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GEOMETRIC MODEL OF HYDROPOWER PLANTS: A FOUNDATIONAL STEP TOWARDS CREATING A HYDROPOWER DIGITAL TWIN

Alwyn Mathew[1], Hamidreza Alavi[1], Guangming Wang[1], Yang Su[2], Weiwei Che[2] and Ioannis Brilakis[1]
[1]University of Cambridge, England, United Kingdom
[2]University College London, England, United Kingdom

Abstract

This paper introduces a domain-specific pipeline for generating semantic 3D models of hydropower plants directly from unstructured laser scan data. Unlike conventional scan-to-BIM methods, which are tailored to buildings or industrial facilities, our approach addresses the unique geometric complexity and lack of standardized schemas in dam infrastructure. The pipeline integrates robust point cloud segmentation, semantic labeling, and relationship graph generation to produce a detailed, functional digital twin. This enhances accuracy, supports predictive maintenance, and enables simulation and analysis tailored to hydropower operations, significantly advancing digital twin capabilities in this underrepresented and technically challenging domain.

Introduction

Digital twin is a digital replica of a physical entity, process, or system, created by combining real-time data with a virtual model to reflect the state, behavior, and performance of the physical world (Jones et al., 2020). By enabling simulation, prediction, and optimization, digital twins allow physical systems to be better understood and managed throughout their lifecycle. In the context of building facilities, digital twins typically leverage multidisciplinary technologies such as sensors, the Internet of Things, and Building Information Modeling (BIM) to create a virtual model of the physical building (Sacks et al., 2018). These virtual models continuously collect and update data from the physical building, forming a dynamic digital copy. Extending this concept to critical infrastructure, the digital twin of a dam is a virtual representation developed using digital modeling techniques combined with real-time sensing data that mirrors the physical structure and operational status of the dam. This model supports real-time performance monitoring, risk prediction, and maintenance optimization (Zhu et al., 2023). For instance, data streams such as water level, pressure, and temperature can be continuously monitored to assess structural health and issue early warnings in case of anomalies. In the face of natural disasters or extreme weather, digital twins enable accurate emergency planning by providing real-time data support, ultimately enhancing dam safety and operational reliability.

Geometric modeling plays a fundamental role in creating accurate digital twins, particularly for dams. A precise geometric model ensures that the virtual representation aligns with the physical dam, allowing for structural analysis, stress simulation, and performance evaluation. The geometry also supports visual inspection in the virtual space, enhancing diagnostic and decision-making processes. However, dam geometries are typically complex, comprising irregular shapes, curved surfaces, and heterogeneous materials. These features make modeling from raw data, such as laser scans, particularly challenging. Additional complications arise from occlusions, noise, and data sparsity—especially since dams are often located in remote or environmentally harsh locations, where high-quality 3D data acquisition can be difficult (Zhu et al., 2024).

To address these challenges, this paper proposes a domain-specific pipeline tailored for generating semantic geometric models of hydropower dams directly from unstructured laser scan data. Unlike conventional scan-to-BIM workflows, which assume standardized components and object libraries, our method adapts to the irregular geometries and lack of schema common in dam infrastructure. The pipeline integrates robust point cloud segmentation, surface meshing, and relationship graph generation. This structured semantic mesh not only improves the geometric accuracy of the digital twin but also enables downstream tasks like visualization, basic simulation, and asset monitoring. By focusing on dam-specific complexities and proposing a complete pipeline to address them, this work contributes a practical framework for advancing digital twin technologies (Malihi et al., 2024) in hydropower infrastructure a domain that remains underexplored in current research.

Background

In recent years, significant advancements in point cloud data processing and digital twin technology have emerged for infrastructure monitoring and management. Jurevičius et al. (2022) propose the use of Unmanned Aerial Vehicles (UAVs) equipped with multispectral and RGB cameras to collect high-resolution data, which is then processed to create precise models of coastal changes and dewatered areas. This method not only enhances environmental man-

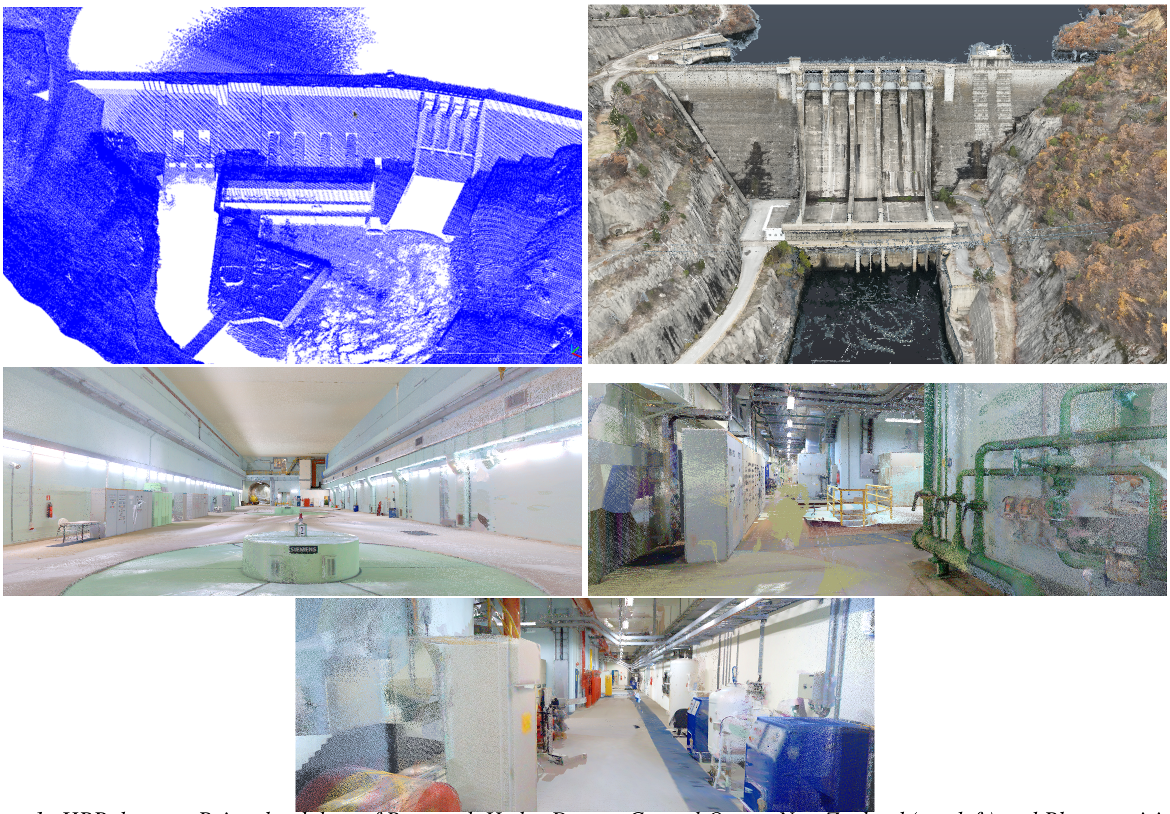

Figure 1: HPP dataset: Point cloud data of Roxgurgh Hydro Dam at Central Otago, New Zealand (top-left) and Platanovrisi dam (top-right) and HPP (rest of the images) at Greece.

agement but also optimizes power generation by enabling more efficient and accurate monitoring of critical zones. Similarly, Xu et al. (2023) employ drone photogrammetry to generate 3D models of dams and virtual crack images, thus diversifying and enriching the available crack dataset. This approach effectively addresses the issue of limited dam crack imagery and supports the detection and quantification of cracks through deep learning models, such as YOLOX, advancing the reliability of structural monitoring and maintenance. In the context of point cloud segmentation, Li et al. (2024) introduced a neural network model optimized for the dam environment. Their model enhances segmentation accuracy by tackling issues such as uneven point cloud density and interpolation point offsets, achieving an impressive improvement in classification accuracy from 96.26% to 98.27% using PointNet++. This advancement provides a high-precision solution for detecting dam deformations. Additionally, the EfficientLO-Net framework, presented by Wang et al. (2023), introduces a novel approach to LiDAR odometry. By using projection-aware representations of 3D point clouds, the method structures raw data to improve computational efficiency. The end-to-end architecture is optimized for adaptive learning, resulting in faster operations like point cloud sampling and grouping, with experimental results showing that it surpasses both recent learning-based techniques and traditional geometry-based approaches like LOAM.

On the digital twin front, Shi et al. (2024) propose a data-driven framework that leverages digital twin simulations and machine learning to monitor tailings dam stability. This system allows for real-time monitoring and early failure detection, integrating predictive modeling with decision support tools, and provides a more effective method for managing tailings dam safety than traditional techniques or other AI-based models. In a broader context of hydropower, Kougias et al. (2019) review recent innovations aimed at mitigating flow instabilities and improving the digitalization of hydropower systems. They explore advances in electro-mechanical components, variable-speed turbine generation, hydro storage, and environmentally friendly hydropower solutions, which are all essential for improving the efficiency and sustainability of hydropower plants.

Furthermore, Baudrit et al. (2022) introduce a methodology for risk management in dam systems using conceptual graphs. These graphs help integrate interdisciplinary knowledge, enabling a deeper understanding of the complex relationships between hazards, dam structures, and human factors. The approach also facilitates forensic civil engineering by storing and processing heterogeneous dam knowledge, issuing alerts, and learning from past failures. When discussing mesh reconstruction, Bassier et al. (2020) compare 3D point cloud data and mesh geometries for scene interpretation in Building Information Modeling (BIM). Their empirical study demonstrates that both point clouds and mesh geometries, when combined with appropriate features, yield an F1 score greater than 75% for identifying structural components, proving their potential for automated navigation and 3D reconstruction. Similarly, Lv et al. (2021) propose a voxel structure-based framework for mesh reconstruction that improves detection accuracy in local regions. By optimizing the mesh structure, their method preserves key geometric features while enhancing processing speed and mesh quality compared to existing approaches. Lastly, Cui et al. (2023) present a method for generating finite element (FE) meshes of tunnel structures from 3D laser point clouds. Their approach addresses challenges like lack of detail and low automation in traditional FE mesh generation methods, successfully applying their method to various tunnel types for numerical analysis, and recommending future advancements in this field.

Dataset

The dataset utilized in this paper consists of point cloud data from the Platanovrisi and Roxburgh Dams as shown in Figure 1. The Platanovrisi Dam, a concrete structure located approximately 7.5 km southeast of the Thesauros Dam in northeastern Greece, became operational in 1999. It forms an artificial lake with a storage capacity of around 90 million cubic meters of water. Alongside the Thesauros Dam, an earthen dam standing 175 meters tall and one of the highest in Europe, the two dams work together as a complementary hydropower system. This system incorporates water reuse and nighttime pumping between reservoirs, optimizing energy production. With a combined power generation capacity of 500 MW, the dams are integral to regional power supply, supported by a Greek-Bulgarian water management agreement. The Roxburgh Dam (Otago, New Zealand), a concrete gravity dam on the Clutha River, was completed in 1956 and remains one of New Zealand's flagship hydroelectric projects. Standing at 86 meters tall, it creates Lake Roxburgh, spanning approximately 30 km upstream. The dam houses eight turbines, generating a total capacity of 320 MW, contributing significantly to New Zealand's renewable energy grid. Over time, the dam has undergone various upgrades to ensure long-term efficiency and reliability.

The open-source point cloud data of Roxburgh Dam was sourced from the OpenTopography portal. This dataset contains only the external scan of the dam, lacking color information. The point cloud was pre-processed by removal of outliers and non-dam surfaces, and the dam components were manually labeled for segmentation purposes. The primary segmentation classes identified include the spillway, auxiliary spillway, downstream face, toe still basin, and crest. For Platanovrisi, additional components were identified, including an intake tower. The Platanovrisi dataset also included laser scans of the interior, specifically two levels of the hydropower plant (HPP). The turbine gallery, located on the ground floor, is a spacious area primarily for turbine maintenance access, while the turbine floor below contains essential operational components such as the turbine well, pipes, tanks, pumps, and control panels.

Methodology

The process of creating a geometric model for a dam involves several crucial steps. Firstly, point cloud data is segmented into distinct components, such as walls, gates, and turbines, to simplify the complex structure into manageable parts. Subsequently, spatial proximity analysis is employed to identify the relationships between these segments, resulting in a relationship graph that elucidates how the components interact. Lastly, surface reconstruction techniques are applied to generate continuous and precise meshes from the segmented point clouds, providing a detailed geometric representation of the dam.

Segmentation

In this study, we adopt and extend the approach proposed in a multiple-plane detection framework to achieve geometric segmentation of hydropower plants. This addresses the unique challenges of creating accurate digital twins for such structures. The methodology begins with point cloud preprocessing, where 3D laser scan data is acquired to capture the structural complexity of the hydropower plant. Noise and outliers in the raw data are removed using statistical and voxel-based filtering techniques. Then, downsampling with voxel grid sampling is performed to reduce computational overhead while retaining essential geometric features. Plane detection is then carried out. This involves estimating surface normals for each point in the cloud using neighborhood analysis to identify potential planar regions. A region-growing algorithm groups points into candidate planar segments based on curvature thresholds and angular similarity. At the same time, RANSAC (Random Sample Consensus) Fischler and Bolles (1981) robustly fits these regions to plane models, effectively mitigating the effects of noise and outliers. In addition, segmenting cylindrical objects is an essential step in the geometric segmentation of hydropower plants. Cylinders are often present in components such as pipes, turbines, and structural supports. The segmentation of these cylindrical objects is performed using a RANSAC-based method, which iteratively fits cylindrical models to point cloud regions that exhibit circular or cylindrical features. This allows for the identification and extraction of cylindrical structures, which are then treated as distinct segments in the overall model. This process is particularly valuable in hydropower plants, where cylindrical elements play a significant role in both structural and functional components.

Detected planes undergo iterative refinement to enhance segmentation accuracy. They are merged based on proximity and orientation thresholds. Boundaries and edges of segmented planes are extracted to improve geometric representation. These planes are hierarchically organized to represent structural elements of the hydropower plant, including walls, floors, and machinery. Semantic labeling is applied to identify and distinguish key components, while adjacency relationships among planes are analyzed to re-

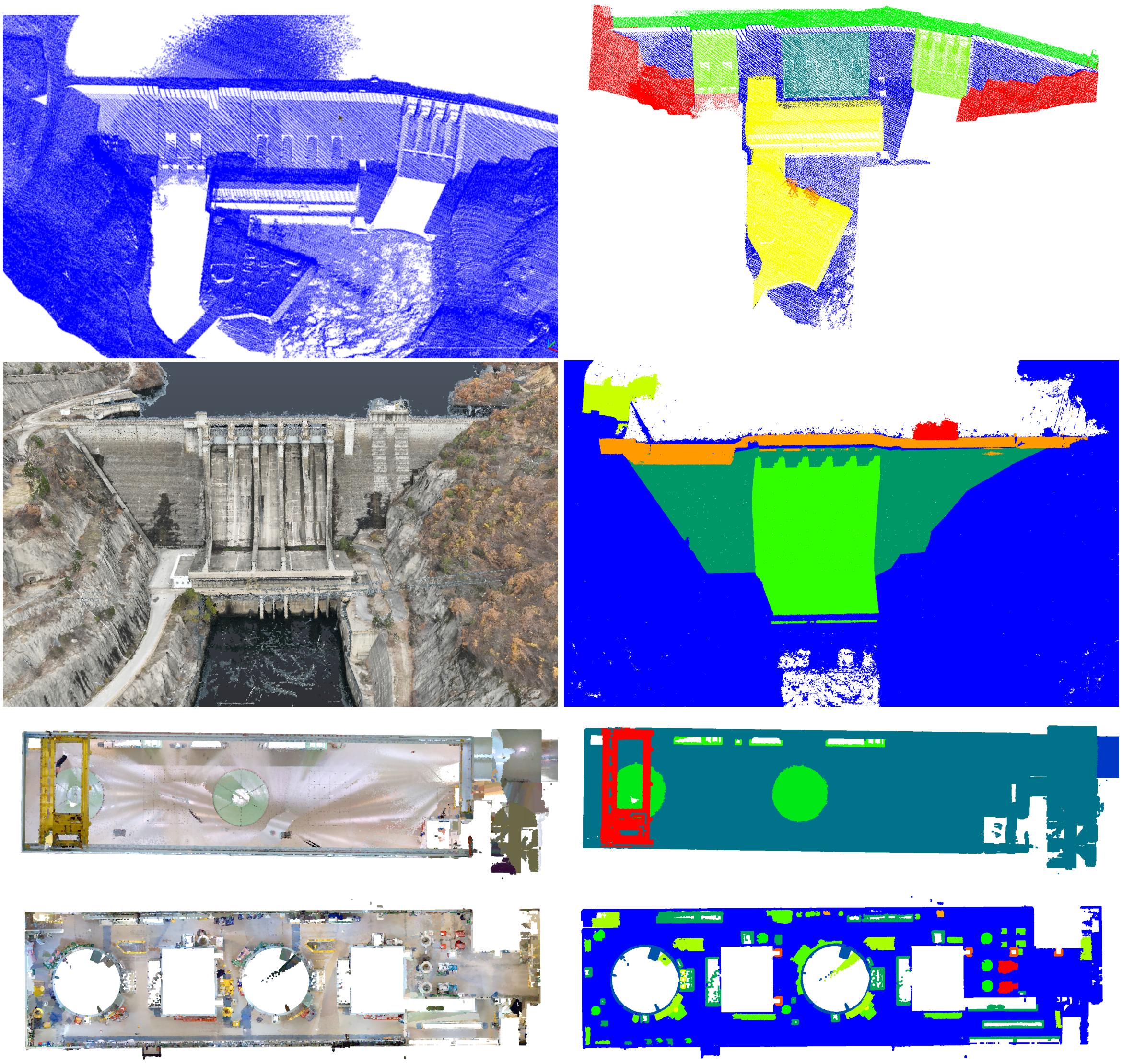

Figure 2: Segmentation of Roxgurgh Hydro and Platanovrisi dam (first two rows), and Platanovrisi HPP ground level and turbine floor (last two rows).

construct the plant's topology. The preliminary segmentation is shown in Figure 2. Post-processing steps, such as smoothing and interpolation, address small gaps and misalignments, resulting in a coherent and precise geometric model.

Unlike buildings, where deep learning models have achieved remarkable success in geometric segmentation due to the availability of extensive and well-labeled training datasets, hydropower plants face significant challenges in this regard. Deep learning approaches heavily rely on such datasets to train models capable of recognizing intricate patterns and structures. However, hydropower plants lack large-scale annotated data, and the unique and often irregular geometry of these facilities makes it difficult to directly apply deep learning techniques. Moreover, the variability in plant designs and components limits the generalizability of models trained on smaller datasets. Consequently, traditional geometric processing methods, such as the one described here, are more suitable for this application. These methods do not depend on large-scale training data and can effectively address the specific challenges posed by noisy and unstructured laser scan data.

Element relationships

In conventional BIM workflows, relationship graphs are typically constructed from well-defined object hierarchies and standardized schemas. However, in the case of dam infrastructure, the development of complete BIM models is currently limited due to the absence of comprehensive schema support in formats such as the Industry Foundation Classes (IFC), which were primarily designed for buildings and industrial facilities. Given this limitation, the approach presented in this study focuses on constructing a relationship graph directly from segmented point cloud data. Unlike comprehensive BIM graphs, the relationship graph proposed here is a lightweight, inferred representation de-

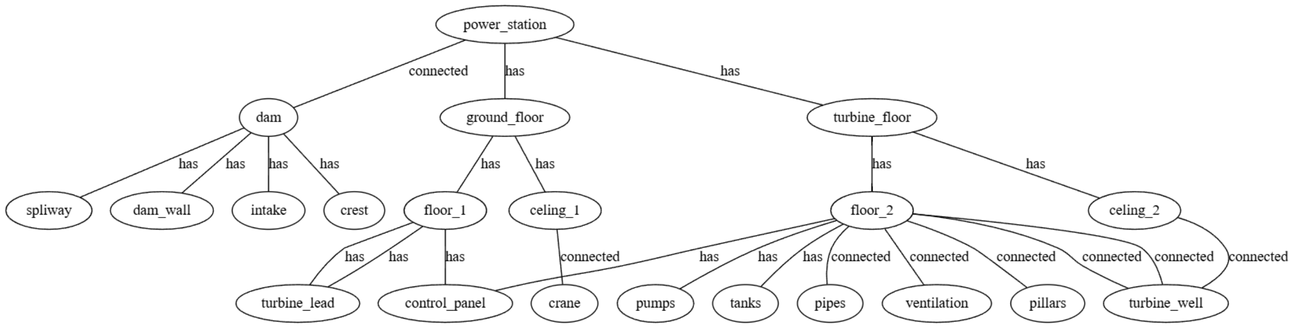

Figure 3: A HPP relationship graph of Platanovrisi HPP.

rived from spatial and semantic cues.

The graph is constructed by identifying ”connected” relationships through spatial adjacency between segmented components. Each node in the graph corresponds to an individual component, while edges represent spatial or semantic associations. To establish spatial relationships, a k-dimensional tree (KD-Tree) is utilized for efficient indexing and nearest-neighbor searches within the point cloud. By evaluating the proximity of points across different segments, the algorithm determines whether they fall within a defined distance threshold. If this criterion is met, an edge is created to denote a ”connected” relationship. The KD-Tree proves particularly effective in managing the geometric complexity and structural variability typical of hydropower plants, which comprise a diverse range of components—such as turbines, generators, and reservoirs—with irregular shapes and configurations. Given these complexities, manually identifying such relationships is impractical, further highlighting the utility of this approach.

In addition to adjacency-based connections, segmented components are manually associated with higher-level abstractions—such as the dam body, ground floor, or turbine floor. When a component is spatially contained within one of these broader regions, a “has” relationship is inferred (e.g., ground floor has pipe). These inferred associations introduce a hierarchical structure to the graph, enabling a more organized semantic representation. While these relationships provide a useful structural foundation, they are limited to spatial logic and do not capture functional or operational dependencies. Such deeper semantics would require predefined schemas and expert domain knowledge, which are currently lacking for dam infrastructure. Nonetheless, the proposed method represents a meaningful step toward structured digital modeling in domains where traditional BIM standards are insufficient. A preliminary example of the resulting relationship graph is shown in Figure 3, illustrating the inferred connectivity and hierarchical groupings among segmented components.

Surface reconstruction

Surface reconstruction is crucial in creating a coherent and continuous geometric model from segmented point clouds. In this study, we leverage the surface normals computed during segmentation to generate precise mesh representations of each component. The reconstruction process bridges the gap between the discrete and irregular nature of point clouds and the continuous surfaces needed for simulations and visualization within the digital twin framework. Surface normals provide local geometric context by indicating the orientation of the surface at each point in the cloud. These normals guide the reconstruction algorithm, ensuring that points are connected accurately to reflect the original structure’s geometry. In particular, surface normals are essential in hydropower plants, where components often have intricate geometries, sharp edges, and smooth surfaces that must be faithfully captured in the mesh.

We use the Ball Pivoting Algorithm (BPA) (Bernardini et al. (1999)) to reconstruct surfaces. BPA is a technique that generates triangular meshes from dense point clouds. It works by rolling a virtual ball of a specified radius over the point cloud and pivoting it around points to form triangle edges. The process begins by identifying triplets of points that form valid triangles, where the ball can simultaneously touch all three points. Once an initial triangle is formed, the ball pivots around the edges to find neighboring points to form new triangles. This iterative process continues until no more triangles can be formed. BPA adapts to varying surface curvatures by adjusting the ball radius. A larger radius is used for smoother regions, while a smaller radius is employed to capture finer details and sharp edges. This ensures that the reconstructed mesh preserves the original topology and geometry of the segmented components. This is particularly important for hydropower plant models, where structures often combine curved, flat, and angular surfaces as as shown in Figure 4.

Reconstructing surfaces from segmented point clouds in hydropower plants poses several challenges. Noise and outliers, caused by scanning artifacts or environmental factors, can disrupt the reconstruction process. Irregular geometries, such as curved turbine blades, pipes, and structural reinforcements, require precise standard estimation and carefully tuned algorithm parameters. Additionally, occlusions may leave parts of the structure partially or entirely invisible in the point cloud, resulting in incomplete data. To address these gaps, reconstruction algorithms

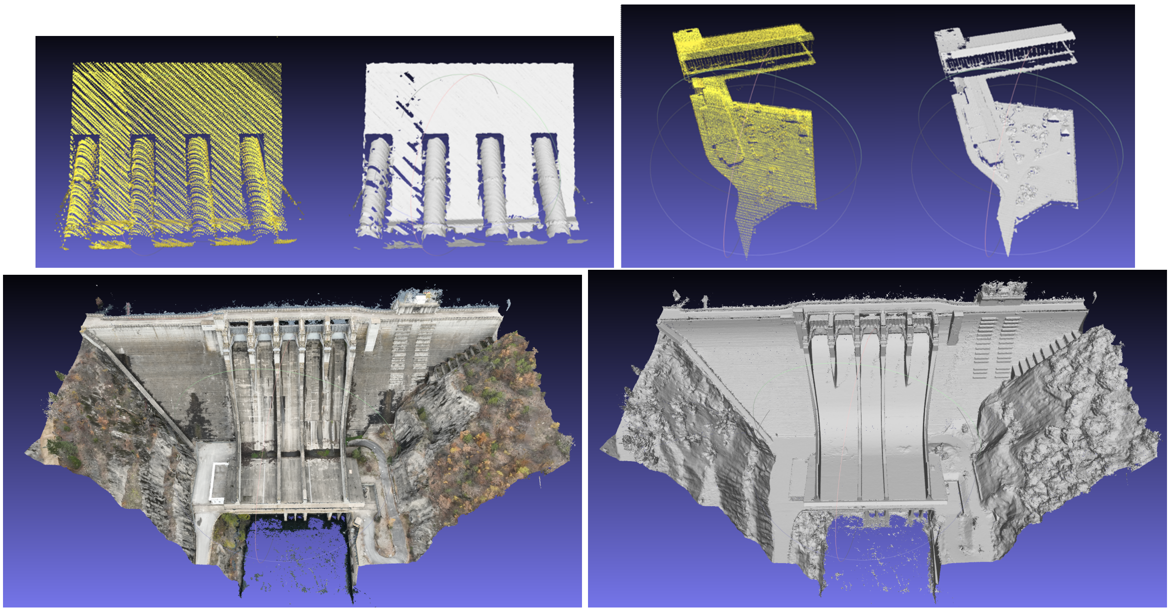

Figure 4: Meshing segmented components of the Roxgurgh Hydro (top) and Platanovrisi dam (bottom).

must interpolate surfaces or leave holes for further refinement. After the initial mesh generation, post-processing techniques like smoothing, hole filling, and mesh decimation are applied to enhance the quality of the reconstructed surfaces. Smoothing eliminates noise and irregularities, while hole filling interpolates small gaps caused by occlusions or incomplete data. Mesh decimation reduces the number of triangles without compromising significant detail, improving computational efficiency for subsequent simulations.

The reconstructed surface plays a vital role in digital twin development by providing a high-fidelity geometric representation that enhances visualization and enables intuitive interaction with the virtual model. In this work, surface meshing is not treated as a standalone process but is used to generate a semantic mesh, rather than just a semantic point cloud. This distinction is crucial, as the semantic mesh serves as the structural foundation for downstream tasks such as asset monitoring and maintenance. The novelty of this approach lies in the integration of segmentation, meshing, and relationship graph construction into a coherent, automated pipeline tailored specifically for the complexities of hydropower infrastructure.

Discussion

The geometric model produced through segmentation, relationship graph construction, and surface mesh reconstruction forms a critical foundation for dam digital twins, offering structured, semantically enriched representations of complex infrastructure. Unlike buildings, dams feature highly non-standardized and irregular geometries—such as curved spillways, inclined faces, and embedded tunnels—that lack support in conventional BIM schemas like IFC. This uniqueness, combined with limited access to public datasets and inconsistent component definitions across dam projects, makes generalization and standardization particularly challenging. Creating geometric models is further complicated by occlusions in scan data, the absence of predefined hierarchies, and difficulties in inferring functional relationships with minimal prior information. The generated semantic mesh and relationship graph provide a lightweight but structured alternative to full BIM, enabling spatial indexing, component-level data integration, and interactive visualization. These outputs support critical digital twin tasks such as inspection planning, monitoring, and geometric change detection, forming the backbone for scalable and adaptive digital twin solutions tailored to dam infrastructure.

Conclusion

This study introduces an integrated pipeline for geometric modeling tailored to the development of digital twins for hydropower plants. By combining point cloud segmentation, spatial relationship graph construction, and surface mesh reconstruction, the proposed approach addresses the unique challenges posed by the complex, non-standardized geometries of hydropower infrastructure—such as occlusions, irregular surfaces, and incomplete schema support in conventional BIM frameworks. The segmentation process decomposes the structure into meaningful components, while the graph-based method infers spatial relationships to build a lightweight, semantically structured representation. The resulting surface mesh further enriches the model, supporting visualization, spatial indexing, and future simulation workflows. This pipeline offers a scalable and semi-automated alternative to traditional modeling workflows, enabling efficient, and adaptable digital twin generation. The outputs lay a strong foundation for monitoring, data integration, and scenario-based analysis, contributing to improved decision-making, predictive maintenance, and long-term sustainability of hydropower assets. Future work will explore the use of learning-based techniques to enhance segmentation accuracy and deepen the understanding of inter-component relationships. Overall, this research highlights the central role of geometric modeling in enabling robust digital twin systems for critical infrastructure.

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