A Mobile Laser Scanning System for Forest Carbon Inventories

Amelia Holcomb[1] and Connor Tannahill[1]

***Abstract*— In the face of the global climate crisis, politicians and researchers increasingly recognize the importance of forests, both for the broad ecological benefits they provide, and as an indispensable option for large-scale carbon sequestration. Government policy interventions and carbon credit markets to promote afforestation require technology to accurately and efficiently measure, report, and verify the extent of forest carbon sequestration. In this paper, we build on previous research to implement a forest inventory system on a mobile phone. This system takes advantage of the dropping costs of high-accuracy mobile sensors, such as the ToF (Time of Flight) sensor, and advances in Augmented Reality such as mobile SLAM (Simultaneous Localization and Mapping). We prototype the first iteration of such a system, using an Android phone equipped with a ToF sensor to estimate tree trunk diameter even with leaf and branch occlusion. We also propose areas for future work, such as creating rich data sets of spatially consistent 3D forest scenes and integrating ground-based sensor data with aerial data to improve machine learning models on the aerial scans.**

***Index Terms*— Environmental monitoring, Internet of Things, Computer vision, Carbon sequestration, SLAM, Mobile laser scanning, Forest inventory**

I. Introduction

Forests play a vital role in sequestering carbon, and that role must grow ever larger in light of the global climate crisis. The UK in particular, which has passed broad legislation requiring net-zero carbon emissions by 2050, targeted releasing around 22% of existing farmland to afforestation and other natural carbon sinks in its most recent land-use report [1]. As part of this work, the UK is also seeking to create a domestic market for carbon offsets [2], and to account these projects against national carbon emissions targets. Crucially, the report says, progress towards these goals will require improved technological methods to verify afforestation projects and measure their carbon sequestration.

Looking closely at the surveying protocol for UK Woodland Carbon Code (WCC) projects [3], we see that as of 2018 the required protocol is almost entirely manual, with a suggested material list that includes a smartphone, GPS or compass, printed paper spreadsheets, and measuring tape. The process is time-intensive and may be quite costly, with surveyors recommended to begin their work 6-12 months before the scheduled verification deadline. It also naturally limits the amount of data that can be collected to just a few summary data points per tree.

Moreover, the problem of accurate measurement, reporting, and verification (MRV) for forest-based carbon projects is not limited to the UK. Both a 2016 review of research into national REDD+ (Reducing Emissions from Deforestation and Degradation) programs and a 2018 report on forest-based carbon projects highlighted MRV as a key challenge [4] [5].

In our research, we create a mobile laser scanning (MLS) system to automate and potentially improve MRV processes in forest inventories. This system makes use of an Android phone equipped with a Time of Flight (ToF) sensor to enable accurate estimation of tree features such as diameter at breast height (DBH) and total height. It is designed to conform with the needs and standards of existing forest carbon inventory projects such as the WCC. We also propose directions for future work, including integrating our Android app with Google ARCore's[1] simultaneous localization and mapping (SLAM) system to create accurate forest maps and spatially consistent point cloud reconstructions. Eventually, this location data could be used to link aerial datasets with terrestrial ones, opening up new possibilities in the area of MRV for forest carbon projects.

II. Background: Forest Carbon Measurement

Forest surveying is a well-established field, encompassing both managed timber forests and partially managed or unmanaged natural growth forests. The Intergovernmental Panel on Climate Change (IPCC) collected peer-reviewed practices in their Land Use Report [6], offering a global standard for forest carbon measurement that is also followed by the WCC. Three of the key steps detailed in the report include:

1) **Establish project strata** Divide the land into roughly homogeneous strata, according to factors like soil type and ground slope. This can also be done after data collection: the primary purpose is to reduce surveying cost by grouping similar stands of trees. Foresters use GIS to specify forest strata and plot maps. [6]
2) **Establish sampling plots** Divide the strata into equally sized plots along a uniform grid. The IPCC report recommends using permanent plots that do not vary when measurements are repeated in subsequent years. In order to most accurately estimate change in carbon stocks, surveyors should measure the same individual trees each year, to maximize the covariance between successive measurements. The plots are typically marked out by hand, using a GPS, tape measure, and rope or ribbon, a laborious and time-consuming process. [3]

[1] Amelia Holcomb and Connor Tannahill are with the David Cheriton School of Computer Science, University of Waterloo, 200 University Avenue, Waterloo, Ontario, Canada N2L 3G1.

[1] `https://developers.google.com/ar`

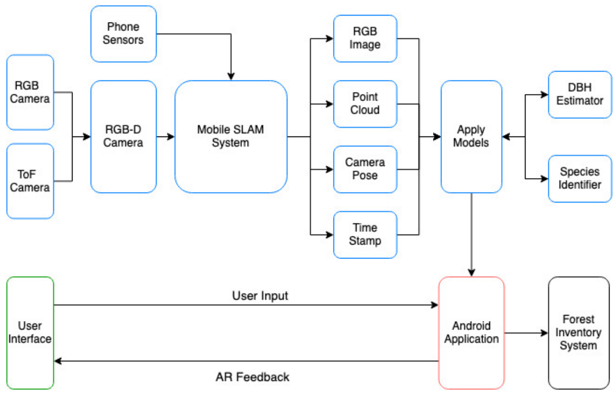

Fig. 1: Proposed system for automated inventories for carbon sequestration forestry projects.

3) **Measure carbon stocks** Tree allometry establishes equations that relate tree biomass to carbon sequestration. Tree biomass is estimated based on DBH and height, and is often refined based on species information (used for wood density). DBH measurements are typically performed either by measuring tree circumference and dividing by π, or using specialized calipers that fit around the trunk [7]. Height can be measured using only a meterstick and trigonometry, but surveyors often use technical equipment such as a hypsometer. Haglöf is a trusted brand, whose devices were used for ground truth in, for example [8]. Top-of-the-line all-in-one devices are around £1500, though there are cheaper models for around £300.[2] Species identification is done manually by field experts.

In addition to the standard manual approach recommended by the IPCC, recent years have seen technology automate and expand various forest inventory tasks. Terrestrial and Aerial Laser Scanning (TLS and ALS), usually with Hyperspectral and LiDAR scanners, are used for tree species, forest area, and biomass estimates, as discussed in the review by Liang et al [9]. These methods are able to cover large areas of ground much more quickly than traditional manual approaches, but they can be quite expensive and physically bulky, with most systems mounted on a vehicle or small aircraft. In addition, ALS is not able to penetrate the forest canopy.

III. Proposed System

Our proposed system attempts to balance affordability and convenience to users while adhering to, and potentially exceeding the current standards for MRV in forest carbon sequestration projects. The system is outlined in Figure 1. The core of the proposed system is an Android mobile phone equipped with a ToF camera. ToF cameras are a reasonably low-cost hardware solution for accurate distance measurements at close range (up to 4 m), which work similarly to LiDAR by measuring the round-trip travel time of an emitted laser pulse. [10]. ToF cameras offer better accuracy and robustness over standard computer vision techniques for depth estimation. A noteworthy benefit is robustness to occlusion, which is a major source of error for standard computer vision techniques [11]. ToF cameras have been shown to be effective for agriculture and forestry applications [12] [10]. High-end smartphones[3] are increasingly adopting ToF technology to enhance image quality and improve the performance of Augmented Reality (AR) applications.

Smartphones equipped with ToF cameras can be used as low-cost MLS systems to create RGB-D point cloud representations of a scene. In the context of forest carbon sequestration projects, these point clouds can be used to reconstruct the morphology of trees and estimate standard features such as DBH and height in real time. This data can also be stored to facilitate more detailed offline analysis. As Liang et al. note of the more expensive LiDAR systems, "TLS has been shown to be capable of determining high-quality tree attributes that are important but are not directly measurable in conventional forest inventories, such as stem volume and biomass components (total, stem and branches), with accuracy levels that are similar to the best national allometric models." [9]

For our work, we were inspired by the system proposed by Fan et al. in [10], which made use of an Android device equipped with supplementary sensors to use the now-deprecated Project Tango Augmented Reality (AR) [13]. These supplementary sensors included a ToF camera for depth estimation, and the authors applied their system to estimate the DBH and height of trees in real time while providing AR feedback to the user through a mobile UI. Additionally, the authors made use of Project Tango's mobile Simultaneous Localization and Mapping (SLAM) system in order to create an accurate map of the forest plot.

A SLAM system offers localization and tracking that is both more precise than GPS and not GPS-dependent. In a mobile phone, it uses available sensors such as the accelerometer, gyroscope, camera, and depth (ToF) sensor to keep track of relative motion and continuously build a map of the surrounding environment. It is commonly used in Augmented Reality applications, especially for handling indoor navigation where a GPS signal is weak and insufficiently precise. Google's ARCore has built in SLAM support.

The key insight of Fan et al. – the possibility of using SLAM within a forest inventory MLS system – offers two major opportunities for improved forest inventory technology. First, as the authors note, Global Navigation Satellite Systems such as GPS can be fairly inaccurate in forest environments [10]. However, position mapping is still key to accurately delineating plots, especially with the need to re-identify the same plot, and even the same tree, year after year. SLAM could provide a strong alternative to GPS in this context. Second, SLAM has the potential to help create spatially coherent RGB-D point clouds, taking into account relative location between subsequent image captures as well as camera pose. This could yield accurate 3D reconstructions of individual tree morphology within the plot as a whole.

[2]Sample devices can be found at `forestrytools.com.au`

[3]Around £800 for an unlocked phone, though the price point may come down as ToF cameras are standardized.

Such a dataset would be incredibly valuable for offline analysis, permitting more detailed measurements than are typically available from forest inventories and opening up the possibility of efficiently combining terrestrial and aerial datasets.

While the work in [10] meets several of the aims that our system, there are several areas where it can be improved to make it more effective for forest inventories. We have identified a few of these:

- **Less specialized hardware**. The work in [10] made use of Project Tango, which required specialized smartphones with sensors not commonly available on other commercial devices. Our proposal only relies on devices with ToF cameras that are ARCore compatible. It is expected that ToF cameras will become increasingly popular on high-end android smartphones and it is expected that these devices would be supported by ARCore, as AR is one of the primary motivations for their inclusion.
- **Robustness to occlusions**. The previous work only considers timber forests. Many forests are full of branches, low ferns, and shrubs, among other things, which can complicate measurements of tree features. Segmentation techniques could be used to isolate relevant parts of the tree of the RGB-D point cloud, such as the trunk or crown. Plant segmentation more generally was considered in [14], which details several methods that have been successful in the past.
- **Tree species identification**. Allometric equations for calculating tree biomass (used in carbon sequestration estimates), are often refined by tree species [7]. Species estimation for plants is a well-researched area, with [15] covering some modern approaches. Deep neural networks trained to perform semantic segmentation on RGB images of plants, with per-pixel species classification, currently achieve the best benchmark scores. With the rich RGB-D point cloud data generated by our proposed system and a specific focus on tree species, we may be able to improve these classifications. The review [16] indicates some progress with machine learning semantic segmentation using RGB-D data, however progress is hampered by lack of sufficient training data, especially for outdoor scenes.
- **Integration of MLS and ALS Data Sets**. ALS systems are highly efficient in surveying large forest areas and are commonly used for large scale national forest inventories [17]. As ALS systems can only observe the forest canopy, there is a large body of research using this incomplete data to estimate quantities such as forest biomass and species composition. However, land survey data is required to create, validate, and improve these models. A SLAM-equipped MLS system can efficiently generate ground-based data and accurately localize it to the level of individual trees, allowing integration of ground-based and aerial data sets. This provides an opportunity to significantly improve the aerial models by increasing the coverage and detail of training data while reducing costs.

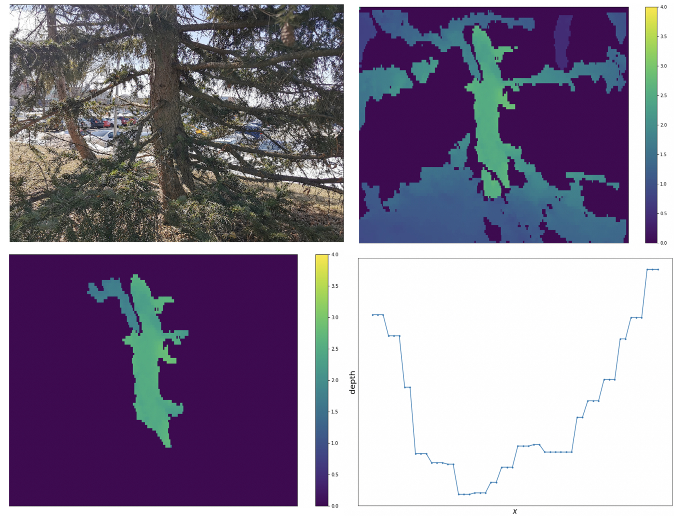

Fig. 2: *Top left:* Photo of sample with branches obscuring the tree trunk, making DBH estimation less straightforward. *Top right:* Depth map obtained from the ToF sensor. *Bottom left:* Segmented depth map. *Bottom right:* Depth values obtained from the ToF camera for the sample at approximately breast-height. Note that points outside the range of the ToF senor are assigned depth 0.

IV. Current Implementation and Experimentation

Of all of the components of our system, the most vital requirement for consistency with existing forest carbon measurement is obtaining accurate and unbiased DBH. We created an Android application to capture depth point clouds,[4] from which we can estimate DBH. We implemented this system of a Huawei P30 Pro smartphone, which is equipped with a ToF sensor and is Google ARCore compatible.[5] Though we did not implement a full integration with ARCore, the application is able to share its camera, allowing the ARCore system to continue to use the camera for pose and position estimation.

We collected images of five trees around a university campus setting, with varying trunk diameter and levels of branch occlusion, standing around 1-2 meters away from the trunk. For ground truth, we used a measuring tape around the circumference of the tree at breast height, divided by π. To estimate tree diameter, we (1) segmented the image to isolate the tree trunk and (2) transformed the image coordinates to obtain real-world measurements. We discuss each below.

[4] In the future, we expect to be able to capture RGB-D images, however we learned that the phone cannot simultaneously use an RGB camera and a ToF camera. The ToF camera emits light in order to measure depth, which interferes with the RGB camera. As a result, the capture requests to the two cameras must be carefully interleaved, which we were unable to finish during a short research time frame. This limitation is not fundamental.

[5] https://developers.google.com/ar/discover/supported-devices

Sample	Measured DBH	Estimated DBH	% Error
1	21.3	19.6	7.9%
2	16.1	15.9	1.3%
3	3.9	3.9	2.7%
4	46.6	43.5	6.6%
5	29.5	28.3	4.2%

TABLE I: Comparison of measured DBH values for sample trees with DBH values estimated using a ToF sensor generated depth map.

A. Image Segmentation

In order to compute the tree diameter, we first identified the boundaries of the tree trunk in the image. We used k-means segmentation from skimage, based on the algorithm in [18]. We set a low compactness parameter (0.001) because the tree figure is long and extends radially in different directions. Figure 2 shows the segmentation result for our most heavily obscured tree sample. We also tried simple Otsu thresholding [19], but we found that this fails in the face of almost any occlusions. In our supervised k-means segmentation, we manually selected the segment identified by k-means that corresponded to the tree trunk. In future work, we may want to try other types of supervised segmentation, or try seeding the segmentation with boundaries from a non-linear algorithm such as a Canny edge detector [].

B. Diameter Estimation

To estimate real-world tree diameter based on image coordinate pixels, we transformed pixel coordinates to world coordinates using the intrinsic camera parameters provided by the Android Camera API. Note that this transformation only yields proportional values; the real-world depths from the ToF sensor give us the correct scale factor. This would not be possible using only one image from an RGB camera.

We made the simplification that the picture was taken with the phone held straight at roughly breast height (though the camera pose could instead be estimated from the phone sensors). This means that the diameter is along the pixel scanline that lies halfway up the image. We compute the diameter, D, as

$$D = \sqrt{(x_l - x_r)^2 + (d_l - d_r)^2}$$

where x is the x-coordinate of the left and right endpoints of the trunk diameter, and d is their respective depth values. Our results are displayed in Table I; we are able to obtain below 8% error in all five samples, including under heavy branch occlusion. In future work, we may want to try fitting a circle or oval to the depth values and taking images from multiple angles to obtain a denser point cloud.

V. Conclusion

Inspired by the urgent global need for carbon sequestration and the limitations of existing protocols for forest carbon MRV, this paper brings together the fields of computer science and forestry to develop a mobile forest inventory system. We propose improvements to the cutting edge of prior work by using less specialized hardware, robustly handling occlusion, adding automatic tree species identification, and integrating MLS and ALS datasets. We prototype a first iteration of this system and show its potential at accurately measuring key forest inventory metrics even in the face of leaf and branch occlusion.

References

[1] "Land use: Policies for a Net Zero UK," Tech. Rep., Committee on Climate Change, Jan. 2020.

[2] "The Woodland Carbon Code scheme for buyers and landowners," .

[3] "UK Woodland Carbon Code," .

[4] Richard S Mbatu, "REDD+ research: Reviewing the literature, limitations and ways forward," *Forest Policy and Economics*, vol. 73, pp. 140–152, Dec. 2016.

[5] Julia Grimault, Valentin Bellassen, and Igor Shishlov, "Key elements and challenges in monitoring, certifying and financing forestry carbon projects," Tech. Rep. 58, Institute for Climate Economics (I4CE), Paris, Nov. 2018.

[6] "Good Practice Guidance for Land Use, Land-Use Change and Forestry," Tech. Rep., Intergovernmental Panel on Climate Change, 2003.

[7] Bastienne Schlegel, Jorge Gayoso, and Javier Guerra, "Manual de Procedimentos para Inventarios de Carbono en Ecosistemas Forestales," Tech. Rep. D98I1076, Jan. 2001.

[8] Tomáš Mikita, Přemysl Janata, and Peter Surový, "Forest Stand Inventory Based on Combined Aerial and Terrestrial Close-Range Photogrammetry," *Forests*, vol. 7, no. 8, pp. 165, Aug. 2016.

[9] Xinlian Liang, Ville Kankare, Juha Hyyppä, Yunsheng Wang, Antero Kukko, Henrik Haggrén, Xiaowei Yu, Harri Kaartinen, Anttoni Jaakkola, Fengying Guan, Markus Holopainen, and Mikko Vastaranta, "Terrestrial laser scanning in forest inventories," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 115, pp. 63–77, May 2016.

[10] Yongxiang Fan, Zhongke Feng, Abdul Mannan, Tauheed Ullah 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*, vol. 10, no. 11, pp. 1845, Nov. 2018.

[11] Richard Szeliski, *Computer Vision: Algorithms and Applications*, Texts in Computer Science. Springer International Publishing, 2 edition, 2010.

[12] Wajahat Kazmi, Sergi Foix, Guillem Alenyà, and Hans Jørgen Andersen, "Indoor and outdoor depth imaging of leaves with time-of-flight and stereo vision sensors: Analysis and comparison," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 88, pp. 128–146, Feb. 2014.

[13] Eitan Marder-Eppstein, "Project Tango," in *ACM SIGGRAPH 2016 Real-Time Live!*, Anaheim, California, July 2016, SIGGRAPH '16, p. 25, Association for Computing Machinery.

[14] Teja Kattenborn, Jana Eichel, and Fabian Ewald Fassnacht, "Convolutional Neural Networks enable efficient, accurate and fine-grained segmentation of plant species and communities from high-resolution UAV imagery," *Scientific Reports*, vol. 9, no. 1, pp. 1–9, Nov. 2019, Number: 1 Publisher: Nature Publishing Group.

[15] Kenta Itakura and Fumiki Hosoi, "Simple and effective tool for estimating tree trunk diameters and tree species classification," *Applied Optics*, vol. 59, no. 2, pp. 558–563, Jan. 2020.

[16] Yuxing Xie, Jiaojiao Tian, and Xiao Xiang Zhu, "A Review of Point Cloud Semantic Segmentation," *arXiv:1908.08854 [cs, eess]*, Sept. 2019, arXiv: 1908.08854.

[17] Joanne C. White, Nicholas C. Coops, Michael A. Wulder, Mikko Vastaranta, Thomas Hilker, and Piotr Tompalski, "Remote Sensing Technologies for Enhancing Forest Inventories: A Review," *Canadian Journal of Remote Sensing*, vol. 42, no. 5, pp. 619–641, Sept. 2016, Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/07038992.2016.1207484.

[18] Radhakrishna Achanta, Appu Shaji, Kevin Smith, Aurelien Lucchi, Pascal Fua, and Sabine Süsstrunk, "SLIC Superpixels Compared to State-of-the-Art Superpixel Methods," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 11, pp. 2274–2282, Nov. 2012, Conference Name: IEEE Transactions on Pattern Analysis and Machine Intelligence.

[19] Nobuyuki Otsu, "A Threshold Selection Method from Gray-Level Histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62–66, Jan. 1979, Conference Name: IEEE Transactions on Systems, Man, and Cybernetics.