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Rice Disease Spots Extraction Based on Machine Vision

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Abstract

Development of the automation system for recognizing diseases of the infected rice is a growing research field in precision agriculture. So, the first and foremost thing we should do is to extract the disease region from rice images. The objective of this paper is to propose an image segmentation method for rice disease spots based on machine vision. The algorithm consists of two main steps: image gray-level transformation and disease region segmentation. Firstly, the color image was transformed into a gray-level image by the color indices $2G-R-B$*, which making an important contribution for this kind of images. Secondly, the information fusion between the self-adaptation threshold which was obtained by the mean and standard variance of the grey-scale image and the green component distribution features in color image was used to form a new segmentation standard to detect disease region. To test the accuracy and robustness of the proposed algorithm, it was tested with a broad of set of images and compared with the classical approach based on other grey-level convert methods and Otsu's method. Test result shows that the accuracy of new algorithm appears higher and it can be applied to segment rice disease spots effectively.*

Keywords: *Rice disease spots extraction; Otsu; color feature; mean value*

1. Introduction

Rice is one of the most important economic crops in the world, especially in Asian countries. During the growth period of rice, a variety of diseases occur every year due to the loss of quite amazing [1]. Diagnosis and identification of the diseases and pest insect accuracy can lessen its influence on rice yield and quality efficiently.

Traditionally, farmers recognize the rice disease condition in their crops by manual methods, such as the guide books, their experiences, and experts. It is applicable for farmers to detect the typical diseases. However, errors may occur during the process of identifying diseases. Misidentification usually leads to some inadequate control treatment, such as untimely and indiscriminate use of pesticides.

With the development of computer technology and the urgent needs of agricultural information, crop diseases diagnosis based on computer vision technology, automatic identification and diagnosis of field research have gradually become a hot topic [2]. Automatic diagnosis of crop diseases saves the products from quantitative loss and plays a vital role in country's economic growth. Image processing technology can overcome the influence of manual factors and has been widely applied to the segmentation and recognition of crop diseases and pests. Performance of the machine system lies on the result of the infected region segmentation of the diseased vegetable images. Because the most direct crop disease manifested as appearance of the lesion, the general approaches of these researches are similar. First, disease images are acquired through scanners or

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cameras. Second, disease spots are segmented from background. Many different methods are proposed for disease spots segmentation. Such as neural networks [3], Fisher discriminate [4], etc. Previous studies including many fields, such as wheat diseases, corn diseases, rice diseases, etc. Corn disease spots have been segmented in [5]. Firstly, the corn leaves were extracted from the background by select threshold automatically through iterative method using the $2G-R-B$ images. Then the disease spots were detected from leaves based on $R-G$ images. The results showed that some points which have not been etiolated cloud not be segmented accurately. Thresholding [6] is also a widely used segmentation technique [7]. Based on image region, Long et al. [8] proposed an interactive document images thresholding segmentation method, which was greatly affected by artificial factors. In addition, Sathya et al. [9] applied a bacterial foraging method based multilevel thresholding and Gao, et al. [10] presented a patch part segmentation using improved Otsu's algorithm in their study. Recently, Xu et al. [11] displayed a new weighted threshold algorithm by estimating the best threshold for obtaining minimal centroid error in the image, which considered a higher accuracy, but too many parameters were involved. The effect of disease spot segmentation directly affects the recognition results. However, due to more types of crops, and disease on a variety of the same crop, characterized by diversified and complicated, and therefore, there is not a universal recognition method needs to be studied separately for different crops specific lesion, so in this study, we proposed a detection method for rice disease.

According to the experts' opinions, visual symptoms of rice in the infected and its surrounding regions will be different. In this paper, by enhancing comparison between disease region and the surroundings is considered as one of the important reason for grey-scale image. Then a self-adaptation threshold was got by calculating mean and standard deviation of the grey-scale image pixels. Finally, the disease region was segmented by the new threshold and feature of green component G in color image.

The rest of the paper is settled as follows. In section 2, we give experimental material and methods. Firstly, three famous grey-level transformation methods were used to convert a color image to grey-scale image, and then combined with Otsu's method to test the segmentation results. Secondly, the proposed threshold method was applied with the three grey-level transformation to segment the rice disease. Finally, according to the algorithm evaluation results prove the effectiveness of the proposed algorithm. Section 3 gives experiments results and discussion in detail, and Section 4 summarizes our contributions and the draft of future work.

2. Material and Methods

2.1. Image Source and Experimental Equipment

The samples of rice leaves in this study were collected from the trial base of China National Rice Research Institute of Fuyang City in Zhejiang Province [12]. The images were captured using Nikon D80 digital camera. In this present study, the rice leaves were affected by Blast and Sheath blight respectively, as illustrated in the rice disease images in figures 1(a) and (b). More than 300 color images were sampled.

Image processing was performed using a personal computer with an Intel Core 2 Duo CPU, 2.60 GHz, 1.88GB RAM, and the algorithm was developed using Matlab R2009a (Math Works) under a Windows 7 operating system.

(a) (b)

Figure 1. Original Image of Disease Rice: (a) Rice Blast; (b) Sheath Blight

2.2. Gray-level Transformation

First of all, which is familiar to almost all image processing plant detection algorithms, is the gray-level transformation. Its purpose is to emphasize the living vegetation tissue and weaken the rest of image. This can be achieved in an RGB color space. Therefore, color indices [13, 14] for RGB images have been applied to stress the plant pixels while restrain other elements. The well-known color indices contain the following:

(1) $2G - R - B$ [15]

where R, G and B are the actual pixel values from the agronomic images based on RGB color space.

(2) Excess green (ExG) index [13]

$$ExG = 2g - r - b \qquad (1)$$

where r, g and b are the chromatic coordinates.

$$r = \frac{R^*}{R^*+G^*+B^*},\; g = \frac{G^*}{R^*+G^*+B^*},\; b = \frac{B^*}{R^*+G^*+B^*},\; r+g+b=1. \qquad (2)$$

and R^*, G^* and B* are the normalized RGB values ranging from 0 to 1 and are defined as follows:

$$R^* = \frac{R}{R_{\max}},\; G^* = \frac{G}{G_{\max}} \text{ and } B^* = \frac{B}{B_{\max}} \qquad (3)$$

where $R_{\max} = G_{\max} = B_{\max} = 255$ for 24-bit color images.

(3) $1.262g - 0.884r - 0.311b$ [16]

As for the above three color indices, the normalization of the values was used of each spectral band in the second and third color indices.

Typically, in an RGB image, the components of R and G are the major parts in disease area, which provides a good basis for the identification of disease area and the rest region.

In figure 2, we have analyzed the distribution of R, G and B components in the color image. From the images displayed, the two blue horizontal lines across the images in figures 2(a) and 2(b) were drawn to observe the statistical distribution of each color component. Figures 2(c) and 2(d) show the corresponding component distribution, three colors curve represent the R, G and B components. It is clear to see, in the background area, leaf green component G is far higher than the red component R and blue component B, while in the disease area of blade, the three component of the gap is slight. Therefore, in order to better identify the disease area from the surroundings, method transforming the ratified image to a grey-scale image with strengthen the green component, inhibit the red and blue components was adopted in this study. As the three grey-level methods mentioned above.

Since all images were collected in rice field under natural conditions, it was inevitable that insects' excrement, dewdrop, and dust might influence the images. They were considered as the image noises which could disturb the image segmentation in the future image analysis, so after the gray-level transformation, they were removed or weakened before segmentation with a 3*3 rectangle median filter window in our study.

The gray-scale images are shown in figures 3 (a) ~(c) and figures 4(a) ~(c). As can be expected, according to the process of emphasizing the green value, the background had a higher gray value, while the disease area had a lower gray value, which presented dark. This condition lasts throughout the whole disease period. It could be concluded from figures 3 and 4 that the methods for emphasizing the green value were effective for the rice disease images under natural conditions during disease recognition period.

The above three gray-level transformation methods were combined with Otsu's algorithm to test the segmentation results.

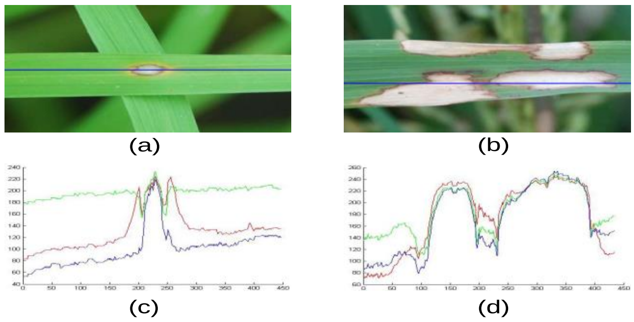

Figure 2. The statistical Figure of R, G, B Components: (a) Statistical Area for Rice Blast; (b) Statistical Area for Sheath Blight; (c) Color Statistical Chart of (a); (d) Color Statistical Chart of (b).

2.2. Rice Disease Spots Extraction based on Otsu

In this section, the grey-scale images in figures 3(a) ~(c) and figures 4(a) ~(c) were segmented with Otsu's method, and the test results are shown in figures 3(d) ~(f) and figures 4(d) ~(f). The pixels of target are shown as black, representing the disease region in the binary image, surroundings appear white. Results show that Otsu's method considers some pixels in the non-infected region as infected. In a word, the disease area was not segmented accurately. Although the algorithm based on $2G-R-B$ is relatively better, it cannot reach the expected purpose. This is because the one-dimensional Otsu's algorithm is lacking adaptability to noise image segmentation, it is not suitable to be used for disease recognition directly.

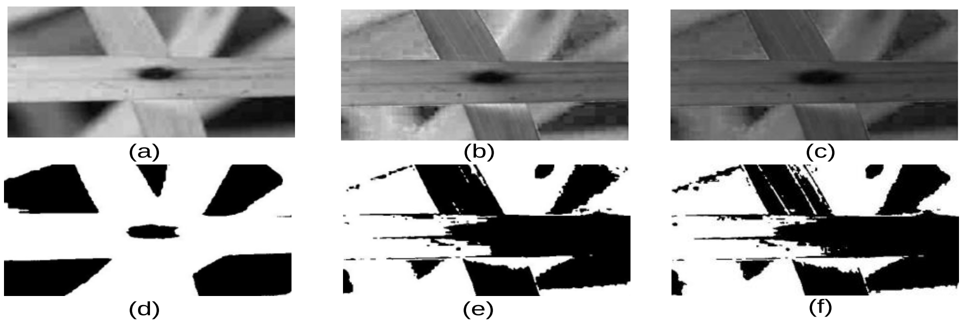

Figure 3. Resulting Images after Grey-scale Transformation and Otsu for the Rice Images Shown in Figure 1 (a): (a) Grey-scale Image by $2G-R-B$, (b) grey-scale Image by $2g-r-b$, (c) Grey-scale Image by $1.262g-0.884r-0.311b$, (d) the Result of Image Segmentation by Otsu for 3(a), (e) the Result of Image Segmentation by Otsu for 3(b), (f) the Result of image Segmentation by Otsu for 3(c)

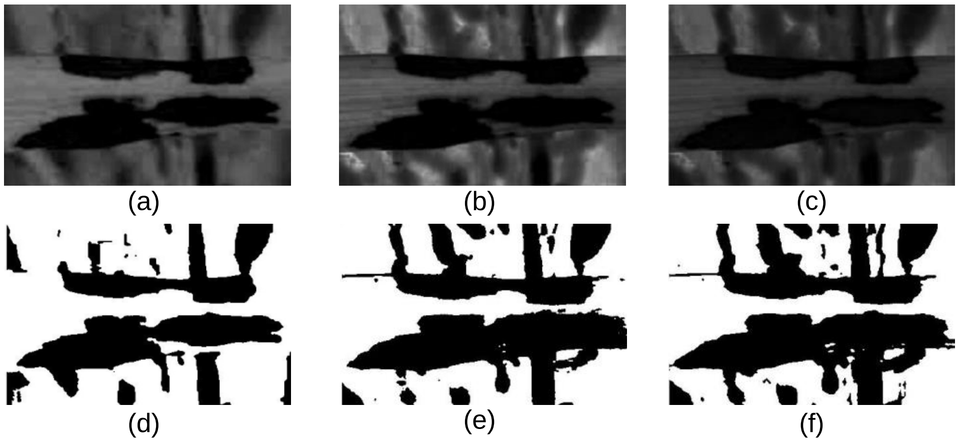

Figure 4. Resulting Images after Grey-scale Transformation and Otsu for the Rice Images Shown in Figure 1 (b): (a) Grey-scale Image by $2G-R-B$, (b) Grey-scale Image by $2g-r-b$, (c) Grey-scale Image by $1.262g-0.884r-0.311b$, (d) The Result of Image Segmentation by Otsu for 4(a), (e) The Result of Image Segmentation by Otsu for 4(b), (f) the Result of Image Segmentation by Otsu for 4(c)

2.3. Rice Disease Spots Extraction based on Proposed Algorithm

To overcome the above mentioned shortcoming of the Otsu's method, this paper proposes another algorithm based on a self-adaptation threshold. The gray-scale image was segmented with the threshold calculated as the following steps:

Step 1: The average value of the median filtered gray-scale image (t) was calculated as follows:

$$t = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} pixel(i, j)}{m \times n} \tag{4}$$

Where m is the width of the image and n is the height of the image, $pixel(i, j)$ expresses grey value of $point(i, j)$ in the grey-scale image, limit to [0,255].

Step 2: The standard deviation value of the median filtered gray-scale image (s) was obtained using equations 5 and 6:

$$S_o = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} [t - pixel(i, j)]^2}{m \times n} \tag{5}$$

$$s = \sqrt{S_0} \tag{6}$$

Where S_o represents the variance value of the gray-scale image; s is the standard deviation value.

Step 3: After a large statistical experiment for lots of images, the self-adaptation threshold was calculated as:

$$T = floor(t - 6 \times s) \tag{7}$$

After the threshold T was confirmed, the gray-scale image was converted into the binary image with the threshold T. However, the segmentation result only based on the threshold is still not ideal. Then we analyzed from a new point view of color features in original image. We found that the component G in color image was higher than 150 in disease spots. Therefore, the color feature is formed a new constraint to detect disease spots. Now the judgments is integrated the threshold T and the component G feature. The test results are shown in figures 5(a) ~(c) and 6(a) ~(c).

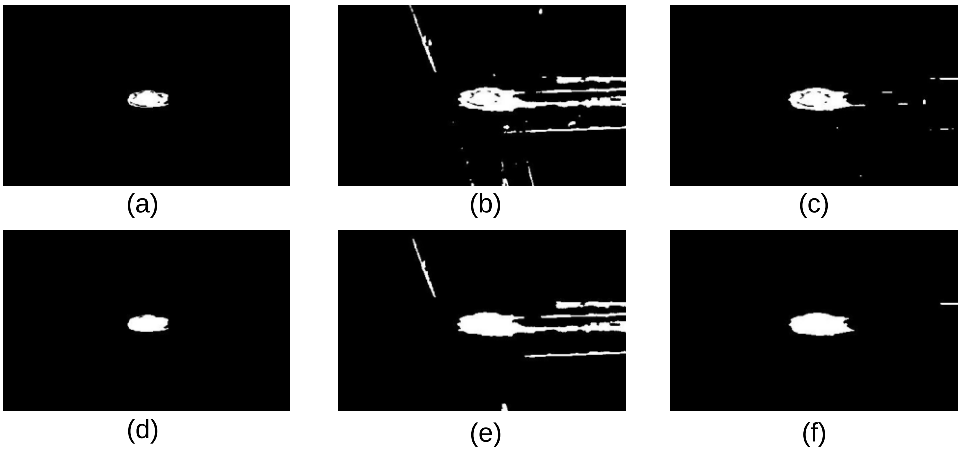

Figure 5. Segmentation of Rice Disease by the Proposed Method for the Rice Image Shown in Figure 1(a): (a) Segmentation before Filling Cavity and Denoising for $2G-R-B$ Grey-scale image, (b) Segmentation before Filling Cavity and Denoising for $2g-r-b$ Grey-scale Image,(c) Segmentation Before Filling Cavity and Denoising for $1.262g-0.884r-0.311b$ Grey-scale Image, (d) the Final Result of Rice Disease for 5(a), (e) the Final Result of Rice Disease for 5(b), (f) The Final Result of Rice Disease for 5(c)

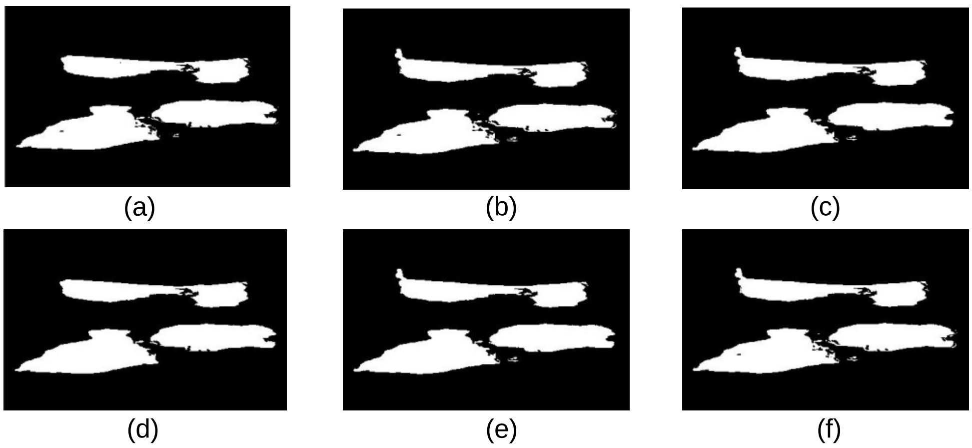

Figure 6. Segmentation of Rice Disease by the Proposed Method for the Rice Image Shown in Figure 1 (b): (a) Segmentation before Filling Cavity and Denoising for $2G-R-B$, (b) Segmentation before Filling Cavity and Denoising for $2g-r-b$, (c) Segmentation Before Filling Cavity and Denoising for $1.262g-0.884r-0.311b$, (d) the Final Result of Rice Disease for 6(a), (e) the Final Result of Rice Disease for 6(b), (f) the Final Result of Rice Disease for 6(c)

In the rice disease region, however, some holes might be found. So it should be filled. Here, we called “imfill” function in Matlab to fill holes.

The gray-scale images in figures 3(a) ~(c) and 4(a) ~(c) were segmented with the self-adaptation threshold, and the study results are shown in figures 5 and 6. Figure 5(d) is the result of grey-scale image which by $2G-R-B$; figure 5(e) is the result of $2g-r-b$; and figure 5(f) is for $1.262g-0.884r-0.311b$. As can be seen from the figure, the proposed method combination of the $2G-R-B$ and this self-adaptation threshold algorithm more accurately separates the infected and uninfected pixels than the other two normalization methods. Furthermore, from figures 5 (a), (d) and figures 6(a), (d) displayed, using filling holes and noise removal methods, the performance of the segmented images will be better.

2.4. Algorithm Evaluation

In order to test the efficiency of the proposed algorithm that grey-level $2G-R-B$ and the self-adopted threshold combination, contrast from many experiments has been computed on the basis of the average values of features of adjacent regions [17]. Test data are shown in Tables 1 and 2. Contrast can be computed on the basis of the average values of features of adjacent regions. Uniformity is computed as a measure within each region independent of the surrounding regions, while contrast is computed between adjacent regions assuming that they have a uniform feature value equal to the average of that feature. The comparison between two regions R_i and R_j is calculated as following:

$$c_{ij} = \frac{\left| f_i - f_j \right|}{\left| f_i + f_j \right|} \tag{8}$$

Where f_i and f_j is the average gray level of each area. R_i represents disease area, R_j is the background region.

This is seen to be which has a maximum accurate rate value between zero and one will be the best method.

Table 1. Contrast Data of Figure 1(a)

Method	2G-R-B	2g-r-b	1.262g-0.884r-0.311b
Otsu	41.67%	25.89%	23.93%
Proposed method	92.96%	64.48%	84.63%

Table 2. Contrast Data of Figure 1(b)

Method	2G-R-B	2g-r-b	1.262g-0.884r-0.311b
Otsu	69.11%	64.49%	58.19%
Proposed method	87.25%	68.38%	57.63%

It can be inferred from figures 5 and 6 that different algorithms can acquire segmentation result. However, its effect is not obvious. But based on the comparisons by Tables 1 and 2, it is clearly known that, under the same experimental conditions, the accurate rate of proposed algorithm $2G-R-B$ and the self-adopted threshold combination is about 91% higher than the other grey-level and Otsu's methods.

In addition, the results from the figures 5 and 6, Tables 1 and 2 imply that the proposed algorithm can get ideal segmentation results.

3. Results and Discussion

The proposed methods were applied on 300 infected rice disease images. Samples of acquisition images are shown in Figure 1.

From the figure 2 displayed, the rice disease image mainly consists of disease area and the surroundings due to the image was obtained in the RGB color model. The infected area and the rest region have great difference in color, so color was considered as the feature. A pixel where the predominant spectral component is the green is considered surrounding region. In this paper, the images this assumption is acceptable due to the nature of the leaf images and because they were captured in the rice fields, so as to distinguish between disease region and the surroundings. So in the first step, three kinds of famous grey-scale transformation methods which strengthen the green component inhibit the red and blue components were adopted. Image noises which could disturb the image processing were removed or weakened by a 3×3 rectangle median filter window in figures 3(a) ~(c) and figures 4 (a) ~(c). Then the Otsu's method combined with the three grey-level transformation methods to segment the disease region. As is show in figures 3(d) ~(f) and 4(d) ~(f), Otsu's method did not achieve the desired purpose. Plant disease area cannot be perfect partition.

The new method this study proposed was satisfactory in detecting the disease region of the rice in figures 5 (d) and 6 (d). Through the calculation of mean and standard variance of a gray image of the element, and the combination of the distribution characteristics of green components in color images, a new self-adopted threshold was calculated. Finally, combined with the new threshold, the rice disease area was segmented successfully. Meanwhile, as can be seen from the figures 5 and 6, the performance of the grey-scale transformation method $2G-R-B$ combined with new threshold algorithm proposed in this paper, is superior to method $2g-r-b$ and $1.262g-0.884r-0.311b$.

From the figures 5 (a), (d), and 6 (a), (d) displayed, some holes could be filled by the Hole filling operation and noises could be removed by comparing noises area with the disease area.

To measure the effectiveness of the proposed algorithm, an algorithm evaluation study was carried out with the grey-level transformation and Otsu's methods. The results are visible in Tables 1 and 2. It is seen that the accurate rate of $2G-R-B$ and the self-adopted threshold value segmentation measure is higher, and this proposed method meets the demand of segmentation sufficiently.

4. Conclusion

In this paper, an algorithm was completed to rice diseases segmentation. The method based on the green value in the RGB image being larger than that of blue and red for rice during the entire cultivation management period. The method $2G-R-B$ grey-level transformation applied provides adequate contrast for disease region and background.

The self-adaptation threshold calculated by the mean value and standard variance of the grey-scale image could overcome the Otsu's method shortage. Then the threshold of grey-scale image and the green component G in color image constitute a new threshold range.

The rice diseases can be segmented effectively using methods $2G-R-B$ and the proposed segmentation threshold value.

In future work, we plan to explore a more efficient method for segmentation with complex background and disease of image.

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