Integrating Photogrammetry and Topological Data Analysis within a Digital Twin Framework for Missing Bolt Detection in Bridges

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Abstract

Reliable inspection of bridge infrastructure is essential for maintaining structural safety, particularly in identifying missing bolts that may compromise system performance. This study represents an extension of our previous work with a methodology that integrates point cloud-based Digital Twin (DT) models with Topological Data Analysis (TDA), to enable accurate detection and localization of missing bolts. A high-resolution 3D representation of bridge joints is first generated using a photogrammetric reconstruction process. YOLOv8 is then employed to detect and localize bolt positions within the point cloud data. Subsequently, Alpha complexes are utilized within the TDA framework to capture topological features and identify anomalies associated with missing bolts. The approach is validated through a benchmark case study, demonstrating high accuracy in detecting missing bolts and robustness to variations in point cloud density. The results indicate that the integration of DT and TDA provides an effective and reliable solution for advanced structural health monitoring applications.

1. Introduction

Emerging technologies such as Digital Twins (DTs) (Mousavi et al., 2025) and decision support systems (Rashidi et al., 2025b) have become key tools in bridge management, enabling improved assessment of critical structural components for informed maintenance decisions. Structural bolts are considered as essential components in bridge engineering, acting as primary connectors that stabilize different structural elements. Over the lifespan of a bridge, these connections are exposed to a range of mechanical and environmental influences, such as traffic-induced vibrations, fluctuating dynamic and thermal loads and progressive material deterioration that can cause loosening or loss of bolts which significantly compromise the structural integrity and safety of bridges (Yao et al., 2024; Rashidi et al., 2023). Consequently, routine inspection and assessment of bolted joints are indispensable for ensuring the serviceability and longevity of steel bridges. Conventionally, these evaluations are performed through manual inspections by trained personnel to guarantee the reliability of bolted assemblies. However, this traditional approach is highly labour-intensive, time-consuming, and financially demanding, leading to considerable maintenance costs and logistical challenges for infrastructure agencies (An et al., 2019). Therefore, the development of accurate, rapid, and cost-efficient techniques for detecting missing or loose bolts using advanced technologies has become a critical research priority in bridge health monitoring.

Recent progress in SHM, particularly the incorporation of Computer Vision (CV)-based methods, has opened new possibilities for automating defect detection in bridges (Mousavi et al., 2026). Vision-based strategies are increasingly recognized as effective and economical solutions for identifying missing bolts as one of the most common types of structural defects (Noori Hoshyar et al., 2023; Lee et al., 2024). For instance, Liu et al. (2016) adopted a sliding-window technique to extract potential bolt regions, followed by gradient orientation histogram features and Support Vector Machine (SVM) classification to detect missing bolts. Similarly, Cha et al. (2016) utilized the geometric dimensions of bolt heads, specifically their horizontal and vertical lengths, as input features to train a linear SVM classifier capable of distinguishing between tight and loose bolts. Ramana et al. (2019) presented a learning-based detection approach combining gray-level co-occurrence matrix features, local binary patterns, discrete wavelet transforms, and an SVM classifier to identify missing bolts.

Advancements in deep learning have further enhanced the performance of computer vision methods for bolt detection. Wang et al. (2019) implemented Faster Region-Based Convolutional Neural Network (R-CNN) and You Only Look Once (YOLO) architectures to locate critical components in train systems, successfully identifying missing bolts. Yuan et al. (2021) employed Mask R-CNN to perform pixel-level segmentation and identification of loosened bolts. Zhou and Huo (2021) utilized the YOLOv3 algorithm to identify fractured bolt regions resulting from delayed cracking, while Pan and Yang (2022) applied the YOLOv3-tiny model in conjunction with optical flow analysis to detect bolt rotation continuously. Collectively, these studies demonstrate the potential of modern vision-based models in automated bolt condition assessment.

Despite these advances, existing methods are predominantly restricted to 2D image analysis, which imposes inherent limitations. The accuracy of detection in 2D imagery is highly dependent on the viewing angle, lighting conditions, and camera positioning, resulting in outcomes that are not spatially consistent or comprehensive (Pan and Yang, 2023). Conversely, 3D point cloud data provide a more detailed and accurate geometric representation, enabling the precise spatial localization of missing bolts within complex structural environments. However, although point cloud applications have advanced significantly in recent years, their use for defect quantification, especially for missing bolt detection, remains limited. With the recent emergence of DT technologies for bridge monitoring, point clouds can serve as a fundamental data source for building continuously updated, high-fidelity virtual models capable of identifying structural deficiencies more effectively than traditional 2D vision methods (Pan and Yang, 2023). Nonetheless, previous studies employing DT frameworks have mainly focused on Terrestrial Laser Scanning (TLS) data for generating digital models. To date, there is a lack of research integrating point-cloud-based DTs for missing bolt detection and localization.

In response to this gap, the present study introduces a novel approach for 3D detection and localization of missing bolts that leverages a point-cloud-based Digital Twin integrated with Topological Data Analysis (TDA) (Carlsson, 2020). The proposed DT framework allows for real-time synchronization and integration of multi-source data, resulting in an adaptive, context-aware model that accurately reflects the current structural condition. Unlike traditional geometric feature extraction methods that depend on static descriptors, the DT framework supports dynamic comparison between as-designed and as-is models, thus enhancing the accuracy of damage localization and interpretation (Mousavi et al., 2024).

The incorporation of TDA offers an additional layer of robustness by focusing on the underlying topological properties of point cloud data rather than purely geometric attributes. TDA captures persistent topological features that remain stable under various transformations and is resilient to data sparsity and noise (Carlsson, 2020; Edelsbrunner et al., 2002). This makes it especially effective for analysing complex and noisy structural environments. Unlike deep learning-based object detection methods, which primarily detect missing bolts in 2D images without spatial context, the combined DT-TDA framework ensures precise 3D spatial localization of missing bolts. This study represents an optimization and extension of our previous work (Rashidi et al., 2025a), incorporating improved detection strategies and enhanced topological analysis for more reliable performance. The proposed methodology aims to increase the autonomy of the bolt missing detection process during inspections. The primary contributions and novelties include:

- Integration of DT and TDA: This work represents the integration of Digital Twin technology and Topological Data Analysis for accurate and reliable detection and localization of missing bolts in bridges.
- Automated 3D detection framework: Development of an automated methodology that identifies and localizes missing bolts directly in 3D space, significantly reducing the need for manual intervention.
- Experimental validation: Implementation and verification of the proposed pipeline on a benchmark model.

2. Background

Topological Data Analysis (TDA) has developed into a prominent analytical framework since the early 2000s, originating from advances in algebraic topology and computational geometry. TDA provides a robust methodology for capturing intrinsic geometric and structural properties of data, especially in the context of point clouds defined in Euclidean or general metric spaces. Its applicability has expanded across diverse disciplines, supported by efficient computational techniques and software tools such as GUDHI (Gudhi, 2026) and Ripserer (Ripserer, 2026). This section outlines the essential theoretical concepts relevant to this study.

2.1 Simplicial Complex

The representation of discrete datasets in TDA begins with the construction of simplicial complexes, which extend traditional graph models to encode higher-order relationships among data points. Unlike simple graphs, simplicial complexes allow for the modelling of multi-point interactions, enabling a richer description of data structure.

The fundamental elements of these complexes are simplices, defined as fully connected sets of vertices. Depending on dimensionality, as shown in Figure 1, these include points (0-simplices), edges (1-simplices), triangular faces (2-simplices), and tetrahedral volumes (3-simplices), with higher-dimensional analogues extending this concept. By combining such elements, complex geometric structures can be systematically represented.

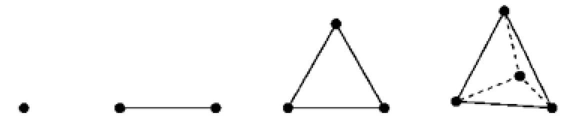

Figure 1. Illustration of simplicial elements, including a vertex (0-dimensional), edge (1-dimensional), triangular face (2-dimensional), and tetrahedral volume (3-dimensional).

Various approaches exist for constructing simplicial complexes, including Čech, Nerve, Alpha, and Vietoris-Rips (VR) methods. Among these, the VR complex is widely adopted due to its computational efficiency. In this approach, a simplex is formed when all pairwise distances among a set of points are below a predefined threshold (ε)(Zomorodian, 2010).

Following construction, homological analysis is applied to extract topological invariants, known as Betti numbers, which quantify features such as connected components, loops, and higher-dimensional voids. These invariants provide a basis for distinguishing between different topological structures.

2.2 Filtration and Persistent Homology

Single-scale topological analysis is often insufficient for capturing complex structures present at multiple resolutions. Persistent Homology (PH) addresses this limitation by evaluating how topological features evolve as the scale parameter varies.

This is achieved through a filtration process, where a sequence of nested simplicial complexes is generated by gradually increasing the threshold ε. During this progression, topological features appear and disappear at different stages. Each feature is characterized by its birth (the scale at which it emerges) and death (the scale at which it vanishes), forming a persistence interval.

Features that persist across a wide range of scales are considered structurally significant, whereas those with short lifespans are typically regarded as noise. This multi-scale analysis enables robust identification of meaningful geometric patterns.

An intuitive interpretation of this process can be obtained through the union-of-balls model, where expanding spheres centred at data points progressively intersect, leading to the formation of connected regions, loops, and higher-dimensional structures (Chazal and Michel, 2021).

2.3 Persistence Diagram

The results of persistent homology are commonly visualized using persistence diagrams and barcode representations, both of which encode the lifespan of topological features.

In a persistence diagram, each feature is represented as a point in a two-dimensional space, with its birth value on the horizontal axis and its death value on the vertical axis. The diagonal line serves as a reference, and the distance of each point from this line indicates the persistence of the feature. Features located farther from the diagonal correspond to more significant structures.

Alternatively, barcode representations depict each feature as a horizontal interval spanning its birth and death values. These visual tools provide an intuitive means of identifying dominant topological characteristics within the data and facilitate comparison across datasets of varying complexity. A sample of a persistence diagram and barcode representation are illustrated in Figure 2.

3. Proposed Methodology

This section outlines the proposed framework for identifying missing bolts within point cloud data through the application of PH. The complete processing pipeline is depicted in Figure 2, illustrating the sequential stages of the detection approach. Recent studies have explored comparable experimental configurations for vision-based assessment of bolt loosening, as reported in prior works (Pan and Yang, 2023), providing a relevant foundation for the development of the present methodology.

The proposed framework integrates photogrammetric reconstruction, deep learning-based detection, and topological analysis to identify missing bolts within point cloud data. Initially, 3D point clouds are generated from images acquired using non-metric cameras. A convolutional neural network (CNN)-based multi-view detection approach is then applied to determine bolt locations. Subsequently, topological descriptors are extracted using one-dimensional persistence diagrams derived from PH. A filtering strategy is employed to isolate prominent void-like structures within the point cloud, which may correspond to absent bolts. To further refine these candidates, Persistent Entropy is utilized to identify the most representative topological features. The outcome provides the spatial localization of missing bolts. Detailed descriptions of each stage are presented in the following subsections.

3.1 Image-Based 3D Reconstruction

The methodology begins with reconstructing a 3D representation of bolted structural components using multi-view imagery. Image acquisition is performed from multiple viewpoints, either through conventional high-resolution cameras or unmanned aerial systems equipped with RGB sensors for field applications.

The reconstruction process starts by establishing correspondences between images to form a scene graph. Feature detection algorithms such as Scale-Invariant Feature Transform (SIFT) (Lowe, 2004) are employed to extract distinctive keypoints, which are then matched across overlapping images. In UAV-based photogrammetry, approximate camera positions obtained via Global Navigation Satellite Systems (GNSS) can assist in simplifying this matching process.

Next, a Structure-from-Motion (SfM) procedure is applied to estimate camera parameters and reconstruct a sparse 3D point set. This involves feature matching, epipolar geometry estimation, and triangulation. Bundle Adjustment (BA) is subsequently performed to refine camera parameters and minimize reprojection errors, improving the geometric consistency of the reconstruction.

Finally, dense reconstruction is carried out using multi-view stereo techniques, where depth information is estimated for individual pixels, resulting in a dense point cloud. To ensure reconstruction reliability, quality assessments such as image matching consistency (Mousavi et al., 2021a), camera orientation accuracy, and geometric validation of the generated point cloud are essential (Mousavi et al., 2021b).

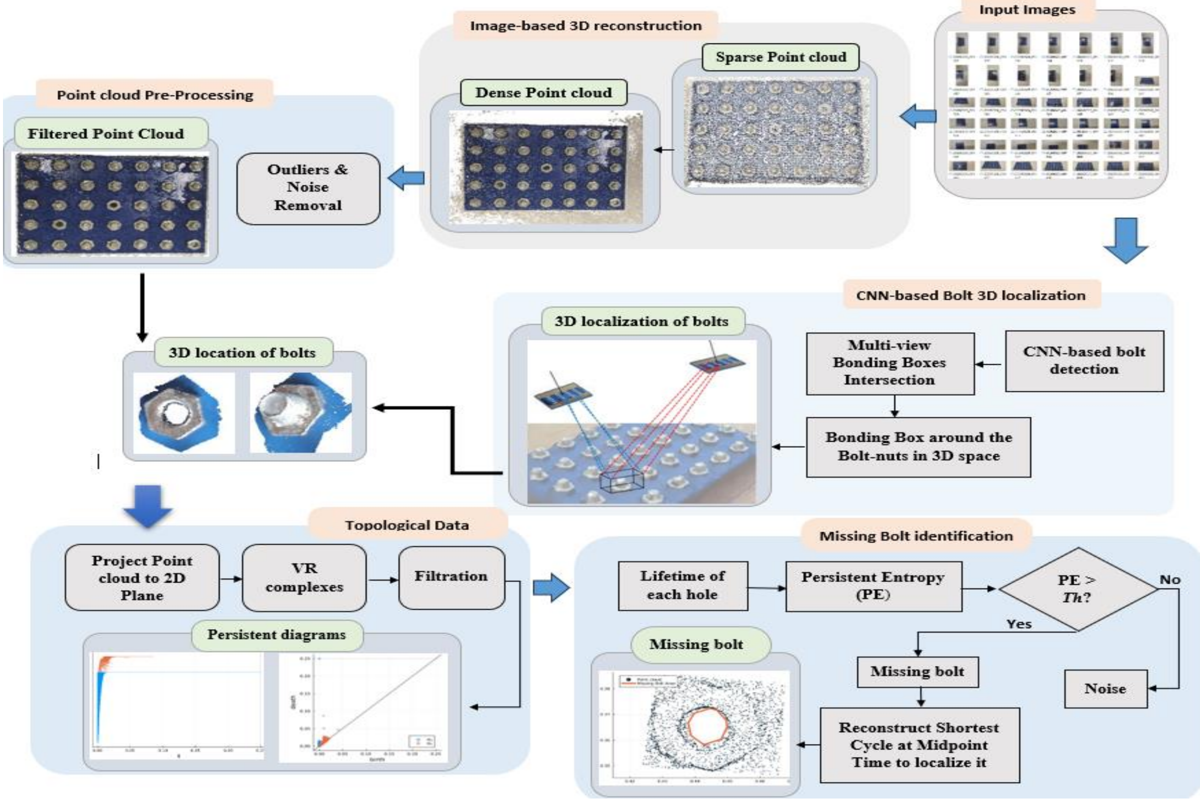

Figure 2: The overall flowchart of the proposed methodology.

3.2 Point Cloud Pre-processing

Following reconstruction, the dense point cloud is subjected to pre-processing to reduce noise and improve data quality. Noise in point clouds typically includes small-scale positional deviations as well as significant outliers caused by mismatches or reconstruction inaccuracies. To address these issues, filtering techniques are applied to remove outliers and smooth the data. This step is critical for enhancing the accuracy of subsequent bolt detection and topological analysis.

3.3 CNN-Based Bolt 3D Localization

This stage focuses on identifying bolt locations within the reconstructed scene. Accurate localization is essential, as it defines regions of interest for subsequent topological analysis and reduces computational complexity by limiting processing to relevant subsets of the point cloud.
Direct application of point cloud-based detection algorithms may be computationally demanding and sensitive to noise, occlusions, and data density variations. Therefore, an image-based detection strategy is adopted. A CNN-based object detector built upon the YOLOv8 architecture is employed to identify bolts in 2D images. Given that the detection task involves a single object class, a lightweight yet efficient model is sufficient.

3.3.1 YOLOv8 Detection Network

The YOLOv8 framework is adopted in this study for bolt detection due to its demonstrated effectiveness in recent object detection research. The architecture comprises key components, including an input layer, a backbone network for feature extraction, a neck for feature aggregation, and a detection head for prediction tasks. Input images are resized to a standardized resolution before being processed by the backbone, which is designed to efficiently capture hierarchical features through convolutional operations.
The backbone outputs multi-scale feature maps, which are refined through the neck module using feature fusion strategies to enhance both spatial and semantic information. This design enables improved representation of objects at different scales, which is particularly beneficial for detecting small structural components such as bolts.
The detection head performs multi-scale predictions, estimating object locations, confidence scores, and class probabilities. Compared to earlier YOLO versions, YOLOv8 introduces architectural improvements that enhance detection accuracy, training efficiency, and inference speed. Its anchor-free design and optimized feature processing contribute to more reliable detection performance.
YOLOv8 was selected for this study based on evidence from recent literature demonstrating its strong performance in detecting small and complex objects under varying conditions. This makes it a suitable choice for bolt detection tasks in challenging structural environments.

3.3.2 Multi-View Bounding Box Intersection

The 3D positions of detected bolts are estimated through a multi-view geometric intersection procedure based on photogrammetric principles. This approach utilizes the exterior orientation parameters (camera position and rotation), intrinsic camera parameters, and corresponding two-dimensional detections obtained from multiple overlapping images.
For each image, projection relationships are established to link image coordinates of detected bounding boxes with their corresponding spatial coordinates in the object space. By combining observations from multiple viewpoints, a system of equations is formed, relating 2D detections to the unknown 3D positions.
To determine the optimal solution, the well-known least squares adjustment is employed. This method minimizes the cumulative reprojection error between observed image coordinates and the projections of estimated 3D points. As a result, the solution remains robust in the presence of measurement noise and redundant observations, effectively reducing inconsistencies across different views.

3.4 TDA-Based 3D Missing Bolt Identification

This stage introduces the proposed approach for identifying missing bolts using TDA. The procedure consists of two main components: extraction of topological features via PH and subsequent identification of missing bolts based on these features.

3.4.1 Persistent Homology (PH)

PH is employed to analyse the multi-scale topological structure of the point cloud by capturing features such as connected components, loops, and voids along with their corresponding birth and death scales. In this study, particular focus is placed on one-dimensional features, which represent loop-like structures associated with potential bolt absence.
The PH computation is performed using Alpha complexes, which provide a geometrically meaningful representation of the underlying data by incorporating both distance and spatial relationships between points. Unlike distance-based approaches, Alpha complexes are derived from the Delaunay triangulation of the point cloud, enabling a more accurate reconstruction of the underlying geometry. Based on our previous evaluations, the use of Alpha complexes demonstrated improved computational efficiency and reduced memory consumption compared to alternative approaches (Rashidi et al., 2025a).
The process begins with the construction of the Alpha complex from the input point cloud. This is achieved by generating simplices from the Delaunay triangulation and selecting those that satisfy a predefined radius parameter (α), which controls the level of geometric detail. By varying α, a sequence of nested simplicial complexes is obtained.
Next, homology groups are computed to identify topological features, where k-dimensional cycles are distinguished from their corresponding boundaries. This enables the classification of structural elements such as connected components, loops, and higher-dimensional voids.
Betti numbers are then calculated to quantify the number of features at each dimension, where β_0 denotes connected components, β_1 represents loops, and β_2 corresponds to voids. A filtration process is subsequently applied by progressively increasing the α parameter, allowing the evolution of these features to be tracked across multiple scales.
Finally, the results are represented using a persistence diagram, which records the birth and death of topological features throughout the filtration. Features that persist over a wide range of α values are considered structurally significant, whereas short-lived features are typically associated with noise.

3.4.2 Missing Bolt Identification

The detection of missing bolts is achieved through the analysis of topological features derived from PH. In this context, loop-like structures with extended persistence are generally interpreted as stable voids within the point cloud, which may indicate the absence of bolts. However, relying solely on

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persistence can be insufficient, as certain long-lived features may not correspond to meaningful structural characteristics.

To enhance the reliability of feature discrimination, Persistent Entropy is introduced as a complementary metric. This measure evaluates the distribution of feature lifetimes, enabling a more robust distinction between significant topological structures and noise.

The computation begins by determining the lifetime of each topological feature (l_i) as the difference between its death and birth values extracted from the persistence diagram. These lifetimes are then collected into a set and used to compute their total sum:

$$S_L = \sum_{i=1}^{n} l_i \tag{1}$$

Subsequently, the lifetimes are normalized to form a probability distribution, and the Persistent Entropy of the filtration is calculated as:

$$PE_k = -\sum_{i=1}^{n} \frac{l_i}{S_L} log \frac{l_i}{S_L} \tag{2}$$

This formulation quantifies the relative contribution of each feature to the overall topological structure. Features associated with higher entropy contributions are considered more representative of meaningful structural patterns.

A thresholding criterion is then applied to classify the features. If the computed entropy value exceeds a predefined threshold (*Th*), the corresponding feature is identified as a significant topological structure and is interpreted as a missing bolt. Conversely, features that fall below this threshold are treated as noise.

By integrating persistence-based analysis with entropy-driven filtering, the proposed approach effectively isolates structurally relevant voids from spurious artifacts, thereby improving the accuracy and robustness of missing bolt detection data.

3.5 Missing Bolt Hole Illustration

This section describes the procedure for visualizing missing bolt locations based on the outcomes of PH analysis. To represent voids associated with absent bolts, the Reconstructed Shortest Cycles approach is adopted. When evaluated at the midpoint of each persistence interval, this technique enables effective tracking of the evolution of topological features throughout the filtration process.

In particular, the reconstructed cycles corresponding to mid-interval values provide a clear geometric representation of stable void structures. These cycles emphasize persistent holes within the point cloud, allowing accurate visualization of regions likely associated with missing bolts. As a result, both the spatial location and structural characteristics of these voids can be effectively interpreted.

4. Experiments and Parameter Analysis

This section presents the experimental validation of the proposed framework using benchmark datasets. The evaluation involves processing point cloud data through the complete pipeline and analysing performance under varying conditions. A parameter sensitivity study is conducted by considering different levels of point cloud density to assess the robustness of the approach. The implementation details are first described, followed by a discussion of the experimental findings.

4.1 Implementation Details

A benchmark dataset was constructed using 168 high-resolution images (4080 × 3060 pixels) captured with an RGB camera. Consistent with prior studies, a simplified structural model containing 35 bolts was selected to demonstrate the core functionality of the proposed method. This controlled setup enables a focused evaluation of the methodology before extending to more complex scenarios.

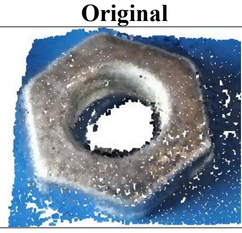
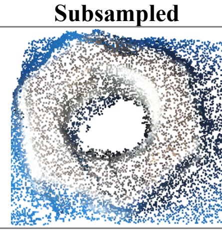
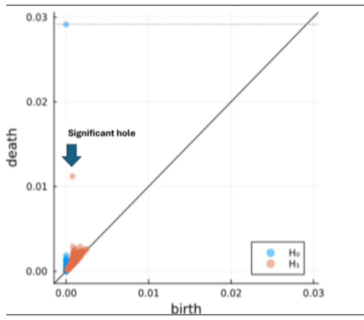
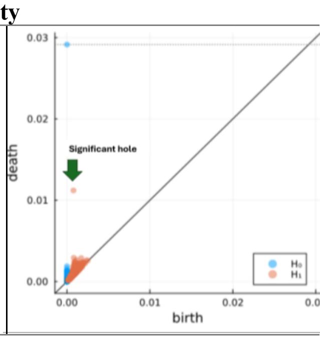
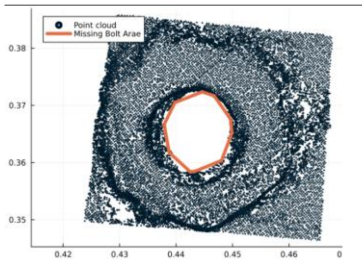
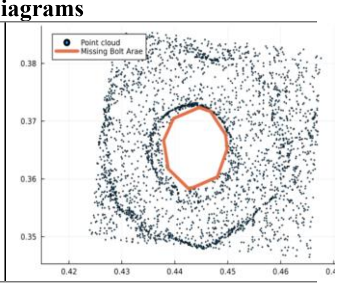
Dense point cloud reconstruction was performed using a SfM workflow implemented in Agisoft software. For bolt detection, the YOLOv8 network was trained using a combination of publicly available datasets and images collected from real-world case studies at Western Sydney University. Data augmentation techniques were applied to improve model generalization. The dataset was divided into training and testing subsets with a 70:30 ratio. The initial learning rate was set to 0.001.

Model training was conducted in Python using a high-performance computing setup comprising an RTX 2080 GPU. For topological analysis, Persistent Homology computations were carried out using the GUDHI library.

4.2 Point Cloud Density Analysis

Given that point clouds can vary significantly in resolution and sampling density, an additional evaluation was conducted to investigate the influence of point density on the performance of the proposed method and results are presented in Table 2. This analysis involved systematically reducing the number of points through subsampling and comparing the detection outcomes with those obtained from the original datasets.

Table 2. The detection results of original and sub-sampled point clouds.

Original	Subsampled
	
23006	5967
Density	
	
Persistent Diagrams	
	
Results	

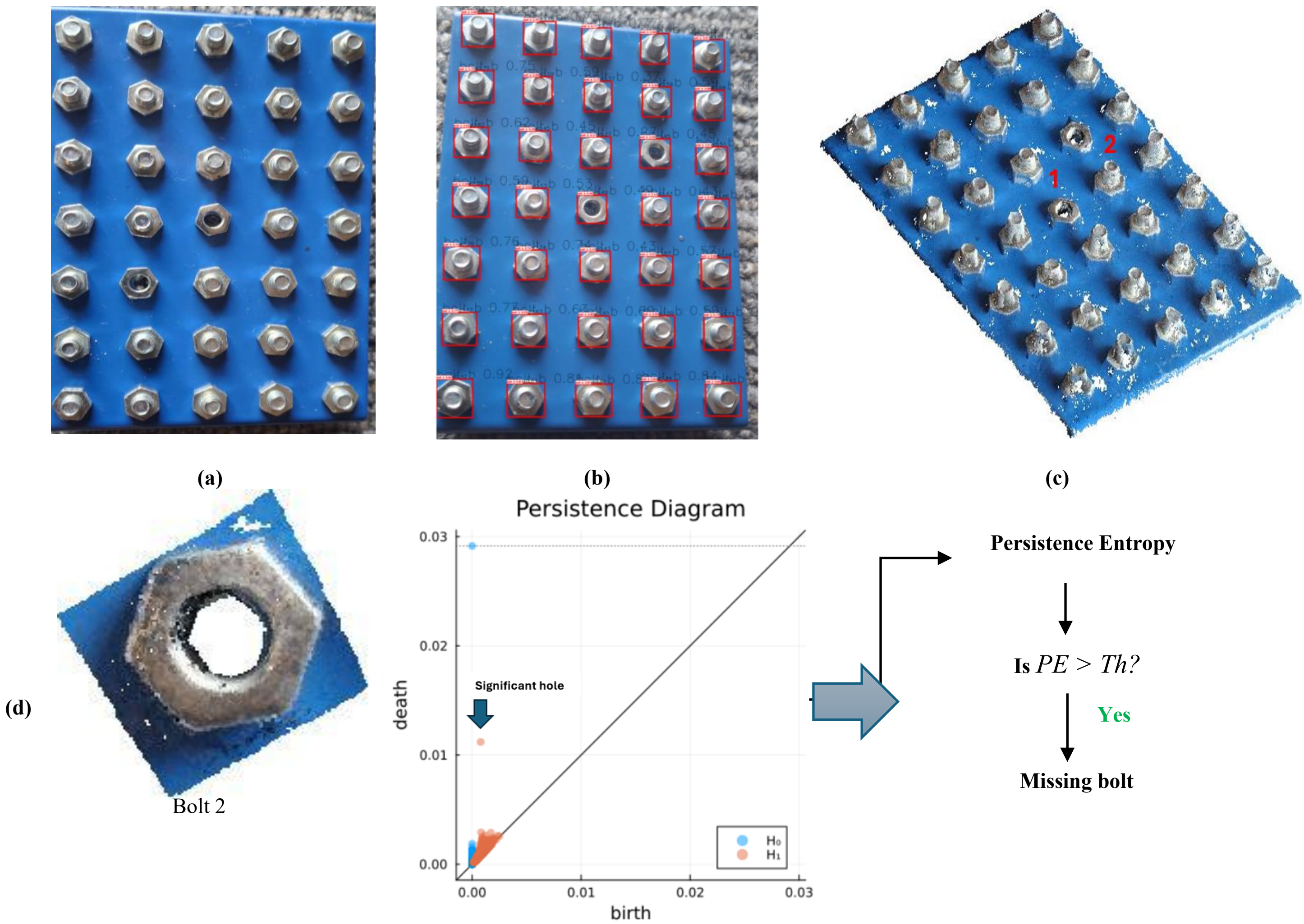
In the first experiment, the initial point cloud consisted of approximately 23,006 points. The corresponding persistence diagram indicated the presence of a prominent 1D feature associated with a missing bolt. The dataset was then downsampled to 5967 points, and the analysis was repeated. Despite the substantial reduction in point density, the persistence diagram continued to exhibit a significant topological feature, confirming the successful identification of the missing bolt.
These results indicate that the proposed approach maintains robustness under varying point cloud densities. Even with substantial reductions in data resolution, the method effectively captures persistent topological features, highlighting its suitability for practical applications where data quality may vary.

5. Results and Discussion

The performance of the proposed framework was assessed through a controlled benchmark experiment. This assessment focused on validating the detection capability using a simplified benchmark model.

5.1 Benchmark Model Case Study

The results obtained from the benchmark model are illustrated in Figure 3. The test scenario consists of a structural assembly with 35 bolts, where one bolt is intentionally absent to simulate a defect condition.
In the first stage, the CNN-based detection model was applied to identify bolt locations in the captured images. These detections were then projected into 3D space using the multi-view intersection approach to determine precise bolt coordinates. The resulting point cloud was subsequently processed using the proposed topological analysis pipeline to detect missing bolts.
The findings demonstrate that PH effectively identifies the absence of a bolt within the point cloud. As shown in Figure 3(d), a prominent topological feature corresponding to a void is detected in the persistence diagram. This feature exhibits a sufficiently long persistence interval and is further validated through Persistent Entropy analysis. Since the computed entropy value exceeds the predefined threshold, the feature is classified as a structurally significant hole, indicating the location of a missing bolt.



(e)

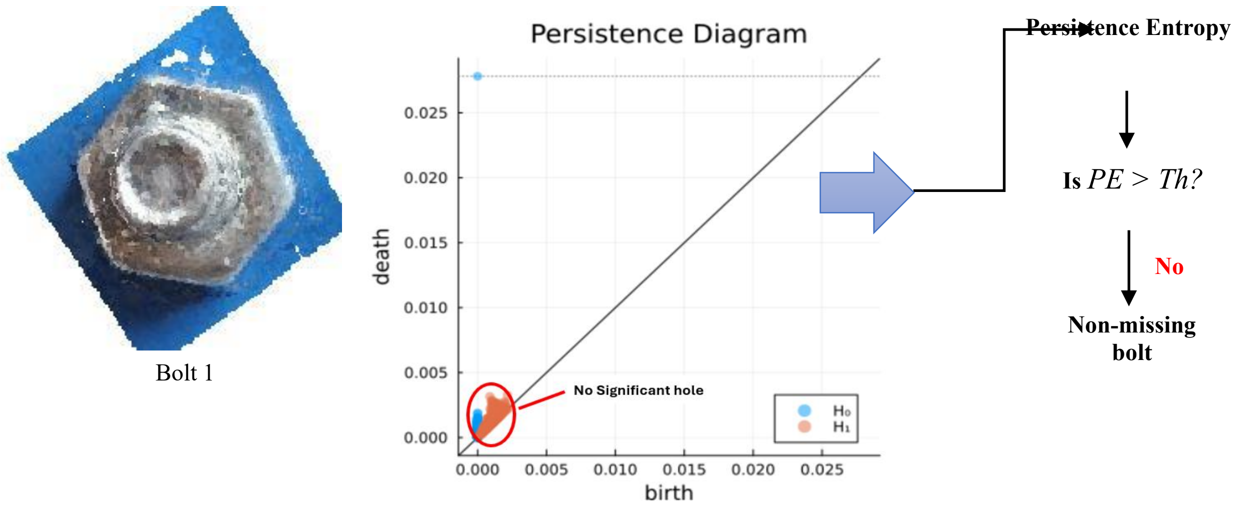


Figure 3: Missing bolt detection results; (a) captured image, (b)CNN-based bolt detection, (c)reconstructed 3D point cloud, (d) case 1 showing a significant topological feature with entropy above the threshold, indicating a missing bolt, and (e) case 2 showing no significant feature with entropy below the threshold, indicating no missing bolt.

In contrast, the second case study presented in Figure 3(e) corresponds to a scenario in which no bolt is missing. In this case, the persistence diagram does not exhibit any dominant 1D features. Consequently, the calculated Persistent Entropy remains below the threshold, and no missing bolt is identified. This confirms the method’s ability to distinguish between true structural defects and normal conditions.

Overall, the benchmark results demonstrate the effectiveness of the proposed approach in accurately detecting and localizing missing bolts, while also avoiding false detections in intact configurations.

5.2 Potential Limitations

Despite the effectiveness of the proposed framework in achieving accurate and efficient bolt detection in 3D space, several limitations should be acknowledged to inform future developments.

A primary constraint lies in the dependence of the CNN-based detection component on the quality and diversity of the training dataset. Insufficient representation of varying bolt geometries, surface conditions, and environmental scenarios may reduce the generalizability of the model in real-world applications. Expanding the dataset to include a wider range of conditions could enhance robustness. However, increasing dataset size may lead to longer training times, although ongoing advancements in high-performance computing hardware are expected to mitigate this issue.

Another limitation is related to detection performance under occlusion. When bolts are partially or heavily obstructed, the model may fail to extract sufficient visual features for reliable identification. Such scenarios can result in missed detections, particularly in complex structural environments where overlapping components are common.

From a computational perspective, scalability remains a challenge. While the overall pipeline is designed to be efficient, persistent homology computations are constrained by the capabilities of existing software libraries, particularly when handling large-scale point clouds. Consequently, regions containing multiple detected bolts often need to be processed in smaller subsets, which may increase processing time for extensive datasets.

6. Conclusions

Bridge structures rely heavily on bolted connections to maintain structural integrity, making the detection of missing bolts a critical task in infrastructure maintenance. Failure to identify such defects can lead to progressive deterioration and potential safety risks.

This study presented a novel methodology that integrates Digital Twin modelling, convolutional neural network-based detection, and Topological Data Analysis for identifying missing bolts in three-dimensional space. Unlike conventional 2D vision-based approaches, the proposed framework leverages point cloud data and persistent homology to enable more accurate and spatially precise detection.

The effectiveness of the method was demonstrated through controlled benchmark experiments. The results confirm that the proposed pipeline can reliably detect and localize missing bolts while reducing the need for manual inspection. Furthermore, the method maintains robustness under varying point cloud densities, highlighting its practical applicability.

Overall, the proposed approach provides a promising solution for enhancing structural health monitoring of bridge infrastructure. By improving detection accuracy and automation, it has the potential to support more efficient and reliable maintenance practices in real-world environments.

Future research will focus on improving both the computational efficiency and detection capability of the proposed framework.

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