



Digital twin-based bridge geometric quality inspection using knowledge mapping and data-driven method



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ARTICLE INFO

Keywords:

Knowledge mapping
Point cloud segmentation
Digital twin
Geometric quality inspection
Bridge

ABSTRACT

Accurate geometric quality inspection is vital for detecting bridge defects during construction. To address the challenges of limited point cloud segmentation accuracy at bridge component connections and insufficient detection efficiency, a digital twin bridge geometric quality inspection method based on knowledge mapping and data-driven is proposed. In the digital space, a reusable bridge geometric quality inspection knowledge model is established to enhance the scalability of knowledge. In the twin data processing space, a large-scale point cloud segmentation network based on hybrid feature aggregation and neighbor feature enhancement (HANE-Net) is proposed to improve the segmentation accuracy. The network achieves superior performance in the S3DIS dataset and real bridge point cloud, with mean intersection over union of 66.8 % and 95.44 %, respectively, surpassing the baseline method RandLANet by 3.2 % and 0.79 %, respectively. Finally, a prototype system is designed based on Revit to prove the feasibility of the proposed method.

1. Introduction

Frequent and accurate quality inspections during the building life-cycle are crucial for assessing construction quality. These inspections ensure that the project complies with established standards and specifications, thereby enhancing the reliability of the construction process [1]. Common construction quality inspections include geometric quality inspection (measuring dimensional deviations between the as-built model and the as-designed model) [2,3], surface quality inspection (evaluating flatness, cracks, etc.) [4,5], deformation and displacement inspection (tracking structural deformation and changes in relative position) [6,7]. As a critical component of modern infrastructure, the geometric quality of bridges directly impacts the overall structural safety and durability. This paper establishes the mapping relationship between the physical bridge structure and the digital model through the study of digital twin geometric quality inspection methods. It aims to identify potential structural issues and construction defects in bridges, ensuring that bridge construction meets design standards and engineering specifications.

In the actual construction processes, deviations are inevitable due to factors such as construction errors, structural deformation, and site subsidence. Therefore, frequent and timely quality inspections and error identification are necessary to facilitate prompt corrections and repairs [8,9]. Traditional manual deviation inspection methods face challenges such as high labor intensity, time consumption, and susceptibility to subjective human factors. Additionally, they lack deep integration with digital technologies like building information modeling (BIM), making them inadequate for meeting the demands of intelligent bridge construction management. Manual inspections also rely on contact-based measuring tools, such as tapes and calipers [9]. As a result, non-contact measurement methods such as 3D laser scanners have been widely adopted by researchers to capture the geometric shapes and intricate details of bridges in the real world. The scanned point cloud models are then used as virtual data for further analysis and processing. Laser scanners can emit and capture hundreds of thousands of points per second with millimeter-level accuracy, enabling the precise and rapid acquisition of geometric data [10]. Researchers process the point cloud data collected by 3D laser scanners through point cloud segmentation to

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extract the geometric parameters of individual components. These parameters are then compared with the design data from the BIM model to detect potential geometric deviations [11,12]. The application of 3D laser scanning technology addresses the time-consuming and labor-intensive issues of manual inspections. However, it still faces the following challenges:

Firstly, most current methods show significant shortcomings in the reuse of geometric quality inspection knowledge. During the bridge geometric quality inspection process, a large amount of design data, acceptance standards, and actual inspection information is accumulated. However, this knowledge is often scattered and lacks effective integration and management. Many methods focus solely on simple numerical calculations for each inspection task in isolation, without a structured framework to integrate the dispersed knowledge. As a result, when facing new inspection tasks, existing experience and knowledge cannot be fully leveraged, leading to considerable repetition of work.

Secondly, point cloud segmentation is an indispensable step in extracting geometric parameters of bridges. Point cloud segmentation methods are mainly categorized into voxel-based methods [13–15], projection-based methods [16–18], and point-based methods [19–22]. This paper primarily focuses on point-based methods, among which the widely discussed RandLANet [22] introduces a random sampling strategy into the large-scale point cloud segmentation process, effectively improving point cloud processing efficiency. It employs an encoder-decoder framework based on the UNet architecture for large-scale point cloud segmentation. Subsequent research has improved and extended RandLANet, further enhancing network performance. However, several challenges remain: (1) Most methods rely solely on the relative coordinate information of points for local feature aggregation, which fails to fully capture the complex geometric relationships between the central point and its neighboring points. (2) Point-based methods commonly use K-Nearest Neighbor (KNN) to generate neighboring points. However, when using only the KNN method to obtain adjacent points, there is an issue of class mixing, as it cannot ensure that all neighboring points belong to the same category. This affects the point cloud segmentation accuracy at the connections of bridge components. (3) A skip connection mechanism is used by RandLANet to fuse encoder and decoder features at the same scale. However, simple concatenation overlooks the semantic gaps between features, failing to fully leverage the local details of shallow features and the semantic information of deep features.

To address the above issues, we propose a digital twin bridge geometric quality inspection method based on knowledge mapping and data-driven to achieve geometry quality inspection of rigid components (pier, slab, etc.) with regular geometric boundaries in bridges. Although the BIM model can be regarded as a geometric digital twin model of the bridge, it mainly focuses on the structural form and spatial layout of the bridge, and lacks the expression of multi-dimensional information such as acceptance standards and bridge physical properties. Therefore, we integrate the scattered design data and acceptance standards into a structured framework through ontology-based knowledge mapping, and establish a geometric quality inspection knowledge model in the digital space. The digital twin process of bridge geometric quality inspection is constructed through the BIM model and the knowledge model, and the twin data is compared with the real data to identify potential bridge geometry deviations. Knowledge management throughout the entire bridge geometric quality inspection process becomes more organized and efficient through knowledge mapping. In future construction projects, whether for similar types of bridges or structures, this ontology knowledge can be reused with appropriate adjustments based on the specific project requirements. As new design concepts, construction technologies, and acceptance criteria emerge, the knowledge can be easily expanded and updated on the existing ontology-based knowledge model, ensuring the continued advancement and practicality of the knowledge system. Additionally, in the twin data processing space, we design a large-scale point cloud segmentation network based on hybrid

feature aggregation (HFA) and neighbor feature enhancement (NFE) to extract the as-built geometric parameters of bridge components. The network incorporates both gradient information and relative positional data into the encoding process, enhancing its ability to understand complex point cloud scenarios. A feature enhancement module is used to quantify the differences between the central point and its neighboring points, addressing the class mixing issue introduced by KNN. Moreover, a multi-layer feature adaptive interaction structure deeply fuses the local details of shallow encoder features with the semantic information of deep features.

The main contributions of this paper are as follows:

- (1) A knowledge model for digital twin bridge geometry quality inspection is established through ontology-based knowledge mapping. Additionally, the digital twin process for bridge geometry quality inspection is constructed based on the BIM model and knowledge model.
- (2) A large-scale point cloud segmentation network based on hybrid feature aggregation and neighbor feature enhancement is proposed, which improves the segmentation accuracy at the connections of bridge components.
- (3) Comparative experiments on public datasets and real bridge data demonstrate the superiority of the proposed point cloud segmentation network. Additionally, a prototype system is designed based on Revit to validate the feasibility of the proposed geometric quality detection method.

The structure of the remainder of this paper is as follows: Section 2 introduces the research background of geometric quality inspection, large-scale point cloud segmentation, and knowledge mapping. Section 3 describes the technical details of the proposed digital twin bridge geometric quality inspection method. Section 4 presents related validation experiments to evaluate the performance of the proposed method. Section 5 concludes the paper.

2. Literature review

2.1. Digital twin geometric quality inspection

Geometric quality directly affects the overall stability and safety of a project's structure. Geometric errors can lead to stress concentrations, deformations, or even failure, impacting the service life of the structure. Traditional manual inspection methods are time-consuming and labor-intensive, especially in large-scale and complex projects, where the inspection process is slow. The advancement of computer vision and related technologies has enabled researchers to extract high-precision geometric features from images or laser scan data, significantly improving inspection efficiency. For example, Kaveh et al. [1] proposed an end-to-end automated dimensional quality inspection method for building structural components, achieving end-to-end detection from raw point clouds to component geometric dimensions. Shu et al. [2] developed an innovative method for the automated dimensional quality assessment of precast concrete components, enabling high-precision identification of various typical components and accurate estimation of the dimensions of precast concrete elements. Tan et al. [12] designed a geometric quality inspection method for prefabricated housing units based on BIM and laser radar ranging to address the time-consuming and error-prone issues of traditional prefabricated component quality inspection. Experimental results showed that the precision of detecting geometric errors in structural elements using this technology reached 0.7 mm. Kim et al. [23] proposed a method for dimensional quality assessment of concrete component forms and reinforcement using 3D point cloud data. Seongrae et al. [24] proposed a dimensional quality estimation method for shipbuilding and offshore plant construction based on ground laser scanning and computer-aided design (CAD) models. The method evaluates dimensional quality by calculating the

errors between corresponding measurement points. Li et al. [25] proposed a mirror-assisted, registration-free geometric quality inspection technique, which enables full-surface geometric quality inspection of constructed building components without the need for point cloud registration.

The application of computer vision technology has significantly enhanced the automation level of geometric quality inspection. Meanwhile, the successful implementation of digital twin technology in industries such as mechanical manufacturing, aerospace, and construction provides a new solution for geometric quality inspection. By building a closed-loop interaction between physical entities and virtual models, the inspection process can be transformed from static inspection to dynamic tracing. For example, Li et al. [26] proposed a digital twin-based quality assessment method for aero-engine assembly, establishing a geometric deviation analysis model. Fu et al. [27] reviewed research on digital twins in machining error identification and provided insights into future development trends. Tran et al. [9] proposed a digital twin-based method for the geometric quality assessment of as-built prefabricated facades, enabling automated quantitative comparison between the 3D as-built digital replica reconstructed from 3D laser scanning point clouds and the 3D as-designed model. The above studies demonstrate the application potential of digital twins in precision manufacturing and construction acceptance. In the field of bridge geometric quality inspection, digital twins can dynamically align BIM models with point clouds to achieve staged closed-loop feedback on geometric deviations. Additionally, by leveraging knowledge models, existing inspection experience and expertise can be integrated to enhance inspection efficiency.

In recent years, geometric quality inspection has gradually evolved from traditional manual measurement to computer vision-based automated detection. Perception technologies, represented by laser scanning, combined with image recognition and deep learning methods, have significantly improved the accuracy and efficiency of extracting geometric features of components. In scenarios such as prefabricated and concrete components, existing studies have achieved end-to-end automatic detection processes from point clouds to geometric parameters. However, current methods mainly focus on the construction industry and often fail to effectively integrate engineering inspection standards. Additionally, while digital twins have been proven to be highly effective in geometric error assessment and feedback in industries such as manufacturing and construction, challenges still remain in bridge scenarios. Specifically, how to dynamically align BIM models with point cloud data using digital twins to detect geometric deviations remains a challenge. Therefore, it is necessary to develop a digital twin bridge geometric quality inspection method, which integrates as-designed BIM model, actual point cloud data, and industry standards to identify component geometric deviations, providing technical support for geometric quality inspection in bridge engineering.

2.2. Point cloud segmentation

By accurately segmenting the bridge point cloud data, the complex bridge structure can be divided into different components, providing a foundation for subsequent geometric deviation assessment. Point cloud segmentation methods are primarily categorized into voxel-based methods [13–15], projection-based methods [16–18], and point-based methods [19–22]. This paper mainly focuses on point-based methods. PointNet [19] is the first deep learning framework to directly process unordered point cloud data. It achieves efficient point cloud segmentation by independently learning the features of each point and aggregating global features. Building on PointNet, PointNet++ [20] introduces a hierarchical feature extraction structure to capture local features of the point cloud, thereby further improving the accuracy of point cloud segmentation. Dynamic Graph Convolutional Neural Network (DGCNN) [21] constructs a dynamic KNN graph and dynamically updates it within the network, allowing the feature extraction

process to not only consider the features of individual points but also incorporate the relative features of neighboring points. This enables DGCNN to better capture the local topological relationships of the point cloud, addressing the issue in PointNet where local features between nodes are missing. Although the above methods have achieved good results in point cloud segmentation on certain datasets, they suffer from high computational complexity and large memory consumption, making them ineffective for point cloud segmentation in large-scale scenarios. RandLANet [22] introduces a random sampling strategy into the large-scale point cloud segmentation process, effectively improving point cloud processing efficiency. Although random sampling significantly improves efficiency in terms of computation and memory, it can result in the loss of some information. As a result, many studies have made improvements and extensions based on RandLANet to further enhance network performance. For example, Shuai et al. [28] designed a backward attention fusion mechanism based on RandLANet to bridge the semantic gap between encoder and decoder features, enhancing the discriminative ability of the final features. Zhou et al. [29] further improved the feature fusion module to achieve better segmentation results, while also incorporating directional information into local feature encoding. Zhou et al. [30] alleviated information loss during decoder upsampling by dynamically integrating neighboring information. Xu et al. [31] addressed the issue of the KNN algorithm's inability to accurately capture semantically similar neighboring points by discarding neighbors that are far apart in semantic space, thus extracting more accurate neighbor information.

In summary, existing point cloud segmentation methods have achieved good results in small-scale, regular scenarios, especially with methods like PointNet series and graph-based DGCNN, which have significantly advanced the application of point cloud data in intelligent perception. However, in the practical engineering scenario of bridge geometric quality inspection, where point clouds are large in scale, the structure is complex, and the semantic boundaries between components are ambiguous, existing methods face challenges such as high computational resource consumption and weak local semantic understanding. Although RandLANet performs excellently in large-scale point cloud processing efficiency, its use of random sampling strategies may lead to feature loss, which affects the accurate extraction of key component boundaries. Therefore, it is urgent to introduce feature enhancement mechanisms with structural awareness and semantic-guided strategies to improve the model's expressiveness and component differentiation ability in bridge point cloud segmentation. This will lay a reliable and accurate semantic foundation at the component level for subsequent geometric quality inspection.

2.3. Knowledge mapping

Knowledge mapping is a process and method that associates, integrates, and transforms knowledge from different sources, forms, and levels. Its goal is to reveal the intrinsic connections between knowledge, construct the structure of the knowledge system, and promote the management, sharing, innovation, and application of knowledge. Many scholars have used technologies such as ontology or knowledge graphs to achieve structured representation and semantic relationships of knowledge. Through the effective integration and association of different types of knowledge, a comprehensive knowledge mapping system is ultimately constructed. Liu et al. [32] proposed an ontology-based semantic approach for extracting construction-oriented quantity calculation information from as-designed BIM models. They developed a prototype system based on Revit that allows semantic querying of BIM models through SPARQL. Shen et al. [33] used ontology to enable the sharing, reuse, and accumulation of safety risk management knowledge in the construction of prefabricated buildings. This approach provides timely information and knowledge for decision-making regarding construction safety risks and visually presents this information. Zhou et al. [34] established a domain ontology for a dam safety monitoring system

and implemented SPARQL queries. Compared to traditional database queries, their proposed method aids in the effective integration of dam safety monitoring information while significantly reducing retrieval time. Wang et al. [35] addressed the issue of ineffective knowledge management mechanisms in safety management, which resulted in the underutilization of existing behavioral safety management knowledge. They constructed an ontology framework that facilitated the seamless exchange and retrieval of traditional construction behavioral safety knowledge. Doukari et al. [36] developed an ontology-based safety management system for building renovation. Its effectiveness in automatically identifying area-specific hazards was validated through multiple scenario cases, laying the foundation for future digital safety management. Pfitzner et al. [37] utilized knowledge graphs to integrate time-series data with spatial information, accurately capturing the relationships among workers, vehicles, equipment, and building components, thereby enabling detailed monitoring and analysis of construction projects. Zhou et al. [38] proposed a method that integrates knowledge enhancement with deep learning. By constructing a semantic knowledge base of subway construction risks and incorporating domain knowledge into a pre-trained model, they achieved intelligent generation of risk mitigation measures. Ramonell et al. [39] developed a knowledge graph-based modular data integration system, which integrates BIM models, IoT platform metadata, and process information through a microservice architecture to build a unified virtual model of digital twin for building assets. Gao et al. [40] proposed a hierarchical knowledge graph construction method for bridge maintenance, effectively addressing the limitations of traditional approaches in semantic representation and graph data mining. They also designed a closed-loop application framework to enhance the efficiency of maintenance decision-making. Xia et al. [41] proposed a graph-based BIM model generation method that integrates multi-domain knowledge through progressive ontology development, effectively supporting information collaboration and semantic enhancement in project management and generative design. In addition, many scholars [42,43] have combined knowledge mapping with the study of BIM model compliance checking. By constructing a semantic relationship network between design data and standard specifications, they have enabled automated BIM model compliance review, addressing the time-consuming and labor-intensive issues of manual inspection. Some studies [44,45] have also implemented compliance checking of BIM models based on industry foundation classes (IFC) and ontologies. As a widely adopted open data standard in the architecture, engineering, and construction (AEC) industry, IFC provides a unified structural representation of building components, attributes, and spatial relationships, serving as a core interface for BIM data across platforms and project phases. By semantically mapping IFC models to domain ontologies, it becomes possible to automatically transform design data into semantic models, thereby enhancing the interpretability and reusability of information. In summary, compared to discrete storage, structured knowledge is more conducive to efficient information management and utilization. Through structured knowledge representation, knowledge from different stages and fields can be systematized and standardized, facilitating cross-stage and cross-domain data integration and sharing. This not only enhances the efficiency of information retrieval but also provides stronger support for decision-making. It enables the optimization and improvement of various stages, such as architectural design, construction, and operation, based on a clear knowledge system.

In summary, knowledge mapping, as a key technology for unified knowledge representation and semantic integration, has demonstrated promising applications in various domains such as architectural design, construction management, and safety monitoring. By constructing structured knowledge systems through ontologies and knowledge graphs, it not only improves the organization and management efficiency of engineering information but also provides crucial support for automatic querying, knowledge sharing, and intelligent decision-making. Particularly in tasks such as quantity takeoff, safety

management, and model checking, knowledge mapping technologies exhibit strong scalability and adaptability. Ontology can provide a unified knowledge expression and structured representation. By explicitly modeling concepts, attributes, and relationships within the domain, it can transform unstructured knowledge into a computer-recognizable, structured form, thereby enabling standardized knowledge management. Additionally, SPARQL can be used to flexibly define complex query statements, allowing for the rapid location and extraction of target information from the knowledge network, which facilitates efficient information retrieval and data analysis in bridge geometric quality inspection. Therefore, we establish a reusable knowledge model between the as-designed bridge model and acceptance standards through ontology-based knowledge mapping, enabling the sharing and reuse of relevant knowledge.

3. Methodology

This section systematically introduces the key technical paths for digital twin bridge geometry quality inspection. In [Section 3.1](#), a digital twin bridge geometry quality inspection framework is proposed. In [Section 3.2](#), a knowledge mapping method for bridge geometry quality inspection is introduced. A knowledge model for the digital twin bridge geometry quality inspection process is established in the digital space. In [Section 3.3](#), a large-scale point cloud segmentation network is designed to enable bridge point cloud segmentation in the twin data processing space.

3.1. Digital twin bridge geometry quality inspection framework

The technical route of the digital twin bridge geometry quality inspection method based on knowledge mapping and data-driven is shown in [Fig. 1](#). It is divided into three layers: physical space, digital space, and twin data processing space. The physical space refers to the bridge and its surrounding environment, while the digital space is the bridge's digital model constructed based on data from the physical space. The twin data processing space refers to the space where these data are analyzed and processed. We implement digital twin geometry quality inspection based on this three-layer architecture. The specific steps are as follows:

(1) First, point cloud data of the as-built bridge is collected in the physical space using laser scanning devices.

(2) Then, in the digital space, a corresponding twin model is established. We integrate the scattered design data and acceptance standards into a structured framework through ontology-based knowledge mapping, establishing a geometric quality inspection knowledge model. The digital twin process of bridge geometry quality inspection is constructed in the digital space through BIM model and knowledge model.

(3) Finally, the as-built point cloud from the physical space and the twin model from the digital space are transmitted to the twin data processing space, where the data is analyzed and processed to perform bridge geometric quality inspection. The twin data processing involves the following steps:

Step 1: Based on DotNetRDF, SPARQL queries are used to retrieve the design parameters of the corresponding components from the knowledge model, as well as to query the acceptance standard associated with specific projects or components. This process provides clear standard references for compliance judgment in bridge geometric quality inspection.

Step 2: Perform instance segmentation of the as-built point cloud model using a large-scale point cloud segmentation network based on HFA and NFE. After segmentation, measure the parameters of the segmented components to extract the geometric parameters of the as-built point cloud model.

Step 3: Compare the as-designed parameters with the as-built parameters, and assess the compliance of the component's geometric quality by considering the allowed ranges in the acceptance standards.

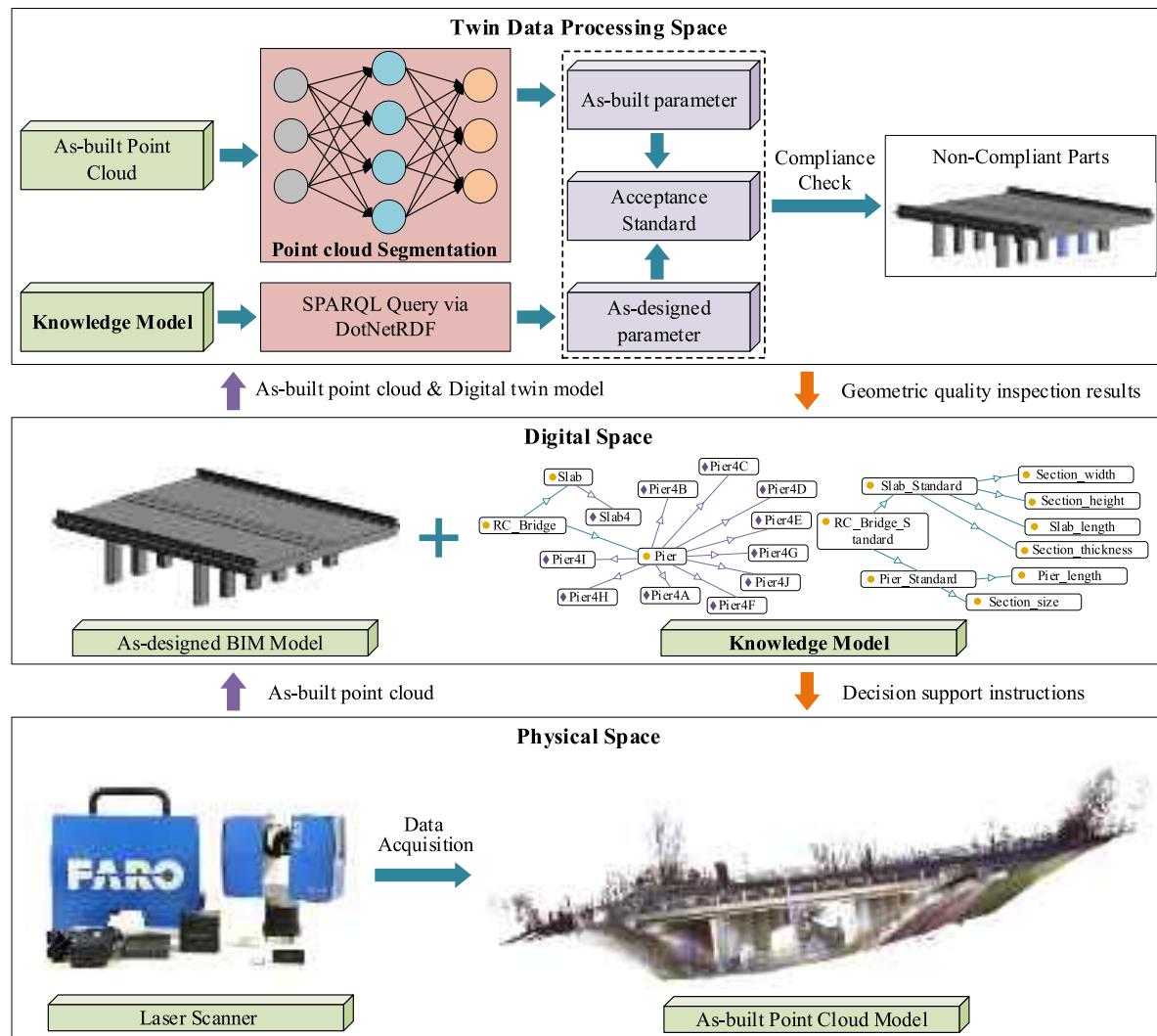


Fig. 1. Digital twin bridge geometry quality inspection method based on knowledge mapping and data-driven.

Use the Revit application programming interface (API) to highlight non-compliant components in the as-designed BIM model, enabling automatic inspection of bridge geometric quality.

The above three steps are used to realize the geometric quality inspection of bridges in the twin data processing space, and the inspection results are transmitted to the digital space to realize the visualization of the inspection results. Then, corresponding decision-making instructions (such as maintenance or repair) are sent to the physical space. These instructions are executed by the actual engineering operators, thus forming a closed-loop feedback mechanism that enables digital twin bridge geometric quality inspection. The proposed method focuses on the geometric quality inspection of the main structure of the bridge, especially the rigid components with clear geometric boundaries and regular shapes, such as piers, cap beams, slabs, etc.

3.2. Knowledge mapping method for bridge geometry quality inspection

In this section, we establish a knowledge model for the digital twin bridge geometric quality inspection in the digital space through knowledge mapping. In bridge geometric quality inspection, the sources of knowledge are extensive, including geometric data from the BIM model during the design phase, acceptance standards, and actual measurement data from the as-built phase. The purpose of knowledge mapping is to integrate these scattered knowledge with the help of ontology to form a comprehensive knowledge system of bridge

geometry quality inspection, so as to establish a knowledge model for the digital twin process of bridge geometry quality inspection in the digital space. This ensures that different inspectors and inspection projects can understand and apply the relevant knowledge based on a unified ontology, thereby effectively avoiding redundant knowledge construction and misunderstandings caused by differences in interpretation. The ontology, through a pre-defined hierarchical structure of concepts and relational rules, accurately infers potential quality issues based on known bridge geometric parameters and acceptance standards. In addition, the ontology can be easily extended and updated to accommodate the ever-changing inspection requirements and newly published standards. When new bridge types or inspection standards emerge, they can be directly incorporated into the existing ontology without the need to rebuild the entire knowledge system. This allows for reuse across different inspection projects and systems, enhancing the efficiency of knowledge sharing and utilization. The process of knowledge mapping for bridge geometric quality inspection can be divided into three parts: knowledge representation and storage, knowledge query and parse, and knowledge reuse and update, as shown in Fig. 2.

3.2.1. Knowledge representation and storage

The purpose of knowledge representation and storage is to establish a bridge geometric quality inspection knowledge model in the digital space, mapping unstructured geometric parameter information and acceptance standard texts into structured knowledge, facilitating

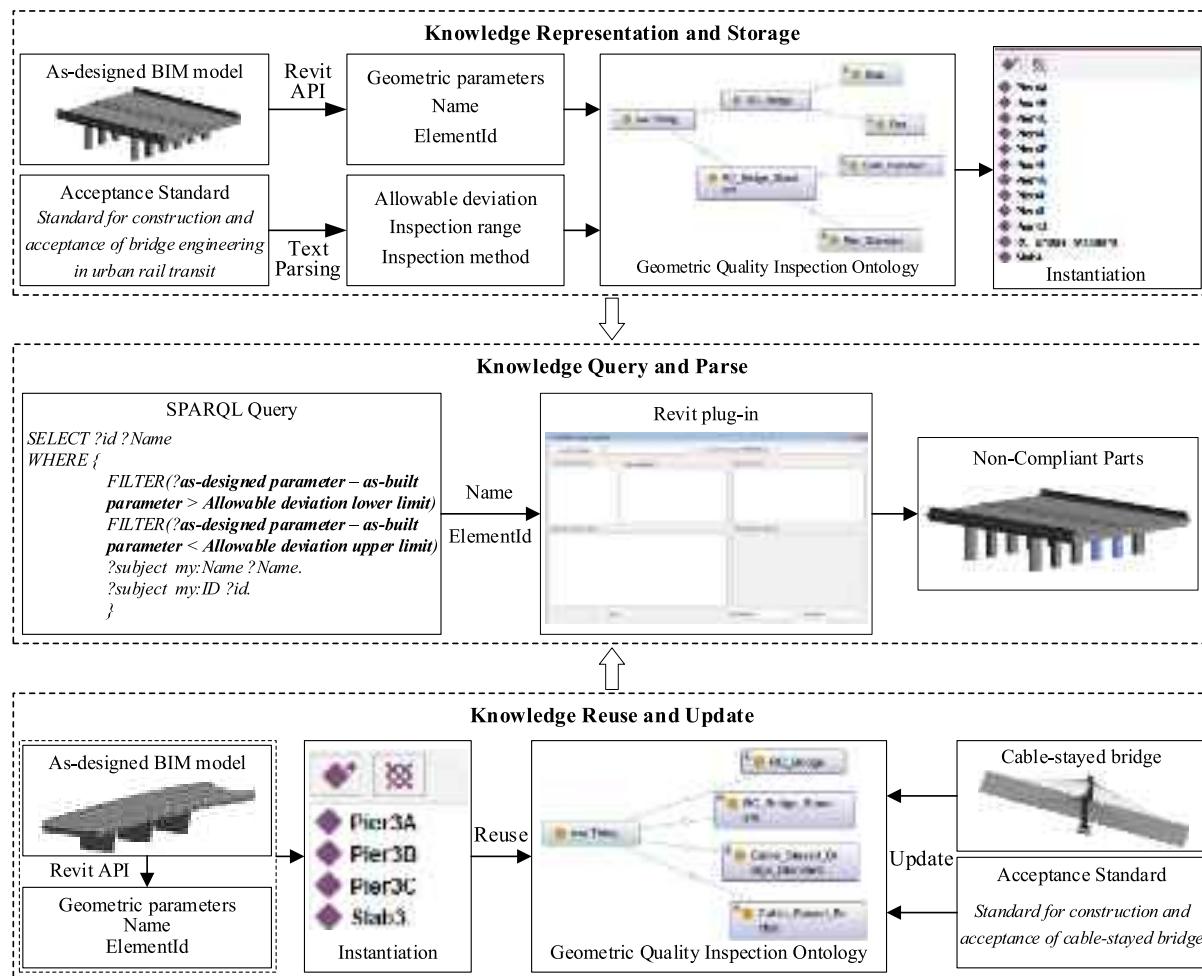


Fig. 2. Knowledge mapping method for bridge geometry quality inspection.

knowledge acquisition and understanding. First, it is necessary to define the scope of the ontology, including the types of bridges, geometric quality indicators, inspection methods, and other relevant aspects. Next, it is necessary to define the core concepts and classes of the ontology. For example, the “Bridge” class can be divided into subclasses such as “Beam Bridge”, “Arch Bridge”, “Cable-Stayed Bridge”, and each subclass can be further subdivided into more specific bridge structure subclasses. Our research primarily focuses on the geometric quality inspection of Reinforced Concrete (RC) Bridges. Then, relevant attributes should be defined for the classes within the ontology to describe their characteristics and status. For instance, data attributes such as “height” and “width” can be defined for components like piers. At the same time, relationships between classes can also be defined. Finally, based on the actual as-designed BIM model parameter information and relevant acceptance standards, the ontology is instantiated. For example, a pier instance can be created, and specific values can be assigned to data attributes such as height and width.

We have constructed an ontology for bridge geometric quality inspection using RC Bridge as an example. It can be subdivided into subclasses of RC_Bridge and RC_Bridge_Standard, representing geometric structures and acceptance standards, respectively. The attributes of the acceptance standards are derived from the “Standard for Construction and Acceptance of Bridge Engineering in Urban Rail Transit”, with some of the acceptance standards shown in Table 1. Different types of bridges correspond to different standards.

As shown in Table 1, RC_Bridge_Standard can be subdivided into Pier_Standard and Slab_Standard. Each category also contains several subcategories. The structure of the bridge geometry quality inspection

Table 1
Bridge acceptance standards.

Type	Item	Allowable deviation (mm)	Inspection range	Inspection method
Pier	Pier length	(-10,+5)	Each component	Check the four sides of the component
	Section size	(-5,+5)	Each component	Check the ends and the middle of the component
	Length	(-10,+5)	Each span	Measure with a steel ruler
Slab	Height	(-10,+5)	Each span	Measure with a steel ruler
	Section size	Width (30,+30)	Each span	Measure with a steel ruler
	Thickness	(0,+10)	Each span	Measure with a steel ruler

ontology is shown in Fig. 3.

The bridge geometric quality inspection ontology includes 13 data attributes. Data attributes are key elements used to describe the specific characteristics or properties of individuals, as shown in Table 2. These data attributes describe the geometric characteristics and acceptance standards of various components of the RC Bridge, such as the height and width of piers, allowable deviations, and other relevant parameters.

After establishing the bridge geometric quality inspection ontology,

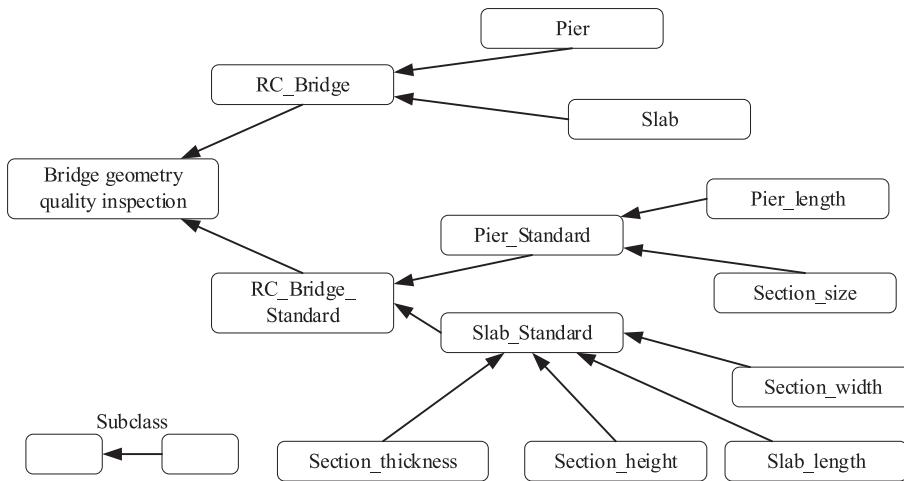


Fig. 3. Bridge geometric quality inspection ontology structure.

Table 2
RC Bridge ontology data attributes.

Num	Data properties	Domain	Range	Description
1	Pier height	Pier	Double	Vertical dimensions of the pier
2	Pier thickness	Pier	Double	Lateral dimensions of the pier
3	Pier width	Pier	Double	Horizontal dimensions of the pier
4	Section size	Pier	Double	Section size
5	ElementId	Pier, Slab	String	Component unique ID
6	Name	Pier, Slab	String	Component unique name
7	Slab length	Slab	Double	Slab length
8	Section height	Slab	Double	Section size
9	Section width	Slab	Double	Section size
10	Section thickness	Slab	Double	Section size
11	Allowable deviation	Acceptance standard	String	Allowable deviation
12	Inspection range	Acceptance standard	String	Inspection range
13	Inspection method	Acceptance standard	String	Inspection method

the next step is instantiation. Instantiation is the critical process of associating abstract ontology concepts with specific bridge engineering data. Extract geometric parameters, ElementId, Name and other information of as-designed BIM models through Revit API. The acceptance standards are parsed to obtain the allowed deviations, inspection range, and inspection methods, which are then populated into the corresponding individuals. This process completes the instantiation of the relevant data attributes for the specific instances.

3.2.2. Knowledge query and analysis

After the representation and storage of knowledge, effective methods are needed to query and analyze this knowledge so as to combine the as-built data for geometric quality inspection in the twin data processing space. We use SPARQL queries to retrieve knowledge and specifically filter out the deviations between as-designed parameters and as-built parameters. Through knowledge query and analysis, inspectors can query the ontology for information about the geometric features of specific bridge components, quality indicator requirements, applicable inspection methods, and more, based on specific inspection needs. Based on the relationships between geometric features and the constraints of quality indicators defined in the ontology, the system can automatically analyze whether the inspection data meets the quality requirements.

The main content of the SPARQL query for geometric quality inspection is as follows.

$$\text{FILTER}(\text{?}P_{Ad} - \text{?}P_{Ab} > Ad_{ll}) \quad (1)$$

$$\text{FILTER}(\text{?}P_{Ad} - \text{?}P_{Ab} < Ad_{ul}) \quad (2)$$

P_{Ad} represents the as-designed parameters, P_{Ab} represents the as-built parameters, Ad_{ll} and Ad_{ul} represent the lower and upper limits of the allowable deviation, and then *FILTER* is used to filter. The filtered information is the non-compliant information. This form of SPARQL statement can be used to determine whether the bridge meets the acceptance specifications.

3.2.3. Knowledge REUSE AND UPDATE

Knowledge reuse refers to the practice of reusing existing knowledge as much as possible in different bridge geometric quality inspection projects. Through the sharing and reuse mechanism of the ontology, the constructed ontology can be applied to new projects, reducing redundant work. For example, for bridge inspection projects of similar types, the existing bridge geometric quality detection ontology can be directly used, with only minor adjustments and extensions based on the specific project requirements. With the continuous development of bridge design, construction, and inspection technologies, the knowledge of bridge geometric quality inspection is also constantly updated. The ontology can reflect these changes in a timely manner, adding and updating new knowledge to ensure its timeliness and accuracy. As shown in Fig. 2, the ontology stores the geometric quality detection knowledge for RC Bridge. When a new type of bridge, such as a cable-stayed bridge, requires geometric quality inspection, the existing ontology knowledge only needs to be extended and updated, and then the knowledge can be queried and analyzed.

3.3. Large-scale point cloud segmentation network structure

In the twin data processing space, it is necessary to measure the as-built parameters of the point cloud data from the physical space, in which point cloud segmentation plays an extremely critical role. Therefore, based on the architectures of RandLANet [22] and GAF-Net [29], we propose a large-scale point cloud segmentation network based on hybrid feature aggregation and neighbor feature enhancement (HANE-Net), achieving high-precision point cloud segmentation for bridges. The network details are shown in Fig. 4 and consist of four main parts: pointwise feature extraction, encoding layer, multi-layer feature adaptive interaction, and decoding layer. The input point cloud is first passed through the pointwise feature extraction module to capture the deep information of the point cloud. Then, in the encoding layer, the

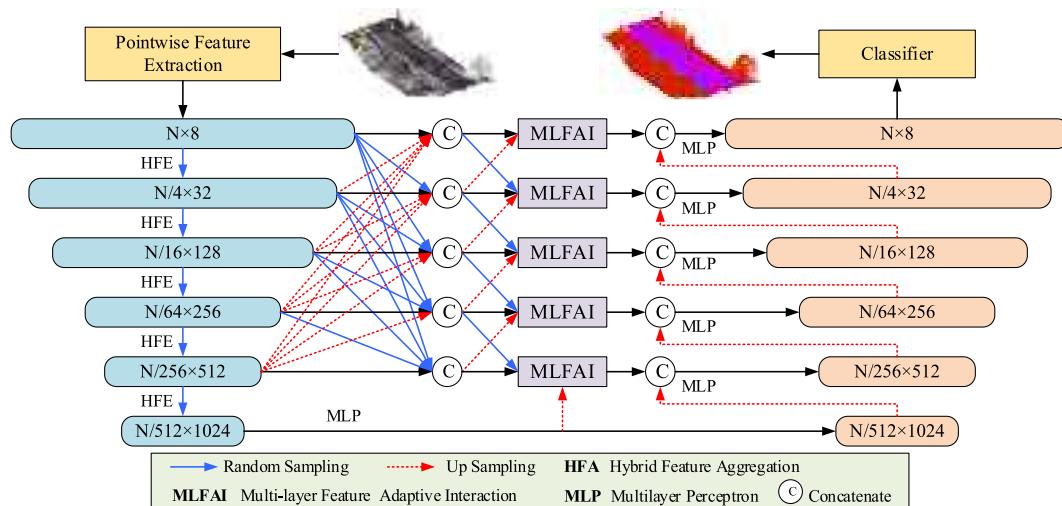


Fig. 4. Large-scale point cloud segmentation network based on hybrid feature aggregation and neighbor feature enhancement.

hybrid feature aggregation module is used to learn and aggregate local features, with random sampling applied for downsampling. During the random sampling process, the number of points gradually decreases, while the feature dimension increases, with the specific change ratio shown in Fig. 4. The encoded features from each layer are then adaptively fused through the multi-layer feature adaptive interaction module, effectively enhancing feature representation capabilities, followed by concatenation with the decoder features via skip connections. Finally, in the last layer of the decoder, a classifier is used to predict the semantic label of each point. This section involves many main variable symbols. To enhance the clarity of expression, we have summarized the important symbols used in the formula and their meanings, as shown in Table 7 in Appendix A.

3.3.1. Pointwise feature extraction

Compared to directly using fully connected layers to extract pointwise features, the attention mechanism can focus on the key information of the point cloud and integrate spatial correlation information, better uncovering the deep information of the point cloud and providing the encoder with point cloud features that have higher feature representation capabilities, thereby improving the network accuracy. Therefore, we design a pointwise feature extraction module based on CosFormer, as shown in Fig. 5. In the figure, Q, K, and V represent the Query, Key, and Value vectors in the attention mechanism. In this mechanism, the input point features are first mapped into Q, K, and V vectors to perform weighted aggregation of surrounding point features,

thereby enhancing the model's ability to capture long-range feature dependencies in the point cloud.

The input to the module consists of the 3D coordinates, RGB information, and the combination of both. First, the feature extraction module (FTM) aggregates the high-dimensional features of these three elements, initially integrating the point cloud features from different aspects. Then, the already aggregated features are fused again using FTM to optimize the quality and representation ability of the features, making the point cloud features more distinctive. FTM is based on CosFormer [46]. Compared to traditional attention mechanisms, CosFormer consumes fewer computational resources and has lower computational complexity, making it well-suited for large-scale point cloud processing. The attention mechanism computation equation is as follows.

$$O = Q^{\cos}(K^{\cos}V) + Q^{\sin}(K^{\sin}V) \quad (3)$$

$$Q^{\cos} = Q\cos\left(\frac{\pi i}{2N}\right), Q^{\sin} = Q\sin\left(\frac{\pi i}{2N}\right) \quad (4)$$

$$K^{\cos} = K\cos\left(\frac{\pi j}{2N}\right), K^{\sin} = K\sin\left(\frac{\pi j}{2N}\right)$$

where $i, j = 1, 2, \dots, N$.

The pointwise feature F_p is calculated as follows.

$$F_p = \text{FTM}(\text{FTM}(XYZ, RGB), \text{FTM}(XYZ), \text{FTM}(RGB)) \quad (5)$$

Where FTM represents a feature extractor composed of four layers of

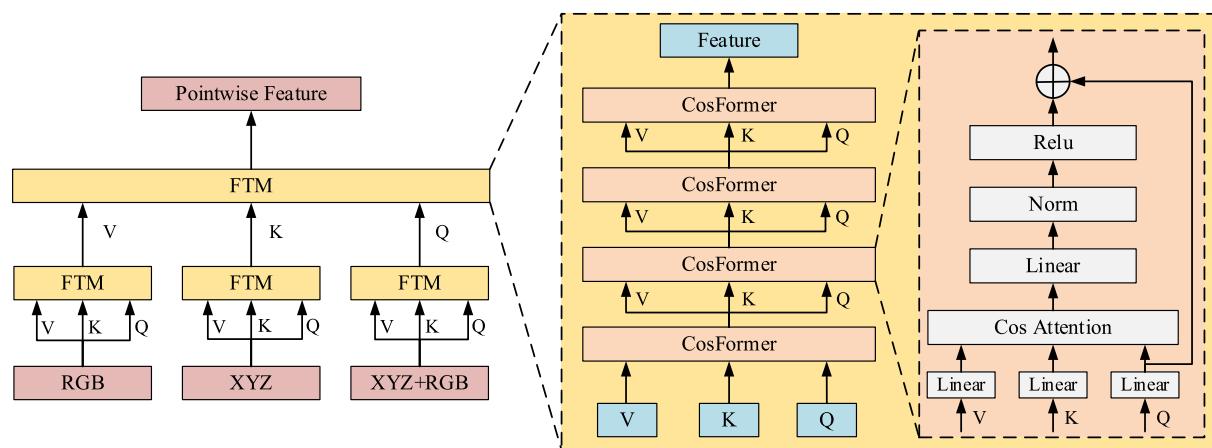


Fig. 5. Pointwise feature extraction.

cosformer, *XYZ* and *RGB* represent the coordinate information and color information of the point cloud respectively.

3.3.2. Hybrid feature aggregation

The hybrid feature aggregation module, shown in Fig. 6, mainly consists of two parts: hybrid feature extraction and feature enhancement. Most point cloud segmentation methods rely on the relative coordinate information of points for local feature aggregation. The relative position information is defined as follows.

$$r_i^k = (p_i, p_i^k, (p_i - p_i^k), \|p_i - p_i^k\|) \quad (6)$$

Where p_i^k is the k th nearest neighbor of the center point p_i . We use the K nearest neighbor algorithm to calculate the K nearest neighbor points $\{p_1^1, p_1^2, \dots, p_i^k, \dots, p_i^K\}$ of the center point. $\|p_i - p_i^k\|$ represents the Euclidean distance. The relative position information contains the absolute coordinate information of the center point, the absolute coordinate information of the neighboring points, the relative coordinate information and the distance information.

However, the relative position information can only reflect the spatial position relationship between the points in the point cloud, and cannot fully capture the complex geometric relationship between the center point and its neighbors [29]. It lacks the high-dimensional geometric detail information contained in the trend of surface changes. Therefore, we design a hybrid feature extraction structure that incorporates gradient information and relative position information into the encoding process. This allows the generated feature vectors to not only contain the spatial position relationships of the points but also the trend of surface changes in the point cloud. This fusion method enables the network to simultaneously learn the local geometric structure of the point cloud and its variation patterns in space, thus enhancing the network's ability to understand complex point cloud scenarios. When processing complex bridge point clouds, gradient information can help distinguish areas with significant geometric changes, such as the edges and corners of bridges, allowing the network to more accurately identify different bridge structural components and thereby improve the accuracy of semantic segmentation. We use the Azimuth angle and Zenith angle to represent the gradient information [47], as shown in the Fig. 6, and the specific calculation method is as follows:

$$\begin{aligned} \sin\theta_i^k &= \frac{z_i^k}{\sqrt{(x_i^k)^2 + (y_i^k)^2 + (z_i^k)^2}}, \cos\theta_i^k = \frac{\sqrt{(x_i^k)^2 + (y_i^k)^2}}{\sqrt{(x_i^k)^2 + (y_i^k)^2 + (z_i^k)^2}} \\ \sin\beta_i^k &= \frac{x_i^k}{\sqrt{(x_i^k)^2 + (y_i^k)^2}}, \cos\beta_i^k = \frac{y_i^k}{\sqrt{(x_i^k)^2 + (y_i^k)^2}} \\ (x_i^k, y_i^k, z_i^k) &= p_i - p_i^k \end{aligned} \quad (7)$$

$$g_i^k = (\sin\theta_i^k \sin\beta_i^k, \sin\theta_i^k \cos\beta_i^k, \cos\theta_i^k) \quad (8)$$

For the K nearest neighbor points of the center point, r_i^k contains the relative position information, and g_i^k contains the gradient information. By combining these features, it becomes easier to capture the complex geometric relationships between the center point and its neighboring points. We use a shared Multilayer Perceptron (MLP) to encode the hybrid features.

$$f_i^k = \text{MLP}(r_i^k, g_i^k) \quad (9)$$

In RandLANet, feature encoding is directly concatenated with the features of neighboring points obtained through the KNN algorithm. However, there is a problem of class mixing when directly acquiring neighboring points through the KNN algorithm. We address this issue by using a Feature Enhancement (FE) module to quantify the feature differences between the center point and its neighboring points. This module builds a feature association evaluation mechanism to select features of the same category and suppress interference from unrelated categories, thereby automatically focusing on neighboring point features that are of the same class or have higher correlation with the center point, and mitigating the impact of features from neighboring points of different classes.

$$w = \text{softmax}\left(R(f_{p_i}) - f_{p_i^k}\right) \quad (10)$$

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}} \quad (11)$$

$$\tilde{f}_{p_i^k} = \text{MLP}(f_{p_i}, f_{p_i^k} \cdot w) \quad (12)$$

Where w represents the learned weighted parameter, f_{p_i} represents the center point feature, $f_{p_i^k}$ represents the neighboring point feature, R represents the repeat operation to make the two dimensions consistent,

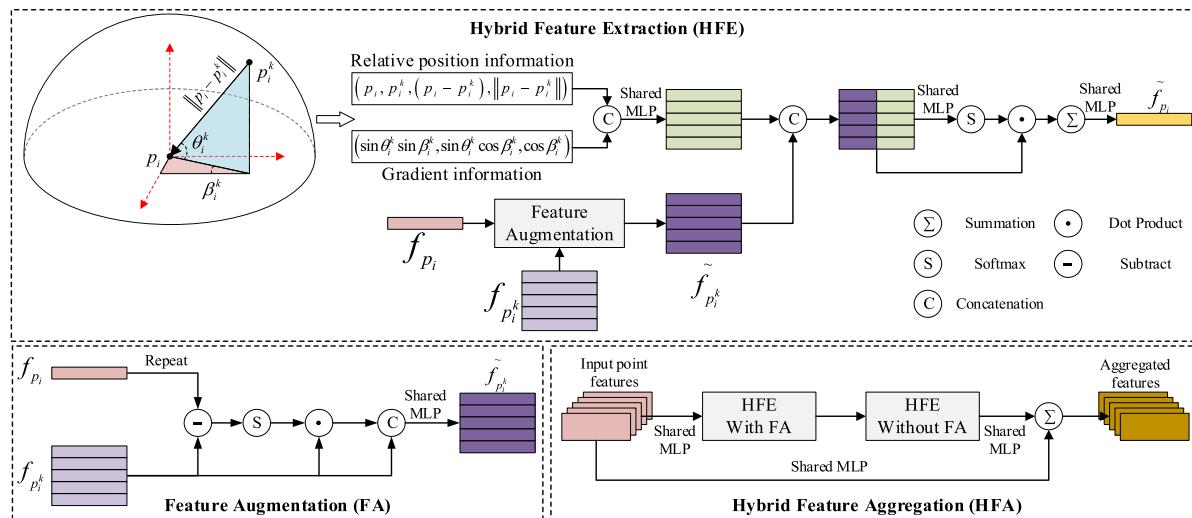


Fig. 6. Hybrid feature aggregation.

and \tilde{f}_i^k represents the enhanced neighboring point feature. The Softmax function is used to convert a multi-dimensional input vector into a probability distribution, where the sum of the probabilities is 1. We use it to normalize feature weights, thereby enabling a set of learnable weighted parameters. The enhanced neighboring point feature will be concatenated with the hybrid feature and then attention pooling will be performed.

$$\tilde{f}_i^k = \tilde{f}_{p_i^k}^k \oplus f_i^k \quad (13)$$

$$\tilde{f}_{p_i} = \text{MLP} \left(\sum_{k=1}^K \left(\tilde{f}_i^k \odot \text{softmax}(\tilde{f}_i^k) \right) \right) \quad (14)$$

\tilde{f}_{p_i} represents the mixed features obtained through attention pooling aggregation, which includes relative position information, gradient information, and enhanced neighboring point feature. This allows for stronger feature representation and richer information content.

The structure of the hybrid feature aggregation module is similar to the dilated residual block structure in RandLANet. The difference lies in our redesign of the local feature aggregation structure. To avoid excessive consumption of computational resources and prevent information loss due to over-transformation of features, we only apply the feature enhancement module in the previous Hybrid Feature Extraction (HFE). Compared to RandLANet's dilated residual block structure, the feature information extracted by HFE is more comprehensive, effectively capturing the complex geometric relationships between the center point and its neighboring points, while suppressing the interference from neighboring points of different classes, thereby improving the network's performance.

3.3.3. Multi-layer feature adaptive interaction

We design a multi-layer feature adaptive interaction module (MLFAI), as shown in Fig. 7. By fusing features from different layers, we combine the local details of shallow features with the global semantic information of deep features, enhancing the representation ability of the encoder features and effectively bridging the semantic gap between the encoder and decoder features.

The encoder features at layer l can be expressed as follows.

$$F_e^l = \begin{cases} PFE(P), & \text{if } l = 1 \\ RS(HFE(F_e^{l-1})), & \text{otherwise} \end{cases} \quad (15)$$

Where PFE represents the pointwise feature extraction module, RS represents random sampling, and P is the input point cloud, $l \in \{1, 2, 3, 4, 5, 6\}$.

Before feature fusion, concatenate is used to concatenate encoder features of different layers to form a high-dimensional feature vector F_e^l , further improving the feature representation capability.

$$F_e^l = \begin{cases} \text{MLP}(F_e^l), & \text{if } l = 6 \\ \text{MLP}(\text{cat}(F_e^l, RS(F_e^a), US(F_e^b))), & \text{otherwise} \end{cases} \quad (16)$$

Where cat represents the concatenation operation, US represents upsampling, $a, b \in \{1, 2, 3, 4, 5\}$ and $a < l, b > l$.

Then, encoder features F_{mf}^l with richer information content are generated through multi-layer feature adaptive interaction.

$$F_{mf}^l = \begin{cases} \text{MLFAI}(F_e^l, \text{MLP}(US(F_e^{l+1})), \text{MLP}(F_e^l)), & \text{if } l = 1 \\ \text{MLFAI}(F_e^l, \text{MLP}(RS(F_e^{l-1})), \text{MLP}(US(F_e^{l+1}))), & \text{if } 1 < l < 6 \end{cases} \quad (17)$$

The process of multi-layer feature adaptive interaction is shown in the Fig. 7 and can be expressed as follows.

$$\begin{aligned} F_a^l &= \text{MLP}(F_e^{l+1}) \cdot \text{sigmoid}(F_e^l) \\ &+ \text{MLP}(F_e^{l-1}) \cdot (1 - \text{sigmoid}(F_e^l)) \end{aligned} \quad (18)$$

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (19)$$

$$F_{mf}^l = \text{MLP}(\text{cat}(F_a^l, F_e^l)) \quad (20)$$

The Sigmoid function is an activation function that maps any real-valued number to the $[0,1]$ range. It is used to generate adaptive interaction weights between multi-level features, thereby guiding the network to effectively fuse semantic information from different layers. By learning a weighted parameter, the shallow features' local details and the deep features' global semantic information are adaptively fused, resulting in encoder features with stronger representation capability. These features are then fused with the decoder features. Finally, at the last layer of the decoder, a classifier is used to predict the semantic label of each point.

$$F_d^l = \begin{cases} F_e^l, & \text{if } l = 6 \\ \text{MLP}(F_{mf}^l, US(F_d^{l+1})), & \text{otherwise} \end{cases} \quad (21)$$

4. Experimental results and case study

To validate the effectiveness of the proposed method, point cloud segmentation experiments are first conducted on both public datasets and real bridge point cloud data in this section. Then, geometry quality inspection is carried out on the bridge point cloud data. Finally, the experimental results are analyzed and discussed.

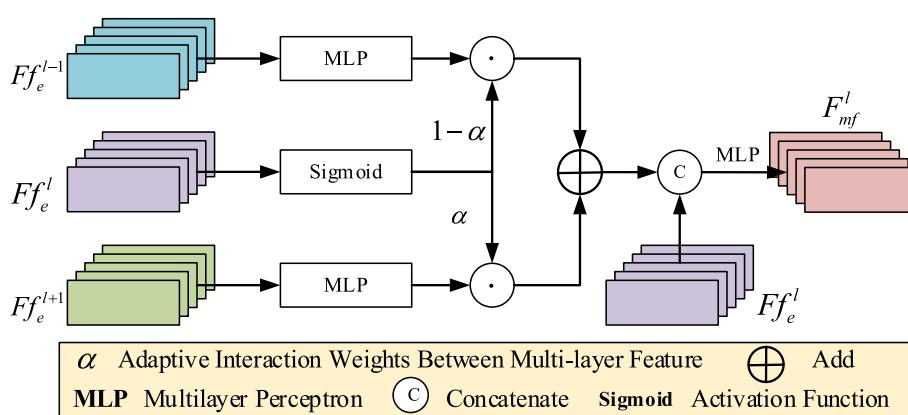


Fig. 7. Multi-layer feature adaptive interaction.

4.1. Point cloud segmentation experimental results and analysis

The proposed point cloud segmentation network is experimentally validated in this section. Experiments are conducted on both the S3DIS dataset and the bridge point cloud dataset, and ablation experiments are performed to verify the effectiveness of each module of the network.

4.1.1. Experimental settings and evaluation metrics

The point cloud segmentation network in the twin data processing space is optimized using the Adam optimizer, with a weighted cross-entropy loss function. The initial learning rate is set to 0.01. The network is trained for 100 epochs, with the learning rate reduced by 5% after each epoch. The number of neighbors in KNN is set to 16, and the batch size is set to 6. Our network is implemented based on PyTorch and trained on an NVIDIA RTX 3090 GPU. To ensure a fair and unbiased experimental process, all compared methods are run in the same hardware environment and trained and tested using the same data distribution. For methods whose code is not open-source, we use the results reported in the original paper for comparison. To quantitatively evaluate the segmentation performance of the proposed method, we used overall accuracy (OA), mean class accuracy (mAcc), per-class intersection over union (IoU), and mean IoU (mIoU) as evaluation metrics, as follows.

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \quad (22)$$

$$mAcc = \frac{1}{n} \sum_1^n \frac{TP}{TP + FN} \quad (23)$$

$$IoU = \frac{TP}{FN + FP + TP} \quad (24)$$

$$mIoU = \frac{1}{n} \sum_1^n \frac{TP}{FN + FP + TP} \quad (25)$$

Among them, TP , TN , FP , FN represent true positive, true negative, false positive, and false negative samples respectively, and n represents the number of categories.

We validate the effectiveness of the proposed point cloud segmentation method on two datasets: the large-scale indoor space dataset S3DIS [48] and the real bridge point cloud dataset [49].

S3DIS Dataset: S3DIS is a large-scale indoor scene dataset collected by Matterport, consisting of 272 rooms across 6 large areas. Each point contains coordinate and color information, with a total of 13 categories. We use areas 1–4 and area 6 for training and tested on area 5.

Bridge Point Cloud Dataset: This dataset consists of real-world collected point cloud data of reinforced concrete bridges. Each bridge includes background, piers, and slabs. Since the original data does not provide labeled point clouds, we performed segmentation on the raw data using CloudCompare [50] to generate ground-truth labels for the background, piers, and slabs. We use Bridge2, Bridge6, and Bridge8 as training data, and Bridge3, Bridge4, and Bridge5 as test data. Additionally, we perform reverse modeling to generate corresponding as-designed BIM models.

4.1.2. S3DIS dataset segmentation results

The comparison methods include RandLANet [22], BAF-LAC [28], DE-Net [51], LGGCM [52], and MNAT-Net [53]. The segmentation results of different methods on the S3DIS dataset are shown in Table 3, with bolded data representing the best results and italic data representing the second-best results. Our proposed method outperforms the other methods in all three evaluation metrics: mIoU, OA, and mAcc, achieving improvements of 3.2%, 1.9%, and 2.7%, respectively, over RandLANet. Moreover, in 13 categories, our method performs better than others in five specific categories: wall, door, table, sofa, and board, and achieves the second-best results in three specific categories: chair, book, and clutter. To provide a more intuitive comparison of semantic segmentation results, we visualized the semantic segmentation results of RandLANet, BAF-LAC, and our method on the S3DIS dataset, as shown in Fig. 8. In the figure, ground truth (GT) refers to manually annotated true labels, representing the true component categories. The visualization results indicate that our proposed method exhibits more accurate scene segmentation results and smoother boundary segmentation curves.

4.1.3. Bridge point cloud segmentation results

The comparison methods include RandLANet [22] and BAF-LAC [28]. The structure of bridge point clouds is relatively simple, so all three methods achieve good segmentation results. However, our proposed method still demonstrates the best segmentation performance. As shown in Table 3, it achieves optimal segmentation accuracy in three specific categories: Background, Pier, and Slab, highlighting the superiority of our method. Compared to RandLANet, the three evaluation metrics improve by 0.79%, 0.15%, and 0.91%, respectively. Compared to BAF-LAC, the three evaluation metrics improve by 1.07%, 0.35%, and 1.08%, respectively. Fig. 9 shows the visual comparison of semantic segmentation results for RandLANet, BAF-LAC, and our method on Bridge3. Our proposed method achieves higher segmentation accuracy at the bridge connection points. This improvement is due to the feature enhancement module in the network, which reduces the category mixing problem caused by KNN to some extent, improving segmentation accuracy at bridge connection points and thereby reducing measurement errors in the as-built parameters.

4.1.4. Ablation experiment

This section conducts a series of ablation studies to evaluate the effectiveness of each module in the network. All experiments are conducted on the bridge point cloud dataset. HANE-Net consists of four core modules: Pointwise Feature Extraction (PFE), Feature Enhancement (FE), Multi-Layer Feature Adaptive Interaction (MLFAI), and Hybrid Feature Extraction (HFE). We perform ablation experiments on these four modules, and the results are shown in Table 5. Model 1 represents the replacement of the PFE module with fully connected layers. Model 2 represents that feature enhancement is not applied. Model 3 directly uses the skip strategy without adaptive fusion between encoder features. Model 4 considers only relative position information, excluding gradient information. Model 5 represents the complete configuration of HANE-Net.

Model 1 uses fully connected layers for pointwise feature extraction, which does not focus on the deep-level information of point clouds. In this case, the mIoU is 94.66%. After introducing the PFE module, the

Table 3

Segmentation results of different methods on S3DIS (Area5). (The bold data represent the best results, and the italic data represent the second best results)

	mIoU	OA	mAcc	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board	clut.
RandLA Net	63.6	87.2	72.2	91.3	97.5	81.2	0.0	23.3	60.0	44.4	77.4	87.9	73.6	69.9	68.6	51.3
BAF-LAC	64.6	87.8	73.3	93.6	96.3	81.7	0.0	34.6	61.3	43.1	76.4	86.0	72.3	70.3	71.2	53.6
DE-Net	63.9	88.0	—	93.3	96.9	81.0	0.0	25.1	62.8	47.1	80.0	81.7	75.3	69.6	66.3	53.1
LGGCM	63.3	88.8	71.2	94.8	98.3	81.5	0.0	35.9	63.3	43.5	80.2	88.4	68.8	55.8	64.6	47.8
MNAT-Net	66.0	—	72.8	92.3	98.6	78.6	0.0	38.9	68.0	63.8	76.2	85.5	67.3	65.8	68.1	55.0
HANE	66.8	89.1	74.9	92.8	97.8	84.4	0.4	30.4	61.6	66.4	81.8	88.0	68.8	70.0	71.9	54.1

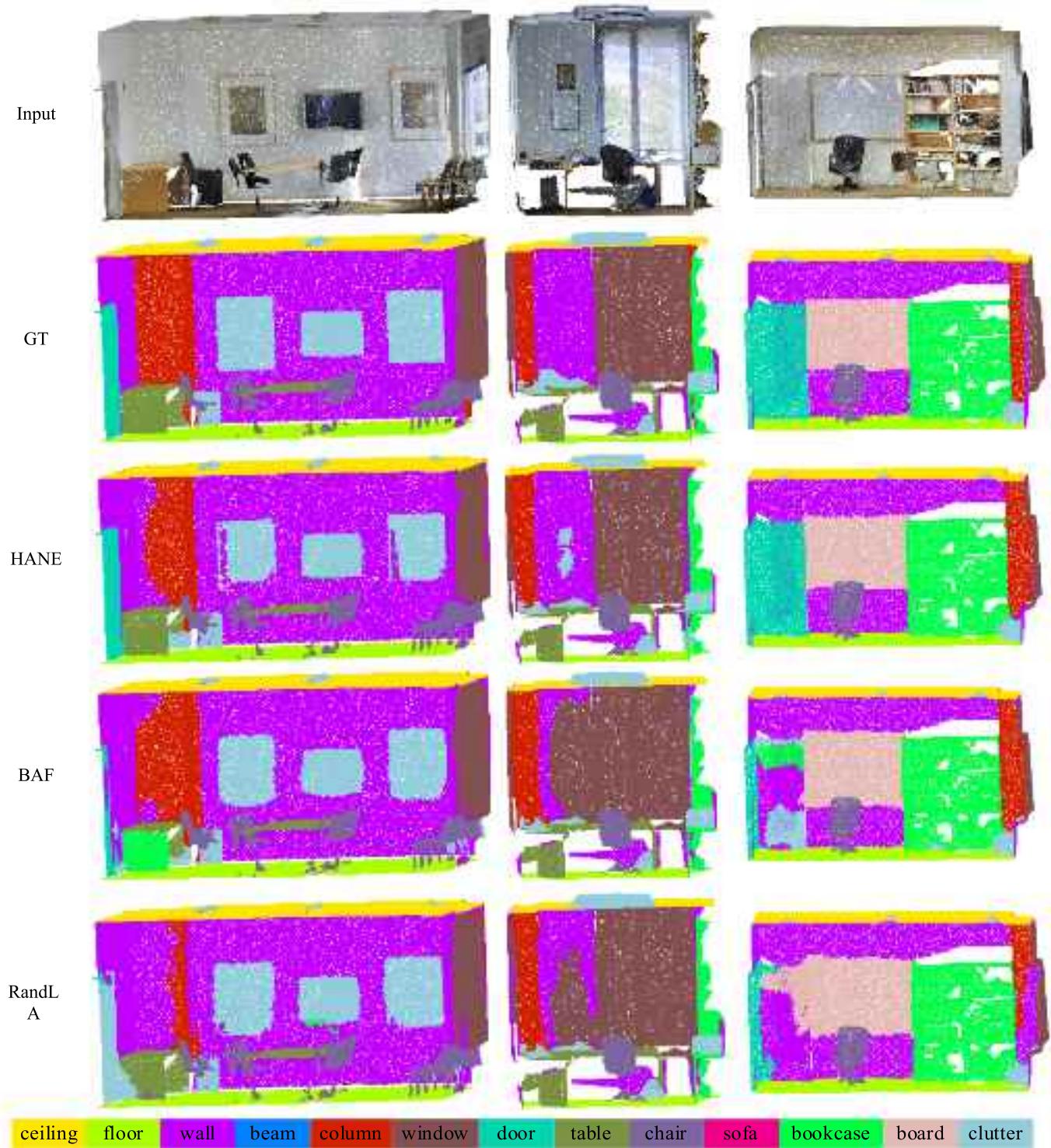


Fig. 8. Comparison of semantic segmentation results on S3DIS.

mIoU improves by 0.78 %, demonstrating that PFE can provide the encoder with point cloud features with higher feature representation capabilities, thereby enhancing the segmentation accuracy of the network. Model 2 removes the FE module from HANE-Net, leading to category mixing issues when the KNN algorithm selects neighboring points, which adversely affects segmentation accuracy. The FE module effectively quantifies the differences between the central point and its neighboring points' features, suppressing the influence of neighboring points from different categories. Model 3 employs a direct skip-

connection strategy, which fails to fully utilize the local details of shallow features and the semantic information of deep features. By incorporating the MLFAI strategy, the representation capability of encoder features is enhanced, effectively bridging the semantic gap between encoder and decoder features, resulting in a 0.7 % improvement in mIoU. Model 4 relies solely on the relative coordinate information of points for local feature aggregation, lacking the high-dimensional geometric detail information contained in point cloud surface variation trends. By incorporating gradient information, the

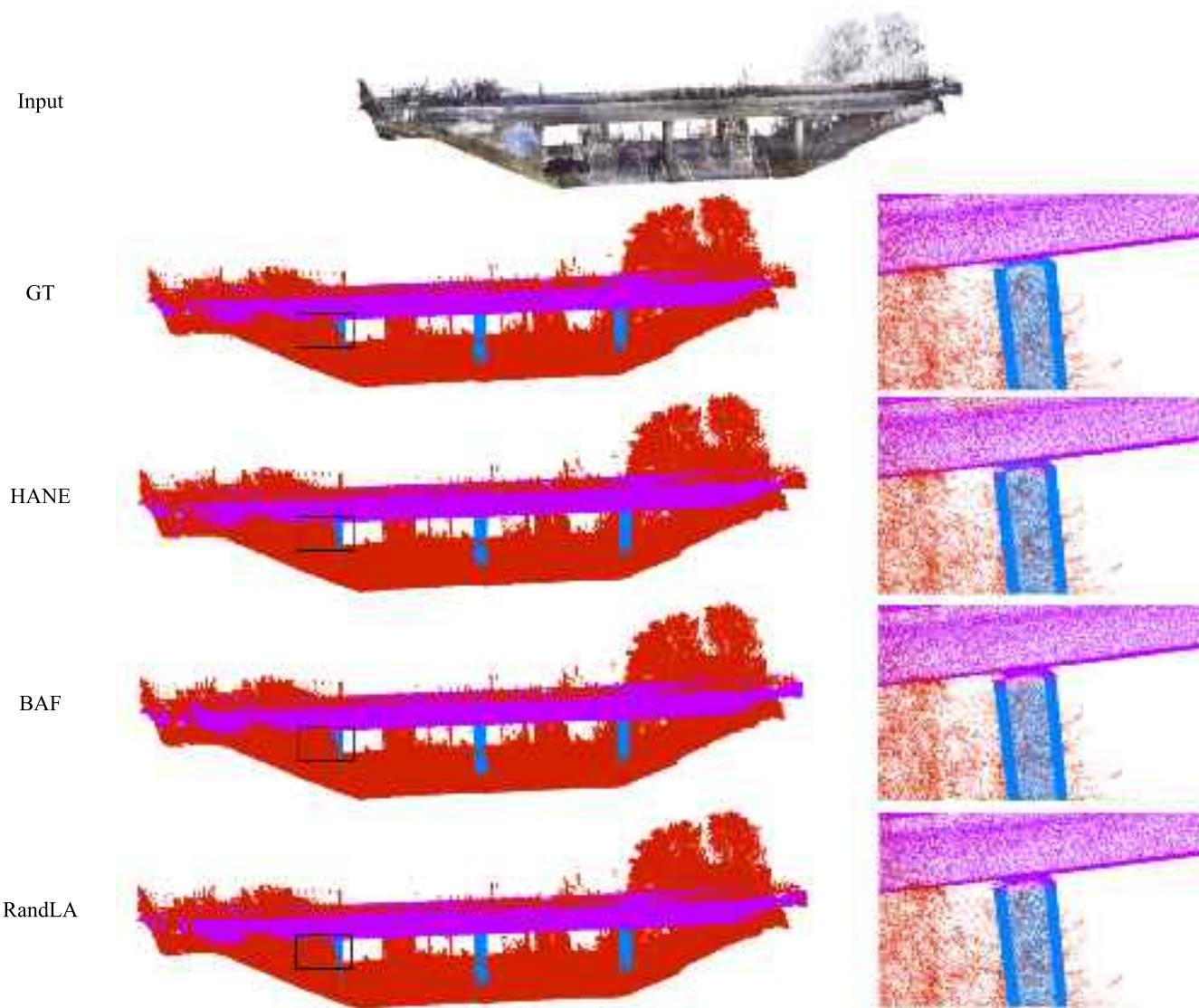


Fig. 9. Comparison of semantic segmentation results on bridge point cloud.

understanding of complex point cloud scenarios is enhanced, aiding in distinguishing areas with significant geometric variations, such as bridge edges and corners. This improvement further boosts segmentation accuracy.

4.2. Bridge geometry quality inspection

This section integrates the proposed method to implement bridge geometric quality inspection. Based on the approach in Section 3.2, a bridge geometric quality inspection ontology model is established using Protégé, as shown in Fig. 10. The figure illustrates the ontology's classes, and instantiated individuals. The instantiated individuals include specific as-designed parameters and corresponding acceptance standards information. For example, the ontology includes four individuals: Slab3, Pier3A, Pier3B, and Pier3C, representing the slab and three piers of Bridge3's as-designed BIM model. These individuals store information such as the names, IDs, and geometric parameters of these basic components. SPARQL query statements can then be used to extract relevant information from the ontology and compare it with actual measurement data to perform geometric quality inspection. When new inspection projects arise, the ontology can be directly extended and updated, or existing knowledge can be reused. This ensures a more structured and efficient knowledge management process within the overall workflow of

bridge geometric quality inspection.

The as-built parameters for geometric quality inspection are derived from the dimensional measurements of semantically segmented components. In Section 4.1, the semantic segmentation of bridge point cloud data is implemented. The segmented results are imported into Cloud-Compare, where the distance visualization tool is used to verify the validity of the proposed method. The distances between the projected points of the segmented point cloud and the ground truth on three planes are shown in Fig. 11. The left side of the figure shows the distance distribution between the projected point clouds. Darker blue indicates a smaller distance, while colors shifting toward red indicate larger distances. The color bar on the right quantifies the distance values represented by different colors, ranging from blue to red. For example, deep blue at the bottom indicates a distance of 0. In addition, each image displays information for two selected points labeled as "C2C absolute distances = 0", meaning that the absolute distance between the segmented point cloud and the ground truth point cloud at those selected points is zero. The figure demonstrates that although there are some discrepancies between the segmentation results and the ground truth, the edge points show zero error. Since the measurement points are chosen at the edge points of the point cloud, this ensures that the measurement of geometric parameters such as height, width, and thickness is not affected. Similarly, the cross-sectional dimensions of the



Fig. 10. Bridge geometry quality inspection ontology model.

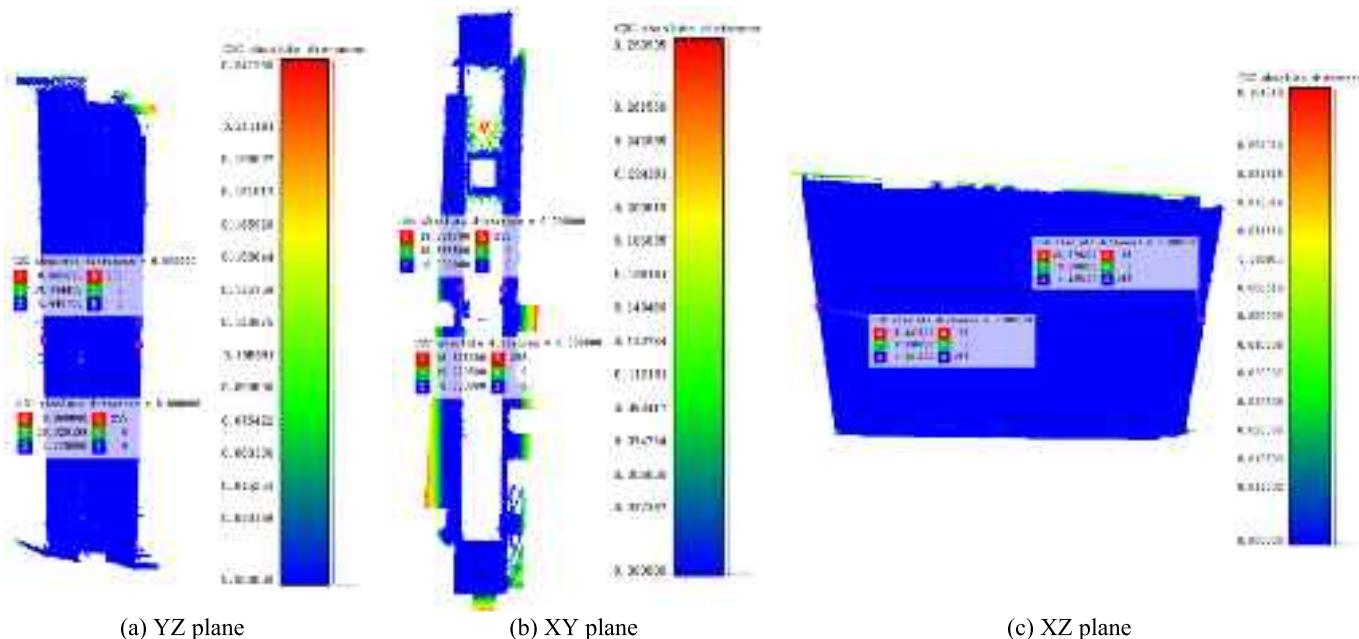


Fig. 11. Distance between projected point clouds.

slab can be measured using the same approach.

The retrieved as-designed parameters are compared with the measured as-built parameters, and combined with the acceptance standard retrieved, the geometric quality compliance of the components can be determined. To validate the feasibility of the proposed method, we develop a prototype system for bridge geometric quality inspection based on C# and Revit. The system structure is shown in Fig. 12. This system consists of seven modules: "Load Ontology" for loading the bridge geometric quality inspection ontology model; "Load AS-Designed BIM Model" for loading the as-designed BIM model; "AS-Built Parameter" for loading as-built parameters from the database and displaying them in a list; "Rule Analysis" for parsing the corresponding acceptance

standards from the ontology; "Deviation Detection" for performing geometric quality inspection using SPARQL queries; "Query Result" for displaying detection results, including the names and IDs of non-compliant components. If there are no non-compliant components, "Does not exist" will be displayed; "Visualization Result" for highlighting non-compliant components.

We verify the effectiveness of the developed system by detecting the geometric quality of the pier and slab in Bridge3. Bridge3 consists of three piers and one slab, and some of its as-designed parameter and as-built parameters are shown in Table 6. The allowable deviation for pier parameters, referring to the pier length in Table 1, is (-10, 5). The allowable deviation for slab height, referring to the section size in

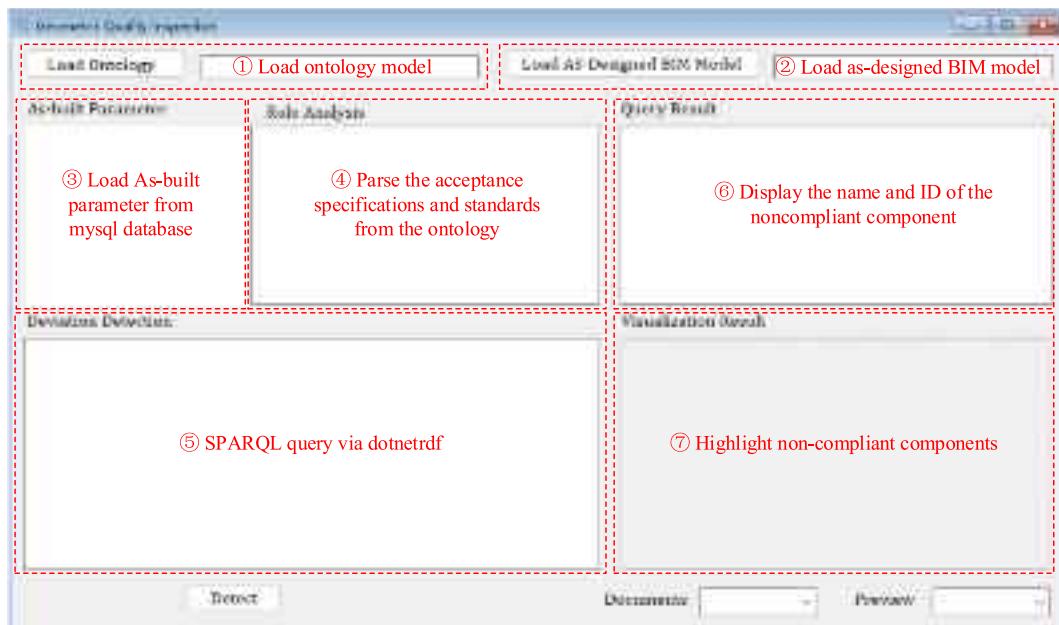


Fig. 12. Bridge geometry quality inspection prototype system.

Table 1, is $(-10, 5)$. The parameter errors are within the allowable deviation range. Based on eqs. (1) and (2), we define the SPARQL query statements, and the query results are shown in Fig. 13(b). The detection result is “Does not exist”, indicating that there are no non-compliant components, which meets the expectations. To demonstrate that the system can detect non-compliant components, we artificially change the design parameters of the bridge pier, modifying the pier thickness from 799.1 to 769.1 and the section height from 1022.3 to 1122.3. The system’s operational results are shown in Fig. 14, with the detection result being “The Name and ID of the non-compliant component is: ?Name = Pier3A, ?id = 214885, ?Name = Slab3, ?id = 214981”. The system successfully detects that the pier and slab do not meet the requirements and highlights the non-compliant component, which aligns with the expected result. Therefore, the developed bridge geometric quality inspection prototype system can effectively detect non-compliant components.

4.3. Results and discussion

In this section, the effectiveness of the proposed point cloud segmentation network is first validated on two datasets. On the S3DIS dataset, the proposed point cloud segmentation network achieves optimal segmentation performance, as shown in Table 3. Compared to the baseline model RandLaNet, HANE improves by 3.2 %, 1.9 %, and 2.7 % in the three evaluation metrics mIoU, OA, and mAcc, respectively. Compared to BAF-LAC, HANE improves by 2.2 %, 1.3 %, and 1.6 %, respectively. HANE outperforms other methods in five specific categories: wall, door, table, sofa, and board, and achieves the second-best results in three categories: chair, book, and cluster. Additionally, HANE segments part of the beam category. Since the beam category has a relatively small proportion in Area 5 of S3DIS, most methods achieve an IoU of 0 for the beam category. However, HANE still correctly identifies part of the beam category. This is mainly because the proposed method incorporates both gradient and relative position information

Fig. 13. Geometric quality inspection result.

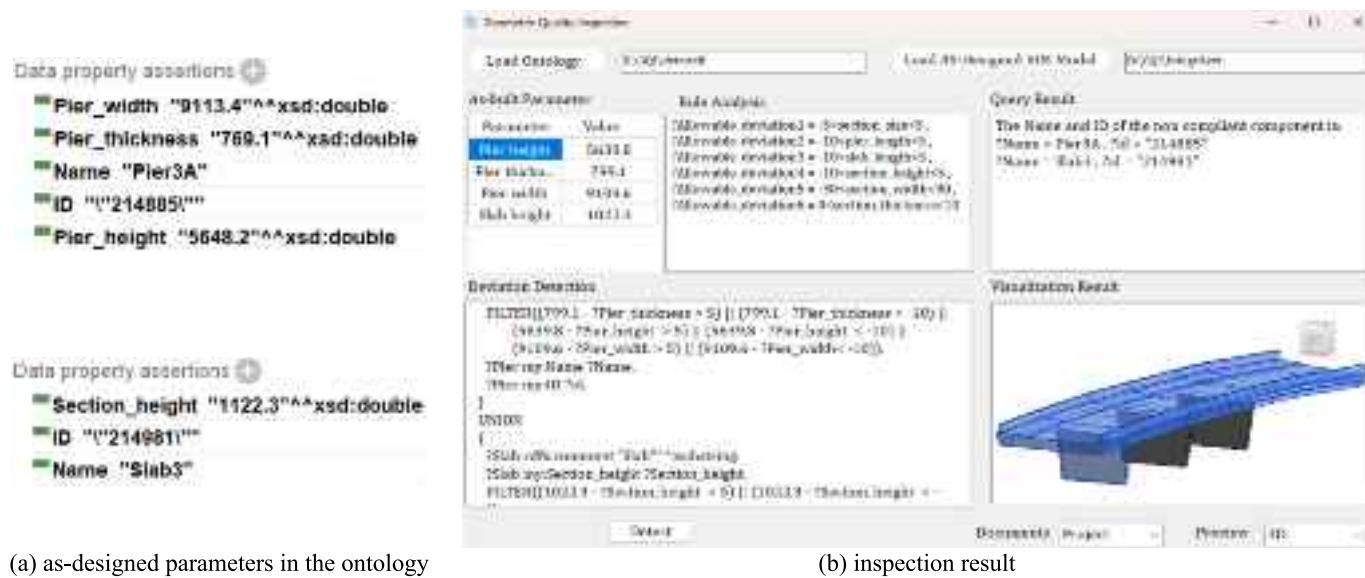


Fig. 14. Geometric quality inspection result after changing as-designed parameters.

into the encoding process and uses a multi-layer feature adaptive interaction structure to deeply integrate the local details of shallow encoder features with the semantic information of deep features, enhancing the understanding of complex point cloud scenes. Furthermore, the feature enhancement module quantifies the feature differences between the central point and neighboring points, eliminating the category mixing problem caused by KNN, and improving the classification accuracy of boundary points. Therefore, HANE achieves better point cloud segmentation performance.

Next, we conduct point cloud segmentation comparison experiments on real bridge point cloud data. The experimental results are shown in Table 4 and Fig. 9. The segmentation accuracy of the bridge point cloud affects the measurement of component geometric parameters. Compared to RandLaNet and BAF-LAC, HANE still achieves optimal segmentation performance, especially in the recognition of the pier category. HANE improves by 2.11 % compared to RandLaNet and by 1.99 % compared to BAF-LAC. The visual results in Fig. 9 also demonstrate that the proposed method exhibits better segmentation performance at the bridge connections, indicating that HANE can effectively improve the segmentation accuracy at the bridge connections, which is beneficial for geometric parameter measurement. By incorporating gradient information into the encoding process, HANE enhances its understanding of complex point cloud scenes, which helps distinguish regions with significant geometric changes, such as bridge edges and corners. Additionally, the neighbor feature enhancement automatically focuses on the features of neighboring points of the same category or with higher correlation with the center point, suppressing the impact of neighboring point features from different categories. This effectively solves the problem of low segmentation accuracy at bridge connections, which is caused by a large number of connecting points and contact surfaces between bridge components. We also conduct ablation experiments on HANE's core modules, and the ablation results in Table 5 confirm the effectiveness of each module.

Finally, we develop a bridge geometric quality inspection prototype

Table 4
Segmentation results of different methods on bridge point cloud.

	mIoU	OA	mAcc	Background	Pier	Slab
RandLaNet	94.65	98.11	97.24	97.19	91.04	95.71
BAF-LAC	94.37	97.91	97.07	96.83	91.16	95.12
HANE	95.44	98.26	98.15	97.44	93.15	95.73

Table 5
Ablation experiment results.

Model	PFE	FE	MLFAI	HFE	mIoU	OA	mAcc
Model 1		✓	✓	✓	94.66	97.89	97.47
Model 2	✓		✓	✓	95.06	98.16	97.91
Model 3	✓	✓		✓	94.74	97.72	97.74
Model 4	✓	✓	✓		95.17	98.12	97.89
Model 5	✓	✓	✓	✓	95.44	98.26	98.15

system based on Revit, with the system structure shown in Fig. 12. First, we implement knowledge mapping for the relevant as-designed parameters and acceptance standards based on Protégé and establish the bridge geometric quality inspection ontology model. The ontology model defines related instances, including bridge as-designed parameters and acceptance standards, as shown in Fig. 10. Then, the ontology is queried and parsed using the SPARQL language. Through the SPARQL statement forms shown in eqs. (1) and (2), the system can automatically analyze whether the inspection data meets the quality requirements. The inspection results are shown in Fig. 13. The relevant as-designed parameters and as-built parameters are listed in Table 6. As seen in the table, the deviation between the as-built parameters and as-designed parameters is within the allowable deviation range, so the inspection result shows that there are no non-compliant components. To further demonstrate that the system can detect non-compliant components, we manually modified the as-designed parameters defined in the ontology. The deviation between the modified as-designed parameters and the as-

Table 6
Some geometric parameters of Bridge3.

	Type	Parameters	Value
As-Designed Parameters	Pier	Pier height (mm)	5638.2
		Pier thickness (mm)	799.1
		Pier width (mm)	9113.4
	Slab	ElementId	214,885
		Name	Pier3A
		Slab height (mm)	1022.3
As-Built Parameters	Pier	ElementId	214,981
		Name	Slab3
		Pier height (mm)	5639.8
	Slab	Pier thickness (mm)	799.1
		Pier width (mm)	9109.6
		Slab height (mm)	1022.3

built parameters is now outside the allowable range, making the component non-compliant. The inspection result after re-running the detection is shown in Fig. 14. The system indicates that Pier3A is a non-compliant component and highlights it in the model, which meets the expected result. This proves that the system we developed can effectively conduct bridge geometric quality inspection. The proposed point cloud segmentation network effectively improves the segmentation accuracy at bridge connections. However, how to more accurately measure the geometric parameters of the segmented point cloud remains a problem that needs to be solved. In the future, we plan to use the concept of bounding boxes to fit the geometric shape of the point cloud and achieve accurate geometric parameter measurements, avoiding errors caused by noise points.

Although the proposed geometric quality inspection method has demonstrated promising results, there are still some limitations and potential areas for improvement in practical applications. First, the detection of auxiliary components on the bridge superstructure (such as railings) remains challenging due to their small size, diverse forms, and indistinct boundaries, making it difficult to achieve recognition performance comparable to that of larger components like piers. Additionally, for components such as stay cables in cable-stayed or suspension bridges, their slender structures make it difficult to accurately reconstruct spatial geometric features, resulting in limited stability and accuracy in error detection. Furthermore, the current method does not take into account the influence of operational loads and temperature effects. In future work, we plan to progressively incorporate the analysis of geometric changes induced by temperature and load variations, aiming to transition toward full lifecycle deviation management based on monitoring data. Finally, we will further expand a platform-independent solution centered on IFC to enhance flexibility and scalability in practical applications.

5. Conclusions

This paper presented a digital twin bridge geometry quality inspection method based on knowledge mapping and data-driven. Firstly, a knowledge model of bridge geometric quality inspection is established based on Protégé. The name, ID, geometric parameters and other information of bridge foundation components are stored through instances in the ontology, which is convenient for extracting relevant parameter information in the ontology using SPARQL query statements, and then compared with the actual measurement data. Secondly, a large-scale point cloud segmentation network based on hybrid feature aggregation and neighborhood feature enhancement is proposed. The local details of the shallow features of the encoder and the semantic information of the deep features are deeply fused through a multi-layer feature adaptive interaction structure. The feature enhancement module is used to quantify the feature differences between the center point and the neighboring points, eliminate the category confusion problem caused by KNN, and effectively improve the segmentation accuracy. On the S3DIS dataset, compared with the baseline model RandLaNet, the proposed method improves the three evaluation indicators mIoU, OA, and mAcc by 3.2 %, 1.9 % and 2.7 % respectively, and improves by 2.2 %, 1.3 % and 1.6 % respectively compared with BAF-LAC. In the recognition of the bridge pier category, it improves by 2.11 % compared with RandLaNet and 1.99 % compared with BAF-LAC. It has been demonstrated that the proposed method can effectively improve the segmentation accuracy at bridge connections, which is more conducive to the measurement of geometric parameters. Finally, a bridge geometry quality inspection prototype system is established based on Revit. The ontology is queried and parsed through SPARQL. When the error between the as-built parameters and the as-designed parameters is not within the allowable deviation range, the system can correctly find the non-compliant bridge components and highlight them in the model, thus realizing the bridge geometry quality inspection. In future research, we will introduce self-supervised learning and pre-training mechanisms to

Table 7

Explanation of variable symbols.

Variable	Description	Variable	Description
Q, K, V	Query, Key, and Value vectors in the attention mechanism	$f_{p_i^k}$	The neighboring point feature
F_p	Pointwise feature	f_{p_i}	The center point feature
r_i^k	Relative position information	\tilde{f}_{p_i}	The mixed features
p_i	Center point	F_e^l	The encoder features at layer l
p_i^k	The k th nearest neighbor of the center point	cat	The concatenation operation
g_i^k	Gradient information	US	Upsampling
f_i^k	Hybrid features	RS	Random sampling
MLP	Multilayer Perceptron	F_d^l	The decoder features at layer l
$\tilde{f}_{p_i^k}$	The enhanced neighboring point feature	$softmax, sigmoid$	Activation function

mine common feature expressions in point cloud data and enhance the generalization ability of point cloud segmentation networks in multiple types of bridges. In addition, the geometric feature recognition method based on bounding box and contour extraction is studied to realize the automatic measurement of bridge geometric parameters.

CRediT authorship contribution statement

Junwei Yan: Writing – review & editing, Supervision, Methodology, Funding acquisition. **Hao Zhang:** Writing – original draft, Visualization, Validation, Methodology. **Qingsong Ai:** Supervision, Project administration, Funding acquisition. **Yongyang Xu:** Software, Investigation, Data curation. **Jun Yang:** Supervision, Software, Resources. **Wei Meng:** Resources, Project administration, Data curation. **Tuyu Bao:** Visualization, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by National Key Research and Development Project of China (2021YFB2600302).

Data availability

The authors do not have permission to share data.

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