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PCA-Based Method for Extracting Outer Crop Row Lines

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Abstract: China has the largest white radish cultivation area in the world, but its level of mechanized harvesting remains low, relying mainly on manual labor. In complex field environments, accurately extracting crop row lines is key to improving harvesting efficiency and reducing crop damage. Traditional image processing techniques perform poorly under varying lighting conditions, weed interference, and plant occlusion. To address these challenges, this study proposes a method for extracting outer crop row lines in white radish fields based on Principal Component Analysis (PCA). This method processes field images through grayscale conversion, binarization, and morphological filtering, combined with PCA for dimensionality reduction, to extract feature lines between crop rows. These feature lines effectively separate the outermost crop row for accurate extraction. Experiments demonstrate that the method shows strong robustness under different lighting conditions and planting patterns, with an overlap rate (OR) exceeding 81%. This method greatly improves the automation of white radish harvesting and provides a valuable reference for row line extraction in other root crops.

1. Introduction

China is the largest country in the world in terms of white radish cultivation area and production, and this trend continues to grow [1]. However, the level of mechanized harvesting for white radishes remains relatively low, with operations still primarily relying on manual labor [2]. In some regions, semi-mechanized operations are employed, where machinery is used for soil loosening and digging, followed by manual picking and bagging. This process is not only labor-intensive but also demands a high workforce and results in low operational efficiency. In contrast, European and American developed countries, due to different dietary habits, primarily grow carrots and have developed advanced combine harvesters [3-4]. These countries began the development of harvesters much earlier, leading to mature technology that has largely achieved full mechanization and automation from planting to harvesting. However, these machines still lack the level of intelligence required to meet the demands of precision agriculture [5-6].

In recent years, with the rapid development of agricultural mechanization and precision agriculture technologies, the application of intelligent agricultural machinery in production has become increasingly widespread [7-8]. The extraction of crop row lines along the edges of ridges has garnered significant attention, as it is a critical step in crop harvesting, detection, and precision fertilization. This is particularly important in the harvesting process for white radishes, as the pull-type harvesting method requires the harvesting equipment to precisely align with the crop rows on the outer side of the white radish field. As such, crop row information not only influences harvesting efficiency but also plays a crucial role in reducing crop damage. However, challenges such as complex field environments, lighting variations, and plant occlusion make the automatic extraction of crop row lines particularly difficult [9]. In modern agriculture, precision navigation technology has become a key means of improving crop harvesting efficiency and reducing labor costs [10]. For the harvesting of root crops like white radishes, accurate crop row line extraction is essential to ensure that harvesting machines align correctly with the rows, preventing missed harvests or crop damage [11]. Traditional methods for extracting crop row lines primarily rely on image processing techniques such as edge detection and threshold segmentation [12]. While these methods can achieve good results under specific conditions, their performance is often unsatisfactory in complex field environments, particularly during different stages of crop growth [13-14]. Therefore, the key research focus is on how to enhance the robustness of crop row line extraction by incorporating advanced data processing techniques.

Principal Component Analysis (PCA), a commonly used dimensionality reduction and data analysis method, has been widely applied in fields such as pattern recognition and feature extraction [15]. The core idea of PCA is to extract the principal components of data, retaining the main features while reducing dimensionality. In the extraction of white radish crop row lines, PCA can reduce noise and simplify data, extracting feature lines related to crop rows and thus improving recognition accuracy and processing efficiency. Previous studies have shown that PCA-based image processing methods can significantly enhance feature extraction in agricultural field scenes. This study aims to explore how to utilize PCA analysis techniques to automatically extract crop row lines in white radish fields during the mature growth stage. By applying PCA-based dimensionality reduction to field images, the method analyzes the feature differences between crop rows and the background. Combined with image processing techniques, it accurately extracts the crop row lines. This approach not only improves the automation of agricultural machinery operations but also provides a reference for further development of visual navigation systems in farmland.

2. Materials and Methods

2.1. Image Acquisition Environment and Experimental Equipment

To ensure the feasibility and accuracy of the crop row line extraction experiment at the edges of ridges, this study selected the representative "Xueyu 182 White radish" variety as the experimental subject. The experimental site consisted of standard single-row and double-row ridges planted in white radish fields. The experimental fields were located in a white radish cultivation area in Beijing, China, and the images were collected during the mid-to-late growth stages of the white radish plants, a period characterized by complex field environments. During this stage, vigorous plant growth, weed interference, terrain variations, and uneven lighting conditions may all affect the extraction of crop row lines at the ridge edges. The average ridge width in the experimental field was 70 cm, and the ridge height was about 30 cm, while the white radish plants' height ranged between 30-50 cm. The weather during the experiment was mostly clear, but some scenes were affected by shadows and cloud cover. A RGB color camera was used for image capture, with a resolution of 1280×640 pixels and a frame rate set at 60 frames per second. The camera was positioned at a height of about 70 cm from the ground and angled 30°downward. Image processing was carried out on a computer equipped with an Intel i5-9400F CPU (2.90 GHz) and 16 GB of RAM. Data collection was conducted via video recording to ensure a rich dataset of images at various stages of white radish maturity.

2.2. Image Preprocessing

To ensure the accuracy and efficiency of subsequent PCA analysis, the collected images underwent necessary preprocessing steps. The specific steps included the extraction of the region of interest (ROI), Excess Green (ExG) grayscale conversion, Otsu thresholding, and morphological filtering. These steps effectively enhanced the ridge features in the images, reduced environmental noise, and improved the reliability of outer row line extraction.

2.2.1. Region of Interest (ROI) Thresholding

Under complex field conditions, noise and non-target areas (such as weeds, stones, etc. in the background) can interfere with the extraction of crop row lines at the ridge edges. To address this, the study first applied a threshold segmentation method to extract the region of interest (ROI) from the image, ensuring that subsequent processing focuses solely on the area where the ridges are located, eliminating unnecessary interference from other white radish rows in the field of view. The extraction principle is as follows: where (i, j) are the pixel coordinates of B, $I_{(i,j)}$ represents the pixel value at the corresponding position in the input image, and x, y, W, H are the specified coordinates of the top-left corner and the width and height of the region. The original white radish planting map is shown in Figure 1a, and the result after ROI extraction is shown in Figure 1b. The equation is shown in Equation (1).

$$B(i,j) = \begin{cases} I(i,j) & j \in [y, y+H], i \in [x, x+W] \\ 0 & else \end{cases} \tag{1}$$

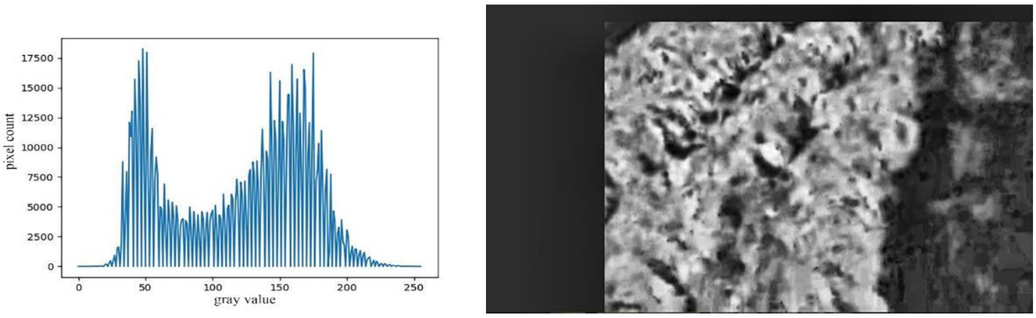
(a) Original image (b) Cropped image

Figure 1: Region of Interest (ROI) extraction.

2.2.2. ExG Grayscale Conversion of Farmland Images

In the RGB color space, the G color component of the white radish canopy accounts for a larger proportion compared to the R and B components. Based on this characteristic, the G component is enhanced during grayscale conversion to separate crops from the soil background. The Excess Green (ExG) grayscale method can suppress background noise such as dry grass and soil (as shown in Equation (1)). However, ExG processing does not effectively highlight crop features. In this study, the ExG grayscale factor was improved. Since the R component in the soil is relatively large, this method increases the G component and limits the R component to distinguish green plants from soil. Additionally, the 2G(x, y) - B(x, y) method is employed to determine the grayscale value, reducing grayscale differences between different parts of the same plant. The image after ExG grayscale conversion is shown in Figure 2a, and the corresponding grayscale histogram is shown in Figure 2b. The equation is shown in Equation (2).

$$gray(x,y) = \begin{cases} 2G(x,y) - R(x,y) - B(x,y) & else \\ 255 & 2G - R - B > 255 \\ 0 & 2G - R - B < 0 \end{cases} \tag{2}$$



(a) Grayscale histogram (b) Grayscale image

Figure 2: Excess Green grayscale conversion.

2.2.3. Otsu Binarization Processing

Following grayscale conversion, the Otsu binarization method was employed in this study to further distinguish the foreground (ridges and crops) from the background. The Otsu method automatically determines the optimal threshold that maximizes between-class variance, enabling efficient image segmentation. The specific steps are as follows: first, the histogram of the grayscale image is calculated to analyze the pixel distribution between the foreground and background; then, the Otsu algorithm is applied to automatically compute the threshold that minimizes within-class variance, which is subsequently used for binarization. Foreground pixels (ridges and crop areas) are assigned a value of 255 (white), while background pixels are assigned 0 (black). The binarized image is presented in Figure 3a.The Otsu method eliminates the need for manual threshold setting by automatically adjusting to each image's characteristics. This makes it especially suitable for field environments with significant variations in lighting conditions. The binarization process enhances the distinction between the ridge areas and the background, making the separation more distinct. To better demonstrate the binarization effect, a mask was created by applying the binarized image onto the original image. The resultant masked image, shown in Figure 3b, clearly demonstrates the effective separation of the green white radish plants from the background.

(a) Binarized image (b) Masked image

Figure 3: Otsu thresholding.

2.2.4. Morphological Image Processing

Although binarization can effectively separate the foreground from the background, some noise or incomplete boundaries may still remain, potentially affecting the extraction of crop row lines at the ridge edges. To address this, morphological filtering was further employed in this study, utilizing erosion and dilation operations to improve image quality. Erosion was first applied to remove small noise points in the image. By shrinking the foreground regions, it eliminated isolated noise introduced during the binarization process. Subsequently, dilation was performed to restore the incomplete edges of the foreground caused by the erosion step, ensuring the continuity of the foreground boundaries. The dilation operation enlarged the foreground region, making the ridge boundaries smoother and more coherent. Through repairing discontinuous edges and removing noise, the morphological processing significantly enhanced the clarity and completeness of the ridge row lines. The image before morphological processing is shown in Figure 4a, and the image after morphological processing is shown in Figure 4b.

(a) Pre-processed image (b) Post-processed image

Figure 4: Morphological filtering.

2.3. Crop Row Line Extraction Method Based on PCA Analysis

During the mature growth stage of white radishes, the canopies between crop rows often overlap. In the binarized images after preprocessing, the white radish crop rows are connected, making it difficult to effectively separate them. Since white radishes are planted in row-based sowing patterns, the crop rows exhibit a clear linear trend in the planting direction. The soil areas between the crop rows, which are not covered by the canopies, also follow a linear trend along the planting direction. Based on this characteristic, Principal Component Analysis (PCA) can be employed to analyze the soil regions between the crop rows that are not occluded by the canopy. PCA can perform dimensionality reduction on the binarized images, transforming high-dimensional data into low-dimensional data while preserving the main features of the data and outputting principal component vectors. Each principal component vector represents the direction of a straight line, thereby determining the soil regions between the crop rows. These inter-row lines can be used to segment the image, separating the outer white radish crop rows from the rest, which facilitates the subsequent extraction and fitting of the crop row lines.

The specific workflow is as follows:

Step 1: Area filtering is applied to the preprocessed image to eliminate minor interferences and retain the target crop rows, as demonstrated in Figure 5a.

Step 2: A minimum convex hull algorithm is utilized on the area-filtered image to generate convex hull contours, subsequently filling the outer convex hull, as shown in Figure 5b.

Step 3: Convex hull contours are identified, and hole-filling is applied to the voids within the convex hull, resulting in the clear identification of the soil regions between the crop rows, as depicted in Figure 5c.

Step 4: Area filtering is performed on the identified soil regions to remove noise artifacts, as illustrated in Figure 5d.

Step 5: Principal component analysis (PCA) is conducted to extract the principal component vectors, thereby obtaining the directional lines of the soil regions between the crop rows, as shown in

Figure 5e.

Step 6: The extracted directional lines are used to segment and isolate the outer white radish crop rows, as demonstrated in Figure 5f.

Step 7: Contour detection is carried out, and the center points of each region are calculated to ensure the complete separation of the connected outer crop rows, as shown in Figure 5g.

Step 8: Contour detection and center point identification are repeated to further refine the separation of the outer crop rows.

Step 9: PCA is again applied to the separated crop rows, resulting in the final delineation of crop row lines, as depicted in Figure 5h.

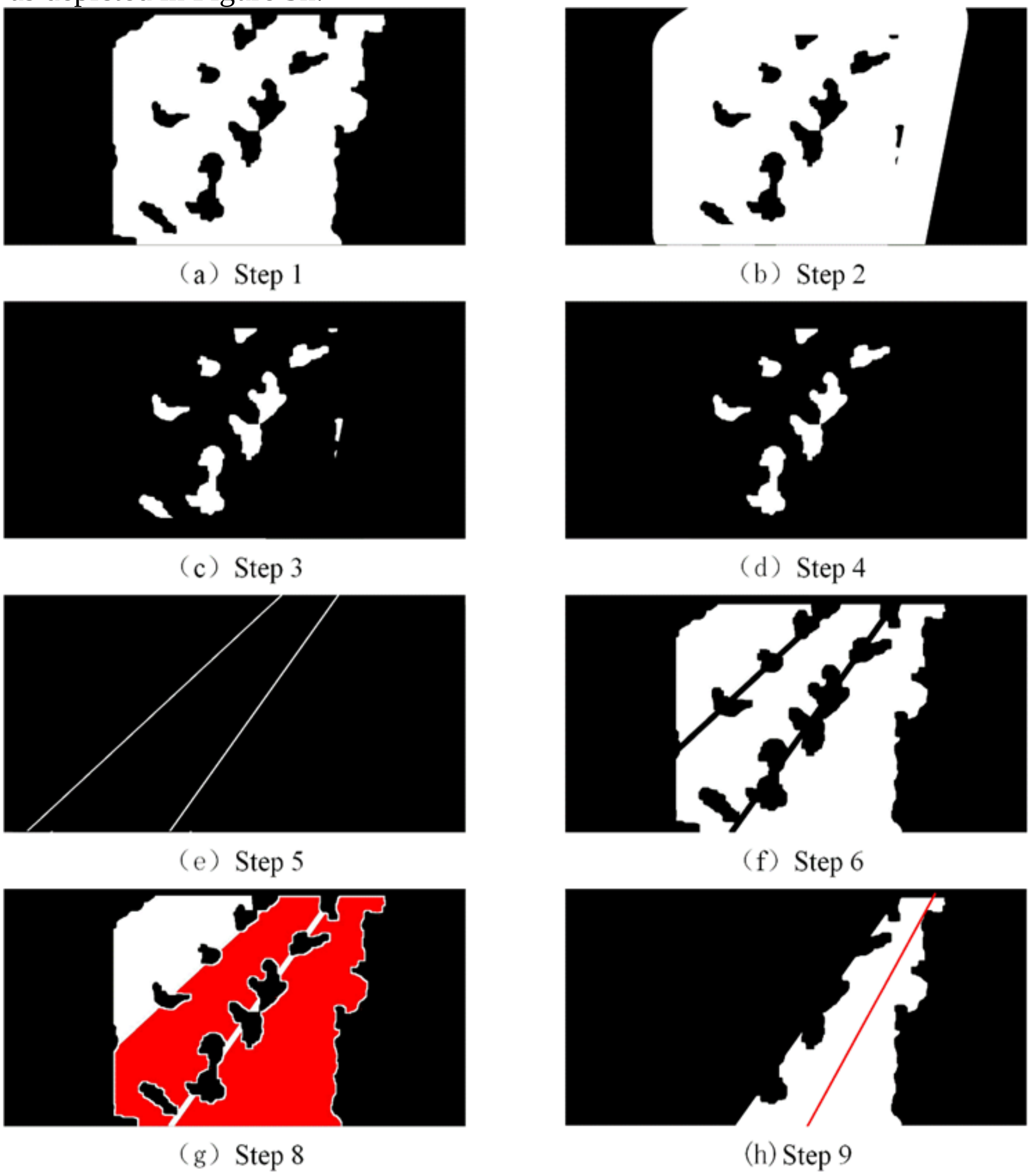


Figure 5: Crop Row Line Extraction Based on PCA.

3. Simulation Experiment and Analysis

3.1. Crop Row Line Extraction Method Based on PCA Analysis

To comprehensively assess the effectiveness of the crop row line extraction method based on the combination of PCA and the least squares method, a series of experiments were designed, focusing on the performance of the method under different environmental conditions. The experimental variables included ridge structure, lighting conditions, and plant growth stages. Specifically, the experimental setup involved selecting white radish fields with both single-row and double-row planting modes to simulate the impact of different planting densities on the row line extraction algorithm. Lighting conditions included sunny, cloudy, partial shading, and twilight scenarios to evaluate the algorithm's robustness against lighting variations. Photos of white radish fields under different environmental conditions are shown in Figure 6. Manually labeled optimal crop row lines were used as the reference standard, and the angular deviation between the extracted row lines and the optimal row lines was analyzed as the primary evaluation metric. The extraction accuracy, measured by the Overlap Rate (OR), reflects the degree of spatial matching between the extracted and actual row lines. If the angular deviation is within ±5 °, the extraction result is considered accurate. A higher OR value indicates a better match between the extracted row lines and the actual row lines. The accuracy of the results is measured using angular deviation, and the OR value is calculated based on this relationship, with higher OR values indicating better alignment between the extracted and actual row lines.

Figure 6: Different Environments of White White radish Fields.

3.2. Experimental Results Analysis

Through the analysis of various experimental scenarios, the results of this study show that the proposed crop row line extraction algorithm for the outer rows of white radish fields exhibits high stability and accuracy under different conditions. In the single-row planting mode, the Overlap Rate (OR) of the crop row lines reached 92.6%, indicating that the method has strong adaptability in standard planting patterns. In the double-row planting mode, due to higher crop coverage between rows, the OR slightly decreased to 91.2%, but the algorithm still performed well under dense planting conditions. The algorithm also maintained stable performance under different lighting conditions. In sunny and cloudy conditions, the OR values were 93.4% and 85.8%, respectively. Under more complex lighting conditions, such as partial shading and twilight, the OR value slightly decreased to 80.7%. This suggests that PCA-based dimensionality reduction effectively mitigates the interference caused by lighting variations. However, under extreme lighting conditions, shadows and plant reflections may blur image features, affecting the accuracy of some extraction results. The test results under different scenarios are shown in Table 1

Table 1: Experimental results under different scenarios.

Test Environment	Overlap Rate (OR)
Double-row	92.6%
Single-row	91.2%
Sunny	93.4%
Cloudy	85.6%
Partial Shading and Twilight	81.7%

4. Discussion

The crop row line extraction method proposed in this study, based on PCA and the least squares method, demonstrates several advantages. For example, the PCA-based dimensionality reduction technique effectively reduces noise interference in complex field environments, such as plant occlusion, lighting variations, and soil impurities. Experimental results show that the algorithm maintains stable extraction performance under different lighting conditions and planting patterns, which is of great significance for enhancing intelligent agricultural harvesting and precision farming. Moreover, although this study focuses on the extraction of white radish crop row lines, the method has good generalizability and can be extended to the extraction of ridge row lines for other root crops. Even in densely planted fields with severe inter-row occlusion, the method maintains a high level of extraction accuracy.

While the row line extraction method proposed in this paper exhibits high robustness in most cases, there are still certain limitations under extreme conditions. Under strong light or complex shadow scenarios, especially during sunrise and sunset when the sun is at a low angle and shadow variations are significant, the dimensionality reduction effect of PCA diminishes, leading to reduced fitting accuracy. Future research could explore integrating spectral analysis or deep learning techniques, using multispectral imaging or neural networks to enhance feature extraction under uneven lighting conditions. In the late stages of plant growth, the heavy overlap of crop canopies between rows makes it difficult for PCA to accurately segment the soil regions between rows. To address this issue, future research could consider incorporating 3D point cloud-based deep learning methods, combined with RGB-D (depth information) cameras, to accurately reconstruct the 3D spatial structure of crop rows and further improve row line extraction accuracy.

5. Conclusion

This study proposed an automated crop row line extraction method based on Principal Component Analysis (PCA) for detecting and extracting outer crop rows in white radish fields. Experimental validation demonstrated that the method exhibits excellent robustness and adaptability under various complex field conditions. By leveraging PCA for dimensionality reduction, the algorithm effectively reduces noise and extracts key features of the crop rows, leading to accurate crop row line extraction. The experimental results showed that the algorithm processes a 1280×640 pixel image in approximately 1.68 seconds, with an accuracy rate of over 81% for crop row line detection, meeting the navigation requirements for agricultural machinery. Furthermore, the proposed method has strong generalizability and scalability, making it applicable not only to white radishes but also to the automated row line extraction of other root crops.

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