# Extraction of Features From LIDAR Waveform Data for Characterizing Forest Structure

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***Abstract*—Determination of structural characteristics of forests at large scales is an important problem in both scientific studies and development of management practices. Light detection and ranging (LIDAR) waveform data have been demonstrated to be valuable for estimating forest structural parameters even in dense forests, although challenges inherent to the LIDAR acquisition systems must be addressed. A new approach for processing LIDAR waveform data to estimate forest structural parameters is proposed. It was applied to Laser Vegetation Imaging Sensor waveform data acquired over old-growth tropical forest in the La Selva Biological Station, Costa Rica. Linear and nonlinear feature extraction methods were utilized to derive a lower dimensional feature space from high-dimensional LIDAR waveform data. The resulting features were used to estimate mean canopy heights through multiple linear regression analysis. Experimental results obtained by the new approach were statistically comparable to estimates obtained using features extracted via traditional waveform analysis, and the proposed approach successfully discovered another meaningful lower dimensional feature space without manual interpretation.**

***Index Terms*—Dimensionality reduction, feature extraction, forest structure, manifold learning, waveform light detection and ranging (LIDAR).**

## I. Introduction

STRUCTURAL attributes of forests play a critical role in diverse applications, including global carbon cycle studies, forest management, and wildlife habitat investigations. Estimates of these characteristics provide an understanding of how a forest ecosystem functions at large scales by providing valuable input to models [1]. Traditional field-sampling-based methods are known to perform reasonably well in plot level studies. However, these methods not only are destructive, time consuming, expensive, and limited to local scale studies but also may be biased due to human interpretation and field conditions throughout a campaign period [2], [3]. To overcome the limitations of field-sampling-based approaches, various remote sensing technologies have been investigated to acquire data from which to infer forest structure. Traditional multispectral and hyperspectral sensors provide chemistry-based and some structural information on tree canopy structure. Active remote sensing technologies, such as synthetic aperture radar [4] and light detection and ranging (LIDAR) [5]–[7], have also been utilized to characterize the forest structure. While researchers have had considerable success in using conventional microwave and optical sensors to estimate forest structural parameters in relatively low-biomass forest environments, estimating characteristics of dense forests whose leaf area index (LAI) exceeds three continues to be problematic [8]. Full-waveform LIDAR technologies have recently attracted considerable attention for obtaining measures of forest structure, as detailed information on the vertical structure of forests is better represented by the LIDAR waveform data than by the traditional discrete-return LIDAR data. For example, the capabilities of Scanning LIDAR Imager of Canopies by Echo Recovery [5], [9], Ice, Cloud, and Land Elevation Satellite [6], [7], [10], and Laser Vegetation Imaging Sensor (LVIS) [11], [12] waveform data have all been utilized in studies of forest structure. In these studies, features related to vertical structure were predefined by experts and extracted from the waveforms recorded by the system. The resulting features were then georeferenced using median energy location and aggregated to generate representative features for every grid cell. Finally, the resulting features were used to develop regression models to estimate forest structural parameters.

Although LIDAR waveform data have great potential for estimating forest structural parameters even in heavily vegetated areas, extraction of robust informative features from what can be considered *high-dimensional* LIDAR waveform data is a topic of considerable research interest. High-dimensional data provide rich information on the target, but extraction of relevant information embedded in the data is challenging due to issues such as the Hughes phenomenon [13] and the curse of dimensionality [14]. Finding a representative lower dimensional feature space embedded in the high-dimensional data is an important step prior to further analysis. Traditionally, features extracted from the LIDAR waveform data have been inspired by field-based sampling and focused on predefined physical characteristics. Examples include canopy height metrics (e.g., maximum, mean, and various percentiles of the height distribution), canopy cover, and leading and trailing waveform extent [5]–[7]. However, loss of information is inevitable during the feature extraction process, and features which are not easily discoverable but explain complex characteristics may not be revealed by such approaches. Unsupervised approaches have been investigated to discover a low-dimensional highly explanatory feature space from high-dimensional data, including

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remote sensing image data. The principal component analysis (PCA) linear transformation obtains a set of features where variances of the transformed features are maximized while the orthogonality among the new features is preserved. Nonlinear transformations have also been investigated, particularly within the machine learning community. Among these, the Isomap [15] transformation finds the shortest path between points using a geodesic distance (distance along manifolds) measure in conjunction with multidimensional scaling to embed high-dimensional data into a low-dimensional space. Although PCA and Isomap transformations have been widely used to extract a lower dimensional feature space from traditional spectral images, they cannot be directly applied to LIDAR waveform data since the recorded waveforms are not consistent relative to a given reference. Waveforms are recorded in terms of elapsed time after the firing of an outgoing laser shot. In order to reduce storage requirements, only the return signal whose response is greater than a threshold value is preserved, and the elapsed time representing the beginning of the waveform is recorded. Because of this data storage scheme, every waveform has a unique time origin, and the value of the onset of one waveform does not have a consistent physical relationship to the time of the onset of other waveforms. Thus, either shift-invariant features must be defined and extracted from waveforms as in the previous studies, or waveforms must be transformed prior to applying dimensionality reduction algorithms so that they have a common origin and the same physical meaning.

The objective of this study was to develop a new approach for processing LIDAR waveform data to estimate forest structural parameters, while enabling an automatic discovery of a lower dimensional feature space. In the proposed approach, a single representative waveform is reconstructed for every grid cell, and a lower dimensional feature space is then derived from the reconstructed waveforms using unsupervised feature extraction algorithms. Linear (PCA) and nonlinear (Isomap) feature extraction methods are investigated to extract lower dimensional features from the reconstructed waveform data. The extracted features are then used to develop regression models to estimate mean canopy height.

## II. Methods

The proposed approach consists of three components: 1) processing of LIDAR waveform data; 2) extracting features from the processed data using unsupervised feature extraction algorithms; and 3) developing a multiple linear regression model to predict structural parameters using the extracted features. The key idea of the proposed approach is to utilize unsupervised feature extraction methods to derive lower dimensional features from the LIDAR waveform data. The first component is critical in this process and is thus a focus of the proposed approach. The following sections describe the preliminary waveform data processing, which consists of five steps: 1) LIDAR waveform decomposition; 2) georeferencing of the decomposed components; 3) waveform reconstruction; 4) waveform normalization; and 5) waveform shifting.

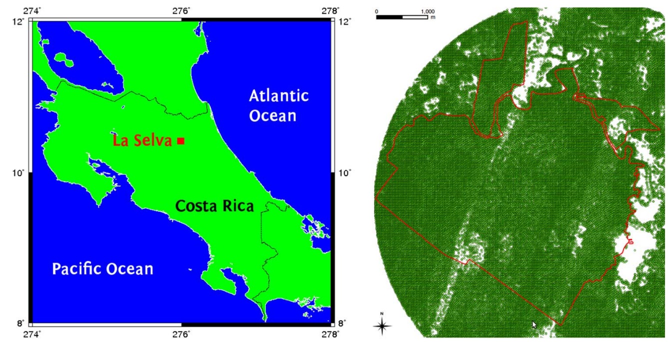
*1) LIDAR Waveform Decomposition:* LIDAR waveform decomposition refers to the process of decomposing a return waveform into distinct components which are then used to characterize the original waveform data. The most common statistical model used for representing LIDAR waveforms is a Gaussian mixture [16] whose parameters include mixing coefficients, the mean, and the standard deviation of each component. A mixture model for the waveform decomposition is preferred for the proposed method as the decomposed components can be georeferenced individually and utilized to reconstruct waveforms in order to remove scan angle effects from the recorded waveforms. Components extracted by statistical models such as the fast Fourier transform or a wavelet decomposition involve transformation of the characteristics of the recorded waveform and, hence, cannot be georeferenced individually. The decomposition results generate three parameters for each component: amplitude $(\alpha)$, mean $(\mu)$, and standard deviation $(\sigma)$.

*2) Georeferencing of the Decomposed Components:* The decomposed components are georeferenced using the estimated mean of each component in combination with the location and the attitude information of the system at the time of laser shot. The estimated mean is transformed into 3-D coordinates, and each resulting component has five parameters: amplitude $(\alpha)$, 3-D coordinates $(x, y, z)$, and standard deviation $(\sigma)$ after the georeferencing step.

*3) Waveform Reconstruction:* A representative waveform for every grid cell is reconstructed using the georeferenced components. Two-dimensional coordinates $(x, y)$ are used to assign the decomposed components to a specific grid cell, and estimated elevation $(z)$, amplitude $(\alpha)$, and standard deviation $(\sigma)$ are used to reconstruct the components as a Gaussian function in the elevation domain. A representative single waveform for every grid cell is generated by combining all Gaussian functions assigned to the cell as a mixture distribution. Waveforms are recorded in the time domain when they are digitized by the system, but the aggregated waveforms are reconstructed in the elevation-above-sea-level domain. Inconsistent time origin effects are removed by transforming waveforms from time to elevation domain, and each interval of the waveforms then relates to height range.

*4) Waveform Normalization:* LIDAR waveform data are acquired in strips with side overlap, and some grid cells have more assigned components than other grid cells. For this reason, grid cells with more components have higher peak values than those with smaller components after the waveform reconstruction step. To remove the bias, a normalization operation is performed by constraining the total area under the reconstructed waveform.

*5) Waveform Shifting:* Information of interest from LIDAR waveform data for estimating forest structural parameters relates to the shape of the waveform, not the absolute vertical location of the waveform in the elevation-above-sea-level domain. After the normalization step, two waveforms with a similar shape but with different ground elevations are considered to be different. To remove ground elevation effects, the unit of the reconstructed waveforms is transformed from the elevation above sea level to the elevation above ground. The transformation is equivalent to shifting waveforms so that ground elevation is located at the same location among reconstructed waveforms. A digital terrain model (DTM) is required for the shifting




(a) (b)

Fig. 1. (a) Location of the La Selva Biological Station and (b) 2005 LVIS coverage over the station (the solid red line represents the boundary of the La Selva Biological Station, and the white background represents the area which was not covered by the LVIS acquisition.)

operation, but the DTM generated from the waveform data also can be used when no other DTMs are available.

## III. Experimental Results and Discussion

### A. Study Area and Experimental Data

The La Selva Biological Station is located in northeast Costa Rica [Fig. 1(a)]. The station is a 1536-ha tropical research facility whose elevation ranges from about 30 to 140 m above sea level. It is the site of extensive international research, and investigators have contributed to a rich database of *in situ* and remotely sensed data. Land cover consists of a mixture of old-growth forests, selectively logged primary forests, secondary forests, early successional pasture, and abandoned plantations [17]. The area is almost entirely covered by primary and secondary tropical rain forests, and its canopy closure is about 98%–99%. Due to the heavy canopy cover and complex canopy structure, estimating forest structural parameters using remote sensing data has been challenging in the study area. LVIS is a scanning laser altimeter with a full-waveform digitizer. The system can operate at 10-km altitude and has a 1-km swath width with nominal footprints of 25-m diameter. The LVIS system has a 7° potential field of view and emits a 10-ns-width Gaussian-shaped outgoing laser pulse at 1064 nm. Its maximum pulse repetition rate is 500 Hz, and return waveforms are recorded every 2 ns with 8-b resolution [18]. LVIS data were acquired over the La Selva Biological Station in March 2005 [Fig. 1(b)] at an altitude of 10 km with 2-km swath width, and a mean footprint size of the acquisition was approximately 18.3 m in diameter. LVIS Geolocated Waveform products which contain 211 317 waveforms were used in this study.

### B. Reference Data

An airborne discrete-return LIDAR system with a Leica ALS50 sensor was flown over the study area in March 2006. The ALS50 is a discrete-return LIDAR system which has 83-kHz maximum pulse rate, and can operate at 4-km altitude with a maximum field of view of 75°. The average density of the acquisition was 1.99 points/m$^2$. Point cloud data were classified into ground and nonground classes [19], and a 5-m DTM was created by natural neighbor interpolation using only points classified as ground. Kellner *et al.* [20] verified the DTM generated by the natural neighbor interpolation with field elevation measurement data ($N = 4184$) and reported an almost one-to-one relationship with $R^2 = 0.994$ and $rmse =$ 1.85 m. A 5-m digital surface model (DSM) was generated using maximum elevation of points within grid cells, and a 5-m canopy height model (CHM) was created by subtracting the DTM from the DSM. A 25-m mean CHM was created from the 5-m CHM data by averaging 25 grid cells in a 5 × 5 neighborhood. The 25-m mean CHM was used as reference data in this study. A 25-m DTM was also created by averaging grid cells of the 5-m DTM. The 25-m DTM was used to extract physical features from the aggregated waveforms and for shifting waveforms.

### C. Physical Feature Extraction

To evaluate the performance of the proposed approach, mean canopy height estimation results were compared with the traditional physical feature extraction methods. Physical features that are known to perform well in estimating canopy heights include relative height (RH) features such as RH25 (25th percentile of RH), RH50 (50th percentile of RH), RH75 (75th percentile of RH), RH100 (100th percentile of RH), and waveform extents [5]–[7]. Two methods for extraction of the physical features were implemented in this study. The first method $(M1)$ was to extract the physical features from the recorded waveform data assuming the lowest elevation component as a ground return. The extracted features were georeferenced to the mean energy location of the recorded waveform and aggregated in every grid cell. The second method $(M2)$ extracted physical features from the aggregated waveform data. Waveforms were aggregated by georeferencing the recorded waveforms using mean energy location, while the physical features were extracted from the aggregated waveforms by considering the 25-m DTM elevation as a ground elevation. The extracted features were then used in the regression analysis.

### D. LIDAR Waveform Data Processing

LVIS waveform data were processed using the proposed approach over the grids which align with the reference data. Waveforms were decomposed into a mixture of Gaussians using a sequential LIDAR waveform decomposition algorithm proposed by Jung and Crawford [21]. The sequential algorithm utilizes fast simple nonlinear least squares and the greedy expectation–maximization (EM) algorithm for simple waveforms or well-separated mixtures, and the more robust EM and sequential EM algorithms for more complex waveforms in order to improve the overall waveform decomposition process [21]. The decomposed components were then georeferenced using the estimated mean of the components. Initially, waveforms were reconstructed with a dimension of 220 in the elevation-above-sea-level domain, where the lowest elevation corresponded to 30 m and the highest elevation corresponded to 249 m with 1-m elevation spacing. Every reconstructed waveform was normalized and shifted using the 25-m DTM. The dimension of the final reconstructed waveforms was reduced to

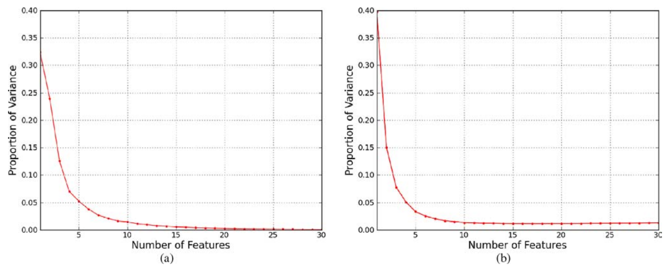



Fig. 2. Scree plots of (a) PCA and (b) Isomap transformations.

80 after the shifting operation, in which the lowest elevation corresponds to $-19$ m and the highest elevation corresponds to 60 m above ground with 1-m elevation spacing.

After the preprocessing step, PCA $(M3)$ and Isomap $(M4)$ transformations were applied to the reconstructed waveform data $(d_o = 80)$ to derive a lower dimensional feature space. The dimension of the initial lower dimensional space was set relatively high $(d_l = 30)$ to guarantee that no meaningful features were lost during the transformation process. Statistically significant features were selected in the later stage via backward elimination multiple regression analysis and scree plots. The first 30 PCA bands were selected as initial lower dimensional features. For the Isomap transformation, the $k$-nearest neighbor approach was used to build a geodesic network, and geodesic distances were computed by calculating the shortest path between points over the network using Dijkstra's algorithm [15]. Manifold coordinates were then computed by applying multidimensional scaling to the geodesic distance matrix with an output dimension of 30.

### E. Mean Canopy Height Estimation

The traditional physical features $(M1$ and $M2)$ and the features extracted by the proposed approach $(M3$ and $M4)$ were used to develop multiple regression models to estimate mean canopy heights. The dependent variable was mean canopy height derived from the reference data, and the independent variables were the extracted features in the regression analysis. Due to the incomplete LVIS coverage over the study area [Fig. 1(b)] and data being acquired in multiple strips, the number of decomposed components assigned to grid cells varied greatly and was location dependent. The mean and the maximum number of components were 13.07 and 50, respectively. Grid cells with too few components may not be able to reconstruct waveforms which represent the vertical structure adequately. Therefore, only grid cells with more than 13 components $(N = 9235)$ were used in the analysis. For the physical feature extraction methods $(M1$ and $M2)$, a stepwise multiple linear regression analysis was performed. All five features were statistically significant $(p < 0.05)$. For the features extracted by the proposed approach $(M3$ and $M4)$, backward elimination was used to develop the model, whereby features that were not statistically significant $(p > 0.05)$ were removed. The first 11 Isomap features and the first 15 PCA features were in the final regression models, which coincide with the elbow points from the scree plots (Fig. 2).

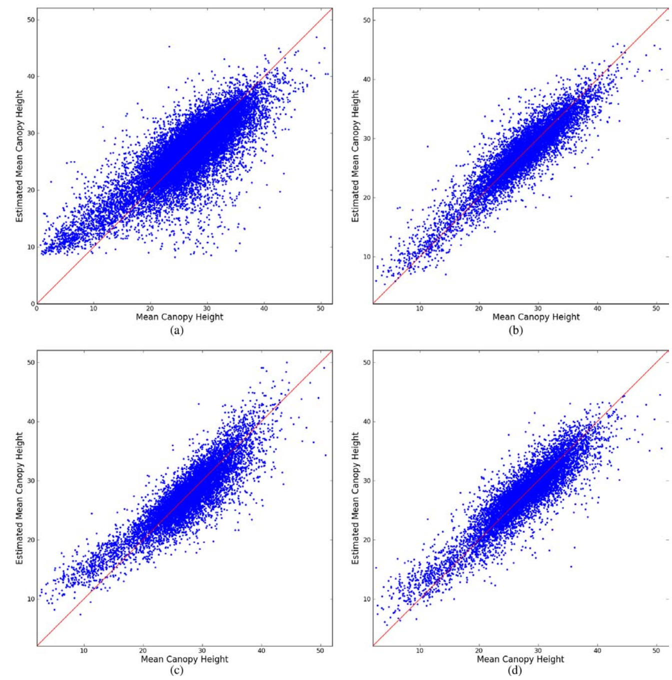



Fig. 3. Scatter plots of estimated mean canopy heights versus mean canopy heights when (a) $M1$, (b) $M2$, (c) $M3$, and (d) $M4$ approaches were used to extract lower dimensional features.

The resulting $R^2$ values were 0.68 and 0.85 for $M1$ and $M2$ and 0.79 and 0.82 for $M3$ and $M4$, respectively. The $M2$ approach yielded the best estimation results, while the $M1$ approach yielded the worst estimates. The results from $M1$ and $M2$ indicate that accurate detection of ground elevation is critical in the estimation performance since the $M1$ approach did not take advantage of the 25-m DTM that was used to generate the reference data, but instead considered the lowest elevation component in the waveform as a ground return. The physical features are shift invariant and heavily dependent on the ground elevation, so the detected ground elevation impacts resulting physical features. The proposed approach yielded better estimates of mean canopy height than the $M1$ approach, while the Isomap transformation yielded comparable prediction errors to the $M2$ approach. Even though physical features that were extracted by the $M2$ approach yielded a model with the best fit results, they are specifically designed to perform well in estimating canopy height metrics. The comparable fit of the $M4$ approach indicates that features extracted by the Isomap transformation successfully discovered another set of lower dimensional features without any input from experts. Comparing results obtained by the $M3$ and the $M4$ approaches, a smaller number of features were included in the final regression model for $M4$ compared to the $M3$ approach, and the resulting $R^2$ value was higher. This result implies that more meaningful lower dimensional features could be found from the LIDAR waveform data via a nonlinear feature extraction method than a linear approach. It should also be noted that some physical features are, in fact, a form of nonlinear transformation, which may be another reason why the Isomap transformation yielded better estimation results than the PCA transformation. In addition to $R^2$ value differences among regression models, scatter plots of estimated versus reference mean canopy heights (Fig. 3) also reveal that the $M4$ approach yielded models with similar fits compared to the $M2$ approach and the $M4$ approach successfully discovered another form of nonlinear transformation that can be used to estimate mean canopy heights.

## IV. Conclusion

Understanding structural characteristics of forests at large scales is important due to their relevance to many research investigations and applications. Among various remote sensing data types, LIDAR waveform data have the greatest potential for estimating forest structural parameters even in dense forests, although inherent challenges remain. In order to deal with those challenges, a new approach which processes LIDAR waveform data to estimate forest structural parameters has been proposed, and the performance of unsupervised linear and nonlinear feature extraction methods has been investigated. In experiments for the tropical forests at the La Selva Biological Station, the proposed approach yielded comparable estimation results to the traditional physical feature extraction methods when an Isomap transformation was used to derive a lower dimensional feature space. The scatter plots also revealed that the Isomap transformation discovered another form of a nonlinear transformation that can be used to estimate mean canopy heights. The main contribution of the proposed approach is the demonstration of capability to discover a lower dimensional feature space from the LIDAR waveform data by utilizing unsupervised feature extraction algorithms without manual interpretation. While the method was evaluated for canopy height and compared to the predictive capability of physically based metrics related to height, it may have even greater potential for predicting structural characteristics such as LAI or biomass that are more difficult to characterize via physical metrics. Although the proposed approach is robust in terms of the analysis, it is a data-driven approach, and its application is site specific. Multitemporal studies would have the same issue, but the problem might be successfully mitigated by manifold alignment [22], given the typical rate of change of structural characteristics.

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