ESTIMATING CROWN VOLUME THROUGH IMPLICIT SURFACE RECONSTRUCTION FROM LIDAR POINTS FOR FOREST FIRE SIMULATION.

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ABSTRACT

Knowledge of tree crown information is critical to the modeling of forest fires. For example, FARSITE, one of the most commonly used fire simulators, uses crown volume to estimate crown fire behavior. Conventionally, tree crown volume is estimated using plot-level regression models from LIDAR (Light Detection and Ranging) data of the canopy structure. Convectional approaches, however, tend to result in rough estimations of crown volume. A more accurate method for computing single stand-level crown volume from LIDAR data would result in improving species characterization, automating tree identification from LIDAR data, and simulating fire behavior more precisely than conventional approaches. In this research, we propose a novel technique which more accurately computes individual tree crown volume from LIDAR data. First, we identify individual trees from unorganized LIDAR data points using a level set method, a shortest path algorithm and known GPS points for the stem locations. Second, we use radial basis functions (RBFs) to reconstruct implicit surfaces approximating individual tree crown shapes. These implicit surfaces, which effectively "wrap" each tree crown, are used to reconstruct a Digital Surface Model (DSM) of the canopy and to estimate individual tree crown volume.

INTRODUCTION

Knowledge of tree crown information is important in forest ecology and management. Tree crown information is critical in analyzing forest fire, plant physiology, stem volume, stand competition, tree crown ratio for monitoring tree health, and habitat space for birds. Tree crown volume estimation is especially important for physical processes with forest fire behavior. For example, forest fire behavior simulation software, FARSITE (Finney, 1998) requires crown volume as one of the main input parameters needed to determine the fuel information. Fuel, topography, and weather are needed to describe characteristics of forest fires (Agee, 1993). Two of these components (fuels and topography) are measurable from active remote sensing data such as Light Detection and Ranging (LIDAR) data.

Emerging technologies such as LIDAR are providing new opportunities to quantify fuels and topography. LIDAR devices determine the physical location of points on three dimensional objects by measuring the time delay between a transmission of a laser pulse directed towards the object and the detection of the reflected signal. The reflected signal, or returns, are classified into four different data sets: first, second, third and last returns. The last returns are used to construct the Digital Terrain Models (DTMs) while all the other returns are used for Digital Surface Models (DSMs). DTMs created from the last LIDAR returns are quite accurate in reconstructing micro topography because of the high density of LIDAR points. Therefore, the landscape parameters of fire behavior model (elevation, aspect, and slope) can be obtained with high accuracy from LIDAR DTMs. DSMs created using conventional approaches are unable to represent the tree shape accurately, and can result in inaccurate estimation of fuel.

Conventional methods to estimate fuel from LIDAR data have been implemented at two scales, a plot and single stand level. The plot level estimation has been conducted by using quantile regression model (Means *et. al.* 2000, N sset *et. al.* 2001, 2002, Andersen *et. al.* 2005), which can only provide a rough estimation. At the single stand level, various classification and segmentation methods have been used to obtain fairly accurate results for single stand fuel information, including stand height, crown base height, crown width, crown bulk density and crown volume. Morsdorf and co-authors (Morsdorf *et. al.* 2004) used K-means unsupervised classification for LIDAR returns to measure the tree height and got 0.92 R^2 between the measurement using LIDAR and actual field measurement. Persson and co-authors (Persson *et. al.* 2002) got 0.76 R^2 for their measurement of crown diameter by using active counter technique. Holmgren and co-authors (Holmgren *et. al.* 2004) defined the crown base height as the height at which point density is less than 1% of the total vertical LIDAR point distribution and got 0.84 R^2 for their measurement of the crown base height.

These researches demonstrated that LIDAR is a good means to understand tree height, crown base height, and crown width at a single stand level. One of the other two elements of single stand level fuel information, crown bulk density, can only be obtained by measuring foliage biomass and fuel weight that requires destructive sampling of trees in the field. Research has already been conducted to obtain crown volume from LIDAR data, but more reliable results could be obtained by creating DSMs that reconstruct tree shapes more precisely from LIDAR returns.

In previous research, standard parametric shapes were fitted to LIDAR points to estimate crown volume. These shapes included are cylinders, paraboloids, cones, ellipsoids (Husch *et. al.* 2003), and Pollock's equation (Persson *et. al.* 2002). In early research, Nelson (Nelson, 1997) attempted to fit these parametric shapes to a LIDAR point distribution by using a regression model. The disadvantage of this approach is that LIDAR points of actual trees are scattered irregularly in three dimensional space and do not match the parametric shapes well. In the present research, we use an implicit surface reconstruction method to visualize the shapes of trees and to calculate crown volume more precisely.

Implicit surface reconstruction is widely used in computer graphics to construct 3D computer models of physical objects from noisy scanned laser points (Carr *et. al.* 1997, 2001, 2003, Wendland *et. al.* 2005). In geography, spatial interpolation methods have been used to construct a digital surface from scanned laser data. S.L.Smith and co-authors (Smith *et. al.* 2005) used the ordinary kringing, bilinear, bicubic, spline, and nearest neighborhood methods to make DSMs from a discrete point cloud dataset of urban landscape. They found that the interpolated surfaces over vegetation area had more errors than those over solid objects such as buildings. Therefore, an alternative approach is required to create DSMs for vegetation area.

The approach developed in this research uses radial basis functions (RBFs) to obtain an interpolated surface that effectively "wraps" the tree crown. To apply RBFs to a single tree, it is essential to separate a set of LIDAR points of a single tree from all the other LIDAR points. One approach is the K-means method (Riano *et. al.* 2003, Morsdorf *et al.* 2004), which is one of the unsupervised classification methods. However, the K-means method has a drawback that it randomly generates seed points but the accuracy of resultant cluster changes depending on the location of seed points. In addition, the iteration times in classification process, which depends on the point distribution and density, also changes the accuracy of results.

To address this concern, we take another segmentation approach. Hyyppä and co-authors (Hyyppä *et. al.* 2001) used the combination of a smoothing filter over local maxima of the laser returns and an image labeling technique for the surface derived from LIDAR data. This technique used significant local maxima as the seed points to segment the surface. And not all peaks were found by their approach. In the present research, we improved upon this approach by automatically setting all local peaks of the surface as seed points. A level set method (the plane slice method for a smooth three dimensional surface) was used for the identification of local peaks, and the gradient flow vector was then used to classify all the pixels on the surface image into the trees of identified peaks. As a result, the single stand level LIDAR points were extracted automatically based on the segmentation image. After the segmentation, LIDAR points on the surface were selected as the target points to reconstruct a wrapped surface. Finally, RBFs were used to construct a surface which "wraps" the points in identified as belong to a single stand. Using a triangulation of this surface, we were then able to estimate crown volume of the stand.

To verify the results, a shortest path algorithm called Dijkstra's algorithm was used as a link between the local peak points identified from the LIDAR points and stem locations collected by fieldwork. This way is an automatic verification process for LIDAR analysis.

In summary, this paper aims to introduce a novel way to wrap tree crown and display nonparametric tree shape from unorganized LIDAR points. The purpose of this research is to display the wrapped surface, to acquire micro scale crown height and crown base height, and to compute crown volume from the wrapped surface as an input parameter of FARSITE. ArcGIS 9.0 was used for the preparation of the data and the computer programs for this study were mainly developed by Matlab (The MathWorks Inc.).

DATA

Research Site

The research site is Mission Creek, which is located in the Wenatchee National Forest in eastern Washington State. The main species are Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*). The climate of the research site is dry and hot during summer, which is one of the factors that cause frequent low intensity forest fires.

Field Data

In Mission Creek, a total of 12 study units were established for fire and fire surrogates studies and assignments of control, burn only, thin/burn, and thin only, with three replications per treatment, were randomly done (Agee *et. al*. 2001). Each plot is 50m x 50m square. The stem locations of the all trees within the plots were collected by using Trimble differential GPS and laser ranging finder in summer 2004.

For the purpose of analyzing the vertical structure of the stands in the plots, the name of species and the nature of stand (dominant, co-dominant, intermediate, and suppressed) were collected for all the trees in the plots. In this study one of the thin/burn treatment plots was used.

LIDAR Data

Small footprint LIDAR data were acquired by an airborne LIDAR system in August 2004. The coordinates of the LIDAR points are UTM zone 10 and NAD83. The pulse of the LIDAR dataset is 7,000 Hz, which means the mean density of points is 3 ~ 5 points m^{-2}. Therefore, a 1 m^2 was used to make DTMs. For this analysis, the DTMs values were subtracted from the ground elevation of all LIDAR points to remove any slope effect.

METHOD

In this section, the two main steps needed to create wrapped surface are explained. In the first step, the data for the wrapping surface over LIDAR points is prepared by segmentation and selection of LIDAR points on the assumed surface. In the second step, a surface interpolating these selected points is constructed from RBFs. Finally, the wrapped surface is visualized as an isosurface of the constructed implicit functions.

1) Segmentation

A. Segmentation of LIDAR points

As a first step in creating wrapped surface around individual tree crowns, we need to segment the LIDAR data into clusters, with each cluster representing points from a single tree. To do this, the 50m x 50m research plot is divided into 1m grid cells. For each grid cell, the local maximum LIDAR point was selected. In order to acquire a smooth and continuous surface from the discrete points, a 3 x 3 Gaussian filter (Hyyppa *et. al.* 2001) was convolved with the local maxima. The 3 x 3 Gaussian filter is given by:

1/ 16	1/ 8	1/ 16
1/ 8	1/ 4	1/ 8
1/ 16	1/ 8	1/ 16

A level set method was used to identify the local peaks of the smooth surface. In this approach, the surface is sliced at a certain height and marches through the surface at height interval 0.1 m recursively from the bottom to the top of the smooth surface. For each sliced plane, value 0 was assigned for the pixels whose height was less than the height of the plane and 1 for the other to create a binary image. Based on this binary image, a connected component analysis was implemented to label and classify the pixels. In order to identify the peaks, one sliced image at a certain height was compared with the other of the next height to see the difference between them. If a total number of labels decrease from one image to the other, the marching sliced plane passed some local peaks of the surface and the locations of the missed local peaks were collected at that height.

After identifying the local peaks of the surface, a gradient flow analysis in eight neighboring pixels was used to determine which peak the surrounding pixels belonged to. All pixels were classified based on an identifying number given to each local peak. From the classified image, all discrete LIDAR points were assigned to point clusters, representing individual trees. Figure 1 shows an illustration of the slice plane marching through the surface.

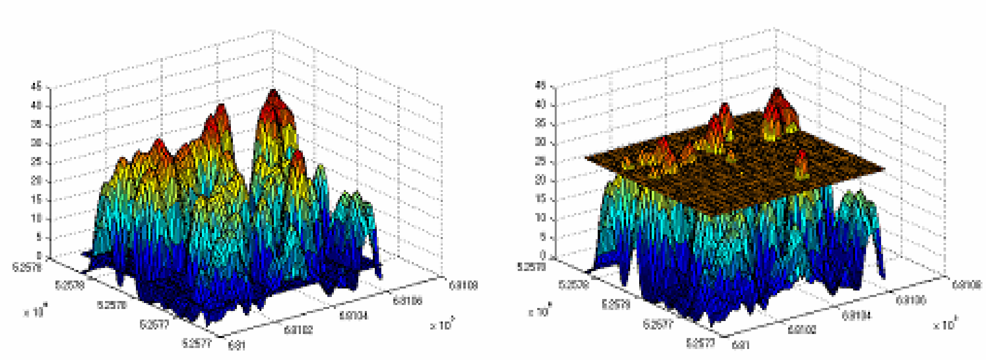

Figure 1. The marching sliced plane used to identify the local peaks of the surface. The smooth surface was created by the local maxima of LIDAR points. The starting plane is shown in the left and the plane at the intermediate step is shown in the right.

B. Selection of points on the surface.

We now have clusters of LIDAR points representing individual trees. However, these points cover not only the surface of tree crowns, but also are taken from the interior of the tree crown. In order to remove the points inside the crown, a two-dimensional convex hull algorithm was used at selected height locations to remove interior points. The crown base height was determined to be the height at which a 1 m height interval first contains three or fewer points from a tree top. Although the convex hull could get most of the point that outlined the crown shape, outlier points still remained. To remove the outliers, a cylinder, which was defined by the mean and one standard deviation from the center of LIDAR x and y coordinates, were applied.

C. Verification of the segmentation results.

Dijkstra's algorithm is one of the shortest path algorithms (Goodrich *et. al.* 2006). After identifying the local peaks from the segmentation method, the location of trees was verified by linking the identified peaks with stem locations in the stem map of the field data.

For Dijkstra's algorithm, all points belonging to an individual point cloud were sorted and connected to the adjacent points to create edges. Dijkstra's algorithm was used to find the tracking path from the local peak identified by the level set method to the GPS stem location. If a peak and stem locations matched with each other, the segmentation result was considered as positive and if not, negative.

2) Creation of the implicit surface wrapping the tree crown

A nonparametric interpolating surface through the surface points of each individual tree was constructed from radial basis functions (RBFs). As a first step toward creating a wrapped surface, the Euclidean distance, which was defined as the distance between any arbitrary points in the space and the closest point on the surface, was calculated by RBFs. After calculating Euclidean distance for all the points in the space, isosurface was used to display closed and wrapped surface created for nonparametric tree shapes in zero level set surfaces.

A. Radial Basis Functions

Radial Basis Functions (RBFs) are one of the interpolation methods. We wish to create a distance function s(x) which describes the distance of any point $x \in \Re^3$ to the implicit surface wrapping an individual tree crown. Our surface is then given by the set of points for which $s(x) = 0$. We represent this function as:

$$s(x) = \sum_{i=1}^{N} \lambda_i \Phi(x - x_i) \qquad (1)$$

where $x \in \Re^3$
N is the number of initial points.
λ_i is the i[th] component coefficient.
The radial basis function Φ used in this study is $\Phi(r) = r$ (linear)

Using the points on the surface, we were able to construct two additional sets of points at a distance 1 and –1 from the desired surface. The total 3N points were used to solve the linear system.

$$s(x_j) = \sum_{i=1}^{3N} \lambda_i \left\| x_i - x_j \right\| = d_j$$

where $d_j =$ 0, +1, or –1.

This gives us the coefficients λ_i. Our implicit surface can now be described analytically as the zero level set of the function.

$$s(x) = \sum_{i=1}^{3N} \lambda_i \left\| x_i - x \right\|$$

where x is any points in $\Re^3$

B. Crown volume from the wrapped surface

To compute the volume enclosed by the zero level set, we use a routine available in Matlab (The MathWorks Inc.) to get the isosurface $s(x) = 0$. This routine gives us a tringulation of the surface, which we can use to visualize the surface, and to compute the volume.

Crown volume was computed by using calculus divergence theorem as:

$$Volume = \int_C \nabla F dV = \int_{\partial C} F\vec{n} dS$$

By choosing *F*=(x,0,0) so then $\nabla F = 1$. The right hand side is applied to compute as:

$$Volume = \int_{\partial C} F\vec{n}dS = \sum_{j=1}^{m} \vec{n}_j^x \int_{T_j} xdS$$

where n_j^x is the normal to the jth triangle T_j.

CONCLUSIONS AND DISCUSSIONS

1) Segmentation

Segmentation of LIDAR points

The result of segmentation is shown in the Table 1. As pixel size decreased, more local peaks were identified. The identified local peaks were verified by using Dijkstra's algorithm, which is shown in Figure 2.

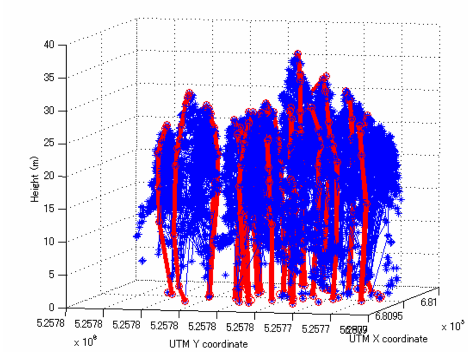

Figure 2. The result of Dijkstra's algorithm. The red line indicates the shortest tracking path to link between the identified local peaks by the level set method and the actual GPS location of trees.

Table 1. The segmentation result. The first row indicates the pixel resolution and the first column indicates the nature of stands. The numbers appeared in the table are the numbers of found links between the peaks identified by the level set method and GPS stem location in terms of the nature of stands.

Pixel resolution	0.5m x 0.5m	0.7m x 0.7 m	1m x 1m	1.5m x 1.5m	Actual number of
Dominant	7	5	5	5	4
Co-dominant	34	19	12	12	18
Intermediate	2	2	2	2	2
Surpressed	1	1	0	0	1
Total	44	27	19	19	25

When pixel size was smaller than 1m x 1m, the identified peaks were more than actual number of trees observed by fieldwork. Eventually, 1m x 1m pixel resolution was found to be appropriate size to find the local peaks.

The Table 1 also showed that all dominant trees were identified, as the smooth surface was made by local maxima of LIDAR points. The co-dominant trees were difficult to find separately from the dominant trees because co-dominant trees exist close to dominant trees.

2) Creation of implicit function

A. Visualization

Finally, the visualization of the wrapped surface of one single stand is shown in Figure 3 and the wrapped surface for one plot is shown in Figure 4. Moreover, the wrapped surface was created for 4 ha research area and displayed in Figure 5.

Figure 3. Visualization of the wrapped surface for a single tree. The single stand LIDAR point is shown in the left and the wrapped surface from the LIDAR points is shown in the right.

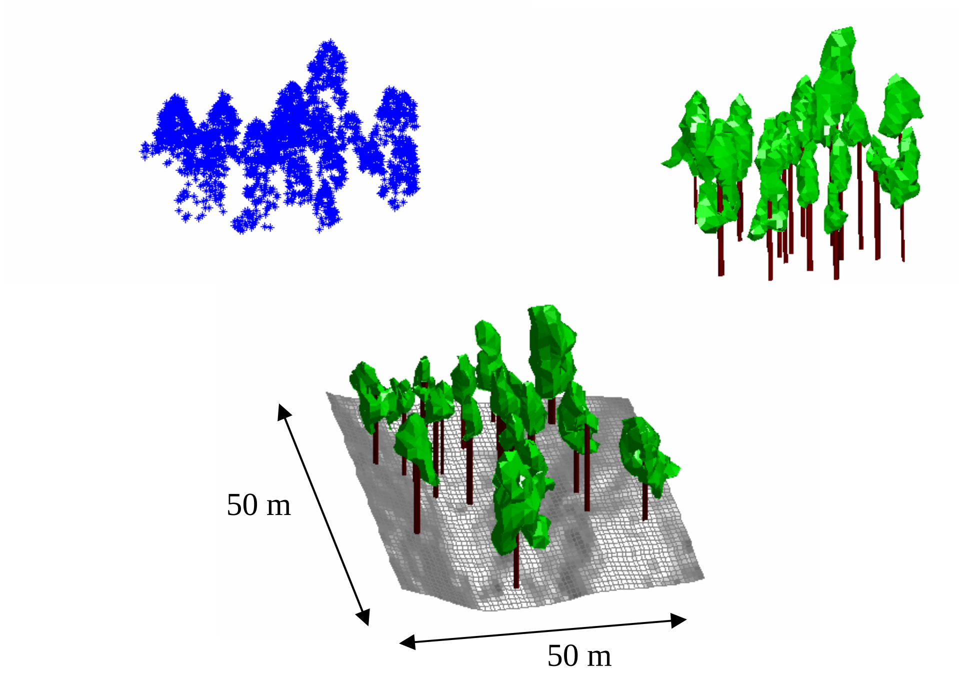

Figure 4. Visualization of the wrapped surface for one plot. The LIDAR point distribution is displayed in the top left and the wrapped surface is displayed in the top right. And the wrapped surface with DTMs is shown in the bottom.

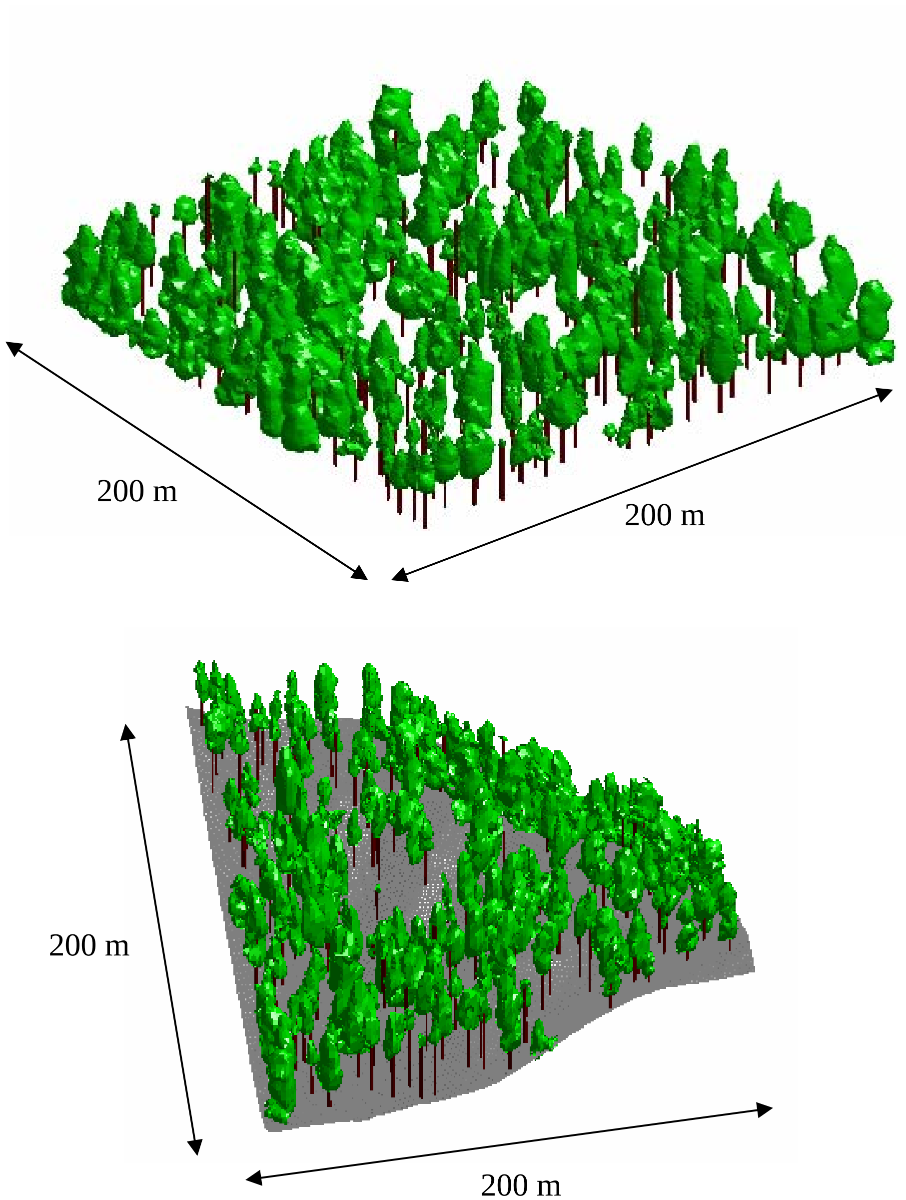

Figure 5. Visualization of the wrapped surface for 4 ha research area. The wrapped surface without DTMs is displayed at the top and the one with DTMs is displayed at the bottom.

B. Crown Volume

The crown volume was obtained from the wrapped surface. The single stand level crown volume was compared between the result from our approach and the result from the approach which Riaño and co-authors (Riaño, 2003) took. The crown volume of the single stand, which is displayed in Figure 3 is 145.8 m^3 from our approach and 17.95 m^3 from their approach. Their approach underestimated the crown volume, because they used a natural log model to fit a tree shape when computing the volume in terms of LIDAR point density. Also the LIDAR point density included the ground LIDAR points. If the number of ground LIDAR points exist more than the points above the ground, the points above the ground have less density and the volume calculated by that density shrank. Therefore, their approach underestimated the volume and the result from our approach improved the volume estimation, because we computed the volume graphically.

C. The parameters of forest fire simulation

The crown base height and tree height were derived from the wrapped surface. These values were more precisely acquired, because the wrapped surface is continuous over the discrete points. The crown base height and crown height are shown in Figure 6.

Figure 6. The tree height and crown base height from the wrapped surface of Figure 4. The crown base height is shown in the left and tree height is shown in the right.

We developed a novel technique to wrap the surface over discrete LIDAR points. Further ground survey is required to verify the accuracy of wrapped surface reconstructed in this research.

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