EXTRACTION OF SUNFLOWER HEADS IN XINJIE MINING AREA BASED ON UAV VISIBLE LIGHT IMAGES

by

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Coal resources play a crucial role in societal development. However, intensive coal mining frequently leads to environmental degradation. Monitoring surface crop growth in mining areas is essential for ecological assessments and a critical component of evaluating mining disturbances. In this study, sunflowers growing on the first mining face of the Xinjie Mine were selected to explore an efficient crop extraction method. Visible-band imagery was captured using a UAV, and the spectral characteristics of the sunflowers were analyzed. A red-blue difference index was developed, and the histogram threshold segmentation was employed for sunflower extraction. Four supervised classification methods containing maximum likelihood, minimum distance, support vector machine, and random forest method were compared to evaluate the performance of each extraction technique.

Key words: *crop identification, mining disturbance, vegetation index, ecological restoration monitoring*

Introduction

Coal mining activities often disrupt surface vegetation and soil, resulting in reduced crop yields and degradation of vegetation [1]. With increasing environmental awareness and advancements in technology, green mining has emerged as a key developmental direction in the coal industry [2]. As a result, accurately monitoring surface vegetation growth has become essential for assessing ecological disturbances in mining areas [3].

The Ordos Mining Region in northwest China is a crucial coal base for the national energy supply, characterized by abundant resources and numerous undeveloped coal fields. The region's predominant vegetation includes sunflowers, corn, and camphor pine. As the main cash crop, sunflowers provide significant economic value while stabilizing soil, reducing erosion, and supporting the growth of other plant species. Accurately extracting sunflower data is vital for evaluating mining-induced disturbances [4].

Traditional manual field surveys are labor-intensive, time-consuming, costly, subjective, and unsuitable for large-scale or long-term monitoring. Therefore, developing efficient and accurate vegetation extraction methods is crucial for ecological monitoring in mining regions. Advances in UAV remote sensing technology and data analysis have made vegetation monitor-

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ing more accessible and cost-effective [5]. The UAV-acquired visible light imagery has gained popularity for crop recognition due to vegetation indices that quantify vegetation distribution and texture details. Numerous studies have proposed innovative vegetation indices to improve plant extraction accuracy. Gao *et al.* [6] developed the ultra-green, red, and blue difference index to reduce interference from similar features and shadows in UAV images. Zhang *et al.* [7] introduced the color index for vegetation extraction, which effectively estimates fractional vegetation cover in mixed cropping systems. Chen *et al.* [8] created the improved red, green, and blue vegetation index, demonstrating high accuracy in plateau regions compared to 13 other visible light-based indices. Hu *et al.* [9] proposed the green-blue-red difference index, which enables fast and accurate extraction of oilseed rape seedlings while distinguishing background features such as weeds and soil. Zhu *et al.* [10] developed a similar color difference vegetation index, which effectively identifies dragon fruit plants and facilitates single-plant extraction.

This study focuses on sunflowers located at the first mining face of the Xinjie Mine. The red-blue difference index (RBDI) was constructed from red, green, and blue (RGB) images, and threshold segmentation was applied to extract sunflower heads. Four supervised classification methods, maximum likelihood, minimum distance, support vector machine, and random forest, were compared to evaluate the accuracy and feasibility of sunflower extraction using this index. The findings offer significant value for real-time monitoring of crop yields and assessments of vegetation conditions in mining areas.

Study area and data sources

Study area

Figure 1 illustrates the study area located in the Xinjie Taigemiao mining region of Ordos city, situated in the southwest of the Inner Mongolia Autonomous Region, China, within the co-ordinates of 109.80°-110.80° E longitude and 38.30°-39.30° N latitude. This region, part of the Inner Mongolia Plateau, has a temperate continental climate. Sunflower, the predominant crop in the area, was selected as the focus of this study to develop an accurate method for extracting and identifying sunflower flower heads.

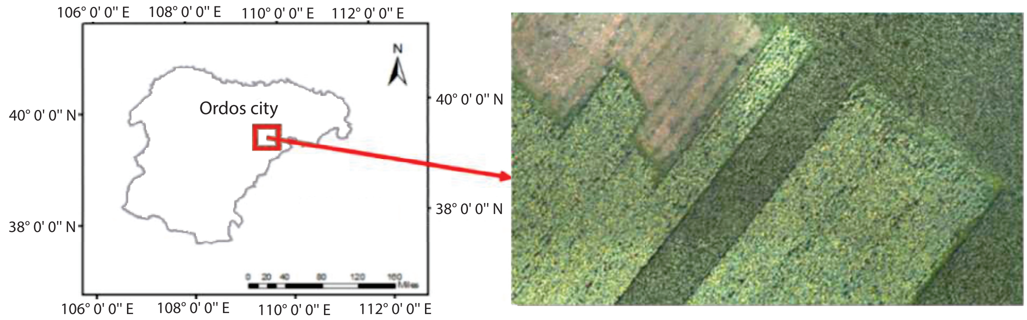

Figure 1. Study area

Data sources

The RGB image data of the study area were collected using a DJI M600 drone equipped with a Phase One IXM 100MP camera. The data acquisition parameters included 80% front overlap, 70% side overlap, and a flight altitude of 500 m. The camera settings were configured for auto exposure and auto white balance, with images saved in IIQ format. Orthophotos with an 8-bit depth were generated using AGISOFT METASHAPE software, and the pixel values ranged from 0 to 255.

Research methodology

Technology roadmap

Figure 2 shows the technical roadmap. The RGB orthophotos were preprocessed, and 106 sunflower training samples and 170 validation samples were extracted. The study employed supervised classification, comparing four techniques, maximum likelihood, minimum distance, support vector machine, and random forest. During the training, the classifiers analyzed features and category labels from the training samples to distinguish between feature types and generate classification results. The exponential method was used for sunflower extraction from the preprocessed images, followed by refinement using a histogram-based single-threshold segmentation method. Classification performance was evaluated by comparing the true values from the validation samples with the classification outputs, and accuracy metrics were calculated accordingly.

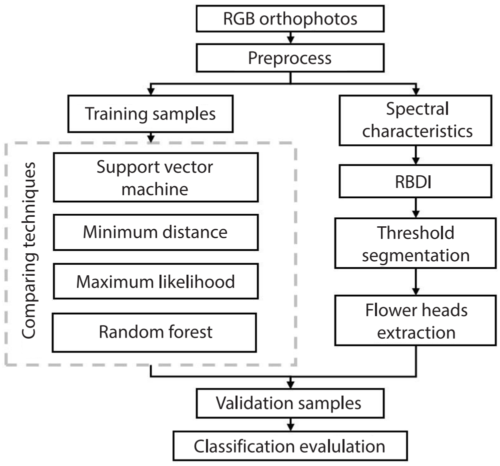

Figure 2. Technology roadmap

Visible light index construction

A visible-light index was constructed by combining the red, green, and blue bands to enhance sunflower differentiation from other features. Spectral analysis of sunflower reflectance revealed that its red band reflectance exceeds that of the green and blue bands, indicating strong red-light reflection and green/blue-light absorption. Utilizing this property, the RBDI was formulated to highlight sunflower spectral characteristics. The RBDI is calculated:

$$RDBI = \frac{2R-3B+G}{B} - \frac{R-2B+G}{B} \tag{1}$$

where R is the red band, G – the green band, and B – the blue band.

Histogram-based single threshold segmentation method and evaluation indicators

Histogram-based threshold segmentation is a widely used image processing technique. The method involves analyzing the grayscale histogram of an image to identify an optimal threshold for segmenting it into distinct regions. Pixels are divided into two groups containing the foreground (gray values above the threshold) and the background (gray values below). In this study, the threshold was chosen to separate sunflowers from other features based on their grayscale distribution. Segmentation performance was evaluated using key metrics, including producer's accuracy, misclassification error, omission error, and overall accuracy, to assess consistency and accuracy relative to true annotations.

Results analysis

Figure 3 shows a grayscale histogram, which represents the statistical distribution of pixel values. It was analyzed to determine the appropriate threshold. As shown in fig. 3, a significant change is at a gray value of 4.8235. It indicates that the sunflower pixels are separated from other features. Therefore, 4.8235 was chosen as the threshold to extract sunflower pixels.

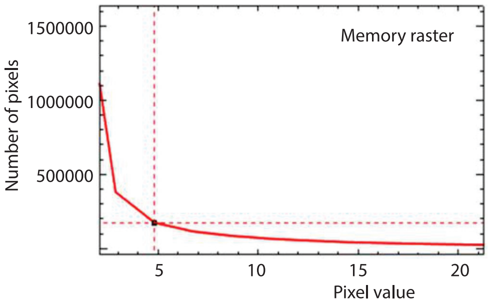

Figure 3. Grayscale histogram representing the statistical distribution of pixel values

Figure 4 compares the extraction results of sunflowers by different classification methods. It can be seen the performance of the exponential method is optimal due to the most accurate recognition results, see fig. 4(f). Quantitatively, some evaluated metrics containing the producer's accuracy, misclassification error, omission error, and overall accuracy are calculated. The maximum likelihood method achieved a producer's accuracy of 95.18%, a misclassification error of 67.27%, an omission error of 4.83%, and an overall accuracy of 56.83%. Similarly, the minimum distance method recorded a producer's accuracy of 69.53%, a misclassification error of 67.23%, an omission error of 30.86%, and an overall accuracy of 66.56%. The random forest method achieved a producer's accuracy of 88.43%, a misclassification error of 2.21%, an omission error of 11.44%, and an overall accuracy of 93.95%. The support vector machine method yielded a producer's accuracy of 87.57%, a misclassification error of 1.75%, an omission error of 12.63%, and an overall accuracy of 93.12%. The vegetation index method achieved a producer's accuracy of 95.42%, a misclassification error of 0.50%, an omission error of 4.28%, and an overall accuracy of 95.26%. For features like sunflowers, corn, and land, the maximum likelihood and minimum distance methods were less effective, frequently misclassifying other features as sunflowers. Both random forest and support vector machine methods could extract most flower heads but still faced misclassification issues. In contrast, RBDI extracted flower heads more accurately, avoiding the misclassification of other features. It amplified the spectral differences between sunflowers and other categories, ensuring precise extraction of sunflower heads. The accuracy metrics highlight RBDI's superiority, achieving higher mapping and overall accuracy while minimizing omission and misclassification errors compared to other methods. Thus, RBDI provides an efficient and reliable approach for accurately extracting sunflower heads.

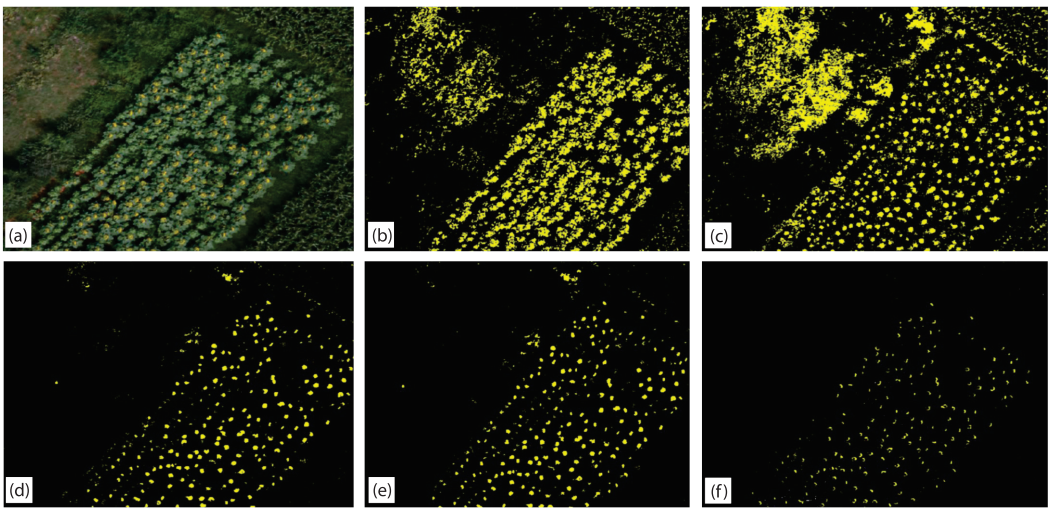

Figure 4. The extraction results of sunflowers; (a) original figure, (b) maximum likelihood, (c) minimum distance, (d) random forest, (e) support vector machine, and (f) RBDI

It is worth noting that the index proposed in this study consists of two-components. The formula $(2R - 3B + G)/B$ effectively highlights sunflowers but fails to accurately extract flower heads, frequently misclassifying stems, leaves, and other features as part of the flower head. To reduce the background's influence on sunflower extraction, the formula $(R + G - 2B)/B$ was used to calculate the background value. Subtracting this value from the initial results significantly suppressed the misclassified areas, resulting in improved extraction through threshold segmentation.

While the combined index and threshold segmentation method effectively extracts sunflower heads and identifies most flower heads in the image, certain challenges persist. Isolated noise points occasionally arise due to sensor noise, illumination variations, or reflections, which may interfere with subsequent image analysis. To address this issue, future studies could incorporate denoising techniques such as median filtering, Gaussian filtering, or advanced algorithms to smooth the image and minimize noise points. Over-segmentation of flower heads presents another challenge. Factors such as image resolution, lighting, or flower head morphology may cause RBDI to segment a single flower head into multiple parts, reducing extraction completeness and impacting feature extraction and classification accuracy. Future research could utilize morphological image processing techniques, such as erosion, dilation, and opening/closing operations, to refine boundaries and correct over-segmentation issues. Algorithm parameter settings also play a critical role in extraction performance. While this study experimentally determined a suitable threshold, variations in image characteristics may necessitate different parameter settings. Future studies could investigate parameter optimization strategies, such as particle swarm optimization, to improve the algorithm's adaptability and generalization.

Conclusion

This study utilized UAV-acquired visible-light images and spectral analysis to develop the RBDI for accurate extraction of sunflower flower heads in the Xinjie Mine sunflower plots. The RBDI demonstrated significant advantages over traditional supervised classification methods-maximum likelihood, minimum distance, support vector machine, and random forest-achieving higher mapping and overall accuracies of 95.42% and 95.26%, respectively, with minimal misclassification and omission errors. The results underscore the effectiveness of spectral-based vegetation indices for crop identification and provide a robust technical approach for vegetation monitoring and ecological management in coal mining areas. This method holds promise for improving precision agriculture and supporting the restoration of disturbed ecosystems.

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Nomenclature

R – red band, [–]
B – blue band, [–]
G – green band, [–]

Acronyms

RBDI – red-blue difference index
RGB – red, green, and blue
UAV – unmanned aerial vehicles

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