Typical Feature Information Extraction of Transmission Corridor Based on UAV Inspection Hyperspectral Image

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Keywords: Hyperspectral, Drone, Transmission corridor, C-SVM, Feature recognition.

Abstract. The difference in growth rates of different types of trees around a transmission corridor leads to different levels of threat to transmission lines. In order to develop a reasonable and efficient maintenance plan for targeted needles, a high-spectral aerial survey of 110kv transmission lines was carried out, and high-threat areas with dense trees were selected for analysis. After using the competitive adaptive re-weighting algorithm (CARS) to select the feature bands, the cluster-support vector machine (C-SVM) algorithm is used to classify the four typical trees around the line with the transmission lines, bare soil, and rivers. The results show that the C-SVM classification can get better classification results, and the accuracy of the classification result reaches about 0.95.

Introduction

With the development of the national economy, electricity consumption has increased year by year, and the power grid has put forward more requirements for operational safety. The development of the West-East Power Transmission Project has enabled the installed capacity in the Southwest to increase year by year. Due to a large number of mountainous areas in the southwest, the transmission corridors are lined with trees, and the threat of tree-sharing to transmission lines has gradually become one of the main threats affecting the safe operation of power grids. The traditional ways to prevent trees from threatening are mostly manual inspections, which have long cycle times, high risk and high labor. In 2019, the State Power Corporation proposed to establish a ubiquitous power Internet of Things to build a smart grid. A smart service system with efficient information processing and convenient and flexible application. Among them, the UAV inspection line has achieved initial success as an efficient power grid inspection method. The use of drones to carry altimeter tools for transmission line inspections and the measurement of threatening trees have been studied. Despite this, studies have shown that the difference in the growth rate of different trees, resulting in unresolved trees, there is a certain safety hazard in the unified deforestation, and unified efforts to increase the deforestation will undoubtedly cause manpower waste. In order to develop a tree harvesting plan and improve the smart grid, the identification of high-threatening tree types in transmission lines is indispensable.

The airborne hyperspectral image was taken with a hyperspectral instrument on an aircraft platform to obtain relevant data. By extracting the hyperspectral information, the judgment of the type of the object can be performed. Literature [1] classifies Indian Pines and Pavia University images (including farmland, buildings, rivers, etc.) by multi-core fusion multi-scale feature classification methods, and identifies more than 90% of small samples. In [2], the ore and black soil were identified by airborne hyperspectral image reconstruction, information extraction, and modeling. In [3], the inversion vegetation cover model was constructed by classical model and NDVI by analyzing the slope of vegetation red edge band. Literature [4] and [5] realized the identification of faults in transmission line components through the analysis of the inspection images of drones. In [6], the multi-spectral remote sensing map carried by the UAV is used to perform corner detection and edge contour feature extraction. The 3D reconstruction of remote sensing image is carried out in combination with the invariant moment feature extraction method of the ground object.
The existing literature has not yet identified the typical feature information along the transmission line. At this stage, the line survey personnel need to combine the ground survey and the manual inspection on the threat of the transmission line. Due to the professional limitations of line workers, existing tree growth models cannot be accurately applied in practice. Therefore, this paper proposes a method for obtaining high-spectral images by using drones, and proposes a method for using aerial photographing hyperspectral images to carry out typical classification of transmission lines and surrounding areas.

**Image Sample Library Creation**

**Acquisition of Image Data**

The line of survey samples used hyperspectral images taken by drones. The shooting location is outside the East Gate of Southwest Jiaotong University. The 110kv high-voltage transmission line has a high-risk tree barrier. The drone adopts the Dajiang company drone and is equipped with the Ronin-MX head to keep the spectrometer running smoothly during shooting. The spectrometer uses the GaiaSky-mini2-VN built-in push-scan UAV hyperspectral imaging system. There are a total of 59 hyperspectral images, including transmission lines with typical threats, high-threat vegetation and rivers around the transmission lines, and land. The single image size is about 700M, including 1057×960 pixels, and there are 176 bands. Select the image with the highest threat level for processing. The image classification includes four types of typical trees and lines, rivers, bare soils, etc., and other non-concerned samples are considered to be the eighth category. For each type of sample, 20% was selected as the training set, and the other part was used as the test set for classification test. The sample types are uniformly scaled to the same size.

![Figure 1. Seven categories of classification samples.](image.png)

**Spectral Correction**

The hyperspectral image acquired by aerial photography is often affected by the non-uniformity of the light source, the response difference of the photosensitive unit itself, the dark current and the offset, etc., and the target of a certain gray level may cause different upper limit of the output intensity of different bands. Phenomenon is not good for target feature extraction and analysis in subsequent image processing.

The most obvious phenomenon is reflected in the difference in the amplitude of the whiteboard model before uncorrected in different bands. The whiteboard reflection spectrum is shown in the Figure 2.
Since the aerial photography height is about 120 meters, the cloud layer has little interference with the image, and the meteorological noise can be ignored. Correct the image directly in black and white. The image of the whiteboard file is $I_{\text{white}}$ (reflectance is 99%); the camera lens is attached to the camera, the camera is turned on, and the image of the blackboard file is captured as $I_{\text{dark}}$ (reflectance is close to 0%). The original image is corrected by $I_{\text{raw}}$, and $R_{\text{cal}}$ is the corrected hyperspectral image. The correction formula is:

$$R_{\text{cal}} = \frac{I_{\text{raw}}-I_{\text{dark}}}{I_{\text{white}}-I_{\text{dark}}}$$  \hspace{1cm} (1)

**Sample Feature Extraction**

Since the spectral data obtained by hyperspectral measurement has a certain collinearity, the calibration model established using the full spectrum data must contain a lot of redundant information [7]. These redundant information will have a negative impact on the discriminative ability of the classification model. It has been shown that, theoretically and experimentally, the performance of the classification model can be improved by using the selected information wavelength instead of using the full spectrum [8-10].

The Competitive Adaptive Weighting Algorithm (CARS) combines the adaptive reweighting technique with the regression model to obtain a set of characteristic spectral segments with the highest correlation.

1) Randomly select $k$ samples to establish a PLS model. Record absolute regression coefficients, calculate weights, and calculate the ratio of variables to use.

2) The adaptive re-weighted sampling (ARS) technique is used to select the wavelength point where the absolute value of the regression coefficient in the PLS model is large.

3) Remove the wavelength point with small weight and use interactive verification to select the lowest subset of RMSECV, which can effectively find the optimal combination of variables.

**Clustering SVM Classifier Establishment**

The traditional SVM classifier is a two-classification algorithm that uses known samples for classification training to establish a hyperplane between two species. Multi-class SVM is usually further derived from the binary classification model. As a supervised algorithm, SVM has its unique advantages. However, due to the similarity between different reflectances of vegetation in hyperspectral imaging, the occurrence of noise causes the staff to judge the classification results. Therefore, the classification results need to be further corrected.

Spatial information is the embodiment of the line superimposed on the overall picture. The traditional use of spatial information is based on the entropy, mean, energy and other information of
the grayscale texture of the image, and is added to the SVM algorithm to classify as a certain feature quantity. However, the research shows that the intra-image similarity clustering is carried out by using the contrast and autocorrelation of the spatial information texture degree. The clustered image is compared with the original classification image, and the classification in the same region is considered to be uniform. This correction algorithm has higher classification accuracy. Due to the difference of different bands, the local spectrum changes, resulting in the gray matter texture difference of the same kind of articles. In order to reduce the difference caused by this change, improve the spectral relationship of adjacent similar objects, and add a spatial filtering algorithm to improve the image. The spatial filtering algorithm uses weighted filtering, and the calculation formula is as shown in equation (2).

\[
X'_i = \frac{X_i + \sum_{k=1}^{w^2} v_k x_{ik}}{1 + \sum_{k=1}^{w^2} v_k} \quad (2)
\]

where \(X'_i\) is the central pixel after weighted average filtering, \(X_i\) is the central pixel of the gray level co-occurrence matrix, and \(x_{ik}\) is the other pixels in the gray level co-occurrence matrix. The whole image can construct a plurality of such matrices according to the window size. \(v_k\) performs spectral segment filtering by weight while measuring the position of the pixel and the center pixel. Its formula is

\[
v_k = \|y(X_i - x_{ik})\| \quad (3)
\]

After that, the processed image is used to process the SVM classification result. When the specified condition is met, the pixel in the small window is considered to be classified and corrected:

1. The converted image matrix has a central pixel point contrast in the small window that is greater than the threshold.
2. Within the small window, the total number of the same species is greater than half of the total number of windows.
3. Analyze the distance of the pixel points in the window from the central pixel point, and perform weighting processing according to the distance to calculate the total classification sample. The specific calculation is as shown in equation (4).

\[
Y_i = \max\left(\frac{1}{\|x_{iy} - X_i\|}\right) \quad (4)
\]

where \(Y_i\) is the maximum classification effect probability value of the window after statistics, \(x_{iy}\) is the pixel point classified as y, and \(X_i\) is the center pixel.

When \(Y_i\) is greater than the threshold, the window classification is considered to require correction. Condition (1), (2), and (3) satisfy any two, and image segmentation is performed with the pixel center as the root, and the image is classified and corrected.

- **Tower and Ground Object Information Identification**

The images in the aerial image with high line threat and high threat trees are selected for classification. After the correction is completed, the feature band extraction, classification and correction are sequentially performed.

- **Extracting Feature Segments**

First, the classification samples in 7 are defined as 1-7, and the corresponding bands are as follows:
The band extraction is performed by CARS. The operation process is shown in Fig. 4. Fig. 4(a) shows the process of decreasing the reaction variables, Fig. 4(b) is the response to the RMSECV of different models in the PLS process, and Fig. 4(c) reflects the wavelength regression. The change in the coefficient. The threshold is set to 0.8. The number of selected bands is 12, which are selected as 10, 14, 55, 71, 73, 110, 116, 127, 128, 147, 150, and 173 bands.

**Classification Model**

The feature bands obtained after processing are input into the classification model, and the traditional SVM model and the clustering SVM model are used to classify the small areas of the excerpt, and the region includes 50 line samples and 200 samples of 2-7 types each. The judgment results are shown in Table 1 and Table 2.

### Table 1. Traditional SVM model classification results.

| line  | bamboo | soil | river | duying | cedar | yinxiang |
|-------|--------|------|-------|--------|-------|----------|
| line  | 29     | 5    | 4     | 0      | 25    | 13       | 1        |
| bamboo| 3      | 124  | 17    | 0      | 8     | 21       | 8        |
| soil  | 0      | 23   | 153   | 0      | 0     | 6        | 23       |
| river | 0      | 0    | 0     | 200    | 0     | 0        | 0        |
| duying| 12     | 22   | 23    | 0      | 114   | 24       | 14       |
| cedar | 6      | 12   | 2     | 0      | 45    | 129      | 2        |
| yinxiang| 3     | 14   | 1     | 0      | 8     | 7        | 152      |

Kappa 0.6704
Table 2. Clustering SVM model classification results.

|        | line | bamboo | soil | river | duying | cedar | yinxiang |
|--------|------|--------|------|-------|--------|-------|----------|
| line   | 38   | 3      | 4    | 0     | 5      | 3     | 1        |
| bamboo | 3    | 171    | 11   | 0     | 10     | 6     | 0        |
| soil   | 0    | 11     | 169  | 0     | 0      | 1     | 16       |
| river  | 0    | 0      | 0    | 200   | 0      | 0     | 0        |
| duying | 4    | 7      | 13   | 0     | 154    | 2     | 14       |
| cedar  | 3    | 4      | 2    | 0     | 23     | 181   | 2        |
| yinxiang | 2 | 4      | 1    | 0     | 8      | 7     | 167      |

Kappa 0.8391

It can be seen that the clustered SVM model has a more accurate classification ability than the traditional SVM classification. At the same time, within a certain range, it compensates for the existence of the wrong point in the same species of trees. Therefore, the traditional SVM classification and clustering SVM classification are performed on the complete images. The specific results are shown in Figure 5. And the correct classification rate reached nearly 95%.

Conclusion

This paper presents a typical feature extraction method for the hyperspectral image of the UAV line of transmission lines. The method firstly performs unified pixel size processing on the acquired images. Then, based on the feature band extracted by CARS, the clustering SVM classification method is used to extract typical features, and the traditional SVM classification algorithm is used for comparison experiments to find clusters. The SVM algorithm can achieve better classification results in the detection of typical objects along the transmission line. Although there is still some misunderstanding in this method, the improvement of the accuracy of the single area still reduces the pressure of staff identification, and the canopy area with high threat is well recognized. The realization of typical ground object identification of transmission lines has laid an important foundation for the construction of smart grids. The next step is to carry out crisis warning treatment on the identified features.

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