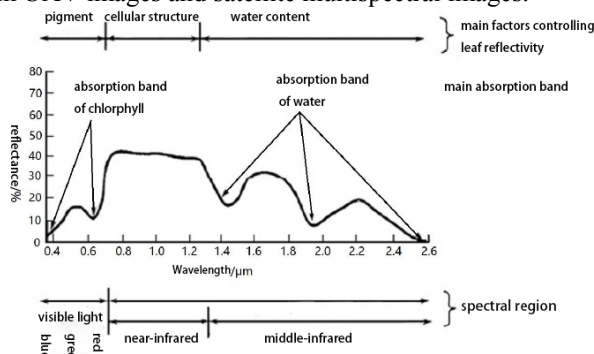


Fig. 7 Spectral response characteristics of green plants

V. CONCLUSION

In this paper, pixel level image fusion technology was used to combine spectral information in satellite multispectral images with spatial information in UAV images. Then three different classification methods were applied to classify original UAV image and data-fused image respectively. Classification results were compared quantitatively by confusion matrix. In contrast to original UAV data without NIR information, we classify fusion-processed data under different methods. The overall classification accuracy, Kappa coefficient have been improved obviously. It can be concluded that by fusing of UAV data and satellite data, the performance of vegetation recognition based on UAV data can be improved. Beyond that, good fusion results can also lay the foundation for subsequent processing of other applications such as feature extraction or image interpretation. The results can provide methodological support for agricultural resources surveys and other precision agriculture sectors.

The verification methods chosen in this paper are all pixel-based classification methods. There is a high degree of fragmentation and relatively low classification accuracy in the recognition of ground vegetation. While with the increasing number of high-resolution remote sensing images, object-oriented image classification methods have been widely studied and applied. Therefore, in the future work, we will combine appropriate segmentation algorithms and use object-oriented classification methods to conduct research, so as to better exploit the advantages of the fused data.

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