Improving Leaf Segmentation by Creating the Automatic Marker Used in Marker-Controlled Watershed Segmentation

Wan Mahani Abdullah, Shahrul Nizam Yaakob

Abstract: Leaves segmentation in a state of nature is absolutely in need of a more complicated process. This is because the leaves that are captured outdoor may be included in a complicated background. The meaning of the complicated background is probably included with soil, residues and branches or overlapped/touched with other leaves that will complicate the segmentation process later. Most research related to leaf segmentation from complex background using watershed segmentation alone is inadequate. This is because, the technique is sometimes still segmenting leaves with imperfect conditions. To get the perfect leaf, post processing technique is needed to obtain the desired leaf. This will rise the time-consuming taken for processing and the technique for post processing should be developed to get the perfect leaf. Therefore, this research introduced the techniques which include the algorithm for automatic marker-controlled watershed transform without applying any post processing technique to obtain desired leaf. According to the previous study, over-segmentation will occurred if the watershed transform technique is directly applied to the gradient image. The problem occurs when there are irrelevant minima, other image irregularities and noise patches. Therefore, marker-controlled watershed transform is one of the approaches that can help decrease over-segmentation. A creation of marker is used to locate coarsely the objects and background. To improve the process of leaf segmentation using marker-controlled watershed transform, an improved algorithm of obtaining foreground marker was developed. The developed algorithm has an ability to create the foreground markers as needed for leaf segmentation. The foreground marker is determined automatically by combining techniques including morphological closing, morphological erosion and morphological reconstruction to the input images. This technique was applied to the gradient HSV images as input images while it is typically applied to binary images or gray scale images. The proposed algorithm will automatically create the foreground marker even though the shape of target leaf was irregular. From the experimental result, 74.1% of leaf images were successfully marked in order to segment individual leaf from complex background.

Index Terms*: *Keywords: Segmentation, Complex Background, Foreground Marker, Background Marker, Watershed Transform.

I. INTRODUCTION

Plants are very important organisms in the universe. This is because plants become dependent on other living things. They are plants which boasts a remarkable ability to produce their own food through photosynthesis from carbon dioxide in the atmosphere. Furthermore, they provide the basis for the food web. Other living things cannot exist without the existence of plants.

Now a day, the technology has growth rapidly. A computer vision technology is used in order to identify plant species or quality inspection (Razali, 2011). The advancement of computer technology, processing and analysis can be visualized and can be very cost effective (Noor Ezan Abdullah, Athirah A. Rahim, Hadzli Hashim & Mahanijah Md Kamal, 2007). The traditional identification or quality inspection method is very time-consuming (Kantip Kiratiratanapruk & Wasin Sinthupinyo, 2011). In addition, it is highly rely on human skill and experience which usually contribute to errors. Identification is a process to recognize an object with its appropriate name based on their similarities or differences between this two or more elements. Plants identification is the technique used to match a sample plant to a recognized group of one or more populations of an organisms. The practice of identifying plants based on certain characteristics has occurred thousands years ago. The practice has led to the introduction of variety of methods which adopted for identification.

The ability to identify plants is very important for some reasons. From the perspective of plant management, this identification helps us to know the identity of the plants. This is because, knowing the identity of plants can determine that the plant is not weeds. In addition, it is also useful for early detection of undesirable new weeds and taking further action to redress the matter or problem. Furthermore, the identification of plant identities also ensures that the plant could only be eaten by us since some of the plants could be poisonous. Identifying plant involves recognizing the plant by one or more characteristics. Then, that recognition can be related to a name, either a common or so-called scientific name. The growth (e.g., size, shape, texture, etc.) (Yong et al., 2012; Manjunath, 2001) can be easily monitored if a cultivated plant is accurately identified. The precise identification can also be very helpful in knowing how to preserve it from pests and diseases. Moreover, plant identification allows us in determining plant maturity, ripeness and quality.

A plant can be identify using many features that available on them. In addition, the features can be used to distinguish

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between plants, such as flower size, flower colour, flower period, seeds, its odor, etc. Among them, leaves are the most obvious and widespread choice for plant species identification where the leaves can be found easily almost throughout the year, are easy to capture as photograph and their shapes present well studied specificities that make the identification possible (Guillaume Cerutti, Laure Tougne, Julien Mille, Antoine Vacavant & Didier Coquin, 2013). The other characteristics may be more apparent. Due to that reason**,** leaves are often the popular characteristic **s**ince they are so easily observed. It is undeniable, there are some plants characteristics can be easily observed or unique without a detailed examination of the plant. Therefore, leaf segmentation is very useful in plant identification. However, capturing the leaves in natural scene is very challenging since the leaf usually contains complex background.

Watershed arithmetic is a kind of nonlinear segmentation of mathematical morphology, and often used to separate connected objects. Its input is grey gradient image or distance transform of binary image, and its output is continuous single pixel edge line. But, because of influence of gradient noise, quantization error and dense texture of object interior, if gradient operator is directly used, over-segmentation phenomenon will be caused after watershed transform. That is, a uniform region could be segmented into several regions.

Various techniques including pre-processing, region merging, marker-controlled watershed segmentation approach, etc. are applied to solve the over-segmentation problem. The most popular technique is a marker-controlled watershed segmentation approach which is based on the concept of markers whose aim is to pinpoint regions that are homogeneous in terms of texture, colour and intensity and then merge them to get relatively accurate segmentation. Various papers can be found in literature using this technique to overcome the problem mentioned in previous paragraph. The important keywords involve in this method are internal/foreground marker and background marker. Internal marker *I(f)* are inside each of the objects of interest, whilst external markers *E(f)* are contained within the background. These markers are used to modify the image wherefore regional minima takes place only in marked location. The image obtained by marker image *M(f)* is a binary image such that pixel belonging to homogeneous region will be marker.

For the case of touching, overlapping and occlusion objects, morphological operation is more suitable in separating the object of interest from others. This situation is considered as complex background. Two popular segmentation methods have been used in the leaf segmentation from complex background which are watershed and graph-cut. In this paper we focus on marking the region of interest for watershed segmentation. Most popular technique to mark interested region is by using morphological reconstruction and gradient modification.

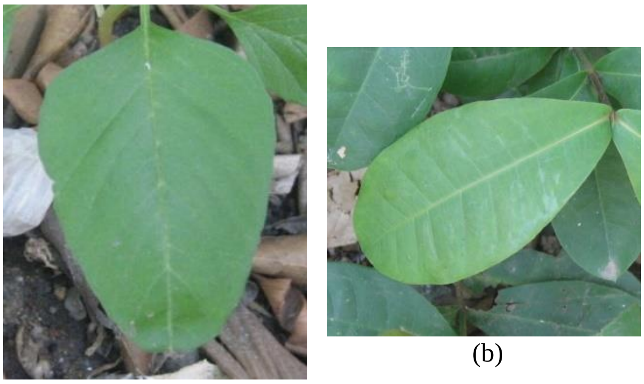
The previous study regarding the leaf segmentation including watershed transform is presented in Section 2. The procedure for finding the foreground marker of the leaf images is presented in Section 3, while experimental results and discussion are given in Section 4, followed by conclusions in Section 5.

II. LITERATURE REVIEW

In Computer Vision, many research have been produced since the past decade. The research based on leaves features are produced which related to algorithms in order to help botanists and non-experts in plants identification. The technology is useful in providing imaging-based automatic analysis in various areas such as medical, agriculture and many more. Instead of leaf features such as leaf shape and leaf margin, the plants have a variety of other botanic features. Therefore, the identification of plant can be performed from several characteristics including flower colour, flower size, their odor, venation pattern, inflorescence and others. Since leaves of various types of plants are unique which different from each other based on a number of characteristics, therefore leaves can be popular features in order to perform plant identification. Therefore, to identify the plant species, leaf recognition is the best and easiest way compared to other criteria.

Thus, leaf segmentation is an essential step for automatic leaf recognition and plant identification. The single leaf to be segmented is refer to the biggest/perfect leaf captured from outdoor. The existence of the soil, residues and most challenging problem is touching/overlapping with other leaves could be considered as the complex background. Even though there are many successful techniques used for leaf segmentation but the problem arise when we face with touching and overlapping leaves. Since both the target leaf and unwanted leaves have almost the same intensity values, the critical part is to segment the target leaf which usually touches/overlaps with other leaves which may create the confusion between the boundaries of adjacent leaves. However, the previous research involved combination of two or more methods to successfully segment individual leaf from complex background. Even though watershed transform is a powerful technique to separate touching or overlapping objects (Gurtej Singh, Gulrej & Er. Sanmmet Kaur Bawa, 2013; Shengzhou Xu, Hong Liu & Enmin Song, 2011; Mariela A. Gonzalez, Teresita R. Cuadrado & Virginia L. Ballarin, 2008), but watershed transform itself in order to segment target leaf from complex background leads to over-segmentation. (M.C. de Andrade, G. Bertrand & A.A. Araujo, 1997). Traditional approach of leaf segmentation is to select the threshold value based on one-dimensional gray image histogram is not enough (Dianyuan Han & Xinyuan Huang, 2010). According to the previous studies, the process of leaf segmentation are limited to plant leaf images in plain/ideal background. However it is still a very challenging task to extract a single leaf from images with complicated background such as with some interference and overlaps between two adjacent leaves (Xiang Rong, Jiang Huanyu &Ying Yibin, 2014; P. Wijethunga, S. Samarasinghe, D. Kulasiri & I. Woodhead, 2008). The complex background in this context refers to an image captured outdoor in natural scene. The image of target leaf with complex background may touching or overlapping with other leaves. Due to that, the problem arise dealing with objects of uniform intensity (Kazanov, 2004). The complex background also may consist of soil, residue, branches and etc. (D S Guru & P B Mallikarjuna, 2010). Therefore, the process of target leaf segmentation could be difficult and challenging task (Tapio Pahikkala et al., 2015; S. T. Anjomshoae, M. S. M. Rahim & A. Javanmardi, 2014).

According to the previous studies, the main problem of watershed transform is over-segmentation (Manisha Bhagwat, R.K.Krishna & V.E.Pise, 2010). Classical watershed segmentation does not require the information of foreground and background marker. However, the markers are needed since the recovered boundaries between the objects are sometimes more complex than expected when involved touching/overlapping objects in an input image (George E.Meyer & João CamargoNeto, 2008,). Fig. shows an example of touching and overlapping leaves in the input images. Therefore, marker-controlled watershed segmentation is used in order to overcome the problem of over or under segmentation. The marker will be used to mark the region of interest and also the background region.



(a) (b)

Fig. 1: (a) Touching leaves. (b) overlapping leaves

Xiaodong Tang *et al.* developed leaf extraction algorithm to extract leaf from the image with complicated background. They proposed the marker-controlled watershed segmentation to the Hue and Saturation components leaf classification and plant species identification, since the thresholding, edge detector and morphological processing cannot perform well to segment the target leaf from complicated background. The first step involved the greenness identification. The technique used for greenness identification is based on colour index-based method. The ExG minus ExR which proposed by Meyer in 2004 was employed in this stage. The Otsu thresholding was applied to eliminate non-green background. The problem of small holes were overcomed by morphological approach.

The extraction of leaf from complicated background started by creating markers. The process was ran in HSI colour space. The Intensity channel was used to obtained marker for the first phase of segmentation. The Intensity channel was converted to gradient image. Then, the histogram equalization was done before applying opening by reconstruction operation. After that, the local maxima was computed as marker while applied the minima imposition technique to remove all other minima. The detail steps to create markers is explained in (Xiaodong Tang *et al.*, 2009). The watershed segmentation was applied to the result image hence obtaining the segmentation regions. The region of interest was assumed as the biggest region extracted from the segmentation regions. Then, the second phase of the proposed algorithm was employed to the region of interest from the first phase. The process was implemented in Hue and Saturation channel separately. Xiaodong Tang *et al.* found that the proposed method has the percentage of successful of 85% in extracting target leaf from complex background. The author claimed that the main reason of failure for leaf extraction was that the edges of overlapping leaves was blur. The issue had raised the motivation for this research to come out with the new technique to enhance the overlapping edges.

Creating of marker is an essential step in morphological segmentation technique. The presence of homogeneous regions from the image after morphological simplification is identify using the markers (S Anusya, 2005). This step separates the pixels into two categories, labeled pixel is an object while not labeled is belong to uncertain zones. An approach has been used which is based on the concept of marker in order to control over the occurrence of over-segmentation, (Gang Lin et al., 2003). A marker is a connected component that is belonging to an image and is used to locate coarsely the objects and background are connected components (S Anusya, 2005). The markers can be classified into internal marker and external marker. The internal markers is refer to foreground markers which are inside each of the target object. The external markers is refer to the background markers which locate non-target object. Marker extraction is the most critical in watershed segmentation. If the target object is not marked appropriately, then the final segmentation will excluded that object. Therefore, the maker extraction is not an easy task since too many markers lead to over-segmentation while too fewer markers will lead to under-segmentation.

III. METHODOLOGY/MATERIALS

In order to obtain a desired partition by the watershed transform, a set of marker needs to be created in appropriate location in the image so that avoiding under/over-segmentation (J.F. Rivest *et al.*, 1991). Mathematical morphology provided the tools that has been used. The strategy is based on watershed transform that used markers in order to modify gradient image. To improve the process of leaf segmentation using marker-controlled watershed transform, an improved algorithm of obtaining foreground marker was developed. The developed algorithm has an ability to create the foreground markers as needed for leaf segmentation. The foreground marker is determined automatically by combining techniques including morphological closing, morphological erosion and morphological reconstruction to the input images. In contrast to the methods most often used, this technique was applied to the gradient HSV images as input images while it is typically applied to binary images or gray scale images.

A. Morphological Operation

Mathematical morphology is usually presented as a collection of techniques for image processing that process image based on shapes (Senthilkumaran N & Kirubakaran C, 2014; D.Stenning, V. Kashyap, T. C. M. Lee, D. A. Van Dyk & C. A. Young, 2013; Hemant Tulsani, Saransh Saxena & Naveen Yadav, 2013; John G. Stell, 2007). The original definition of morphological operations are based on set theory. It was founded by J. Serra in 1982. The operations for binary images involved binary operations such as Booleans and set theory. The operations extended on gray-scale images which involved multiple-valued logic operations.

B. Gray-scale morphology

The gray-scale morphology can be extended easily from binary morphology. A gray-scale image can be interpreted as a 3-D surface. The 2-D morphological algorithm can be extended to work on 3-D surfaces. The gray-scale morphology is just a generalization of the image where Max and Min operations are used to replace OR and AND operations, respectively, of binary morphology. The later explanation will involved digital image functions. Let say the digital image function are in the form of *f(x,y)* and *b(x,y)* where *f(x,y)* is the discrete input image while *b(x,y)* is a structuring element.

C. Gray-scale dilation and erosion

There are two basic mathematical morphological operations. The operations are erosion and dilation. Indeed most morphological algorithms are based on these two elementary operations (Alka Bishnoi, 2014). Initially developed for binary images, it has been extended first to gray-scale images. The process of dilation typically uses structuring element for expanding the shape of the original image.

The image itself was viewed as a 3-D set when the morphological operation extending to a gray-scale image. The first two elements commonly are the x and y coordinates of a pixels and the third component is intensity value. Gray-scale dilation of *f* by *b*, denoted by $f \oplus b$, is defined in Equation (1) as

$$(f \oplus b)(s,t) = \max\left\{ f(s-x,t-y) - \frac{b(x,y)}{(s-x)}, (t-y) \in D_f; (s,y) \in D_b \right\}, \quad (1)$$

where
f(x,y) is the input image
b(x,y) is a structuring element
D_f and D_b are the domains of *f* and *b*, respectively.
(s-x) and *(t-y)* have to be in the domain of *f*, and *x* and *y* have to be in the domain of *b*.

The notation and mechanics of Equation (3.19) by means of simple 1-D functions could be expressed as shown in Equation (2).

$$(f \oplus b)(s) = \max\left\{ f(s-x) - \frac{b(x)}{(s-x)} \in D_f \ \text{and} \ x \in D_b \right\} \quad (2)$$

An example of dilation in gray-scale image is illustrated in Fig. 2 (a) until (d). Let say Fig. 2(a) is an RGB image, Fig. 2(b) is the matrix for gray-scale image(a), *f* with the size 5x5, Fig. 2(c) is the structuring element, *b* of size 1x3 and Fig. 2(d) is the result after went through the dilation process. The value of dilation at every position is the maximum of the sum of *f* and b in the interval spanned by *b*. The dilation in gray-scale image helps to brighter the output image as well as eliminate or reduce the dark details.

(a)

255	255	249	255	255
255	142	30	141	255
250	43	0	42	249
255	143	31	142	255
255	255	249	255	255

(b)

1	1	1

(c)

255	255	225	255	255
255	255	142	255	255
250	250	43	249	249
255	255	143	255	255
255	255	255	255	255

(d)

Fig. 2: Example of dilation process for gray-scale image

Erosion is a process of removing the pixels from features in an image (Alka Bishnoi, 2014; Suman Rani, Deepti Bansal & Beant Kaur, 2014). The aims is to remove pixels that are not require. The simplest example about erosion is the pixels chosen by the thresholding are within the range of desired brightness but that do not lie within large regions with that brightness. On the contrary, they may have a brightness value that is accidentally in that range due to several factors. The factors such as finite noise in the image which have an average brightness that happens to be within the range selected by thresholding (Alka Bishnoi, 2014). Since the brightness value is almost similar to the desired regions, therefore the simple thresholding is not possible to distinguish the pixels. As the alternative, the pixels can be removed using Boolen operator. After going through the process of erosion, images become lighter and dark details are reduced.

In this circumstances, erosion is used to remove any pixel touching another pixel that is part of the background. Due to that, some sizes are attenuated. Gray-scale erosion, denoted by f Θ b, is defined in Equation (3) as

$$(f \Theta b)(s,t) = \min\left\{ f(s+x,t+y) - \frac{b(x,y)}{(s+x)}, (t+y) \in D_f; (s,y) \in D_b \right\}, \quad (3)$$

where
f(x,y) is the input image
b(x,y) is a structuring element
D_f and D_b are the domains of *f* and *b*, respectively.
(s+x) and *(t+y)* have to be in the domain of *f*, and *x* and *y* have to be in the domain of *b*. The notation and mechanics of Equation (3.21) by means of simple 1-D functions could be expressed as shown in Equation (4).

$$(f \Theta b)(s) = \min\left\{ f(s+x) - \frac{b(x)}{(s+x)} \in D_f \ \text{and} \ x \in D_b \right\}, \quad (4)$$

Note that the set being eroded must totally contain the structuring element. According to Equation 4, the erosion is occurred based on choosing the minimum value of *(f-b)* in the interval defined by the shape of the structuring element. An example of erosion in gray-scale image is illustrated in Figure 10(a) until (d). Let say Figure 3(a) is an RGB image, Figure 3(b) is the matrix for gray-scale image(a), *f* with the size 5x5, Figure 3(c) is the structuring element, *b* of size 1x3 and Figure 3(d) is the result after went through the erosion process. Another effect of erosion operations for a simple gray-scale image is illustrated in Fig. 4.

$$\begin{matrix} 255 & 255 & 249 & 255 & 255 \\ 255 & 142 & 30 & 141 & 255 \\ 250 & 43 & 0 & 42 & 249 \\ 255 & 143 & 31 & 142 & 255 \\ 255 & 255 & 249 & 255 & 255 \end{matrix} \quad \begin{matrix} 1 & 1 & 1 \end{matrix} \quad \begin{matrix} 255 & 249 & 249 & 249 & 255 \\ 142 & 30 & 30 & 30 & 141 \\ 43 & 0 & 0 & 0 & 42 \\ 143 & 31 & 31 & 31 & 142 \\ 255 & 249 & 249 & 249 & 255 \end{matrix}$$

(a) (b) (c) (d)

Fig. 3: Example of erosion process for gray-scale image

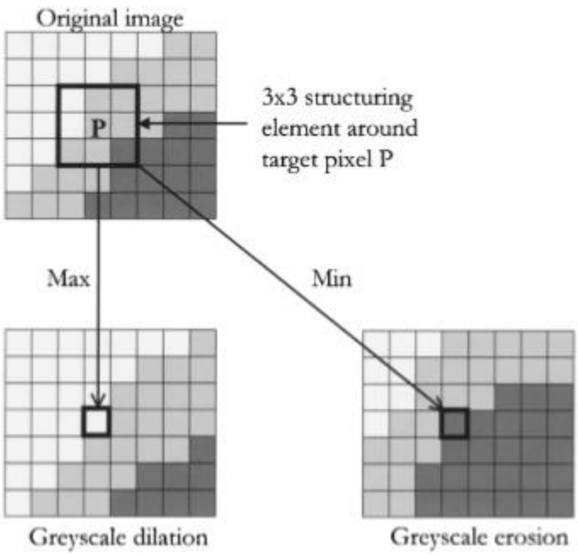


Fig. 4: Effect applying gray-scale dilation and erosion operations to a simple gray-scale image (Antonio Plaza, Pablo Martínez, Rosa Pérez & Javier Plaza, 2002)

D. Gray-scale opening and closing

The morphological opening of *f* by *b* is denoted by is a erosion of *f* by *b* followed by an dilation of the result by *b*. Equation (5) expresses the mathematical representation of morphological opening operation.

$$f \circ b = (f \Theta b) \oplus b \tag{5}$$

In practice, the opening process typically involved removing small light details and at the same time remain the overall gray levels and larger bright features undisturbed (Ivan R. Terol-Villalobos & BDamian Vargas-Vazquez, 2005); (I.R. Terol-Villalobos & D. Vargas-Vazquez, 2002).

The morphological closing of *f* by *b* is denoted by is a dilation of *f* by *b* followed by an erosion of the result by *b*. Equation (6) expresses the mathematical representation of morphological closing operation.

$$f \bullet b = (f \oplus b)\ f\Theta\ b \tag{6}$$

Since the morphological closing can help in removing dark details from an image, while leaving bright features relatively undisturbed, hence suitable as the preliminary stage in obtaining foreground marker. The technique is choose since it could start separate the target leaf from the background. The structuring element of ball with the radius of 7 and the height of 5 is choosed based on try and error.

E. Erosion-Based Gray-Scale Reconstruction

Morphological reconstruction (H. Arefi & M. Hahn, 2005) is suitable for constructing an image from insignificant components or for eliminating features from an image, without varying the shape of the objects in the image. Morphological reconstruction could be applied to binary images as well as gray-scale images. The morphological reconstruction process conceptually involved a source image and a marker image.

Reconstruction by dilation rebuilds bright regions in gray-scale images. The brightness value starts scattering at the marker points to rebuild the neighboring pixels. The process begins at the marker with the highest grey valued pixels and the neighboring pixels are rebuilt from 0 extending to the maximal valued pixel.

Reconstruction by erosion rebuilds dark regions in a gray-scale image. The darkness value starts spreading at the marker points to rebuild the neighbouring. The process begins at the marker with the minimum valued pixels and the neighboring pixels are rebuilt from the minimal valued pixel to the image maximum value.

Theoretically, morphological reconstruction can be assumed as recurring dilations of an image or *marker image*. The process proceed until the outline of the marker image fits under a second image or *mask image*. In morphological reconstruction, the dilation occurs on the peaks in the marker image. Fig. 5 illustrates the morphological reconstruction process in 1-D.

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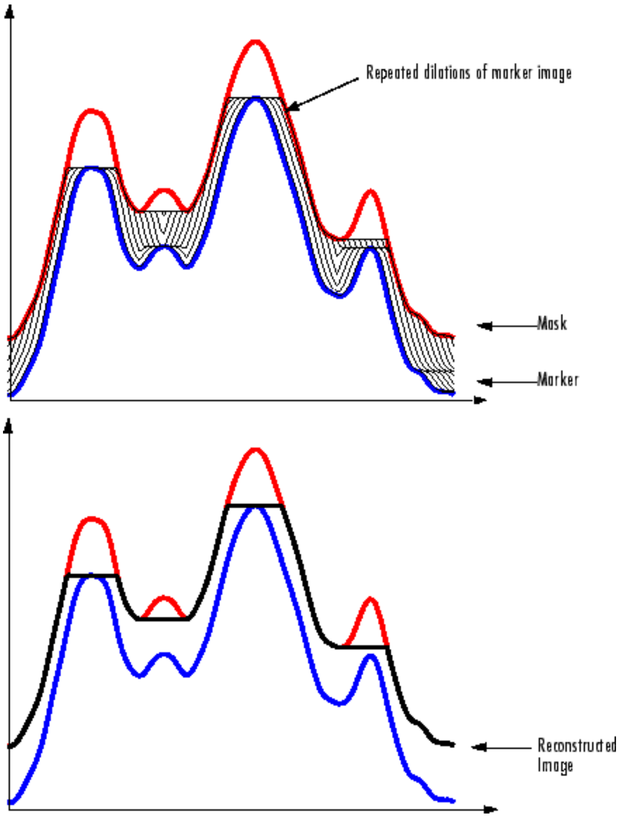


Fig. 5: The basic morphological reconstruction process in 1-D (Mathworks, 2017)

To enhance the performance of marker-controlled watershed segmentation, an improved algorithm was developed. The methodology is started by implementing histogram equalization to the input image obtained from para 3.5. The equalization histogram is done where the values in an intensity image is transformed in order to enhance the contrast of images. A specified histogram is approximately matched by the histogram of the output. Later, the process of morphological closing operation with the structuring element of (7, 5) is applied in order to remove dark details from an image, while the bright features are remain unvarying. The technique is choose since it could start separate the target leaf from the background. Then, morphological erosion was chosen because it would help to reduce the size of initial foreground marker. An appropriate size of structuring element to help reducing the initial foreground marker is one of the size 9. The values of structuring element were choose based on try and error. The experimental result of various structuring element for a few samples of image is illustrated in Fig. 6. If the size of structuring element is 7 or 11, the inaccurate foreground marker were obtained. Therefore, the size of 9 is acceptable.

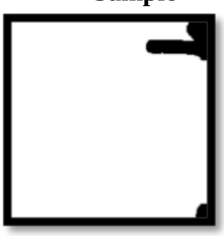
Size of Structuring Element	**Sample**
One(7,7)	
One(11,11)	

Fig. 6: Example of different size of structuring element

Next, the erosion-based gray-scale reconstruction is applied to distinguish the target leaf from the background in order to trace the foreground objects. Then, the regional maxima is obtained as a preliminary foreground marker. The complement of the regional maxima is eroded using the size of structuring element of size 9 in order to obtain appropriate foreground marker. The proposed algorithm used to find the foreground marker is stated in Algorithm 1 which includes the following procedures:

Algorithm : Automatically obtaining foreground marker

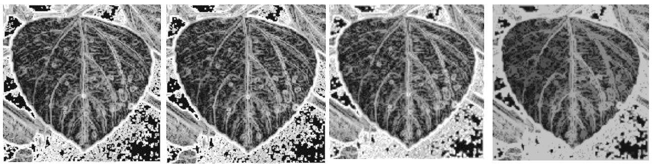
1. Apply morphological closing to the HSV gradient image obtained in section and labelled as f_c.
2. Then, apply erosion-based morphological reconstruction to the image f_c and labelled as f_{cer}.
3. Finding the maximum region of f_{cer}, labelled as $f_{\max}$.
4. Obtain the complement of f_{max} and labelled as f_{comp}.
5. Apply morphological erosion to obtain the appropriate maximum region and labelled as $f_{foreground}$.

IV. RESULTS AND FINDINGS

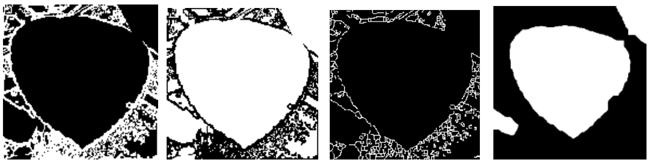
This is the important stage in the leaf segmentation. The result of obtaining foreground marker will influenced the final process which is leaf segmentation. Until now, the researcher still investigate on how to obtain the foreground marker automatically. The process of obtaining foreground marker is not too hard if the targeted objects are in a regular shape. But, the challenge arise when handles the irregular shape. Therefore the main goal in this stage was to obtain the correct foreground marker. The watershed transform is used to measure the performance of the markers. If the marker is created correctly, the individual leaf is perfectly segmented. The process involved the histogram equalization and morphological operations. Fig. 7 shows the results of the process in order to obtain the foreground marker. The sequence of Fig. 7 are (a) gradient HSV image, (b) image gradient after histogram equalization, (c) image after closing operation, (d) image after erode and reconstruction operation, (e) the image with regional maxima, (f) image after complement, (g) the watershed ridge line and (h) the image with foreground marker.

Fig. 8 shows a few examples of foreground marker for the leaf with complex background. The proposed algorithm will automatically create the foreground marker even though the shape of target leaf was irregular. Meanwhile, using other watershed methods, the challenge was to automatically obtain the correct foreground marker.

From the results it can be concluded that the wrong foreground marker will lead to bad segmentation of leaf.



(a) Gradient HSV Image (b) Gradient Image After Histogram Equalization (c) Image After Closing Operation (d) Image After Erode & Reconstruction Operation



(e) Regional Maxima (f) Image Complement (g)Watershed ridge lines (bgm) (h) Foreground marker

Fig. 7: (a) – (h) the sequence of results to obtain foreground marker using proposed algorithm

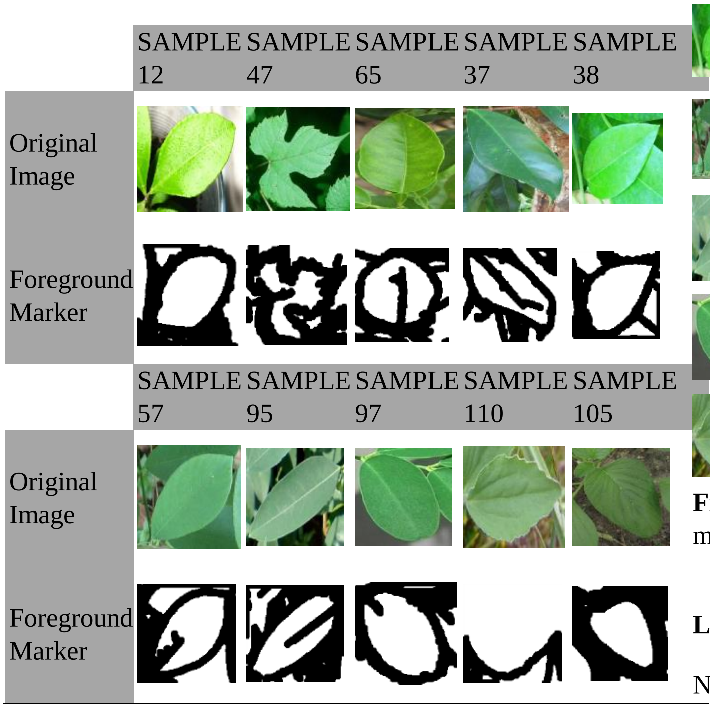


Fig. 8: Examples of foreground marker for the leaf with complex background

A. Performance of Marker-Controlled Watershed Transform

The experiment is done using 116 leaf images. The gradient image is modified so that it has regional minima occur at foreground and background marker pixels. The watershed transform is computed in order to segment the image into desired regions. Fig. 9 illustrates a few example of the results after applying marker-controlled watershed transform. After computing the watershed transform, the leaf is segmented by assuming that the largest area is the region on interest. From the experimental results the proposed foreground marker contribute 74.1% of success rate using watershed segmentation method. In contrast, almost 26% of the other samples are considered as bad segmentation since the proposed technique failed to exactly segment the target leaf.

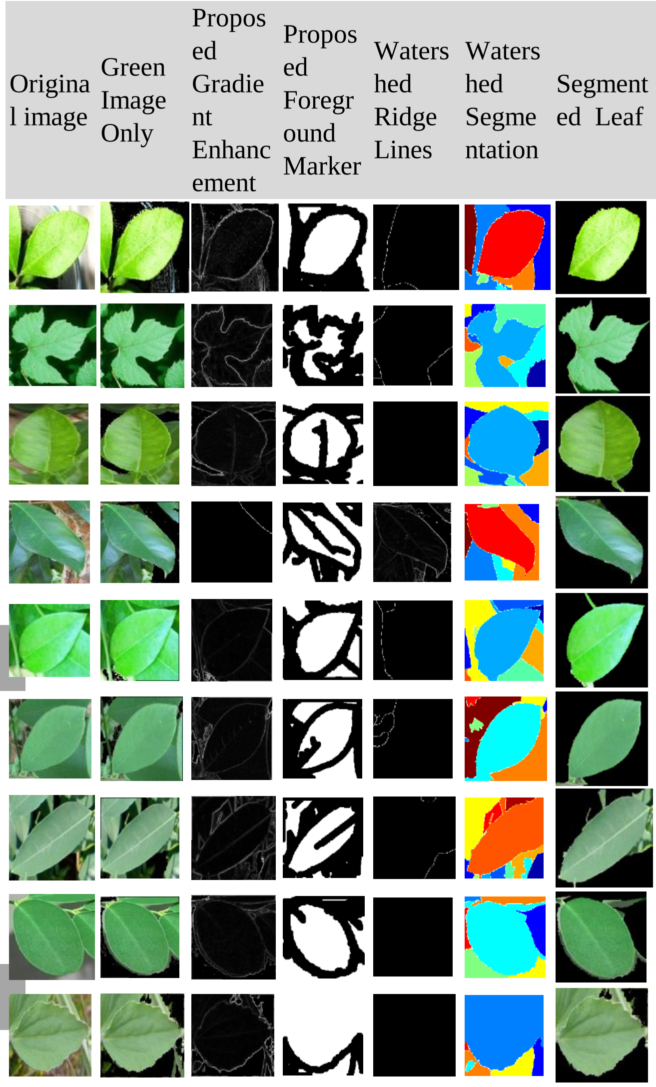


Fig. 9: The results after applying the proposed foreground marker for marker-controlled watershed segmentation

Leaf Extraction	**Good Segmentation**	**Bad Segmentation**
Number of samples	86	30
Percentage	74.1	25.9
Success rate	74.1%	

Table I: The leaf segmentation results by the proposed algorithm

V. CONCLUSION

The process of automatically obtaining foreground marker involved the histogram equalization and morphological operations. The proposed algorithm will automatically create the foreground marker even though the shape of target leaf was irregular. Meanwhile, using other watershed methods, the challenge was to automatically obtain the correct foreground marker. From the results it can be concluded that the wrong foreground marker will lead to bad segmentation of leaf. From the experimental results the proposed foreground marker contribute 74.1% of success rate using watershed segmentation method. In contrast, almost 26% of the other samples are considered as bad segmentation since the proposed technique failed to exactly segment the target leaf. It has been clearly found that the leaf was not successfully segmented if the markers are not contribute the information correctly. Hence, this approach may fail if the foreground and background markers are not created correctly.

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