A Review on Remote Sensing-based Method for Tree Detection and Delineation

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Abstract. Tree detection and delineation has become one of the important factors that contribute to precision agriculture specifically in plantation industry and efficient forestry management. However, this requires tools and technology that would give reliable information and high accuracy data processing. Recent researches aimed at providing this goal by utilizing the advancement of available remote sensing technology and integrate various algorithms. This article reviews these researches with a focus on algorithms applied to remote-sensing imagery for the purpose of tree detection and delineation. It categorizes and evaluates those methods with the respective types of remote sensing imagery used in the area to evaluate the influence of these factors on the method. Finally, it summarizes the finding of the current algorithms, and suggests on the new development that can be expected in the future.

1. Introduction

Studies in tree detection and delineation for forestry and precision agriculture such as for oil palm plantations have been growing over the last few decades particularly adapting remote sensing. In forestry, remote sensing is generally used for mapping, tree crown identification and delineation, assessment of tree species composition and also for forest monitoring [1]–[11]. While for precision agriculture, the application of remote sensing is mostly for land cover detection, tree detection and counting, age estimation, pest or disease detection, land monitoring and mapping [1], [12]–[20].

Throughout the decades, various methods were applied for tree detection and delineation from the traditional image processing in the early years to the latest deep learning-based method in the last 5 years. The rapid development of new algorithm has recently been parallel to the technological advances in the field of remote sensing. However, this assumption is still unclear in showing the relationship between certain algorithms to certain remote sensing data since each study has its own considerations. Thus, this paper has the following objectives: (1) to provide an overview of remote sensing used in forestry and plantation, and (2) to provide an overview of the methodology used for various type of dataset of remote sensing in forestry and plantation. The remaining article is organized as follows: Section 2 starts with the type of remote sensing data acquisition in the field of tree detection, followed by the methodology used covers in Section 3, some discussion in Section 4 and Section 5 concludes on the finding of this review paper.
2. Remote Sensing-based Data Acquisition

As the name implies, remote sensing is how to sense an object from a distance to obtain some information or data which is usually done by using aircraft or satellites [21]. The process of sensing or acquiring data can be divided into two main categories which are by using passive sensor or active sensor. Sensors that collect information from the already available reflected light and radiation are called passive sensors while sensors that initiate its own signal to the object to get the reflection information are called active sensors.

Various types of data using remote sensing were collected to detect and delineate trees particularly for plantations and forestry. Since sensor and computation technologies have been growing rapidly, remote sensing applications in tree detection and delineation also have been evolved from conventional aerial photography or manned aircraft to satellite imagery to the latest technology of unmanned aerial vehicle (UAV). Figure 1 summarizes the data acquisition used for tree detection as presented in the literature from 1996 to 2019. The data used in the studies (total number of included papers N = 50 excluding 10 review paper) are classified into three categories: airborne, satellite and UAV imagery. For the first decade (1996-2005), satellite and UAV were not so popular and the studies about tree detection and delineation were also very limited. The use of UAV and satellite imagery dramatically increased starting from 2011 until 2019 and this trend is expected to increase as the technology is improving.

![Figure 1](image.png)

**Figure 1.** Number of publications studied (1996-2019) on various types of remote sensing data acquisition.

2.1 Airborne / Aerial Imagery

The airborne or aerial imagery usually referred to image captured by using manned aircraft, plane or helicopter. This airborne system is equipped with sensors such as electro-optical sensor [22], infrared sensor [2], [7], spectrometer [18], aerial laser scanner (ALS) [8], Light Detection and Ranging (LiDAR) [23]– [25], multispectral sensor [9] and hyperspectral sensor [4]. In those studies, the altitude of the flight was set from as low as 50m to as high as 3000m above ground. The different flight altitude and speed can give a significant effect to the quality of image acquisition process other than the spatial resolution of the camera used. While for sensor selection, the sensors being used would
depend on the purpose of the study. For instance, LiDAR and ALS sensors are useful for estimating height of the trees which give more details information for tree species classification.

2.1. Satellite Imagery
The most common satellite imagery used for tree detection and delineation in the reviewed studies were WorldView-2 [17], [26], WorldView-3 [25][26], Quickbird [12][15][27]–[29], PALSAR [31] and Google Earth [16], [32] imagery. Most of this satellite imagery is categorized as multispectral (MS) imaging which has typically three to fifteen spectral bands compared to hyperspectral imaging which contain hundreds of contiguous spectral bands. For WorldView-2, there are eight multispectral bands and one panchromatic band with a nominal resolution of 1.84m and 0.46m respectively. While for WorldView-3, the eight MS bands has a nominal resolution of 1.24m and 0.31m which is better that the previous one [26]. However, only five of the eight Worldview-2 bands were found relevant for the analysis of tree vegetation which are Red, Green, Blue, Red edge and Near infrared band.

2.2. Unmanned Aerial Vehicle (UAV)
In recent years, Unmanned Aerial Vehicle (UAV) or mostly known as ‘drone’ has been widely used in many applications including precision agriculture and forestry. With the availability of wide range of sensors, users can define high spatial resolution of imagery and generate 3D data which lead to the advancement of UAV data acquisition. UAV can be programmed to fly autonomously or remotely control from the ground and the performance of fixed wing and rotary wing UAV would be different and specific for certain kind of application. For instance, fixed wing is preferable for large land coverage while rotary wing may be more suitable for high spatial resolution of data acquisition [33]. There are variety of payload sensing instruments that can be carried by UAV including Radar, LiDAR, thermal infrared (TIR), near infrared (NIR), shortwave infrared (SWIR) and visible light sensors [33]. The development of lightweight camera sensor for UAV has enabled a very high spectral and spatial resolution for aerial measurement with ground sampling distance (GSD) less than 10cm. The GSD is the distance between the center points of image taken on the ground, where the bigger the GSD value, the lower spatial resolution of the image would be.

3. Methodology
Over the past few decades, existing methods for detecting tree from remote sensing can be classified into four categories: (1) the image processing-based methods; (2) the machine learning-based methods (3) the dense point cloud method and (4) the deep learning-based methods. Based on the literature, the type of data acquisition would somehow affect the kind of methods used for tree detection. Thus, this paper will give some review on the different methods applied for different data acquisition method. The image processing-based method includes local maximum filter, edge detection and segmentation, morphological operation, template matching and the vegetation indices for feature extraction method. Many studies in the early years (1996-2005) that used digital aerial imagery such as [22],[2] and [7] applied this traditional image processing-based method.[22] use template matching (TM) method which involve geometric and radiometric aspects by developing a synthetic model for different crown size and shape to be matched with the aerial images. [7] use a multiple-scale algorithm for edge contours and curves in high spatial resolution infrared images for the delineation of individual tree crowns. [2]designed local transects extending outward algorithm from tree apex resulting 91% accuracy of tree detection. The need for very high-resolution imagery in delineated tree crown diameter has been proved by testing the variation of image resolution.

Using airborne high spatial resolution (1m) image,[18] proposed an oil palm tree extraction method based on texture and spectral analysis, segmentation of edge and morphological operation and blob analysis for tree counting obtaining to achieve 95% of counting accuracy. A quite similar approach was also done for processing high resolution multispectral satellite imagery including edge detector using Sobel, texture analysis, high-pass filter, opening filter and morphological operation of dilation and erosion [15].
The image processing-based method is also applied in many studies [12], [17], [34]–[36] that use various vegetation index values for feature selection. Different vegetation index has been defined for specific task and some indices cannot be computed depending on the spectral data available. [12] applied several vegetation indices which are derived from the multi-spectral satellite imagery for local peak detection of oil palm. The indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Index (NDI), Green Normalized Difference Vegetation Index (GNDVI) and Transformed Vegetation Index (TVI) are used. The best index is chosen by comparing the histograms generated from all the index values which maximize the dissimilarity between the oil palm tree and the background.[35] successfully determines that the low-cost UAV platform and RGB digital compact camera with modified filter (capture NIR) able to be used by smallholders in monitoring the palm tree growth condition, where the higher the value of reflectance, the higher the greenness (healthier) of the oil palm tree. This result can be derived from the combination of both Soil Adjusted Vegetation Index (SAVI) and Normalized Difference Vegetation Index (NDVI).

The machine learning-based (ML) tree detection methods usually require feature extraction, image segmentation, classifier training, and prediction [17][20][30][31][36][37]. The classifier which is the most important part in ML can be categorized as supervised or non-supervised. Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT) and Neural Network are some examples of supervised classifier while K-Nearest Neighbour (k-NN) and K-means clustering are non-supervised classifier. Supervised ML requires images database labelled as positive and negative with corresponding categories (i.e. tree and background) which is used for training samples. From the ALOS-PALSAR Orthorectified Mosaic images,[31] proposed three classification algorithms which are Decision Tree, SVM, and K-Means clustering to map oil palm plantations in Cameroon. Results show that SVM has good overall performance with accuracy of 86% to 92% depending on training samples sizes while Decision Tree algorithm outperforms the others in terms of speed for large scale mapping. The use of Google Earth Engine (GEE) is demonstrated by [32] using Classification and Regression Trees (CART), Random Forests (RF) and Minimum Distance (MD) classifier for detection of industrial oil palm. [20] proposed a novel method using Scale Invariant Feature Transform (SIFT) to extract key points from UAV image. These key points were then analysed using Extreme Learning Machine (ELM) classifier to distinguish between palm trees and non-palm trees.

The airborne imagery that fused with LiDAR data provide a three dimensional (3D) high spatial resolution image in a form of point cloud data which can generate many features that are difficult to obtain from spectral imagery such as tree height, quartile heights and crown base height[39]. This point cloud features were useful in obtaining a Digital Surface Model (DSM) and Digital Terrain Models (DTM) which were further use for the derivation of Canopy Height Model (CHM). In a few studies, this attributes was combined with hyperspectral [4] and multispectral data [40] for tree species classification. The fusion of active sensor (LiDAR) and passive sensor (multispectral, hyperspectral, RGB camera) data is also done for the satellite and UAV imagery. [27] proposed a method from Worldview 3 satellite imagery and LiDAR data using an integrated OBIA height model and SVM analysis for oil palm counting and age estimation. [41] studies the comparison of ALS and structure from motion (SfM) point cloud for assessing individual tree information including the terrain height and the horizontal and vertical distribution of forest canopy. Both studies show that the LiDAR and ALS point cloud data can provide tree height information accurately which complements the geometrical and spectral information from multispectral and RGB imagery.

Many studies also show that the dense point cloud data can be derived from RGB digital images by using SfM which mostly applied for UAV imagery [1][3][41]–[45]. For instance, [44] use a data fusion of UAV based point cloud data and hyperspectral image in boreal forest for individual tree detection and classification. The results show 3D point cloud derived from UAV photogrammetric data produced good result for the individual tree detection. However, it did not improve the result of tree species classification compared to the spectral features derived. As an alternative to LiDAR data, [43] proposed feature extraction algorithm using SIFT to extract features point from UAV imagery but the dense point cloud generated is not sufficient to extract tree parameters accurately. The usefulness
of modern software such as Agisoft Photoscan Professional v1.0.0 software to produce 3D point cloud data resulting higher accuracy of more than 85% in the study of individual tree detection in open canopy forest [42]. The CHM was derived from the SfM algorithms on RGB photographs based on the location of the images with respect to each other as well as the objects viewed within them.

In recent years, several studies applied the deep learning-based method including fruit counting [47], land cover mapping [48] and tree detection [25][27][29][49]. The deep learning-based methods for tree detection studies are mostly applied to high resolution satellite images based on the sliding window technique combined with the CNN. [28] manually selected 5000 palm tree samples and 4000 background sample and randomly selected 7200 of this as training samples. The sliding window of 17x17 pixels was tested to predict labels in image dataset which result in accuracy of more than 96%. While in the other study which involve a large scale study area (around 5km²), [30] proposed a two-stage convolutional neural network-based method for oil palm tree detection. Four classes of 20,000 samples were trained including oil palm, background, cloud and other vegetation for object classification and land cover classification. In their study, [30] compare their deep learning-based method with earlier methods (the template matching, the ANN, and the local maximum filter method) in all selected regions in their previous studies [28]. The results show that the CNN-based method outperforms other oil palm detection methods by 3 to 10 percentage points in terms of the F1-Score.

4. Discussion
The study of tree detection and delineation either in forestry or plantation such as oil palm plantation is an important issue for researchers especially in remote sensing community. This paper has reviewed 60 papers which consist of 50 research papers and 10 review papers from the year 1996 till 2019. The contribution of researchers in terms of objectives, remote sensing data acquisition, methodology and accuracy assessment for tree detection in forestry and plantation were considered. The effect of remote sensing data acquisition to various method used for tree detection has been studied. Table 1 summarizes the advantages and disadvantages of specific algorithm used in each method group.

| Method                        | Example of Algorithm Used | Advantages                                                                 | Disadvantages                                                                 |
|-------------------------------|---------------------------|-----------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| Image processing-based method | Watershed segmentation    | Easier for crown detection.                                                 | Can be over segmented for non-similar crown size trees.                     |
|                               | Template matching         | Suitable for well separated tree.                                           | Not suitable for dense tree canopy.                                          |
|                               | Vegetation Index          | Well suited for crop health and tree growth monitoring.                    | Requires more spectral data such as NIR band.                               |
| Machine learning-based method | Support vector machine    | High accuracy for small and good training dataset.                         | Need longer time to train dataset.                                          |
|                               | K-means clustering        | Need no training dataset and runs faster.                                   | Less accurate.                                                              |
|                               | LiDAR /ALS                | Accurate estimation for vertical tree structure                            | High cost.                                                                 |
| Point cloud-based method      | Structure from motion     | Low cost, provide greater spatial coverage.                                 | Cannot measure terrain altitude in dense canopy area.                      |
|                               | (SfM)                     |                                                                             | Requires thousands of training dataset and expensive GPU.                   |
| Deep learning-based method    | Convolution Neural Network| High accuracy in any difficult condition; can cover large scale area.     |                                                                             |
The image processing-based method can be concluded as the most versatile method since it can be applied for any remote sensing data acquisition and can be fused with many other advance methods. This method not only involve traditional image processing such as image filtering, segmentation, binarization and feature extraction, but a template matching, and vegetation index-based feature extraction are also included as part of the category. The advantages of image processing-based method are it is relatively not complicated, easy to understand, and does not require many tools. It is also suitable for most spatial and spectral resolution of image data. However, the major limitation of this method is the performance of tree crown or tree top detection deteriorates for denser tree area and overlapping tree canopies [14].

Some of the studies using remote sensing not only focus on tree crown detection but also for tree delineation and identifying tree species. The machine learning-based methods can be applied to assess various classifiers for this purpose. Using a supervised or non-supervised machine learning method would depend on the dataset available. However, for best accuracy, this method requires high resolution image, multispectral, hyperspectral or thermal imagery image which can provide wide range of spectral data [5].

In recent years, deep learning has increased attention of many researchers as it shows great success in various studies. This is because deep learning can learn the features from images automatically and can be said as a fully data driven scheme [50]. Studies also prove that the deep learning-based method has outperformed most of the other traditional tree detection method. However, deep learning requires thousands of sampling data set and to train it requires complex data models which can be extremely expensive. Moreover, expensive GPUs and hundreds of machines would also increase the cost.

In term of data acquisition, all remote sensing platform discussed in this paper has their own advantages and disadvantages. Satellite imagery allows much greater areas of coverage and can provide wide range of spectral data such as panchromatic, multispectral, and hyperspectral data. While for aerial and UAV imagery, the spatial and spectral data acquired would depend on the type of sensor and camera used and the area coverage is limited. However, with the development of lightweight multispectral and hyperspectral camera available, with lower cost and more up-to-date, UAV can still be a better choice for small stakeholders or personal commercial uses than satellite imagery. The methodologies of processing the image data for UAV and satellite imagery in most of the studies are almost the same. The major difference is for airborne imagery equipped with LiDAR sensor, which can provide deeper information of forest canopies penetration. Thus, it can be said that for vertical stratification layer information, LiDAR point cloud data is more efficient compared to satellite and UAV imagery which are more reliable in capturing spectral information of the surface or top layer. Some studies show that the algorithm for generating point cloud LiDAR data processing can also be used for processing the derived UAV-based point cloud data. However, the derived photogrammetric point cloud cannot produce accurate detection results as compared to LiDAR point cloud and need further development in the future.

5. Conclusion
Tree detection and delineation studies greatly contribute to both forestry and plantation inventory needs. However, there is still room for improvement and development especially in terms of the methods used. With the increasing availability of remote sensing data, studies would be focusing more on the practicability of the method used with lower cost and higher quality result. The accuracy of the tree detection would not rely on the algorithm only, but also depends on the quality of data acquisition. The fusion of passive and active sensors data might improve the tree detection accuracy and could provide more advance method in the future.

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