INDIVIDUAL TREE CROWN DETECTION AND DELINEATION FROM HIGH SPATIAL RESOLUTION IMAGERY USING ACTIVE CONTOUR AND HILL-CLIMBING METHODS

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ABSTRACT

Efficient forest management requires detailed, timely information on forests. The increasing availability and affordability of high spatial resolution remotely sensed imagery provides viable opportunities for developing automatic forest inventories at fine scale. Individual tree crown detection and delineation has become increasingly important for forest management and ecosystem monitoring. Existing methods aiming at individual tree crown detection and delineation were mainly developed for coniferous tree crown in vertical aerial imagery, and had limited capabilities in the off-nadir imagery that is commonly acquired by satellite-based sensors.

In this paper, we presented a new approach applicable under various imaging conditions. This approach took into account both spectral and shape characteristics of individual tree crowns represented in different imaging conditions, as well as the expert knowledge of the stand to improve tree crown detection. The approach consists of first extracting crown area using a region-based active contour model followed by spectral-shape-based tree top detection within the crown area. The tree tops determine individual tree crown location allowing subsequent clustering of crown pixels using a new hill-climbing algorithm. We tested the approach on a Norway spruce stand using three types of high spatial resolution images: an Emerge natural color vertical aerial image, a QuickBird panchromatic image with an off-nadir view angle, and a natural color Orthoimagery. Evaluation showed our algorithm produced less than 10% tree count estimation error in the three images. Although the algorithm provided lower tree detection accuracy in off-nadir QuickBird imagery than in vertical Emerge image and orthoimagery, the accuracies for the three images were higher than the existing methods. Tree crown diameter estimation errors were less than 0.5m. Future research includes evaluating tree crown detection and delineation results by comparing with ground-based reference data.

INTRODUCTION

Modern forest management requires precise, accurate, timely and complete forest information. Forest information can be acquired by forest inventory, which includes collection of individual tree parameters such as location, Diameter at Breast Height (DBH), tree height, tree crown size and tree species within a sampled forest plot, and also includes the derivation of forest stand measurements such as forest density, mean age, mean height, and

crown closure, etc using statistical extrapolation of plot measurements (Kangas and Maltamo, 2006). Conventional forest inventory involves periodic field measurement of parameters for each tree in the sample plot or visual interpretation of aerial photography. However, both methods are labor and cost intensive, and could not meet the need for the information quality in terms of detail, accuracy and timeliness.

The increasing availability and affordability of sub-meter aerial and satellite image sources provides opportunities for cost-effective and timely forest inventories. A variety of image processing techniques were developed for automated detection and delineation of individual tree crowns. Such techniques make possible the automated estimation of characteristics such as tree crown size and canopy closure, and facilitate species level classification and forest health monitoring (Leckie et al. 2005).

Current tree crown detection and delineation methods utilize the reflectance pattern displayed by a forest in high spatial resolution imagery: for trees with conical structure, bright peaks in the image correspond to the tree tops because of the higher level of solar illumination; reflectance decreases toward the crown boundaries; darker pixels surrounding the bright crown correspond to shading from neighboring tree crowns (e.g. Gougeon 1995, Walsworth and King 1999, Culvenor 2002, Pouliot et al. 2002, Wang et al. 2004, Erikson 2004, Leckie et al. 2005). Most of these methods were applied for vertical aerial imagery over coniferous stands and few applications on satellite imagery were reported. Research has reported that current methods based on this reflectance assumption resulted in low accuracy in off-nadir images (Ke and Quackenbush, 2008).

The objective of our study was to develop a new approach capable of providing accurate tree detection and delineation under various imaging conditions. The new approach was developed based on active contour model and hill-climbing algorithm and considered both spectral and shape characteristics of individual tree crowns represented in different imaging conditions, as well as the expert knowledge of the stand to improve tree crown detection and delineation. The new algorithm was tested using high spatial resolution imagery from different sources.

DATA COLLECTION

Study Area and Imagery

The study area is located in the Heiberg Memorial Forest, approximately 33 km south of Syracuse in upstate New York (42.75° N, 76.08° W). Heiberg forest is a 9637 ha property owned and managed by the State University of New York College of Environmental Science and Forestry (SUNY-ESF). Our study site covered three adjacent Norway spruce compartments established in 1931. Trees were planted at 2×2m spacing when they were 3-year-old saplings. Three plots were selected from this site based on the thinning activities within the compartments. Plot 1 was thinned during between 1979 and 1980; in plot 2, thinning was conducted in 1980 inside the forest stand, while there was no thinning along the road; plot 3 was thinned in 1985.

Three remotely sensed images acquired from different sources were used in this study. Digital Orthoimagery (DOI) was downloaded from New York State GIS Clearinghouse website (http://www.nysgis.state.ny.us). It was an 8-bit natural color digital image acquired using DMC sensor in April 2006, with 2 ft GSD and +/-8 ft horizontal accuracy. The image was georeferenced to UTM Zone 18N, WGS84, and resulted in 0.61m pixel size. The panchromatic satellite image was acquired by the QuickBird space-borne sensor in August 2004 with 11° average look-angle. The original 11-bit QuickBird image was resampled by nearest-neighbor method to the 0.6 m pixel size. Another image was acquired by the Emerge airborne sensor in October 2001. It was offloaded as an 8-bit true colour

vertical image with 0.6 m pixel size. Both Emerge image and QuickBird image were orthorectified and georeferenced to UTM Zone 18N coordinates with WGS 84 datum. Sub-images that covered the study sites were extracted from the full images. Figure 1 demonstrated the Emerge image over the coniferous area.

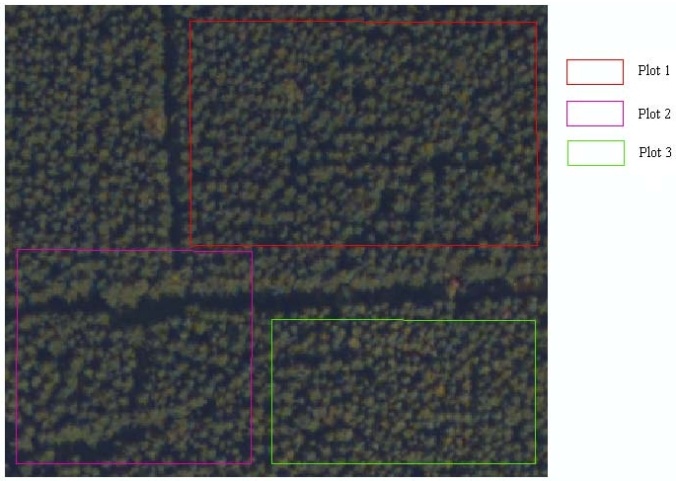


Figure 1. Emerge image showing Norway spruce plots.

Reference Data

Due to the differences in imaging conditions and acquisition time among the three images, reference data was generated for each image separately. Manual delineation of tree crowns in each of the images was performed by three interpreters with forest engineering backgrounds. Each person visually counted individual trees on a computer screen displaying the image. The relative differences between the resultant counts were ≤ 10%. With the average count number used as guidance, one of the interpreters outlined the boundary of each tree crown as polygon layers in ArcGIS 9.2. Specific characteristics of the tree crowns in each plot as identified by the manual interpretation are listed in table 1. Because of the crescent-shape of the crowns in the QuickBird imagery, crown diameters could not be manually derived, therefore, only reference tree counts are listed in table 1 for the QuickBird image.

Table 1. Summary of reference tree crown characteristics

Plot No.	Digital Orthoimagery (April, 2006)					QuickBird panchromatic image (August, 2004)	Emerge image (October, 2001)				
	Reference Count	Tree crown diameter (m)				Reference Count	Reference Count	Tree crown diameter (m)			
		Mean	SD	Range				Mean	SD	Range	
1	597	3.64	0.72	2.11	6.19	611	619	2.95	0.66	1.69	5.30
2	320	3.89	0.81	1.92	6.21	333	342	2.96	0.78	1.25	5.56
3	305	3.51	0.65	1.92	5.71	326	317	2.92	0.69	1.33	5.48

METHODOLODY

A flowchart of our algorithm is presented in Figure 2. The algorithm is composed of three stages. First, the image was segmented using region-based active contour model. The objectives of this stage were to separate tree crown area from background and define initial tree crown boundaries. Subsequently, the tree top detection algorithm was applied in the crown area to locate individual tree crowns. In our algorithm, we considered both spectral and

shape information of individual tree crown image, and utilized expert knowledge to refine tree top detection results. Finally, individual tree crown boundaries were outlined using hill-climbing algorithm based on the tree tops. The following sections address each stage in detail.

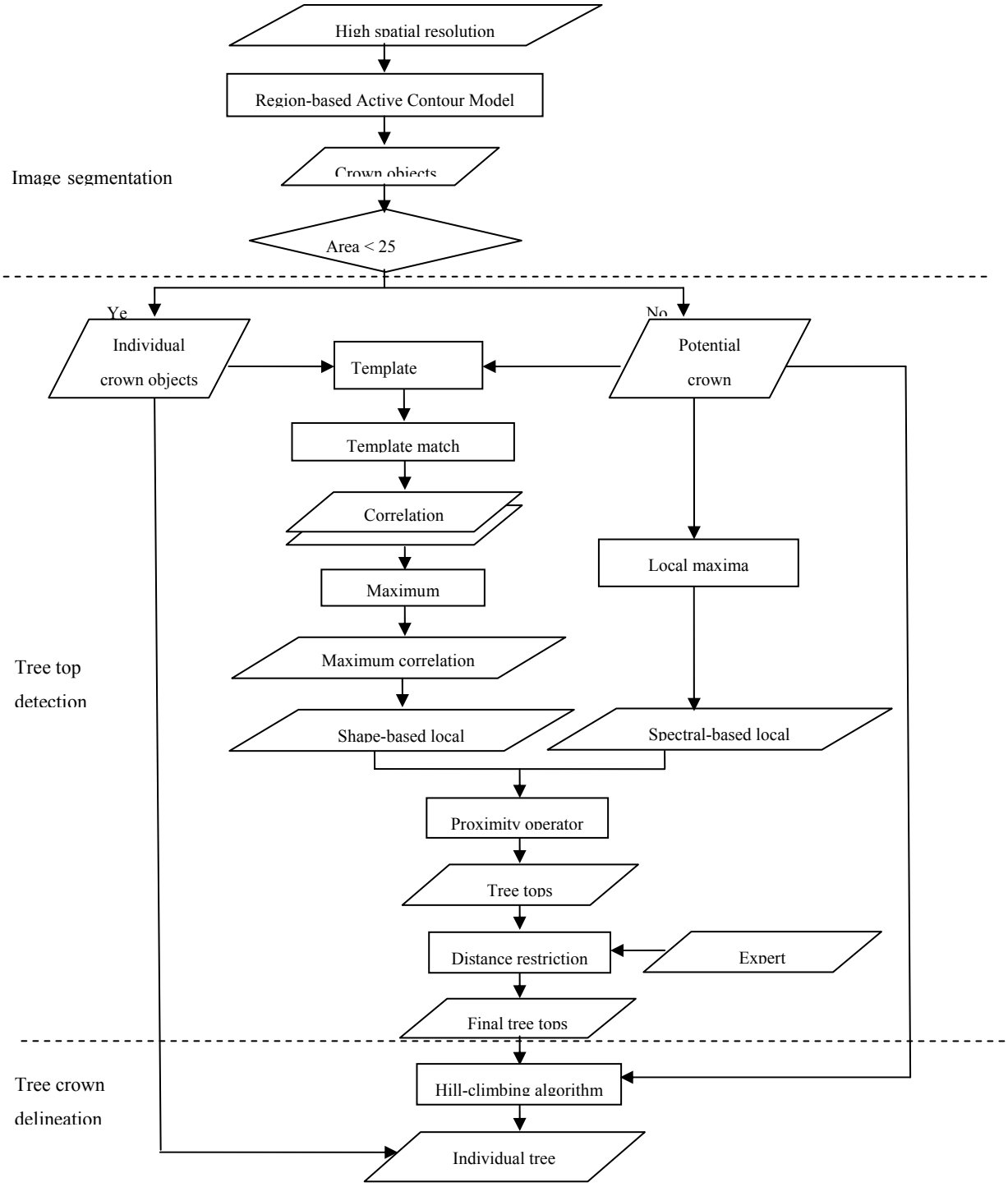


Figure 2. Framework of the algorithm.

Image Segmentation - Active Contour Model

Active contour models have been successfully utilized for image segmentation in computer vision since proposed by Kass et al. in 1987. The basic idea of the active contour models is to evolve a contour (or curve) by a local force such that it moves toward the boundary of the object in the image. The stopping criteria of the evolution were formulated as the minimization of an energy function. In our research, we adopted the active contour model presented by Li et al. (2007). The justifications of utilization of this model are: first, active contour models are proved to be advantageous over traditional edge detectors because it can achieve sub-pixel accuracy of the object boundaries (Xu et al., 2000) and the resultant boundaries are quite regular (Tsai et al., 2003). second, the method accounted for the intensity in-homogeneity within the object by including local properties of image in the energy formulation (see Equation (1)), thus the method is less likely to split larger crowns even it has larger intensity variation.

$$E_x = \lambda_1 \int_{in(C)} K(x-y)\left|I(y)-f_1(x)\right|^2 dy + \lambda_2 \int_{out(C)} K(x-y)\left|I(y)-f_2(x)\right|^2 dy \qquad (1)$$

where I is the intensity image, C represents the contour in image, and $K(u)$ is a localized weighting function that decreases when u increases. $f_1(x)$ and $f_2(x)$ are two numbers that fit image intensities near the point x. The contour C evolves based on level set theory and the final contour is represented by the zero values of level set function which minimizes the energy function. The level set function values are equal to 0 on the contour and less than 0 within the contour. Crown objects can be easily extracted by locating the pixels within the contour.

In the circumstances that neighboring trees touch to each other, active contour model could not isolate individual tree crowns. Thus, the crown objects extracted from this step can be categorized into individual crown objects and crown clusters, which can be distinguished in terms of object area. For example, in Orthoimagery crown objects with area less than 25 pixels were considered as crown clusters in; crown objects with area larger than 25 pixels were called as potential crown clusters since they could be either larger tree crown or tree clusters. The threshold was selected based on the statistical characteristics of our reference data.

Spectral-Shape-Knowledge-based Tree Top Detection

Spectral-based local maxima detection. First, a moving window was used to scan the image and the center pixel of the window was considered as local maxima if it has the highest intensity value within the window (Wulder, 2000). Local maxima located outside the crown objects were removed. The size of the window was set as 3 by 3 so that small tree crowns can be detected. For large crowns, however, could have multiple local maxima detected. The false treetops will be removed in the following refinement steps.

Shape-based tree top refinement. Template matching is a technique in image processing for object recognition. It had the ability of capturing the shape of the object. We utilized the individual crowns as templates and the pixels which were located within the crown were used to calculate the correlation between templates and image. The crown templates were manually selected from two sources: the individual crowns identified from the image segmentation which represent smaller crowns, and the potential crown clusters which were considered by interpreters as single crown which represent larger crowns. Compared to template matching by Quakenbush et al. (2000), the templates in our algorithm were restricted within a single crown area rather than a square window; and the calculated statistical correlation value for each movement of template was assigned to the centroid (i.e., center of mass) pixel of the template rather than the center of window (see Equation (2)). The purpose is to ensure that the

maximum correlation was located on the centroid of the crown when it has similar spectral and shape characteristics with the template crown.

$$\rho_{centroid} = \frac{\sum (x_{ij} - \bar{x})(y_{ij} - \bar{y})}{\sqrt{\sum (x_{ij} - \bar{x})(y_{ij} - \bar{y})}} \qquad (2)$$

Each template was passed across the image and the correlation layers were produced. We created a maximum correlation layer by assigning the maximum correlation value from the layers for each pixel. A 3 by 3 window was applied on the maximum correlation layer to locate the shape-based local maxima within the crown objects.

The spectral-based local maxima detected in previous step were refined under the restriction "only those spectral-based local maxima that were located around shape-based local maxima could be potential tree tops". By applying a 3 by 3 proximity operator which defines the maximum distance allowed between the two types of local maxima, we obtained the potential tree tops.

Knowledge-based tree top refinement. This step was based on the expert knowledge of the forest regarding the interval between the trees. This was especially useful for plantations. In our study area trees were initially planted at 2×2m spacing, thus we assumed that the spacing between tree tops could not be less than 2m, i.e. around 3 pixels in the image. Thus, we consider those tree tops that were too close to the others and have lower intensity value as spurious tree tops. Therefore, the final tree tops not only represent the points which have highest sun illuminations but also have the most proper locations. The final tree tops were then labeled and used as input of next step.

Crown Delineation - Hill-climbing Algorithm

With trees detected and located in the above section, the goal of this step is to define individual tree crown area. Hill-climbing is a mathematical optimization algorithm which aims at locating maximum value of an objective function. The basic idea is to always towards a state which improves the current one (Huang and Shibasaki, 1995). In our study, we adopted the idea of hill-climbing algorithm to classify the pixels within crown clusters according to the tree tops. Figure 3 illustrates the three-dimensional view of image intensity within a crown object where two tree tops were detected. For each pixel, we need to decide which tree crown it belongs to. Suppose a moving point stand at the position of a pixel and it could only move one step (or one pixel distance) from the current position, the basic principle of the clustering is let the point climb the hill until the peak (tree top) was reached.

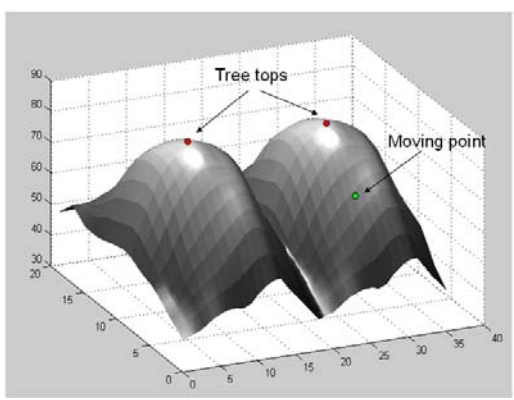


Figure 3. 3D view of crown objects with two tree tops (vertical axis represent the intensity value).

Specifically, the rules of hill-climbing are:

Rule 1: The moving point is only allowed to go up instead of going down;

Rule 2: If the moving point could reach both peaks (e.g., at the valley between the hills), it must follow the shortest route to the peak (tree top).

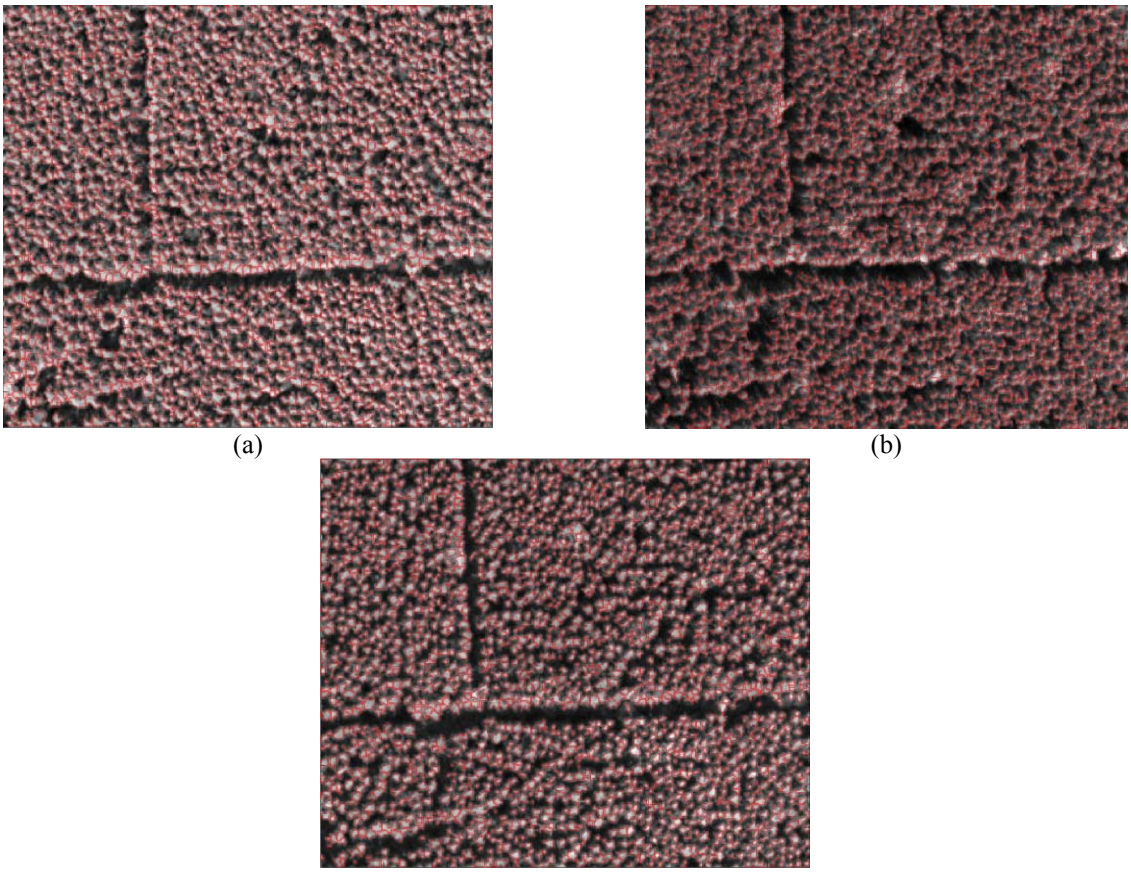
After applying these two rules to the image objects, there might be some pixels where the moving point could not move anywhere. This situation occurred when the variation of the intensity cause multiple peaks within one crown but only one tree top was defined. Under this circumstance, the moving point will follow the third rule:

Rule 3: The moving point is allowed to move downward if the difference between the current pixel intensity and the next pixel intensity is less than a cut-off value, and then it continues to climb to the peak. The cut-off value was selected as 5 for Emerge and orhtoimagery, 10 for QuickBird image. Each pixel was clustered to a tree top and assigned the same label as the tree top.

RESULTS

Tree Crown Detection Assessment

The results of applying our algorithm to the three images are illustrated in figure 4. The majority of Norway spruce trees were generally extracted from the background and delineated separately on all of the three images. The crescent shape of the tree crowns in QuickBird imagery was also captured by the algorithm. The three images also demonstrate the growth of tree crowns. Tree crowns in the Orthoimagery acquired in 2006 were apparently larger than those in the Emerge imagery acquired in 2001.



(a) (b) (c)

Figure 4. Individual tree delineation over Norway spruce stand on (a) digital Orthoimagery (April, 2006), (b) QuickBird (August, 2004), and (c) Emerge imagery (Octorber, 2001). Red lines represent the boundaries of individual tree crowns.

Table 2 lists the crown count estimation results from our algorithm for each of the plots in three images. Overall, the algorithm produced less than 10% tree count error. The tree counts errors for QuickBird panchromatric image and Emerge image were less than 1%.

Table 2. Tree count estimation error (%): negative error indicates underestimation compared to reference data; positive error indicates overestimation

Plot No.	Digital Orthoimagery (April, 2006)	QuickBird panchromatic image (August, 2004)	Emerge image (October, 2001)
1	-0.8	-1.1	-0.2
2	9.1	1.0	-0.8
3	7.2	0	-0.6

The plot level accuracy reported the above reflects the aggregated accuracy of tree detection. However, the tree count accuracy can be misleading due to the potential for cancellation of commission and omission errors. Tree crown detection accuracy was further analyzed using a method adapted from Larmar *et al*. (2005) where user's accuracy and producer's accuracy were introduced from pixel-based classification. In our study, the producer's accuracy was defined as the portion of reference crowns which were 1:1 perfectly match with delineated crowns, and the user's accuracy was defined as the portion of delineated crowns which were 1:1 perfectly match with reference crowns. Table 3 summarizes the user's and producer's accuracy for the three images. Our algorithm

obtained over 75% producer's and user's accuracy in Orthoimage and Emerge image for plot 1 and plot 3; accuracy obtained in QuickBird image for the three images were lower. Comparison between the three plots demonstrates that accuracies in plot 2 were lower than the other two plots. Although the accuracies for QuickBird panchromatic image were less than 70%, comparison with the existing methods indicates our algorithm outperform the existing algorithms for all the three images (Ke and Quackenbush, 2008).

Table 3. Producer's accuracy and user's accuracy for three images

Plot No.	Digital Orthoimagery (April, 2006)		QuickBird panchromatic image (August, 2004)		Emerge image (October, 2001)	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
1	79	77	73	69	79	79
2	68	62	63	56	63	64
3	86	80	69	64	79	79

Tree Crown Delineation Assessment

Delineation accuracies were also evaluated by comparing the diameter of the delineated tree crowns with that of the reference crowns for the perfect 1:1 matched trees. The accuracies were summarized using mean error, absolute error and root mean square error (RMSE). RMSE was calculated using the following equation from Pouliot *et al.* (2002):

$$RMSE = \sqrt{\sum (del_i - ref_i)^2 / n} / \overline{ref} \qquad (3)$$

Where n is the number of correctly delineated trees, del_i is the estimated diameter for i^{th} correctly delineated crown, ref_i is the reference diameter for the corresponding reference crown, and $\overline{ref}$ is the mean reference crown diameter. Crown diameter was derived from the crown area by assuming a circular crown shape. Due to the off-nadir view angle when acquiring the QuickBird image, the assumption of a circular crown was violated so that a delineated crown dimension calculated in this manner cannot be directly associated with the reference crown; hence, the results here focus on analysis of the Emerge imagery and orhtoimagery. The algorithm tended to overestimate the crown diameter (by 0.24–0.42m). RMSE errors were around 14% to 21% (table 4).

Table 4. Summary statistics of delineation results on Emerge imagery

Plot No.	Digital Orthoimagery			Emerge image		
	Mean error (m)	Mean absolute error (m)	RMSE (%)	Mean error (m)	Mean absolute error (m)	RMSE (%)
1	0.29	0.43	14	0.32	0.47	20
2	0.27	0.43	14	0.42	0.55	21
3	0.37	0.44	15	0.24	0.43	17

CONCLUSIONS AND DISCUSSIONS

The study developed a tree crown detection and delineation method based on region-based active contour model and hill-climbing algorithm. The approach consists of three stages: image segmentation using region-based active contour model, tree top detection and crown delineation. Region-based active contour was utilized to provide initial boundaries of crown object. Individual tree top were detected within each crown object. The tree top detection accounted for both spectral and shape information of individual tree crowns in the tree top detection, and the expert

knowledge of the forest stand was utilized to refine the tree top detection. Hill-climbing algorithm classified every pixel within the crown object to one of the tree tops considering the three-dimensional spectral characteristics of the individual crown and the spectral variation within the individual crown was considered.

The new algorithm is successful in tree detection and crown boundary delineation from both vertical aerial images such as Emerge image and Orthoimage and off-nadir QuickBird satellite image. The results from different images, as well as from different testing plots, verified that the algorithm is applicable and robust. The accurately delineated tree crown data is valuable for forest inventory analysis such as tree volume estimation. Our future research is to evaluate the algorithm by comparing the results with ground-based reference data.

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