From Bark to Byte: Automating Forest Inventory Data Collection Through Camera and Mobile LIDAR

Robin Young
robin@rayoung.org

Abstract

Accurate forest inventory data are essential for tracking carbon sequestration, estimating carbon emissions from deforestation, assessing plant and animal habitats for biodiversity, and predicting environmental risks such as wildfires. Traditional methods of data collection have faced challenges in either scale or precision. The advent of terrestrial laser scanners addressed some of these issues but faced limitations in cost and mobility. This paper proposes a new approach using mobile LIDAR for forest inventory data collection. By integrating advancements in computer vision, the methodology aims to provide comprehensive individual tree data, including parameters like diameter at breast height, volume estimations, species identification, and temporal tracking of individual trees. This proposed research direction addresses current gaps in the use of LIDAR and camera inference for forestry data where existing work does not generate domain context-aware data by narrowly focusing collection on isolated tree attributes.

1 Introduction

Understanding forests and their interactions with the carbon cycle is integral to addressing anthropogenic climate change. Forests are essential to human societies, with 20% of the world population being dependent on forests for livelihoods [31]. Furthermore, forests account for ~45% of the accumulated carbon in the terrestrial biosphere [5] and ~12% of accumulated anthropogenic carbon emissions through forest degradation and land use change releasing stored carbon [32]. So far, woodland surveys have largely relied on either remote sensing by satellite or aerial imagery or manual sampling efforts from foresters. Recently, terrestrial laser scanners have been used to acquire data at individual tree level resolution without manually measuring each tree individually; however cost and mobility of scanner equipment remains as an obstacle for large scale viability.

Mobile LIDAR is compact, low cost and has the potential to enable fast tree level information retrieval across a wide geographical area. Recent papers [21, 12] explored the possibility of using mobile LIDAR and camera towards environmental sensing in forests with initial success in estimation of tree trunk diameters at breast height (DBH) in field tests. This paper proposes work to develop further capabilities of computer vision to characterize trees in a way that is compatible with current domain applications of tree-level data. Where existing studies have focused only on the inference of one or two attributes of trees, it makes the resulting data impractical for domain applications. This work will expand the utility of the resulting data for uses such as carbon pool estimation, growth tracking and projection, and ecological monitoring [19]. Novel forestry inventory capacity that enables accurate carbon accounting for forest degradation and reforestation sequestration has major implications for the possibility of decarbonization policies such as carbon credits trading or emissions taxing; this can also enable better assessments of environmental risk in forests such as wildfire risk prediction [17].

Preprint. Under review.

2 Literature Review

In climate change literature, afforestation [27] and degradation prevention [31] have often been discussed as a part of possible nature-based solutions toward adaptation and mitigation of climate change impacts. In order to understand the viability of reforestation for carbon sequestration, or to conduct better estimates of deforestation impacts, it is necessary to understand the actual emissions or sequestration of changes in forestation [24]. However, doing so requires forest inventory data that provides the basis of carbon, ecological, and land use modeling [9], which is often constrained in either geographical availability or data resolution due to surveying difficulties. Due to the impracticalities of scaling manual measurements to large areas, survey programs usually make use of sampling sites and inferring the population data [2], or remote sensing via aerial photography or satellite imagery. The resulting forest inventory data imprecision limits efforts in forest carbon modeling [9].

Studies [22, 30] have utilized terrestrial laser scanners for environmental sensing, which improves field surveys by generating point clouds where post-processing can extract properties of interest. This method is much more precise than manual measurements, but the drawback comes in the form of low mobility and high cost. Mobile LIDARs have emerged as a low cost alternative to terrestrial scanners with aerial [25] or ground [11] implementations. There seems to be no existing mobile LIDAR based approaches that collects all of the proposed measurements on an individual tree basis in forest environments, which covers the conventional measurements made in conventional surveying practices [1]. This gap in the current application of remote sensing and computer vision to environmental monitoring is preventing the current body of work from generating practical impact in applications and fields where existing conventional tree data are used.

The ability to collect tree-level information also has important implications for evaluating wildfire risk in the context of fuel management. Information such as fuel density, the distribution of crown height and species of trees are important for inferring characteristics of wildfires [18, 6]. The proposed method in this paper can be utilized to measure current density and predict growth trends. By systematically studying the forest structures and fire dynamics after a fire, we can gain a better understanding of wildfire dynamics, particularly by analyzing the attributes of trees that were either affected or unaffected by the fire. Anomaly detection for disease and pests also have important implications for wildfires. There is evidence that bark beetles [4, 26] or mass tree death [15] from diseases significantly alter the fire risk and dynamic of an area. Hence, the proposed methodology on forest inventory collection can result in application potential in several different domains.

3 Methodology

The proposed contributions to the existing literature will be to integrate and expand the current methods to enable collection of forest inventory data that is ecologically useful as drop-in improvements to current data. The outcome of this research will be the capacity to extract the proposed properties of trees from LIDAR point clouds and camera data and integration of the data into a longitudinal database. This research addresses gaps in current literature by attempting to infer a set of ecologically relevant physical measurements of individual trees instead of just one or two parameters, thus connecting current research in environmental sensing with the overall conventional context of forest inventory methodology in order to generate relevant datasets for scientific use. Mobile phones present an opportunity to improve data collection with built in camera and LIDAR capacity without incurring high equipment costs in more sophisticated equipment. The mobility advantage is very important for field applications, where traversal of landscape can be a major obstacle for larger devices like terrestrial laser scanners.

To achieve the stated goals, this paper proposes several methods to extend the capabilities of current methods in literature beyond the primary focus of DBH estimation to infer and integrate additional measurements. In conventional forest inventory methods, other measurements are made that are essential for scientific and commercial usages, which needs to be implemented before mobile LIDAR becomes a viable alternative to current methods. There are also possible improvements on current volume estimation methods that can be enabled by LIDAR data. For example, in order to estimate the carbon content of a tree, conventional methods assume the carbon content is a fraction of the dry volume of the tree, with the factor being species dependent [28, 29]. With LIDAR point cloud data, it is possible to account for trunk irregularities and branches with segmentation and conic volume estimation methods [7, 20].

Carbon content of tree species factors vary significantly [14], along with growth trajectory and age inference [19]. To address this problem, deep learning methods such as convolutional neural networks [13] or vision transformers [36] can be used to identify tree species, and existing cameras on mobile phones can be leveraged towards achieving this function. If processing power is limited, an alternative method [34] where functional morphologies of trees are used infer clades instead of species can be considered, or alternatively post-processing can be considered after initial data collection. Additionally, features such as burls and branch structure can also be identified and labeled, alongside anomaly detection such as disease or insect infestation.

Current gaps in the capacity to track trees longitudinally at scale can be addressed by creating unique identifiers for each surveyed tree based on identified features. Tree skeletons can be generated [16] and be used with coordinate records for matching algorithms [23]. With a digital method that can be applied to all trees in a forest consistently, it becomes feasible to conduct periodical surveys for longitudinal analysis. One foreseen challenge associated with building spatial-temporal records for trees is the implementation of simultaneous localization and mapping (SLAM) which is typically complex and expensive computationally, and dense forests may prove to be a challenge that cause issues like drift errors. However, previous research [8] has indicated that SLAM could be implemented on mobile phones in a forest environment. Alternatively, non-spatial temporal tracking may be possible with the phenotyping method described in Schunck et al. [23].

In order to implement and verify the proposed methodology, the functions described above will be trained with and validated against known datasets. These datasets which have been previously collected and validated serve as a benchmark, which enables model training without manually producing tagged data where appropriate as well as comparison of results. Existing tagged tree-level RGB photo [3, 10] and point cloud [33, 35] data will be used as references for methodology, training, and evaluation where possible. By comparing the outcomes derived from the proposed approach with these established datasets, discrepancies can be identified and addressed. Depending on the results of a more comprehensive literature review, the work plan may include the construction of small ground truth samples for validation if no existing datasets are close by for this purpose.

4 Pathways to Climate Impact

The existing research into mobile LIDAR, despite its high mobility, adequate precision, and affordability, has yet to fully exploit its potential in forest ecology applications. By leveraging the advantages of mobile LIDAR with context-informed objectives, the proposed work has the potential to massively constrain empirical uncertainties or enable advancements in methodology in scientific studies that use forest inventory data by providing the capacity to collect individual tree level data across large geographical areas across time.

The climate impact of this proposed research will extend across multiple applications. Greater accuracy can be achieved in forest carbon accounting, which aids in climate change mitigation and adaptation efforts and facilitates sustainable precision forestry management. The detailed, tree-level data will enable enhanced wildfire risk modeling, making it possible to predict future risks and develop effective strategies for prevention and mitigation. Accurate, tree-level data will help with better understanding of composition and health of forest ecosystems, which is crucial for biodiversity conservation.

References

[1] Thomas Eugene Avery and Harold E. Burkhart. *Forest measurements*. McGraw-Hill series in forest resources. McGraw-Hill, 4th edition.

[2] William A. Bechtold and Paul L. Patterson. The enhanced forest inventory and analysis program: National sampling design and estimation procedures.

[3] Sara Beery, Guanhang Wu, Trevor Edwards, Filip Pavetic, Bo Majewski, Shreyasee Mukherjee, Stanley Chan, John Morgan, Vivek Rathod, and Jonathan Huang. The Auto Arborist Dataset: A Large-Scale Benchmark for Multiview Urban Forest Monitoring Under Domain Shift. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 21262–21275, New Orleans, LA, USA, June 2022. IEEE.

[4] Barbara J. Bentz, Jacques Régnière, Christopher J. Fettig, Everett Hansen, Jane Leslie Hayes, Jeffrey A. Hicke, Rick G. Kelsey, José F Negrón, and Steven J. Seybold. Climate change and bark beetles of the western united states and canada: Direct and indirect effects. 2010.

[5] Gordon B. Bonan. Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. 320(5882):1444–1449.

[6] Brooke A. Cassell, Robert M. Scheller, Melissa S. Lucash, Matthew D. Hurteau, and E. Louise Loudermilk. Widespread severe wildfires under climate change lead to increased forest homogeneity in dry mixed-conifer forests. *Ecosphere*, 2019.

[7] Guangpeng Fan, Liangliang Nan, Feixiang Chen, Yanqi Dong, Zhiming Wang, Hao Li, and Danyu Chen. A New Quantitative Approach to Tree Attributes Estimation Based on LiDAR Point Clouds. *Remote Sensing*, 12(11):1779, June 2020.

[8] Yongxiang Fan, Zhongke Feng, Abdul Mannan, Tauheed Khan, Chaoyong Shen, and Sajjad Saeed. Estimating Tree Position, Diameter at Breast Height, and Tree Height in Real-Time Using a Mobile Phone with RGB-D SLAM. *Remote Sensing*, 10(11):1845, November 2018.

[9] Lucia A. Fitts, Matthew B. Russell, Grant M. Domke, and Joseph K. Knight. Modeling land use change and forest carbon stock changes in temperate forests in the united states. 16(1):20.

[10] Vincent Grondin, Jean-Michel Fortin, François Pomerleau, and Philippe Giguère. Tree detection and diameter estimation based on deep learning. *Forestry: An International Journal of Forest Research*, 96(2):264–276, March 2023.

[11] Han Kyul Heo, Dong Kun Lee, Jin Han Park, and James H. Thorne. Estimating the heights and diameters at breast height of trees in an urban park and along a street using mobile LiDAR. 15(3):253–263.

[12] Amelia Holcomb, Linzhe Tong, and Srinivasan Keshav. Robust Single-Image Tree Diameter Estimation with Mobile Phones. *Remote Sensing*, 15(3), 2023.

[13] Tae Kyung Kim, Jeonghyun Hong, Daun Ryu, Sukyung Kim, Si Yeon Byeon, Woojin Huh, Kunhyo Kim, Gyu Heon Baek, and Hyun Seok Kim. Identifying and extracting bark key features of 42 tree species using convolutional neural networks and class activation mapping. 12(1):4772.

[14] S.H. Lamlom and R.A. Savidge. A reassessment of carbon content in wood: variation within and between 41 north american species. 25(4):381–388.

[15] Margaret R. Metz, Kerri M. Frangioso, Ross K. Meentemeyer, and David M. Rizzo. Interacting disturbances: wildfire severity affected by stage of forest disease invasion. *Ecological applications : a publication of the Ecological Society of America*, 21 2:313–20, 2011.

[16] Lukas Meyer, Andreas Gilson, Oliver Scholz, and Marc Stamminger. Cherrypicker: Semantic skeletonization and topological reconstruction of cherry trees. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, pages 6243–6252, June 2023.

[17] Yongqi Pang, Yudong Li, Zhongke Feng, Zemin Feng, Ziyu Zhao, Shilin Chen, and Hanyue Zhang. Forest Fire Occurrence Prediction in China Based on Machine Learning Methods. *Remote Sensing*, 14(21):5546, January 2022.

[18] Marc Parisien, Quinn E. Barber, Mike D. Flannigan, and Piyush Jain. The effect of broadleaf-tree greenup on springtime wildfire occurrence in boreal canada. *The Third International Conference on Fire Behavior and Risk*, 2022.

[19] Kevin M. Potter and Barbara L. Conkling. Forest health monitoring: national status, trends, and analysis 2020.

[20] Covadonga Prendes, Carlos Cabo, Celestino Ordoñez, Juan Majada, and Elena Canga. An algorithm for the automatic parametrization of wood volume equations from Terrestrial Laser Scanning point clouds: application in *Pinus pinaster*. *GIScience & Remote Sensing*, 58(7):1130–1150, October 2021.

[21] Alexander Proudman, Milad Ramezani, Sundara Tejaswi Digumarti, Nived Chebrolu, and Maurice Fallon. Towards real-time forest inventory using handheld LiDAR. 157:104240.

[22] Pasi Raumonen, Mikko Kaasalainen, Markku Åkerblom, Sanna Kaasalainen, Harri Kaartinen, Mikko Vastaranta, Markus Holopainen, Mathias Disney, and Philip Lewis. Fast automatic precision tree models from terrestrial laser scanner data. 5(2):491–520.

[23] David Schunck, Federico Magistri, Radu Alexandru Rosu, André Corneließen, Nived Chebrolu, Stefan Paulus, Jens Léon, Sven Behnke, Cyrill Stachniss, Heiner Kuhlmann, and Lasse Klingbeil. Pheno4d: A spatio-temporal dataset of maize and tomato plant point clouds for phenotyping and advanced plant analysis. 16(8):e0256340.

[24] Nathalie Seddon, Alexandre Chausson, Pam Berry, Cécile A. J. Girardin, Alison Smith, and Beth Turner. Understanding the value and limits of nature-based solutions to climate change and other global challenges. 375(1794):20190120.

[25] Xin Shen and Lin Cao. Tree-species classification in subtropical forests using airborne hyperspectral and LiDAR data. 9(11):1180.

[26] Carolyn Hull. Sieg, Rodman Ray Linn, François Pimont, Chad M. Hoffman, Joel D. McMillin, Judith Winterkamp, and L. Scott Baggett. Fires following bark beetles: Factors controlling severity and disturbance interactions in ponderosa pine. *Fire Ecology*, 13:1–23, 2017.

[27] W. L. Silver, R. Ostertag, and A. E. Lugo. The potential for carbon sequestration through reforestation of abandoned tropical agricultural and pasture lands. 8(4):394–407.

[28] Michael T. Ter-Mikaelian and Michael D. Korzukhin. Biomass equations for sixty-five north american tree species. 97(1):1–24.

[29] Sean C. Thomas and Adam R. Martin. Carbon content of tree tissues: A synthesis. 3(2):332–352.

[30] Jan Trochta, Martin Krůček, Tomáš Vrška, and Kamil Král. 3d forest: An application for descriptions of three-dimensional forest structures using terrestrial LiDAR. 12(5):e0176871.

[31] United Nations Framework Convention on Climate Change. UN-REDD programme 2016-2020 strategic framework.

[32] G. R. van der Werf, D. C. Morton, R. S. DeFries, J. G. J. Olivier, P. S. Kasibhatla, R. B. Jackson, G. J. Collatz, and J. T. Randerson. CO2 emissions from forest loss. 2(11):737–738.

[33] Hannah Weiser, Jannika Schäfer, Lukas Winiwarter, Nina Krašovec, Fabian E. Fassnacht, and Bernhard Höfle. Individual tree point clouds and tree measurements from multi-platform laser scanning in German forests. *Earth System Science Data*, 14(7):2989–3012, July 2022.

[34] Huili Wu, Wenhua Xiang, Xi Fang, Pifeng Lei, Shuai Ouyang, and Xiangwen Deng. Tree functional types simplify forest carbon stock estimates induced by carbon concentration variations among species in a subtropical area. 7(1):4992.

[35] Jie Yang, Xiaorong Wen, Qiulai Wang, Jin-Sheng Ye, Yanli Zhang, and Yuan Sun. A Novel Algorithm Based on Geometric Characteristics for Tree Branch Skeleton Extraction from LiDAR Point Cloud. *Forests*, 13(10):1534, September 2022.

[36] Qing Zou, Xiu Jin, Yi Song, Lianglong Wang, Shaowen Li, Yuan Rao, Xiaodan Zhang, and Qijuan Gao. An Improved Vision Transformer Network with a Residual Convolution Block for Bamboo Resource Image Identification. *Electronics*, 12(4):1055, February 2023.