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Reconstruction of As-built Civil Infrastructure using LiDAR to Support Digital Twin Visualization

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RECONSTRUCTION OF AS-BUILT CIVIL INFRASTRUCTURE USING LIDAR TO SUPPORT DIGITAL TWIN VISUALIZATION

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Dedication

This work is dedicated to the people who served as inspiration, support, and extended their help during the conception of this research. To mention a few, my academic advisor, classmates, friends, faculty, staff, and most importantly my family.

RECONSTRUCTION OF AS-BUILT CIVIL INFRASTRUCTURE USING LIDAR TO SUPPORT DIGITAL TWIN VISUALIZATION

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Abstract

Digital twin (DT) technology is state-of-the-art for engineering processes using a virtual model of a physical system with near real-time data exchange (either fully or semi-automated) during the process (collection and feedback). The potential of DT for as-built civil infrastructure remains relatively unexplored. To achieve the expectation of a DT, three main capacities must be met: (1) accurate virtual twin of physical asset (2) continuous data acquisition and data management (3) automated or semi-automated decision making from the data exchange. The challenge addressed herein is to determine a feasible approach to create an accurate virtual model (efficiently) from light detection and ranging (LiDAR) data for existing infrastructure. The scope of this research focuses on the first capacity by comparing various virtual twin model creating methods for visualization of an existing pedestrian bridge, determining compatibility with data input, and proposing a data structure for predicting hidden structural components not captured by LiDAR. The initial attempts to improve infrastructure management practices by leveraging a DT for various applications were investigated in the literature review. The methods investigated were direct, manual conversion from scan to Building Information Modeling (BIM), and algorithm-based reconstruction techniques via an open-source software. In all cases, it was found that the end results were short of the requirements to integrate into a DT, and that substantial human input was still required. A potential for closing the gap between these technologies and DT was identified via automated approaches like machine learning or artificial intelligence, but this would require substantial amounts of data that is not yet available.

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Chapter 1: Introduction

1.2 Background

A Digital Twin (DT) is a virtual model of a physical asset or process with near real-time data exchange. The term digital twin was coined by Michael Grieves (2015) for industrial manufacturing processes. More recently, the idea of DT has become increasingly popular in the research community. Although the concept of DT was initially introduced for manufacturing processes, it can be applied to civil infrastructure with recent technological innovations. Technologies such as Internet of Things (IoT), real-time sensing equipment, cloud computing and storage, and machine learning for data interpretation enable DT for the monitoring of civil infrastructure conditions (Tao et al., 2019). Numerous lab-controlled case studies effectively modeled disaster management, maintenance, and inspections processes for infrastructure with more research needed at a city-wide scale.

According to Batty (2018) the physical twin and digital twin exist in parallel with the need to communicate between the two systems for it to be useful. A DT built using terrestrial Light Detection and Ranging (LiDAR) scans creates a snapshot in time of the geometric condition of the infrastructure, but with limited additional information on the physical asset (i.e., no details that cannot be viewed externally). The systems, virtual and physical, remain separate processes. To connect the real-time behavior of the physical twin, the data input to the digital model needs to lead to a decision to affect the physical twin. The initial challenge is to create a virtual model of the existing infrastructure using point cloud data to create a model compatible with digital twin software and for simplified data integration. Laser scanned data at a large scale increases the computational requirements for processing the data. To understand DT technologies and the process to achieve a DT for infrastructure applications, first a visualization of the digital model of the as-built infrastructure must be created.

Advancements in visualization methods for a geometric replica model of a real physical system, such as photogrammetry and LiDAR, have become viable options. Three-dimensional laser scanning for LiDAR requires large storage capacity for the scanned data to be a feasible option for infrastructure modeling. The amount of data captured from a terrestrial laser scan (TLS) requires substantial computational power to process efficiently and integrate to DT software. Several techniques for improving the 3D reconstruction of infrastructure from scanned data have been researched but the manageability of the data set, storage, quality, and processing remains a challenge (Limberger & Oliveira, 2015). The quality of the scan is affected by self-shadowing, scan limitations (e.g., range), and noise. Alternative methods to perform laser scanning, such as aerial(manned), unmanned aerial vehicle (UAV), or GPS can be used. However, the accuracy and processing of data for 3D reconstruction remains challenging for larger data sets (Hinks et al., 2009).

Several geometric 3D reconstruction methods from point cloud data and the current limitations of the technology are evaluated in this work. The one-way integration of data (infrastructure to virtual model) to a 3D model of an existing infrastructure is known as a digital shadow. A bridge infrastructure system was selected to create a digital shadow. The existing pedestrian steel bridge located in the university campus will include sensors for monitoring the structure (outside the scope of this work). The available 3D reconstruction techniques for built structures were investigated based on accuracy, efficiency, and compatibility with data. The three methods used were: 1) Scan-to-BIM approach, 2) algorithm reconstruction techniques via open-source software, and 3) data-driven reconstruction. The processing of the large data sets from an infrastructure scan remains computationally expensive, requiring extensive memory capacity and high amounts of RAM for processing. There is a need to find methodologies and techniques within this process to reduce the computational time and resources, and to optimize human input (Mirzaei et al., 2022).

The methods selected for model reconstruction include a.) a manual approach via tracing the point cloud in a Building Information Modeling (BIM) software, b.) automated approaches leveraging available algorithms to automate the model reconstruction from point cloud data, and c.) combinations of both. Then a method to structure a database for predicting the hidden structural components (not captured from the laser scan) using machine learning is proposed. The infrastructure case study explored in this thesis is the Interdisciplinary Research Building (IDRB)—specifically the pedestrian bridge adjacent to the building—on the campus at The University of Texas at El Paso (UTEP). LiDAR was used to create a detailed digital geometric model of an existing pedestrian bridge using several reconstruction methods. The design drawings, provided by UTEP, were utilized as a reference to evaluate the accuracy of the scan-to-BIM model. The state-of-the-art in infrastructure design utilizes Building Information Models (BIM) but is currently limited by the fact that BIM models generally only exist for new construction. For operational infrastructure, IoT equipment to monitor and manage structural soundness in unison with a complete geometrical visual model increases the value to any DT efforts. A roadmap for standardizing and integrating digital data for already built infrastructure assets, and an understanding of available resources with its limitations is needed to improve the integration of a digital model for DT civil infrastructure assets.

1.2 Objective

The objective of this research is to implement and assess standard approaches to geometric reconstruction of point cloud data in order to find a simple, effective approach that is scalable, manageable, and reliable.

1.3 Research Question

The primary research question addressed herein is:

What approach or combination of approaches (if any) to geometric model reconstruction of point cloud data is efficient, reliable, accurate, and scalable such that it will facilitate widespread geometric replication of the built environment for Digital Twins?

1.4 Thesis Breakdown

Task 1: Literature Review

This section defines digital twin, the origin of DT, the applications in manufacturing, and the initial applications for infrastructure. The existing literature of the technologies available for the geometrical reconstruction of a digital twin using LiDAR, the methods for data collection, model definition, and available algorithms for processing point cloud data are presented.

Task 2: Data Collection of Pedestrian Bridge

This section presents the methodology for the data collection for terrestrial laser scanning. The scanning techniques used to obtain detailed scan data of the structure, registration of the scans (aligning the scans), noise filtering process, and data file classification. Also, the segmenting used for processing and manipulation of point clouds.

Task 3: Three-Dimensional Reconstruction from Point Cloud Data

Detailed measurements for the external dimension of individual components were collected from the point cloud data to identify the material sections and compute accuracy. Then, reconstruction methods were used to generate a three-dimensional model of the bridge from the point cloud. The methods range from manual measurements of the point cloud to the use of available algorithms to computationally generate planes for the mesh. The algorithms utilized involve creating planes using octree structure and primitive shape detection using the point cloud to perform mathematical computations.

Task 4: Comparison of Reconstruction Methods

The accuracy of the point cloud data (as-built structure) with respect to the design drawings was calculated. Then the data was used to determine if the point-to-point measurements match to AISC girder/beam dimensioning data to aid in the reconstruction of the resultant model. The reconstruction methods were compared in terms of the time to generate the model, the computational efficiency, and the accuracy of the mesh with respect to the point cloud.

Task 5: Analysis of Results (Qualitative and Quantitative analysis)

Based on the accuracy obtained from the comparison, a database structure is proposed to aid in the 3D reconstruction of hidden components of a bridge using machine learning algorithm. These components were hidden within the structure or were not captured during the laser scanning.

Chapter 2: Literature Review

The existing literature was reviewed to understand the previous applications and available resources for digital twins in manufacturing and infrastructure. In addition, the application of laser scanning and its limitations, 3D model reconstruction methods, and machine learning algorithms as applied to point cloud usage were studied for the application of DT for infrastructure management. The structure of the literature review is as shown in Figure 1.

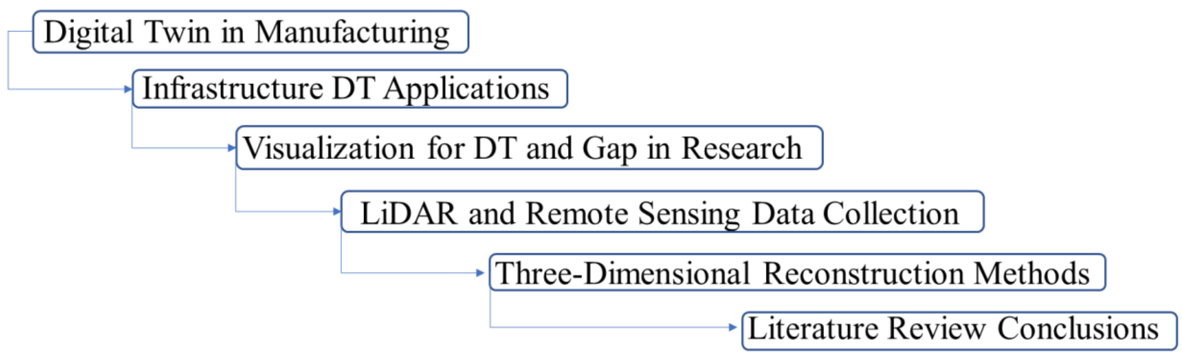


Figure 1. Image. Literature Review Structure

2.1 Digital Twin and Applications in Manufacturing

The original definition of DT for a virtual factory digital twin was defined to include three main parts: (1) a physical product, (2) a virtual product, and (3) the connection of the products using data and information (Grieves, 2015). The virtual product or model is done through tools such as Computer-aided Design (CAD), Computer-aided Engineering (CAE), and BIM. Technological advances have become sufficient for wireless communication of large data sets into the cloud; therefore, data sharing and processing can be established near real time. Artificial Intelligence (AI) through proper dataset structuring and training can provide additive advancement with human-machine collaboration (HMC) (T. Wang et al., 2020). The structuring of the data and applying appropriate thresholds to the data is needed to implement algorithms to automatically make decisions for the system by relaying this information to both the operators and the physical system itself. Only when these requirements are met is it feasible for a digital twin to be functional for improved management and decision making to the system.

As result of the fourth industrial revolution, the exponential growth in technology and AI became widely accessible and affordable to the public (Scepanovic, 2019). The promise of connectivity between the physical and the virtual realities of a DT through the innovations in Internet of Things (IoT), database quality, machine learning, and software as a service (SaaS) remains elusive. The high fidelity of the virtual model to physical process creates challenging issues for constructing a reliable DT (Y. Lu et al., 2020). For the machining process of aerospace components a DT for the manufacturing was developed to include mimicry of the geometry and progress information during the process to monitor machining characteristic and equipment, and aid in decision making. (S. Liu et al., 2020). The virtual-physical integration of a DT for smart manufacturing is possible using big data collected during the manufacturing process using radio frequency identification (RFID), various sensors, gateways, and IoT (Qi et al., 2018).

The entire product lifecycle assembly workflow of the manufacturing process can be managed virtually by leveraging the signature of the materials during the assembly of product in the manufacturing process (temperature, effects of gravity on thin material, etc.) (Polini & Corrado, 2020). A DT can aid in the optimization of the schedule of the dynamic production using edge computing and the manufacturing process data (Xu & Xie, 2021). The dynamic schedule improves the process itself by decreasing the delays and optimizing machining procedure. When using a DT to model an enclosed system (i.e., laboratory) the operations model reached high accuracy then used to optimize the maintenance of equipment, and detected equipment failure (M. Li et al., 2020).

2.2 Initial Application of DT for Infrastructure

DT was initially introduced and widely accepted for manufacturing purposes, but the principle can be applied to infrastructure to understand interdependencies of multiple systems in management practices (Taylor et al., 2021). A DT is a virtual twin of an actual structure or infrastructure system with near real-time data exchange with the goal of monitoring the processes affecting the physical twin for improved decision making (Polini & Corrado, 2020). A DT is composed of three main aspects: a physical or experimental reality, collected data describing the experimental reality, and the virtual reality (physical asset, semi-automated two-way data exchange, and virtual model)(Angjeliu et al., 2020). Modern design methods, such as BIM, are used to create detailed virtual model.

Infrastructure management value is provided when there are complex interconnected systems or unique operational challenges that would benefit from the use of a DT (Curl et al., 2019). Therefore, there is a need to understand and develop standards for the application of DT based on the importance of the infrastructure and limitations of the technologies ((Gatziolis & Andersen, 2008), (Ford & Wolf, 2020)). Examples of the types of data received from the actual processes include energy consumption(Lydon et al., 2019; Teng et al., 2021), waste production (Samimpay & Saghatforoush, 2020), air quality, utilities (Curl et al., 2019), structural soundness (Ye et al., 2019), among others and is dependent on the sensing technology placed on the physical asset.

The application of DT technology to existing infrastructure presents a solution to improve the monitoring of quality and management of these built assets(Ford & Wolf, 2020). The current infrastructure is not monitored sufficiently, and the inspection process is done using methods that have not been updated in several decades. The current method for inspection of infrastructure is through visual inspection of roads, buildings, bridges, water management, and sewage system. This is inherently subjective and lacks the consistency of data-driven, quantitative approaches.

A DT of infrastructure faces challenges with unpredictable environmental conditions and effects of external stimuli, among many other challenges (Moselhi et al., 2020). Understanding how to apply technology like DT effectively to the built environment is critical to improve management practices for infrastructure systems. Infrastructure management with efficient communication for connectivity between individual systems, such as transportation infrastructure systems, storm water management, and water quality systems, enables better decision making. In the last decade, mobile devices have become a substantial source of data. The technology used for tracking changes based on electromagnetic waves, such as waves emitted by smartphones and smartwatches, is used for tracking occupancy, location, and behavioral patterns (Widhalm et al., 2015). This is bound by user privacy issues and legal restrictions therefore it is not widely available without the users' consent. The mobility data collected in real-time from drivers, vehicles, and surrounding vehicles aids a DT to predict problematic areas (Kumar et al., 2018). The use of available resources for human mobility data, such as Wejo, Streetlight, and Inrix, effectively improves mobility but the disconnect of the knowledge with policy makers creates gaps for city application (A. Wang et al., 2020). This data, in the context of civil infrastructure applications, can improve serviceability of highway and roads management. Such as the case of evacuation planning routes, maintenance practices for high traffic use, and new transportation infrastructure development based on need.

In water utility management a virtual model was created to simulate potential operational challenges by simulating the facility's hydraulics at maximum flow scenarios, control operations, and performance data of the process (Curl et al., 2019). The process flow diagrams, piping, instrumentation diagrams, and sensing equipment are used for data acquisition. Water utilities benefited from improve planning strategies, operator training, collaboration, and communication. (Curl et al., 2019)

2.2.1 Smart Cities DT

The use of a DT for the management of civil infrastructure and its operations is initiative to achieve the promise of smart cities. A DT for smart cities was developed for disaster management by predicting damages and developing emergency response preparations to impending disasters by simulating condition from historic data collected about communities during disaster conditions (Ford & Wolf, 2020). The use of DT based simulation facilitates management strategies for decision makers by reliably forecast the potential impacts of proposed decisions. Additional work is required to develop smart cities digital twin at a community level for general community management during natural disasters to mitigate the effects of relocating people, measure the individual disruption to individual infrastructure systems, and the interactions between them (Ford & Wolf, 2020). Communication and coordination during a disaster was improved using artificial intelligence for efficient event extraction, entity recognition, speech recognition, and natural language processing (Fan et al., 2019).

2.2.2 Structures DT

A DT to predict the structural health of a prestressed steel structure was achieved by reconstructing the physical asset virtually, and using data from sensors such as the cable force, displacement, and the service data of the structure (Z. Liu et al., 2020). This method allowed to monitor the structure near real-time and used the data received for decision making to affect the structure. To understand the real-time behavior of the physical structure, the movement, the degradation of materials, and overall structural safety need to be monitored using sensors. For example, accelerometers, displacement transducers, pressure cells, and temperature sensors have been used to measure the global response of physical assets. (Angjeliu et al., 2020). The data from set in-place sensors used to measure the effects of applied loads monitors the structure over a brief period, but the challenge is to continuously monitor the structure for the entirety of its design life.

The energy expenditure of monitoring a system in real-time requires a sustained amount of energy to keep the system running. This is but a small fraction of the computational energy costs associated with storing and processing the copious amount of data being collected by a DT. One criticism of DT is that the technology may not be sustainable. In terms of sustainability, maintenance and replacement of the sensors and data storage facilities need to be considered. The application of digital twin to monitor and collect sensor data for an extended time is limited by the large volume of data collected, recording and storage of the data, and management practices to make the data useful.

2.2.3 Bridge DT

The most ubiquitous approaches to data acquisition tools for three-dimensional geometric representation and visualization of virtual twins for built infrastructure are LiDAR and photogrammetry. To model bridge behavior, the digital model required must be at a high level of detail (LOD) at the individual components level with information of the structural (e.g., rebar detailing, section properties, material properties, internal dimensions) and nonstructural characteristics (e.g., guardrails and drainage) (Channg-Su, Shim et al., 2019). The bridge industry, unlike buildings, is just now experiencing a critical mass of research and effort in support of applying BIM to bridges. We are in the initial stages of this application which means it is the perfect time to modify the process to support digital twin construction. Like buildings, existing bridges would not benefit from this, but unlike buildings, bridges must be inspected every two years. This means that humans will be at the bridge observing and taking measurements. This required touch point could be leveraged to build a database of existing bridge BIM models in support of widespread DT.

A geometrical digital twin for visualization begins with an automation of 3D reconstruction for build assets by using a structured database of the components (currently not available). To achieve a digitization of bridges for DT visualization, a structured database of the individual components and the subcomponent with specific parameters of the design needs to be recorded to enable the ability to reconstruct 3D models of existing infrastructure bridges using automated methods. Using an accurate visual of the bridge structure a digital twin model was achieve to propose maintenance practices and monitoring the structural health to a reliability of 85% in terms of level of safety(Z. Liu et al., 2020).

In regard to monitoring maintenance needs, a DT model was developed to inventory and update data when maintenance or retrofit was done to the structure ((Channg-Su, Shim et al., 2019)). AI coupled with monitoring and sensing equipment and Internet of Things (IoT) provide automation opportunities in real-time data to monitor the performance and optimize the maintenance practices for built infrastructure (Angjeliu et al., 2020). Note that the requirement for biannual inspection provides a unique and consistently applied mandatory human touch point which could be used to augment data collection.

2.3 Visualization for DT

To address the first challenge of a visualization model for existing infrastructure, a method to efficiently create the model needed. An accurate visual of the structure will aid in the effort to achieve a complete digital twin of infrastructure by attaining a geometry with a higher level of detail. An approach to address the issues that constitute the promise of a digital twin is to compartmentalize the tasks and solve them individually then integrate for a complete DT. The three general challenges of a digital twin are:

1. 3D modeling: accurate representation of the visualization model for the physical structure with data compatibility
2. Data: data acquisition (sensors or generated), high volume data storage and recording, and data management using the cloud
3. Integrating data to model: algorithm-based machine learning for automated processing and feedback

In industry, BIM is used in the conception of the design phase for new infrastructure projects and has increased in popularity in the past few years (Vilutienė et al., 2020). Standards and regulations for final project design documents of BIM models (particularly for bridges) are under development and even though the adoption of modern three-dimensional modeling methods, many established firms maintain 2D drawing as the preferred design method.

Building SMART standards for IFC and open BIM facilitate the transfer of BIM files by enabling compatibility of the project during the design phase and sharing through a cloud-based storage system. The standards apply to the geometric reconstruction of built assets using laser scanning data. A roadmap by buildingSMART to create international standards IFC4 for BIM is in progress for the year 2023 (buildingSMART, 2020). The level of compatibility, collaboration, and team management for the design process using the cloud-based system allow the project changes to update in real-time. The communication exchange between individual expertise, design model components, teams, and project are facilitated.

Recent innovations in technology (i.e., programming techniques, developer tools, data compatibility, and simulation) have become increasingly multidisciplinary to fully understand the potential and the appropriate application of the technology to improve the process of creating an accurate three-dimensional model of existing infrastructure. There has been considerable advancement in modeling software (e.g., BIM) but there is a lack of acquisition of behavioral data during the entirety of infrastructure's design life. The improvement in cloud computing, Internet of Thing (IoT) technologies, and modern sensing technologies permit near real time data communication but is limited by the ability to integrate the data received from the physical asset and the feedback sent back. The model needs open compatibility with application programming interfaces (API) for data visualization. The use of these sensing technologies remains on a project-by-project basis to enable accurate information exchange between the virtual and physical systems, yet a step towards the promise of digital twins for the built infrastructure assets.

2.3.1 Gap in Geometrical Data for Infrastructure DT Visualization

The data needed from existing infrastructure assets to create a functional DT is both geometrical and behavioral. To apply digital twin technology for infrastructure, a system for data collection, management, and processing methods is needed. The first challenge is to record the geometric data in detail to develop a digital model for geometric representation of an as-built structure (R. Lu et al., 2019). For bridges specifically, the geometrical data needs to be retrieved for each individual component to increase the detail from the already complex projects, all while taking into consideration the limitations associated with the technology since it requires human intervention for optimal accuracy. Without the available of design documentation and/or digital construction documentation (i.e., BIM) for every existing structure, creating DT models for the built environment will remain a huge challenge. There is a need to develop tools and methodologies to create the building blocks of a DT (e.g., geometric models, BIM, design details) from remote sensing and other data collection approaches.

2.4 LiDAR and Remote Sensing Data Collection

Laser scanning is but one method to obtain the geometrical characteristics of an infrastructure and reconstruct a three-dimensional model efficiently. A physical asset's geometric properties (i.e., dimensions) can be efficiently obtained through LiDAR or photogrammetry. LiDAR data can be collected through a terrestrial scanner, a vehicle-mounted scanner, or aerially. The equipment is expensive but efficient to capture a large area in a few minutes. The laser captures data of the geometry of a structure by transmitting light and measuring time of flight for the light to hit an object and return. The total time of flight is used to determine the distance of a single point. The laser scanner rapidly captures millions of points within a radius of the equipment for

360-degree (in the horizontal plane) visualization of the surrounding area. The vertical aperture can vary based on sensor (e.g., 300-degrees angle of view). The laser scan does not discriminate between the area of interest (e.g., building from trees), therefore, to create digital replica of the physical structure of interest further processing and noise filtering is required.

The three main laser scanning methods are:

1. Terrestrial LiDAR Scanning (TLS): A stationary tripod mounted scanner for high accuracy, and least expensive when compared to the other laser scanning methods.
2. Aerial LiDAR scanning: Aircraft mounted for faster scanning rates and accuracy, therefore reducing cost and time of laser scanning of large areas (Gatziolis & Andersen, 2008). Optimized scanning patterns mitigate these effects of self-shadowing. (Hinks et al., 2009).
3. Vehicle Mounted LiDAR Scanning: Work well for road mapping and scanning large areas

The concept of laser scanning for modeling has been available for quite some time now. The complete procedure to achieve a digital model from laser scanning has been investigated in terms of terrestrial laser scanning, point cloud processing requirements, mesh generation, and level of detail (Remondino & El-hakim, 2006). An application of laser scanning was used in a study to predict floods caused by melting ice caps in Alaska, leading to sea level increases. This was done by predicting flood scenarios using LiDAR data generated model of the coastal terrain elevation. The author anticipated 39 % of the buildings destroyed and $215M in damage for a 6-meter flood (Lantz et al., 2020). The laser scanned data was integrated into ArcGIS for the simulation, and the outputs focused primarily on cost.

2.4.1 Challenges of Sensing Technology

Several common challenges in accurately modeling a specific system have arisen through this review, especially related to processing field capture data collected from laser scanning. The most recurring challenges of the laser scanning technology are:

For Aerial LiDAR:

- at low frequencies, the wide or narrow divergence of the scan changes the precision of the reflected light
- use for undulating terrain, fog, rain, or in uncertain climate conditions
- the aircraft is limited to 50 kilometers (about 31.07 mi) of a GPS base station for precision
- unorganized scanning pattern and scan frequency reduce absorption, reflection, and point density

For Terrestrial LiDAR:

- Angle for data collection of taller infrastructure limits field of view and data collection quality
- Complex geometry requires numerous scans to account for self-shadowing etc.
- This type of data collection does not scale well

For Vehicle-mounted:

- Data collection limited to roadways where vehicles may travel

Angle for data collection limits field of view

Specifically for infrastructure, a laser scan of the structure is comparable to a screenshot of the asset at a given point in time capturing the current geometrical conditions at the time of the laser scan. The constant deterioration of the structure, damage, and preventive maintenance is not automated to the digital model created by laser scanning. Subsequent scans over time are necessary to capture the changes in geometrical characteristics. Some factors to consider for these approaches, based on the literature, are cost of adding data acquisition methods, data storage, and maintenance versus the long-term cost benefits through modeling (construction processes, live monitoring, and safety from a DT system).

2.5 Three-Dimensional Reconstruction Methods

There are many approaches to digital reconstruction from point cloud data, many of which are branched from one another or are combinations of approaches. The following methods were reviewed and selected for the case study based on the nature of the infrastructure reconstruction requirement:

- High-fidelity model
- Automated reconstruction algorithms/methods
- Segmentation algorithms and techniques
- Shape approximation and octree structure

2.5.1 Scan-to-BIM Application Toward Bridges

A three-dimensional BIM model of a bridge can be reconstructed from point cloud data by preprocessing techniques to reduce point cloud size then using the point cloud data and design drawings to obtain the bridge geometric and material characteristic. An example of this method was used by reducing number of points, adjusting the coordinate of the point cloud to match the BIM grid, and then imported triangular surface reconstruction to BIM to facilitate the model creation. (Ma, 2019). A scan-to-BIM approach for bridges aid in the 3D reconstruction from laser scanning to mitigate drawing errors, in addition to improved construction management, quantities, and collaboration (Y. Li et al., 2020) There is a need for semi-automated segmentation of highway infrastructure with outputs compatible with Industry Foundation Classes (IFC) compliant file (Soilán et al., 2020)

The level of detail (LOD) used in CityGML or buildingSMART (IFC4) is intended for buildings, but the standards can be followed for bridge components as well. LOD specifications as applied to bridges remains vague and subject to interpretation. According to Thomson and Boehm, there is need for a sustainable method to automate the digital reconstruction of geometry for existing infrastructure assets at a reliable level of detail (Thomson & Boehm, 2015). The use of the visualization model with a high LOD and compatible with data aids in the decision-making process but only in a case-by-case scenario and is dependent on the visual of the infrastructure asset.

Some research has been conducted to improve the ambiguous definition for the LOD specifications in CityGML and EuroSDR 30 Special Interest Group 3D mapping standards (Biljecki et al., 2016). Using these standards (CityGML and BIM), a 3D model was developed for the property management of a condominium. This model defined the physical space and legal aspects of ownership of the space (L. Li et al., 2016).

2.5.2 Machine Learning Reconstruction

Research using machine learning (ML) reconstruction techniques from point cloud data have become increasing popular and has been improved in terms of the accuracy and efficiency of the 3D reconstruction. An unsupervised ML method called Clustering of Symmetric Cross-sections of Objects (COSCO) was developed to pre-process city point clouds by detecting the cross-section of symmetrical vehicles within seconds (Xue et al., 2020). This method is limited to symmetrical objects, the detection of the cross section only for further processing, needs training of machine learning algorithm, and requires expert structuring of the point cloud data.

To achieve a better understanding of the uses of 3D reconstruction, the application to nerve visualization was investigated. In nerve fibers 3D reconstruction deep networks are used to view neurons by training the network using a segmentation process called U-Net Plus. (Q. Li & Shen, 2020). These methods ultimately use photogrammetry to develop a visual of the nerve using similar methods used for 3D reconstruction processes. This method showed promising results yet scalability to infrastructure requires expert knowledge and extensive manual work during the process and may not be optimal for the size of the point cloud obtained from scanned infrastructure.

2.5.3 Segmentation Method for Reconstruction

A method using segmentation using artificial intelligence (AI) to detect specified objects from images or video footage to reconstruct the object in three dimensions. For example, a novel algorithm was used for processing video frames to automatically identify 2D highway assets and automate the asset 3D reconstruction as a point cloud data to enhance classification of highway assets (Golparvar-Fard et al., 2015). This method has been improved but requires expert knowledge in AI in addition to further processing for the reconstruction of the object from cross section.

Specific to bridge reconstruction, the application of sematic segmentation to detect bridge component (i.e., column, pier cap, deck, etc.) from laser scanned point cloud data can be obtained by training machine learning algorithms. The training of ML algorithm was used for automatic segmentation of three major bridge components: (1) deck, (2) pier, and (3) background (Kim et al., 2020). The algorithm can be trained to potentially detect other major bridge components for a more complete bridge model.

A similar method for bridge segmentation is needed for further research for the use of BIM for bridge components. Segmentation requires no geometrical data; the method uses classification of the point cloud based on trained sample, therefore reducing the computational requirement when compared to algorithm processing methods (Xia et al., 2022). Additional research on bridge components segmentation methods using three alternatives; (1) PointNet, (2) DGCNN, and (3) HGCNN, compared and recommended for additional research in export to BIM application (Lee et al., 2021). The CANUPO algorithm for point cloud classification allows for classification of materials by training a small sample of the points to create classifying subsets for each specified material (Brodu & Lague, 2012).

2.5.4 Planar and Primitive Shape Algorithm based Reconstruction

A method to generate planes from point cloud data using the points to generate planes based on the number of inliers with the detected plane simplified the 3D reconstruction, speed up the reconstruction when compared to other approaches. For example, the oriented point sampling (OPS) algorithm was developed to decrease the computation requirement for detecting plane by using a single point to detect a plane (Sun & Mordohai, 2019). This method works well with plane structure (e.g., buildings) but is limited to the model created using planes, the input point cloud file size, compatibility of the resultant model, and lacks material properties for the desired LOD in infrastructure.

Other algorithms are publicly available via open-source software. Algorithms such as the Random Sampling and Consensus algorithm (RANSAC) and Poisson reconstruction are developed and integrated into the software for a user-friendly interface. RANSAS, in specific, is used for planar and primitive shape reconstruction for point clouds with clearly separated planes within a threshold. A modification to this algorithm, also known as CC-RANSAC, was developed to reduce the distance required for the separation between points for shape detection from the point cloud data (Gallo et al., 2011).

The algorithm generated models can be considered a reduced-order model with a focus on the representation with reduced dimensionality using the minimum number of parameters for the automated generation of the model or as an intermediary step to obtaining a LOD 300 model. The overall positive and negative aspects of the technology on DT help understand its application.

2.6 Conclusions from Literature Review

Based on this review of the literature, the following conclusions which directly motivate and shaped the research presented herein, are provided:

- DT for already-built infrastructure is possible, but requires substantial effort in terms of data collection, in contrast to DT for infrastructure in construction now, where digital construction documentation like BIM models are available.
- Digital geometric representation of infrastructure is a critical component of DT moving forward

- LiDAR technology (terrestrial, aerial or vehicle mounted) is a suitable approach to data collection for digital geometric representation of infrastructure
- For bridge structures, LOD 300 or greater is desired since much of the bridge functionality is tied to structural components that are either not visible (e.g., rebar detailing in concrete) or are dependent on size (e.g., flange dimensions on a steel beam).
- 3D reconstruction of bridges using LiDAR point cloud data is an open challenge that requires human intervention, but many approaches such as AI and ML show promise
- There is a need to explore the specific challenges and limitations to 3D reconstruction of bridges as compared to design documentation.

Chapter 3: Methodology

This chapter discusses the bridge selected for the case study including the laser scanning process, the point cloud data noise filtering, the level of detail of the model, and a detailed explanation on each of the methods used for the reconstruction of the pedestrian bridge from point cloud data.

3.1 Visualization Component of Existing Bridge Structures for Digital Twin

3.1.1 Scope

The extent of the application is to evaluate the use and limitations of available 3D reconstruction methods for as-built infrastructure, determine areas for improvement, identify 3D model for data compatibility extent (sharing and visualizing sensor data) and propose a roadmap for digitizing bridges. The gaps in current state of the art technology and 3D reconstruction methods were identified when using LiDAR to generate the 3D model of the infrastructure.

3.1.2 Background

A crucial aspect for the digital twin of an existing infrastructure is the reconstruction of the as-built physical asset in digital form (Zhang et al., 2014). To do so, a laser scan of a pedestrian bridge was done to capture a highly detailed virtual model. The pedestrian bridge used in this case study is located at the University of Texas of El Paso adjacent to the Interdisciplinary Research Building, as seen in Figure 2**Error! Reference source not found.**. The bridge was scanned using a BLK 360 laser scanner. The set-up of the laser scanner while capturing the substructure of the bridge is shown in Figure 3.The registration of the point cloud was done using Cyclone Register to combine scans, edit bridge scans, and record the metadata (date, time, duration, and location of each scan with respect to the bridge). The point cloud file was converted, using Autodesk Recap, to a file format compatible with BIM software and algorithms used for the virtual model reconstruction (e.g., .rcp, .e57, etc.). A single scan captures hundreds of millions of points (e.g., 200,000,000 or more) making the processing time consuming for large infrastructure scanning. A complete scan of a structure requires multiple scans to capture the most detail.

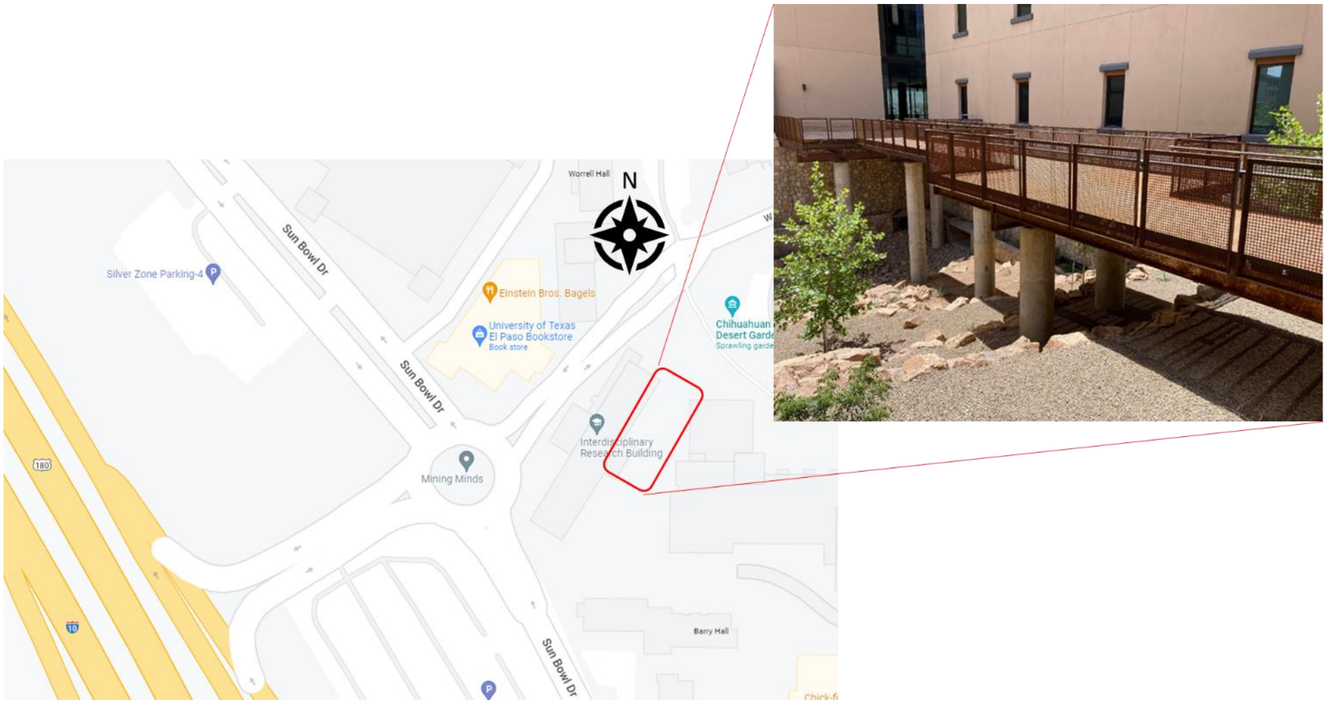


Figure 2. Image. Pedestrian bridge location in university campus

The point cloud data becomes a challenge when using algorithms to generate the model. The input data for the algorithm is limited to the file size to maintain maneuverability of the scan in software (e.g., open-source software Cloud Compare) and is dependent on the available computational capacity. For example, the point cloud data file for the pedestrian bridge becomes computationally expensive and reduces the processing speed when the surrounding buildings, terrain, and vegetation is kept for the processing the scan. This is considered noise when the focus is the structural components of the bridge. The surrounding environment is ideal for reconstruction such as the topology of a construction site or visualization of space. To improve the workability of the scan and optimize the model creation using the point cloud data the surround environment was manually removed (cleaned). The process to create a mesh using available algorithms, or scan-to-BIM model becomes manageable.

Figure 3. Photo. Set-up of Terrestrial LiDAR Scanner (BLK 360)

The pedestrian bridge scan file (.e57) size was 670.1 MB after removal of noise, adjacent structures, and vegetation. The model detail is dependent on the points captured therefore size of the file generated from the scanned infrastructure. An alternative would be to develop a new more efficient method or algorithm to do so. In specific, BIM software such as Revit requires a .rcp file format, while Cloud Compare (CC) is compatible with .e57, .pts, .xyz formats. Additional file transfer such as Unity require .ply and Oriented Point Sampling (OPS) require .pcd file formats. The captured scan import into Autodesk Recap can be seen in Figure 4.

Figure 4. Image. Autodesk Recap Point Cloud

In this case study, available algorithms were used to compare the efficiency of three-dimensional reconstruction methods for point cloud data of the pedestrian bridge. To achieve an accurate representational virtual twin of the bridge, multiple methods were investigated to recreate the existing bridge in digital form, then compared based on the application to the pedestrian bridge reconstruction. Subsampling the point cloud data is a method to improve the digital manipulation of the scan and enhance computation. A point cloud data file size of 3.5 Gigabytes was the input limit to algorithms for a laptop Intel core i7 with 16 GB RAM, and 258 GB of storage, with professional computational capacity.

The methods selected use a mathematical approach to calculate the normal vectors, and to approximate the geometry of the scanned data by assigning planes or by detecting primitive shapes The geometry from unorganized data is limited to an object file for the "shell" of the 3D object. These algorithms use a data tree structure to organize the modification to the point cloud (i.e., subsampling, algorithm reconstruction) and parameter input.

3.2 Existing Bridge Characteristics

The pedestrian bridge is composed of seven circular reinforced concrete columns, and weathering steel superstructure (shown in Figure 5). The steel superstructure is made of various W-sections; (1) W-14 x 22 (beams), (2) W-14 x 26 (beams), (3) W-18 x 40 (girders), and (4) W-16 x 40 (girders). Much of the deck is composed of steel channel planks with welded steel railing as shown in Figure 6. A portion of the deck connecting to the building on the southern section of the bridge has the tallest columns which support a concrete deck on metal sheeting (shown in Figure 7). The member connections: (1) girder-to-girder, (2) beam-to-girder, and (3) column-to-girder can be seen in Figure 8. These connections are bolted with half-inch bolts and reinforced with stiffeners welded perpendicular to the web of the beams and girders. The column-to-girder connection is by 1-inch anchor bolts, and 12-inch by 12-inch by ¾ inch base plates.

Figure 5. Photo. Bridge substructure and superstructure

Figure 6. Photo. Steel channel planks(left) and railing(right)

Figure 7. Steel channel planks (left) and concrete slab on metal sheet for decking (right)

Figure 8. Photo. Steel beam to girder bolted connection(left), beam to beam bolted connections (center), and haunch at steel girder and reinforced concrete column connection (right)

3.3 Geometrical Data from Point Cloud

The components of the bridge were individually measured using the point cloud data, then cross-referenced to the available design drawing. The bridge point cloud data was modified in Recap using the boxing tool to segment individual components and measure the points in the cross-section to visible structural elements of the bridge. This process was done manually to accurately measure the dimensions of each individual structural component, specifically steel w-section dimension (depth, width, flange, and web thickness). The total number of beams, girders, and columns is 15, 5, and 7, respectively. Alternative methods to detect columns have been developed to algorithmically detect the cross section and assign a column designation to point cloud data (Chen & Cho, 2018), but were outside the scope of this work.

3.3.1 Component Labeling and Designation

A girder designation was defined as the member which carries a heavier load, is a horizontal member, supports smaller beams members, and consist of various point loads. Beam was defined as a member which carries load from slabs, transfers loads to girder, and carries distributed load (Civil Concept, 2022). The columns were labeled starting in the south end of the bridge moving from left to right towards the northern part of the bridge. A similar approach was used for girders, beams, and deck. To simplify the deck measurements on the south end of the bridge, only the area supported by the structure was considered and divided into 4 sections consisting of:

1. Section 1 includes an area of 16 x 12 concrete tiles (concrete on metal sheeting)
2. Section 2 includes 44 12”x 48” planks
3. Section 3 includes 32 12”x 48” planks
4. Section 4 includes 24 12”x 48” planks

This allowed for a simplified comparison of data with measured dimension of the point cloud. The sectioning is shown in Figure 12. The measurements for the component dimensioning from both point cloud data and design drawings are provided in the appendix in Table 21 (Beams), Table 22 (girders), Table 23 (columns), and Table 25 (deck). The accuracy is presented in the results. The bridge component labels for columns, girders and beams are shown in Figure 9, Figure 10, and Figure 11, respectively.

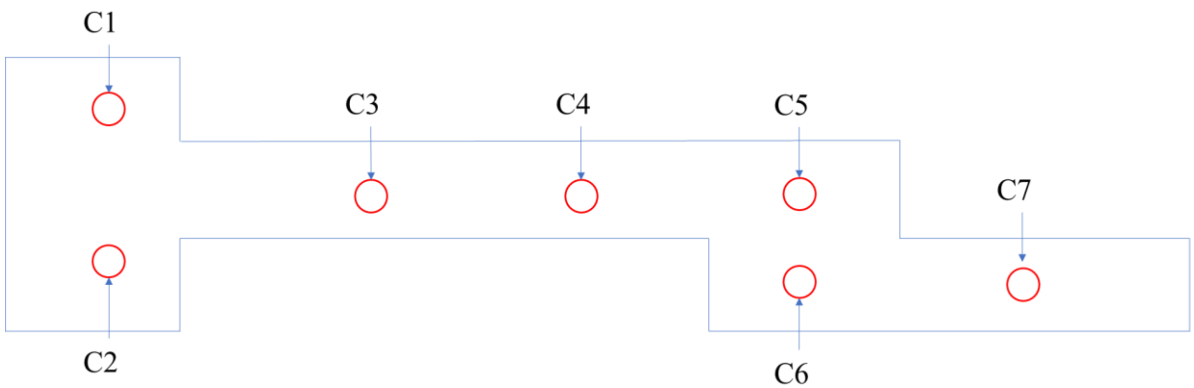


Figure 9. Image. Column Labeling

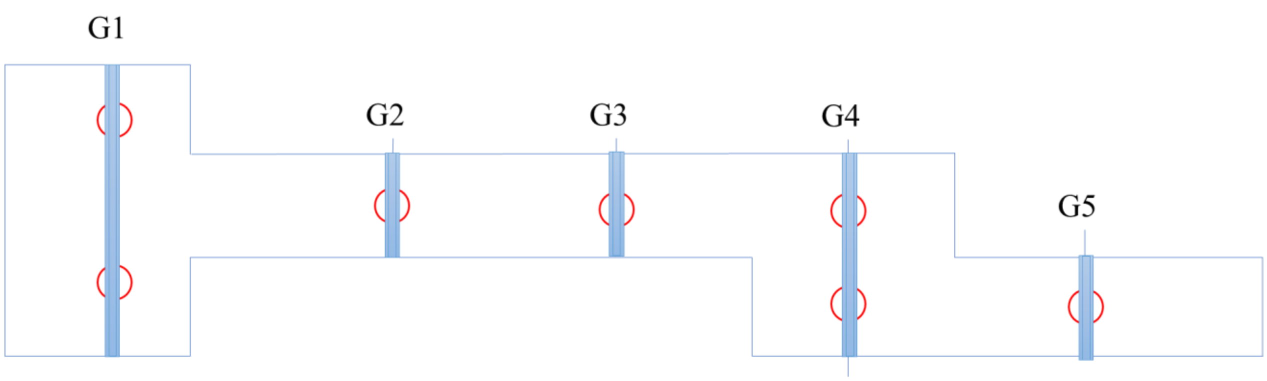


Figure 10. Image. Girder Labeling

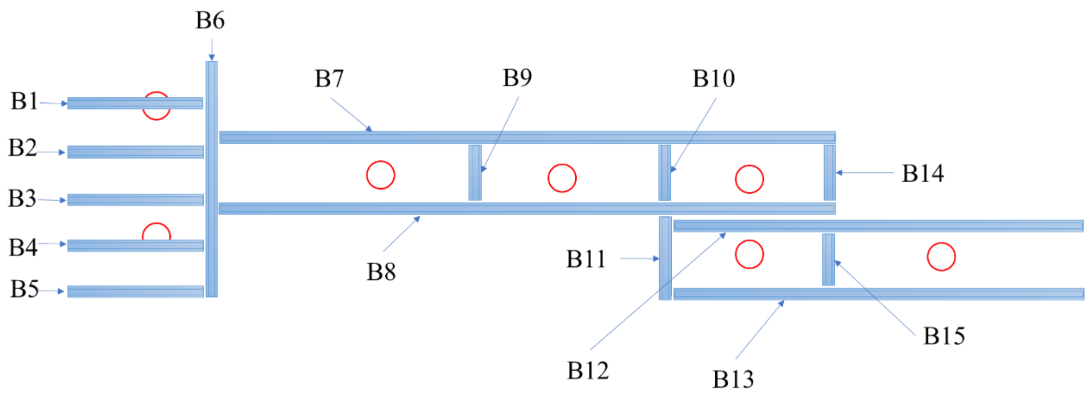


Figure 11. Image. Beam Labeling

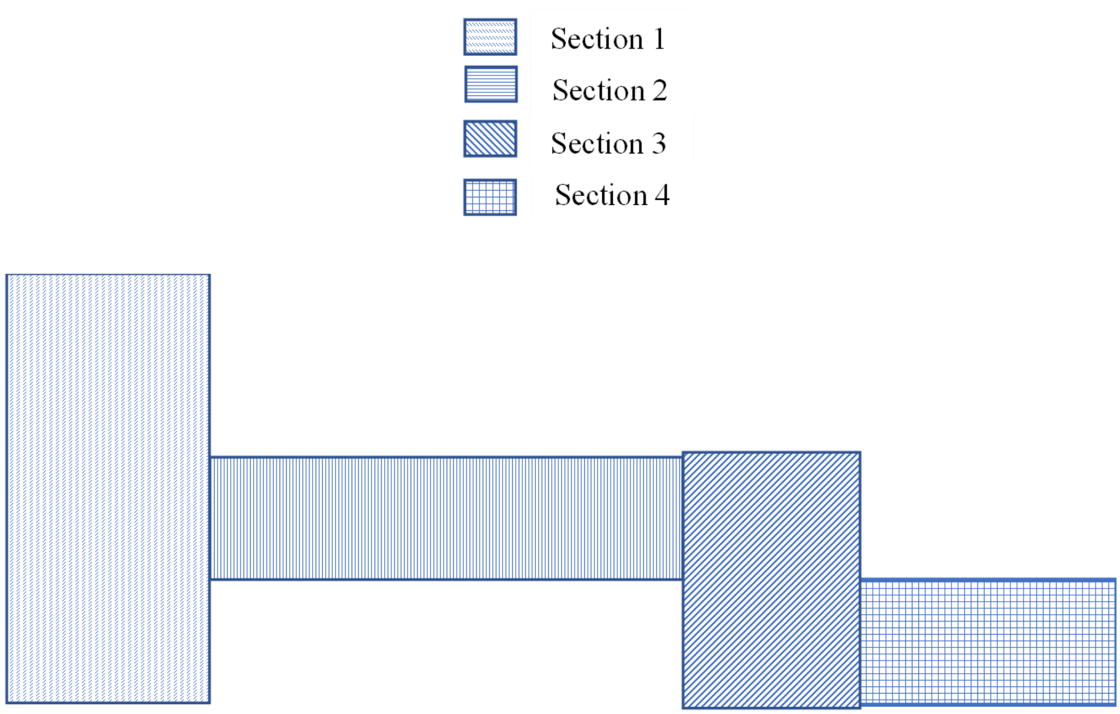
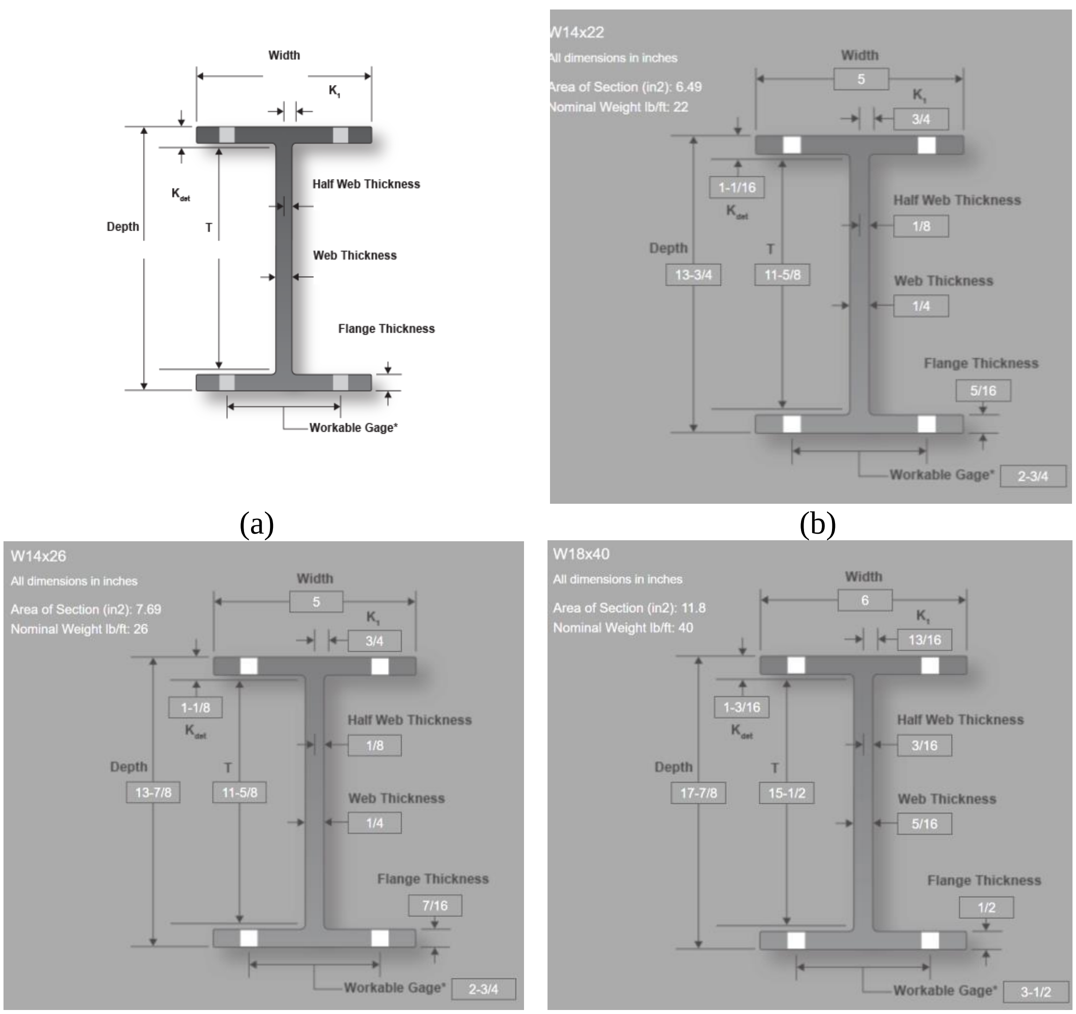


Figure 12. Image. Decking Sectioning for Deck Dimensioning

3.3.2 Analysis of Point Cloud data

The Structural Steel Dimensioning Tool by AISC was used to obtain steel w-section dimensions and the values were later compared with measurements obtained from point cloud data to measure the accuracy of the as-built scan to the design drawings specification. The measurements taken from the point cloud data matched to the measurement obtained from the AISC dimension tool: (1) width (across flange) (2) depth (along web) (3) flange thickness and (4) web thickness. The depth of the w-section was measured from the exterior of the bottom flange to the exterior of the upper flange. The schematic for the dimensioning can be seen in Figure 13.



(a) (b)

(c) (d)

Figure 13. Image. Cross-Sectional Dimension for Steel W-section Beams (AISC, 2022)

The measurements from the point cloud for the beam, girder, and column sections were taken by using the cross-section. An example of this method is seen in Figure 14.

Figure 14. Cross-section view for point cloud measurements

The distance accuracy of the measurements from the point cloud varies depending on the quality of the scan. The measurements were taken using the limit box tool in Autodesk recap to increase the focus on the cross-sectional view of the specific components without affecting or detecting points from the original point cloud. Some measurements for the flange and the web thickness were apparently inaccurate when obtaining the data from the point cloud. For example, the areas where the laser path was at a steep angle with respect to the web, the flange caused a shadowing effect on the web therefore the quality of the points were either missing or inaccurate (shown in Figure 15). In addition, the thickness of the flange was not captured properly by the laser scan. Most of the scans were performed at ground level with the tripod mounted terrestrial laser scanner. This prevented the laser from capturing the accurate thickness of the flange and was prone to noise as seen in Figure 16.

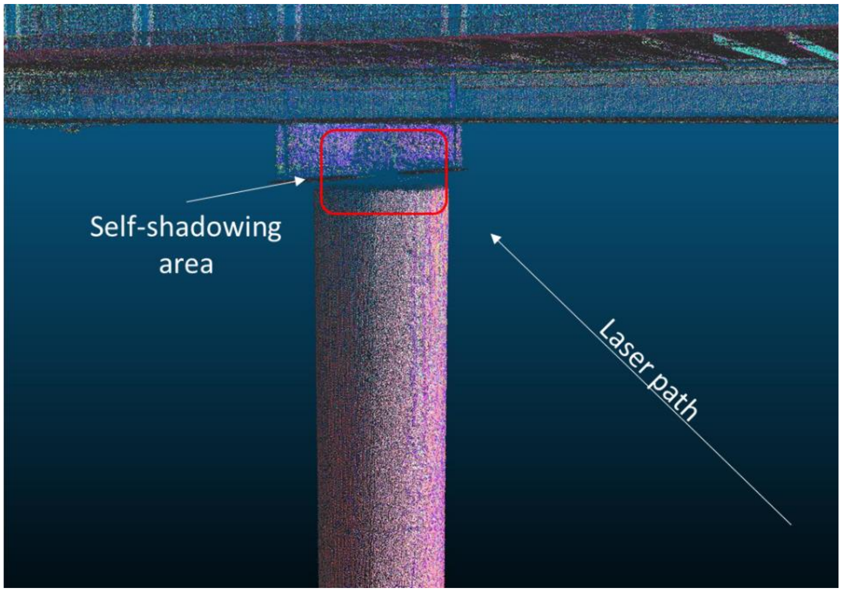


Figure 15. Image. Self-shadowing of beam due to proximity to column

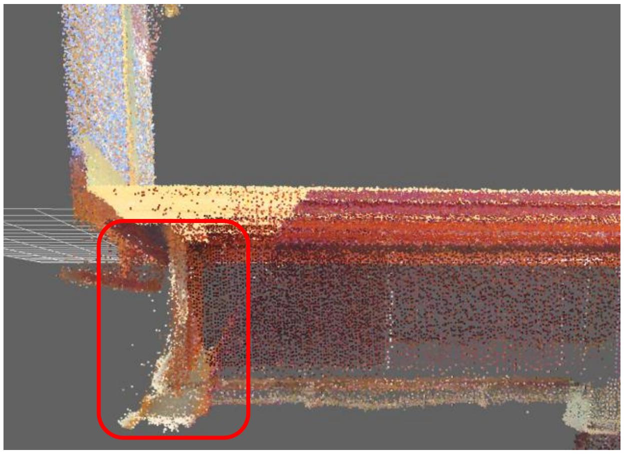


Figure 16. Image. Self-shadowing of flange at beam-to-beam connection

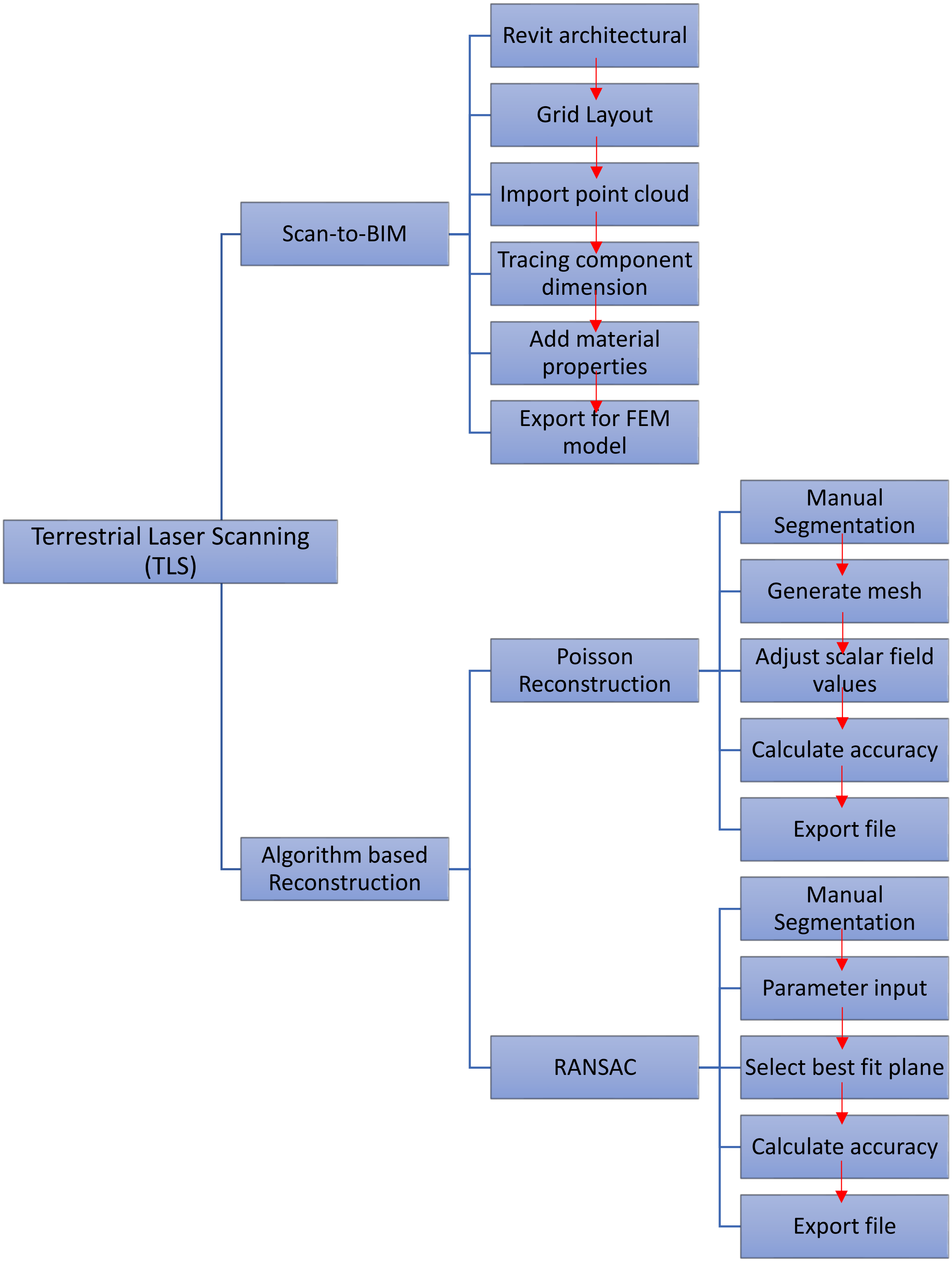


Figure 17. Outline chart for reconstruction methods

3.4 Scan-to-BIM

The BIM model for the pedestrian bridge was created using Revit and the available material properties. The challenge of using laser scan data is to reverse engineer infrastructure elements accurately without any information on internal or hidden components of the structure. In this case, the design drawing of the bridge was available as reference to generate the three-dimensional model and provide a reliable check on the other approaches that were implemented. The BIM model was achieved by tracing the point cloud and using the measured data to determine the correct structural components. The scan-to-BIM method was done as an attempt to expand BIM applications to bridges (Y. Li et al., 2020).

3.4.1 Columns

The first step was to create a grid on the xy-plane to the center point for the location of the columns, then determine the elevation plan for: (1) bottom of column, (2) top of column, (3) bottom of beam and (4) top of beam. The columns of the pedestrian bridge were created using nine levels in the structural plan to maintain consistency with elevation change. Since the bridge is level at the top of beam most of the levels were created to indicate the elevation at the ground. This can be seen in Figure 19 for the eastern view of the elevation plan and the south elevation view in Figure 20.

In addition, the hidden components either underground for the foundation or reinforcement in concrete were not considered. The set foundation piles were selected from the available foundation types in Revit for aesthetics purposes only.

3.4.2 Girders and Beams

The beam and girder are I-beams therefore, the measurements for depth and width were matched the correct w-section member sizing. For example, steel section based on the measured distances was matched to the AISC specification for the member, then the correct material properties and extrusion was applied. The BIM model, although accurate in the material properties faces challenges when reconstructing existing connections with limited information from the laser scan. For this application connections, the decking material, railing, and concrete deck were not considered. Figure 18 shows the BIM model created using the Revit and point cloud later with respect to the true north.

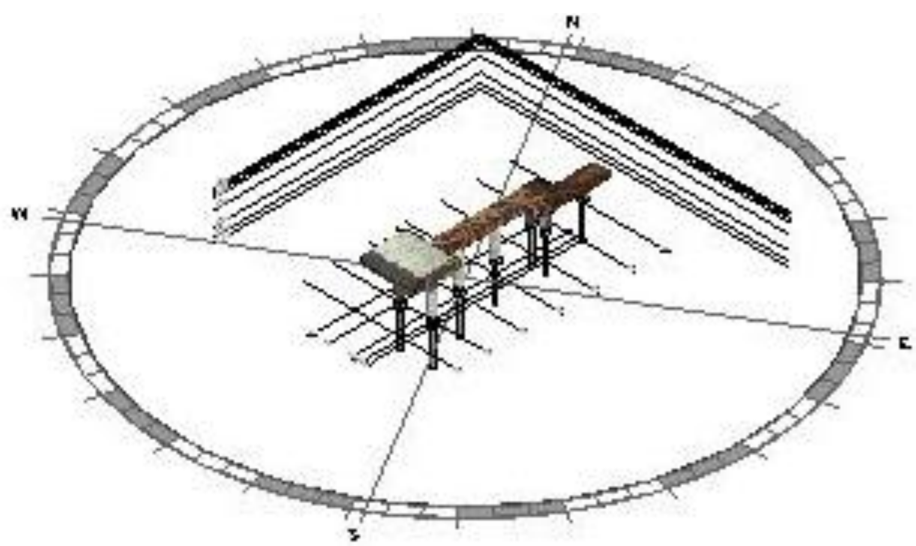


Figure 18. Image. Revit model from point cloud data

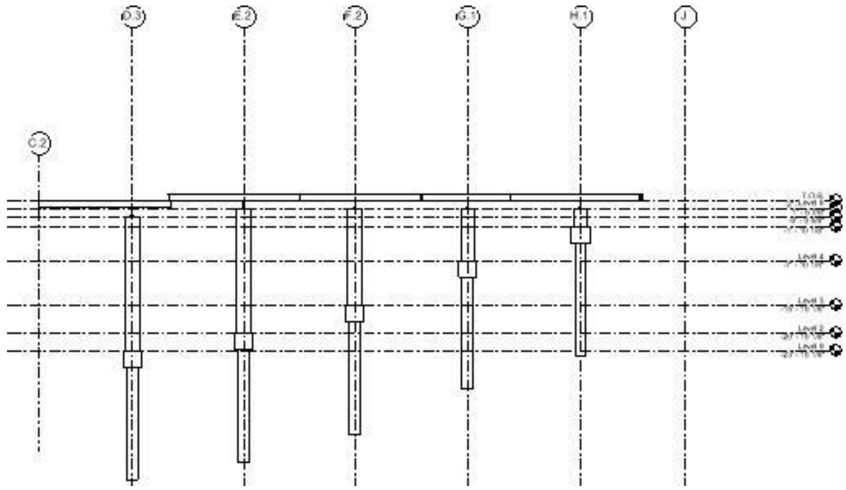


Figure 19. Image. Revit East Elevation View

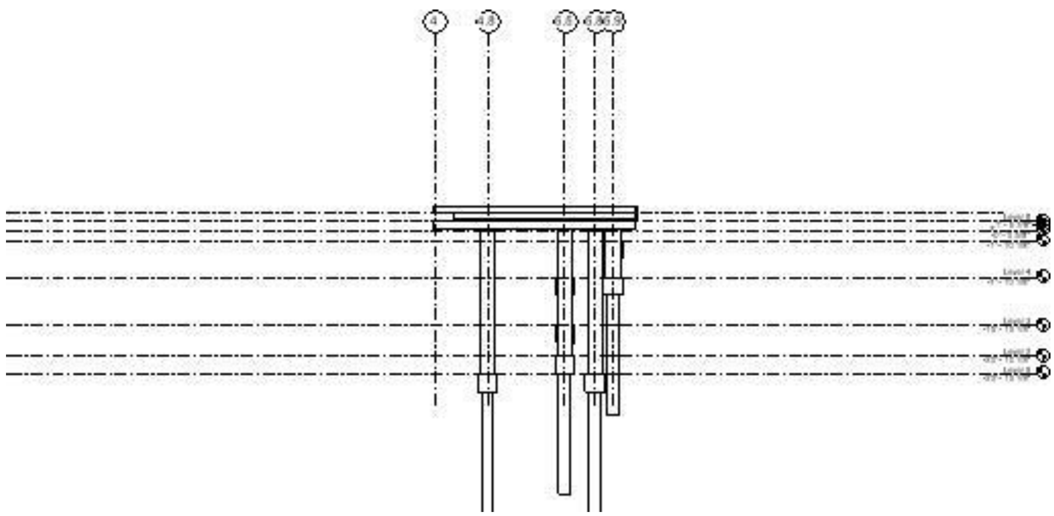


Figure 20. Image. Revit South Elevation View

3.4.3 Structural Analysis Finite Element Model

The reconstructed BIM model was easily converted to Autodesk Robot for structural analysis. In this model, links were used to connect stacked members and represent the bolted connection. The FEM is shown in Figure 21. For simplicity, the FEM did not include the concrete slab on the south end of on the pedestrian bridge.

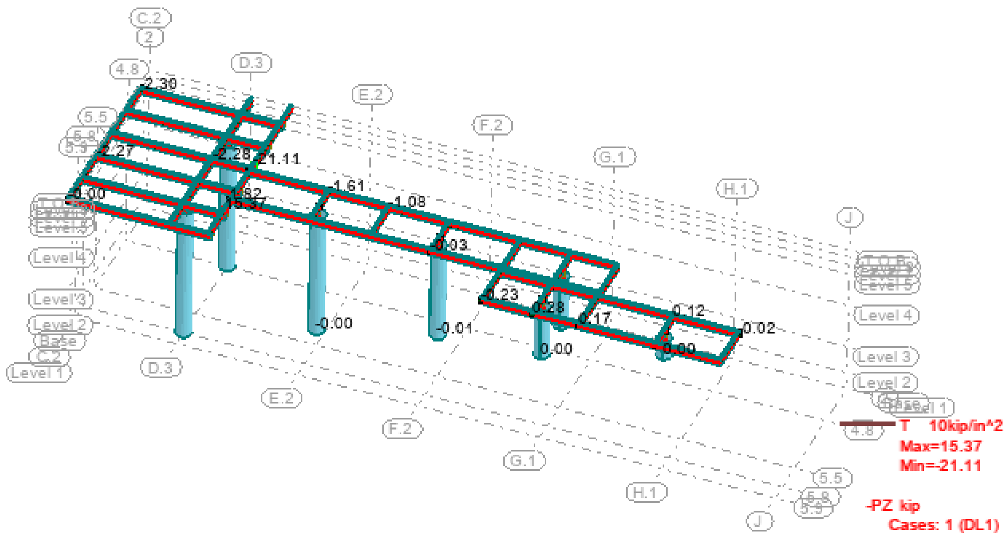


Figure 21. Image. Robot FEM 3D View

3.5 Algorithm Reconstruction Methods

3.5.1 Pre-Processing for algorithm approaches

The preprocessing of the point cloud included removal of the adjacent building and vegetation plus additional noise filtering based on a 0.0001 spacing between points. Then, the point cloud data was subsampled to 1%, 2%, and 3% percent of the total point cloud size and saved separately for input in various algorithms. The number of points used for the random subsample are shown in Table 1. In addition, a segmentation approach was used to reconstruct the point cloud by reconstructing a single structural component and determine if the accuracy of the reconstruction improves when compared to the reconstruction of the entire bridge point cloud (noise filtered).

Table 1. Number of points for random subsample

Subsample (%)	Points
original	23826288
3	714788.64
2	476525.76
1	238262.88

3.5.2 Random Sampling Consensus (RANSAC)

The RANSAC (shape detection) algorithm was created by Ruwen Schanbel et al. from Bonn University. The open-source software Cloud Compare was used to run the RANSAC algorithm which provides a user-friendly interface for iterative parameter inputs. The point cloud file was imported to the software as an .e57 format to conserve the red, green, and blue (RGB) color scheme of the physical environment captured during laser scanning. The point cloud subsamples were processed separately and the data for total time, shapes generated, leftover point, and inputs were recorded. The input parameter was iteratively selected to determine the best reconstruction and shape detection for the most efficient time and accuracy of the model. The values selected for the RANSAC reconstruction of the point cloud data are shown in Table 2. Input values for RANSAC algorithm

Table 2. Input values for RANSAC algorithm

Parameters	Input
Min support points per primitive	2000
max distance to primitive	0.173
sampling resolution	0.346
max normal deviation	7 degrees
overlooking probability	0.005

The RANSAC algorithm was adjusted to detect various combination of the available shapes to measure the accuracy of the model based on the input parameters. For example, a combination of only cylindrical and sphere shapes detection was specified in the input parameter to measure the number of shapes generated time to construct the model and visual accuracy. A comparison of these parameter was done to determine optimal shapes for algorithm to detect for the bridge reconstruction.

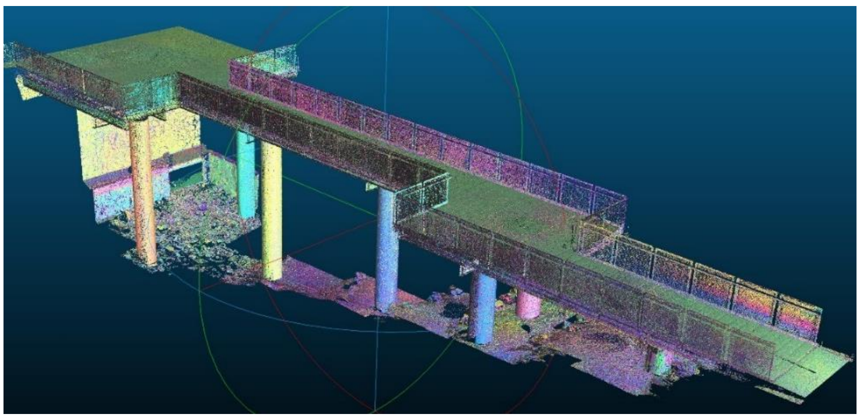


Figure 22. Image. RANSAC shape detection algorithm generated model

The algorithm randomly assigns a color to generated shapes. For example, entire columns are detected in a single shape. Also, the deck was assigned a single plane. Inconsistency in shape detection was found due to the type of steel channel planks and railing used in the structure (shown in Figure 22. The color changes indicate multiple shapes were assigned to this area. The serrated surface of the steel channel planks, and the railing used for the decking create open space therefore many shapes were detected.

3.5.3 Poisson Reconstruction

Poisson Reconstruction algorithm, created by Misha Kazhdan from Johns Hopkins University, is used to generate a triangulated mesh from point cloud data. This method used an octree structure to generate a mesh. Using a higher octree level increases the accuracy of the mesh. Subsequently, the procession speed decrease. After several iterations using various octree level depth inputs, a 10-octree level generates the 3D reconstruction efficiently and with high accuracy. A maximum value of 12 octree depth level increases the detail in the mesh reconstruction of the 3D model but increases the computational requirements. A greater octree level significantly increasing the amount time needed to generate the model for high density point clouds. This limitation is dependent on computational resources.

An additional step to refine the model was used to remove areas with low density points. The Poisson reconstructed model has two color schemes used to view and refine the mesh, scalar field and RGB. Using the scalar field parameters, the displayed density was adjusted to hide triangles with vertices with low density points. The triangles with high density point were kept while low density values were separated from the mesh using the density value for the scalar field. This can only be done for scalar field values and the RGB color scheme was not affected.

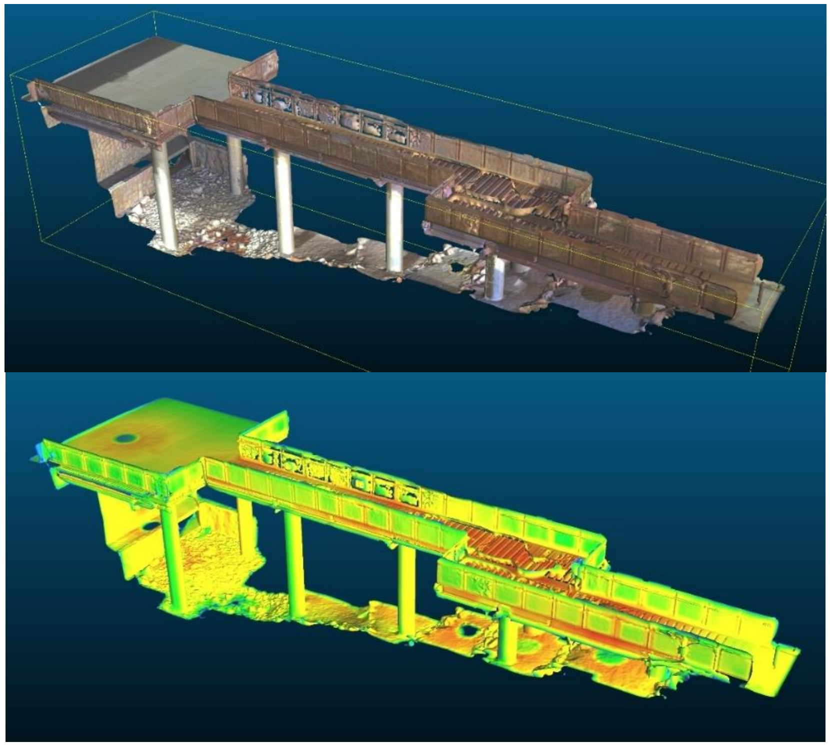


Figure 23. Image. Pedestrian Bridge Poisson Reconstruction RGB (top) and Scalar field (bottom)

The scalar field histogram in Figure 24, shows the saturation values for the density of the point cloud relative to the red and blue color scales. Colors are randomly set to the scalar field with respect to the density of the points with blue representing lower point density and red higher point density.

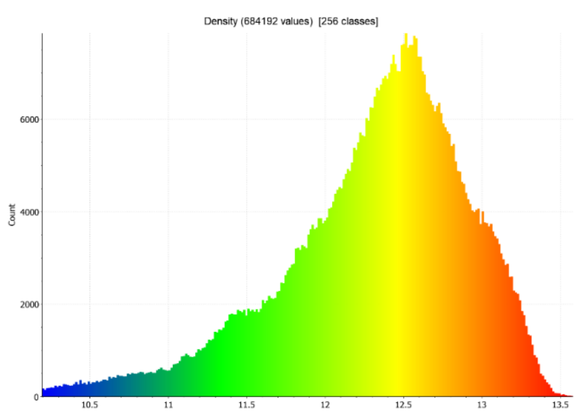


Figure 24. Image. Histogram of Density of Scalar Field for Poisson Reconstruction

The output mesh was modified using the scalar field density values to remove the section with low point density (as shown in Figure 25). The output mesh was split using the optimal scalar field value by visually approximating the best fit density. The reconstructed mesh is shown in Figure 23 for both RGB and scalar field color schemes.

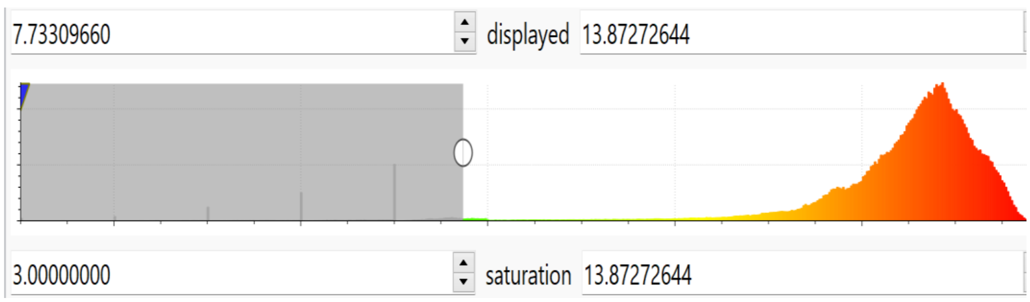


Figure 25. Image. Scalar Field Selected Density for Poisson Reconstruction

The accuracy of the mesh was calculated using a tool to measure the distance of the mesh by using the point cloud data as a reference. The accuracy is computed by iteratively by identifying the nearest octree cell to the point and measuring the distance. The parameter used for the distance computation is shown in Figure 27.

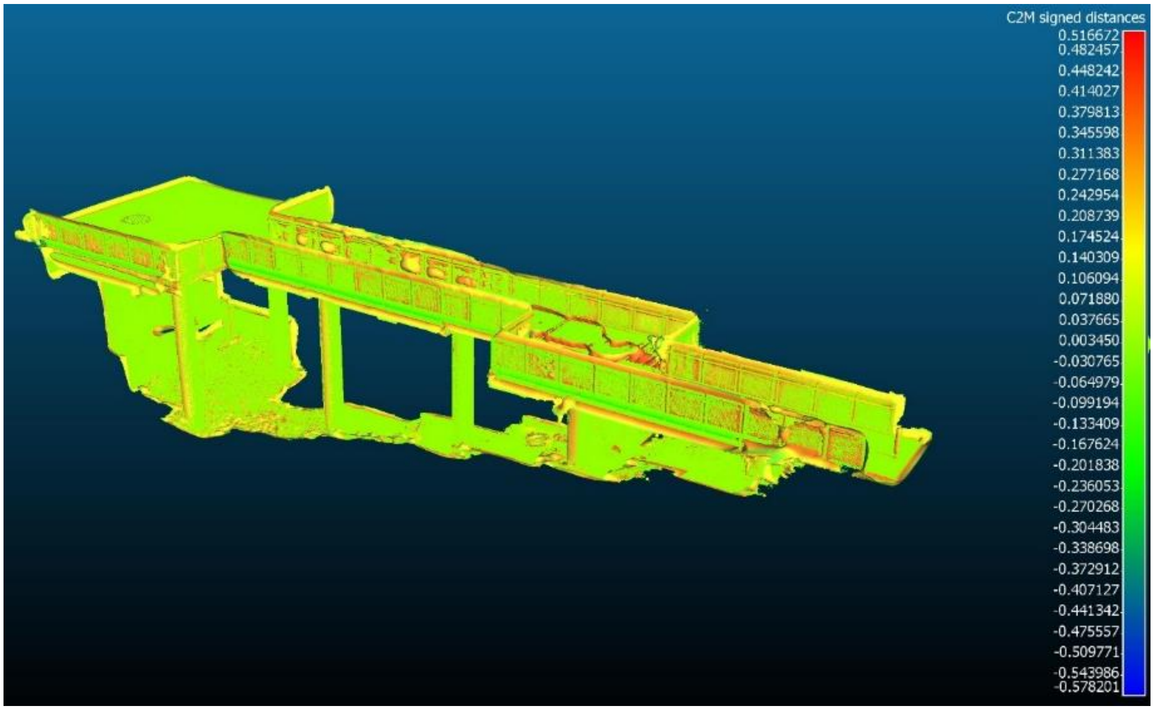


Figure 26. Image. Distance of mesh to point cloud

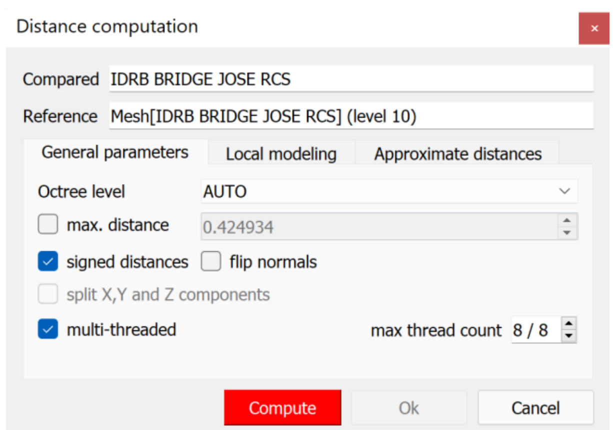


Figure 27. Image. Distance Computation parameters

3.6 Data Driven Component Prediction using Machine learning

A three-dimensional model facilitates three-dimensional reconstructing by automating a method for predicting material properties using machine learning through training of a neural network. The neural network can be trained based on infrastructure specific geometrical (e.g., material, member dimensioning, etc.) and logistic data (i.e., design engineer, general location, etc.) The use of a structured database of existing bridge components and material properties of existing bridges using training of a machine learning algorithm can aid in the prediction of internal or hidden components of the as-built bridge (e.g., rebar in reinforce concrete column). This is useful for bridge structures when identifying the internal components of columns and assigning the material properties and specification to a digital twin model. An application of these predicted components can be used when design documents are missing, lost to fire, or mismanaged.

3.6.1 Study of available databases

A reconstruction of as-built infrastructure can benefit from a ML algorithm trained by component dimensioning to automatically determine structural components and increase accuracy in the predictions. The geometrical data retrieved from the point cloud can be used to automate the detection of components and aid in the reconstruction of a 3D model by assigning the correct structural member designation. For steel beam w-sections, the manual measurements of the point cloud can be used to match to the dimensions of a steel section specification. For this to work, a data sheet with the correct structuring needs to be developed. For data structuring, the data needed was identified, and the available databases were reviewed to suggest the replicability of this method to other bridges.

The Federal Highway Administration (FHWA) databases (National Bridge inventory and Nation Bridge Element) and the Texas Department of Transportation (TXDOT) database were reviewed. The database information includes the coordinates for bridge location available, bridge identification number, count on the number of bridges, year built, owner, condition rating. The data is general including a count for bridges with poor condition, fair condition, and good condition with no specific information of the geometrical characteristics of each bridge. In terms of material properties, a general total of area (in meters squared) is recorded for a specific bridge condition (poor, fair, good). Additional information is needed specific to the geometrical characteristics obtained from a laser scan, or detailed design drawings for the components of a bridge (e.g., rebar, ties, etc.).

The current mesh generated by point cloud data allow for a digital visual of existing external elements of infrastructure. The goal of a digital twin model is a high level of detail and functionality to visualize the data captured by real-time monitoring systems. Therefore, there is a need to develop a method to identify the internal components of the infrastructure for a complete 3D model (e.g., BIM). This can be done by three methods: (1) access to design drawings (2) additional field data collection (e.g., GPR (Ground Penetrating Radar)) and (3) data driven material properties prediction using machine learning based on the external geometrical data. The challenge is to identify the internal components of the infrastructure and then incorporate material properties to the generated model without the need of the design drawing. A data structure for the prediction of these components using information retrieved from a laser scan is presented in the results.

Chapter 4: Results and Discussion

4.1 Brief Recap

When reconstructing a 3D model from point cloud data, the model must have a high level of detail plus compatibility with other software and the ability to integrate data. Many major companies offer a digital twin software solution including the Bentley iTwin Platform, Ansys Twin builder, Microsoft Azure Digital Twin, and Autodesk BIM software. Other platforms, such as game engines (e.g., Unity) and simulation software, are being used in unison with data visualization. The commonalities between these platforms are cloud storage, Application Program Interfaces (API), web access, large scale database capacity, and data visualization capacity.

The existing methods for digital twin applications from major software companies include visualization methods to create the model but are proprietary technologies and usually subject to an annual cost. For example, the Autodesk workflow for built infrastructure point cloud data would require preprocessing in Autodesk Recap before BIM modeling in REVIT or structural analysis in ROBOT. This creates a barrier to widespread implementation of infrastructure reconstruction. Therefore, there is a need to facilitate the reconstruction of existing infrastructure by studying available (i.e., affordable or open-source) resources.

The main challenge noticed in algorithm-generated-models is the limited information generated compared with the effort to collect and process the data. The models generated automatically are usually the exterior of the structure with the need to include more information about the hidden components of physical asset and material properties. Algorithm-generated models through open-source software are user-friendly but there is a need to improve the 3D modeling in general. The complex nature of improving the algorithm is out of the scope of the research but with reconstruction techniques using the point cloud data, the process by which the model is reconstructed from the laser scan can be improved.

4.2 Scan-to-BIM and Point Cloud Data Accuracy

The data collected from the point cloud was used to identify the correct steel section used in the constructed pedestrian bridge and to measure the accuracy of the scan to the reference design drawings. To do so, the components were individually measured in the point cloud and then compared to the specifications from the design documents. Using the point cloud of the bridge structure, detailed geometrical measurements were retrieved for the visualization and analysis of the as-built structure. The data collected from the point-to-point measurements can be seen at the appendix from Table 21 to Table 25 Table 21. Beam measurements from point cloud data, design drawing, and AISC steel section dimensioningfor beam measurements from point cloud data, design drawing, and AISC steel section dimensioning. This data was used to:

1. Compute the variation in the distance (at the component level for steel beam, girders, and columns) from the terrestrial lidar scanning to design drawings and member sizing.
2. Calculate the error of the beam-specific dimensioning to the standardized sizes of material (steel beams) used in the construction of the bridge with specification of beam section for the W-section and design drawings.
3. Determine the accuracy of the scan relative to the design drawings (members sizing, height of columns, overall design vs as-built structure)

These measurements were used during the reconstruction of the BIM model and referenced with the design drawings. Assuming no design drawing are not available, the W-section dimensions (width, depth, flange thickness, and web thickness) can be used to identify the W-section used (as shown the flowchart in Figure 30). Assuming prismatic members, this can then extrude to the measured length. To validate this method of reconstruction using a point cloud data only, the percent error for individual components was measured to determine the efficacy of the method, by point-to-point measurements. The calculated accuracy of beams and girders was over 90% for length, width, and depth of the flange. These measurements are easier to obtain because they are more visible (exposure) and tend to be larger in size. More detailed measurement such as the flange and web thickness show greater variability and lower accuracy of the measurements. The average accuracy for the beam flange thickness and web thickness measurements are 57% and 62%, respectively. The accuracy for each component dimensioning is shown in **Error! Reference source not found.**.

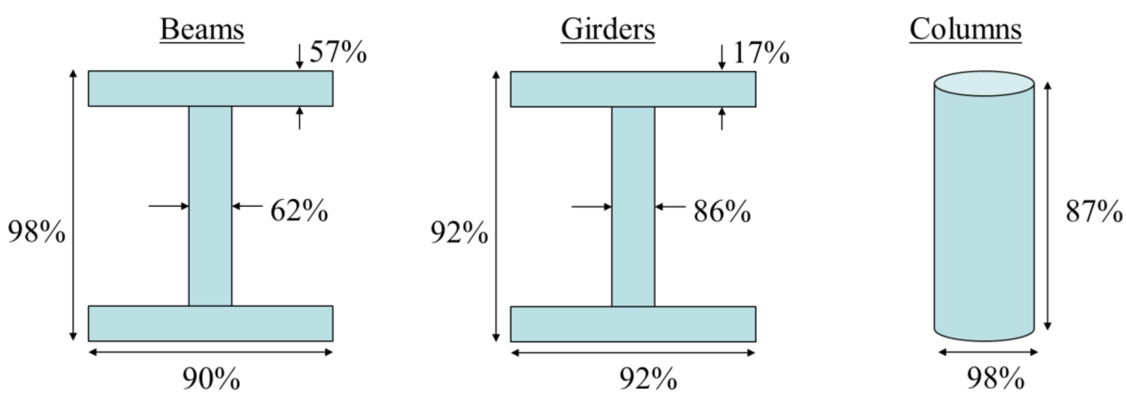


Figure 28. Image. Summary of accuracy for individual dimension per component

There are several factors which may contribute to these errors:

1) the angle and distance for the terrestrial scanning
2) self-shadowing at the flange or enclosed areas (as shown in Figure 29),
3) additional noise captured in the area for the detailed scan,
4) human error when point picking,

5) hidden components at the connection with the building and the patio area

Figure 29. Photo. Enclosed space between beams in pedestrian bridge

For column diameter and the deck area the average accuracy was over 97%. In, contrast a lower average accuracy of 87% was observed for the column height. The three tallest columns at the south end of the pedestrian bridge presented the highest percent error close to 20%. This area serves for the storm water drainage inlets therefore site landscape may cover a portion of the bottom of the column. The summary of the data for the calculated values is shown in Table 3, Table 4, and Table 5 for beams/girders, columns, and deck, respectively.

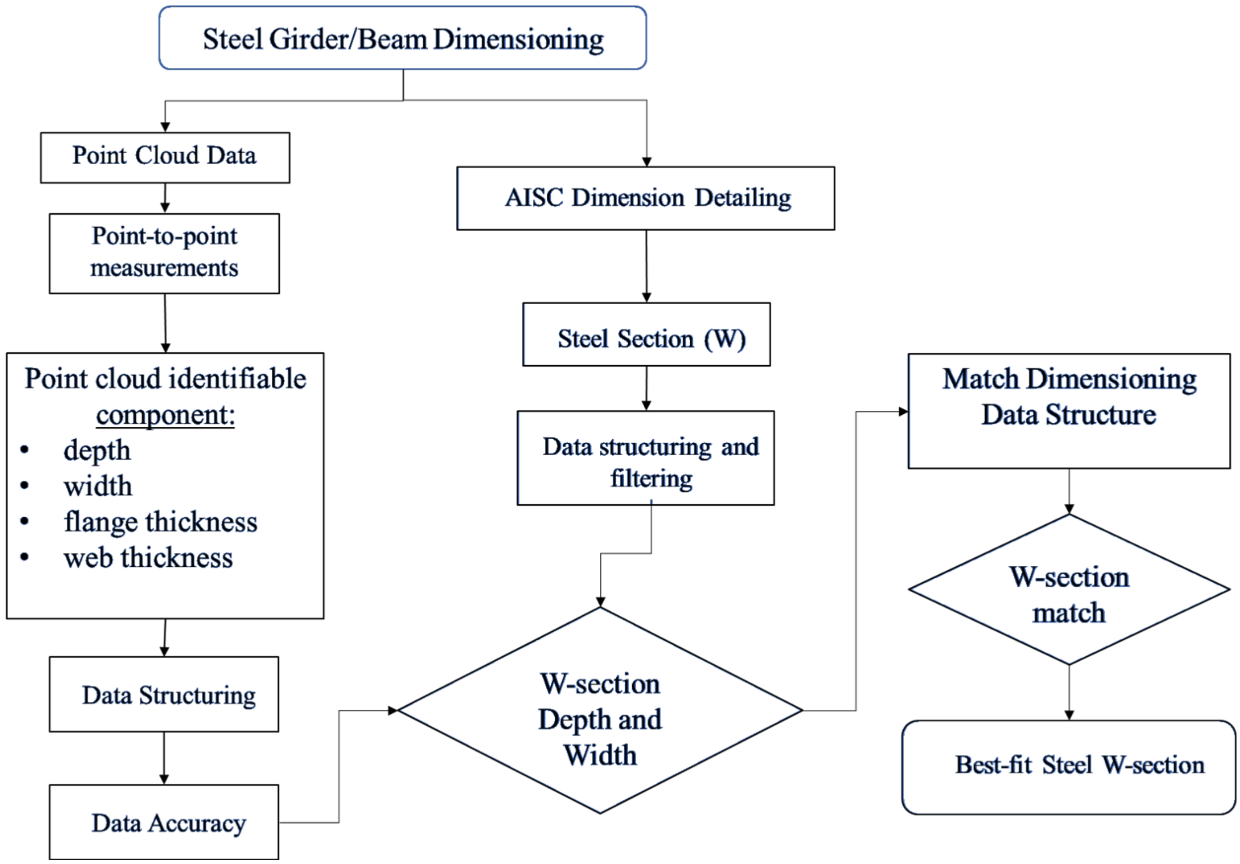


Figure 30. Image. Steel Girder/Beam W-Section Matching Process

Table 3. Summary of Beam and Girder Measurements

Summary table			Length	Width	Depth	Flange Thickness	Web Thickness
Beams	Distance difference (in)	mean	16.114	0.501	0.217	0.363	0.096
		std. dev.	14.889	0.369	0.116	0.171	0.052
	error (%)	mean	7.761	10.026	1.576	43.464	38.408
		std dev.	6.005	7.371	0.842	18.830	20.884
	Average Accuracy (%)		92.24	89.97	98.42	56.54	61.59
Girders	Distance difference (in)	mean	15.431	0.413	0.453	0.924	0.033
		std. dev.	23.288	0.293	0.704	0.144	0.018
	error (%)	mean	6.576	7.717	2.726	82.914	13.386
		std dev.	4.503	5.023	3.871	11.964	7.043
	Average Accuracy (%)		93.42	92.28	97.27	17.09	86.61

Table 4. Summary of Column Measurements

Summary table			height	diameter
columns	Distance difference (in)	mean	24.917	0.472
		std. dev.	18.242	0.241
	error (%)	mean	12.869	1.575
		std dev.	4.014	0.802
	Average Accuracy (%)		87.13	98.43

Table 5. Summary of Deck Measurements

Summary table			Length	Width
Deck	Distance difference (in)	mean	3.287	7.933
		std. dev.	5.093	12.152
	error (%)	mean	1.348	2.656
		std dev.	1.760	3.062
	Average Accuracy (%)		98.65	97.34

The individual calculated values for the difference in the distance, percent error, and accuracy are shown in:

- Beams: Table 7 (calculated difference), Table 8 (percent error), and Table 9 (accuracy)
- Girders: Table 10 (calculated difference), Table 11 (percent error), and Table 12 (accuracy)
- Columns: Table 13 (calculated difference), Table 14 (percent error), and Table 15 (accuracy)
- Deck: Table 16 (calculated difference), Table 17 (percent error), and Table 18 (accuracy)

The rows highlighted in orange for the accuracy tables signifies the problematic area for manual measurements obtained from a point cloud. These values were either under 50 % accuracy or the dimensions were unidentifiable during the point-to-point measurements.

To complete the BIM model the total process took about 20 hours. This includes the recording measurements from point cloud needed to setup the grid in Revit, identifying the steel structural components, span lengths, and rendering the bridge (15 beams, 5 girders, and 7 columns). This does not include additional measurement done to compute the accuracy of the point cloud data. The breakdown of the duration per task in shown in

Table 6.

Table 6. BIM task breakdown and approximate duration

Tasks:	Time (hrs)
Record measurements from point cloud	3.5
Grid setup span lengths and elevation	6.5
Identify the steel structural	2
Render bridge	6-7
Total time	19.5

Table 7. Beam calculated distance difference per component

Component		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Beams	Difference in distance measurements (inch)	B1	W16 x 26	6.61	0.43	0.33	0.40	0.03
		B2		9.87	0.35	0.33	0.19	1.44
		B3		8.97	0.39	0.21	0.23	0.09
		B4		8.54	1.10	0.06	0.23	0.10
		B5		9.40	1.10	0.06	0.15	0.05
		B6	W14 x 22	59.20	0.67	0.27	0.38	0.14
		B7		7.11	1.26	0.32	0.13	0.06
		B8		0.49	0.16	0.31	0.42	0.05
		B9		12.14	0.43	0.03	0.61	0.18
		B10		15.21	0.24	0.13	0.50	1.21
		B11		22.22	0.16	0.36	0.50	0.14
		B12		39.98	0.12	0.34	0.50	0.46
		B13		13.36	0.24	0.21	0.65	0.46
		B14		15.21	0.43	0.15	0.14	0.50
		B15		13.40	0.43	0.15	0.42	0.62
		mean		16.114	0.501	0.217	0.363	0.096
		std. dev.		14.889	0.369	0.116	0.171	0.052

Table 8. Beam calculated percent error per component

Component		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Beams	Error Point Cloud Data Measurement	B1	W16 x 26	0.02	0.09	0.02	0.91	0.10
		B2		0.04	0.07	0.02	0.44	-
		B3		0.03	0.08	0.02	0.53	0.37
		B4		0.03	0.22	0.00	0.53	0.42
		B5		0.03	0.22	0.00	0.35	0.21
		B6	W14 x 22	0.15	0.13	0.02	0.34	0.57
		B7		0.01	0.25	0.02	0.12	0.26
		B8		0.00	0.03	0.02	0.37	0.21
		B9		0.13	0.09	0.00	0.55	0.73
		B10		0.16	0.05	0.01	0.44	-
		B11		0.05	0.03	0.03	0.44	0.57
		B12		0.08	0.02	0.03	0.44	-
		B13		0.14	0.05	0.02	0.57	-
		B14		0.16	0.09	0.01	0.13	-
		B15		0.14	0.09	0.01	0.37	-
			mean	7.761	10.026	1.576	43.464	38.408
			std dev.	6.005	7.371	0.842	18.830	20.884

Table 9. Beam calculated accuracy per component

Component		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Beams	Accuracy point cloud based on reference Design Drawings	B1	W16 x 26	97.66	91.34	97.61	9.00	89.76
		B2		96.50	92.91	97.61	56.02	-
		B3		96.82	92.13	98.46	47.02	62.99
		B4		96.97	77.95	99.60	47.02	58.27
		B5		96.67	77.95	99.55	65.02	78.74
		B6	W14 x 22	85.30	86.61	98.07	66.49	42.52
		B7		99.02	74.80	97.64	88.01	74.02
		B8		99.93	96.85	97.78	62.99	78.74
		B9		87.35	91.34	99.79	45.49	26.77
		B10		84.15	95.28	99.07	55.99	-
		B11		95.33	96.85	97.35	55.99	42.52
		B12		91.60	97.64	97.49	55.99	-
		B13		86.08	95.28	98.50	42.52	-
		B14		84.15	91.34	98.93	87.49	-
		B15		86.04	91.34	98.93	62.99	-
		Average Accuracy (%)		92.24	89.97	98.42	56.54	61.59

Table 10. Girder calculated error per component

Component		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Girder	Error Point Cloud Data Measurement	G1	W18x 40	0.142	0.134	0.095	0.741	0.102
		G2	W14 x 22	0.060	0.102	0.022	0.965	0.260
		G3		0.057	0.000	0.015	0.685	0.102
		G4		0.022	0.063	0.002	0.825	0.102
		G5		0.048	0.087	0.002	0.930	0.102
			Mean	0.066	0.077	0.027	0.829	0.134
			Std. dev.	0.045	0.050	0.039	0.120	0.070

Table 11. Girder calculated distance difference per component

Component		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Girder	Difference in distance measurements (inch)	G1	W18x 40	57.074	0.803	1.694	0.787	0.026
		G2	W14 x 22	5.764	0.512	0.305	1.086	0.065
		G3		5.488	0.000	0.207	0.771	0.026
		G4		4.244	0.315	0.030	0.928	0.026
		G5		4.583	0.433	0.030	1.046	0.026

Table 12. Girders calculate accuracy per component

Component		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Girder	Accuracy point cloud based on reference Design Drawings	G1	W18x 40	85.825	86.614	90.524	25.938	89.764
		G2	W14 x 22	93.996	89.764	97.781	3.500	74.016
		G3		94.283	100.000	98.497	31.496	89.764
		G4		97.790	93.701	99.785	17.498	89.764
		G5		95.226	91.339	99.785	6.999	89.764
Mean				93.424	92.283	97.274	17.086	86.614
Std. Dev.				4.503	5.023	3.871	11.964	7.043

Table 13. Column calculated distance difference per component

Difference in distance			
Component	Label	Height	Diameter
Column (in)	C1	55.716	0.394
	C2	35.283	0.709
	C3	37.369	0.433
	C4	17.921	0.079
	C5	10.621	0.827
	C6	10.976	0.433
	C7	6.535	0.433
mean		24.917	0.472
Std. Dev.		18.242	0.241

Table 14. Column calculated percent error per component

Percent error (%)			
Component	Label	Height	Diameter
Column	C1	19.517	1.312
	C2	12.359	2.362
	C3	13.946	1.444
	C4	8.617	0.262
	C5	9.487	2.756
	C6	9.803	1.444
	C7	16.353	1.444
Mean		12.869	1.575
Std. Dev.		4.014	0.802

Table 15. Column calculated accuracy per component

Accuracy Columns			
Component	Label	Height	Diameter
Column (in)	C1	80.483	98.688
	C2	87.641	97.638
	C3	86.054	98.556
	C4	91.383	99.738
	C5	90.513	97.244
	C6	90.197	98.556
	C7	83.647	98.556
mean		87.131	98.425
Std. Dev.		4.014	0.802

Table 16. Deck calculated difference per section

(Based on decking dimensions)		Difference in Measurements	
		Length (in)	Width (in)
Deck	D1	10.890	25.913
	D2	0.205	0.417
	D3	1.409	4.756
	D4	0.646	0.646
	mean	3.287	7.933
	Std. Dev.	5.093	12.152

Table 17. Deck calculated percent error per section

(Based on decking dimensions)		% Error	
		Length	Width
Deck	D1	3.946	7.042
	D2	0.039	0.435
	D3	0.734	2.477
	D4	0.673	0.673
	mean	1.348	2.656
	Std. Dev.	1.760	3.062

Table 18. Deck calculated accuracy per section

(Based on decking dimensions)		Accuracy (%)	
		Length	Width
Deck	D1	96.054	92.958
	D2	99.961	99.565
	D3	99.266	97.523
	D4	99.327	99.327
average accuracy		98.652	97.344

4.3 RANSAC

The RANSAC algorithm in the open-source software Cloud Compare was used to create a mesh by assigning shapes to the point cloud based on the parameter input. Various iterations were done to select the best fit combination of primitive shapes (plane, cylinder, sphere, cone, torus) to generate the mesh. The search time for the best fit mesh was 205 seconds (about 3 minutes 25 seconds). This includes time associated with shape detection and with creating a shape generated model. The model includes 289 cylinders, 170 cones, 21 spheres detected, and leftover points removed that did not fit into the input parameters (shown in Figure 22). The time for algorithm to detect the primitive shapes for the various iteration is shown in Table 19. If compared to the LOD specification provided for BIM, the level of detail produced by the RANSAC model is in between 200-300. The model generated can be used as an intermediary step to obtain the geometrical and material properties of the bridge structure for further processing.

The accuracy of the model was calculated using a Cloud Compare tool by measuring the distance between the point cloud data and the point cloud created from the primitive shapes The shapes remain as a point cloud format which make the file compatible with other software for further processing. Based on the automated calculations from point-to-point distance, the model is highly accurate (according to point cloud to shapes detected distance measurements) and efficient in the time the algorithm took to detect and assign a shape. But the primitive shapes detected do not make sense if we consider the planar nature of the faces in the beam and girders. The algorithm randomly assigned shapes to the point clusters that met the parameter inputs shown in Table 2 and Table 19. When segmenting a single column, beam, and girder the RANSAC algorithm will either oversimplify a beam/girder to a single plane or in the case of the column (as shown in Figure 32), multiple cylinders are detect assigned per column (as shown in Figure 31).

Table 19. RANSAC shape detection for multiple iterations

Parameter input	Time for shape detection (seconds)	No. of planes	No. of cylinders	No. of spheres	No. of cones	No. of torus
Plane	79.487	404	0	0	0	0
Cylinder and sphere only	208.866	0	422	42	0	0
Cylinder, sphere, cone	302.939	0	258	27	192	0
Cylinder, sphere, cone, torus	205.837	0	289	21	170	0

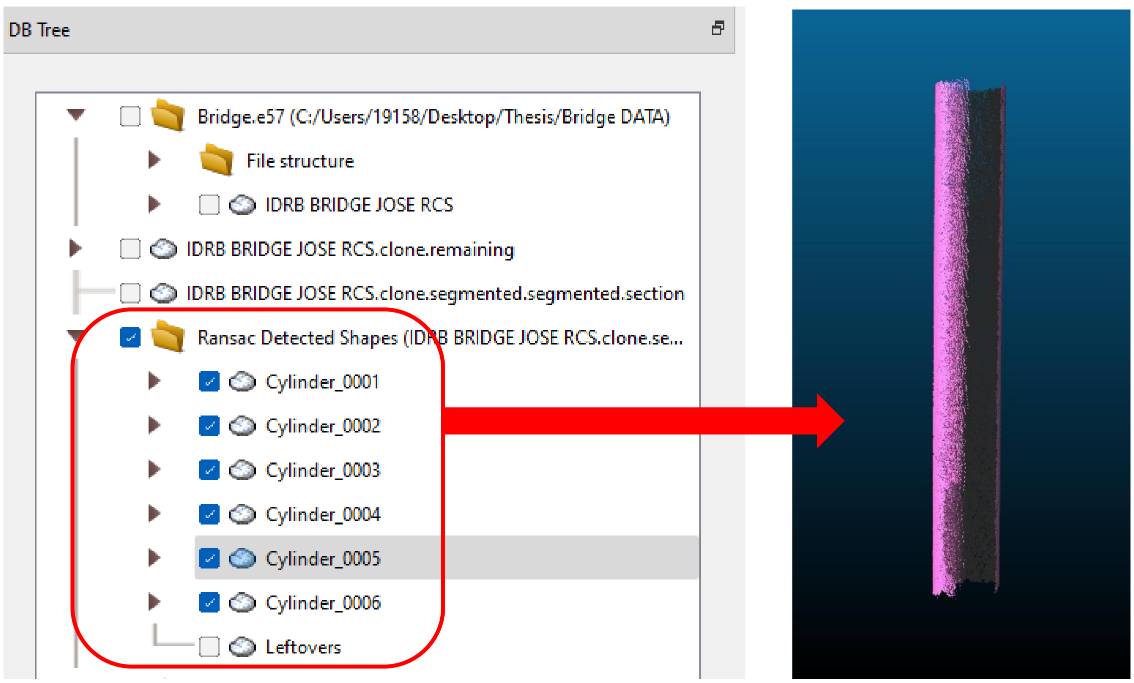


Figure 31. Multiple planes detection at component level

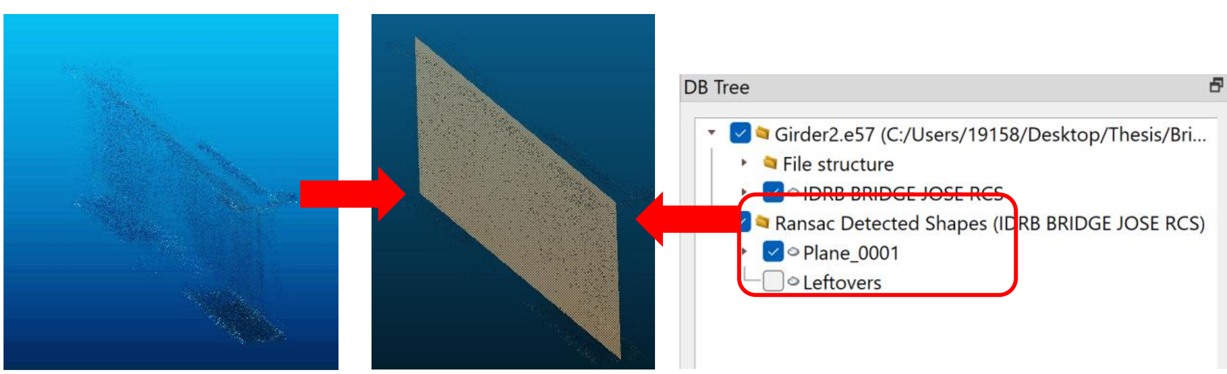


Figure 32. Girder Plane Detection

4.4 Poisson Reconstruction

The three-dimensional reconstruction of the mesh was generated in approximately 20 seconds. The Poisson reconstruction method was completed after 16.2 seconds and generated 1,437,671 triangles with 717,998 vertices. The distance computation for the point cloud to measure time was 88.47 seconds. The mean distance was 0.00346 with a standard deviation of 0.013764. Based on these results the mesh created proved to be accurate when compared to the scan. The Poisson Reconstructed mesh although accurate according to the measurement of the distance from the point cloud data, the mesh visually presents a lack of detail in the reconstruction of the beam and girders. There are visible patches in the reconstruction when viewing the component level reconstructions (as shown in Figure 33). The mesh generates shell of the bridge structure showing the external geometry with no material properties.

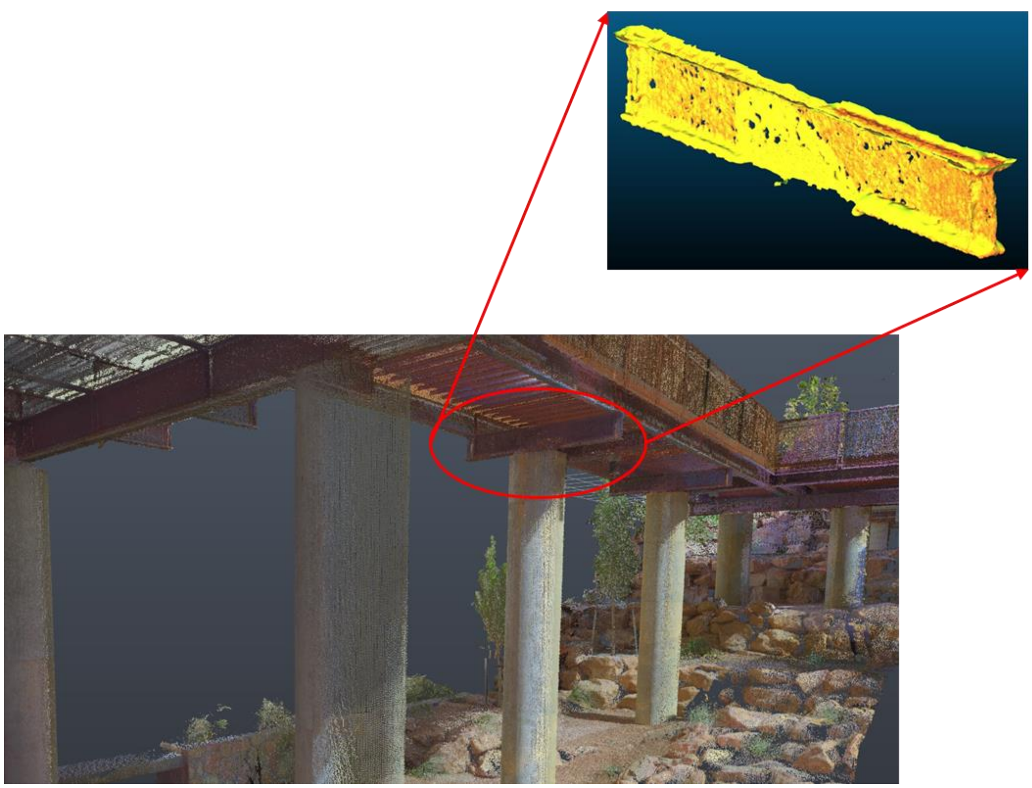


Figure 33. Poisson Reconstruction of girder

The Poisson reconstruction automates the process to create a mesh, but the reconstruction does not allow for further data visualization and the reconstruction methods remain dependent on the quality of the scan.

4.5 Comparison

The method presented each have advantages and disadvantages. The use of algorithm generated model simplify the reconstruction by automating the computation procedure to generate the model and measure the accuracy with a few seconds. The disadvantage is the model is not created with specific information on the component and material properties. A building information model approach enables a high accuracy model with specific material properties and individual components. The disadvantage is recreating the model from point-to-point measurement or tracing. The algorithm reconstructed methods have several limitations. The model generated by shape detection creates an over simplified model or inaccurate by randomly assigning shapes to point cluster. The Poisson reconstruction generates a single mesh with no material section or properties. In addition, all methods are dependent of the quality of the scan, and exposure to the laser scanner field of vision. A complete comparison for the three-dimensional model created is shown in **Error! Reference source not found.**.

Table 20. Comparison between the reconstruction methods

	Computational requirement	Compatibility with software	Data Integration	Efficiency	Accuracy
Autodesk Recap As-built Point Measurement	• Medium to high (dependent of point cloud data file size • User-friendly tools for segmenting points of interest (bridge components, beams, columns, etc.)	• High compatibility • File conversion to Revit file format • Additional file format available (.laz, .e57, .pts, tec.)	• Limited data integration • Insert images, videos, text to point • Point -to-point accuracy measurements (dependent on scan quality)	• Medium to high efficiency (point cloud data file size dependent) • Simple data extraction and sharing • Smooth maneuvering and point cloud segmentation	• Medium to high accuracy of measurement (dependent on quality of scan)
Scan-to-BIM	• Low to medium • Software knowledge (grid set-up, elevation set-up, data integration, and IFC compatible file)	• High data compatible with other BIM software (IFC classes) • Data integration	• Construction management data • Scheduling • Material count	• Medium efficiency (when compared to algorithm mesh) • Manual tracing dependent on user	• High accuracy • Time consuming (when compared to algorithm)
Poisson Reconstruction	• Low computation requirement • User-friendly parameter input and point cloud tools	• Medium compatibility with most point cloud file types • Export file format for mesh import to additional software	• Limited to point cloud data (merging, distance computation, topographic/ elevation segmentation)	• High efficiency when generating a mesh (dependent on octree level for detail and size of point cloud data)	• High accuracy (dependent on octree level and quality of laser scan)
RANSAC	• Low computation needed to run algorithm • Fast shape detection (within seconds)	• High compatibility with point cloud files and export file formats	• Low external data integration • Simplified shape of component (e.g., only one plane detected for beam	• High primitive shape detection • Low quality when assigning correct primitive shapes to point cloud • Oversimplified shape detection	• Low accuracy • Random assigning of primitive shapes when processing entire model
ROBOT FEM	• Low to medium (dependent on size of project and computational power	• High direct link to Autodesk BIM software	• Dependent on external data integrated • Simulation based	• Direct export from BIM model • Links used to represent connections	• High accuracy • Limited to structural elements

Chapter 5: Conclusions

5.1 Summary

The use of DT technology for infrastructure management is in its infancy. A three-dimensional model for as-built infrastructure assets is an important aspect of a DT. The model should include the geometrical characteristics, section and material properties, simulation capabilities, and real-time data visualization. The geometrical characteristics of the infrastructure asset can be retrieved using laser scanning. A method to aid in the three-dimensional reconstruction of infrastructure is with geometrical data captured with laser scanning or through the inspection of bridges.

The geometrical data for a pedestrian bridge case study on the UTEP campus was captured using terrestrial LiDAR scanning. The point cloud data was then measured to determine the difference in distance from the captured scan to the design drawings and section dimensioning. The measurements were used to compute the accuracy of using the point cloud as the reference to create a virtual model. Then the point cloud data was used to create a virtual reconstruction of the bridge using both BIM and algorithm reconstruction methods.

The point cloud measurements of the external characteristics can be used to identify the section properties of the infrastructure for steel sections and the external geometry for concrete sections, but this requires human input. This process to match point cloud cross sectional measurement the dimensions to the steel section could be automated using simply filtering. For concrete, more robust tools would be required. General conclusions and future research directions are summarized below.

5.2 Limitations of the Study

This study was focused on using LiDAR laser scanning to build geometric replica models of infrastructure. There were several limitations.

First, the scanning layout and density were determined in a non-systematic manner that was consistent with the research team's relative novice experience at the time. No efforts were made to scan from elevations other than the ground and deck elevation. Filtering and data cleanup were conducted through manual approaches, including manual evaluation of filter parameter variance on appearance of results. We did not explicitly validate numerous filtering approaches. We only considered two specific, relatively common approaches to automated reconstruction.

The study focused on gross external measurements for structural components. The scope was limited to identifying LOD 300 information for structural components. The specific scenario considered for the case study focused on a relatively low traffic pedestrian bridge. As such, many of the logistical limitations that might be experienced on an operating highway bridge were not included.

5.3 General Conclusions

5.3.1 General issues with scanning

- The information captured by a detailed terrestrial laser scanning process is limited to the external geometry of infrastructure and quality of the scan.
- The laser scan quality is affected by the angle of incidence. A steep angle creates self-shadowing effect on the flange.
- The quality of the scan is dependent on the exposure of the infrastructure to the scanning equipment. Clear line of sight is important.

- The access to the site presents a challenge considering most bridges are constructed over bodies of water or operating roadways. For this case study, the laser scanning was conducted in terraced, complex terrain.
- The scan is prone to self-shadowing of staggered members (e.g., column-to-girder connection)

5.3.2 Issues with scan to BIM

- Onsite scanning and data analysis is time consuming. For this study, the reconstruction of the pedestrian bridge alone took about 20 hours excluding the point-to-point measurements
- The state-of-the-art in Scan-to-BIM still requires substantial human interaction including manual point-to-point measurements of the individual components, grid set-up based on point cloud measurements (column and beam spacing layout and orientation with respect to true north), and component identification of structural materials.
- Structural geometry needs to be approximated using the measurements obtained from point cloud and is dependent on the quality of the scan.
- The process to determine the section properties without the use of design drawing is challenge. For a steel member, for example, it requires matching the point cloud measurements to a steel section detail (i.e., AISC detail dimensioning).
- There is no automated approach to assign material properties. This requires human input based on images or site assessment.
- Certain critical design details like member-to-member connections are difficult to obtain from scans because the regions where these details are located are harder to scan and because the functionality of the connection is determined by rather small (i.e., weld size and location) details.

5.3.3 Issues with Algorithmic approach – RANSAC

- The RANSAC algorithm assigns shapes to point clusters that meet the input criteria, generating shapes seemingly at random sometimes to create the model. As an example, beams were often assigned cylinders.
- When segmenting the point cloud to a particular structural component (beam, girder, or column), the algorithm often assigns an oversimplified shape to the points (a single plane to beams/girders and cylinders for a column)
- The model created requires further processing to reconstruct the individual components correctly and to assign section and material properties. The result is not close to implementation in a DT.

5.3.4 Issues with algorithmic approach – Poisson Reconstruction

- Self-shadowing and scan quality affect the reconstruction by leaving patches for missing points or extending to incorrect points.
- The mesh is limited to the external geometry of the components with the need for further processing to assign section and material properties to the geometry.
- The model is one mesh and does not distinguish between different structural elements. If segmented to a component level the mesh is prone to patching or overextending. The result is not ready for implementation in a DT

5.4 Observed Challenges and Potential Solutions

5.4.1Challenge 1: All approaches are dependent on scan quality

Scan quality appears to be a key driver for what information can be obtained. However, scans are time consuming to obtain. A single scan is created in just 3 to 6 minutes depending on the quality, but even for this relatively small pedestrian bridge, 14 scans were required. Considering time to setup, scan, and move to the next spot, a single bridge can take several hours. This also does not include challenges like traffic.

Even if one ignores those challenges, there is a theoretical limit to how much information we can obtain from scans, particularly from ground level. Subsequent scans, including scans at the bridge bearing level, are very costly while providing only minimal additional value. Given that scans will never show the interior of concrete elements, or any details that are not visible from line of sight, it is impossible that scanning will provide everything needed even for a BIM model of a bridge, much less a DT. There will always be gaps between scan data and BIM and/or DT models.

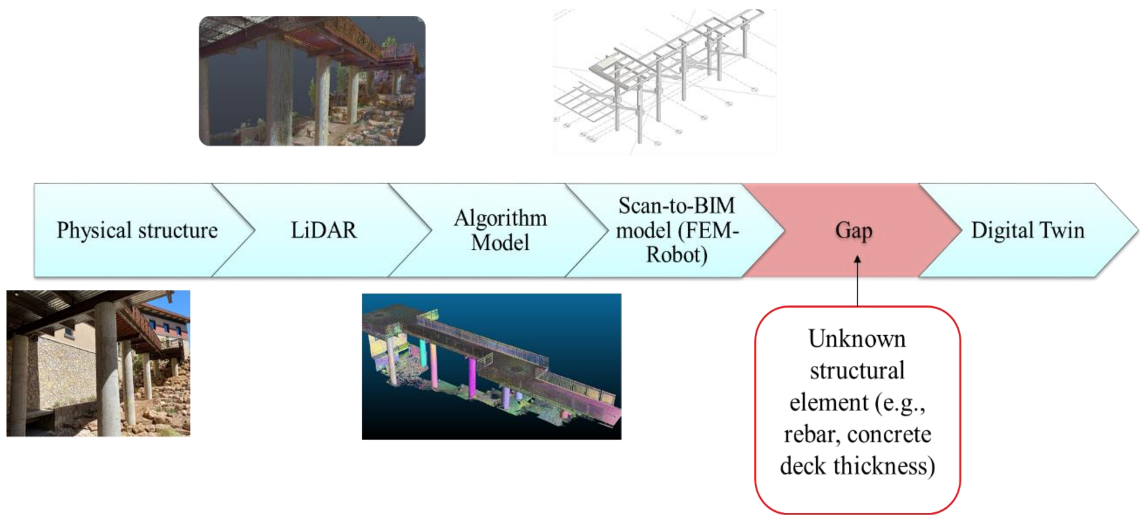


Figure 34. Image. Gap in LiDAR based model reconstruction

5.4.2 Potential Solution 1: ML and AI can help to fill gaps

ML or AI approaches offer one potential solution to close the gaps (seen in Figure 34). A ML algorithm can be trained to predict with quantifiable confidence these unknown parameters to help create a DT-ready model from a scan. However, this creates a subsequent challenge to be addressed. This approach would require substantial, large, and diverse training datasets.

5.4.3 Challenge 2: ML and AI require training data

Currently, there is not enough training data available to implement ML and AI approaches for this problem. We would need large sets of specific geometric, section, and material property data so that we could confidently correlate measurable parameters (e.g., beam depth and flange width of a steel section) with unmeasurable parameters (e.g., beam web thickness). This example with a steel section is illustrative but would not likely require ML or AI since the correlation between depth and width is very strong with internal dimensions. A simple filtering process would be sufficient. However, if one considers concrete elements, the challenge is clearer. Concrete deck thickness is not measurable, for example, but could be predicted based simply on bridge location, or span length/girder spacing.

Collecting this data would be a substantial effort. The training data would have to be structured in such a way as to maintain the spatial relationships that are defined by a bridge (i.e., individual girders on a multi-girder bridge).

5.4.4 Potential Solution 2.1: Augment bridge inspection protocols to include field data collection

One way to reduce the cost of this data collection would be to leverage the Federal bridge inspection program. Bridge inspectors are out on bridges once every two years to conduct visual inspection. Their mandate could temporarily be expanded to include measurement of key parameters that would feed into a BIM for Bridge model to facilitate widespread model construction. This dataset could be used for training, and BIM for bridges could manage the spatial variation in this data.

5.4.5 Potential Solution 2.2: Paper study approach

A second approach which would be costly but would not involve bridge inspectors would be to create a database of bridge characteristics that are required for DT models via a paper study – manual/automated review of bridge construction drawing archives. Again, in this scenario there is a need for a BIM for bridge model to act as a translator that can relate scan data to individual bridge elements via their spatial location.

5.5 Future Research

The use of machine learning and cloud computing for integrating, structuring, and using data to understand what is happening to the physical infrastructure system is key to remotely monitoring city scale infrastructure from a single access point. Specifically for bridges, a database with bridge components can improve the 3D reconstruction of the model for a high level of detail. This database is currently not available or has not been recorded.

To understand the current method for collecting data from current bridge geometry we determined a gap in the current data being collected and introduced additional data collection criteria for potential machine learning trained algorithms. Even after creation of a geometric replica model that can be incorporated into a DT model, there are still challenges with integrated real-time data efficiently and using that data to change behavior of the real system in the DT.

The idea of DT and optimized 3D modeling methods need to aim for advancement in application of technology for infrastructure and consider the future visualization at a city scale. Gaming engines such as Unity have proven to work well for 3D reconstruction and visualization of the built infrastructure in a virtual environment. The vision is to fully replicate infrastructure digitally but to do so the capabilities of modeling software, algorithm reconstructions, and gaming engines in terms of visualization and compatibility with data need to be well understood. Unity is compatible with data from sensing equipment using programming languages and proficient when creating a complete dashboard to monitor the near real-time condition of the sensor. In future research, this can be expanded to include real-time data for building energy consumption, utilities (water, gas), transportation infrastructure serviceability (numbers of cars, speed, vision-based sensing, vehicle type, etc.).

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Appendix

Table 21. Beam measurements from point cloud data, design drawing, and AISC steel section dimensioning

Component		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Beams	Design Drawings (in)	B1	W16 x 26	282	5.0	13.875	0.4375	0.25
		B2		282	5.0	13.875	0.4375	0.25
		B3		282	5.0	13.875	0.4375	0.25
		B4		282	5.0	13.875	0.4375	0.25
		B5		282	5.0	13.875	0.4375	0.25
		B6	W14 x 22	402.625	5.0	13.75	1.125	0.25
		B7		726	5.0	13.750	1.125	0.25
		B8		726	5.0	13.750	1.125	0.25
		B9		96	5.0	13.750	1.125	0.25
		B10		96	5.0	13.750	1.125	0.25
		B11		476	5.0	13.750	1.125	0.25
		B12		476	5.0	13.750	1.125	0.25
		B13		96	5.0	13.750	1.125	0.25
		B14		96	5.0	13.750	1.125	0.25
		B15		96	5.0	13.75	1.125	0.25
	Point Cloud (in)	B1	W16 x 26	275.394	4.567	13.543	0.039	0.276
		B2		272.126	4.646	13.543	0.630	1.693
		B3		273.031	4.606	13.661	0.669	0.157
		B4		273.465	3.898	13.819	0.669	0.354
		B5		272.598	3.898	13.937	0.591	0.197
		B6	W14 x 22	343.425	4.331	14.016	0.748	0.394
		B7		733.110	6.260	13.425	1.260	0.315
		B8		725.512	4.843	14.055	0.709	0.197
		B9		83.858	4.567	13.780	0.512	0.433
		B10		80.787	5.236	13.622	0.630	1.457
		B11		453.780	4.843	13.386	0.630	0.394
		B12		436.024	4.882	14.094	0.630	0.709
		B13		82.638	4.764	13.543	1.772	0.709
		B14		80.787	4.567	13.898	0.984	0.748
		B15		82.598	4.567	13.898	0.709	0.866

Table 22. Girder measurements from point cloud data, design drawing, and AISC steel section dimensioning

		Label	Steel Section	Length	Width	Depth	Flange Thickness	Web Thickness
Girder	Design Drawings (in)	G1	W18x 40	402.625	6	17.875	1.0625	0.25
		G2	W14 x 22	96	5	13.75	1.125	0.25
		G3		96	5	13.75	1.125	0.25
		G4		192	5	13.75	1.125	0.25
		G5		96	5	13.75	1.125	0.25
	Point Cloud (in)	G1	W18x 40	345.551	5.1969	16.181	0.276	0.276
		G2	W14 x 22	90.236	4.4882	14.055	0.039	0.315
		G3		90.512	5.0000	13.543	0.354	0.276
		G4		187.756	4.6850	13.780	0.197	0.276
		G5		91.417	4.5669	13.780	0.079	0.276

Table 23. Column measurements (drawing and point cloud)

Column Drawings		Design Drawings Measurements				Point Cloud Data Measurements	
Component	Label	T.O.C.	T.O.F.	Height (in)	Diameter (in)	Height (in)	Diameter (in)
Columns	C1	3839.79	3816	285.48	30	229.764	29.606
	C2	3839.79	3816	285.48	30	250.197	29.291
	C3	3841.33	3819	267.96	30	230.591	29.567
	C4	3841.33	3824	207.96	30	190.039	29.921
	C5	3841.33	3832	111.96	30	101.339	29.173
	C6	3841.33	3832	111.96	30	100.984	29.567
	C6	3841.33	3838	39.96	30	33.425	29.567

Table 24. Foundation Design Drawing Measurements

Design Drawings					
Component	Label	TC Elevation	BC Elevation	Depth (ft)	Diameter (ft)
Foundation	1	3816	3798	18	3
	2	3816	3798		
	3	3819	3801		
	4	3824	3806		
	5	3832	3814		
	6	3832	3814		
	7	3838	3820		

Table 25. Deck Dimension Data (design drawings and point cloud)

(Based on decking dimensions)		Design Drawings			Point Cloud		
		Length (in)	Width (in)	Area (in^2)	Length (in)	Width (in)	Area (in^2)
Deck	D1	276.000	368.000	101568	286.890	342.087	98141.14793
	D2	528.000	96.000	50688	96.417	527.795	50888.60748
	D3	192.000	192.000	36864	190.591	187.244	35686.95517
	D4	96.000	96.000	9216	95.35433071	95.35433071	9092.448385
Total				198336.00			193809.159

Curriculum Vita

Jose Luis Lugo is a graduate student in the Department of Civil Engineering at the University of Texas at El Paso (UTEP). He is a student researcher at the PASS Lab where his research focuses on creating a roadmap for the application of Digital Twin technologies for new and current infrastructure. His research interest is understanding interconnectivity of infrastructure systems using building information modeling (BIM), automated data collection, and management of civil infrastructure systems. He was funded as part of the C2SMART UTC program at UTEP and worked as a graduate teaching assistant during Spring 2020.

He earned a B.S. in Civil Engineering in the Fall of 2019. During his undergraduate studies, he worked as a research assistant at the Center of Transportation Infrastructure Systems (CTIS) where he helped develop guidelines and performance testing for sustainable mix design of flexible pavements. In addition, he was awarded the Dwight David Eisenhower Transportation Fellowship (DDTEFP) for two consecutive years. As an undergraduate, he was active in extracurricular activities and student organizations. He served as captain for the AISC Steel Bridge Competition and president for Chi Epsilon National Honor Society for the University of Texas at El Paso chapter. During his spare time, he enjoys being judge for local middle and high school science fair projects.

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