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Data Optimization for Urban Green Space Management

Automated Inventorization of Urban Trees by Converting LIDAR Data to GIS Records

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***Abstract*— This study introduces a method for automatically identifying trees, including their diameters and heights, from readily available LIDAR satellite data and converting the information into compact GIS records. This approach streamlines urban park and green area inventory processes by reducing data storage requirements from gigabytes to kilobytes. Combining machine learning with geospatial analysis, the method enhances efficiency in managing urban green spaces while supporting sustainable development and environmental monitoring. The case study demonstrates its effectiveness and potential for broader applications in urban planning.**

***Keywords*— geospatial analysis; remote sensing; LIDAR satellite data; GIS; urban green space; environmental monitoring; tree recognition**

I. INTRODUCTION

Urban green spaces, such as parks and recreational areas, play a pivotal role in enhancing the quality of life in cities by improving air quality [1], mitigating the urban heat island effect [2,3], and providing spaces for recreation and social interaction [4,5]. These green spaces not only support biodiversity and ecological balance but also contribute significantly to public health and well-being. Effective management and conservation of urban green spaces depend on the availability of accurate, up-to-date inventories of trees and vegetation. Traditionally, these inventories are compiled through field surveys, which, while providing highly accurate data, are often time-consuming, labor-intensive, and not suitable for large-scale or continuous monitoring.

In response to these challenges, remote sensing technologies have emerged as a promising alternative for gathering detailed and spatially extensive data on vegetation. Among these technologies, airborne LIDAR (Light Detection and Ranging) has proven to be particularly useful due to its ability to capture high-resolution three-dimensional data of the Earth's surface. LIDAR systems can measure various tree attributes, such as height, canopy structure, and spatial distribution, with impressive accuracy, making it an ideal tool for vegetation analysis across large urban areas. However, the large volume of raw LIDAR data poses significant challenges in terms of storage, processing, and integration into practical applications. In urban environments, where efficient data management is crucial, this becomes a key obstacle for widespread adoption.

This study proposes a novel approach to overcoming these challenges by automatically recognizing tree attributes, including diameters and heights, from readily available satellite-derived LIDAR data. By converting this information into compact GIS (Geographic Information System) records, this method significantly reduces the size of stored data, enhancing the practicality of LIDAR data for urban park and green area inventories while maintaining a high level of accuracy. This approach aims to streamline the process of urban green space management, making it more efficient and scalable while also ensuring that the data is easily accessible and usable for urban planners and policymakers.

II. LITERATURE REVIEW

The integration of LIDAR data into urban vegetation analysis has seen significant advancements in recent years. Various algorithms, often incorporating machine learning or point cloud processing techniques, have been developed to classify LIDAR points as vegetation, identify individual trees, and estimate their attributes with remarkable precision. Remote sensing data for such analysis can be derived from airborne platforms, including multispectral, hyperspectral, and LIDAR sensors, as well as spaceborne multispectral remote sensing systems [6]. These datasets have been widely utilized in forestry applications [7-11], urban gardening [12], and particularly for the monitoring and planning of urban green spaces [13].

LIDAR's unique ability to penetrate tree canopies and capture the underlying ground surface makes it particularly suitable for tree recognition. By analyzing the 3D information provided by LIDAR data, it is possible to extract detailed tree characteristics such as height, diameter at breast height (DBH), canopy structure, and spatial distribution. For example, one recent study introduced a multi-scale individual tree detection (MSITD) algorithm, which combines both raster-based and point-based approaches to detect individual trees in LIDAR data with high accuracy [14]. Other methods, such as Convolutional Neural Networks (CNN), have also been employed for individual tree detection in urban environments, yielding promising results for large-scale tree recognition and classification [13,15].

Despite the progress made in applying LIDAR data for tree recognition and urban vegetation analysis, many existing methods focus primarily on maximizing accuracy and improving the sophistication of models. However, these approaches often overlook the practical challenges of data size reduction and ease of integration with urban planning tools. The raw point cloud datasets generated by LIDAR systems can be enormous, and while high precision is desirable, the large size of these datasets often makes them difficult to manage and utilize effectively in real-world applications.

Furthermore, most existing systems for tree recognition and classification rely heavily on extensive preprocessing and computational resources, which can be prohibitive for urban planners who require accessible and efficient tools. While GIS remains the primary tool for urban planning and green space management, many of the current methods for tree recognition from LIDAR data do not produce outputs that are easily integrated into standard GIS workflows. This limitation reduces the practical applicability of such methods for urban planning professionals who need user-friendly and scalable solutions for managing urban green spaces.

The need for methods that not only recognize and model trees effectively but also reduce the size of the data and integrate seamlessly with GIS tools is increasingly pressing. By addressing these challenges, tree recognition from LIDAR data can be transformed into a powerful tool for urban planning and management. When coupled with GIS, this technology can enable the creation of detailed and easily navigable digital inventories, facilitating better decision-making in urban forestry, environmental monitoring, and green space planning.

In summary, while significant advancements have been made in tree detection and recognition from LIDAR data, there remains a gap in methodologies that balance accuracy with data efficiency and ease of integration into commonly used planning tools. The proposed approach aims to bridge this gap by providing an effective solution for urban tree mapping that is both accurate and practical for large-scale applications in urban environments.

III. Problem Formulation

Tree parameter recognition methods, based on either laser scanning (LIDAR) or aerial photography, can generally be classified into three categories: raster-based methods, point-based methods, and combined methods [16]. Each of these methods has its strengths and weaknesses depending on the data resolution and the environment in which they are applied. Two critical challenges in tree recognition are:

- Separating individual trees from a group of trees—a task that becomes more complex when trees grow closely together or are obscured by surrounding vegetation.
- Species identification—in urban environments, especially in parks or areas where trees have been artificially planted, determining the species from LIDAR data is notably challenging.

In natural forests, where trees grow freely without interference, it is generally easier to estimate or infer the size and shape of individual trees [17]. However, urban environments present unique difficulties, as trees are often pruned and shaped artificially, leading to distorted or non-natural forms that complicate tree recognition. Furthermore, the urban landscape is typically diverse, with various tree species planted in close proximity, further hindering the ability to distinguish between species based solely on tree crowns.

A. Challenges in Tree Recognition from LIDAR Data

One of the most significant difficulties in tree recognition from satellite LIDAR data arises from the low resolution typically offered by these datasets, which generally ranges between 5 and 15 cm. This resolution is insufficient for detailed analysis of finer features like leaves or branches, making species identification via these characteristics impossible. In this case, recognition is primarily based on the shape and color of the tree crowns.

A common approach in forestry applications to differentiate tree species is the use of machine learning algorithms, such as the Random Forest method [17,18]. These models are trained with sample data that provide known characteristics of tree species, and then applied to classify new trees. However, this approach works best when the species are already known and the task is to differentiate and size them [19]. In urban environments, especially in parks where trees have been planted artificially, there is a greater degree of variability in tree species, making it more difficult to apply the Random Forest method effectively. Additionally, the presence of numerous tree varieties and the artificial shaping of crowns complicate the task. In such cases, larger and more complex sample datasets are required to improve the accuracy of species recognition.

Despite the challenges, LIDAR data has become widely available, with global datasets now accessible for free to cover all of Earth's surface [20]. However, the application of LIDAR data is still limited due to the significant computational resources required to process and visualize it. Regular computer systems used by everyday consumers are often not capable of handling or displaying such large-scale datasets effectively. In the context of urban planning, the typical data needed includes tree size, species, and location, all of which can be extracted from point cloud data.

B. Characteristics and Classification of LIDAR Data

LIDAR data is typically composed of millions of 3D points, each having spatial coordinates along with spectral information. These points are usually classified into categories such as ground surface, vegetation, artificial surfaces, and buildings. The precise classification can vary depending on the dataset and the methods used for processing [21]. For tree recognition, the classified vegetation points represent the most relevant data, as shown in Figure 1, where trees are included under the category of "High Vegetation."

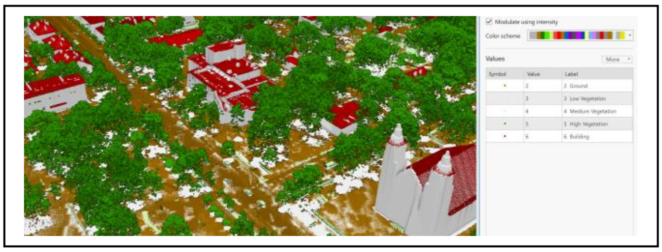

Fig. 1. *Classified LIDAR points (trees appear under category "High Vegetation").*

In urban environments, trees can be categorized into several types based on their spatial arrangement:

- Solitary Trees: These are individual trees that grow separated from other vegetation.
- Lined Trees: These trees are arranged in rows, often forming alleys or lining streets.
- Grouped Trees: These trees grow closely together, forming dense clusters.

The most complex tree group to recognize and separate is the grouped trees, where individual trees are difficult to distinguish due to overlapping crowns and interlocking branches. In such cases, the methods used to divide the group into separate trees may vary depending on species, the volumetric size of the group, and other environmental factors. Unfortunately, no method can guarantee 100% accuracy when attempting to separate these groups, making this step one of the most challenging in the tree recognition process.

C. *GIS Integration and Visualization*

Geographic Information Systems (GIS) are widely used in urban planning and management, allowing for the efficient handling and visualization of spatial data [22]. While LIDAR data can be visualized in GIS, its high computational requirements make it impractical for everyday use by urban planners or citizens. Most GIS software used for town planning comes with built-in 3D tree symbols that allow for the visualization of trees in their environment, along with their crown types.

In GIS, trees are typically represented by point features with associated attributes such as crown height, width, and species. With LIDAR data, the tree crown form can be recognized and assigned to one of the standard tree crown types, enabling more effective visualization.

By converting LIDAR data into actionable GIS records, urban planners gain a comprehensive understanding of the trees within their jurisdiction. The ability to visualize this data quickly and easily reduces the need for storing large amounts of raw data. This makes the process more efficient, improves urban tree management, and ensures that all relevant information about trees—such as their size, species, and location—is readily available for decision-making.

IV. METHODOLYGY

Tree Recognition from LIDAR Data: Step-by-Step Process

The process of recognizing trees from LIDAR data involves several key steps that enable accurate extraction of tree attributes while ensuring compatibility with GIS systems. These steps include data filtering, segmentation, attribute extraction, classification, and record creation. Below is an expanded and detailed description of each stage:

A. *Filtering LIDAR Points for Vegetation and Ground Surface*

The first step in tree recognition involves filtering the LIDAR data to isolate points representing vegetation and ground surfaces while discarding other categories, such as buildings and artificial structures. This is typically an automated task performed within GIS software, which classifies LIDAR points based on their spectral and spatial properties. By narrowing the dataset to vegetation points, this step ensures that only relevant data is processed in subsequent stages, reducing computational requirements and improving efficiency.

B. *Separating Points for Individual Trees and Tree Groups*

The next step is to segment the filtered vegetation points into individual trees and tree groups. This can be achieved using tools like the Treeiso MATLAB plugin [23]. During this process, tree clusters are categorized as either linear groups or massive groups:

- Linear Groups: These are common in urban settings, where trees are planted in rows along streets, pathways, or buildings. Trees in linear groups are typically evenly spaced, making them easier to separate and identify individually.
- Massive Groups: These consist of densely packed trees, often found in parks or natural green areas. Segmenting massive groups into individual trees is more challenging due to overlapping canopies and irregular growth patterns. Typically, larger and taller trees are located in the center of the group, and their crowns can be sized relative to the group's overall height. Trees in such groups tend to grow taller and narrower than solitary trees, adding to the complexity of this task.

Accurately dividing tree clusters into individual trees remains a significant challenge, especially for massive groups, and requires advanced algorithms that consider spatial relationships, crown overlap, and height variations.

C. *Extracting Tree Attributes from 3D Crown Points*

Once individual trees or tree groups are identified, the 3D points representing each tree's crown are analyzed to extract key attributes. These include:

Tree Height: Measured as the vertical distance from the ground to the highest point in the crown.

Maximum Crown Radius: The largest horizontal distance from the tree's center to the edge of its crown.

Crown Volume: Estimated based on the distribution of points within the crown.

Crown Form Code: A text-based representation of the tree's crown shape, derived from radii measured at regular intervals (e.g., every 2 meters). For instance, the text line: "5.17/5.17/4.75/4.23/3.93/3.52/2.81/2.07/0.67" encodes the crown's form in Figure 2.

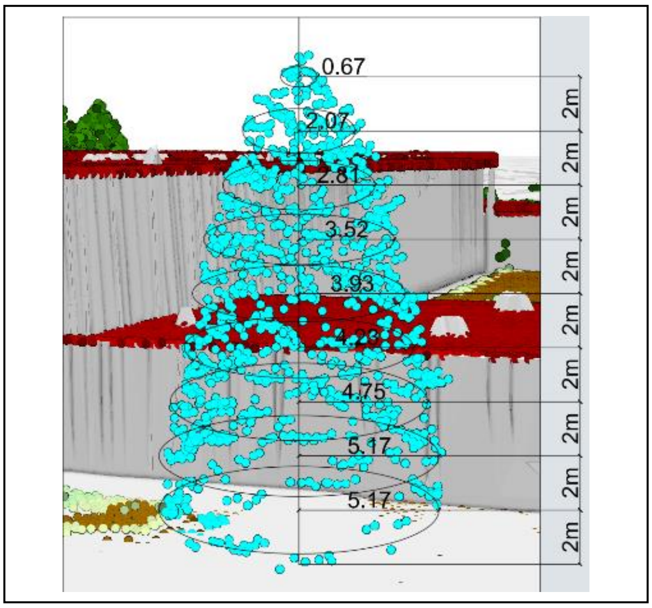

Fig. 2. *Tree crown form data is represented in a text line showing radiuses in 2m steps.*

This crown form code can also serve as input for deep learning algorithms trained to recognize tree species. However, urban environments present unique challenges:

Tree species in urban areas are often highly diverse, even within small regions. Many urban trees have artificially pruned or shaped crowns, making species recognition more difficult. In such cases, the crown form code is more practical for visualization purposes than species identification.

D. Assigning Tree Forms and Classifications

Using the extracted crown form code, trees can be categorized into predefined crown shapes (see Figure 3). These standard forms are commonly used in GIS-based 3D symbology, facilitating accurate visual representation and easy integration into urban planning workflows.

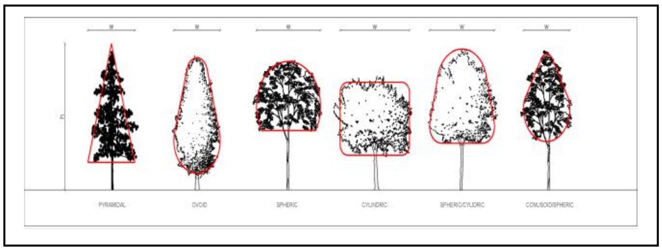

Fig. 3. *Tree crown types.*

E. Creating GIS Records for Tree Data

The final step involves converting the extracted tree data into GIS-compatible records. Each tree is represented as a point feature, with its longitude and latitude coordinates marking the trunk position on the ground. While this trunk position may not be entirely accurate for asymmetrical trees, it provides a practical approximation for GIS applications.

Each point feature includes attributes such as tree height, crown radius, crown volume, and species or crown form code. These compact GIS records eliminate the need to store vast amounts of raw LIDAR data, making visualization and manipulation of tree data both fast and efficient.

Benefits for Urban Planning

With this processed data, urban planners gain access to a comprehensive digital inventory of trees within the urban environment. This allows for:

- Rapid visualization and assessment of tree locations and attributes.
- Streamlined integration into existing GIS workflows.
- Significantly reduced data storage requirements, as gigabytes of raw LIDAR data are condensed into kilobytes of useful information.
- By automating and optimizing the tree recognition process, this method enhances urban green space management and supports data-driven decision-making for sustainable urban development.

V. CASE STUDY

For this case study, we selected a 500x500-meter LIDAR scan data rectangle of Zarasai, a verdant small town in Lithuania, Europe. The chosen area encompasses the town's main square, streets lined with planted trees, smaller rows of decorative trees in the central park, and several naturally occurring groups of trees. This diversity of vegetation types offered an ideal testbed for evaluating the performance of our tree recognition methodology.

The LIDAR data, provided in LAS format, was sourced from a state-authorized institution's online platform, geoportal.lt. Once unarchived, the dataset's size amounted to 429 MB. The data included classifications into categories such as ground surface, buildings, and vegetation (as detailed in Figure 1). To isolate tree-specific data, the classified vegetation points were extracted into a separate LAS file for further processing.

Initially, the extracted data was processed using the Treeiso MATLAB plugin [23], which grouped the points into potential tree clusters. While this step successfully separated some trees, it often failed to divide densely packed tree groups into individual entities. This limitation was particularly evident in areas with naturally grown trees, where overlapping canopies made segmentation more complex.

To address this issue, the data underwent additional processing using Python, specifically the segment_lidar library. While this step improved the segmentation to some extent, it still resulted in errors, particularly with densely vegetated areas. The inability to reliably separate individual trees within large clusters remains a significant limitation of the current method.

This segmentation challenge highlights the need for more sophisticated algorithms tailored to urban environments, where trees often grow in irregular patterns and form complex clusters. Future improvements could involve integrating advanced logic-based rules, such as combining tree height, crown dimensions, and spatial distribution patterns, to enhance the accuracy of segmentation.

Despite these challenges, the case study provided valuable insights into the strengths and weaknesses of the proposed method. While the approach performed well in areas with solitary or evenly spaced trees, further refinement is needed to improve its effectiveness in segmenting densely grouped trees. These findings underscore the importance of algorithm development for applications in urban green space management, where accurate tree inventory is critical for effective planning and conservation.

TABLE I. GIS ATTRIBUTE TABLE EXAMPLE

Id	*R*	*Volume*	*Sub_form*
1	6.82	83.97	*"6.81/7.42/….*
2	4.21	25.18	*"4.15/4.21/….*
3	5.34	45.67	"5.29/5.34/...
……			
5567	3.45	18.23	"3.10/3.20/...
5568	3.92	21.34	"3.57/3.72/...

The results of the analysis were saved in GIS shapefile (SHP) format, a widely used standard for geospatial data. Visualization of the processed data was conducted using ArcGIS 3.4 Educational version. While this software is powerful and versatile, it has certain limitations when displaying attributes such as the radius and height of point entities directly. Due to these constraints, only the R (radius) value was used to set the size of the tree symbols in the visualization. As a result, the generated map provided a simplified representation of tree sizes, which did not fully reflect the actual crown dimensions or heights, leading to a less accurate visualization (Figure 4).

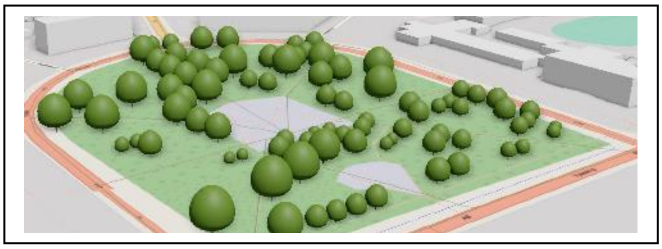

Fig. 4. *Tree recognition result for the main square*

When applied to the remaining territories, the results exhibited variability, primarily due to the aforementioned limitations in accurately dividing tree groups. As shown in Figure 5, densely vegetated areas posed particular challenges, where individual trees within groups were not always correctly segmented. This issue was most evident in parks and areas with naturally growing vegetation, where overlapping canopies and irregular growth patterns complicated the separation of trees into distinct entities.

Fig. 5. *Tree recognition result for the outskirts of the town*

To address these visualization and segmentation challenges in future work, a combination of enhanced tree separation algorithms and advanced GIS symbology could be implemented. For example, incorporating both height and radius into symbol definitions, supported by more detailed classification and segmentation workflows, could improve the representation of urban trees. Such advancements would lead to more accurate visualizations and better support for urban planning and green space management.

VI. CONCLUSIONS

This study presents a streamlined method for recognizing and analyzing urban trees from freely available satellite LIDAR data, offering a practical solution to the challenges of traditional tree inventory methods. By extracting essential tree attributes such as height, diameter, and crown structure, and converting them into compact GIS records, the proposed method bridges the gap between advanced remote sensing technologies and urban planning applications.

A key strength of this approach lies in its ability to significantly reduce data storage requirements, transforming gigabytes of LIDAR data into lightweight, user-friendly GIS datasets. This enables urban planners and policymakers to efficiently manage urban greenery without the need for extensive computational resources. The integration of this method with existing GIS workflows ensures seamless adoption by professionals, while its scalability supports large-scale urban green space monitoring and management.

The case study demonstrated the effectiveness of this approach, although challenges remain, particularly in accurately segmenting trees within dense vegetation groups. Future improvements should include refining segmentation algorithms, addressing inconsistencies in tree grouping, and enhancing tree classification processes using species-specific data. Additionally, the development of more advanced artificial intelligence techniques, such as deep learning, could enhance the identification of tree species and crown types even in urban environments where tree morphology is highly variable due to artificial shaping.

Beyond its technical contributions, this study highlights the potential for combining remote sensing data with geospatial tools to support sustainable urban development. By providing an accessible, efficient, and scalable solution, the proposed method empowers urban planners to make informed decisions about green space management, biodiversity conservation, and climate adaptation. Its application in diverse urban settings ensures that cities can better adapt to the challenges of rapid urbanization while maintaining the ecological and social benefits provided by urban greenery. This approach offers a significant step forward in leveraging cutting-edge technologies for smarter, greener cities.

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