Integration of template matching and object-based image analysis for semi-automatic oil palm tree counting in UAV images

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ABSTRACT: Unmanned aerial vehicles (UAVs) are efficient remote sensing acquisition systems allows immediate intervention and interactive measurements based on the particular requirements of customer. In this paper, we present a technique for oil palm counting in UAV-captured images using template matching and object-based image analysis (OBIA). The method consists of four stages. First, the UAV image is preprocessed and prepared for analysis. Second, the corrected UAV image is segmented to create image objects using color information. Third, a correlation image is generated based on a manually selected template from the corrected image. Finally, oil palm trees are counted by applying a threshold for average correlation value at each image object. Oil palm trees are finally segmented, converted into vector layer, and mapped in GIS (geographic information system) environment. A comparison is made with only template matching algorithm and their accuracies are discussed. The potential applications of the proposed algorithm are rapid tree counting for effective decision making by farmers.

1. INTRODUCTION

One of the main economic crop in Malaysia is Oil palm. The number of oil palm trees in the plantation area is necessary to know for Plantation and environmental management in order to maximize the productivity from planting. The knowledge about the number of oil palm tree in each plantation area can convenience the product prediction. The easiest way for detection oil palm trees is to manually mark the oil palm trees on imageries or ground surveying using GPS to gather the locations of oil palm trees and show their locations on the image. Yet, in large area include further than 1000 oil palm tree, detection manually and ground surveying can be expensive and a time consuming procedure. For this case, remote sensing technique will be used. Remote sensing is one of the most valid measurement instrument for precise observing over large areas [1]. High resolutions remotely sensed data are vital in plantation management, as it prepare detailed data for plantation managers for better decision making. Remote sensing data can be provided either from airborne sensors such as Unmanned Aerial Vehicle (UAV) or from satellite sensors such as QuickBird, Ikonos, etc.

Satellite remote sensing offers successive perceptions of land surface and has been applied for oil palm mapping plantations in many studies [2], [3]. However, near real time and precise data is required for a supportable oil palm plantation management [4]. Recently, UAVs are being deployed for many remote sensing applications. A UAV can fly at different altitudes depending on its mission and UAV type. This flexibility allows for optimization of the operations according the actual weather conditions over a given area and the user requirements. Data acquired from UAV is becoming popular and multiple studies have been demonstrated for remote sensing and related applications including cadastral mapping [5], post-flood analysis [6], [7], vegetation cover assessment [8], crop monitoring [9], forest fire [10], traffic monitoring [11]–[18] etc. and the data acquired from these platforms are found to be crucial and attractive by nature of its high spatial resolution and almost real time data collection.

One useful application of UAV is the detection of oil palm trees from large plantations. High spatial and temporal resolution images captured by the UAV can serve as reliable source to localize and detect the trees. One popular technique for detection is template matching. Template matching algorithms tend to use the object's boundary as the main feature [19]. In some cases however, the boundary can get distorted or occluded resulting in failure [20]. In addition, the template matching method can be affected by the geometry and scale of oil palm trees in the UAV images. To overcome the limitations of template matching, an object-based analysis can be applied where the boundary of object is defined through segmentation method. Segmentation parameters that are suitable for various geometry and scale of trees can result to an accurate detection. In this study, an integration of template matching and object-based image analysis is applied to overcome the weakness of template matching and improve the method of oil palm counting on UAV images. In this work we have compared the oil palm counting using template matching and the proposed integrated approach.

2. MATERIAL AND METHOD

For image data collection, we used a Canon S100 (12-mega pixels) camera that was mounted onto a fixed-wing J-HAWK UAV (Fig. 1). The oil palm plantation area being studies was the Melaka Pindah located in Malacca, one of the sates in Peninsula Malaysia.

Figure 1. Fixed-wing J-HAWK UAV

Figure 2 shows the overall workflow of the proposed tree counting algorithm. Firstly, the UAV captures individual images where each image is processes to output a mosaicked image. Secondly, an optimized template for oil palm tree is selected for the mosaic image. The UAV image is then visually examined and several templates are selected. These templates are tested to predict the location of other trees thereby the optimized template is selected and stored for further analysis. Once, the optimized template is prepared, a template matching algorithm is applied to generate a correlation image. In this image, each pixel demonstrates the correlation factor between the template and the subset image from the original image. After that, this image is further processed to generate a thematic layer which is a shapefile containing points, each point represents a tree in the image. These points are generated by using a correlation threshold. For example, if a threshold of (0.7) is selected, then all pixels in the correlation image are converted into points representing the oil palm trees in the image. On the other hand, all other pixels are labeled as non-trees. To appropriately select this threshold, a sensitivity analysis is required. In the current study, several thresholds were examined and the best threshold based on the prediction capability is then selected. In addition, the mosaicked image is analyzed to create image objects by using multiresolution segmentation technique. These segments along with spectral and spatial attributes are used to generate two classes of segments, oil palm trees and background. The segments which are classified as oil palm trees are integrated with the result of template matching method to produce an improved result. After that, a comparison between the proposed method and the template matching algorithm is applied and their results are validated using manually selected samples. Finally, results are exported into GIS and oil palm trees are counted.

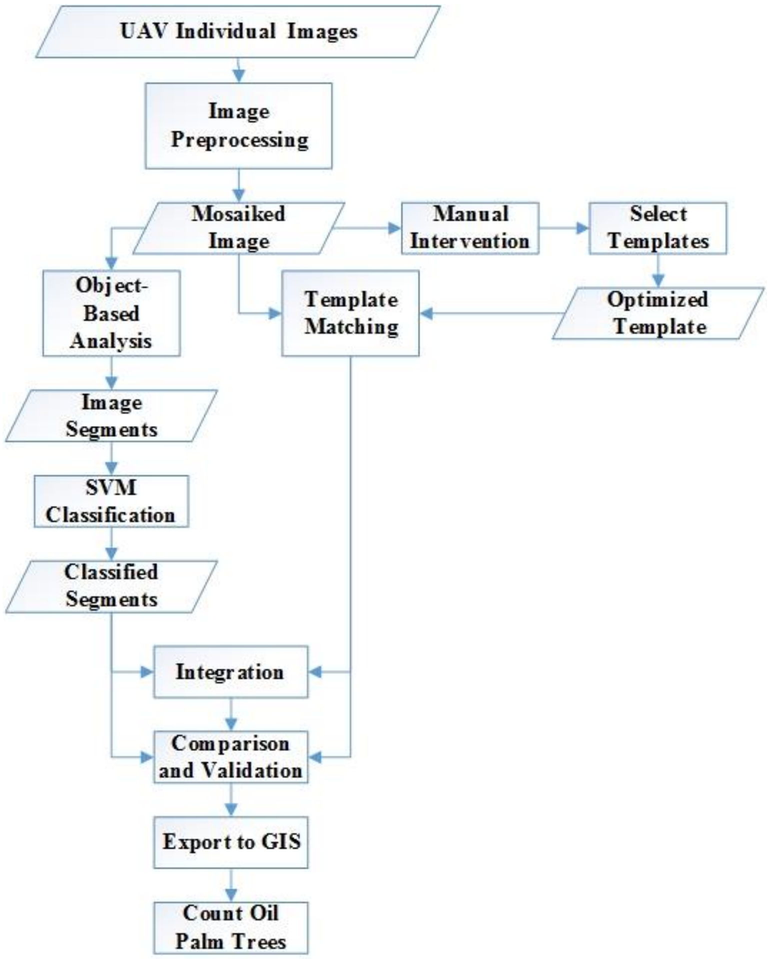

Figure 2. A general flow chart of the hybrid method

2.1 Image pre-processing

Several pre-processing steps have been applied to prepare the data for further analysis. Firstly, individual UAV images were visually evaluated to keep only the high quality images and removing the noisy and blurred images. This step is necessary because low-quality/noisy images can significantly affect the feature matching process during the image orthorectification and mosaicking. Salient features are then identified and matched in individual images for image registration. Based on the found features in UAV images, a mosaicked image was generated using the Agisoft Photoscan [21], then a subset of area was selected to conduct the experiments of the current research.

2.2 Template matching

Template matching is a technique used to find an area in a larger image that matches a specific and smaller template image (i.e. a sub-image of that larger image), hence has been instrumental in tasks such as object recognition [22]. One way to perform template matching is via calculating the cross correlation between the image, which is then compared using the squared Euclidean distance.

$$d_{f,t}^2(u,v) = \sum_{x,y}[f(x,y) - t(x-u, y-v)]^2 \quad (1)$$

(the sum is over x, y under the window containing the feature positioned at u, v). In the expansion of d^2

$$d_{f,t}^2(u,v) = \sum_{x,y}[f^2(x,y) - 2f(x,y)t(x-u,y-v) + t^2(x-u,y-v)]^2 \quad (2)$$

The term $\sum_{x,y} t^2(x-u, y-v)$ is fixed. If the term $\sum_{x,y} f^2(x,y)$ is nearly constant then the remaining cross correlation term

$$c(u,v) = \sum_{x,y} f(x,y)t(x-u, y-v) \qquad (3)$$

Template matching is a measure of the similarity between the image and the feature [23]. Basically, the algorithm compares a template that contains the shape we attempt to find (here is an oil palm tree, figure 3) to an image. In order to achieve high quality detection of trees, an optimized template was selected based on an iterated process. First, several templates were identified in the original image and stored in a database. Second, these templates were classified into three classes, *oil palm tree, error, not sure*. The templates were assigned into these three classes by the visual investigation. In order to select the best final template (with the best image quality), the existing templates were further analyzed and evaluated for oil palm tree counting for a small image subset. The accuracy of the tree counting was determined for each template using the correlation coefficient (R^2). The template that had the highest R^2 score was selected as the best template and it used in the subsequent processes.

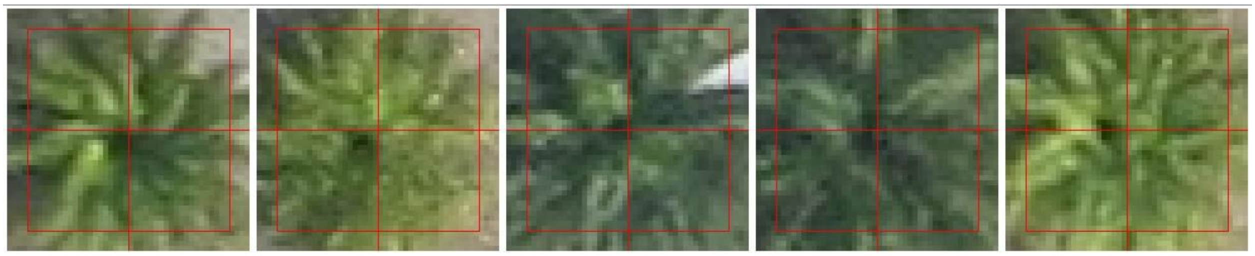

Figure 3. Sample of template

Based on the optimum template, a correlation image was constructed. In this image, each pixel value represents the correlation coefficient between the template image and the subset image of the original image. The high correlations were represented by white color, whereas the dark pixels represent the low correlation values. It can be seen that the oil palm trees as shown in Figure 4a were represented by white colors in the corresponding image (Figure 4b). This indicates that the template matching algorithm detected the location of oil palm trees. However, in order to count these trees, further analysis was required. The pixel that has a correlation value greater than a threshold (T) were converted into points (vector format). The threshold (T) of 0.65 was selected by trial and error approach to generate a point shapefile represent the oil palm trees in the image. This data was exported into a GIS software and oil palm trees were counted.

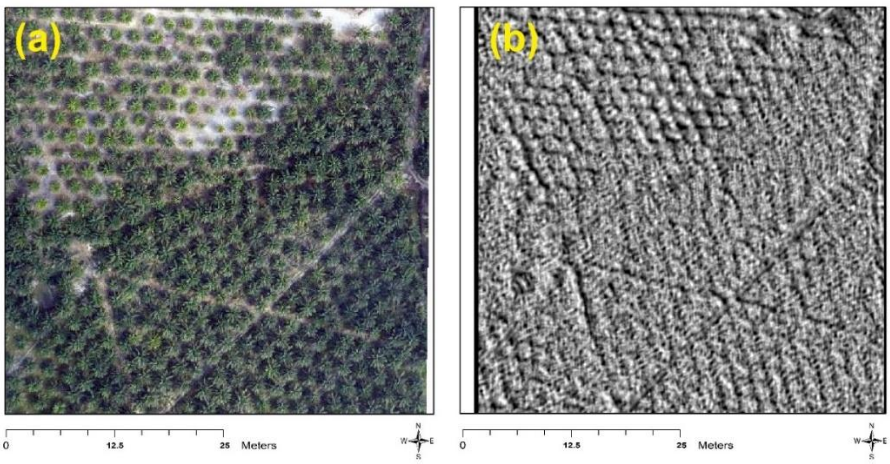

Figure 4. (a) original image (b) correlation image

2.3 Object-based analysis

Object-based analysis involves generating image objects (segments) prior to the final classification step. To perform this segmentation, image pixels are grouped into non-overlapping homogenous regions based on some criteria. In this work the multiresolution segmentation algorithm [24] was used. The multiresolution algorithm has three main parameters, namely, scale, shape and compactness. Since these parameters are data and application dependent, in this study, we have opted to select them empirically via trial and error. This means that, the best values were determined via visual examination of the segmentation results. The selected values for the scale, shape

and compactness are 85, 0.4, and 0.5, respectively.
After the segmentation process, several attributes were selected to be used as class predictors in the classification algorithm. From the spectral attributes, the three bands of the UAV image were selected. On the other hand, for spatial attributes, shape index, roundness, compactness, and density were used. Next, 20 samples including oil palm trees (10 objects) and background (10 objects) randomly were selected as training segments to train the classifier. In the classification step, the Support Vector Machine (SVM) algorithm was used. This is because of its relatively simplicity an generalization capability and because it works good with limited training dataset [25]. The parameters of SVM including the kernel function and penalty were selected by five-fold cross validation method. Finally, SVM algorithm was applied to the image segments using the training segments to classify all the available segments into two classes, oil pam trees and background.

3. EXPERIMENTAL RESULTS

Figure 5 shows the original UAV image and the segmented image by the multiresolution segmentation algorithm. Even though the quality of image segmentation was relatively good, several challenges were identified. Some of the trees were merged into one segment (over-segmentation), whereas other individual trees were represented by two or more segments (under-segmentation). Another challenge was shadows, where the shadows posed great challenges in generating accurate image segments. This is seemingly because the dark areas were considered to be trees. These issues degraded the quality of segmentation and soleyly relying on OBIA method could not be used for oil palm tree counting. The use of template matching with OBIA could overcome most of limitations of segmentation process in OBIA method.

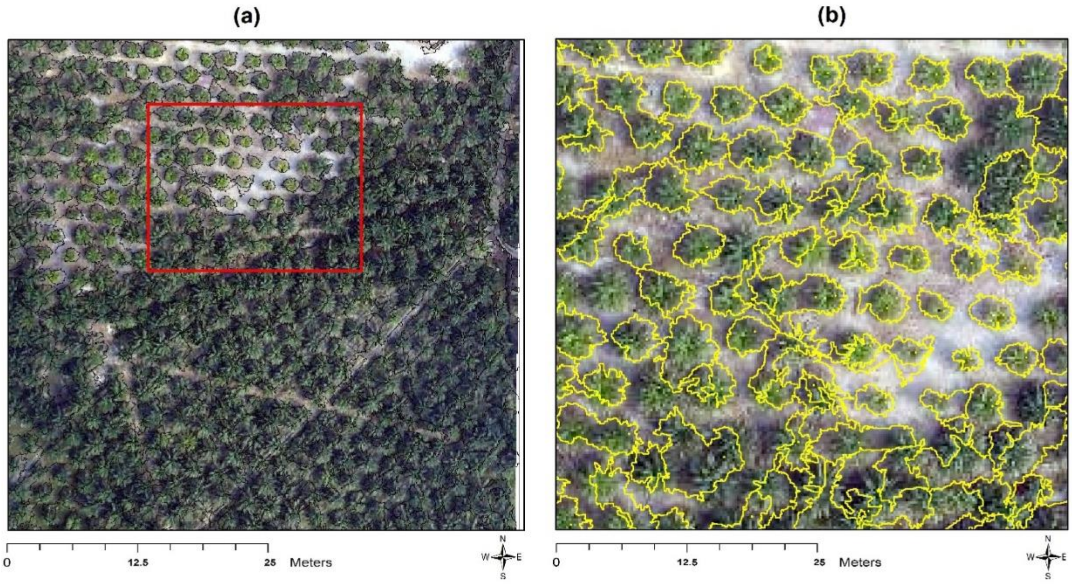

Figure 5. (a) original image (b) segmented image using automatic image segmentation method

Figure 6 shows the results of oil palm tree detetction as vector points in a GIS enviroenmnt. Figure 6a shows the results of template matching method. The detected oil palm trees were reprsented as red dots. It can be seen that most of the trees were detected accurately, however, the main challenge was that some trees were counted twice or more especially, in dense areas. In areas where palm trees are seprated, the template matching algorthm works well as most of the trees aree accurately counted. This can be seen in the north part of the study area (Figure 6a-lower view). On the other hand, we can see that many errors occurred in dense areas such as those in the north part of the study area.
In addition, Figure 6b shows the result of the oil palm tree detection using the integrated template matching and OBIA method. The first examination of the result indicnates that the results are more accurate than the results obtained by a signle template mathcing method. We can see that most of errors in the template mathcing method were reduced. This can be seen in Figure 6b-lower view. It can be seen that the trees which were represented by more than a dot in the tmplate matching method were accurately counted and repsented by only one dot. On the other hand, the integrated approach also showed some limitations in the very dense areas. For example, some of the trees in the north part of the study area were not detected. Overall, the intergrated approach is better than the only template mathcing method and quantitative assessments were disucssed in the next section.

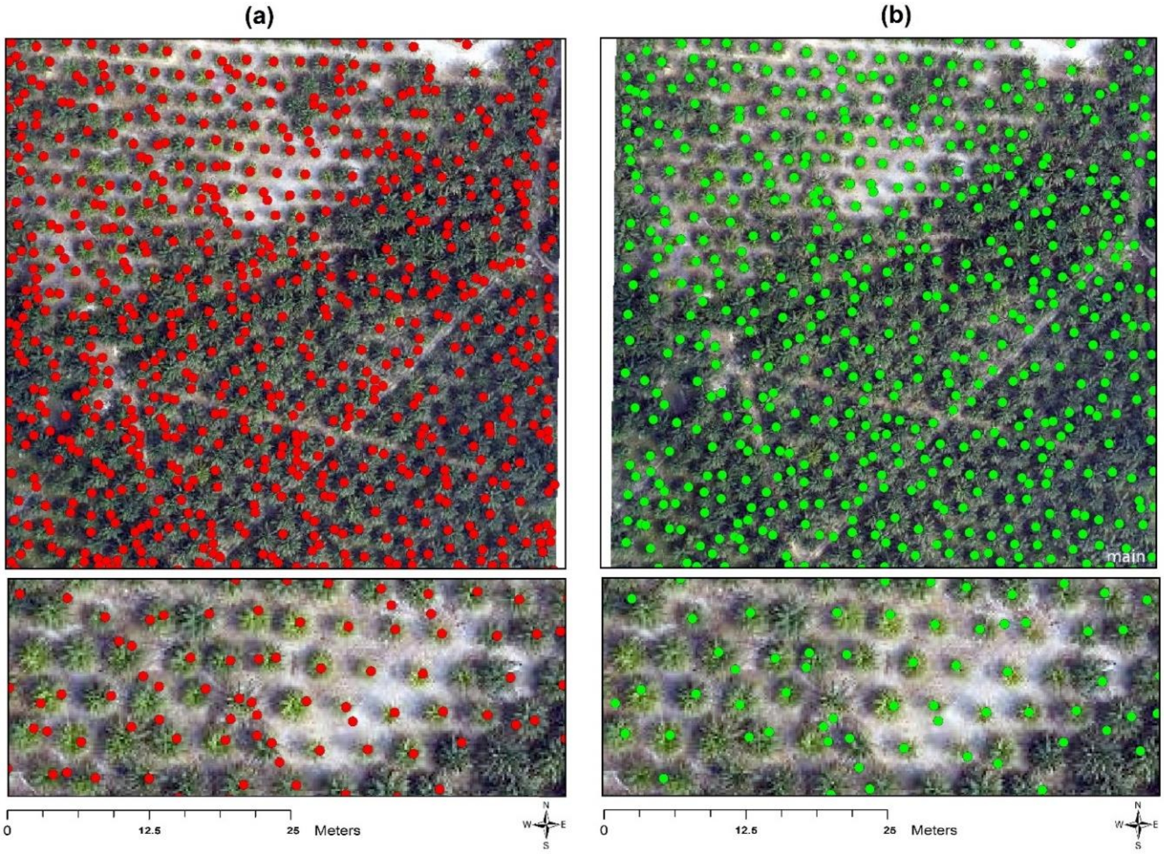

Figure 6. Oil palm detection (a) template matching (b) integration of template matching and object-based analysis

3.1 Accuracy assessment

To evaluate the accuracy of the proposed technique, we compare the detected results from the proposed technique with a ground truth measurement using manual interpretation. The comparison with the ground truth data can be quantitatively shown by common performance metrics which are precision, recall and the F-measure [1], [26], [27].

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{4}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{5}$$

$$\mathrm{F} - \mathrm{measure} = \frac{(1 + \alpha) \times \mathrm{Precision} \times \mathrm{Recall}}{\alpha \times \mathrm{Precision} + \mathrm{Recall}} \tag{6}$$

where a True Positive (TP) is the number of correctly detected oil palm. A False Negative (FN) is an oil palm tree that is not detected. A False Positive (FP) shows a pixel that is recognized as an oil palm tree but it is something else. A $\boldsymbol{\alpha}$ is a non-negative scalar. In this study, $\boldsymbol{\alpha}$ is set to 0.5 as suggested in [26]. 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 Equation (6), 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. Table 1 shows the accuracy evaluation of template matching and the proposed method. As it is clear, oil palm detection using integration of template matching and object-based analysis has highest precision and F-Measure to compare with the template matching method.

Table I. Accuracy evaluation of the template matching method and the proposed method.

Method	Number of Detected Oil Palm Tree	Ground Truth	FP	FN	Precision	Recall	F-Measure
TM	790	509	281	21	0.63	0.95	0.711
TM+ OBA	582	509	73	45	0.86	0.91	0.87

4. CONCLUSION

An oil palm counting technique using template matching and object-based analysis is proposed to detect oil palm from images captured from UAV. The challenge of the detection of single oil palm trees in UAV images was partially solved by the presented integrated method. The precision of oil palm tree counting was improved from 0.63 to 0.86 by the integration of OBIA with template matching algorithm. Some limitations were also identified for the proposed method which need further studies. First, the detection of single trees in dense areas need to be improved. Second, the method needs to be fully automated. Finally, the accuracy of the tree counting should be improved to provide effective decision making tools for farmers and agricultural agencies.

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