AUTOMATED DETECTION AND LOCALIZATION OF BRIDGE ELEMENTS USING TEMPLATE MATCHING WITH POINT CLOUDS

1. Abstract

Accurate detection and localization of structural components are crucial for quality control and structural assessment in bridge engineering. This project focuses on developing a system that utilizes template matching techniques to identify and analyze bridge elements, such as girders, columns, and piles, based on point cloud data captured from construction sites and corresponding 3D models created by engineers. By comparing these datasets, the system detects deviations in position, shape, and rotation, enabling automated change detection and verification. The approach enhances efficiency in structural inspections, reduces manual errors, and supports decision-making in bridge maintenance and construction.

2. Introduction

In bridge engineering, accurate placement and alignment of structural components are critical for ensuring safety, durability, and compliance with design specifications. Even small deviations in the position, orientation, or shape of bridge elements—such as girders, columns, and piles—can lead to significant engineering vulnerabilities, potentially compromising the structural integrity of the bridge and putting lives at risk. If such discrepancies are not identified early, they can be extremely costly to rectify, requiring extensive rework, material waste, and project delays.

Reality capture technologies, such as point cloud scanning, play a vital role in modern bridge inspection and quality assurance. By capturing as-built data from construction sites and comparing it against the design-intended 3D models, engineers can detect discrepancies early in the construction process. This approach minimizes risks, reduces costs, and enhances the overall reliability of bridge projects.

In this project, I developed a system that automates the detection and localization of bridge components using template matching techniques. Working as a software engineer at OpenBrIM, a company specializing in bridge engineering software, I leveraged OpenBrIM's 3D modeling capabilities to create a reference model for comparison. The system utilizes point cloud data collected from the construction site and applies computer vision techniques to detect differences in the position, shape, and rotation of bridge elements. By automating this process, the project aims to improve accuracy, reduce manual inspection efforts, and provide engineers with actionable insights for structural validation.

3. Methodology

3.1 Dataset

The dataset consists of two main components: 3D modeling data and point cloud data. Initially, the aim was to utilize real project data. To achieve this, I contacted one of our clients and obtained the corresponding OpenBrIM 3D model along with the available point cloud data.

However, the provided point cloud data was not of high quality, as it was captured from a high altitude. As a result, the areas of interest had very low intensity, making them unsuitable for precise analysis.

To overcome this limitation, I generated synthetic point cloud data directly from the 3D model. Additionally, I introduced modifications to the 3D model to create detectable differences, ensuring that the dataset could effectively be used for change detection and evaluation.

3.2 3D Modeling

The 3D model used in this study was created in OpenBrIM and represents a three-span steel I-girder bridge with a total length of 400 feet. The bridge consists of:

- Two abutments at both ends,
- One hammerhead pier, and
- One multi-column pier.

To facilitate further processing and analysis, the 3D model was exported as a triangulated mesh in PLY format.

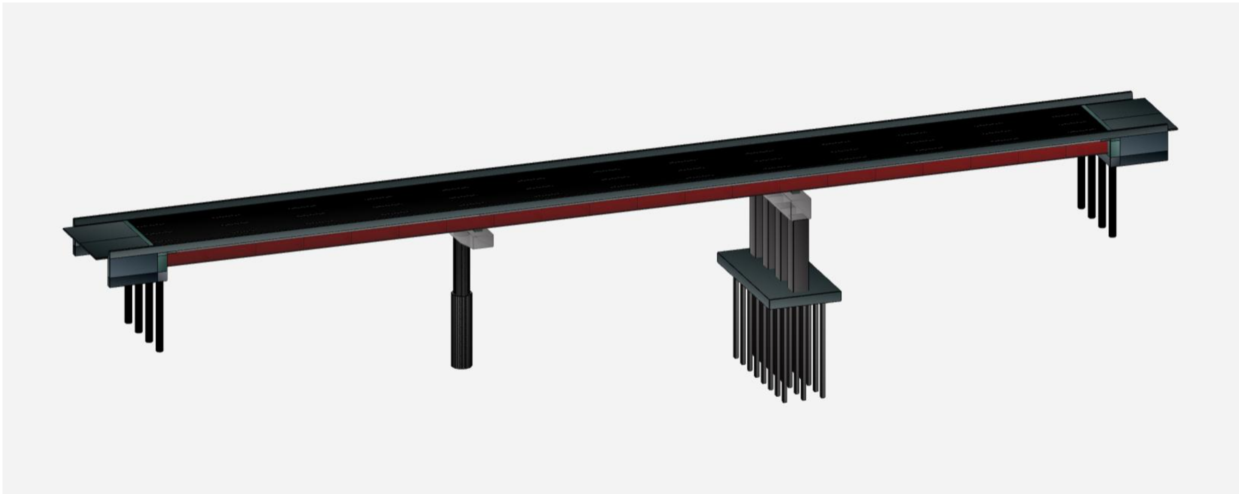

Figure 1. 3D model in OpenBrIM

3.3 Point Cloud Generation

To generate the point cloud, I used Open3D, a Python library for 3D data processing. The process involved the following steps:

1. Loading the Triangulated Mesh – The PLY-format mesh exported from OpenBrIM was loaded into Open3D.
2. Sampling Points – A total of 1 million points were sampled from the 3D model to create a dense and representative point cloud.

This generated point cloud serves as a high-quality dataset for further analysis, including change detection and comparison with real-world scan data.

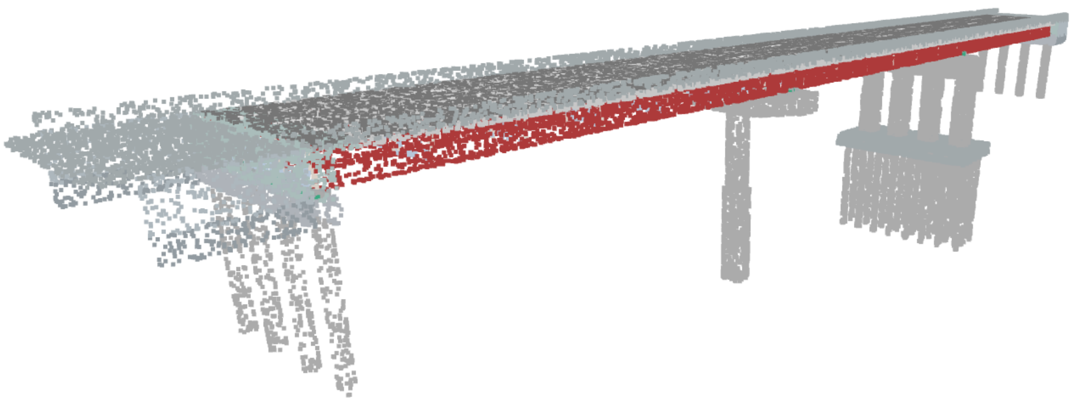

Figure 2. Point Cloud Data

3.4 Template Matching

In this project, I focused on detecting and localizing five critical bridge components: a Steel I-Girder, a Pier Cap, a Pier Column, a Barrier, and a Drilled Shaft. Each of these elements plays a vital role in the overall stability and functionality of a bridge, making precise identification and assessment crucial for quality control and safety verification.

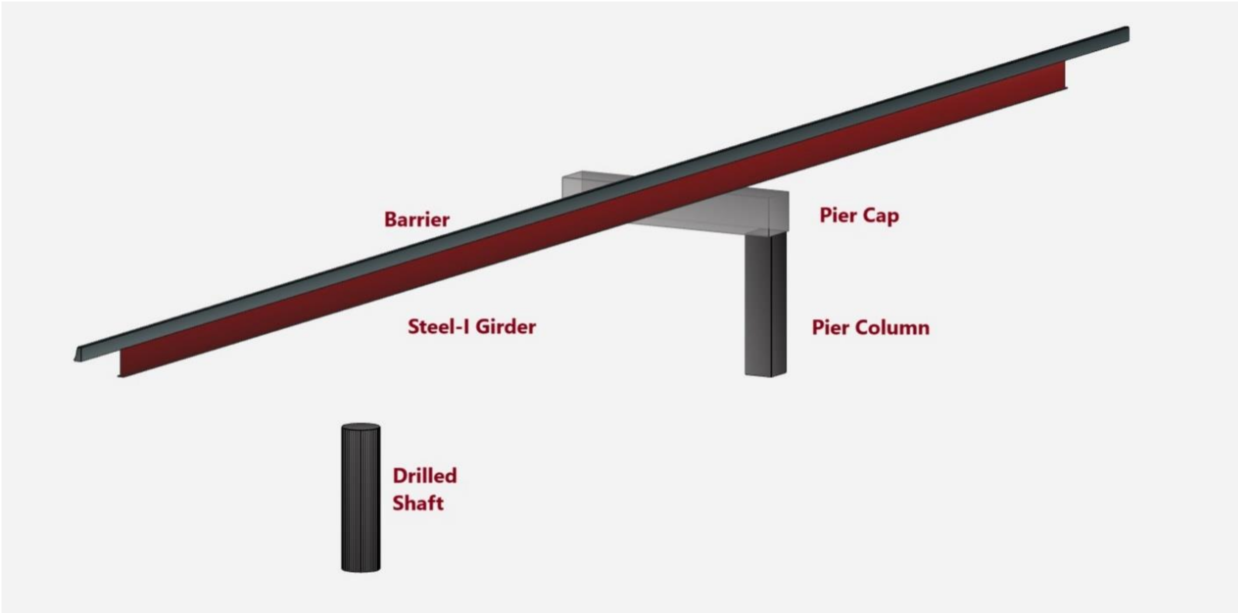

Figure 3. Selected object to analyze

To isolate each object, bounding boxes are computed for the reference models, and the point cloud is cropped to retain only the points that fall within these bounding boxes. However, since bounding boxes may include irrelevant points, further refinement is performed using a nearest-neighbor search, ensuring that only the points closest to the reference object's geometry are retained. The segmented components are then saved as separate point clouds, with distinct colors for visualization.

This segmentation process enables precise comparison between the as-designed and as-built structures, allowing for detection of discrepancies in position, shape, and orientation.

Figure 4. Classified point clouds of selected objects.

3.5 Introducing Changes

- Steel I-Girder: The depth was reduced from 72 inches to 54 inches, representing a fabrication or installation error that could affect the structural load distribution.

Figure 5. Change in the girder depth

- Drilled Shaft: The shaft was moved 5.33 feet, simulating a misplacement in foundation construction. Also increased diameter 48 in to 60 in.
- Bent Cap & Pier Column: These components were displaced by 13.33 feet and rotated by 30 degrees, introducing a significant misalignment and orientation error that could compromise load transfer and overall bridge stability.

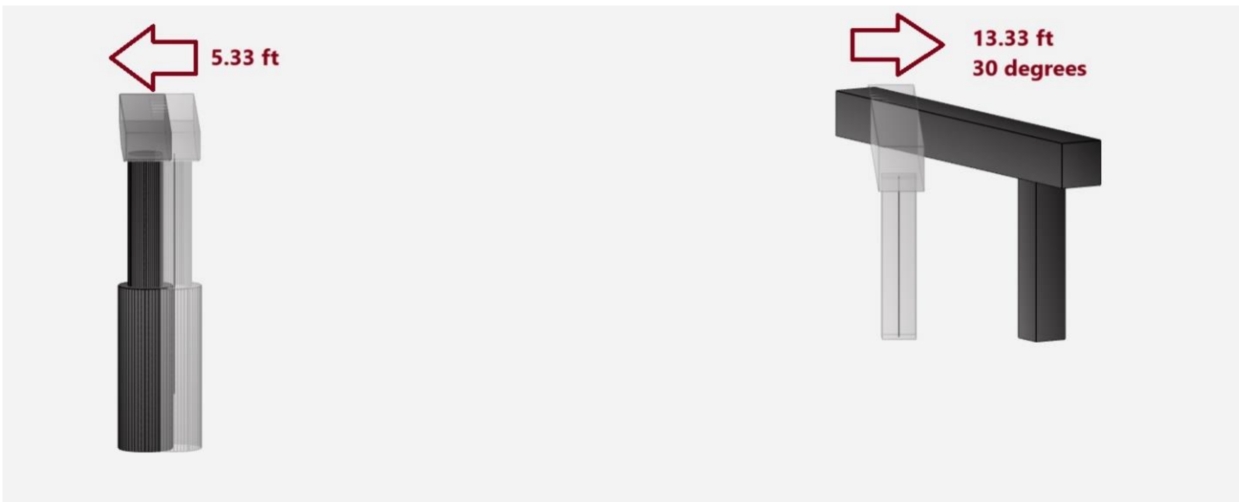

Figure 6. Change in the substructure elements

- Barrier (Unchanged): The barrier remained unaltered as a control element to verify that the system does not falsely detect changes where none exist, ensuring reliability and robustness.

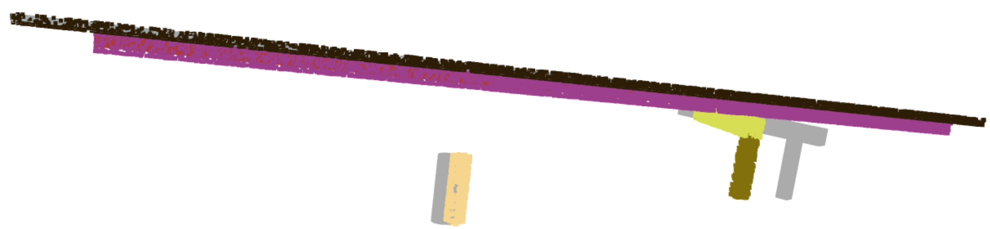

Figure 7. Point cloud and 3d model of the objects after change.

3.6 Change Detection

The following steps outline the approach taken to perform 3D template matching:

Alignment Using ICP

To align the segmented point clouds with the reference templates, the Iterative Closest Point (ICP) algorithm was employed. This ensured optimal transformation estimation between observed and reference objects.

Steps:

- The mesh was converted into a sampled point cloud representation.
- ICP was applied with an initial identity transformation and a defined correspondence threshold.

- The output transformation matrix was obtained, representing translation and rotation changes.

Outcome:

- The transformation matrix provided insight into any positional or rotational deviations between the template and the scanned object.

Position and Rotation Change Computation

The transformation matrix was analyzed to extract:

- Translation Change: The Euclidean distance between the original and transformed object.
- Rotation Change: The rotational difference computed from the transformation matrix.

Thresholds Used:

- Position Change Threshold: 0.05m (5 cm)
- Rotation Change Threshold: 5 degrees

If the transformation exceeded these values, the object was flagged as having moved significantly.

Centroid-Based Deviation Analysis

To further analyze the positional changes, the centroid of both the reference mesh and the segmented point cloud was computed. The difference between these centroids was used to measure positional drift, providing another metric for change detection.

Outcome:

- Centroid shifts indicated systematic displacement of objects.
- A comparison with transformation matrix results helped confirm significant movement.

Structural Changes Using Hausdorff Distance

The Hausdorff distance was computed to measure the maximum discrepancy between corresponding points in the reference and segmented models. This metric helped quantify structural deviations due to:

- Shape deformations
- Missing parts
- Additions or irregularities in the observed object

The Hausdorff distance provided an upper-bound error measure, aiding in detecting significant modifications in object geometry.

Point-to-Mesh Distance Analysis

To detect finer differences between the models, a nearest-neighbor search was performed using a KDTree. This method evaluated the deviation of each segmented point from the nearest reference mesh point.

Key Insights:

- Maximum and Mean Distance Metrics provided an overall assessment of how much the observed object deviated from the expected shape.
- Large deviations signaled surface alterations or inconsistencies.

4. Results and Observations

The change detection system successfully identified and quantified geometric and spatial deviations in the modified bridge components. The results indicate significant differences in position, rotation, and shape for the altered objects while confirming the stability of the unchanged component. Below are the detailed observations for each element:

Steel I-Girder (SIG4)

- The girder depth was reduced from 72 inches to 54 inches, simulating a fabrication or installation error.
- The system detected:
  - Position Change: 0.9436 ft
  - Rotation Change: 0.91 degrees
  - Centroid Position Change: 2.1653 ft
  - Hausdorff Distance: 3.3165 ft
  - Max Point-to-Mesh Distance: 9.4515 ft, Mean: 1.4628 ft
- The detected position and shape deviations confirm the system's ability to recognize changes in girder dimensions and placement.

Drilled Shaft (P1)

- The shaft was moved 5.33 feet and its diameter increased from 48 inches to 60 inches.
- The system reported:
  - Position Change: 13.3638 ft
  - Rotation Change: 5.27 degrees
  - Centroid Position Change: 5.2178 ft
  - Hausdorff Distance: 6.4492 ft
  - Max Point-to-Mesh Distance: 15.5322 ft, Mean: 2.2116 ft
- The larger position deviation (13.36 ft instead of 5.33 ft) may indicate a compounding effect due to increased diameter.

Bent Cap & Pier Column (BentCap1 & PierColumn5)

- Both components were moved 13.33 feet and rotated 30 degrees, with the Bent Cap also elongated.
- System detections:
  - Bent Cap:
    - Position Change: 136.6959 ft
    - Rotation Change: 30.26 degrees
    - Centroid Position Change: 13.3719 ft
    - Hausdorff Distance: 33.5321 ft

        - Max Point-to-Mesh Distance: 43.1117 ft, Mean: 8.9814 ft
    - Pier Column:
        - Position Change: 153.4596 ft
        - Rotation Change: 31.60 degrees
        - Centroid Position Change: 26.3304 ft
        - Hausdorff Distance: 27.4831 ft
        - Max Point-to-Mesh Distance: 29.4716 ft, Mean: 7.1701 ft
- The large position deviations (136.69 ft and 153.46 ft) suggest a potential miscalculation in coordinate mapping or an issue in the registration process.

Barrier (BRRight1) - Control Element

- The barrier was intentionally left unchanged to validate system accuracy.
- The system still detected:
    - Position Change: 0.5773 ft
    - Rotation Change: 1.40 degrees
    - Centroid Position Change: 3.0635 ft
    - Hausdorff Distance: 1.5727 ft
    - Max Point-to-Mesh Distance: 11.1605 ft, Mean: 1.7195 ft
- While the deviation is minor, it suggests potential small-scale noise or slight misalignment in the point cloud registration process.

Key Observations

1. The system successfully detected major changes in position, rotation, and shape for the altered components.
2. The Hausdorff Distance and Max Point-to-Mesh Distance provide useful metrics to quantify deviations, with higher values corresponding to significant misalignments.
3. The unchanged barrier showed minor detected changes, which could indicate system noise or point cloud registration inaccuracies.
4. The extremely high detected position changes for the Bent Cap and Pier Column (136.69 ft and 153.46 ft) suggest a potential scaling or reference frame error in the detection algorithm.

5. Conclusion

The results validate the effectiveness of the detection system in identifying changes in bridge elements, ensuring structural integrity verification. However, minor false positives on the barrier and unexpectedly large displacements for some objects suggest areas for improvement in registration accuracy and error refinement. The system provides a powerful automated tool for bridge inspection and deviation analysis, reducing manual effort and improving engineering decision-making.