An Approach for Oil Palm Tree Detection Using Multispectral Imagery

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Abstract

Oil palm tree is one of the economic crops of Thailand. In order to maximize the productivity from planting, appropriate management of oil palm farm is highly required. The basic required information for oil palm tree management is the amount of oil palm tree in the plantation area. In order to obtain such information, we proposed an approach for palm tree detection. As a result, the amount of oil palm trees in an area can be counted. The proposed method is based on the use of multispectral imagery for the computation of vegetation index i.e. NDVI. The rank transformation is then applied to enhance the discrimination between the oil palm tree and the background. To detect oil palm trees, we hypothesize that the location of the oil palm trees are located at the local peak of the vegetation index image after the rank transformation is applied. To perform the local peak detection, the non-maximal suppression is employed. The performance of the proposed method is tested on several multispectral images and the accuracy of the detection result is reported.

Keyword : Oil palm tree, detection and counting

1. Introduction

Broadly speaking, the oil palm tree detection is the tree detection problem. The goal of tree detection is to extract tree's positions or tree crowns from given data i.e. photograph or point cloud. Wulder et al. (2004) proposed a tree detection method based on the use of local maximum filter to detect tree location on high spatial resolution imagery i.e. airborne and satellite-borne images. Namely, the local maximum filter is applied to the intensity image to find local peaks, which are hypothesized to be the likely positions of trees. Similarly, Gebreslasie et al. (2011) used the concept of local peak detection for locating individual trees in plantation forest in KwaZulu-Natal, South Africa. This method is based on the use of Gaussian filter to smooth satellite remote sensing imagery in order to eliminate noise. Furthermore, extremely bright and dark areas are removed by using natural break classification. In order to determine the window size for local peak detection, the semi-variogram was employed.

A line of research uses LiDAR data for tree detection. Falkowski et al. (2006) proposed a method for automatically estimating location, height and diameter of trees based on the use of spatial wavelet analysis, particularly, 2D Mexican hat wavelet. The concept is to convolve the 2D Mexican hat wavelet with the LiDAR canopy height models, which is a raster image interpolated from LiDAR points. The location of trees can then be detected by detecting the local peak of the wavelet transformed image. To make this method work properly, a priori knowledge of the tree height crown diameter relationship is required. In Morsdorf et al. (2003), the authors applied a clustering approach i.e. K-mean clustering, to detect a single tree from LiDAR point cloud. That is, K-mean is used to segment a tree from point cloud. Since the K-mean is an iterative method, the staring positions for the process are then obtained form the local maxima of digital surface model.

The combination of LiDAR data and multispectral imagery can be used to detect a specific specie tree. Popescu and Wayne (2004) developed a method for measuring tree height. The basic concept for detection still relies on the local peak detection using window filter. To make the approach robust, the size of the window depends on the tree's specie which can be determined by the classification using multispectral data.

In this study, we attack the problem of oil palm tree detection from the image of oil palm plantation area, which is well structured. The input data is a high resolution multi-spectral image and the oil palm plantation area's boundary is manually marked. The concept of the proposed method is based on the local peak detection on the vegetation index image i.e. NDVI. To estimate an appropriate window size used in the detection of oil palm tree, the 2D semi-variogram approach is utilized. In addition, to increase the dissimilarity between oil palm and non-oil palm objects, we propose to use rank transformation to the vegetation index image prior to the local peak detection. In this paper, the local peaks are detected using the non-maximal suppression algorithm.

2. Material and method

2.1. Dataset

To conduct experiment for showing the performance of the proposed palm detection method, we utilize the QuickBird imagery of the Phang-nga province in the southern region of Thailand. The area consists of oil palm tree, rubber tree and building. The imagery has ground sampling distance about 50 centimeters per pixel and 4 multispectral bands including green, blue, red and near-infrared bands. We manually selected the palm plantation areas and mark their boundaries.

2.2. Oil palm tree detection method

We propose a method for detecting oil palm tree using a high-resolution multi-spectral image. Particularly, the method is invented for detecting oil palm tree on the image of oil palm plantation area. Remind that the boundary of the plantation area is manually marked. The proposed method is based on the use of local peak detection approach. In this approach, the tree crown locations are assumed to have locally maximal vegetation index i.e. NDVI. Namely, the most likely crown positions have digital number greater than that of surrounding neighbors within the window. The local peak detection can be implemented by using 2D window function. The determination of the window size is hence very important. In this paper, we proposed to use a fixed-windows size estimated by using 2D semi-variogram technique because the pattern of oil palm plantation area is normally well structured i.e the distances between an oil palm tree and its neighbors are almost fixed. After the appropriate feature and window size are determined, the method proceeds to the enhancement of the index image. In order to maximize the distinction between oil palm and non-oil palm trees, the rank transformation is applied to the image. The local peaks are then detected by using non-maximal suppression algorithm. The workflow of the proposed method is summarized in Figure 1.

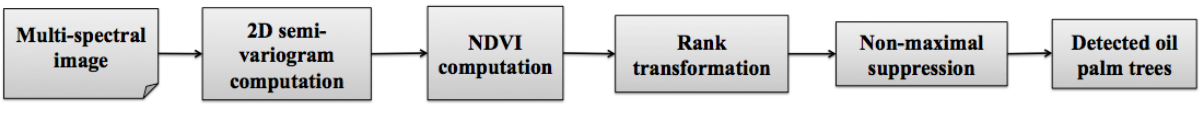


Figure 1: Workflow of the proposed method

2.2.1 2D Semi-variogram

To estimate an appropriate window size for rank transformation and non-maximal suppression, we assume that the spatial pattern of palm tree is well structured, e.g. two consecutive palm trees is equally spaced. The semi-variogram technique is employed to extract the spatial pattern of the palm tree farm. As a result, an approximated distance between two neighbor palm trees can be obtained and used as the upper-bound for the window size of rank transform and the parameter of the non-maximal suppression.

The semi-variogram, which is referred to experimental variogram in this paper, is a technique for image texture characterization, Atkinson and Lewis (2000). Namely, the spatial arrangement of object in image can be extracted including the spatial distance between object, surface roughness or orientation of the pattern. As an example, Trias-Sanz (2006) used 2D semi-variogram to analyze the structures of plantation fields. The variogram V of an n-band image I can be obtained by first compute:

$$D(\mathrm{u}) = \sqrt{\frac{\sum_{p\in S_u} \mathrm{d}\big(\mathrm{I(p)},\mathrm{I(d+u)}\big)}{\mathrm{card}(S_\mathrm{u})}}, \tag{1}$$

where $\mathbf{u}$ is the directional lag, S is the set of pixels where the image I is defined, $S_u = \{\mathbf{p} \in S | \mathbf{p} + \mathbf{u} \in S\}$ and d is a generic distance between pixel values. For a multi-spectral image, the distance function d can be defined as:

$$\mathrm{d}\big(\mathrm{I(p)}, \mathrm{I(d+u)}\big) = (I(\mathbf{p}) - I(\mathbf{p}+\mathbf{u}))^T \mathbf{M}(I(\mathbf{p}) - I(\mathbf{p}+\mathbf{u})), \tag{2}$$

where $\mathbf{M}$ is a symmetric positive definite matrix. Two commonly choices for the matrix $\mathbf{M}$ are identity or the inverse of variance-covariance matrix.

The normalized semi-variogram V of the image I can then be computed by first finding the minimum and maximum of D while ignoring the values near the origin:

$$D_{max} = \max_{\|\mathbf{u}\|\geq k_0} D\,(\mathbf{u}) \qquad D_{min} = \min_{\|\mathbf{u}\|\geq k_0} D(\mathbf{u}), \tag{3}$$

$$V(\mathbf{u}) = \Pi\left(\frac{D_{max} - D(\mathbf{u})}{D_{max} - D_{min}}\right), \tag{4}$$

where the function Π is defined such that:

$$\Pi(x) = \begin{cases} 0 & : \quad x < 0 \\ 1 & : \quad x \geq 0 \\ x & : \quad otherwise \end{cases}. \tag{5}$$

As a result, the semi-variogram V is then normalized to the range [0,1]. The average distance between local peaks on the 2D semi-variogram V and its neighbors is assumed to be the average distance between palm trees and will be used as the window size for rank transform and a parameter of non-maximal suppression.

2.2.2 Vegetation index

To detect objects of interest on an image, the first step is commonly to reduce the amount of information by using image features. Since, the proposed method is oriented toward green segmentation i.e. palm tree, vegetation index is hence a good feature for this purpose. One of the commonly used vegetation index is the Normalized Difference Vegetation Index (NDVI) defined as:

$$NDVI = \frac{NIR - RED}{NIR + RED}. \tag{6}$$

As a result, its value varies between -1 and 1. Theoretically, NDVI value of green vegetation is more than 0 and that of bare soil is around 0. Therefore, The NDVI index is suitable for detecting oil palm tree because the NDVI index of oil palm tree is higher than that of ground i.e. soil.

2.2.3 Rank transformation

The rank transformation is originally developed for the problem of stereo matching, Zabih and Woodfill (1994) and Hirschmuller and Scharstein (2009). Precisely, it was proposed to gain the robustness of the template matching and the expected result from the rank filter is the removal of blurred object borders. Hence, this filter can benefit the proposed method because the discontinuity between the palm and background intensities will be increased.

The concept of the rank filter is based on the relative order of the intensity values in a local region. Namely, the rank filter replaces the intensity of a pixel $\mathbf{p}$ by the number of pixels in the neighborhood of the pixel $\mathbf{p}$ whose intensity is less than the intensity of the pixel $\mathbf{p}$. It can be formally formulated as:

$$I_R(\mathbf{p}) = \sum_{\mathbf{q}\in N_{\mathbf{p}}} U(I(\mathbf{p}) - I(\mathbf{q})), \quad (7)$$

where I is in this case the NDVI image and U is defined such that:

$$U(x) = \begin{cases} 1 & when\ x > 0 \\ 0 & otherwise \end{cases}. \quad (8)$$

Typically, the neighborhood $N_{\mathbf{p}}$ is defined as a squared windows centered at the pixel $\mathbf{p}$. It can be observed from (7) that the output of the rank filter is based on the local order of the intensities and not the magnitude of the intensities. As a result, the rank filter is robust to radiometric distortions that preserve the order of intensities.

One of the factors affecting the result of the rank transformation is the window size. We proposed to use the average distance between a local peak and its nearest neighbor, which is obtained from 2D semi-variogram, because when the window is located at a local peak, which is hypothesized to be the position of palm tree, the window will not cover other local peaks and the intensity where the window is located at will be dominant. In other words, if the windows size is too large, the window will cover many local peaks. As a consequence, the result from the rank transform will be a smooth image and local peaks can disappear.

The promising result from rank filter on enhancement of the image feature in palm tree detection will be illustrated in Section 3.

2.2.4 Local peak detection

The result from the feature enhancement methods is then used for the detection of palm tree. Since the possible region of palm trees are the regions with high digital number, which is performed by using local peak detector. However, a local peak detector cannot be directly applied to the image because the possible palm tree regions can have flat intensity over a local region. To diminish this problem, the Gaussian filter is first applied to the image. Moreover, by applying Gaussian filter, which is a low pass filter, the multiple peaks problem in a local area is then relieved.

In this proposed work, we employ non-maximal suppression algorithm for detecting local peaks. To perform non-maximal suppression efficiently, we employ the algorithm proposed by Neubeck and van Gool (2006) shown in Figure 2 and H and W are the height and width of the image I. The algorithm seeks to find the local peak in $(2n+1)$ by $(2n+1)$ windows; the parameter n can be estimated such that $2n+1$ is close to the average distance between oil palm tree, which is obtained from semi-variogram technique.

The crucial parameter of the non-maximal suppression is n. That is, if n is to large, the searching window will contain many local peaks which will be missing in result from non-maximal suppression. According to the Algorithm 1, it is analogous to finding local peak in $2n \times 2n$ window. Therefore, we suggest to used the half of the average distance between a local peak and its nearest neighbor obtained from the variogram for the parameter n because the searching window is less likely to cover other local peaks which is hypothesized as the locations of oil palm trees.

3. Result and discussion

3.1 Oil palm tree detection results

The detection process begins with the determination of the average distance between oil palm tree by using semi-variogram approach. The lag u is defined as $u \in \{-u_m, \cdots, u_m\} \times \{-u_m, \cdots, u_m\}$ and the image has 4 bands i.e. blue, green, red and near-infrared. The parameter u_m is set to be 32 which covers enough amounts of oil palm trees because the approximated diameter of the oil palm canopy is about 3-4 meters which corresponds to 8 pixels. Figure 3.a shows an example of the image used in the performance evaluation. Its semi-variogram in Figure 4 shows the approximate spatial variation of the palm trees. The average distance between a local peak and its nearest neighbor is used to determine the window size of rank transformation and the parameter for non-maximal suppression. For this image, the average distance is about 17 pixels.

```
for (i, j) ∈ {n, 2n + 1, ...} × {n, 2n + 1, ...} ∩ [0, W − n] × [H − n] do
    (i_m, j_m) ← (i, j);
    for (i_2, j_2) ∈ [i, i + n] × [j, j + n] do
        if I(i_2, j_2) > I(i_m, j_m) then
            (i_m, j_m) ← (i_2, j_2);
        end
    end
    for (i_2, j_2) ∈ [i_m − n, i_m + n] × [j_m − n, j_m + n] − [i, i + n] × [j, j + n]
    do
        if I(i_2, j_2) > I(i_m, j_m) then
            goto failed;
        end
    end
    Report local maximum at (i_m, j_m);
    failed;
end
```

Figure 2: the non-maximal suppression algorithm

In order to reduce the amount of information, each band of the image is then smoothed with the Gaussian filter prior to computing the NDVI index. The NDVI index of the image in Figure 3.a is illustrated in Figure 5.a and the rank transformation of the NDVI image is shown in Figure 5b. As it can be observed, the rank transformation of the NDVI images improves the discontinuity between hypothesized palm tree location and background. Namely, the edges of the oil palm trees are more separated from background due to the enhancement from rank transformation. After the rank transform is applied, the local peaks on the index image are then detected by using the non-maximal suppression. The oil palm trees detected from the image shown in Figure 3.a is illustrated in Figure 3.b

3.2 Performance evaluation

To evaluate the performance of the proposed method, the detection results from the proposed methods must be compared with reference data which is manually detected. The comparison with the reference data can be quantitatively shown by commonly used performance metrics. Before proceeding to the discussion about the performance metrics, let us first introduce some important terms including True Positive (TP), False Positive (FP) and False negative (FN). TP, in this context, is the amounts of oil palm trees that are correctly detected by the proposed method while FN the amounts of oil palms that are not detected. FP represents the amount of oil palm trees that are incorrectly detected. These three terms are then used to derive the performance metrics.

For the object detection problem, common performance metrics for evaluating a detection strategy are the precision, recall and F-measure, Liu et al (2011) and Marchesotti (2009). These metrics are defined as following:

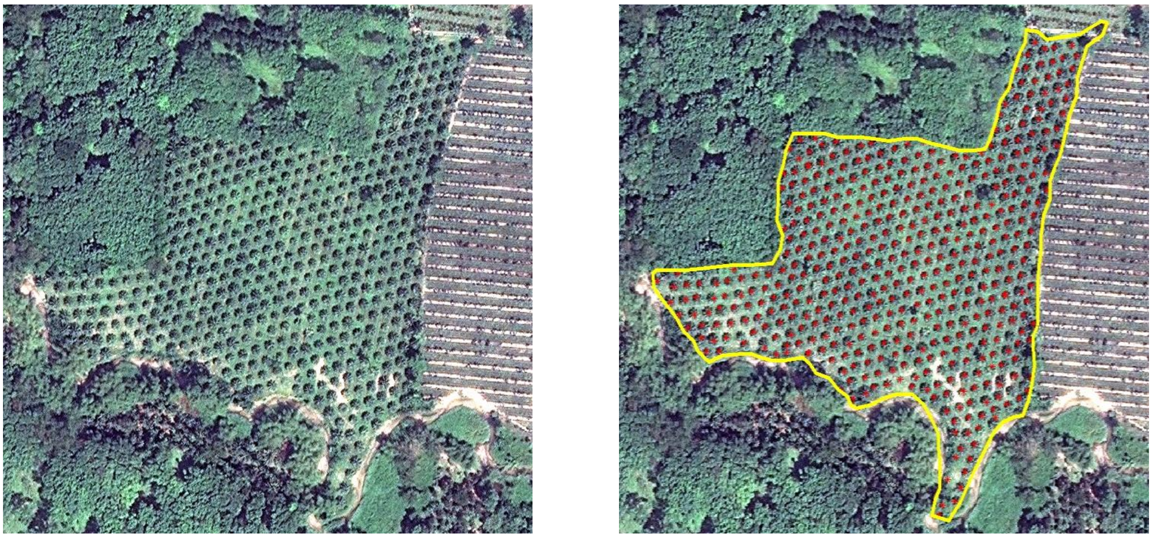
$$Precision = \frac{TP}{TP+FP} = \frac{numbers\ of\ correctly\ detected\ oil\ palm\ tree}{numbers\ of\ all\ detected\ oil\ palm\ tree}, \tag{9}$$

$$Recall = \frac{TP}{TP+FN} = \frac{numbers\ of\ correctly\ detected\ oik\ palm\ tree}{numbers\ of\ oil\ palm\ tree\ in\ the\ ground\ truth\ data}, \quad (10)$$

$$F - measure = \frac{(1+\alpha)\times Precision \times Recall}{\alpha \times Precision + Recall}, \quad (11)$$

where α is a non-negative scalar. In this paper, α is set to 0.5 as used in Liu (2011). In this context, precision can be interpreted as the probability that a detected oil palm tree is valid and recall is the probability that the correct oil palm tree (ground truth) is detected. As shown in (11), the F-measure is defined as the (weighted) harmonic mean between precision and recall. That is, the precision and recall are combined into a single performance measure. As a consequence, it can be used as an overall performance metric.

The proposed method was tested on 3 images of oil palm tree areas. The detection performances of the proposed method on each test image are reported in Table 3. The false positive appears in the detection result because the area is not homogeneous. Some oil palm trees were miss-detected because their crowns are close together.



(a) (b)

Figure 3: (a) one of the test images (b) The detection result where the positions of the detected oil palms are labeled with red dot and the oil palm plantation area, which is manually marked, is draw with solid yellow line.

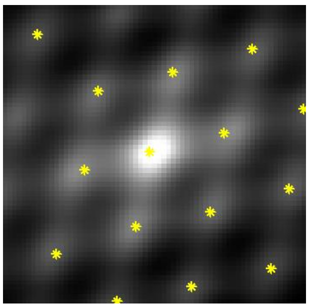
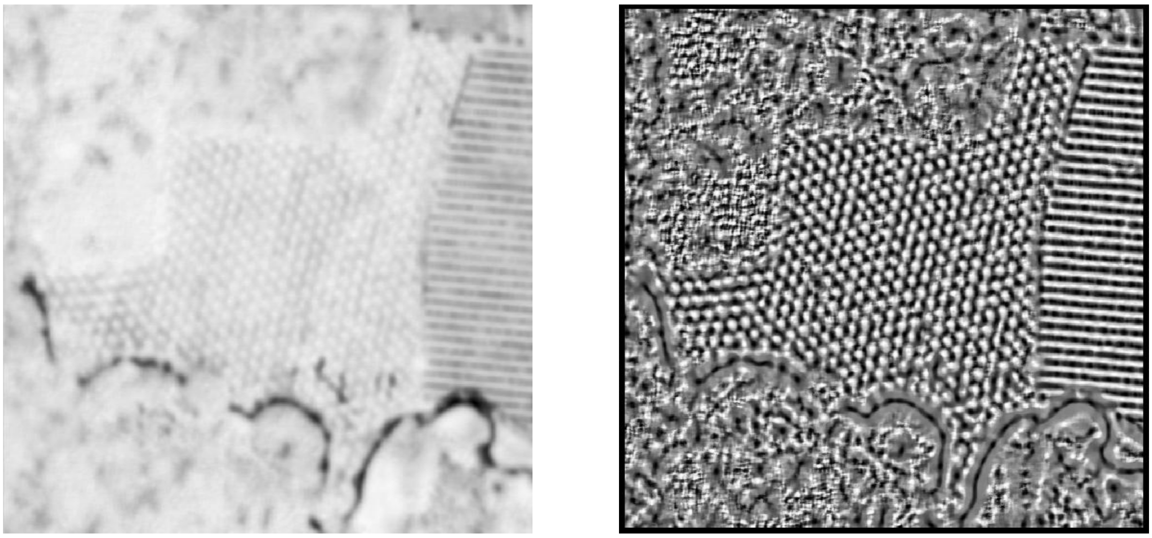


Figure 4: the 2D semi-variogram of the test image shown in Figure 3 (a). The yellow dot locates the local peak reflecting the spatial variation of the oil palm trees.

Table 1: the detection performance of the proposed method

	Number of detected oil palm trees	Ground truth	FP	TP	FN	Precision	Recall	F-measure
Test image 1	458	446	22	433	11	0.945	0.971	0.953

Test image 2	145	142	5	140	2	0.966	0.986	0.972
Test image 3	612	597	16	596	1	0.974	0.998	0.982



(a) (b)

Figure 5: (a) the NDVI image of the test image shown in Figure 3(a). (b) The rank transformation of the image 5(a).

4. Conclusion and future work

In this paper, we proposed a novel method for oil palm tree detection. The proposed method's concept is based on the green segmentation, which is referred to segmenting green object (oil palm tree) from background. The process begins with the computation of 2D semi-variogram which is used to approximate the windows size for later processes i.e. rank transformation and non-maximal suppression. After the semi-variogram is obtained, the NDVI image is generated which is then transformed by rank transformation. With the hypothesis that the position of the oil palm trees are at the peak of the rank transformed NDVI image, we therefore use non-maximal suppression algorithm. The proposed method was tested with 3 images and its performance was evaluated by using commonly used performance measure for objet detection i.e. precision, recall and F-measure. For the future work, the feature selection method will be applied in order to select an optimal feature from various vegetation indices for improving the performance of the method.

References

Atkinson P., Lewis P., 2000, Geostatistical classification for remote sensing: an introduction, *Computers and Geosciences*, (26) 361 –371.

Falkowski M.J., Smith A.M., Hudak A.T., Gessler P.E., Vierling L.A., 2006, Crookston N.L. Automated estimation of individual conifer tree height and crown diameter via two-dimensional spatial wavelet analysis of lidar data, *Canadian Journal of Remote Sensing* (33) 153–161.

Gebreslasie M.T., Ahmed F.B., Van Aardt J., Blakeway F., 2011, Individual tree detection based on variable and fixed window size local maxima filtering applied to IKONOS imagery for even-aged eucalyptus plantation forests, *International Journal of Remote Senssing* (32) 4141–4154.

Hirschmuller H., Scharstein D., 2009, Evaluation of stereo matching costs on images with radiometric differences, *IEEE Transactions on Pattern Analysis and Machine Intelligence* (31) 1582 –1599.

Liu T., Yuan Z., Sun J., Wang J., Zheng N., Tang X., 2011, Learning to detect a salient object, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, (33) 353–367.

Marchesotti L., Cifarelli C., Csurka G., 2009, A framework for visual saliency detection with applications to image thumbnailing. *IEEE 12th International Conference on Computer Vision*.

Morsdorf F., Meier E., Allgoewer B., Nuesch D., 2003, Clustering in airborne laser scanning raw data for segmentation of single trees, *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* (34) 27–33.

Neubeck A., van Gool L., 2006, Efficient non-maximum suppression, *12th International Conference on Pattern Recognition*.

Popescu S.C., Wynne R.H., 2004, Seeing the trees in the forest: Using lidar and multispectral data fusion with local filtering and variable window size for estimating tree height, *Photogrammetric Engineering and Remote Sensing* (70) 589–604.

Trias-Sanz R., 2006, Texture orientation and period estimator for discriminating between forests, orchards, vineyards, and tilled fields, *IEEE Transactions on Geoscience and Remote Sensing* (44) 2755–2760.

Wulder M., White J., Niemann O., Nelson T., 2004, Comparison of airborne and satellite high spatial resolution data for the identification of individual trees with local maxima filtering. *International Journal of Remote Sensing* (25) 2225–2232.

Zabih R., Woodfill J., 1994, Non-parametric local transforms for computing visual correspondence, *European Conference on Computer Vision*.