# Segmentation Method Based on Artificial Bee Colony for Recognizing Leaf Lesion 

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#### Abstract

Many studies on object detection have been initiated but these methods have some limitation. A segmentation method was proposed to recognize a leaf lesion in leaf images and overcome the limitation of existing object detection method in terms of accuracy and processing time. The method includes steps based on Artificial Bee Colony, Otsu, and geometry. The method was conducted in three phases, image preparation, lesion recognition and measurement, and evaluation. The paper shows results of the evaluation phase. The results show that the proposed segmentation method achieved better percentage of accuracy and produced a shorter processing time.


Index Terms-Leaf Lesion; Area Size; Hybrid; Artificial Bee Colony; Otsu.

## I. Introduction

Plants are an important source of food and if infected by some diseases and not immediately addressed, the damage caused can be catastrophic. Millions of people will be deprived of food if plant diseases are not treated [1]. Because of the severe damage that plant diseases create, early detection of a disease is crucial. Many studies on plant disease detection have been initiated using several methods through the use of leaf color and lesion area. For example, in terms of leaf color, the green color on the leaf surface will slowly change to yellow color if a plant is infected by a disease. The color will then change to red dark if the plant is dying. Thus, the level of severity can be determined using color features [4]. Currently, five categories of plant disease are used: Grade 0 (zero infection), Grade 1 ( $0-25 \%$ infection), Grade 2 ( $26-50 \%$ infection), Grade 3 ( $51-75 \%$ infection), and Grade 4( $>75 \%$ infection).
In terms of color, the Leaf Color Chart (LCC) has been popularly used by farmers to classify the grade of plant disease. However, the method has some limitations: LCC consumes time in identifying the level of a disease, and the grade levels produced are less accurate. To overcome the problems, methods such as fuzzy logic, k-means, clustering, histogram matching, wavelet decomposition, and neural networks have been used [5-6].
Recently, leaf lesions have been used to determine the level of plant disease's severity [7-8]. A large lesion area denotes that a plant is highly infected by a disease, while a small area denotes vice versa. In a study by [11], Artificial Bee Colony (ABC) was used to segment image and recognize an object in a shorter time. Ma et al. [12] proposed a method to identify the threshold optimal value of grayscale color between pixels, and [13] applied $A B C$ to recognize objects in selected images. The objective of their work was to find a pattern or template of an object anywhere on grayscale and color images. Their method when experimented on grayscale and
color images showed that the performance of ABC was faster in finding a pattern than Evolutionary Algorithm (EA).
In another study, [8] used leaf segmentation to search for a lesion. However, this method is less accurate in determining a lesion area. The reason being the method sometimes over counts the pixels and sometimes understate the number of pixels. In another study, [9] have used the threshold method known as Otsu to measure the lesion area. However, Otsu was found to be unsuitable for images of large size and in some cases, lesions were not recognized. Due to the limitations, a better method has been sought. Several researchers explored the possibilities of using artificial intelligence methods. For example, ABC has been applied to solve thresholding, segmentation and object detection problems. [10] proposed an automated threshold algorithm using ABC and found that it was better than an existing technique, (Otsu). These have shown that ABC is suitable for global search, while Otsu fits well in local search.
Since this research aims to achieve an optimal search and recognize an object, ABC and Otsu were thus, combined to recognize an object, specifically a lesion in green leaf images.
In terms of measuring an object area, it was found that geometry has been widely used in areas such as engineering [14], biometric [15], nuclear technology [16], and agriculture [17]. The method has been proven to be easy, fast to perform calculation, and produce accurate results. Complicated shapes and sizes are suitable to be used with this method because it includes theorems and formulas for determining areas for various shape and size. Thus, in this study, geometry was used to calculate the overall lesion area. The geometry method was integrated with ABC to determine the degree of leaf unhealthiness.

## II. Method

The segmentation method consistof three phases, image preparation, lesion recognition and measurement, and evaluation.

## A. PHASE 1: Image Preparation

In this phase, several steps were conducted. These include converting images from JPEG or RGB to TIFF; converting TIFF images into grayscale; and performing data cleansing. The following paragraphs elaborate the steps:
a. Step 1: Converting images from JPEG or RGB to TIFF

The data for this study are leaf images that are of green color. These images were taken from www.forestryimages.org. The images, originally in RGB and JPEG format were converted to TIFF format using Microsoft Paint software. The conversions were done to obtain sharper
and clearer leaf images. Figure 1(a) and 1(b) show a leaf image before and after conversion.


Figure 1(a): Before: Leaf image is less sharp


Figure 1(b): After: Leaf image is sharper

## b. Step 2: Filtration

The aim is to obtain relevant leaf images. This was done by categorizing the leaf images into three categories, healthy, unhealthy, and dying. An algorithm was developed to perform the process. Detailed description of the algorithm can be referred to [3]. Based on the identification of the three categories, only the unhealthy leaves are relevant to this study and used for analysis. The other two categories, healthy and dying were eliminated as the leaves were not meaningful.

## c. Step 3: Converting TIFF Images into grayscale

Next, the unhealthy leaf images were converted into grayscale. The process is necessary because grayscale will reduce the number of colors found in colored images to one. This in turn will reduce the storage size during processing and results to a decrease in computing time. The conversion was done using Octave software. Figure 2(a) and 2(b) show before and after conversion of a green leaf image into a grayscale image.


Figure 2(a): Before: Leaf image in green color


Figure 2(b): After: Leaf image in grayscale

## d. Step 4: Data Cleansing

In order to obtain quality images such as images that are sharper, smoother and cleaner, the grayscale images were then filtered using the Gaussian technique. The filtration produces images that are free from dust, blurriness, and unwanted spots.

## B. PHASE 2: Lesion Recognition and Measurement

In this phase, an algorithm was enhanced based on [19] to recognize a lesion and calculate its area. [19] developed an algorithm based on ABC to detect the lesion on leaf surface. However, the algorithm has some limitation in terms of accuracy and processing time.
The algorithm by [19] was enhanced to include steps to identify a lesion, and calculates its area using an identified formula. This was done by incorporating ABC, Otsu and geometry. In this research, a few adjustments were made to the algorithm produced by [19]. These include (i) performing segmentation of image into smaller portions; (ii) using new optima value and number of bees; (iii) using a new nectar value; (iv) using a new number of reading images (sources); (v) using a new time detection value; (vi) using a new grayscale properties value; and (vii) producing detection symbol (+) when bees detect the object.

The global and local search processes are shown in Figure 3 and Figure 4 respectively. The detail explanation on Phase 2 can be found in [13]. In summary, three steps are involved. A brief description of the steps are given below.

## a. Step 1: Global Searching

In this phase, the pixels on a grayscale leaf image were checked for intensity value. That is, the intensity is determined by using the highest property value ( 0 to 85 ). If an intensity pixel is found, it indicates that a lesion is recognized. The coordinates of the pixel were then recorded. Details of the steps can be found in [20]. Figure 3 shows the global search process flow.

## b. Step 2: Local Searching

The coordinate values found in Step 1 were used to set the lesion border using a small window. The window was adjusted repeatedly until the major and minor axis values were obtained. Figure 4 shows the local search process flow.

## c. Step 3: Lesion area measurement

Using the major and minor axis values and a geometry formula, the lesion area was calculated. Eq1 shows the formula used:

$$
\begin{equation*}
\text { Area }=\pi r^{1} r^{2} \tag{1}
\end{equation*}
$$

where, $r^{1}$ is the semi major axis of the ellipse and $r^{2}$ is the semi minor axis of the ellipse.

## C. PHASE 3: Evaluation

The algorithm produced in Phase 2 was executed on selected images. The images are in three different sizes, small, medium and big. The experiment was repeated for four


Figure 3: Global Searching process flow


Figure 5: Blue symbol and red symbol
times to get a consistent output. The segmentation method was then compared with pixel counting [21] and the real lesion area.
The algorithm was assessed in terms of time (millisecond) taken to calculate the lesion area. The time measured was from the start of execution until the total area of lesion was obtained.


Figure 4: Local searching process flow


Figure 6: Border of lesion area

## III. Results and Discussion

Figure 5 and Figure 6 are the output produced by the enhanced algorithm. Figure 5 shows the output of intensity pixels found in an image (Phase 2 (Step 1). Figure 7 shows the small window created based on the coordinates found in Phase 2 (Step 2).
Based on Figure 5, several blue (+) symbols and red (+) symbols can be seen. These symbols are intensity points that denote whether an object is recognized (blue (+) symbol) or not recognized (red (+) symbol). In this research, only the blue ( + ) symbols are used for further analysis. The red ( + ) symbols were discarded as an object is not recognized.

The blue (+) symbols were then sequentially checked to identify whether it is a lesion. If it is a lesion, the coordinate values were recorded and denoted as a lesion.

These coordinate values obtained from the previous step was used to create a border or termed as a "small window". The small window was adjusted repeatedly until major axis and minor axis values were obtained. Figure 7 shows the final adjusted window. The value of the x and y axis were then used for calculating the lesion area. The lesion area obtained from the segmentation method is shown in Table 1. Table 2 shows the performance of the segmentation method when compared to pixel counting. The performance was made in terms of area calculated area in (pixels ${ }^{2}$ ).

Table 1
Lesions area calculated from the segmentation method

| Leaf Image | I1 (Big) | I2 (Medium) | I3 (Small) |
| :---: | :---: | :---: | :---: |
| $\left.\begin{array}{c}\text { Lesion area } \\ (\text { pixels }\end{array}{ }^{2}\right)$ | 52882.26 | 6410.00 | 3477.00 |

Table 2
Comparison in terms of calculated area (pixels ${ }^{2}$ )

|  |  | Lesion Images |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | I1 (Big) | I2 (Medium) | I3 (Small) |
| 1 | Original size | 46415.00 | 6106.00 | 3235.00 |
| 2 | Area obtained from pixel counting | 25817.81 | 7107.44 | 3642.10 |
|  | Difference of area from original size | -20597.19 | 1001.44 | 407.10 |
|  | Percentage of difference from original size | -44.38 | 16.40 | 12.58 |
| 3 | Area obtained from the segmentation method | 52882.26 | 6410.00 | 3477.00 |
|  | Difference of area from original size | 6467.26 | 304.00 | 242.00 |
|  | Percentage of difference from original size | 13.93 | 4.98 | 0.07 |

Based on Table 2, the three right-most column denote leaf images in three size categories (Big, Medium, and Small). Row 1, 2, and 3 denote the calculated area of (i) original size, (ii) obtained from pixel counting, and (iii) obtained from the segmentation method. The measurement unit is number of pixels. From Table 2, it can be seen that the pixel counting method could recognize a lesion correctly in all lesion sizes. However, the pixel counting method is less accurate in calculating the lesion area. The
segmentation method is able to calculate lesions areas with less difference than pixel counting for all image sizes.

Table 3 shows the comparison results in terms of percentage of accuracy and processing time. Based on Table 3, the first column denotes leaf images in three size categories (Big, Medium, and Small). Column 2 and 3 denotes the percentage of accuracy obtained using pixel counting, and the segmentation method. Column 3 and 4 denotes the processing time ( ms ) obtained from using pixel counting, and the segmentation method.

Table 3
Comparison in terms of accuracy and processing time

|  | Accuracy (\%) |  | Processing Time (ms) |  |
| :---: | :---: | :---: | :---: | :---: |
| Image | Pixels <br> Countin <br> g | Segmentation <br> method | Pixels <br> Counting | Segmentation <br> method |
| I3 | 55.62 | 86.07 | 0.113 | 0.015 |
| I2 | 83.60 | 95.02 | 0.116 | 0.015 |
| I1 | 87.42 | 99.93 | 0.055 | 0.015 |
| Average | 75.55 | 93.67 | 0.095 | 0.015 |

From Table 3, it can be seen that the segmentation method is superior to pixel counting method in calculating lesion area for all lesion sizes. That is, the segmentation method achieves higher percentage of accuracy (average of $93.67 \%$ ) in calculating the lesion area than pixel counting. The method produced closer lesion area to the actual size of the lesion. In terms of processing time, on average the segmentation method is able to calculate lesion areas faster $(0.015 \mathrm{~ms})$ than pixel counting.

## IV. CONCLUSION

The segmentation method that incorporate global searching, local searching, and mathematical formula through ABC, Otsu and geometry were proposed. The method was evaluated in terms of percentage of accuracy and processing time. Results show that the proposed method was able to produce good results. This shows that ABC combined with Otsu could be used to detect objects in images accurately and in a shorter time. The calculation base on geometry is able to produce lesion area with less difference from the original area than pixel counting.

## RECOMMENDATION

Further experiments will be conducted to test on a larger set of data, using leaf images of different color, and using leaf images with multiple lesions.

## References

[1] Chakraborty S. and Newton a. C., 2011. Climate Change, Plant Diseases and Food Security: an Overview, Plant Pathology, 60: 214.
[2] Horsfall J. G. and Heuberger,J. W. 1942. Measuring Magnitude Of A Defoliation Disease Of Tomatoes, Phytopathology 32: 226-232.
[3] Ahmad F. and Airuddin, A. 2014. Categories Leaf Healthiness Using Rgb Spectrum and Fuzzy Logic, in 7th Knowledge Management International Conference (KMICe) 2014, Langkawi, Kedah, Malaysia.
[4] Abdul, M. et al., 2013. Measuring Leaf Chlorophyll Concentration from Its Color: A Way in Monitoring Environment Change to Plantations, arXiv:1305.1148v2 [physics.bio-ph].
[5] Dadwal M. and Banga, V. K. 2012. Estimate Ripeness Level of fruits Using RGB Color Space and Fuzzy Logic Technique,

International Journal of Engineering and Advance Technology (IJEAT), 2: 225-229.
[6] Arivazhagan, S. et al., 2013. Detection Of Unhealthy Region Of Plant Leaves And Classification Of Plant Leaf Diseases Using Texture Features, Agricultural Engineering International: CIGR Journal, 15: 211-217.
[7] Chen, X. M. 2005. Epidemiology And Control Of Stripe Rust (Puccinia Striiformis F. Sp. Tritici) On Wheat, J. Plant Pathol., 27: 314-337.
[8] Ahmad, S. et al., 2010. Prediction of Yield Losses in Wheat (Triticum Aestivum L.) Caused By Yellow Rust In Relation To Epidemiological Factors In Faisalabad, Pak. J. Bot., 42: 401-407.
[9] Phadikar, S. et al., 2012. Classification of Rice Leaf Diseases Based on Morphological Changes, Int J Geogr Inf Sci, 2.
[10] Ye, Z. et al., 2011. Automatic threshold selection based on artificial bee colony algorithm, in Intelligent Systems and Applications (ISA), 3rd International Workshop: 1-4.
[11] Zhang Y. and Wu, L. 2011. Optimal Multi-Level Thresholding Based On Maximum Tsallis Entropy Via An Artificial Bee Colony Approach, Entropy, 13: 841-859.
[12] Ma, M. et al., 2011. Sar Image Segmentation Based On Artificial Bee Colony Algorithm, Applied Soft Computing, 11: 5205-5214.
[13] Chidambaram C. and Lopes, H. S. 2009. A New Approach For Template Matching In Digital Images Using An Artificial Bee

Colony Algorithm, in Nature \& Biologically Inspired Computing: 146-151.
[14] Mokarrami A. and Ebadi, H. Title, unpublished.
[15] Choraś, M. 2005. Ear Biometrics Based on Geometrical Feature Extraction, Electronic Letters on Computer Vision and Image Analysis 5(3):84-95.
[16] Richards, F. M. 1985. Calculation of Molecular Volumes and Areas for Structures of Known Geometry.
[17] Soltani, M. et al., 2011. Modeling The Main Physical Properties Of Banana Fruit Based On Geometrical Attributes, Int J Multidiscip Sci Eng, 2: 1-6.
[18] Rajan, A. S. 2012. Image Processing Techniques for Diagnosing Paddy Disease, in Procceding Of The World Congress On Engineering 2012, London, UK.
[19] Sharma, P. K. et al., Artificial Bee Colony and Its Application for Image Fusion, I.J. Information Technology And Computer Science, 11: 42-49.
[20] Ahmad F. and Airuddin, A. 2014. Leaf Lesion Detection Method Using Artificial Bee Colony Algorithm, in Advanced in Computer Science and its Applications, ed: Springer: 989-995.
[21] Gulhane V. A. and Gurjar, A. A. 2011. Detection of Diseases on Cotton Leaves and Its Possible Diagnosis, International Journal of Image Processing (IJIP), 5: 590-598.

