Remote Sensing of Environment 194 (2017) 63–76

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Rapid measurement of the three-dimensional distribution of leaf orientation and the leaf angle probability density function using terrestrial LiDAR scanning

Brian N. Bailey*,[1], Walter F. Mahaffee*

USDA-ARS Horticultural Crops Research Laboratory, 3420 NW Orchard Avenue, Corvallis, OR 97330, USA

ARTICLE INFO

Article history:
Received 8 April 2016
Received in revised form 9 September 2016
Accepted 12 March 2017
Available online 27 March 2017

Keywords:
Leaf angle distribution function
Leaf orientation measurement
Plant reconstruction
Terrestrial LiDAR scanning

ABSTRACT

At the plant or stand level, leaf orientation is often highly anisotropic and heterogeneous, yet most analyses neglect such complexity. In many cases, this is due to the difficulty in measuring the spatial variation of the leaf angle distribution function. There is a critical need for a technique that can rapidly measure the leaf angle distribution function at any point in space and time. A new method was developed and tested that uses terrestrial LiDAR scanning data to rapidly measure the three-dimensional distribution of leaf orientation for an arbitrary volume of leaves. The method triangulates laser-leaf intersection points recorded by the LiDAR scan, which allows for easy calculation of normal vectors. As a byproduct, the triangulation also yields continuous surfaces that reconstruct individual leaves. In order to produce a probability density function for leaf orientation from triangle normal vectors, it is critical that the proper weighting be applied to each triangle. Otherwise, results will heavily bias toward normal vectors pointed toward the the LiDAR scanner. The method was validated using artificially generated LiDAR data where the exact leaf angle distributions were known, and in the field for an isolated tree and a grapevine canopy by comparing LiDAR-generated distribution functions to manual measurements. The artificial test cases demonstrated the consistency of the method, and quantitatively showed that errors in the predicted leaf angle distribution functions decreased as scan resolution was increased or as the density of leaves was increased. The isolated tree field validation showed qualitatively similar trends between manual and LiDAR measurements of distribution functions. Manual measurements of leaf orientation in the vineyard were shown to have large errors due to high leaf curvature, which illustrated the benefits of the more detailed LiDAR measurement method.

1. Introduction

It is often necessary to account for the variability in leaf orientation in meteorological, climatological, or remote sensing analyses of plant systems. Because the preferred orientation of leaves is driven by solar radiation, it is not surprising that the probability density function (PDF) of leaf orientation is an important component of radiation transport in plant canopies. Anisotropic leaf orientation generally results in anisotropic radiation transfer, which necessitates a description of leaf orientation in analysis (Bailey et al., 2014; Myneni and Ross, 1991; Ross, 1981). Since leaf orientation dictates how light is reflected and scattered, it is also an important consideration in the interpretation of remote sensing data collected in vegetative environments (Jones and Vaughan, 2010; Nilson and Kuusk, 1989). The preferred orientation of leaves also influences other processes not related to radiation interception such as drag (Schuepp, 1993), particle deposition (Raupach et al., 2001), and convection (Bailey et al., 2016; Schuepp, 1993).

Despite the known importance of leaf orientation in many environmental processes, previous work has been unable to faithfully represent the spatial and temporal variability of the leaf angle PDF in analyses. This is primarily due to the difficulty in obtaining adequate measurements of leaf orientation, which can be highly heterogeneous in space (Kull et al., 1999; Raabe et al., 2015) and variable over daily and seasonal scales (Shell et al., 1974; Thanisawanyangkura et al., 1997). In order to measure the leaf angle distribution function, a large number of individual measurements of leaf orientation can be collected to generate the PDF. Manual measurement of leaf orientation is extremely tedious, and can be difficult to perform in dense or tall vegetation. Manual measurements also have many potential

---

* Corresponding author.
E-mail address: bnbailey@ucdavis.edu (B.N. Bailey).

[1] Current address: University of California, Davis, Department of Plant Sciences, One Shields Avenue, Davis, CA 95616, USA.

http://dx.doi.org/10.1016/j.rse.2017.03.011
0034-4257/

sources for error, as each measurement requires a judgement call on the part of the individual. A passage from Norman and Campbell (1989) stresses these issues: "Direct measurement of leaf angle distributions requires much determination and extraordinary care; *let the uninitiated beware*."

The simplest and most common approach for dealing with such difficulties in analyses is to remove the effects of leaf orientation and make the assumption that leaves have no preferred orientation. This has been demonstrated to be a poor assumption in a vast number of cases (see Pisek et al., 2013). Regardless, it is an assumption that is often made out of necessity when measurements are unavailable. There is clear opportunity for improvement of many meteorological and climatological models, measurements, and general analyses by faithfully including the effects of leaf orientation.

In cases where some measurement of the leaf angle distribution function is desired but direct methods are not feasible, indirect methods have also been developed that use a collimated source of radiation at some known orientation to infer leaf angle distributions. The most easily accessible source of collimated radiation is sunlight. By recording how sunlight is attenuated by vegetation, one can invert the well known Beer's law for radiation interception to estimate leaf orientation (cf. Norman and Campbell, 1989). These methods are limited by the fact that all results are integrated along the path between the sun and the instrument, making it difficult to obtain three-dimensional information. They also generally require an estimation of the leaf area density (LAD), which can lead to compounding errors. A more recent indirect method that has gained popularity is to manually identify leaf angles from digital photographs (Ryu et al., 2010). This method is a bit more efficient than direct measurement, but it cannot measure leaf azimuth and only considers leaves in direct view that are approximately parallel with the camera view direction.

Terrestrial LiDAR scanning, which is the focus of this paper, has seen increasing usage in obtaining measurements of canopy structure (e.g., Henning and Radtke, 2006; Hosoi and Omasa, 2006; Radtke and Bolstad, 2001; Rosell et al., 2009; Yang et al., 2013). Terrestrial LiDAR scanners emit concentrated beams of radiation in the form of laser pulses into the spherical space surrounding the scanner. In the event that the beam hits an object, the distance to the object can be determined by analyzing the radiation reflected back to the scanner. Unlike methods utilizing the attenuation of sunlight, LiDAR can quickly obtain millions of data points that provide three-dimensional information about radiation attenuation from many directions, which can be inverted to provide information about canopy structure such as leaf area density (Béland et al., 2011; Hosoi and Omasa, 2006). One important limitation in the use of LiDAR data to measure LAD distributions is the general lack of knowledge of the behavior of the leaf angle distribution function, which plays a critical role in performing such measurements.

Some recent work has began developing methods to measure leaf orientation using LiDAR data. Zheng and Moskal (2012) estimated leaf normals using an algorithm that fits a plane to neighboring LiDAR leaf intersection points. The method performed well for small potted plants, but showed poor agreement with measurements when applied to a tree in the natural environment. Their method also did not properly weight leaf normals when calculating the PDF of inclination, leading to a biased PDF (see Section 2.2). Hosoi and Omasa (2015) manually identified leaves within LiDAR point cloud data, and used planar fits to calculate and average leaf normals. This method allows easy access to the entire plant, but it is comparable in effort to performing manual measurements in the field. As with any manual measurement technique, there is also the potential for user bias in results, which has not been quantified through validation exercises.

In this work, we seek to develop and validate an algorithm that autonomously calculates the three-dimensional distribution of leaf orientation in natural vegetation from LiDAR data. The ultimate goal is to rapidly generate the leaf angle PDF for an arbitrarily defined volume of leaves, providing a direct measurement of how the PDF changes in space and time.

2. Methods

2.1. Triangulation and calculation of surface normals

The LiDAR scan creates a uniform grid of sample points in spherical space. Let Θ and Φ denote the range of zenithal and azimuthal directions explored by the LiDAR, respectively. The number of scan points in the zenith (N_Θ) and azimuthal (N_Φ) directions gives the resolution of the scan. Thus, the zenithal angle between adjacent scan points is $\Delta\theta = \Theta/N_\Theta$, and the azimuthal angle is $\Delta\varphi = \Phi/N_\Phi$. For each of the $N_\Theta \times N_\Phi$ scan points, the instrument reports the distance to the nearest object in the direction (θ,φ).

The strategy for computing the distribution of leaf normals was to first triangulate laser-leaf intersection points. A successfully constructed triangular mesh along leaf surfaces would allow for easy calculation of normal vectors at the location of each triangle. Triangles are desirable because they comprise the minimum number of points necessary to compute a normal vector. This means that only three adjacent hit points are required on a given leaf to calculate a normal vector and obtain an estimate of its orientation. Standard triangulation algorithms are not applicable for discrete surfaces such as leaves. Examples are (Press et al., 2007) Delaunay triangulation which in three dimensions seeks to create tetrahedral cells and not surfaces, or the convex hull algorithm which seeks to create a continuous convex surface. There are numerous algorithms designed to reconstruct continuous solid objects from point cloud data (e.g., Bernardini et al., 1999). Since plant leaves consist of a field of many individual surfaces, this work will develop a simpler algorithm below that is specifically designed to efficiently identify and reconstruct individual leaves without connecting each of them together to form a single object.

The scan data can be stored into a two dimensional data structure (denoted as A_{ij}), where columns denote each azimuthal scan direction and rows denote each zenithal scan direction (Fig. 1a and Table 1). If the (i,j) scan point does not intersect an object (denoted as a 'miss'), A_{ij} is set to false, whereas if the point intersects an object (denoted as a 'hit'), A_{ij} is set to a unique identifier corresponding to the hit point. For practical purposes, a bounding box can be established that encompasses only points of interest, with all hit points lying outside of this box considered misses.

To triangulate the (i,j) hit point, neighboring points in the table A_{ij} were searched for hits (Fig. 1a and Table 1). If the $(i+1,j)$ and

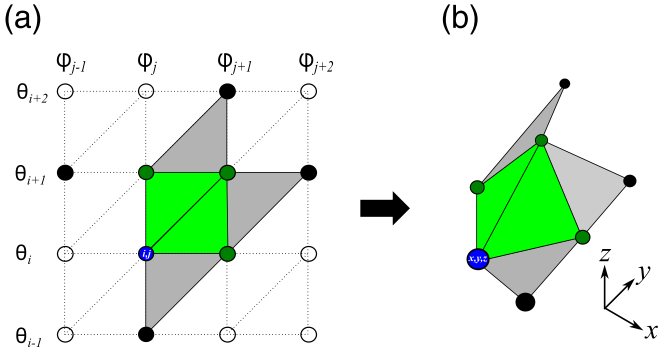

Fig. 1. Visual depiction of point cloud triangulation. (a) shows how points are first triangulated using the two-dimensional grid of (θ_i,φ_j) pairs. Leaf-laser intersection points (hits) and non-intersection points (misses) are denoted respectively by closed and open circles. At any hit point, a triangulation is attempted with the (θ_i,φ_j), (θ_{i+1},φ_j), $(\theta_{i+1},\varphi_{j+1})$ points and the (θ_i,φ_j), $(\theta_{i+1},\varphi_{j+1})$, (θ_i,φ_{j+1}) points. (b) shows the triangulation mapped to the (x,y,z) hit coordinates.