Three-dimensional shape signatures for characterizing individual tree crowns derived from LiDAR data

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Abstract. Three-dimensional (3D) shape signatures based on the distance distribution of random point pairs are introduced and the effectiveness evaluated using computer simulations and samples of oak and Douglas fir canopies selected from Light Detection and Ranging (LiDAR) point clouds and Digital Surface Models (DSMs). The results suggest that comparison of 3D canopy shapes can be effectively reduced to the comparison of frequency distributions of distances between random points, and that it is more computationally efficient when shape signatures are derived from raster surfaces. The results also suggest that the statistically-based 3D shape signatures are relatively insensitive to noise and other small local variations, which is important for canopy shape analysis in real-world environments.

Keywords: 3D shape signature; Tree canopy; LiDAR point clouds; Digital surface model

1. Introduction

Three-dimensional shape description is a basic requirement for tree canopy characterization, which is important for a variety of natural resource management and monitoring activities, including biomass estimation, biodiversity monitoring, wildlife habitat assessment, and wildfire risk assessment. Although numerous shape measures have been proposed in the fields of computer vision, graphics, pattern recognition, and machine intelligence in the last decades (Danielsson 1978, Gosh 1988, Kartikeyan and Sarkar 1989, Rosin 2003, Bribiesca 2008), the application of these measures in other areas such as geography, forestry, and ecology has been relatively limited. In recent years, many researchers have studied tree height, crown width, basal area, crown base height, and crown volume using LiDAR data (Alexlsson 1999, Lim *et al.* 2003, Moffiet *et al.* 2005, Koch *et al.* 2006, Lee and Lucas 2007, Kim 2008, Popescu and Zhao 2008, Kato *et al.* 2009). However, few studies have focused on automated characterization of 3D canopy shapes using LiDAR data (Omasa *et al.* 2007, Kato *et al.* 2009). A review of the measurement of these canopy parameters using LiDAR can be found in Kato *et al.* (2009).

Inspired by the work of Osada *et al.* (2002) on computing 3D shape signatures for arbitrary objects in computer graphics, this study aims to evaluate the effectiveness of 3D shape signatures for characterizing individual tree canopies derived from LiDAR data. Computer software tools were designed and implemented using Microsoft Visual Basic and ESRI's ArcObjects to process both vector and raster data. The high resolution LiDAR data were collected on March 29, 2007 by the GeoEarthScope Northern California LiDAR project (Prentice *et al.* 2009). A 1000 m by 1000 m tile in the Soquel Demonstration State Forest near Santa Cruz, California was selected as the study area. The tile has over 9.6 million LiDAR points (about 9.6 points per square meter) and a 0.5-m resolution digital surface model (DSM) created using kriging interpolation of the points. Both the LiDAR point clouds and the DSM were downloaded from the Geosciences Network (GEON) via the GEON portal at the San Diego Supercomputer Center.

2. Methods

2.1 Three-dimensional shape signatures

Osada *et al.* (2002) described a method for computing 3D shape signatures and dissimilarity measures for arbitrary objects. The basic idea is to transform an arbitrary 3D object into a parameterized function that can easily be compared with others (Figure 1). A 3D shape signature is represented as a probability distribution (called shape distribution) sampled from a shape function measuring geometric properties of the 3D object. In the research by Osada *et al.* (2002), five shape functions were proposed. However, only one function, D2, is used in this study due to length limitations. D2 measures the distance between two random points on the 3D surface. After a certain number of iterations (e.g., 10000) for D2 calculation, the sorted distances are put into 50 histogram bins to show the frequency distribution, which can be further converted to probability distribution. The properties of the 3D shape signatures include invariance, robustness, efficiency, and generality (Osada *et al.*, 2002).

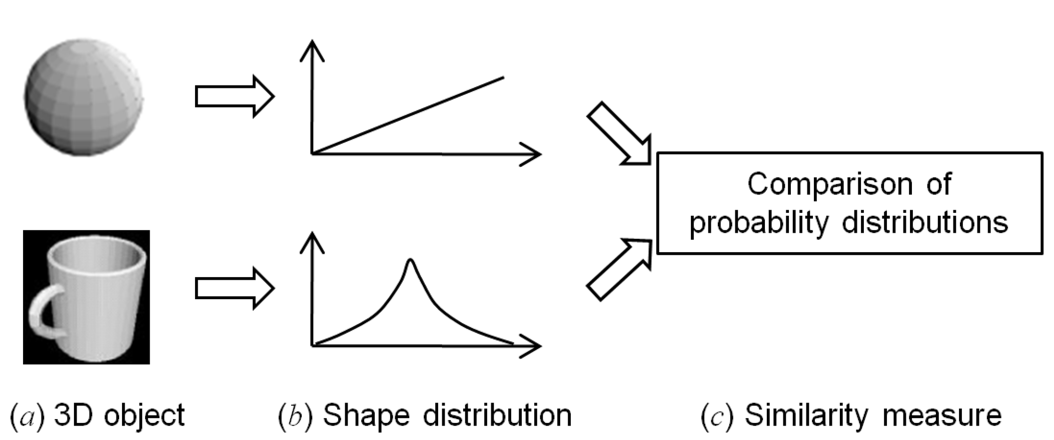

Figure 1. Shape distribution and shape matching of 3D objects (Adapted from Osada *et al.*, 2002).

2.2 Computer simulations

To test if the shape signatures can reveal differences between objects through random points on or near the object surfaces, computer simulations were carried out using three simple geometric models: cone, hemisphere, and half-ellipsoid (figures 2a, 2b, and 2c). For a random point (x, y) in 2-D Euclidean space, the z value of the point in 3D can be calculated using the following equations:

$$z = -\frac{\sqrt{x^2+y^2}}{\tan\theta} + h(t-0.5) \quad (x^2+y^2 \le 1, 0<\theta<90°) \qquad (1)$$

$$z = \sqrt{1-x^2-y^2} - 1 + h(t-0.5) \quad (x^2+y^2 \le 1) \qquad (2)$$

$$z = \sqrt{1-9x^2-9y^2} - 1 + h(t-0.5) \quad (x^2+y^2 \le \tfrac{1}{9}) \qquad (3)$$

where h is the amplitude of fluctuation, and t is a random number between 0 and 1. $h(t - 0.5)$ is used to add random fluctuations to the z values, so that simulated points are distributed on or near the intended surface. Each model was then run five times, and 10000 random point pairs (a total of 20000 points) were generated for distance calculation in each run. It can be seen that the 3D shape signatures for the three models are quite different (figure 3).

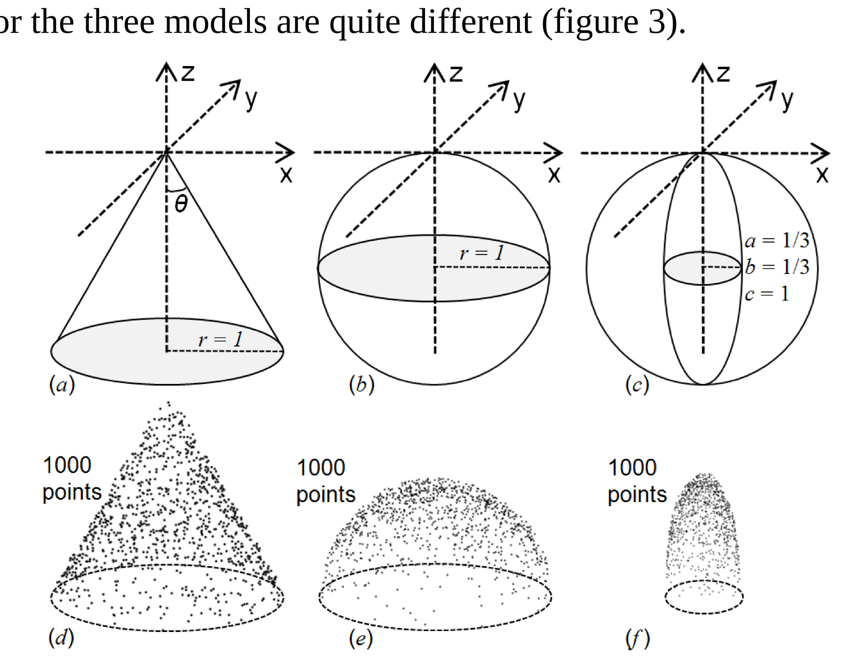

Figure 2. Three geometric models and simulated random points (h = 0.1, θ = 30).

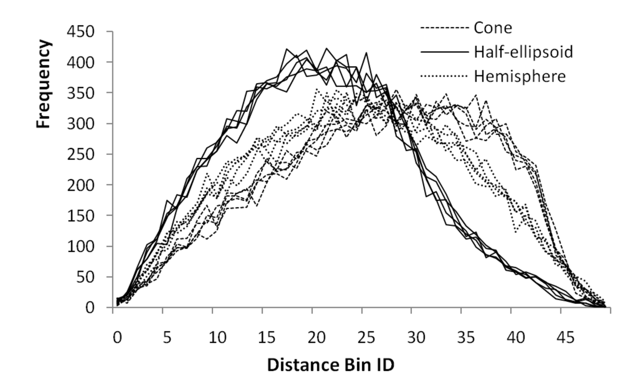

Figure 3. 3D shape signatures of three geometric models.

3. Results and discussions

3.1 Results from LiDAR point clouds

Figure 4 shows the LiDAR points for an oak tree and Douglas fir displayed in 2-D and 3D. Points near the ground were removed based on the elevation histograms, leaving 1791 oak canopy points and 2251 Douglas fir canopy points for analysis. 3D shape signatures for the oak and Douglas fir canopies were calculated using 1000 random point pairs (figure 6a), 5000 random point pairs (figure 6b), and 10000 random point pairs (figure 6c), respectively. Calculations for each canopy were repeated five times. It can be seen that oak and Douglas fir can be well separated using their 3D shape signatures generated from 5000 random point pairs (figure 6b) and 10000 random point pairs (figure 6c). While some differences between the two canopies are visible from the shape signatures generated using 1000 random point pairs, the signatures are not stable. The results suggest that 3D shape signatures can reveal the differences between the two canopies when enough random point pairs (for example, at least two times the number of LiDAR points) are used for distance calculation.

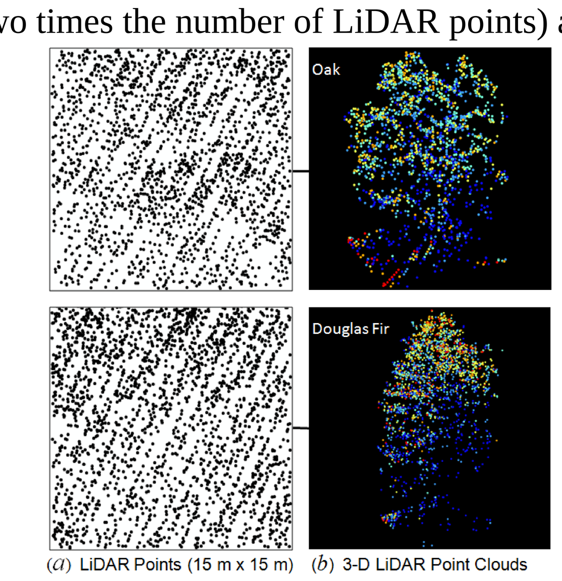

Figure 4. LiDAR points for an oak tree and a Douglas fir displayed in 2-D and 3D. The color scheme (from blue to red) shows the LiDAR intensity levels (from low to high).

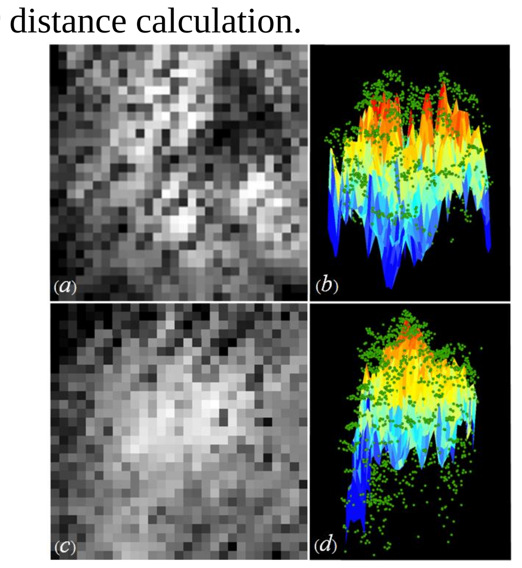

Figure 5. 0.5-m resolution DSMs for oak (a) and Douglas fir (c). Combined 3D views of point clouds and DSMs (b and d) are also shown for comparison.

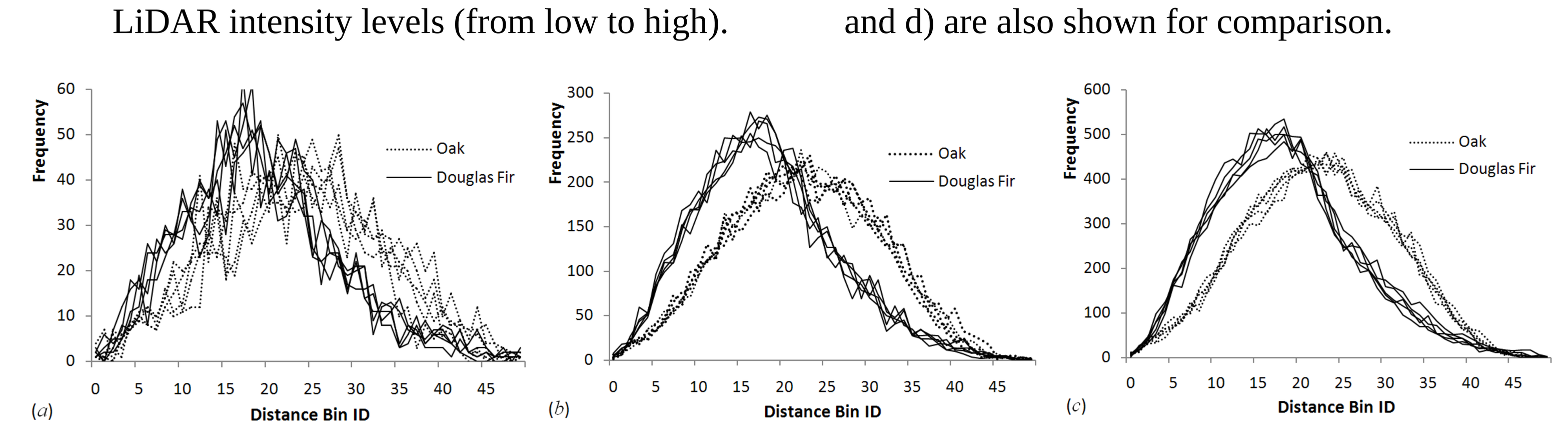

Figure 6. 3D shape signatures for the oak and Douglas fir canopies calculated from point clouds using (a) 1000 random point pairs, (b) 5000 random point pairs, and (c) 10000 random point pairs.

3.2 Results from LiDAR-derived digital surface models

Since raster DSMs are often created from LiDAR point clouds, it is natural to question if DSMs can be used to for 3D shape signature analysis. Figure 5 shows the 0.5-m resolution DSMs for the same canopies shown in figure 4. It seems that many details in the point clouds were lost after conversion to DSMs through spatial interpolation. However, as can be seen in figure 7, the 3D shape signatures derived from the DSMs show similar results compared with those from the point clouds.

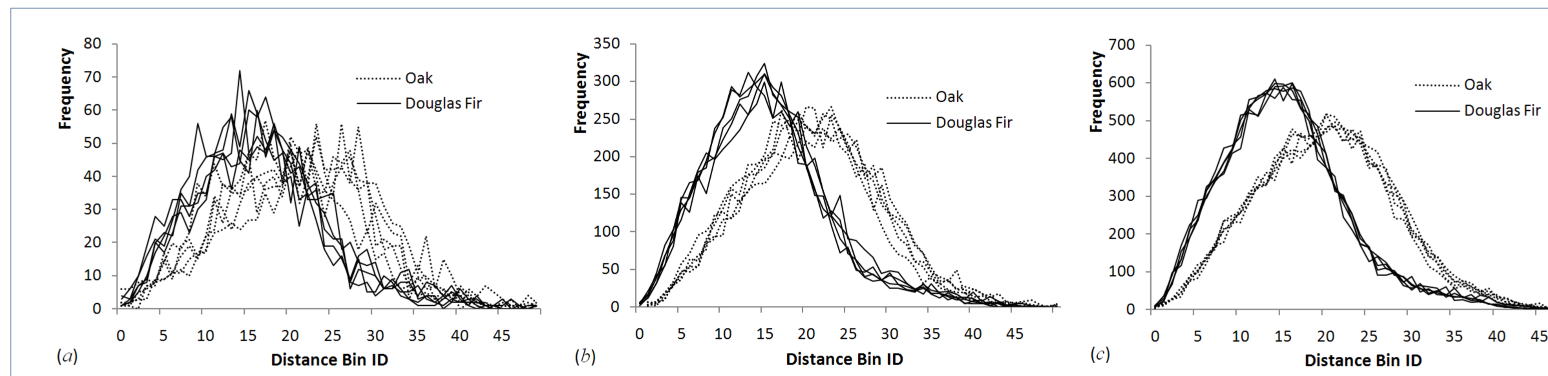

Figure 7. 3D shape signatures for the oak and Douglas fir canopies calculated from DSMs using (a) 1000 random point pairs, (b) 5000 random point pairs, and (c) 10000 random point pairs.

Figure 8 is a comparison of processing times using point clouds (2251 points for a Douglas fir canopy) and a raster surface (30 x 30 cells with 0.5 m resolution) for the same canopy on a computer with 2.53 GHz Duo CPU processor and 4 GB RAM. It can be seen that calculation of 3D shape signatures is computationally very efficient for both point data and raster data, and raster data seem to be more efficient than point data.

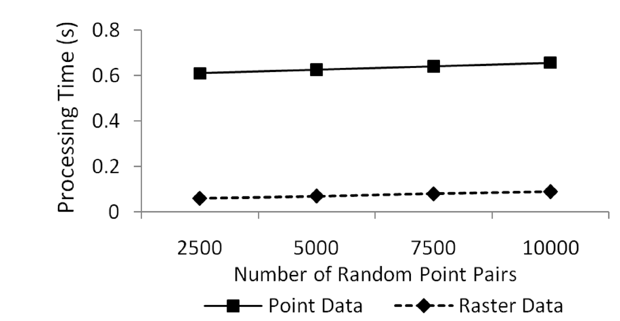

Figure 8. Comparison of processing time between 2251 points and 30 x 30 cells for Douglas fir.

To further demonstrate the performance of the 3D shape signatures in separating two different types of canopies, five oak canopies (red polygons) and five Douglas fir canopies (green polygons) were manually delineated from the 0.5-m resolution DSM (figure 9). It can be seen that the 3D shape signatures of the two groups have distinct differences (figure 10).

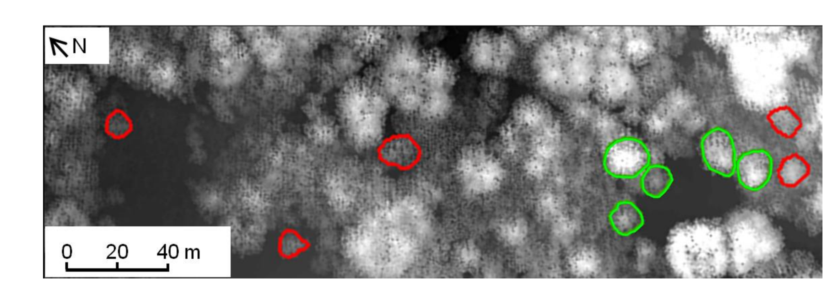

Figure 9. Oak (red polygons) and Douglas fir (green polygons) canopies delineated from DSM.

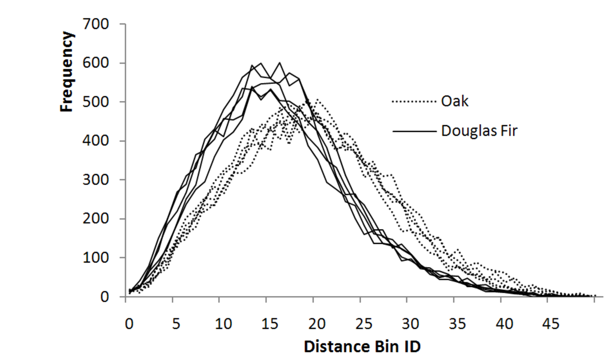

Figure 10. 3D shape signatures for the oak and Douglas fir canopies calculated from samples shown in Figure 9 using 10000 random point pairs.

Based on the above results, some relevant discussions are presented below.

• *Dissimilarity of 3D shape signatures*. As expected, the shape signature of Douglas fir is similar to that of the half-ellipsoid in Figure 2, while the shape signature of oak is closer to that of a hemisphere. Through 3D shape signatures, the comparison of 3D canopy shapes is successfully reduced to the comparison of frequency distributions which is much easier. Although the dissimilarity measures are not discussed here due to length limitations, they can be implemented easily to provide quantitative measures of differences in 3D shape signatures.

• *Sensitivity of 3D shape signatures*. It is believed that the statistical nature of the 3D shape signatures in this study makes them relatively insensitive to noise and other small local variations, which also explains why the shape signatures from raster surfaces are similar to those from point clouds even though raster surfaces are less accurate than original point clouds. This property is important for canopy shape analysis because small portions of adjacent canopies are often included during canopy shape signature analysis.

• *Automated feature extraction.* To test the effectiveness of 3D shape signatures in discriminating different tree canopy shapes, manually selected/delineated canopies are used in this study. Progress has been made to incorporate 3D shape signature analysis into automated canopy extraction procedures, which will be reported in a separate paper.

4. Conclusions

Three-dimensional shape signatures based on the distance distribution of random point pairs are presented and the effectiveness of the signatures evaluated using computer simulations, LiDAR point clouds, and LiDAR-derived digital surface models. The results from samples of oak and Douglas fir canopies suggest that comparison of 3D canopy shapes can be effectively reduced to the comparison of frequency distributions of distances between random points. The results also indicate that the statistically-based 3D shape signatures are relatively insensitive to noise and other small local variations, which is important for canopy shape analysis in real-world environments. The 3D shape signatures are computationally very efficient, and have potential to be incorporated into automated feature extraction procedures for LiDAR data analysis.

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References (omitted)