

Automated Extracting Tree Crown from Quickbird Stand Image

Guang Deng, Zengyuan Li, Honggan Wu, Xu Zhang

► **To cite this version:**

Guang Deng, Zengyuan Li, Honggan Wu, Xu Zhang. Automated Extracting Tree Crown from Quickbird Stand Image. 4th Conference on Computer and Computing Technologies in Agriculture (CCTA), Oct 2010, Nanchang, China. pp.304-311, 10.1007/978-3-642-18333-1_36 . hal-01559554

HAL Id: hal-01559554

<https://hal.inria.fr/hal-01559554>

Submitted on 10 Jul 2017

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Automated Extracting Tree Crown From Quickbird Stand Image

Guang Deng¹, Zengyuan Li¹, Honggan Wu¹, Xu Zhang¹

¹Institute of Forest Resource Information Techniques, Chinese Academy of Forestry,
Beijing, 100091, China
{[dengg.zy.whg.zhangxu](mailto:dengg.zy.whg.zhangxu@caf.ac.cn)}@caf.ac.cn

Abstract. Artificial intelligence technologies with spatial information technologies play more and more roles in precision agriculture and precision forestry. This paper puts up a new artificial intelligence algorithm which based on seeded based region growth method to extract tree crown on Quickbird forest stand image. It is a kind of object based canopy and gap information extracting method specially suited for high-resolution imagery to get meaningful tree crown object. The main processes to carry out the experiment and validation on the Quickbird satellite images in Populus×xiaohei plantation even stand at Xue JiaZhuang wood farm in Shanxi Province of China is described in detail in the paper. The average tree numbers identification error is 18.9%. The result shows that this algorithm is an effective way to get segmented crown in real stand image. This algorithm can be powerful tools for precision forestry. We suggest users to choose suitable features and parameter values try by try in forehand applying.

Keywords: Tree crown recognition algorithm; Seeded based region growth segmentation; Object based information extracting

1 Introduction

Precision forestry is defined by Taylor et al. [1], as planning and conducting site-specific forest management activities and operations to improve wood product quality and utilization, reduce waste, and increase profits, and maintain the quality of the environment. Principle of precision forestry was based on precision agriculture. Precision agriculture uses set of tools, which has been successfully introduced and now it is used in precision forestry. Artificial intelligence technologies with spatial information technologies play more and more roles in environment information extraction and environment effect analysis. This paper puts up a new artificial intelligence technology which based on seeded based region growth method to extract canopy and canopy gaps on Quickbird forest stand image. Tree detection can provide estimates of tree abundance and spatial pattern that are useful for evaluating density and stocking objectives. Delineation of individual tree crowns can get crown diameter

of tree to be used to model tree structural variables such as height, volume, or biomass. Individual tree and clumped trees information are basal knowledge for forest management in precision forestry level. From the view of forestry machinery, this technique can make the positioning capability of forest harvesting machinery more precise which can be integrated the artificial intelligence forest road, trees and forest open area identified.

In past 15 years, many scientists put up methods to extract tree from high spatial resolution imagery to get more efficiently and more accurately results. [2,3,9,10] Gougeon [2] developed a valley-following algorithm for the isolation of individual crowns in Canadian Boreal forests. The method finds crown boundaries by first following the shaded areas (radiometric valleys) between trees, and then refining the boundaries using a rule-based program. Culvenor's TIDA[3] method use the (local) radiometric maxima and minima as the primary image features used for the crown delineation process, being indicative of crown centroids and boundaries, respectively. Though these methods boost the tree crown recognition research in optics remote sensing area, but it has long distance to practice level for precision forestry management. Validating and comparing these methods are now days mission for information precision forestry research area.

2 Object Based Canopy and Gap Information Extracting Method

Conventional image classifications focus on the differentiation of spectral values for each pixel. Because objects are groups of pixels on high spatial resolution remote sensing imagery, statistical values such as mean or standard deviation can be derived, which provides additional information. In addition to spectral metrics, texture and geometric characteristics of the objects can also be used for classification. This method can improve the conventional pixel-based classification methods to get relatively satisfactorily result far from pixel classification result on high spatial resolution remote sensing images. As its results are some image segments, they can be used for object based image analysis for detailed knowledge forest stand in modeling and digital forest management.

From 2000, eCognition[4] became the first commercially available software for multi resolution segmentation and object-oriented fuzzy-rule classification, specially suited for high-resolution imagery[5]. Segmentation follows a proprietary bottom-up region merging technique [6] starting with one-pixel objects, which are iteratively merged into larger objects based primarily on a user defined scale parameter. To the specifically object in nature scene, object based technique only provides a methodology, the fine expression of the object must be looked for.[7]

The tree top seeded based region growth tree detection and crown delineation algorithm for analyzing QuickBird satellite images has six main steps, which are described in details as follows.

(1)Primary segmentation. Primary segmentation puts on the stand image after image fusion and color composition and get series image object elements with small area for latter tree crown seed extraction.

(2)Reducing the treetop searching scope. In stand image, there is many area covering by tree shade or bare land, grass ,shrub and so on. By masking operation with $NDVI > 0.38$ of study image, the non trees areas are be shielded.

(3)Treetop selection. Treetop selection uses non maximum oppression method to distinguish tree top from image object segments. The local maximum of ratio of near red band (NIR) of pixel (defines in formula (1)) is selected as treetop seed which is as center in a window within surrounding 3 image objects. If the two equal local maximum are found, they both be accepted as treetop seed and be marked.

(4)Seed growing. This step is to get tree crown extent. The condition of seed growing is set down as mean ratio of near red band (NIR) (defines in formula (2)) of candidate image object element and seed greater than 0.9 and lesser than 1.[8]

(5)False treetop seed wiped off. This is necessary because anterior steps get many seeds which are not true treetop anyway. Computing the mean NDVI value and mean red band standard deviation value (defines in formula (3)) of seeds, the false treetop is cognized by much smaller value in theses two index. That means that the preserving seeds are true treetop.

$$ratio_L = \mu_L / \sum_{i=1}^{n_L} \mu_i \tag{1}$$

$$\mu_L = \frac{1}{n} \cdot \sum_{i=1}^n v_i \tag{2}$$

$$\delta_L = \sqrt{\frac{1}{n-1} \cdot \sum_{i=1}^{n_L} (v_i - \mu_L)^2} \tag{3}$$

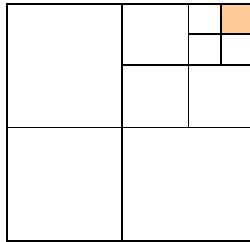


Fig. 1. Quad tree segmentation

(6)Tree crown shape optimization. The crown boundary is not smooth enough, so some cycling segmentation is done on image objects elements enveloping the treetop objects. Here the quad tree segmentation performs by recursively combining (merging) the image segments as leafs and regions to get more smooth canopy outline. By comparing the character of smaller image objects elements enveloping the treetop objects with the treetop objects , some smaller image objects elements will be combined into the ambient tree crown object.

3 Research Area and Data

The presented approach selects a research area for analyzing Quickbird satellite images in Populus×xiaohei plantation even stand at Xue JiaZhuang wood farm in Shanxi Province of China which location are presented in Fig. 1, because Populus is a very popular broadleaf and has important value in use. The research area 's east longitude is 112033 ,north latitude is 39018 ,its average year air temperature is 7 ;its average year precipitation is 400mm; its average year evaporation is larger than 2700mm . It is drought and the forest soil is bare. The dominant specie in research area is Populus×xiaohei which planted in April 1977 has 21.6 hm² area. The terrain of research area is plain. The soil type of research area is meadow soil.

By programming ordering, the Quickbird imagery covering the research area on 6 May 2004 was gained, which has pan band and multi spectrum bands. The quality of image is good and there is no cloud on the image. The geodetic coordinate of up left corner of the image is 635167.20m,4352983.20m and down right is 635664.60m,4352655.00m. The 30 sub compartment of Xue JiaZhuang wood farm corresponding the above Quickbird image with 501*344 pixels was selected for tree crown extraction. In the surveying table of 30 sub compartment, the value of canopy closure is 0.7.

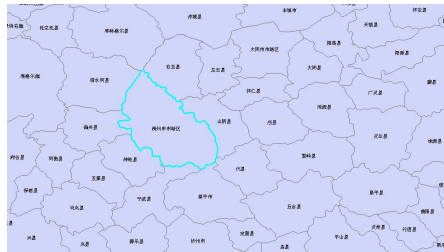


Fig. 2. Regional map of research area

In May 2004, we surveyed this area. Considering the growth condition of the stand, we selected 3 kinds of plantation density stands, which is 2m × 5m (1000 trees/ha) 、 4m × 5m (500 trees/ha) 、 4m × 10m (250 trees/ha) . In every plantation density, 3 standard sample plots were set up. In total, 9 standard sample plots were gained. The area of every standard sample is 900m²(30 m×30m). The standard samples of 2m×5m plantation density named A1,A2,A3, the standard samples of 4m×5m plantation density named B1,B2, B3, the standard samples of 4m×10m plantation density named C1,C2,C3. The location, tree height and tree diameter of all these trees were measured and these trees had been marked on the printed image photos. Using these truth data , the auto and semi auto tree crown recognition algorithm can be validated.



Fig. 3. Location of research stand on Quickbird image

4 Implement and Results

In the algorithm implemented period, there are some parameters must be selected cautiously. In Primary segmentation, the small value of segmentation scale must be selected. After testing from 3,5 and else values, we select 3 for segmentation scale, 0.3 for weightiness of shape and 0.7 for weightiness of compactness. In seed growing step, the mean ratio of near red band (NIR) of candidate image object element and seed is greater than 0.9 and lesser than 1. In the quad tree segmentation for crown shape optimization, the time of cycle is set 3. Table 1 shows the some key features and values of parameters used in this algorithm. Fig. 4 is the image of plot C1 and the Fig. 5 is the 3d view of its spectral values.



Fig. 4. Image of plot C1

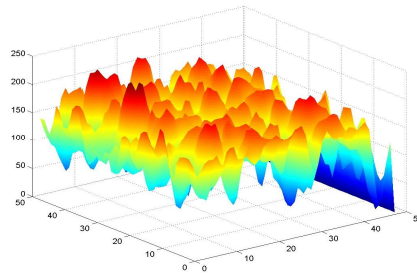


Fig. 5. 3d View of plot C1's spectral values

Table 1. Features and values of parameters in this algorithm

Function of features	Features	Value of parameters
Distinguish vegetation	Mean NDVI	>0.38
Treetop seeds	Ratio of NIR	Max
	Image object window size	3
Seed grows conditions	Mean ratio of NIR	(0.9,1)
Crown shape Optimization	Cycle times	≤ 3

The result of above method is a tree crown map from the Quickbird image. Fig. 6 is the stand tree crown image map with whole sub compartment.

The validation method is carried in 9 standard samples on stand image by automated tree crown recognition to the manual delineation after field work described in section 3. The two results are overlaid, and each tree crown image object, for each layer, is assigned to the object in corresponding layer for which it has the greatest overlap in area. A correct tree crown occurs when a tree crown image object from the recognition algorithm and a tree crown image object from manually delineation are assigned uniquely to each other.[10]

**Fig. 6.** Tree crown map from the Quickbird image

Three types of errors are defined for the comparison. Firstly, dissection occurs when more than one image object from the recognition algorithm is associated with the same manual tree delineation. Secondly, aggregation is when more than one image object from the manual tree delineation associated with a single tree crown image object from the recognition algorithm. A combination error is when parts of the recognition algorithm are aggregated, and parts dissected, as shown by the assignment of multiple image objects from each layer to the same image object in the other layer.[10]

5 Conclusion and Discussions

Computing the precision of average identified tree numbers by linear regression of tree numbers of recognition algorithm and tree numbers of field work. The result is shown in formula(7), in which auto means the tree numbers of recognition algorithm and manual means the tree numbers of field work. The square correlation coefficient 0.4693 means the recognition algorithm has real effect.

The top line in Table2 shows the criterion evaluating the results of the algorithm. The definition of them show below. From comparing tree numbers of field work and software identification by tree matching, the confusion matrix, overall accuracy, commission error, omission error is computed which shows in Table2.

$$\text{Overall Accuracy, OA} = (\text{Tree numbers of correctly recognition trees by algorithm} / \text{Tree numbers by field work}) * 100\% \quad (4)$$

$$\text{Omission Error, OE} = (\text{Tree numbers of omission by algorithm} / \text{Tree numbers by field work}) * 100\% \quad (5)$$

$$\text{Commission Error, CE} = (\text{Tree numbers of commission by algorithm} / \text{Tree numbers of correctly recognition trees by algorithm}) * 100\% \quad (6)$$

$$\text{auto} = 1.0892\text{manual} + 0.3558 \quad R^2 = 0.4693 \quad (7)$$

The main result is that this algorithm's accuracy, commission error, omission error far from different crown closures. Computed crown diameters after program crown delineation has similar distribution of field measure crown diameters, but they have bigger values and more dispersed range. Through grouped plantation density results analyzing, the performance of this algorithm on 0.6 crown closure plots get well. Omission error of 0.8 crown closure plots is high to 34% and commission error of 0.7 crown closure plots is high to 63%. This result means that the algorithm will be more well for the moderate crown closure forest stand. For the very low and very high crown closure forest stand, the error variance will increase.

Table 2. Accuracy analyses of auto tree number identification from different plantation density stands

Plantation density	OA(%)	OE(%)	CE(%)
A	40	34	16
B	60	6.7	63
C	71	8	40
Total	57	16	40

The presented tree top seeded based region growth tree detection and crown delineation algorithm for QuickBird satellite images uses crown model which is focus on basic radiometric properties of tree crowns. This method puts vegetation classification and crown segmentation under an unified framework. We use 9 plots with different plantation density (crown closure) to validate the above method. Average tree numbers identification error is 18.9%, $R^2 = 0.4693$. Ultimately, our tree top seeded based region growth tree detection and crown delineation algorithm is an

effective tools for getting segmented crown in real stand image. This research shows that the artificial intelligence technology can be useful in precision forestry. This research uses comprehensive and highly accurate field survey data to validate the algorithms. And the evaluation indicates the distance with satisfactory results and the direction to improve on the algorithm.

Acknowledgment. Financial supports from 863 project of No. 2007AA12Z181 of Chinese MOST and CAF project of RIFRITZJZ2007010 are highly appreciated.

References

1. Taylor, S.E., McDonald, T.P, Veal, M.W. & Grift, T.E: Using GPS to evaluate productivity and performance of forest machine systems.Proceedings of the First International Precision Forestry Cooperative Symposium: University of Washington, College of Forest Resource, June, pp.151-155(2001)
2. Gougeon,F. A: A Crown-Following Approach to the Automatic Delineation of Individual Tree Crowns in High Spatial Resolution Digital Images.Canadian Journal of Remote Sensing, 21(3): 274-284(1995)
3. Culvenor,D. S:TIDA: An Algorithm for the Delineation of Tree Crowns in High Spatial Resolution Remotely Sensed Imagery. Computers & Geosciences.28,33-44(2002)
4. Definiens: eCognition Version 5 Object Oriented Image Analysis User Guide[M]. Munich, Germany: Definiens AG(2005)
5. G.J. Hay et al.:An automated object-based approach for the multiscale image segmentation of forest scenes. International Journal of Applied Earth Observation and Geoinformation. 7,339-359(2005)
6. Baatz,M. and A. Schape: Multiresolution Segmentation - An Optimization Approach For High Quality Multi Scale Image Segmentation. In: Angewandte Geographische Informationsverarbeitung XII, Ed. J. Strobl et al.,AGIT Symposium,Salzburg,Germany.,12-23(2000)
7. Yu, Q., P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schironkauer: Object-based Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery. Photogrammetric Engineering and Remote Sensing, 72(7): 799-812(2006)
8. Noguet,D.,Merle,A.,and Lattard,D: A data dependent architecture based on seeded region growing strategy for advanced morphological operators. In: Mathematical Morphology and its Applications to Image and Signal Processing,P. Maragos,R. W. Shafer,and M. A. Butt,Eds. Kluwer Acad. Publ.,Dordrecht, 235-243(1996)
9. Pouliot,D. A.,D. J. King,F. W. Bell,and D. G. Pitt: Automated Tree Crown Detection and Delineation in High-Resolution Digital Camera Imagery of Coniferous Forest Regeneration. Remote Sensing of Environment.82,322-334(2002)
10. Warner et al.:Segmentation and classification of high resolution imagery for mapping individual species in a closed canopy deciduous forest. Science in China: E Technological Sciences. v49 iSupp. I: 128-139(2006)