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Research Article

Hevea Leaves Boundary Identification based on Morphological Transformation and Edge Detection Features

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Abstract: The goal of this study is to present a concept to identify overlapping rubber tree (*Hevea brasiliensis*-scientific name) leaf boundaries. Basically rubber tree leaves show similarity to each other and they may contain similar information such as color, texture or shape of leaves. In fact rubber tree leaves are naturally in class of palmate leaves, it means that numbers of leaves are joining at their base. So it reflects the information of the position of the leaves whether the leaves are overlapped or separated. Therefore, this unique feature could be used to distinguish particular leaves from others clone to identify the type of trees. This study addresses the problem of identifying the overlapped leaves with complex background. The morphological transformation is often applied in order to obtain the foreground object and the background location as well. However, it does not yield satisfactory results in order to get boundaries information. This study, presents on improved approach to identify boundary of rubber tree leaves based on morphological operation and edge detection methods. The outcome of this fused algorithm exhibits promising results for identifying the leaf boundaries of rubber trees.

Keywords: Edge detection, image segmentation, morphological transformation, overlapping, rubber tree leaves

INTRODUCTION

Malaysia has the significantly large rubber plantation areas in Asia (Shigematsu *et al*., 2011). It is necessary to set up a database for types of rubber tree in order to prevent from possible extinction. Nowadays plant classification is being done by computational models of leaf recognition systems. Most plant species have unique leaves which differ from each other by characteristics such as the shape, color, texture and the margin (Thibaut *et al*., 2011; Casanova *et al*., 2012). However, rubber tree leaves are similar one to another and they almost contain the similar features such as color, texture or shape of the leaf, except one feature which is positions of the leaves. Rubber tree leaf positions possibly might be overlap or separate. In this study, we propose new features to identify the boundary of overlap rubber tree leaves in order to classify type of tree. Figure 1 illustrates the rubber tree leaf images with different features.

Recognizing the overlapping objects in images is considered as challenging image processing problem (Saba *et al*., 2012). Nonetheless, several techniques are derived to get information about the object boundaries by involving Law's texture and Canny's edge detection (Saba and Rehman, 2012; Canny, 1986). However single boundary detection method might not be fruitful as objects need to be extracted from complex background (Sharon *et al*., 2001). This study addresses the problem of identifying the overlapped leaf from the complex background.

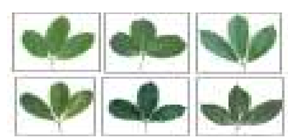

Fig. 1: Rubber tree leaf images with different features

One of the well-known methods to distinguish the foreground and the background object is morphological transformations which are exploited by many image processing operations from background detection to image enhancement (Jiménez-Sánchez *et al*., 2009; John *et al*., 2011). However, it does not yield satisfactory results to get boundary information.

Therefore, in this study we suggest a fused strategy to identify boundary of rubber tree leaf based on morphological transformation and edge detections techniques. The first step is to calculate Sobel edge mask to specify the edges roughly. Latter, morphological operation is applied to mark the foreground object and the object is subtracted from the foreground object to get the object boundaries. Finally, thresholding operation is applied for the background object. The process of identifying the rubber tree leaf boundaries will be discussed in detail in next section.

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PROPOSED APPROACH

Segmentation of overlapping object in an image is considered to be a complex process in image processing (Saba *et al*., 2011). Although some segmentation methods has been proposed as discussed below.

Valliammal proposed a new approach to extract the leaf edges by combination of thresholding method and H-maxima transformation (Valliammal and Geethalakshmi, 2011). The primary step applied is segmentation coarsely to define the vein regions based on the intensity histogram using thresholding (Saba and Altameem, 2013). At that point H-Maxima transformation applied to remove the unwanted regions for contrast simplification. Morphological filters like the h-maxima transform belong to the class of connected operators. They preserve contour information and produce regions with approximately the same grey values but whether this is an advantage or disadvantage is depends on application.

Recently, Valliammal and Geethalakshmi (2012) and Saba *et al*. (2010) worked on non-linear k-means algorithm to improve the segmentation results for high resolution images. At the first level of segmentation K-means clustering is carried out to distinguish the structure of the leaf. The process continued by Sobel edge detector to eliminate the unwanted segments to extract the exact part of the leaf shape. However this method does not separate touching objects well, particularly if the overlapping objects have similar level of intensity.

Meanwhile, color features used for segmentation purpose in Jie-Yun and Hong (2011). The traditional transformation from RGB model to HSI model is improved, at the same time the leaf color information is extracted by similarity distance between pixels. It has a high degree of accuracy for 24-bit true color images but on the other hand the algorithm is not producing rapid result.

Active contour model is another method for image segmentation that Cerutti has used in his project with particular enhancement of method proposed by Guillaume *et al*. (2011). They presented a system for tree leaf segmentation in natural images that combines basic segmentation step with an estimation of descriptors shows the general shape of a simple leaf. The algorithm has promising results compare to standard active contour however the algorithm is not reasonable for overlapping object.

Other study is done by Noble that the method takes advantage of the NIR wavebands for separating leaves from one another and explored the utility of classical edge detectors for defining leaf and leaf boundaries by Noble and Brown (2008). The upper and unconnected leaves segmented effectively and simply in the image from those underneath. However, the algorithm is not able to differentiate the overlapping leaves and the Sobel operation eliminates a significant portion of the leaf area.

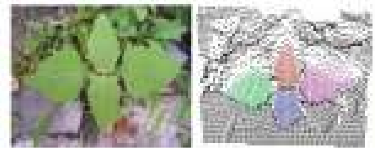

Fig. 2: Teng's 2-D/3-D joint segmentation result

Kennedy performed segmentation by edge detection techniques on tomato and bean plants leaves that used shadows from multiple light source and differently illuminated images to identify shadow edges (Kennedy and Noble, 2007). The method is high processor time demanding as it needs to be solved by the several computing techniques.

Chin-Hung *et al*. (2011) presented a unique segmentation strategy by incorporating set of sophisticated algorithms. They applied a technique of structure from motion to recover the 3-D structure of the scene. Authors did this by applying a very accurate regularization-based optical flow computation algorithm to search for image correspondences. The 3-D points on the leaves can be clearly distinguished from those points on the background as shown Fig. 2. Although some points near leaf boundaries are not very accurate due to motion discontinuities. The system is applicable to a variety of image conditions, however the system is not fully automatic and some user intervention is required to achieve the task.

Consequently, it could be concluded from reviewed researches that single method alone does not yield satisfactory segmentation results. Accordingly, our contribution is to propose a strategy that could identify the boundaries based on morphological operation and edge detection technique.

METHODOLOGY

In this study we work on only position of leaflets which are overlap and separate. MATLAB 7.0 environment is used to test the proposed algorithm. Initially 24-bit color image is converted to gray scale format picture before pre-processing. The process framework is demonstrated in Fig. 3. The phases which are involved in this study explained as follow:

Image data set: Figure 4 shows the rubber tree leaf images which are used as sample for process of identifying the boundary of rubber tree leaf.

Pre-processing: A natural image or object is simply viewed as a continuous array of various colors (Sulong *et al*., 2010). In order to obtain a digital image of this constant range of colors, the original image is sampled so that each color becomes quantized to an integer value. In this study, images converted to grayscale digital images. Grayscale intensity values are the color range only between intensity 0 (black) and intensity 255

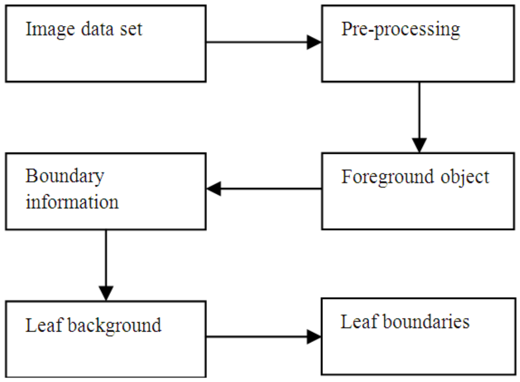

Fig. 3: Research framework for rubber tree leaf boundary identification

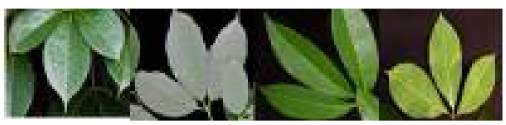

Fig. 4: Rubber tree leaf-data set for our algorithm

(white). The sampling and quantization of the continuous array of colors in the natural image or object will convert each original color to a brightness intensity level between 0 and 255 (Rehman and Saba, 2011).

The second step on pre-processing phase is started with segmentation function using gradient magnitude by using Sobel edge mask and some arithmetic. Sobel kernels compute the gradient with smoothing by decomposing as the products of an averaging and a differentiation kernel. G_x and G_y are two variable functions that at each point contain the x horizontal and y vertical derivative that could be written as:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} \tag{1}$$

The x-coordinate is defined here as increasing in the right direction and the y-coordinate is defined as increasing in the down direction. The result can be combined to produce the gradient magnitude at each point in the image by using:

$$G = \sqrt{G_x^2 + G_y^2} \tag{2}$$

This will result the high gradient at the borders of the objects and low mostly inside the objects.

Foreground object: Most well-known morphological operations are erosion, dilation, opening and closing. Often combinations of these operations are used to perform morphological image analysis (Terol-Villalobos, 2005; Serra, 1982). The processes which involved in this study are:

- Opening $\gamma_{\mu B}(f)(x)$, closing $\varphi_{\mu B}(f)(x)$
- Erosion morphological operations (Bhatia and Chahar, 2011)

Opening, closing and erosion operations: Morphological opening and closing are expressed as follow:

$$\gamma_{\mu B}(f)(x) = \delta_{\mu \breve{B}}\left(\varepsilon_{\mu B}(f)\right)(x)$$

$$\varphi_{\mu B}(f)(x) = \varepsilon_{\mu \breve{B}}(\delta_{\mu B}(f))(x)$$

where, μ a homothetic parameter, size is μ means a square of (2μ + 1) × (2μ + 1) pixels. In this study B is the structuring element of size 3×3 (here μ = 1) covers its origin which is located at center. Following by erosion operation applied to removing small blemishes without affecting the overall shapes of the objects. Erosion of image f by structuring element s is given by f θs. The structuring element s is positioned with its origin at (x, y) and the new pixel value is determined using the rule:

$$g(x, y) = \begin{cases} 1 \; if s hits f \\ 0 \; othervise \end{cases}$$

In the above equation hit refers to the structuring element covers a pixel in the image. Here regional maxima calculated to obtain good foreground markers. A regional maximum of a grayscale image *f* is a connected component of pixels with a given value *h*, such that every pixel in the neighborhood of *m* has a strictly lower value (Sulong *et al*., 2010). Lastly closing operation carried out respectively with erosion to clean the edges of the marker blobs and shrink them a bit.

Boundary information: The foreground image g which is the result of morphological operations is subtracted from the original image f to create a more uniform background:

$$\delta = g - f$$

The foreground marker image is combined on the original image to help interpret the result.

Leaf background: Thresholding is the simplest method of image segmentation to create binary images (Rehman and Saba, 2012). In this study Otsu's method is used to perform histogram shape-based image thresholding (Otsu, 1979). The algorithm assumes that the image to be thresholded contains two classes of pixel as we did foreground and background. Then we calculate the optimum threshold separating those two classes. The algorithm searches for the threshold that minimizes the variance within the class, defined as a weighted sum of variances of the two classes:

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$

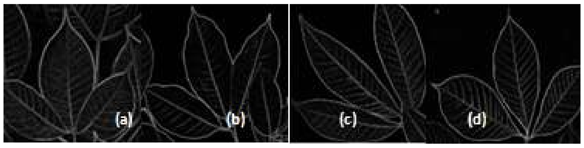

Fig. 5: (a-b) Overlap image and (c-d) non-overlap image gradient magnitude with sobel edge mask

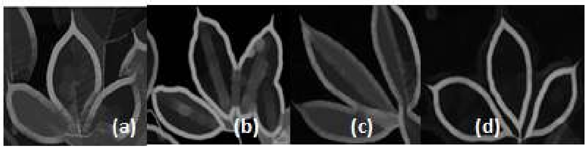

Fig. 6: (a-b) Overlap image and (c-d) non-overlap image morphological operation for foreground object

Fig. 7: (a-b) Overlap image and (c-d) non-overlap image thresholding operation

Fig. 8: (a-b) Overlap image and (c-d) non-overlap image foreground object and background object are superimposed

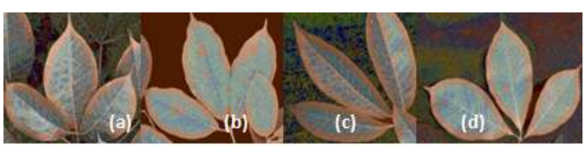

Fig. 9: (a-b) Overlap image and (c-d) non-overlap image visualization based on transparency

Weights w_i are the probabilities of the two classes separated by a threshold t and σ_i^2 variances of these classes.

Results: The foreground markers, background markers and segmented object boundaries are superimposed on the original image. These results are discussed in detail in the next section.

EXPERIMENTAL RESULTS

Natural Hevea tree leaf images are collected from internet source. Two overlap and two non-overlap leaf images used as input for experiments. As we mentioned the first step is converting the image to gray scale.

Steps and outputs of the algorithm have been discussed as followed. Figure 5 demonstrates the gradient magnitude by using Sobel edge mask result for overlap (a, b) and non-overlap (c, d) images. It produced the edges visible as white lines where the gradient of the image intensity is high.

Figure 6 displays the foreground object result. This process involved several steps. Morphological techniques are used to identify the foreground object as mentioned on methodology section. The significant part is the boundaries that highlighted by using subtract algorithm. It is successfully applied on both leaf set as overlap and non-overlap.

The background is extracted through thresholding process. The threshold operation separates the foreground object and background object in the meanwhile preserves the boundary of the leaf as shown Fig. 7.

The foreground object, background object and object boundaries are combined on the original image to get final segmentation result. The outcome of the method is demosntrated below Fig. 8.

Since the final segmentation on gray scale image yields gloomy result, visualization is implemented based on transparency using *AlphaData*. This visualization technique is often used to evaluate image fusion algorithms. Figure 9 demonstrates the final result. However segmentation is very accurately completed through this technique.

CONLUSION AND RECOMMENDATIONS

Basic concept presented in this study is to identifying the foreground object with its boundaries in an image. The method is derived from opening by reconstruction morphological transformation and thresholding operation with noteworthy enhancement. The method which has been proposed is accomplished on overlap and non-overlap images to yield promising segmentation results. For future work, proposed method might be tested with higher number of data set or with different plant leaves to measure the performance of the proposed approach.

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