Developing Computer Vision-based Digital Twin for Vegetation Management Near Power Distribution Networks

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Abstract –

The rapid development of digital twin technology has opened new avenues for infrastructure management, particularly for addressing vegetation encroachment risks near power lines. This paper builds upon our previous work in LiDAR-based proximity detection by proposing a framework for creating digital twin for vegetation management near power distribution networks. The framework leverages the RandLA-Net model for semantic segmentation of power lines, poles, and vegetation followed by clustering and rule-based thresholding for data refinement. Detecting vegetation encroachment is achieved through KDTree-based spatial analysis, ensuring efficient identification of risk zones. The segmented and processed point cloud data is then transformed into detailed 3D models, forming the basis of the digital twin, which can be enhanced in the future by adding advanced semantic attributes and predictive tree growth models, enabling proactive vegetation management. The methodology is demonstrated through a case study, highlighting its potential to enhance operational efficiency and the resilience of power distribution networks.

Keywords –

Digital Twin, Computer Vision, 3D Point Cloud, Power Lines, Semantic Segmentation, Vegetation Management

1 Introduction

Vegetation encroachment near power lines is a critical issue that threatens the reliability and safety of power distribution networks. Approximatively 40% of the distribution outages are caused by vegetation. Power outages often happen when vegetation is exposed to severe weather conditions [1]. Traditionally, vegetation management has relied on manual inspection, which is labor-intensive, time-consuming, and often limited in accuracy and frequency. This highlights the need for automated solutions capable of delivering accurate, consistent, and cost-effective monitoring. Advancements in sensing technologies, such as Light Detection and Ranging (LiDAR), and machine learning algorithms have significantly improved vegetation management processes [2]. LiDAR's ability to capture high-resolution 3D spatial data enables precise detection of vegetation and its proximity to power lines, surpassing the capabilities of traditional 2D imaging or visual inspection. However, the vast volume of data generated by LiDAR systems presents computational challenges, particularly in efficiently segmenting and classifying power lines, poles, and vegetation. Semantic segmentation models have been pivotal in overcoming these challenges, offering high-accuracy classification of large-scale point clouds [3].

On the other hand, digital twin technology provides a novel framework for addressing these challenges by enabling the creation of dynamic virtual replicas of vegetation and power distribution networks. Digital twins integrate real-world data with advanced modeling and analytical capabilities, offering several benefits, including the potential to model the dynamic behavior of trees, such as growth patterns, movements under loads, and responses to environmental factors like wind [4, 5]. This capability is further enhanced by incorporating additional attributes such as tree type and age, allowing for predictive and adaptive management strategies. Additionally, digital twins facilitate improved asset management for utility poles and power lines by integrating attributes like material type, age, and condition, enabling comprehensive and data-driven maintenance planning.

In our previous work, we demonstrated the application of RandLA-Net for vegetation segmentation and proximity detection, achieving improved accuracy and operational efficiency [6]. Building on this work, the present study advances these efforts by developing a digital twin for vegetation management near power distribution network. By leveraging 3D models derived from LiDAR data, this study aims to enhance the identification and management of vegetation risks near power lines. The proposed framework integrates refined segmentation, clustering methods and proximity analysis, supporting proactive maintenance strategies and real-time operational insights. The contributions include an integrated framework for accurate risk detection, a digital twin with 3D models, and a scalable solution that can be used for improving the resilience of distribution networks, as well as for managing the assets of these networks. The paper is structured as follows: Section 2 reviews existing works on digital twins based on point cloud analysis. Section 3 describes the proposed framework. Section 4 presents the implementation of the framework. Section 5 discusses findings and future directions, while Section 6 concludes the paper and outlines potential areas for further research.

2 Related Work on Digital Twins Based on Point Cloud Data

Digital twins can be used for assessing risks and managing vegetation near power lines. These models leverage point cloud data to create detailed 3D models, enabling precise monitoring of spatial relationships between trees and infrastructure.

Surface reconstruction is a critical step in translating raw point cloud data into usable 3D models. Techniques such as Delaunay triangulation and KD-tree (k-dimensional tree) indexing, as highlighted by Glumova and Filinskih [7], have proven effective for generating high-quality meshes from unstructured data. Similarly, Ismail et al. [8] explored methods like Poisson Reconstruction and Ball Pivoting Algorithm, focusing on their adaptability and simplicity for applications like building modeling in digital twins. Tagarakis et al. [9] emphasized maintaining geometric accuracy during mesh generation, which is vital for capturing intricate details like tree branches critical for proximity assessments. Chen et al. [10] proposed integrating dynamic simulation data to enhance mesh precision, offering better insights into environmental interactions and vegetation growth.

Alignment of point cloud data with pre-existing models is facilitated by advanced matching algorithms. Zhang and Li [11] utilized simulation tools such as Blender and the Grove plugin to model tree growth under various environmental conditions, ensuring accuracy through comparisons with LiDAR-derived ground truth. Gobeawan et al. [12] extended this by introducing species-specific growth models, precisely aligning these models within spatial constraints derived from point clouds to represent biological and structural tree characteristics effectively.

Digital twins offer continuous monitoring and risk assessment capabilities for power line management. Buonocore et al. [13] demonstrated their use in predicting vegetation growth and simulating environmental impacts, such as weather events, to mitigate risks.

Kim et al. [14] introduced a framework integrating semantic segmentation, geometric processing, and data export into CityGML, streamlining the generation of accurate indoor models from point clouds. Other researchers, such as La Guardia and Koeva's [15] developed interactive 3D web navigation model. Wu et al. [16] proposed a precision alignment method for CAD data to enhance digital twin applications in urban and industrial contexts. Agapaki and Brilakis [17] proposed a deep learning approach for matching point cloud clusters with CAD models. Li et al. [18] developed GRNet framework for 3D object detection and demonstrated the potential of digital twins in diverse infrastructure scenarios. While digital twins have been proposed in urban modeling, existing studies lack an integrated framework that combines LiDAR-based segmentation with digital twin modeling for vegetation management.

3 Proposed Framework

This study extends our prior work [6], where we developed a computer vision framework for managing vegetation near power lines, employing the Random Sampling in Large-scale Point Cloud Analysis Network (RandLA-Net) [19] for semantic segmentation of large-scale 3D point clouds. This framework also included post-processing techniques such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [20] for object isolation and rule-based thresholding to filter urban elements and mitigate noise. Furthermore, a proximity detection method was utilized to assess potential risks by analyzing spatial relationships between vegetation and power lines in urban settings. Building on this framework, the current study enhances and integrates these processes into a comprehensive digital twin framework tailored for vegetation management near power distribution networks. The extended framework advances the previous work by creating detailed, dynamic 3D models of power lines, poles, and vegetation using LiDAR data. These models facilitate continuous monitoring and risk assessment, aligning with the concept of a digital twin. Figure 1 shows the proposed integrated framework, where the segmentation and post-processing pipeline serves as the core data processing engine, while the new components enable the generation of the digital twin for enhanced decision-making and management capabilities.

(1) Semantic Segmentation: The RandLA-Net model [19] is employed for segmenting LiDAR point clouds into key classes such as power lines, poles, and

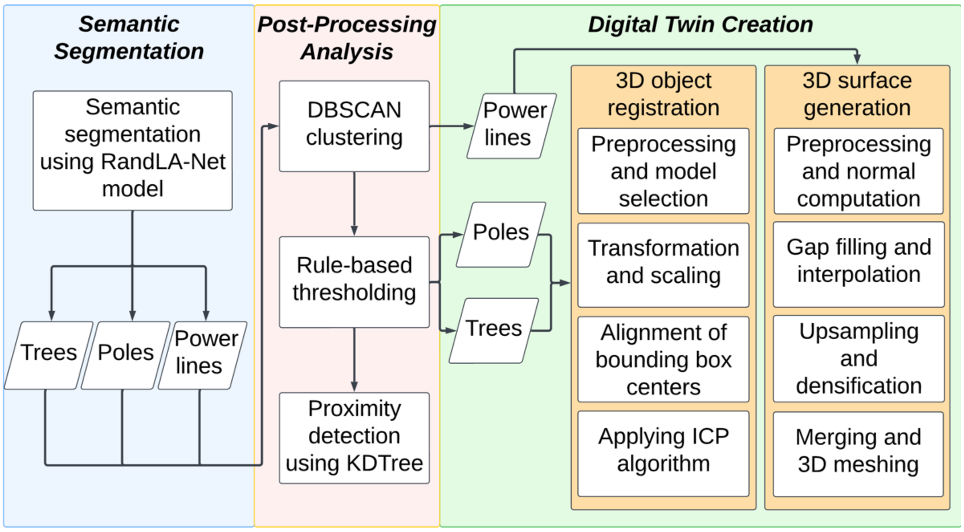


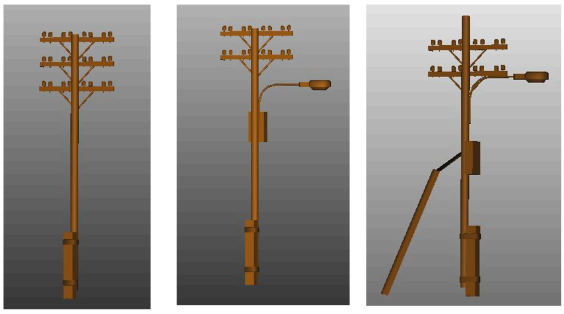
Figure 1. Proposed framework

vegetation, leveraging its efficiency in processing high-density data. This model is chosen for its ability to achieve high accuracy on large-scale datasets, including its notable performance on the Toronto-3D dataset, where it demonstrated superior overall accuracy compared to other methods. RandLA-Net employs random point sampling for downsampling, significantly reducing computational overhead while preserving critical geometric details within the point cloud. Its architecture integrates innovative components, including a local feature aggregation module, comprising local spatial encoding and attentive pooling, which effectively captures complex local structures. Additionally, its use of shared Multilayer Perceptrons (MLPs) and dilated residual blocks enhances both processing speed and scalability, enabling it to handle up to one million points per iteration efficiently. To evaluate the model's performance, the Intersection over Union (IoU) metric is utilized, providing a robust measure of the overlap between predicted and ground truth classifications for each class.

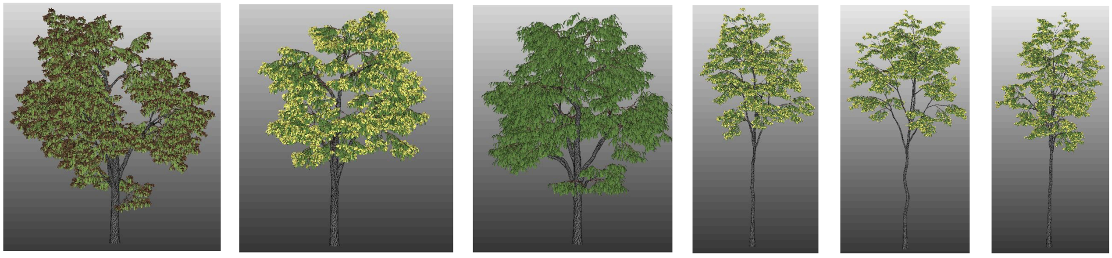
(2) Post-processing: Following the segmentation process, the output data undergoes a series of post-processing steps to enhance its accuracy and utility. DBSCAN algorithm is employed to identify clusters within the segmented point cloud, leveraging its capability to detect clusters of varying shapes and densities without requiring predefined cluster counts. Key parameters, such as epsilon and minimum samples, are carefully tuned to suit the complex structure of urban environments, ensuring sensitivity to variations in density and distribution. Complementing DBSCAN, rule-based thresholding is applied to further refine the output, using class-specific thresholds, such as height and point count, to isolate critical features like trees and poles while effectively filtering noise and irrelevant data. To evaluate proximity risks, that could cause the encroachment of vegetation on power lines, a K-Dimensional Tree (KDTree) structure is used for efficient spatial querying. This approach allows for rapid identification of the nearest tree to each power line, leveraging the KDTree's capacity for efficient multi-dimensional space queries. Proximities are then compared against safety thresholds to flag potential hazards. However, the current proximity detection and risk assessment rely on static conditions, which limits their ability to account for dynamic environmental factors such as wind, tree movement, or weather changes.

(3) Digital Twin Creation: This study employs a systematic approach to construct a seamless representation of power lines, poles, and trees from segmented point cloud data, using Python for 3D data handling and analysis. For power lines, the process begins with importing the segmented point cloud, representing discrete points corresponding to power line geometry. To estimate normal vectors and curvature at each point, a k-nearest neighbor (KNN) search algorithm (K=10) is applied, balancing efficiency and accuracy in densely populated regions. Normal vectors are calculated by fitting a plane to the nearest neighbors, with curvature derived from deviations of neighboring points from the fitted plane, enabling precise modeling of intricate power line geometries. To address data gaps in the segmented point cloud, Radial Basis Function (RBF) interpolation is used for its effectiveness in reconstructing missing points while ensuring smooth, continuous outputs. Additionally, upsampling is employed to achieve uniform point density, enhancing the resolution and accuracy of power line representation.

For poles and trees, segmented point cloud data are aligned with reference 3D models sourced from libraries like Sketchfab [21] and CGTrader [22], assuming all



(a) Examples of poles 3D models



(b) Examples of trees 3D models

Figure 2. Poles and trees libraries

trees belong to the Honey Locust species, which is common in Canada. Figures 2 (a) and (b) show examples of the poles and trees libraries, respectively). The Iterative Closest Point (ICP) algorithm is used for alignment, iteratively refining transformation parameters (translation, rotation, and scaling) to minimize discrepancies between the segmented objects and reference models. Bounding box centers of segmented objects and reference models are aligned for accurate spatial placement, while a scaling step is included to adjust for size differences by computing and applying appropriate scaling factors based on bounding box dimensions. This process involves initializing alignment parameters, applying an initial transformation matrix, and iteratively refining alignment to ensure better matching of the model, location, and size.

4 Implementation

The implementation of the proposed framework builds upon the methodologies discussed earlier, extending the capabilities established in previous work to realize a comprehensive digital twin system for vegetation management near power distribution networks. The process was executed in the following stages:

(1) Data Acquisition: This study utilized the Toronto-3D dataset [23], a high-density point cloud dataset collected via Mobile Laser Scanning (MLS) along a one-kilometer stretch of Avenue Road in Toronto, Canada. The dataset, consisting of approximately 78.3 million points with an average ground point density of 1,000 points per square meter, is particularly suited for capturing intricate details of urban environments. Each data point includes attributes such as XYZ coordinates, LiDAR intensity, RGB reflectance, GPS time, scan angle, and class labels, which classify features like roads, trees, poles, power lines, and buildings. The dataset's high density and comprehensive labeling make it ideal for semantic segmentation tasks in this study. Preprocessing steps involved grid subsampling at a 0.06-meter resolution to balance data volume and feature retention. Additionally, projection indices were generated to map processed results back to the original dense point cloud, ensuring consistency and accuracy. These preparations provided a well-structured dataset optimized for semantic segmentation and further analysis. Figure 3 shows point cloud data of a sample area.

(2) Semantic Segmentation: The RandLA-Net model was trained and optimized using the Toronto-3D dataset, focusing on the segmentation of vegetation, poles, and power lines. The training process involved dividing the dataset into sections for training and testing, with three sections designated for training and one for evaluation. The model underwent 100 epochs of training using the Adam optimizer with an initial learning rate of 0.01, which decreased by 5% per epoch to improve convergence. A batch size of 4 was selected to balance computational efficiency and training performance.
Training was conducted over 124 hours and 33 minutes on a workstation equipped with an NVIDIA RTX A6000 GPU and a 48-core CPU, ensuring high computational power for processing the dense point cloud data. However, the inference time takes about 10 minutes. The model incorporated geometric features along with RGB

Figure 3. A sample area of point cloud data

and intensity attributes to enhance segmentation accuracy. To ensure optimal model performance, various configurations of RandLA-Net were tested on the Toronto-3D dataset. This involved systematically exploring different combinations of hyperparameters to evaluate their impact on classification and segmentation accuracy. The best-performing configuration from these tests was selected and utilized in the subsequent stages. The test results demonstrated high IoU scores for individual classes, achieving 97.05% for trees, 87.44% for power lines, and 82.33% for poles, ensuring reliable classification for the target features. This robust performance underpins the digital twin framework by providing precise and detailed semantic segmentation of the urban environment.

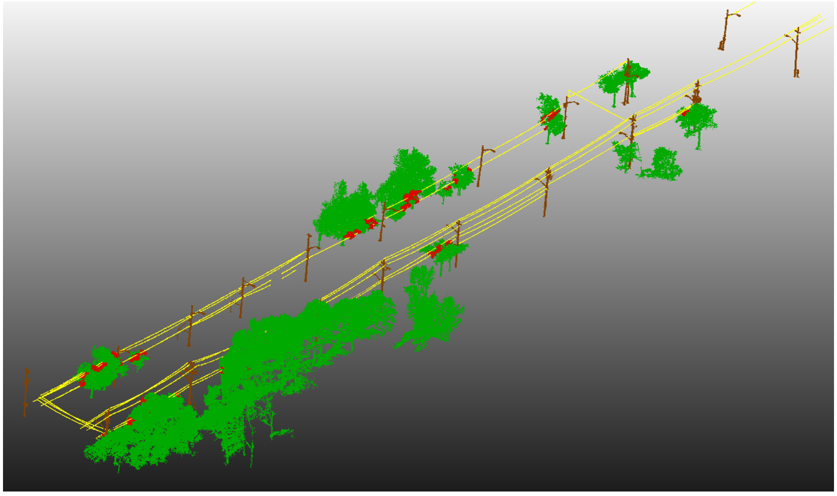
(3) Post-Processing: In the post-processing phase, DBSCAN clustering was utilized to refine the segmented point clouds by identifying and isolating critical features based on spatial density and predefined thresholds for height and point count. Parameters such as epsilon (maximum distance between samples) and the minimum number of samples were carefully calibrated to align with the attributes of the Toronto-3D dataset. Clusters exceeding specific thresholds, such as a height threshold of 8 meters for poles or a minimum point count of 500 points for vegetation, were retained, while irrelevant features and noise were filtered out. This approach ensured that significant urban elements were clearly distinguished for further analysis. To assess proximity risks, KDTree spatial queries were employed to calculate the distances between vegetation and power lines in a 3D space. These distances were compared against a safety threshold (e.g., 1 meter) to identify hazardous tree regions encroaching on power lines. These flagged areas were then prioritized for risk management, supporting effective vegetation maintenance and infrastructure safety. Figure 4(a) shows the post-processed semantic segmentation result, highlighting hazardous tree areas (red points) within the safety perimeter of power distribution lines.

(3) Digital Twin Development: For the utility lines, the implementation of the methodology was carried out using Python and its specialized libraries for point cloud processing. Segmented point cloud data was imported, and a KNN algorithm was applied to compute the 10 nearest neighbors for each point. Normal vectors were calculated by fitting a plane to these neighbors, and curvature was estimated by measuring deviations from this plane. To ensure continuity in the utility lines, RBF interpolation was employed to fill gaps in the point cloud. This process created a seamless structure by reconstructing missing data points. An upsampling step was then applied to increase point density in sparse regions, enhancing the model's resolution and uniformity. Finally, the segmented sections were integrated into a single, cohesive representation, ensuring geometric continuity.

The process for poles and trees involved aligning segmented point cloud data with reference 3D models using Python. Reference models were imported, and alignment began with the initialization of parameters based on approximate geometry and spatial data. A transformation matrix, incorporating rotation, translation, and scaling, was applied for preliminary alignment. The ICP algorithm was then used to iteratively refine these parameters, minimizing alignment errors and ensuring a precise fit. To ensure spatial and size accuracy, the bounding box centers of segmented objects and reference models were aligned, and a scaling factor was applied based on a comparison of their bounding box dimensions. Finally, the geometrical attributes of the created 3D objects are added to these objects. Figure 4(b) illustrates the digital twin model integrating the 3D models of trees, poles, and utility lines derived from the point cloud data.

5 Discussion

Digital twins offer a dynamic, continuously updated virtual representation of power lines, poles, and



(a) Post-processed result of semantic segmentation, highlighting hazardous tree areas near power lines

(b) Digital twin model

Figure 4. Digital twin model based on point cloud data

vegetation, that can be a part of a federated digital twin at the urban level. The work presented in this paper is limited by the fact that the digital twin developed so far is static. However, by integrating diverse data sources, including point clouds, GIS data, satellite imagery, and real-time weather updates, the digital twin can be further developed to provide a high-fidelity, dynamic model for vegetation management near power distribution networks. A critical advantage of this digital twin lies in its ability to simulate and predict how various factors, such as vegetation growth and adverse weather, affect overhead power lines. This predictive capability can be bolstered by deep learning (DL) algorithms, which enable accurate forecasting of vegetation dynamics, offering actionable insights for proactive management [24, 25]. Key attributes such as tree height, canopy spread, and species types are indispensable for evaluating risks to power infrastructure. Tree height helps identify potential threats from vegetation of comparable or greater height than poles, while canopy spread highlights horizontal encroachments even from distant trunks. Species type offers further context, enabling growth pattern predictions and customized maintenance strategies. Incorporating these attributes into the digital twin enhances risk assessment, providing utility managers with a robust framework for mitigating vegetation-related hazards.

Furthermore, this digital twin can integrate weather simulation to assess and address compound risks, such as the interplay of high winds and dense tree canopies, which exacerbate outage probabilities. By analyzing historical weather data and integrating live forecasts, this digital twin can dynamically update risk profiles, enabling timely interventions like proactive pruning or operational adjustments to minimize disruptions. This real-time adaptability transforms network management from reactive to preventive, which can optimize resources [4, 5]. Moreover, this digital twin fosters organizational collaboration by serving as a centralized platform that unifies data across departments. This shared understanding of network conditions enhances communication and aligns teams toward common objectives, such as reliability and resilience. The capacity to simulate the outcomes of various vegetation management strategies, such as modified pruning schedules or low-maintenance species planting, supports sustainable practices that balance operational demands with environmental considerations.

While the creation and maintenance of digital twins require an initial investment, their unparalleled benefits justify the effort. Unlike static models, they provide not only visualization, but also actionable intelligence for strategic planning. For example, predictive growth models informed by species-specific data and environmental conditions (e.g., climate, soil) allow precise forecasts of tree encroachment on power lines. Adopting digital twins also opens avenues for sustainable vegetation management. By optimizing trimming schedules and employing selective pruning techniques, they minimize carbon emissions associated with vegetation maintenance. While traditional methods focus on clearing immediate risks, digital twins enable long-term planning that preserves larger trees while maintaining network safety. This approach aligns utility management goals with environmental stewardship, enhancing biodiversity and urban air quality [26, 27].

6 Conclusions and Future Work

This paper presents an integrated framework for computer vison-based digital twin for power distribution network management, focusing on vegetation management and risk assessment. The framework leverages the RandLA-Net model for semantic segmentation of power lines, poles, and vegetation, coupled with post-processing techniques such as DBSCAN clustering and rule-based thresholding to refine data outputs. Proximity detection using KDTree spatial analysis ensures precise identification of hazardous zones. The processed data is utilized to generate accurate 3D models, forming the foundation of a digital twin. By addressing key challenges such as data segmentation and geometric refinement, the framework enhances proactive vegetation management strategies and contributes to infrastructure resilience. The study demonstrates the potential of integrating computer vision and point cloud data processing techniques for developing digital twins for vegetation management near power distribution networks. The proposed framework effectively combines semantic segmentation, clustering, and proximity analysis to provide detailed 3D models for risk assessment and maintenance planning. The results highlight the scalability and reliability of the approach, offering a practical solution for improving vegetation management and infrastructure safety. These findings represent a significant step toward leveraging digital twin technology for utility management, with potential applications across a wide range of urban and industrial systems.

While the proposed framework offers significant advancements, several limitations remain. The framework has been tested primarily on the Toronto-3D dataset, which may not capture the diversity of urban and rural environments. Future work should involve testing on datasets with varying complexities and characteristics to enhance generalizability and robustness. Additionally, the RandLA-Net model and post-processing techniques, such as DBSCAN clustering and KDTree queries, require substantial computational resources. Optimization efforts are necessary to enable real-time processing and scalability for larger networks, especially in resource-constrained settings.

Beyond these points, as explained in Section 5, additional limitations include incorporating real-time and multi-source data streams, predictive vegetation growth modeling, and sustainability practices. Addressing these topics will be essential to fully realize the potential of the proposed framework for comprehensive risk assessment and more resilient power distribution systems.

Acknowledgments

This research is supported by a grant from Canada First Research Excellence Fund and additional funding from Hydro-Quebec.

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