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Analysis of Rubber Tree Recognition Based on Drone Images

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Abstract *Hevea brasiliensis*, the rubber tree is a tree belonging to the family Euphorbiaceae. It is the most economically important member of the genus *Hevea* because the milky latex extracted from the tree is the primary source of natural rubber. Rubber trees are important economic crops in tropical areas. Accurate knowledge of the number of rubber trees in a plantation area is important to predict the yield of rubber trees, manage the growing situation of the rubber trees and maximize their productivity. The aim of this study is to analyse the detection of rubber tree based on drone images. In order to solve this issue, this study proposes a novel automated method for processing and analysing the individual rubber tree using images from drone. A drone of Parrot ANAFI was used to acquire aerial images and trees in surveyed area. In order to develop the database of rubber tree based on drone images, the position of rubber tree and non-rubber tree was marked on selected three of drone images. A total number of 154 rubber tree and 149 non-rubber tree have been divided into training and testing set. Next, the features of rubber tree and non-rubber tree will be extracted by three selected algorithms of image processing. The algorithms used in this research study including Gray-Level Co-occurrence Matrix (GLCM), Wavelet Transform and Template matching. The database are tested based on the three algorithm by using Support Vector Machine (SVM) to see which algorithms gives highest accuracy and will be used for detection and enumeration of individual rubber trees using images from unmanned aerial vehicles (UAVs). The result of the analysis show Gray-Level Co-occurrence Matrix (GLCM) has the highest accuracy for window size 150 x 150 pixel which is 83.56%. This show that drone images have high potential for rubber tree recognition despite the difficulty of detecting the crown of rubber tree during marking process.

1. Introduction

For last five decades, the Southeast Asian region such as Thailand, Indonesia and Malaysia have dominated global rubber cultivation. The distribution data with accurate and updated finer resolution maps of rubber plantation was very important to any country. The traditional agriculture activities and non-agriculture land are convert to commercial-agriculture purposes due to the expanding global and regional markets. Rubber plantation in most of the mainland in Southeast Asia were growing rapidly and poor monitoring [1][2]. [1] stated that more than one million hectares of land in areas of China, Laos, Thailand, Vietnam, Cambodia and Myanmar have been change into rubber tree plantation. Due to the rapid expansion of rubber plantation which is basically are not natural phenomena and also not traditional grown, the specific of natural ecosystem have been disturbed in term of habitat that may lead to changing of ecosystem and environment. The expanding of land used for rubber tree plantation can be managed and monitored wisely with the accurate distribution data. It also will help to reduce the impact on the ecosystem and environment.



The industry of rubber become the second major product in Malaysia after the oil palm. Thailand are the largest country that producing rubber and Malaysia become the third largest in rubber production behind the Indonesia [3]. The total rubber area at Malaysia is about 1.07 million hectares which is about 7.21 percent was owned by plantation companies. There are two basic types of rubber being produced in rubber industry which is natural and synthetic. The natural rubber was used to produce tire, seals, coupling, footwear, hoses, shock mount and others. Most of rubber tree plantations in Kelantan are located Jeli. Local people that staying in Jeli mostly are working as rubber tappers. So it become attraction to other people to go and work at there. The government encouraged the locals to own a small rubber plantation around 24,000 m² to 200,000 m² in size to start a great area of agriculture. Geographic Information Systems and Remote Sensing was used to conduct monitoring, observation and data analysis process.

In Malaysia, research study has been conduct by [4], related to distribution and rubber plantation in Negeri Sembilan. In the study, Landsat 5 TM 30m was applied to map rubber tree distribution, land-cover was generated by practiced and examined of Maximum Likelihood and Mahalanobis Distance classifier. From the data, the study area has been compare in certain period which are 2006 and 2010 and it showed that the tools that used to obtain land cover areas data for rubber, mangrove and others and concluded that Maximum Likelihood classifier provides better accuracy compare to the Mahalanobis Distance classifier. A sustainable and monitoring need to be done to rubber tree plantation area [4].

In the management context, it is majoring to the tapping frequency and consistency, chemical input and optimal tree densities. Unmanned aerial vehicle (UAV) that used in this study was Drone Anafi from Parrot which convey lightweight digital cameras that can take high resolution images and set to capture images at basic interims, and digital memory is economical and unlimited. The pictures can geometrically correct to a uniform scale, adapted to a typical geographical coordinate system and stitched together. The drone can produce spatially precise maps by lightweight GPS system [5]. There are different type of maps that produce by UAVs which is thermal maps, elevation model, geographically orthorectified 2D maps and 3D model [6]. The utilizing photograph stitching such as Agisoft software was used to make a mosaic from aerial imagery. The software will blends a series of overlapping aerial image into a specific photo. But it need geometric adjustment which is a procedure that separate the angle misinterpretation from aerial image to measure distance accurately.

2. Materials & Methods

2.1 Study Area

The study of rubber tree detection and counting was conducted in near Jalan Air Chanal – Lakota, Bandar Jeli, 17600 Jeli, Kelantan. The rubber plantation were located at 5°42'27.4"N 101°51'41.2"E.

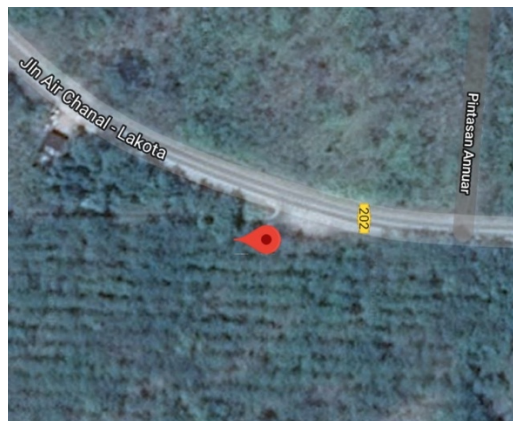


Figure 1. Location of rubber tree plantation near Bandar Jeli



Figure 2. View on-site of the rubber tree plantation

2.2 Data Acquisition

Data that used in this study were an optical drone data. The drone data acquisition was performed by scan the entire rubber tree plantation area at Kelantan from a drone at 70 to 80 m from ground level. The images that capture by the drone were used to made a stitching image and orthorectified image using Agisoft Metaphase software that have been developed. Orthorectified images is a process that apply corrections for optical distortions from the sensor system, and apparent changes in the position of ground objects caused by the perspective of the sensor view angle and ground terrain. The pre-processing part involved of identifying the location of rubber tree and non-rubber tree. This is important to ensure that the data is ready for processing phase.

2.3 Data Processing

Processing part involves automated rubber tree counting works and carried out for subset image by using which is GLCM, Haar-based Wavelet and Template Matching. All stage of data processing is carried out in MATLAB software.

3. Data Processing and Analysis

3.1 Gray-Level Co-Occurrence Matrix (GLCM)

GLCM is a method of extracting second order statistical texture structures, matrix where the number of rows and columns is equivalent to number of gray levels in the image [7]. For remote sensing applications, the GLCM have been used for image processing.

$$c_{i,j} = \sum_{X=0}^{M-1} \sum_{Y=0}^{N-1} P\{I(x,y) = i \& I(x \pm d\phi_1, y \pm d\phi_2) = j\} \quad (1)$$

Where $P\{\cdot\} = 1$ if the argument is true, and will become 0, otherwise.

Of the 14 texture features defined in [8] each of the GLCMs, eight features were selected for the Contrast Analysis (CON), Correlation (CORR), Dissimilarity (DISS), Energy (ENE), Entropy (ENT), Homogeneity (HOM), Mean (MEAN) and Variance (VAR). Other than these eight statistics parameters, offset also are manipulated to see the effects of angle and direction in tree detection [9]. Offset is described as p-by-2 array of integers specifying the distance, d between the pixel of interest and its neighbour.

$$CON = \sum_i \sum_j (i - j)^2 c(i, j) \quad (2)$$

$$CORR = \sum_i \sum_j (i - u_x)(j - u_y) c(i, j) / (\sigma_x \sigma_y) \quad (3)$$

$$DISS = \sum_i \sum_j |i - j| c(i, j) \quad (4)$$

$$ENE = \sum_i \sum_j (c(i, j))^2 \quad (5)$$

$$ENT = \sum_i \sum_j \log(c(i, j))c(i, j) \quad (6)$$

$$HOM = \sum_i \sum_j \frac{1}{1+(i-j)^2} c(i, j) \quad (7)$$

$$MEAN = \sum_{i=2}^i i \cdot c_{x+y}(i) \quad (8)$$

$$VAR = \sum_i \sum_j c(i, j)(i - \mu)^2 \quad (9)$$

Other than these eight statistics parameters, offset also are manipulated to see the effects of angle and direction in tree detection. Offset is described as p-by-2 array of integers specifying the distance, d between the pixel of interest and its neighbour [9].

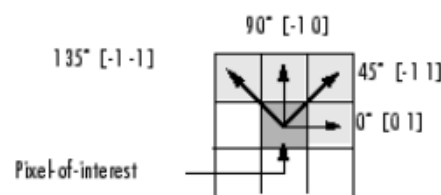


Figure 3. Illustration of offset in GLCM

3.2 Haar-based Wavelet

There are two wavelet types that will be analysed in this study, which are Haar wavelet and biorthogonal wavelet. The way to represent the transient signal is by using the wavelet which has finite-energy function with localization properties. A decomposition of the original signal into set of independent frequency channels is a way to interpret the wavelet transform [9]. Window function of wavelet transform:

$$\psi_{ab}(t) \triangleq \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right) \quad (10)$$

Where a is scale and b is shift parameter known as translation.

The easiest possible wavelet is Haar wavelet but it has the technical weakness which is discontinuous, and therefore not differentiable. This wavelet can be a benefit for the analysis of signals with sudden transitions [9]. The Haar wavelet's mother wavelet function $\psi(t)$ can be described as

$$\psi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2}, \\ -1 & \frac{1}{2} \leq t < 1, \\ 0 & \text{otherwise,} \end{cases} \quad (11)$$

Haar wavelet scaling function can be described as

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1, \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

The biorthogonal wavelet where the associated wavelet transform is invertible but not orthogonal. The biorthogonal wavelets are designed to allow more degrees of freedom compared to orthogonal wavelets. The possibility to construct symmetric wavelets is by adding one more degree of freedom. In the biorthogonal case, there are two scaling functions $\phi, \bar{\phi}$, which may generate different multi-resolution analyses, and accordingly two different wavelet functions $\psi, \bar{\psi}$. So the numbers M and N of coefficients in the

scaling sequences a, \bar{a} , may differ [9]. The scaling sequences must satisfy the following biorthogonality condition

$$\sum_{n \in \mathbb{Z}} a_n \bar{a}_{n+2m} = 2 \cdot \delta_{m,0} \quad (13)$$

Then the wavelet sequences can be determined as:

$$\begin{aligned} b_n &= -1^n \tilde{a}_{M-1-n} \quad (n = 0, \dots, N-1) \\ \tilde{b}_n &= -1^n a_{M-1-n} \quad (n = 0, \dots, N-1) \end{aligned} \quad (14)$$

3.3 Template Matching

Template matching block creates a template and finds the best match of it within an input image. For rubber tree counting study, based on training set of subset image, average image of each class which are young, matured and non-oil palm features is obtained [7]. The numerical index can be determined by the strength of linear association of template, t with the target image, I where the cross-correlation, C_{tI} has been used:

$$C_{tI} = \sum_m \sum_n t(m,n)I(m,n) \quad (15)$$

However, this raw cross-correlation is higher only when darker parts of the template overlap with darker parts of the image, and brighter parts of the template overlap brighter parts of the image. This will lead to different score if matching with different illumination intensities of the same image [9]. In solving the different intensity images, both the pixels of the template and the target image has to be normalized as following:

$$\hat{t} = \frac{t - \bar{t}}{\sqrt{\sum (t - \bar{t})^2}} \quad (16)$$

$$\hat{I} = \frac{I - \bar{I}}{\sqrt{\sum (I - \bar{I})^2}} \quad (17)$$

and the raw cross-correlation in (15) will becomes the normalized cross-correlation, r as follows:

$$r = \frac{\sum_m \sum_n (\hat{t}_{mn} - \bar{\hat{t}})(\hat{I}_{mn} - \bar{\hat{I}})}{\sqrt{(\sum_m \sum_n (\hat{t}_{mn} - \bar{\hat{t}})^2)(\sum_m \sum_n (\hat{I}_{mn} - \bar{\hat{I}})^2)}} \quad (18)$$

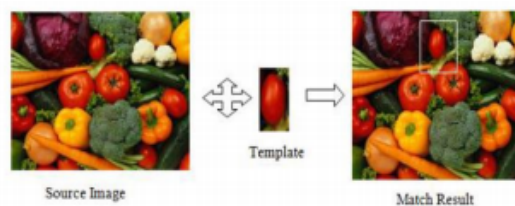


Figure 4. The process of Template Matching

4. Result and Discussion

The drone images of rubber tree plantation is choose into Matlab software, where it is classified based on rubber tree and non-rubber tree as shown in Fig. 5. Based on the drone images, the rubber tree and non rubber tree need to be marked by the pattern of their crown. Because of high spatial resolution data is used in this study, user can differentiate easily between rubber tree and non rubber tree. Different size of window which is 50 x 50 pixel, 100 x 100 pixel, 150 x 150 pixel and 200 x 200 pixel was analysed for selecting the best window size for further classification analysis.

Based on results in Table 1, it is clearly shown that window size 150 x 150 pixel for GLCM has highest accuracy for overall which is 83.56%. While window size 50 x 50 pixel for Template Matching has the lowest accuracy for overall which is 42.47%. Each computation for overall accuracy of each algorithms, statistic parameter and offset for rubber tree and non rubber tree was used 150 x 150 pixels window size. This because texture features mostly have low accuracy in the extraction using small window sizes, while better accuracies were shown in the larger sizes [10]. As shown in Figure 6, the blue window show the location for rubber tree while the red window show the location for non rubber tree for classification analysis.



Figure 5. The image of a) rubber tree and b) non-rubber tree.

Table 1. Accuracy results based on different size of windows

Type of pixel	Accuracy of Overall GLCM (%)	Accuracy of Overall Wavelet Transform (%)	Accuracy of Overall Template Matching (%)
50x50	80.14	54.11	42.47
100x100	79.45	50.68	50.00
150x150	83.56	54.79	49.32
200x200	77.40	61.64	50.00

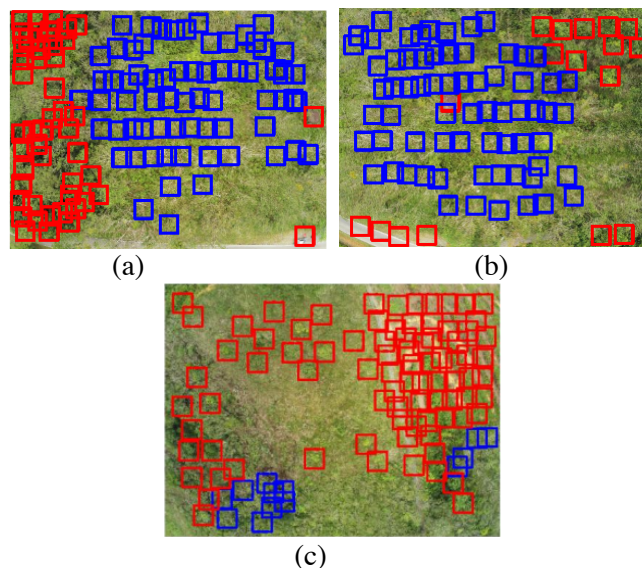


Figure 6. The location of rubber tree and non rubber tree with their window classification analysis for a) image drone_R1, b) image drone_R2 and c) image drone_R3.

Table 2 shows overall accuracy for each algorithm. GLCM obtain highest accuracy because GLCM features that match with the specifications of the rubber tree. However for template matching,

it obtained high accuracy which is 74.03% on rubber tree but 33.73% which is quite low on non-rubber tree.

Table 2. Overall accuracy for GLCM, wavelet transform & template matching

Type of data	Overall (%)	Rubber Tree (%)	Non-rubber Tree (%)
GLCM	81.46	76.62	86.49
Wavelet Transform	52.98	72.73	32.43
Template Matching	54.30	74.03	33.78

For GLCM, statistics parameter that involves are contrast, correlation, dissimilarity, energy, entropy, homogeneity, mean and variance. Based on results in Table 3, it is clearly shown that entropy has highest accuracy for overall which is 72.85%. Energy has highest accuracy on rubber tree which is 79.22% while dissimilarity and homogeneity has 100.00% on non-rubber tree. This statistic can be consider to compute each category for rubber tree. Correlation, entropy and homogeneity can be alternatives in order to increase the accuracy [11]. On the other hand, correlation-variance combinations achieved very high producer's accuracy of rubber tree, but low accuracy for other classes [11].

Other than statistics parameters, offset is another element that being manipulated to see the impact on number of trees detected. Angle of 0°, 45°, 135° and 90° with d of 1 pixel spacing. Table 4 shows the highest accuracy for overall of rubber tree and non rubber on 45° [-1 1] by 81.46%. The rubber tree has highest accuracy on 45° [-1 1] by 76.62% while non rubber tree has highest accuracy on angle of 135° [-1 -1] by 87.84%.

Table 3. Overall accuracy for statistics parameter

Statistic Parameter	Accuracy of Overall (%)	Accuracy of Rubber Tree (%)	Accuracy of Non-Rubber Tree (%)
Contrast	71.52	57.14	86.49
Correlation	49.67	36.36	63.51
Dissimilarity	49.01	0.00	100.00
Energy	65.56	79.22	51.35
Entropy	72.85	62.34	83.78
Homogeneity	49.01	0.00	100.00
Mean	64.90	50.65	79.73
Variance	68.87	48.05	90.54

Table 4. Accuracy of offset with specific distance, d

Offset	Accuracy of Overall (%)	Accuracy of Rubber Tree (%)	Accuracy of Non-Rubber Tree (%)
[0 1]	78.81	71.43	86.49
[-1 1]	81.46	76.62	86.49
[-1 -1]	74.17	61.04	87.84
[0 3]	52.98	72.73	32.43
[-3 3]	52.98	72.73	32.43
[-3 -3]	52.98	72.73	32.43
[0 5]	54.30	74.03	33.78
[-5 5]	54.30	74.03	33.78
[-5 -5]	54.30	74.03	33.78

This is happen due to plantation pattern that requires rubber tree to have certain distance between each other to get enough sunlight, water and fertilizer. For rubber tree, crown between trees are close to each other, which explains by using 45° for offset will obtained more trees then other direction and distance. From the table also it showed that smaller distance will lessen the number of trees detected based on the accuracy.

5. Conclusion

We have demonstrated a novel non-destructive method for analysis of rubber tree based on drone images. Three algorithms has been tested by using Support Vector Machine (SVM) which are Gray Level Co-Occurrence Matrix (GLCM), Haar and biorthogonal wavelet and template matching. While GLCM obtain highest accuracy, manipulating GLCM parameters and offset can improve the accuracy so that user can also applies the algorithm on other application or method. High spatial resolution imagery is suitable to be applied in this field, allows user to see clearly the branches of rubber trees and distinguish the rubber tree from the non-rubber tree.

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