Tree Detection and Delineation of the Cosumnes River Preserve

Sohail Shafii[1], Bernd Hamann[2], Rachel Hutchinson[3], Oliver Kreylos[4], Joshua Viers[5]

[1]University of California, Davis; One Shields Ave; Davis, CA 95616; USA
Telephone: +1-530-574-8547
Email: sohailshafii@yahoo.com

[2]University of California, Davis; One Shields Ave; Davis, CA 95616; USA
Telephone: +1-530-754-7806
Email: bhamann@ucdavis.edu

[3]University of California, Davis; One Shields Ave; Davis, CA 95616; USA
Telephone: +1-530-754-6051
Fax: +1-530-752-9515
Email: rahutchinson@ucdavis.edu

[4]University of California, Davis; One Shields Ave; Davis, CA 95616; USA
Telephone: +1-530-754-9470
Email: kreylos@cs.ucdavis.edu

[5]University of California, Davis; One Shields Ave; Davis, CA 95616; USA
Telephone: +1-530-754-6051
Fax: +1-530-752-9515
Email: jhviers@ucdavis.edu

1. Introduction

Currently, many methods exist that utilise Light Detection and Ranging (LiDAR) data sets in the earth sciences. Methods for its application to ecological sciences are, however, limited. For example, the use of scattered data for tree detection and delineation is a needed improvement in LiDAR processing methods, as it holds the promise to provide ecologists with relevant information about forests (Pouliot et al. 2002). Terrestrial ecologists and foresters have relied on remote sensing methods, such as aerial photography, which can be subjective, time-consuming, and require trained personnel and equipment (Pouliot et al. 2002). More recent advances in optical remote sensing include automatic detection and delineation between trees using top-down image data (Pouliot et al. 2005).

We have developed a RANdom SAmple Consensus (RANSAC)-based (Fischler and Bolles 1981) program, referred to as *StarSac*, which utilises the 'depth' found in LiDAR data for tree detection and delineation. *StarSac* was developed using Oliver Kreylos' Virtual Reality toolkit (http://idav.ucdavis.edu/~okreylos/ResDev/Vrui/index.html) to visualise LiDAR data collected at the Cosumnes River Preserve. The purpose for developing this program is three-fold: 1) to effectively remove vegetation signals from Airborne Laser Swath Mapping (ASLM) data to better understand floodplain development and levee integrity; 2) to understand the growth trajectory of restored riparian forests; and 3) to provide an effective means of monitoring natural forests and orchards that can be used in carbon banking.

To evaluate StarSac, we used polygons that were digitised from a two-dimensional bird's eye view of forested areas in the Cosumnes River region. The Cosumnes River

Preserve, comprised of over 40,000 acres located in California's Central Valley, is engaged in active and passive methods of riparian forest restoration. Using the preserve as a living laboratory, University of California, Davis has conducted exhaustive studies (http://baydelta.ucdavis.edu/) to understand the ecological processes that drive riparian forest recruitment and floodplain development. By allowing and creating levee breaches, the preserve has been able to successfully recruit early successional forest species on sand-splay features in river floodplains (Florsheim and Mount 2003). Monitoring the growth of these forests becomes increasingly difficult as passive restoration projects continue to yield success. By utilising LiDAR acquisition in conjunction with *StarSac*, we can identify and potentially track tree growth, forest composition, and structure while collecting minimal field data.

2. Background

RANSAC, the foundation of our program's methods, has been applied to LiDAR data sets in different ways. Fontanelli et al. (2007) used RANSAC to estimate a position within a mapped environment. Reitberger et al. (2007, 2009) used RANSAC to find tree stem positions. Unlike other projects, we use a modified version of RANSAC to find tree canopies.

The *StarSac* program was developed based on the methods described by Fischler and Bolles (1981), and Torr and Zisserman (2000). The original RANSAC algorithm attempts to find the best model that fits a set of data points. This goal is accomplished by instantiating a model from a minimum number of randomly selected data points and identifying other points that have low error relative to this model (the *consensus set*, which consists of *inliers*). Ideally, the model with a large-enough consensus set, or the model with the largest consensus set, is selected as the model that best fits the original set of data points. In this tree-finding scenario, the best-fit model would be evaluated based on its ability to detect tree locations.

3. Methods

The model that is used for *StarSac* is based on a paraboloid, defined as:

$$f(x,y) = \alpha \bullet \left[(x - x_c)^2 + (y - y_c)^2\right] + z_c \qquad (1)$$

The terms x_c, y_c, and z_c are the coordinates of the centre of the paraboloid. This equation was chosen because it is easy to solve for its parameters (only two points are required) and it allows one to easily evaluate the shape of a model. In the ideal model, the centre should be the maximum of the canopy and the paraboloid should be defined by a negative alpha (concave). The radius is computed by calculating the weighted average height of the consensus set points. The points closer to the centre receive higher weights. The program creates a point with this average height value and measures the distance from that point to the centre.

The current RANSAC algorithm can be summarised as follows:

1. For all LiDAR points 1 … *n*:

a) Find a set of points around the current point to create our window. There must exist at least two points inside our window so that we can determine a model.

b) For iterations 1 … k:

   i. Randomly select a subset of points to create the model. Reject the model if it does not agree with user's specifications.

   ii. Create consensus set based on a user-defined error tolerance. Solve for radius of tree.

   iii. Restrict the window to the tree boundary (to the furthest consensus set point). This allows us to grade (i.e. ratio of outliers to inliers) the tree model in isolation of other points.

   iv. If our model has at most ½ ratio of outliers to inliers in restricted window, grade it and compare it with the best model. Keep track of the best model. If no previous model was found then the current one is chosen.

c) If model was found, mark it. Create shaded graph for delineation.

2. If multiple maxima are within each others' radii, unmark maxima with lower height values.

One must consider various aspects when comparing this algorithm to the original RANSAC. First, it does not return a model if there is not a large-enough consensus set. Second, incompatible models are filtered by shape (alpha) and height. Concerning height criteria, points are chosen with non-negative height values (above ground) since our data sets are fairly flat.

The algorithm's parameters can be set interactively with sliders (see fig. 1) during program execution to match the user's specifications.

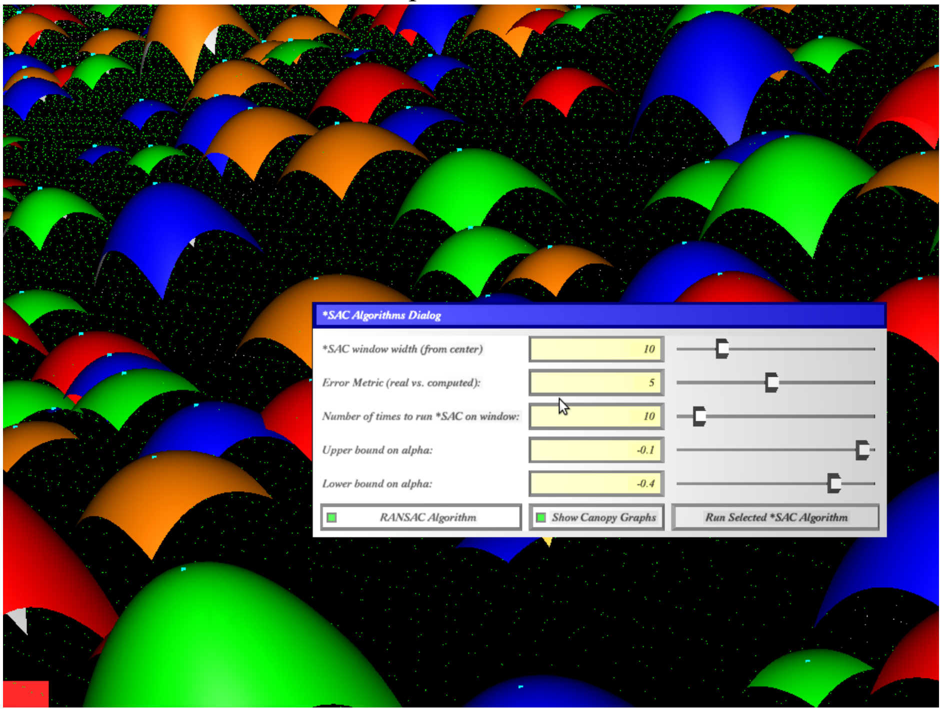

Figure 1. Program screenshot showing shaded canopies. Sliders that control window width, error tolerance, iterations, and shape are shown.

4. Results

We have evaluated *StarSac* against manually delineated tree canopies in a geographical information system (GIS) using near-infrared aerial photography (17 cm IFOV) for a portion of the preserve. We removed all canopies less than 0.50 m radius in our comparison. Our model detected 4953 canopies, compared to 3258 identified by the GIS method, with an average canopy radius of 2.03 m (±0.83 m standard deviation) and 2.11 m (±1.20 m standard deviation). We conducted a matched pairs analysis, where stem centres were closer than canopy radius (n = 2924); radii were significantly correlated (Spearman's $\rho=0.38$; $p<0.0001$) and the root-mean-square error (RMSE) was 0.60 m. The *StarSac* stem centres were also significantly closer to the GIS centres than the next closest neighbour (1st neighbour average distance = 1.06 m; 2nd neighbour average distance = 4.67; $p<0.0001$).

5. Conclusions

These results suggest that *StarSac* can be used to analyse LiDAR data and estimate canopy geometries over large areas with comparable results obtained with standard GIS procedures, which are time-consuming and require human interpretation. With some modification, the program will be able to detect and delineate tree canopies that do not conform to a parabolic shape.

6. References

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