Development of the augmented reality app for forestry application: ForestAR

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Keywords: Forestry, LiDAR, Point Cloud, Augmented Reality, Visualization.

Abstract

Augmented Reality (AR) is being widely applied across various fields, seamlessly integrating with real-world scenarios. In forestry, there is significant potential for the use of AR to improve our understanding of the datasets along with the physical environment of the surroundings. Remote Sensing is a powerful technology that generates highly accurate datasets, with Light Detection and Ranging (LiDAR) Remote Sensing technology being particularly effective in creating geometrically precise point cloud datasets. By integrating LiDAR datasets with AR applications, we can unlock numerous benefits. For one, the development of AR technologies in forestry can significantly improve the visualization, monitoring, management, and education of forest ecosystems by providing immersive digital experiences. This paper aims to demonstrate the potential of an AR application for visualizing different configurations of Terrestrial Laser Scanners (TLS) and Classified Point Cloud (CPC) of a forest plot. Such an AR approach offers a unique way to comprehensively examine forest structures. It also allows for the effective recreation, visualization, and presentation of an interactive environment of forest areas.

1. Introduction

In forest remote sensing, significant advancements have been made in the development of various sensors, leading to more accurate and detailed data collection. These technological innovations have played a crucial role in enhancing our ability to visualize, monitor, and manage forest ecosystems effectively. Light Detection and Ranging (LiDAR) is one such advanced remote sensing technology that produces precise and geometrically accurate point cloud datasets. This representation of complex structures in three-dimensional space can be further utilized to extract different tree parameters (Aijazi et al., 2017).

Virtual forest visualization has emerged as a highly sought-after and valuable approach to understanding forest structure complexity. Virtual forests demonstrate great potential for forest visualization, monitoring, and analytics (Holm and Schweier, 2024), (Murtiyoso et al., 2024). One recent innovation in this field is the development of Augmented Reality (AR) applications that visualize complex datasets, such as LiDAR point cloud data, integrating them with the surrounding physical environment. AR presents a good opportunity for forest owners and land managers to simulate, test, and compare various management strategies before making any decisions. By leveraging this AR technology, decision-makers can visualize potential outcomes of different management approaches, such as thinning, selective logging, afforestation, or conservation practices, within a virtual environment. This capability allows them to assess the long-term impacts of their decisions (Peedosaar et al., 2019). Case studies using AR are being used for educational purposes to create forest classrooms to make the students better understand the different components of forest environments (Rai et al., 2022) (Singh et al., 2023).

Not only forest management strategies, but also forest restoration efforts and activities can be visualized through the AR app, and depending upon the tree growth and current situations in the field, new locations can be mapped and allocated, e.g. for future plantations (Luna et al., 2022). With regard to biodiversity, habitat trees could also be mapped efficiently (Jung et al., 2020). Additionally, real-time measurement of individual tree metrics using AR technology has now become feasible (Wu et al., 2023). AR apps are also being developed to measure Diameter at Breast Height (DBH) and tree position using Simultaneous Localization and Mapping (SLAM) technology (Yan et al., 2023). However, there is still a lot of scope for development to improve the accuracy and make the AR environment more sustainable.

Here, we present an AR-based application specifically designed to visualize LiDAR point cloud datasets obtained from different Terrestrial Laser Scanner (TLS) configurations along with Classified Point Cloud (CPC) in dense forest environments. This supports the users in exploring the structure of the forest as captured in various scanning configurations. The end goal is to provide users with a better understanding of the forest through interactive visualization. We demonstrate a prototype of the application that operates on mobile devices, utilizing an AR Software Development Kit (SDK) to visualize point cloud data from different forest data collection schemes using TLS. For the development of this AR application, we utilized TLS point cloud datasets from the Slovakia region, incorporating a total of six different scanning configurations and CPC datasets for visualization.

This paper is divided into different sections and organized as follows. First, we discuss related work in the domain of forestry, visualization, and AR. Next, we describe our research motivation and objective. Then, we present our forest point cloud datasets and present our methodology, followed by results and discussion. Finally, we present the limitations and conclude the paper along with future scope.

2. Research Motivation and Objective

The primary objective of this paper is to present the potential of an AR app in forestry applications, specifically in relation to forest visualization, monitoring, and management. We visualize the different configurations of TLS datasets in a forest plot, to show how these configurations can affect the overall dataset, and analyze the extent of coverage within the forest plot. We also focus on visualizing different components of the forest structure through an AR app. By assessing the user experience and the accuracy of the AR visualizations, we aim to understand the benefits and challenges of integrating AR with LiDAR remote sensing technology in forest environments.

3. Methodology

3.1 Dataset

The forest point cloud datasets used were considered from the same forest plot that was used in the previous research, which is located in central Slovakia (Kushwaha et al., 2022), (Kushwaha et al., 2023a), (Kushwaha et al., 2023b). In addition, AR app development was tested on different point densities to make it compatible with the hardware and software system. We used a total of seven point cloud datasets, all of which corresponded to the same forest plot. Six of the point cloud datasets were obtained from six different TLS configurations, namely (a) Center Scans (CS), (b) Four Corners Scans (FCS), (c) Four Corners with Center Scans (FCwCS), (d) Four Sides Center Scans (FSCS), (e) Four Sides Center with Center Scans (FSCwCS), and (f) All Nine Scans (ANS) as shown in Figure 1.

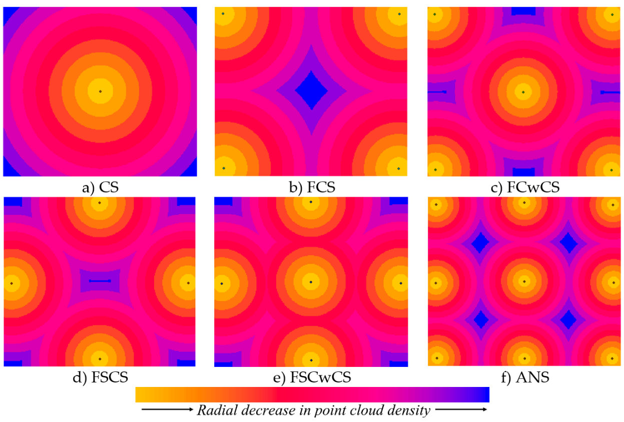


Figure 1. Different TLS scan configurations (a) Center Scans (CS), (b) Four Corners Scans (FCS), (c) Four Corners with Center Scans (FCwCS), (d) Four Sides Center Scans (FSCS), (e) Four Sides Center with Center Scans (FSCwCS), and (f) All Nine Scans (ANS) (Kushwaha et al., 2023b).

The ANS configuration dataset from which Classified Point Cloud (CPC) was obtained is shown in Figure 2 for visualization through the AR app. The forest plot had 49 trees in the range of 576 meters and 611 meters in elevation. The forest point cloud based on elevation color is shown in Figure 2.

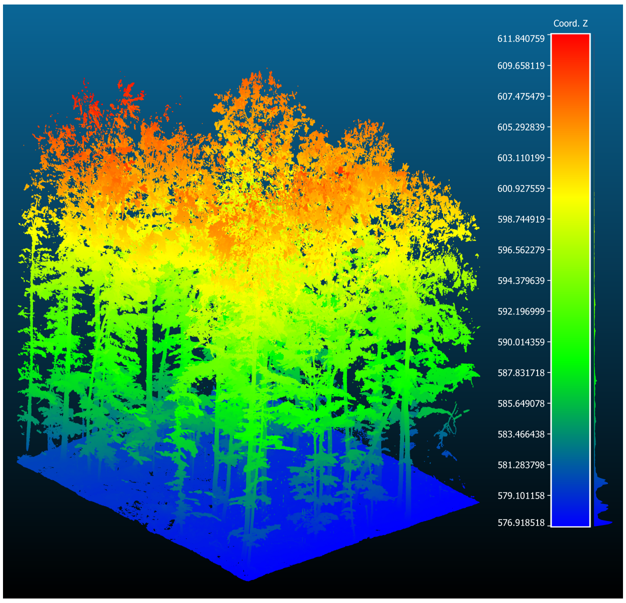


Figure 2. Overview of the forest point cloud data shown as per the height (Mean Sea Level) (Kushwaha et al., 2022).

3.2 Workflow

To develop the ForestAR application, we began by identifying the data set that would be suitable for AR-based visualization. Point clouds collected using TLS in the field are extensively used to gather accurate 3D information about the forest structure. We utilize the dataset (Section 3.1) with different scanning configurations (Figure 1) that illustrate the context captured through the TLS survey and process the data to reveal semantic information about the forest. These TLS scan configurations are crucial in identifying which type of TLS positioning is suitable for collecting different Levels of Detail (LOD) of the forest structure. The TLS datasets are pre-processed to align each individual scan and generate point clouds from all 6 configurations required for the research. The processed point clouds have positional information on the points and intensity values in addition to other information like return number, point ID, scan angle, etc. For the development of the prototype of the AR application, we focused on processing the point clouds to filter out noise points and crop the point clouds to a defined plot size (25m x 25m). We also classified the overall scan configuration, i.e., ANS, which is the point cloud, prepared by combining all the 9 TLS scanning positions using the FSCT algorithm (Krisanski et al., 2021) and referred it as CPC. To visualize and perform basic processing on the point cloud datasets, CloudCompare software was used (CloudCompare, 2024).

Once we have all the 7 point cloud datasets ready for the app development, namely CS, FCS, FCwCS, FSCS, FSCwCS, ANS, and CPC, we move towards the decimation of the point clouds. Point clouds collected using a TLS survey usually have a huge number of points ranging from tens of thousands to hundreds of millions, depending upon the scanning parameters. Such large amounts of data pose a lot of problems, such as high computation and rendering capability. Since we are developing an application that can run on handheld mobile devices like Android phones, which have limited processing power, reducing the point cloud size becomes vital so that mobile devices can handle

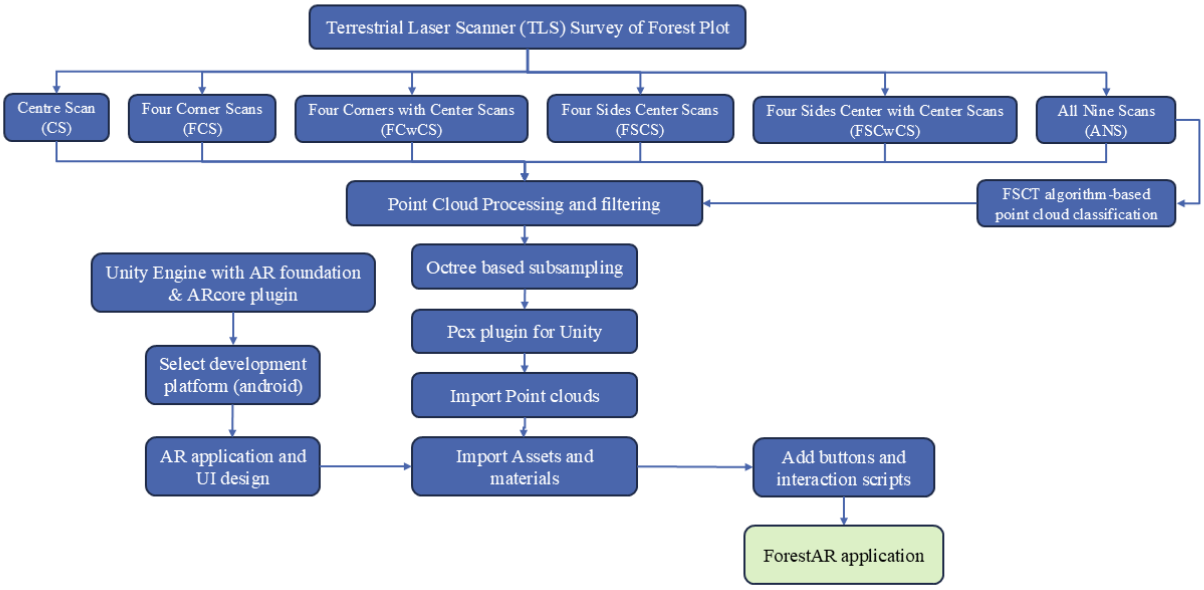


Figure 3. ForestAR App development workflow.

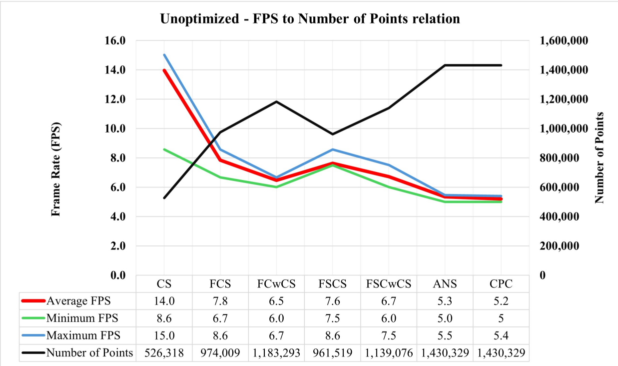
the dataset. We perform octree-based subsampling (Schnabel and Klein, 2006) for the point clouds to reduce the point counts while preserving the geometrical information. We used octree-based sub-sampling as it efficiently partitions 3D space, reduces memory usage, and speeds up computations. Its capability to adapt to point density while preserving geometric details is better than uniform or random sampling. The hierarchical structure of octree allows for multi-resolution representation, making octree-based sub-sampling ideal for large-scale 3D data like TLS scans. Since the point clouds will be used for our AR application, we can also remove the global transformation applied to the point cloud, as this information will only contribute to increasing the size of the point clouds. We translated all 7 point clouds from a global to a local coordinate frame by offsetting each point cloud by the same distance on each axis. This step makes the coordinate values stored in point cloud data smaller and more user-friendly.

The next step is to set up a game engine, e.g., Unity Game Engine environment (Unity, 2021) for AR-based application development. For this, we use a package manager to install AR foundation along with the ARcore plugin since we are developing an application for an Android device. We also need to switch the development platform and select Android. The ARcore plugin is the SDK, which allows us to track and render virtual content on the display device to experience AR content. For this research, we decided to choose a markerless AR experience as it voids the need for printing and keeping a defined marker over which virtual content will be tracked. Instead, in a markerless AR experience, the virtual objects are tagged to an imaginary horizontal plane and tracked using the features or key points present in the environment. After the development environment is set up, we design the User Interface (UI) and scene for the AR application by adding buttons and scripts to control the interaction with the AR content. We also need to import the point cloud datasets prepared earlier. To import and handle the rendering of point cloud data in Unity, we use the Point Cloud Importer/Renderer (Pcx) package (Takahashi, 2019). Each point cloud is imported to Unity using the Pcx importer and converted to a prefab. This lets us handle each point cloud to spawn and control the interactions individually. We also define the rendering settings with Pcx to render points as circles or squares with different sizes. We attach the interactive buttons with scripts to define the desired results, such as increasing or decreasing the size of the virtual asset or moving or destroying it. Once ready, we deploy the Forest AR application to Android devices for testing and interacting with it in an immersive AR experience. The overall research methodology followed throughout this research is shown as a workflow in Figure 3.

4. Results and Discussion

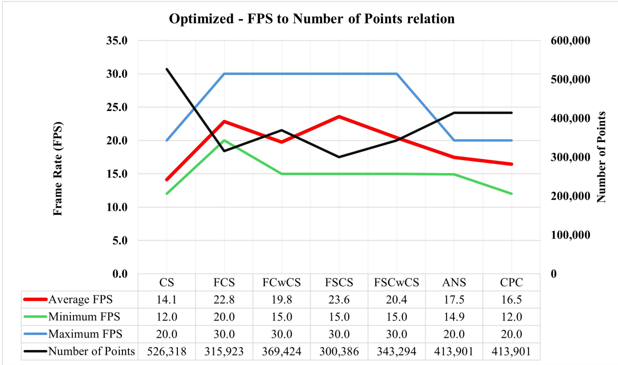
4.1 Performance Assessment and Optimization of the AR Application

We have evaluated the performance of the AR application for visualization of point cloud data of the forest plot. Point cloud data recorded using TLS are huge in size. Such data is extremely heavy, even for high-performance processing units to handle. Thus, to ensure that the AR application provides an immersive experience while having optimal performance, it is necessary to eliminate the redundant points in the data while maintaining the accuracy of the data and saving the crucial information to minimize the computational burden. We performed an assessment to figure out the average performance in terms of Frames Per Second (FPS) under different conditions with varying numbers of points in the data used for visualization. The mobile device used for this assessment was a Samsung Galaxy S10 lite with Android 13 running on a Qualcomm SM8150 Snapdragon 855 (7 nm) chip and 8 GB RAM. Since the performance is relative to the processing power of the



	CS	FCS	FCwCS	FSCS	FSCwCS	ANS	CPC
Average FPS	14.0	7.8	6.5	7.6	6.7	5.3	5.2
Minimum FPS	8.6	6.7	6.0	7.5	6.0	5.0	5
Maximum FPS	15.0	8.6	6.7	8.6	7.5	5.5	5.4
Number of Points	526,318	974,009	1,183,293	961,519	1,139,076	1,430,329	1,430,329

Figure 4. The FPS values obtained correspond to the original number of points in the dataset (unoptimized).



	CS	FCS	FCwCS	FSCS	FSCwCS	ANS	CPC
Average FPS	14.1	22.8	19.8	23.6	20.4	17.5	16.5
Minimum FPS	12.0	20.0	15.0	15.0	15.0	14.9	12.0
Maximum FPS	20.0	30.0	30.0	30.0	30.0	20.0	20.0
Number of Points	526,318	315,923	369,424	300,386	343,294	413,901	413,901

Figure 5. The FPS values obtained correspond to the sub-sampled number of points in the dataset (optimized).

chip, the results shown for the device mentioned are in this experiment. The objective was to identify the maximum number of points that can be rendered while maintaining a stable FPS between 20-30, ensuring a smooth, immersive experience. The performance evaluation involved loading point clouds with different sizes in an AR environment and recording the FPS. We recorded the number of points rendered with the FPS values at every second. The analysis of the FPS with different numbers of points in point clouds revealed that the number of points rendered at a time is inversely proportional to the FPS, which means that if we use a large number of points, the FPS drops significantly. Figure 4 shows the original number of points in the point cloud and the minimum, maximum, and average FPS that was achieved while experimenting to figure out the maximum number of points that the device can handle for optimal performance. We can see that for CS configuration with 526,318 points, the average FPS is 14, whereas, for ANS configuration, the average FPS drops to 5 FPS.

From the analysis, we deduced that for the AR application running on our device, if the point cloud has more than 500 thousand points, the average FPS is 14, which is still at the lower end; hence, to achieve optimal performance, we needed to decimate the point clouds with the number of points less than 500 thousand. Since the data used for this experiment was decimated using an octree-based subsampling with subdivision level 9, for optimal performance, we decimated the point clouds with subdivision level 8 and performed the assessment again. Figure 5 shows the improvement in performance. Since we used subdivision level 8, the number of points in the Center scans was reduced to a mere 171,577 from 26,273,459. This reduction in the data caused the loss of important information, so we used the point cloud with octree subdivision level 9 with 526,318 points. More details on the exact number of points obtained for each dataset at different levels of sub-sampling are presented in the Appendix section (Table 1). We identify that using the subsampled point clouds reduces the number of points in the range of 400 thousand points, and we achieve a stable performance with an average FPS close to 20, which is a great improvement from the previous unoptimized case where the FPS was very low. We also noticed that the minimum and maximum FPS for the center scan with the same number of points as the previous experiment has also drastically improved due to a reduction in the overall size of the points that were loaded in the application, although the average FPS remains the same in both cases. We also noticed that the FSCS, which had 300 thousand points, showed optimal performance with a 24 FPS average, which was the best among all the point clouds. This shows that our device can handle point clouds with 300 thousand points efficiently with a stable 24 FPS. Beyond this threshold, the frame drop and rendering lag are prevalent, indicating the computational limits of the device. This approach and analysis helped in identifying the trade-off between visual fidelity and real-time responsiveness of the AR application to maintain immersivity.

Figure 5, shows the sub-sampled number of points in the point cloud and the minimum, maximum, and average FPS that was achieved.

4.2 Visualisation of Different TLS Configurations through AR App

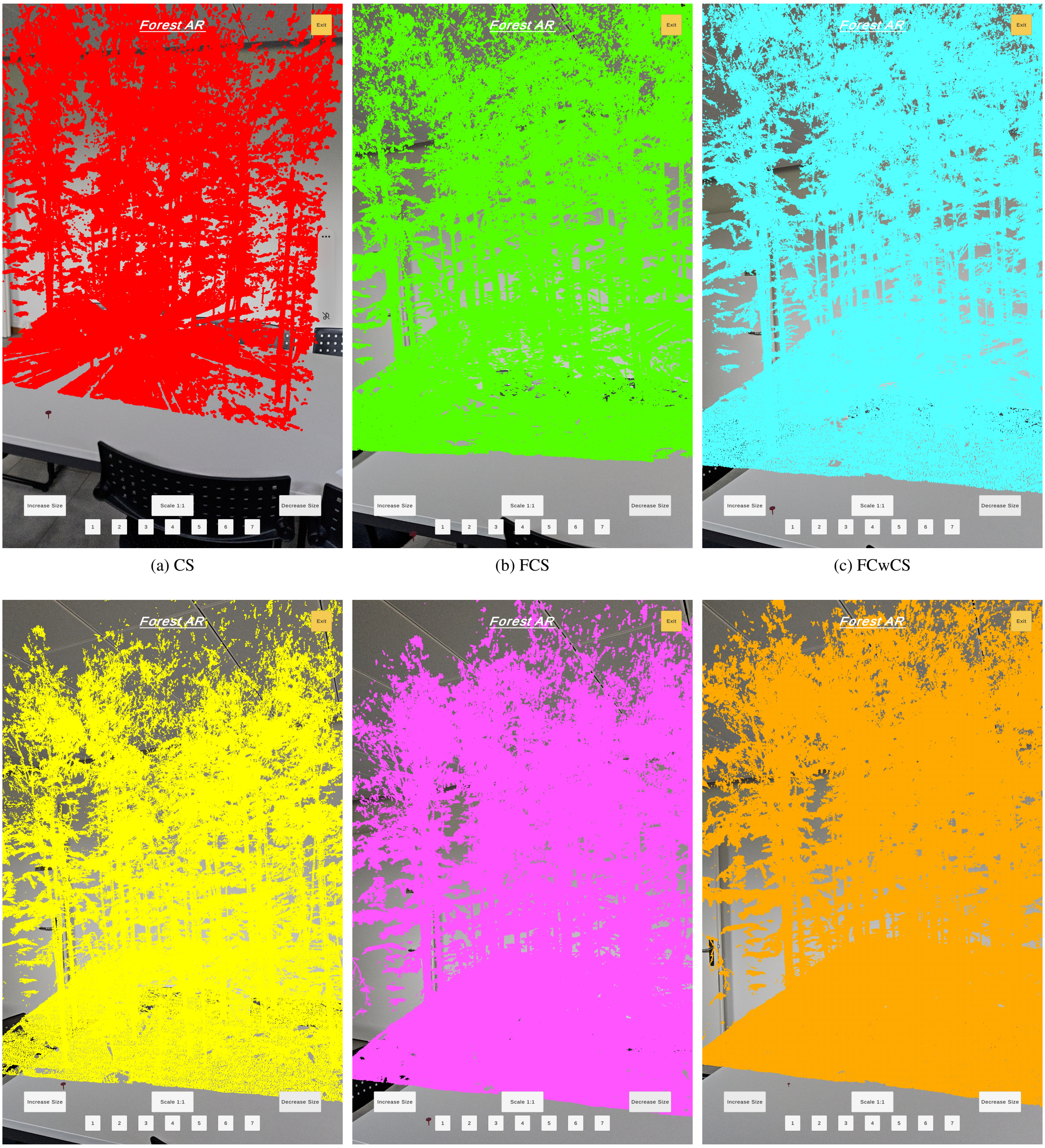
Different TLS scanning strategies impact data quality and coverage, thereby assisting forest managers in making well-informed decisions regarding optimal data collection configurations. Once the outline of the AR app was created, different buttons were used to visualize all six different TLS configurations. Visualization through AR app highlights the transformative potential of AR technology in forestry applications, particularly in understanding and optimizing TLS data collection processes through direct visualization of point cloud characteristics and distribution patterns. The visualization of CS (Red), FCS (Green), FCwCS (Magenta), FSCS (Yellow), FSCwCS (Pink), and ANS (Orange) configurations through the AR app is shown in Figure 6.

4.3 Visualisation of Classified Forest Plot through AR App

The overall forest point cloud obtained from the ANS scan configuration was classified using the FSCT algorithm (Krisanski et al., 2021). The different classes obtained from the classification were stem (red), canopy (green), terrain (violet), and dead wood (yellow) points (Kushwaha et al., 2023a). The classified forest point cloud along with labels, as visualized through the AR app, is shown in Figure 7.

4.4 Visualisation of Classified Forest Plot at Different Scales through AR App

While visualizing through a mobile AR application, the environment can be indoor or outdoor, depending upon the conditions, needs, and preferences. It is more efficient to visualize the datasets at multiple scales as needed by the user. The CPC dataset visualized through the AR app at different scales is shown in Figure 8.



(a) CS (b) FCS (c) FCwCS

(d) FSCS (e) FSCwCS (f) ANS

Figure 6. Forest point cloud dataset used for the AR app development (Kushwaha et al., 2022).

5. Limitation

TLS data collected in forestry is huge in size, and such data pose memory management issues when deployed on handheld mobile devices for rendering in an AR app. Transformation of the point cloud from a global to local coordinates frame also results in loss of geographic information. To render the forestry point cloud data, we need to bargain between the data quality and size of the data to display while maintaining the immersive experience. Better hardware or optimization algorithms to render and handle large point cloud data can solve the problem of reduction of FPS in the AR experience. We also experienced that using a handheld letterbox-style device limits the user’s perception of a truly immersive experience. With the rise in technological advancements in head-mounted AR glasses, we may see great results in this domain. Like all computer vision-based tracking, the marker-less AR experience illustrated in this research is also highly dependent on the features present in the environment, which can be tracked accurately to render the virtual ob-

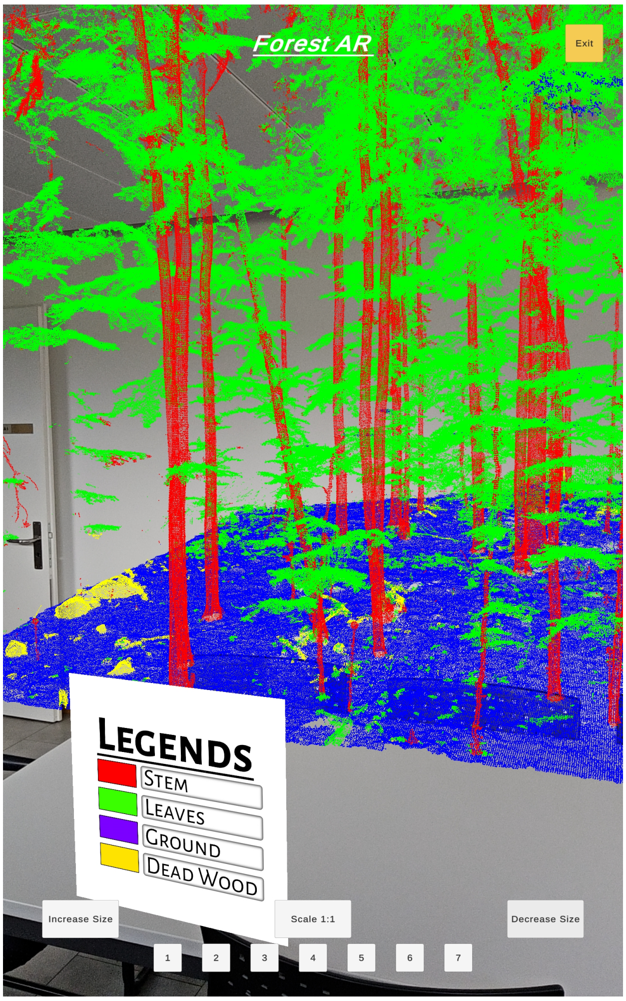


Figure 7. A classified forest point cloud, visualized through the AR app.

jects and keep them positioned at the desired spot. The tracking falters in conditions without trackable features, or the surface or planes are smooth or texture-less. With advancements in deep learning-based tracking approaches, we may be able to achieve even more robust tracking in the coming years.

The assessment of the ForestAR application was done using a single device with an older chipset version. This performance evaluation shows the result on the device at hand during the application development and hence cannot be generalized to other latest chips with better capabilities. The newer versions of chips onboard the latest mobile devices would be able to handle larger data and have better overall performance.

6. Conclusion

We explored the potential of integrating AR technology with LiDAR remote sensing datasets. Our research, involved testing and demonstrating how AR can be effectively utilized to visualize and interact with complex forest point cloud data. Specifically, we examined the impact of different TLS configurations on the overall structure and density of the point cloud dataset representation of a forest plot. Additionally, we developed visualizations incorporating classified forest point clouds, providing an intuitive way to analyze the data. These visualizations included labels representing non-spatial attribute data, allowing

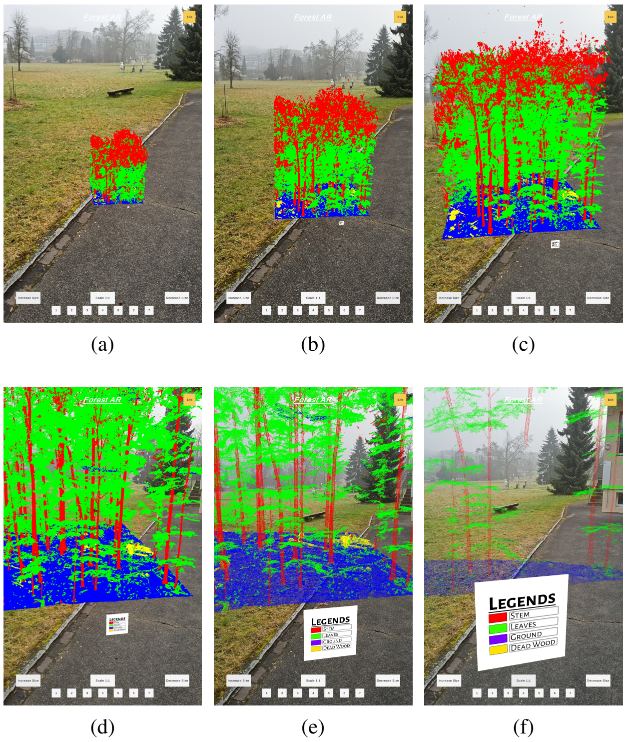


Figure 8. A classified forest point cloud, visualized at different scales through the AR app.

users to interpret various characteristics of forest components in an interactive AR environment.

Throughout the development of the ”ForestAR” application and the integration of TLS point cloud datasets, we encountered several challenges and constraints. These included handling the massive size and complexity of the LiDAR data, optimizing performance, and ensuring seamless interaction within the AR environment. Despite a few challenges, our research highlights the potential of AR as a powerful tool for enhancing the visualization, interpretation, and analysis of forest LiDAR datasets. The performance assessment provided critical insights into the application’s rendering capabilities. By implementing optimization techniques, the AR application was able to sustain a stable FPS, ensuring an interactive and immersive user experience. Developement of these kind of AR apps would definitely help to provide an immersive experience to all the end users.

7. Future Scope

In the future, we aim to expand our study further on AR application development by enhancing its capability to visualize, interact with, and analyze large forest stands in a more immersive and interactive manner. Additionally, we seek to integrate various non-spatial attributes, such as tree species, tree height, DBH, and other relevant forest parameters, into the AR visualization. Incorporating these non-spatial attributes can give users a more comprehensive understanding of the forest’s structure and composition.

Another key aspect of our future work involves visualizing individually segmented trees at a species level within the AR environment. We can enhance the accuracy of individual tree-level visualizations, allowing for better identification and understanding of trees within the forest stand. These advancements will improve the usability of the AR application for researchers, foresters, and educational and environmental professionals. Temporal datasets can be used to observe regular changes through AR visualization, which can help us in more effective forest monitoring and management.

We will perform extensive testing and evaluation of the application and simplify the development process. By incorporating dynamic LOD, we can reduce the computation load on the chip, and we can make the application handle the large point clouds with ease.

Acknowledgment

We thank the European Union (EU) for funding the Horizon Europe project "Digital Analytics and Robotics for Sustainable Forestry" (Digiforest) [101070405] and the Swiss State Secretariat for Education, Research and Innovation (SERI).

The dataset used in this work was supported by grant No. CZ.02.1.01/0.0/0.0/16_019/0000803 ("Advanced research supporting the forestry and wood-processing sector's adaptation to global change and the 4th industrial revolution") financed by OP RDE, by the Scientific Grant Agency of the Ministry of Education, Science, Research, and Sport of the Slovak Republic and the Slovak Academy of Sciences [grant number VEGA 1/0335/20] and by the Slovak Research and Development Agency through Grants No. APVV-18-0305 and APVV-20-0391.

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Appendix

The Link for the ForestAR GitHub repository https://github.com/sunni-kushwaha/ForestAR

		Number of points after octree-based sub-sampling				**Percentage (%) of point cloud reduction**			
Dataset	Original number of points	Level 10	Level 9	Level 8	Level 7	Level 10	Level 9	Level 8	Level 7
CS	26 273 459	1 595 909	526 318	171 577	57 208	6.07	2.00	0.65	0.22
FCS	52 971 311	2 885 846	974 009	315 923	102 835	5.45	1.84	0.60	0.19
FCwCS	79 244 770	3 827 075	1 183 293	369 424	113 605	4.83	1.49	0.47	0.14
FSCS	77 731 677	3 069 899	961 519	300 386	93 885	3.95	1.24	0.39	0.12
FSCwCS	104 005 136	3 789 549	1 139 076	343 294	104 259	3.64	1.10	0.33	0.10
ANS	156 976 447	4 948 556	1 430 329	413 901	121 484	3.15	0.91	0.26	0.08
CPC	156 976 447	4 948 556	1 430 329	413 901	121 484	3.15	0.91	0.26	0.08

Table 1. Different point cloud datasets used for the ForestAR app development along with, actual number of points, number of points after subsampling, percentage of point cloud reduction

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-831-2025