Proposal of Potted Flower Area Segmentation Method Using Hough Transform

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Abstract -
The impact of plant diseases on agricultural production is significant. Therefore, plant diseases must be removed or otherwise treated as soon as they are detected. Conventional methods have attempted to improve the accuracy of disease detection. However, the current situation is costly in terms of collecting a large amount of image data for disease detection, installing and managing monitoring equipment, and extracting disease images. In this study, we propose a method to segment an image of the entire farm field using image processing based on the Hough transform to isolate individual plants. We aim to improve the accuracy of disease detection by performing disease identification on cropped plant images using the proposed method. In the evaluation, we confirmed that the proposed method can trim a single plant with an F-measure of 72.5%, which is approximately 7 percentage points higher than that obtained by segmenting plant parts using CNNs.

Keywords: smart agriculture, plant disease, image processing, Hough transform

1 Introduction

Zadoks et al. reported that more than one-third of agricultural production is wasted due to plant diseases [1]. Since plant diseases are spread by infection among plants, it is necessary to remove or otherwise treat plant diseases as soon as they are detected.

Several types of research conducted on this issue, aiming at automating the prediction and detection of plant diseases. Several methods using deep learning based on Convolutional Neural Networks (CNNs) have been proposed. These researches include the detection of cucumber and tomato diseases [2], [3]. In addition to vegetables, there are also researches to detect diseases of rice plant [4].

Since these researches target the plant disease itself, they require data on specific areas such as diseased leaves. Therefore, more than 10,000 images need to be collected, and the cost of installing and maintaining monitoring equipment and extracting images of diseased areas cannot be ignored. Suwa, et al. propose a method for detecting diseases by extracting plant leaves from images of the entire field [3].

As described above, although disease detection has been conducted for specific parts such as diseased leaves, but the research on disease detection from images of the entire farm has not been established. Therefore, we propose to construct a system that can extract specific parts of a field, such as leaves, from the entire farm field image.

In our study, we focus on potted flowers, which are arranged in a grid pattern and thus each plant is easily extracted. We propose a 2-step disease detection method, in which each plant is extracted from the entire farm field image by segmenting the potted flower area, and then each plant is identified for disease identification. In this paper, we consider a method for potted flower segmentation that uses feature extraction of grid patterns that appear in the field image.

This paper is organized as follows. Section 2 reviews related studies on plant disease detection, and Section 3 describes the proposed method for detecting plant diseases from images of the entire farm field. Section 4 evaluates the proposed method and discusses the evaluation results, and Section 5 concludes the paper.

2 Related Studies

Methods for detecting diseases in vegetables can be classified into 2 categories: methods using deep learning based on CNNs, and methods using image processing.

2.1 Plant Disease Detection Method Using Deep Learning Based on CNNs

CNNs are widely used in image analysis and are also widely used for plant disease detection. Fujita, et al. achieve 83.2% of identification accuracy in the classification of 9 classes of plant diseases on cucumber, including 8 types of diseased leaves and healthy leaves [2]. Since these methods use image data trimmed to a single leaf as training data, it is necessary to collect data on leaves suspected to be diseased. Regarding the leaf trimming problem, Suwa, et al. detected plant diseases from images of the entire farm field and achieved disease detection rate of 91.1% [3]. In this method, a 2-step detection process is used: leaf extraction from the field image, and disease identification on the extracted leaves.

Although the evaluation results of disease detection using CNNs were reported to be generally highly accurate, these methods require a large amount of data, and the cost of data collection is high. About 8,000 images were used in Ref.[2], and about

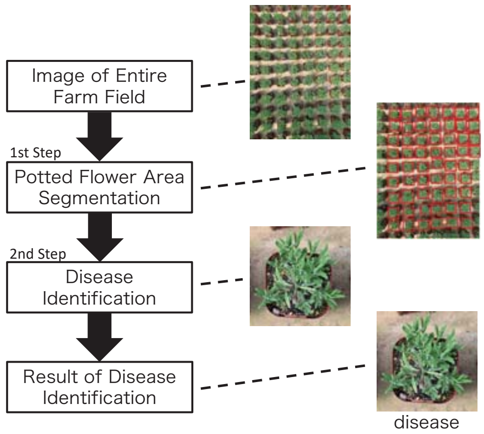

Figure 1: Overview of Proposed System

50,000 images in Ref.[3]. The disease detection rate decreased to 38.9% when images taken in a different farm field from the one used for the training data were applied to the detector [3].

2.2 Plant Disease Detection Method Using Image Processing

Several types of research use image processing to detect diseases with a small number of data. Jadhav, et al. proposed a method to extract only the image area of the disease on leaves [5]. This research also used images of only a single leaf as data like these researches [2], which does not reduce the cost. Kawasaki proposed a method for trimming a single leaf from an image of the entire farm field using image processing [6]. However, this method failed in trimming a leaf image. The reason for this failure is stated to be that the image channels used for feature acquisition are not suitable for leaf detection.

As shown in Ref.[5], it is possible to identify the type and infection level of a disease by extracting only the diseased area if the disease to be detected has prominent features. However, only image processing is difficult to extract leaves from the entire field image. While image processing methods can detect diseases without requiring a large amount of data, features common to all images are required for disease detection.

3 Disease Detection System Using Potted Flower Area Segmentation

In this study, we propose a 2-step system that identifies diseases after individual plants are extracted, to enable disease detection from images of the entire farm field. The proposed system is applied to potted plants, which are arranged in a grid pattern and thus each plant can be easily extracted. Figure 1 shows an overview of the proposed system.

In order to segment potted flower areas using image processing, this method takes advantage of the feature that potted flowers are arranged and grown in a grid pattern over the entire field. Due to this feature, grid lines appear when background images other than potted flowers are extracted. The main idea of this method is to extract each potted flower by trimming using the intersection points of these grid lines. The grid lines that appear between each potted flower are detected using the Hough transform[7]. The process of segmenting the potted flower area using the Hough transform and trimming individual potted flowers is shown in Fig.2.

3.1 Area extraction for applying Hough transform

The pre-processing for detecting grid lines from the farm field images in the proposed system is as follows. Since grid lines appear in background images other than individual potted flower images, this process identifies background images. The proposed method focuses on the green color of the leaf of the individual potted flowers and considers all other colors as the background.

A method for extracting green areas of individual plants use the RGB-based Vegetative Indexes (RGBVI) shown in Expression (1) This Expression (1) makes it possible to extract the features of green areas with high accuracy.

$$\frac{G^2 - (R \times B)}{G^2 + (R \times B)} \tag{1}$$

Our proposed system uses this method to extract green areas from the RGB channels of the entire field image. The image of the entire field has 3 channels, R (red), G (green), and B (blue), and all pixel values are in the range of 0 to 255. After applying Equation(1), the pixel value of -1 to 1 is set to 0 to 255 and converted to a gray-scale image.

The converted gray-scale image is a multi-stage image, and the Hough transform cannot be applied. Therefore, image binarization is required. Our proposed system applies Otsu's binarization algorithm[8]. After binarization, the farm field image is represented as white for individual potted flowers and black for the background. There are white spots in the individual potted flower area and black spots in the background area, which are noise. The proposed method removes these noises by applying expansion processes to the white areas in the image. Since the Hough transform detects white areas as straight lines, the binarized image is inverted to black and white.

This process makes individual potted flower areas and background areas separate from the entire farm field image.

3.2 Line detection by Hough transform

In the image shown in Fig.2(1), the background area is displayed as a linear white area with many line segments and lines mixed in. If the Hough transform is directly applied to the image, many line segments and lines unrelated to potted flowers are also extracted. Therefore, it is difficult to extract the optimal lines for dividing the individual potted flower area and the background

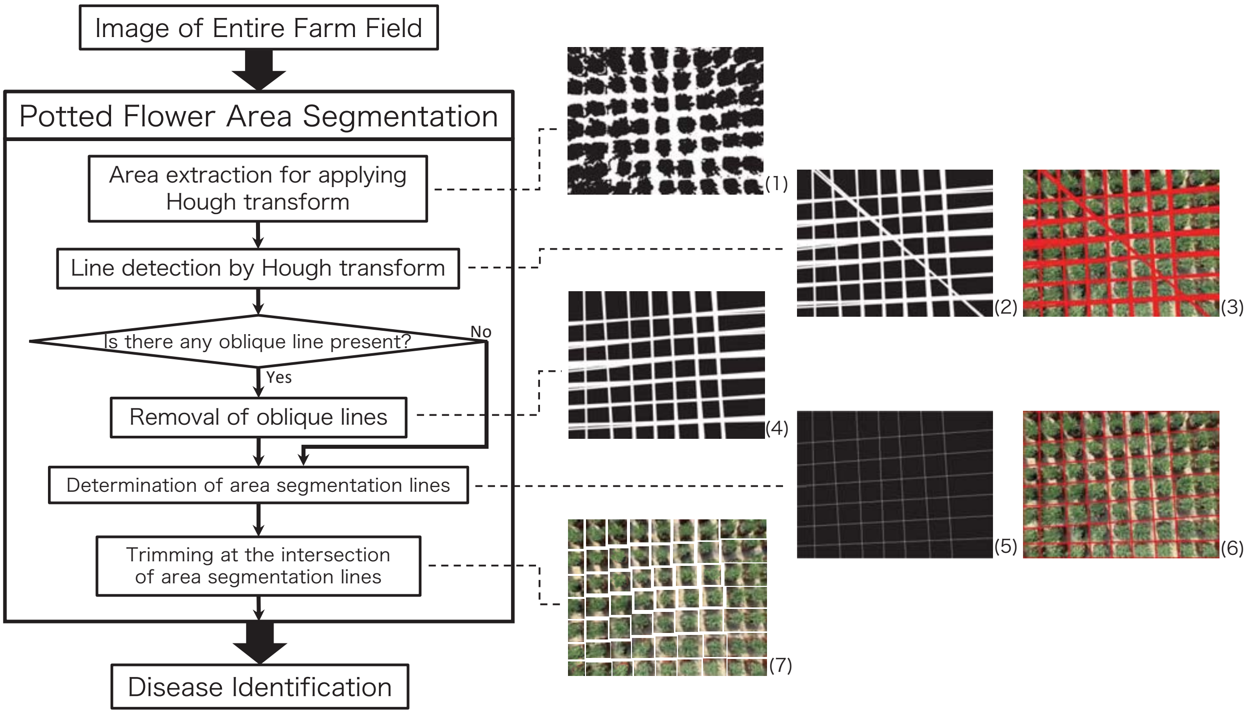

Figure 2: Process of Potted Flower Area Segmentation

area. The proposed system first adjusts the parameters of the Hough transform so that line segments with start and end points in the background area are output. The Hough transform after parameter adjustment is called the segment Hough transform. The segment Hough transform produces line segments that are candidates for line segments that divide the individual potted flower area and the background area. In order to trim the individual potted flower area, these line segments must be straights line that spans the entire image. The overlapping line segments are good candidates for boundaries between areas. Therefore, the line segments outputted by the segment Hough transform are thinned, and then the thinned line segments are expanded. These processes produce straight lines that divide the individual potted flower area and the background area in the entire farm field image. This is called the line Hough transform. When the line calculated here is merged into the input RGB image, it can be seen that a line can be detected in the background.

3.3 Removal of oblique lines

If the image after applying the line Hough transform (Fig.2(2)) contains oblique lines, these lines are noise unrelated to the individual potted flower areas and must be removed. In the process of the Hough transform, the slope and intercept of the detected line are obtained. Based on the slopes, each line is classified using a clustering method to separate the oblique lines. The proposed method uses a density-based clustering method, DBSCAN [9], as the clustering method. Since oblique lines are fewer than straight lines in the horizontal and vertical directions, lines belonging to the top 2 clusters in terms of the number of lines are used as area segmentation lines, and lines belonging to the remaining clusters are removed. If all lines are classified into 2 clusters, no oblique lines are judged.

As an example, the result of clustering the slope of lines for the image shown in Fig.2(2) is shown in Fig.3. Fig.3 explains that the vertical axis represents the slope of the lines, and the horizontal axis is set to 0 as the specified value since the clustering is based only on the slope of the lines. The result shows that the clusters are classified into clusters with 38 lines, clusters with 5 lines, and clusters with 29 lines. The 5 straight lines belonging to the middle cluster are separated as oblique lines and removed (Fig.2(4)).

3.4 Determination of area segmentation lines

Since the image after the line Hough transform has multiple overlapping lines, these lines cannot be used as area segmentation lines for trimming individual potted flowers. Therefore, all the lines are thickened, and the overlapped lines are clustered. If the lines are too thin, they cannot be classified into the same

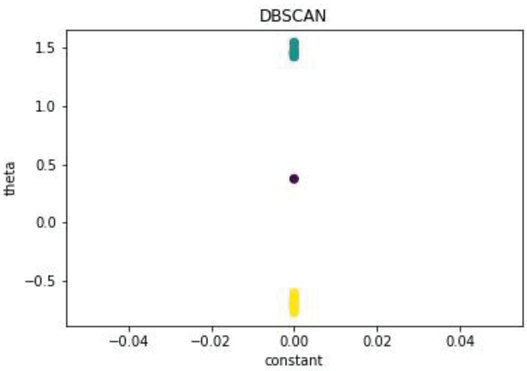

Figure 3: Result of DBSCAN with the Slope of Lines

cluster. If the lines are too thick, lines that should be in different clusters are classified into the same cluster. For this reason, the thickness of the lines should be set to about 20 pixels. The line passing through the center of the clustered lines is used as the area segmentation line (Fig.2(5)). The calculated area segmentation line is found to be the best line for segmenting individual potted flowers(Fig.2(6)).

3.5 Trimming at the intersection of area segmentation lines

Trimming at the intersections of the area segmentation line obtained allows the potted flower to be divided into individual plants. The proposed method trims the largest rectangle with 4 intersections. In this way, the trimmed individual potted flower image retains the maximum amount of image information (Fig.2(7)).

4 Evaluation

We evaluate the potted flower area segmentation method. For the evaluation of the potted flower area segmentation method, we compare the accuracy of the proposed method with that of the CNNs-based segmentation method.

The data used for the evaluation were 78 image. Evaluation data is taken so that "one image shows about 60 plants".

4.1 Evaluation of the Potted Flower Area Segmentation Method

The evaluation criterion of the potted flower area segmentation method is whether or not only one whole plant is trimmed. The term "only one whole plant" here refers to the state in which one whole plant is captured, and only a portion smaller than half of the other plants are captured.

This evaluation criterion are the precision (Equation(2)), the recall (Equation(3)), and the F-measure (Equation(4)).

Table 1: Potted Flower Area Segmentation

	Proposed Method	CNNs-based Method
Precision [%]	78.5	94.3
Recall [%]	67.3	49.5
F-measure[%]	72.5	65.0

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{3}$$

$$\mathrm{F\text{-}measure} = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \tag{4}$$

In this evaluation, TP (True Positive) is the case where potted flowers are trimmed from the test data image, FN (False Negative) is the case where no potted flower is trimmed from the test data image, and FP (False Positive) is the case where the test data image has been trimmed to include parts of the image that are not potted flowers. Therefore, precision is the probability that the trimmed image is a single potted flower, and recall is the probability that multiple potted flower plants are cropped as a single plant. F-measure is the harmonic mean of precision and recall.

Table 1 shows the results of potted flower area segmentation. The proposed potted flower area segmentation method achieved 78.5% precision, 67.3% recall, and 72.5% F-measure, while the CNNs-based segmentation method achieved 94.3% precision, 49.5% recall, and 65.0% F-measure. The proposed method achieves higher recall and F-measure than the CNNs-based method, while the CNNs-based segmentation method achieves better precision. From the results, the proposed method reduces the number of missed potted flower plants compared to the CNNs-based segmentation method.

The reason for the 78.5% precision of the proposed method may be due to the low accuracy of segmentation in the dense areas of potted flowers. The images of unsuccessful segmentation are shown in Fig.4. From the left, the input image, the pre-processed image, and the image after the second Hough transform. The reason for the low segmentation accuracy is that the background area could not be detected due to the distortion from the center to the edges of the image. Recall is also considered to be limited to 67.5% due to the low accuracy of image segmentation as well as precision. Therefore, if the segmentation accuracy of the individual potted flower area can be improved by correcting the distortion of the image and adjusting the parameters of the Hough transform, the overall accuracy of the potted flower area segmentation method can also be improved.

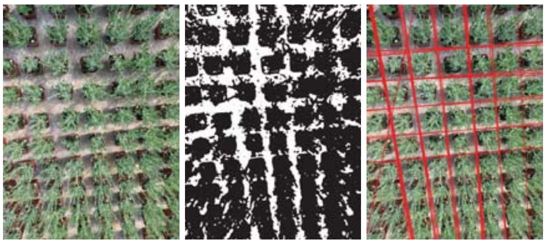

Figure 4: Unsuccessful Segmentation((a): Input image, (b): Pre-processed image, (c): Image after line Hough transform)

5 Conclusion

In this paper, we proposed a method to improve the accuracy of plant disease detection by image processing using the Hough transform. The results of trimming individual potted plant areas in a grid pattern feature using the Hough transform from images of the entire farm showed that one potted plant was trimmed with 72.5% F-measure, which is about 7 points higher than that of the segmentation method using CNNs.

As the results, proposal method achieved high accuracy in the segmentation with 136 images than R-CNN. And the system is capable of segmenting individual potted flowers as long as the target object is green and arranged in a grid pattern.

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