Assessment of the Severity of Brown Leaf Spot Disease in Cassava using Image Analysis

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Abstract

The objective of this research was to develop an image analysis technique for severity rating of brown leaf spot disease in cassava. Samples of cassava leaves were collected from field and imaged under controlled illumination. Images resolution were resized to 640×480 pixels and transformed from RGB to HSI color space. The transformed images were then segmented and feature-extracted in order to determine total leaf area and diseased area. Noise reduction was performed using erosion and dilation procedure. The percentage of inflection was calculated based on diseased area and total leaf area. Comparative assessment by manual scoring based on conventional illustrated diagram key was conducted. The results showed a good agreement between the number of spot counts obtained by manual scoring and by image analysis at an R^2=0.90, but with greater standard diviation for manual scoring. The number of spots was found to affect the accuracy of image analysis.

***Keywords**:* Cassava, Brown leaf spot disease and Image processing

1. Introduction

Brown leaf spot (BLS) disease caused by *Cercosporidium henningsii* Allesch is considered one of important fungal disease in cassava (*ManihotesculentaCrantz*). The symptoms appear as small brown spots with dark borders on the upper leaf surfaces [1]. The disease is usually considered less destructive comparing with other disease such as cassava mosaic disease or cassava bacterial blight. Nevertheless, infection of BLS disease causes leaf chlorosis and extensive defoliation which in turn resulting in yield loss up 20% [2]. Furthermore, the infection of a plant may influence the susceptibility to another disease. Wydra and Verdier [3] found a significant positive correlation between the incidence of cassava anthracnose disease and the occurrence of BLS, as well as implications among the BLS, white leaf spot and root rots. The BLS is more prevalent in humid ecozones while its severity seemed to be increasing with number of surrounding trees and on profusely branching varieties that the BLS disease should not be neglected particularly in the conditions of Thailand.

The plant disease scoring is important procedure to develop diagnostic plant and investigate resistant varieties to the disease. Conventionally, plant pathologists score the disease level based on their own discretion using illustrated diagram key for particular disease. Teri et al. [4] developed a diagram key for classifying the severity of BLS disease into 5 levels. With this method, feasible errors may occur and require much time if the sample set is large. The automated monitoring systems were developed for diagnostic diseases, the computer vision has been applied to identify fall armyworm damaged maize plants [5], Black Sigatoka infected banana leaves [6], and cotton crops damaged by Southern green stink bug, Bacterial angular, and Ascochyta blight [7] and Wang et al. [8] developed segmentation methods to analysis plant disease that the symptoms was shown on leaves. However, Application of digital image analysis technique to diagnostic cassava disease found that only research of Aduwo et al. [9] studied automated vision-based diagnosis of cassava mosaic disease.

The objectives of this research were to develop an image analysis technique for identifying the severity level of BLS disease based on infection area as well as to compare the results with manual scoring using Teri's diagram key.

2. Materials and Methods

2.1 Experimental site and plant materials

Image of cassava leaves were collected from an experimental field located in Kasetsart University (Kamphaengsaen Campus), Nakhon Pathom, Thailand (Lat14º2'11''N and Long 99º57'56''E). The variety of cassava plants was Rayong 5. The age of the plants at sampling was 6 months. The BLS-infected plants were found scattering naturally throughout the field without systematic inoculation treatment.

2.2 Severity assessments by area diagram key

Assessing the severity of brown leaf spot disease by using an area diagram key [10] was categorized percentages of inflection of four levels as show in Fig. 1. Each leaf was visually assessed by seven rater. Assessments were made independently with image analysis methods upon to the discretion of the individual raters.

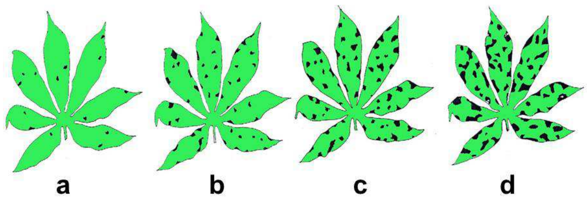

Fig. 1 Diagram key for assessment of brown leaf spot: (a) 5%, (b) 10%, (c) 15% and (d) 30% [10]

2.3 Severity assessment by image analysis

2.3.1 Image acquisition

The samples of 48 images, 1600 pixels horizontally by 1200 pixels vertically, were captured using digital camera (IXY55 model) with under illuminated controller box and connected to computer by USB port. An 8 mm focal length lens was used with a fixed f-stop of 3.5. The Images acquired RGB color images with JPEG type format. A digital camera was set at 50cm (bird's-eye view) from the top of box structure. An inner illuminated controller box was covered with a black canvas and white papers were used to be a background. The illumination system comprised four Day lights D65 (Color temperature 6500K) 18W were Installed at the corners of the top of illuminated controller box at 45º with the axis of the digital camera.

2.3.2 Image enhancement

The Image Processing Toolbox™ for MATLAB® (The MathWorks Inc., MA, USA) was used to analyze all images. First, the original images were resized to 640 pixels horizontally by 480 pixels vertically. Second, The RGB images are converted into HSI color space representation because of the natural way of segmentation the color of an object is based on the hue (H), saturation (S), and Intensity (I), rather than the R, G, and B values of the object [4]; In addition, HSI color space was tolerant to intensity variation.

An image processing algorithm technique was based on HSI color space from converted RGB color space as following equations set.

$$H = \begin{cases} \theta & if\ B \leq G \\ 360 - \theta & if\ B > G \end{cases} \tag{1}$$

$$S = 1 - \frac{3}{(R+G+B)}[min(R, G, B)] \tag{2}$$

$$I = \frac{1}{3}(R + G + B) \tag{3}$$

Where, is θ an intermediate variable and can be calculated using the following equation

$$\theta = cos\left\{\frac{\frac{1}{2}[(R-G)-(R+B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}}\right\} \tag{4}$$

2.3.3 Image segmentation and feature extraction

Image segmentation is procedure to identify an optimum that could differentiate between background and target object (i.e. the region showing the current symptoms of the disease) [6]. Firstly, Intensity (I) of HSI color image was segmented using Otsu's method [12] as shown in Fig. 2(a). Otsu's method is based on an analysis of the histogram of the tonal image [11]. The leaf region was extracted and calculated total leaf area (A_L) from pixels combination.

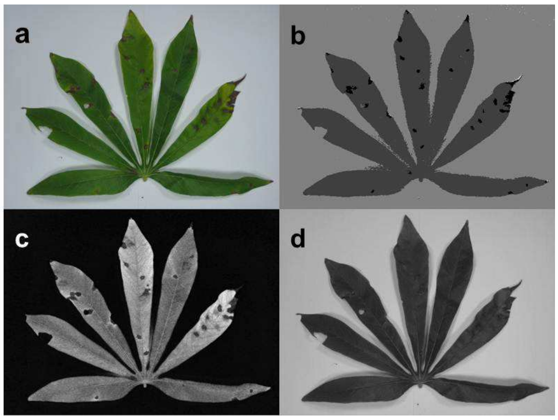

Fig. 2 Sample images: (a) Original image, (b) Hue transformation, (c) Saturation transformation and (d) Intensity transformation

Secondly, the number of brown spots and disease area (A_D) on leaf was performed by segmented in histogram of Hue (H) of HSI color which is define as:

$$g(x, y) = \begin{cases} 0\ if\ f(x, y) > T \\ 1\ if\ f(x, y) \leq T \end{cases} \tag{5}$$

Given by $g(x, y)$ is a segmented image, $f(x, y)$ is gray-level histogram at pixels (x, y), and T is threshold value

After segmentation, the spots were extracted and noise distributed all image as shown in Fig. 2(b). Noise was reduced by erosion and dilation operations as shown in Fig. 2(c) [6] respectively. Finally, the image was used to label components in 2-D binary image which is 8-connected objects technique to counted number of spots by and calculated disease area. Finally, the percentage of infection (PI) is calculated by applying the equation

$$PI = \left(\frac{A_D}{A_L}\right) \times 100 \tag{6}$$

Image processing algorithm and its graphical user interface are shown in Fig. 3 respectively.

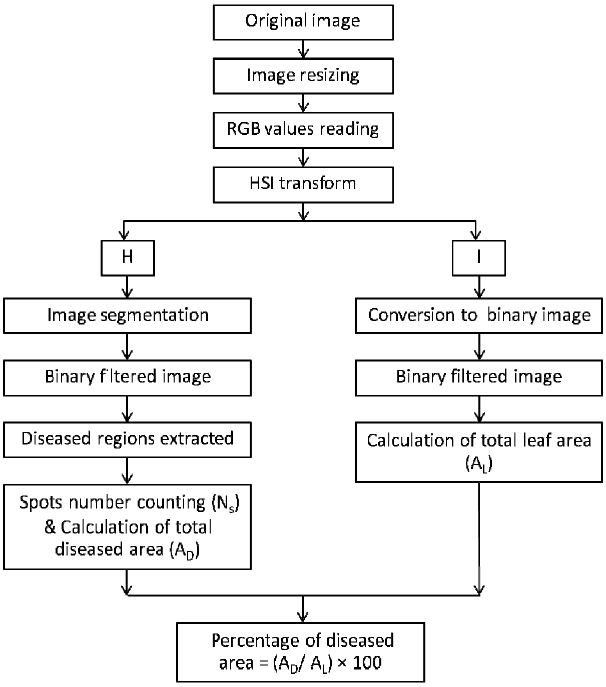

Fig. 3 Image processing algorithm

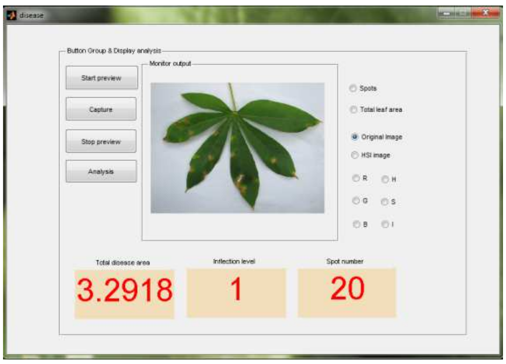

Fig. 4 Graphical user interface for the BLS disease assessment

3. Results and Discussion

3.1 Image analysis on Teri's diagram

The infected pixels were extracted from the healthy portion of the hue image base on hue value differences. The key to successfully performing segmentation is to determine a proper threshold value. In this study, threshold value was manually selected based on a guideline of clearly segmenting the infected pixels from healthy ones. After the infected and healthy pixels were segmented (Fig. 5), The PI value was calculated using Eq. (6). Subsequently, four images of area diagram key for assessment of brown leaf spot were tested and calculated PI value by image analysis.

Analysis of the area diagram key was analyzed by images processing indicated that the number of spots and spots position were correct but percentage of infection area were found considerably different especially in the severity levels of 1–3 (Table 1). The values obtained from image analysis were used as new criteria for further classification of the severity levels.

Table 1 Calibration of area diagram key between Teri's values and image analysis

BLS Level	Teri's values		Image analysis	
	Infected area	Number of spots	Infected area	Number of spots
1	5%	14	0.87%	14
2	10%	53	3.94%	53
3	15%	65	9.87%	65
4	20%	74	18.71%	74

3.2 Assessments of BLS infection severity

3.2.1 Comparison of assessing methods

The percentage of infected cassava samples between digital image analysis and area diagram key as shown in Table 2. When compared all both 2 method found that 3 in 7 of scorer (3, 4, 7) assess BLS disease levels were nearly image analysis. In 48 of samples were classified by digital image analysis found that most samples had PI value less than 4% unless one sample was the highest PI value at 8.20%. The classification of BLS disease level 1 all both methods was similar but another levels, the digital image analysis identified infection level lower than area diagram key, e.g. a sample was classified to BLS disease level 2 by digital image analysis

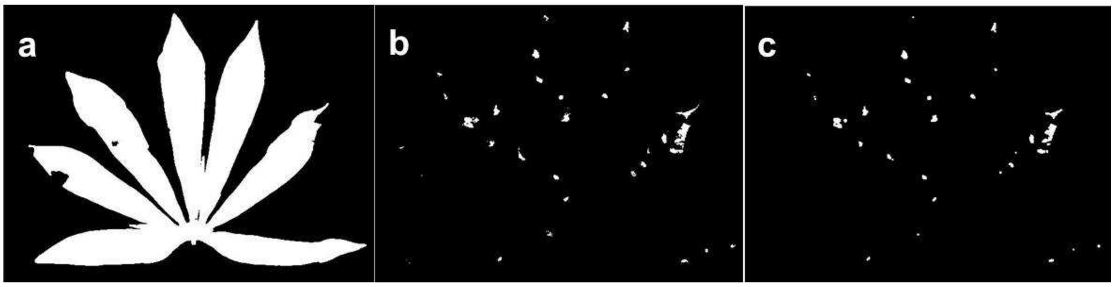

Fig. 5 Segmented and feature extracted images: (a) Total leaf area (b) Diseased regions with noise and (c) Disease regions after noise reduction

while the use of area diagram key by raters identified severity samples in BLS level 3. The using area key diagram with leaf samples depended on decision and experience of raters. Therefore, errors of using area key diagram with naked eye were high occurred and the result of area diagram key showed non-correspond with compared digital image analysis, e.g. the symptom appeared small spots and distributed on leaf, rater evaluated high BLS disease level but in fact, PI was low BLS disease level.

Table. 2 Comparison of BLS disease level between digital image analysis and area diagram key

BLS Level	Number of samples							
	Image analysis	Area diagram key (rater)						
		1	2	3	4	5	6	7
1	47	27	33	41	38	26	32	40
2	1	16	14	7	10	20	15	8
3	0	5	1	0	0	2	1	0
4	0	0	0	0	0	0	0	0
Total	48	48	48	48	48	48	48	48

The mean of BLS disease levels of 7 raters from 48 samples which were unsteady when compared with image analysis. The assessment rating of BLS disease level 2-3 of raters occurred error as shown in Fig. 7. it was difficult to approximated different patterns of BLS disease level 2–3 because of some characteristics of BLS disease samples were similar when rater evaluated by naked eye thus experience in plant pathology and realizing behavior of BLS disease are necessary.

3.2.2 Number of disease spot investigation

The investigated disease spot on cassava leaf samples was found that there were number of spots in rage 2–46, the result showed correlation between manual counting and image analysis at an $r^2 = 0.90$ as shown in Fig. 6. In some cases, the different result was found. In term of digital image analysis was concerned on certain criteria thus it was possible occurred bias from rater decision only.

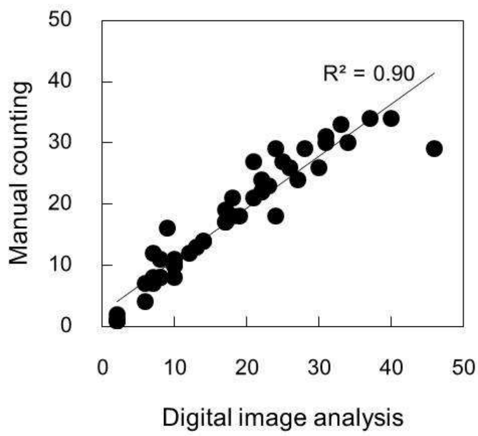

Fig. 6 Comparison of spot counts using digital image analysis vs. manual counting

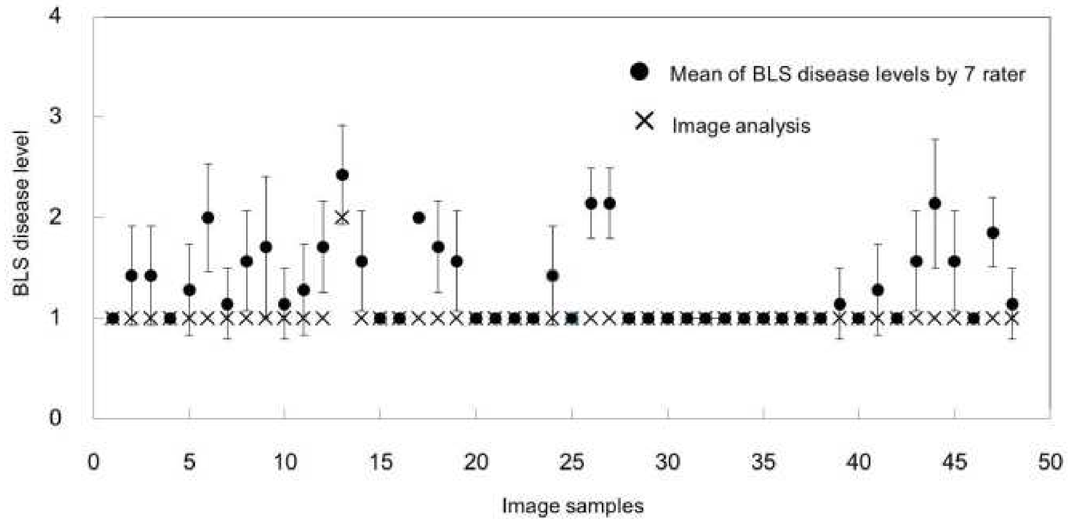

Fig. 7 Comparison of BLS disease level assessment by manual rating and by image analysis

3.3.3 Influence of severity level on the accuracy of image analysis

The result showed error was high occurred when spot less than 10 spots because it was first stage of inflected BLS disease which was small. In erosion and dilation procedure, the small disease spots were possible to be eliminated but more than 10 disease spots, the results of image analysis was high accuracy at 89.30% and 91.37% when disease spots more than 30 spots.

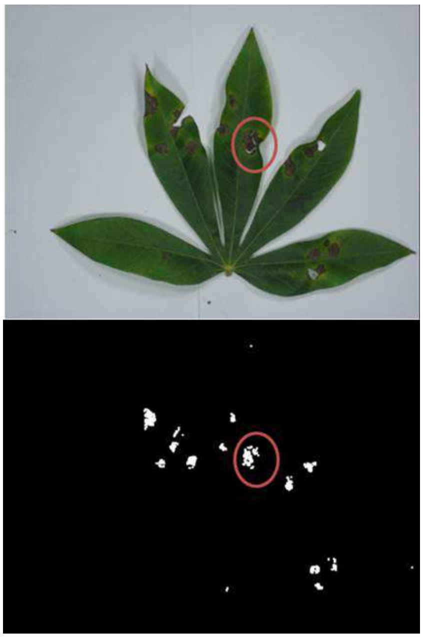

Fig. 8 Error on counting of connected spots

Table. 3 Effect of number of spots on accuracy of spots detection

Number of spot	Accuracy of spots detection
1-10	62.50%
11-20	89.30%
21-30	88.62%
31-40	91.37%
Average	82.94%

In addition, the accuracy of spot counting was implicated criteria of disease pixels, which a disease pixel was envelop by other disease pixels in eight directions and included be one spot after that a spot was counted. Error was occurred when spot had a hole as shown in Fig. 8. In a circle, the algorithm of image analysis detected a spot more than one spot because algorithm could not connect disease pixels and include be a spot.

4. Conclusion

A digital image analysis technique was developed to identify severity of brown leaf spot disease. This technique was used to measure the percentage of disease severity of area diagram key found that values non-corresponded classified criteria value but the number of spots and spot positioning were corrected. The new percentage of inflection of area diagram key were found and used be new thresholds and creating new criterion of BLS disease severity rating base on digital image analysis is a way to solve problem uncertainty of using area diagram key. Comparison of number of spot counts with visual observation indicated an agreement at an R^2 = 0.90, besides, the number of spots was found to affect the accuracy of image analysis. An Image analysis technique will help pathologists overcomes almost all the disadvantages of manual scoring in terms of complexity and time.

5. Reference

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