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Analysis of Oil Palm Tree Recognition using Drone-Based Remote Sensing Images

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Abstract. The oil palm tree, or scientifically called as Elaeis guineensis is native to West Africa, where it grows in the wild, transformed into a crop that later was introduced to Malaysian industry. The cultivation of oil palm improved rapidly under the agricultural sector causes degradation, particularly when the oil palm plantation goes uncontrolled. Tree plantation identification is very important for plantation management, environmental management, biodiversity monitoring and many other applications. Accurate inventories and monitoring oil palm estates can be a challenge and critical towards the plantation management and plant area expansion. Managing oil palm estate manually can almost be impossible, so do the tree counting. Manual field-based tree counting is time-consuming and high cost. Conventional method for tree counting can be carried out by manually marked on images or carry out field surveying using GPS to collect the positions of oil palm trees and display their position on image. Developing easier, simpler and cheaper method for tree counting is needed. The aim of this study is to analyse oil palm trees using drone-based remote sensing images. The algorithms used in this research study including Gray-Level Co-occurrence Matrix (GLCM), wavelet transform and template matching. The database of oil palm tree been developed with a total of 131 oil palm trees and 161 of non-oil palm trees have been collected. The window size of oil palm tree been analysed where 250 x 250 pixels which GLCM showed the best overall accuracy of 73.10% for both oil palm and non-oil palm. In this specific window, the oil palm crown can be covered and the result given is more accurate compared to other window sizes. The resulting analysis shows that wavelet transform algorithm gives the highest overall accuracy value which is 82.07%. The other eight statistic parameters can also used to modify the GLCM in order to observe the accuracy and identify which give the best classification accuracy. The availability and ubiquity of drone technologies with high resolution images and regular basis monitoring, new techniques in image and pattern recognition using drone-based remote sensing images let the idea of high accuracy oil palm tree detection become a reality.

1. Introduction

The oil palm tree belongs to the Arecaceae family, and is named *Elaeis guineensis* scientifically. In palm oil processing, there are two species of Arecaceae that were used for commercial agriculture. Elaeis guineensis and Elaeis oleifera are in there. Such two species can be differentiated according to their native environment. As described by [1], Elaeis guineensis is native to West Africa, while Elaeis oleifera is native to Central America and South America and is sometimes cultivated under the misnomer *Elaeis*

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melanococca. Unlike the African oil palm, America oil palm trunk creeps along the ground and bears flat leaves. The production of oil from American oil palm was possibly used by the early American colonizers to make candles. Many with the names Elaeis guineensis grow in the wild, developed into a crop later introduced to the Malaysian industry. Then, the oil palm plantation becomes Malaysia's main crop. [2] report estimates that the oil palm was planted about 4.2 million hectares with less than 13 percent of Malaysia's total land area. Expanding the oil palm plantation increases people's interest, especially among entrepreneurs. Oil palm is the most productive oil crop globally, where it can yield ten times more oil than soybean, canola or rapeseed, coconut and many others. The plant is also cultivated as an ornamental in many subtropical regions [3]. Over the last 50 years, the international market for oil palm oil has grown exponentially. Oil palms accounted for over 30% of all edible oil production in 2012 and 2013. The analysis of oil palm tree recognition is essential to get the amount of the oil palm tree. This analysis can act as an assessment aspect of measuring the crops. The monitoring process and inventories are essential to the plantation measurement and area expansion.

The oil palm industry expands to meet rising global demand for oil palm, secondary products for food and manufacturing, and more recently for biodiesel. Increases in production were achieved by intensifying production per unit area by breeding, improved agronomy and improved plantation management. This kind of development of oil palm cannot be denied can generate economic income through various production. This exposure leads to the land expansion of oilseeds cultivation and consistency in supplying the excellent quality of oil to meet the increasing global demand. Unfortunately, the cultivation of oil palm trees improved rapidly under the agricultural sector causes degradation, significantly when the oil palm plantation goes uncontrolled. There is an example of this scenario, especially in Indonesia, under oil palm cultivation there has been a significant expansion in the region, involving the conversion of secondary forest and peat swamp. This has caused environmentalists' negative media attention over the loss of biodiversity and the mobilization of greenhouse gas from vegetation and soils that the industry needs to counteract [4]. However, this case can be avoided from happening in Malaysia by monitoring and managing the plantation using a drone-based remote sensing image. The tree detection and counting process can be measured effectively using the choice of method, which is by using a drone-based remote sensing image. Drone-based images can provide a higher spatial resolution to measure the plantation. Data on the number of palm trees within the plantation is one of the primary information needed. Nevertheless, the oil palm can be counted and detected either by ground survey techniques or remote sensing. This can be done either manually counting oil palm tree crowns on imagery or ground surveying using GPS to gather their locations information. This research study can be a part of a solution for managing the oil palm plantation. Furthermore, it is also an innovation process for estimating the yield of oil palm. The data obtained can be used to measure the number of the oil palm tree in an area as it gives a higher accuracy for oil palm detection. It helps in terms of getting a better calculation of the plantation.

2. Materials and Methods

2.1. Study Area
The study of oil palm tree recognition was conducted in near Bandar Jeli, 17600 Jeli, Kelantan. The oil palm plantation located at 5°42'34.3"N 101°50'41.9"E. The flying altitude of the drone is 54.8 m to achieve higher spatial resolution of oil palm plantation images. The coverage area is around 0.0227 km^2.

2.2 Data Acquisition
For this study, the images from an optical drone was used with three band of red, green and blue (RGB) band. The type of drone used is a multi-rotor of Parrot ANAFI drone. The images captured being collected to be analyzed and developing a structured set of database from oil palm tree using images from the drones.

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3. Data Processing and Analysis

There are three main algorithms involved in this work which are Gray-Level Co-Occurrence Matrix (GLCM), Haar and biorthogonal Wavelet and template matching, as been used in [5]. For GLCM, there are eight parameters that need to be manipulated to determine which parameters gives highest impact on tree counting.

3.1 Gray-Level Co-Occurrence Matrix (GLCM)

GLCM is a method of extracting second order statistical texture features, matrix where the number of rows and columns is equal to number of gray levels, G in the image. According to [6], GLCM can be defined as a higher order set of texture measures is based on brightness value spatial-dependency gray-level co-occurrence matrix (GLCM) have been widely used in image processing for remote sensing applications.

$$C_{i,j} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} P\{I(x,y) = i \;\&\; I(x \pm d\emptyset_1, y \pm d\emptyset_2 = j)\} \quad (1)$$

where if the argument is true, and will become 0, otherwise. Among 14 texture features described in [7] for each of GLCM, we have select the following eight for our analysis which were contrast (CON), correlation (CORR), dissimilarity (DISS), energy (ENE), entropy (ENT), homogeneity (HOM), mean (MEAN) and variance (VAR):

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

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

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

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

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

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

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

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

Other than this eight statistics parameter, 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 neighbor. In this study, the GLCM parameters have been measured on five different distances, *d* of 1, 2, 3, 4 and 5 pixels spacing and three different directions, ∅ of 0°, 45° and 90°. Then, by taking the average of measurement based on these ∅ only, the eight texture features are calculated.

3.2 Wavelet Transform

There are two wavelet types that will be analyze in this study, which are Haar wavelet and biorthogonal wavelet. Wavelet is finite-energy function with localization properties which can be used efficiently to represent transient signals. The wavelet transform can be interpreted as a decomposition of the original signal into set of independent frequency channel. Window function of wavelet transform:

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

The Haar wavelet is the simplest possible wavelet. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as monitoring of tool failure in machines. The Haar wavelet's mother wavelet function can be described as

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

Haar wavelet scaling function can be described as

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

For biorthogonal wavelet, it is a wavelet where the associated wavelet transform is invertible but not orthogonal. Designing biorthogonal wavelets allows more degrees of freedom than orthogonal wavelets. One additional degree of freedom is the possibility to construct symmetric wavelet functions. There are two scaling functions in the biorthogonal case, which may generate different multiresolution analyses, and accordingly two different wavelet functions. So the numbers *M* and *N* of coefficients in the scaling sequences may differ. The scaling sequences must satisfy the following biorthogonality condition

$$\sum_{n\in\mathbb{Z}} a_n \tilde{a}_{n+2m} = 2 \cdot \delta_{m,0} \tag{13}$$

Then the wavelet sequences can be determined as:

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

3.3 Template Matching

The critical idea of template matching was to compare a small portion of an image to be detected against all local regions in the image by cross-correlate with a filter [5]. The best linear operator of the filter for finding an image patch is essentially the patch itself. The matching process moves the template image to all possible positions in the target image and computes a numerical index that indicates how well the template matches the image in that position. 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:

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

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. In solving the different intensity images, both the template's pixels and the target image have to be normalized as following:

$$\hat{t} = \frac{t-\bar{t}}{\sum(t-\bar{t})^2}\,,\ \hat{I} = \frac{I-\bar{I}}{\sum(I-\bar{I})^2} \tag{16}$$

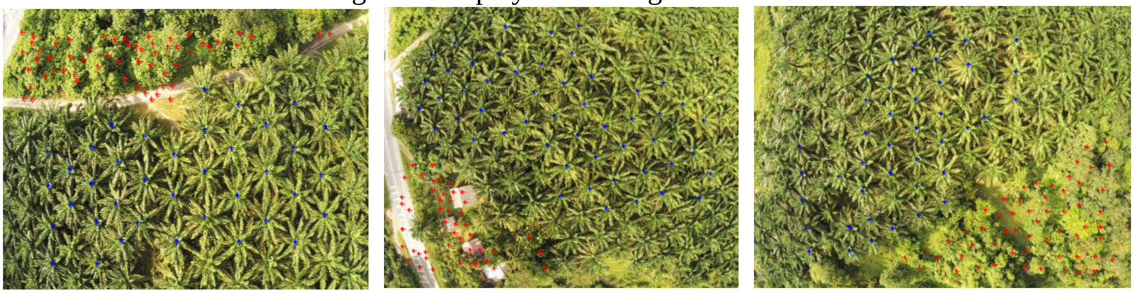
and the raw cross-correlation in (15) will becomes the normalized cross-correlation, r as follows:

$$r = \frac{\sum_m \sum_n (t_{mn}-\bar{t})(I_{mn}-\bar{I})}{\sqrt{(\sum_m \sum_n (t_{mn}-\bar{t})^2)(\sum_m \sum_n (I_{mn}-\bar{I})^2)}} \tag{17}$$

4. Results and Discussions

4.1 Development of Database of Oil Palm Tree

The drone images of the oil palm plantation been analyzed, where they are classified on the basis of oil palm trees and non-oil palm trees. Based on the drone images, the characteristics of each type of oil palm can be determined from its crown. The characteristics of oil palm crown either basically look like flower petals [8] which been used in marking the oil palm tree. The non-oil palm tree also need to be marked to increase the accuracy of classification and identification of oil palm tree. The database of oil palm tree based on the drone images are displayed as in Figure 1.



(a) (b) (c)

Figure 1. The location of oil palm tree (blue mark) and non-oil palm tree (red mark) for (a) S1 image, (b) S2 image and (c) S3 image

Table 1 shows the marking point for both oil palm and non-oil palm trees. For this study, there are three images of oil palm used. For the image S1, the oil palm tree has 38 points while non-oil palm has 58 points. As for the image S2, the point for oil palm tree and non-oil palm tree is 51 and 46. Image S3 consist of 42 points of oil palm and 57 points of non-oil palm tree. The total for oil palm tree is 131 points while non-oil palm is 161 points.

Table 1. Database of rubber tree based on drone images

Drone Images	Oil Palm Tree	Non-Oil Palm Tree
S1	38	58
S2	51	46
S3	42	57

Database is consist of training and testing. The database of oil palm is divided into two categories, train set and test set. Train set will be a model that will classify the image into two categories, oil palm and non-oil palm.

Table 2. Classification of database of oil palm tree

Category	Oil Palm Tree	Non-Oil Palm Tree	Total
Training Set	38	58	147
Testing Set	51	46	145

4.2 Determination for the windows size for classification of oil palm tree database

Before the accuracy results obtained from Support Vector Machine (SVM), the selection of appropriate size of window needs to be determined. It is tested on different window sizes of 100 x 100 pixels, 150 x 150 pixels, 200 x 200 pixels, 250 x 250 pixels and 300 x 300 pixels. Figure 3 shows the clear image of oil palm in different sizes of windows. In this study, 250 x 250 pixels was used. This is because the oil palm crown can be covered on this specific window and the accuracy using this window is higher than another. The window size less than 250 may only covered a few parts of the oil palm crown while 300 x 300 pixels size is too large for the crown images.

Given the results as in Table 3, it has obviously been shown that window size of 250 x 250 pixels for GLCM has the highest overall accuracy of 73.10%. As for Wavelet Transform, the highest ones are 150 x 150 pixels of windows size (86.21%) while for Template Matching is also 250 x 250 pixels with 73.10%. The window size 300 x 300 pixels has the lowest among the five windows mentioned in each overall accuracy. As a result, the window size used for every computation for each algorithm's overall accuracy and the statistic parameter for the oil palm trees and the non-oil palm trees is 250 x 250 pixels.

This is because texture features often have poor extraction accuracy using small window sizes, while better accuracy has been seen in larger sizes [8]. This means that an accurate estimate of the population parameter is only obtained when the sample size is large.

(a) (b) (c)

Figure 2. Image of oil palm tree with window size for (a) 250, (b)100 and (b) 300.

Table 3. Overall accuracy for GLCM, wavelet transforms & template matching for different size of window.

Window Size	Accuracy of Overall GLCM (%)	Accuracy of Overall Wavelet Transform (%)	Accuracy of Overall Template Matching (%)
100 x 100	62.07	80.69	69.66
150 x 150	68.28	86.21	66.21
200 x 200	64.14	82.76	72.41
250 x 250	73.10	82.07	73.10
300 x 300	48.87	45.86	50.38

4.3 Classification Result of Oil Palm Tree Database based on Drone Images

Based on the accuracy of the results obtained from the Support Vector Machine (SVM), the highest accuracy was achieved by using the Wavelet Transform. It is tested on both oil palm and non-oil palm.

Table 4. Overall accuracy for algorithms GLCM, Wavelet Transforms & Template Matching

Type of data	Overall (%)	Oil Palm Tree (%)	Non-Oil Palm Tree (%)
GLCM	73.10	69.23	76.25
Wavelet Transform	82.07	73.85	88.75
Template Matching	73.10	84.62	63.75

Based on Table 4, the wavelet transform algorithm has the value for overall accuracy is 82.07%, 73.85% for oil palm and 88.75% for non-oil palm. The accuracy of GLCM was considered good with the overall accuracy of 73.10%. The template matching obtained the highest accuracy of oil palm with 84.62% but got the lowest accuracy value in non-oil palm with 63.75%. Template matching got the highest due to its wavelet features match the oil palm requirement features. The result concluded the reason why every single parameter is changed to see the difference and the implications on the number of trees detected. For GLCM, the statistical parameters include contrast, correlation, dissimilarity, energy, entropy, homogeneity, mean, and variance.

Table 5 showed the highest accuracy for overall is 64.14% from variance parameter. As for the oil palm accuracy, homogeneity achieved the highest one, which is 98.46%. 100% accuracy for non-oil palm obtained by both energy and entropy and the lowest in oil palm accuracy. This statistic can also be used to measure every category for the oil palm tree. Correlation, entropy and homogeneity can be

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alternatives in order to increase the accuracy [9]. Regards the table below, the oil palm plantation is normally planted using a triangular pattern to provide sufficient nutrition and sunlight [10].

Table 5. Overall accuracy for statistics parameter

Statistic Parameter	Accuracy of Overall (%)	Accuracy of Oil Palm Tree (%)	Accuracy of Non-Oil Palm Tree (%)
Contrast	59.31	40.00	75.00
Correlation	55.17	4.62	96.25
Energy	55.17	0.00	100.0
Homogeneity	51.72	98.46	13.75
Dissimilarity	60.69	66.15	56.25
Entropy	55.17	0.00	100.00
Mean	56.55	70.77	45.00
Variance	64.14	36.92	86.25

5.0 Conclusion

This research study has shown a method that does no harm to the oil palm and facilitates the user to practice the tree's recognition technique. The algorithms including Gray Level Co-Occurrence Matrix (GLCM), Haar and Biorthogonal Wavelet and Template Matching provide a good assist in getting the accuracy of the data. Haar and Biorthogonal Wavelet prove this algorithm can give the highest value on overall accuracy. The other eight statistic parameters also can be used to manipulate the GLCM while offset parameters can improve accuracy so that users can also apply the algorithm to other applications or methods. High spatial resolution imagery by using a multi-rotor drone proves to be essential and ideal for use in this area, allowing the researchers to see the size and pattern of the oil palm tree crown.

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