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Three-Dimensional Geometric Digital Twin of Cable-Stayed Bridges: UAV- and TLS-Based Point Cloud Registration, Fusion Modeling, and Damage Inspection

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ABSTRACT

Advanced inspection techniques are essential for the efficient detection of damage, particularly in long-span bridges situated over challenging terrains, such as rivers. This study introduces an innovative methodology for reconstructing three-dimensional geometric digital twin (DT) models and conducting associated damage inspections on large cable-stayed bridges. The proposed approach utilizes a multi-source registration technique, integrating point cloud data acquired from two types of unmanned aerial vehicles and terrestrial laser scanners. The proposed framework is implemented on an extra-large cable-stayed prestressed concrete bridge located in Jiamusi, China. Three distinct registration methods are employed to achieve fusion modeling of the point cloud data following noise reduction. Experimental results indicate that the automatic registration algorithm significantly improves the absolute accuracy, relative accuracy, and integrity of the DT model by 28.2%, 10.8%, and 18.8%, respectively. Furthermore, the enhanced DT model facilitates the detection of various forms of bridge damage, including surface concrete spalling and deformations in the deck and girders, thereby providing a promising solution for effective bridge maintenance planning.

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1. Introduction

According to the Statistical Communique on the Development of the Transportation Industry in 2023, published by the Ministry of Transport of the People's Republic of China, the country had constructed approximately 1 079 300 highway bridges by the end of 2023, including 10 239 extra-large bridges and 177 700 large bridges [1,2]. This positions China as the global leader in the number of bridges. However, this achievement is overshadowed by a growing incidence of safety concerns originating from the deterioration of bridge performance. Notably, 40% of the bridges in China's highway network have been in service for over 20 years, with 30% classified as being in poor condition and 15% deemed dangerous [3,4]. Similarly, the 2021 Infrastructure Report Card of the American

Society of Civil Engineers indicates that, among more than 617 000 bridges in the United States, 42% are at least 50 years old, and approximately 7.5% are identified as structurally deficient [5]. These concerning statistics highlight the urgent need for regular inspections and structural health monitoring (SHM) to facilitate informed assessments and maintenance decisions, thereby ensuring bridge safety [6,7,8].

Inspection and SHM are crucial in reducing epistemic uncertainties in bridge management and in preventing unexpected service disruptions and structural failure [9,10]. In recent decades, inspection and SHM techniques have advanced significantly, encompassing non-destructive testing (NDT), as well as vibration-based, strain-based, vision-based, and global positioning system (GPS) SHM systems [11]. While SHM systems provide continuous monitoring of changes in structural characteristics and behavior, inspections are typically periodic and focus on the identification of existing defects [12,13]. Visual inspection remains the

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predominant method for assessing the condition of deteriorating civil infrastructure, such as bridges, buildings, and nuclear power plants [14]. Visual inspections are typically conducted as an initial step to detect surface damage prior to employing more advanced NDT techniques, such as ultrasonic or radiographic inspection [15]. However, conventional visual inspection methods present several limitations: they are labor-intensive, subject to human error and variability in inspectors' experience, and can be significantly influenced by environmental conditions, such as field temperature. Meanwhile, the increasing construction of long-span bridges over large rivers, seas, valleys, and channels in recent decades has further complicated inspection activities, particularly in hard-to-access areas of large bridges situated in harsh environments.

To address these challenges, recent advancements in inspection equipment and technologies have been observed, tailored to the unique environmental conditions and structural characteristics of modern bridges. Notable innovations include unmanned aerial vehicles (UAVs), ground penetrating radar, light detection and ranging (LiDAR), and robotic systems [16]. UAVs, for example, can be equipped with high-resolution cameras, LiDAR, and thermal imaging sensors, providing rapid, safe, and detailed aerial views of otherwise inaccessible areas, thereby eliminating the need for scaffolding or road closures. Terrestrial laser scanners (TLSs) utilize laser pulses to generate precise three-dimensional (3D) point clouds and realistic models of bridge structures, facilitating the detection of geometric anomalies, structural damage, and deformation. The integration of data collected from UAVs and TLSs, such as images and point clouds, enables the creation of 3D digital twin (DT) models of bridges. These DT models allow for observation and assessment of surface damage, independent of environmental factors, traffic volumes, or variations in bridge type, height, and span length. DT technology has demonstrated significant effectiveness in defect detection, alignment monitoring, and structural construction management [17,18].

Extensive research has been dedicated to integrating data obtained from advanced inspection methods, such as UAVs and TLSs, into structural performance assessment, prediction, and life-cycle management of deteriorating bridges [19]. In the context of UAV photography to 3D modeling, Siebert and Teizer [20] introduced an innovative approach for evaluating UAV system performance in acquiring mobile 3D mapping data for earthwork project surveys. Iizuka et al. [21] demonstrated the advantages of UAV photogrammetry over satellite remote sensing for landscape analysis, using post-mining sites in Indonesia as a case study. Liu et al. [22] proposed a novel image-based methodology for crack assessment on bridge piers, leveraging UAVs and 3D scene reconstruction. Xu and Zhang [23] utilized UAV imagery to reconstruct 3D models and measure the geometric shapes of bridge components, with a key innovation being the decomposition of large-scale, full-bridge 3D reconstruction into multiple distributed tasks focused on sub-models using sub-image sets. Delgado et al. [24] enhanced UAV localization for 3D reconstruction of bridge undersides—which are challenging due to poor GPS signals and steel-induced interference—by incorporating total station measurements. UAV photography technology, recognized for its flexibility and extensive coverage, has been widely applied to realistic bridge model reconstruction [25]. However, challenges remain, including difficulties in capturing detailed imagery of the middle and lower sections of bridges, as well as technical limitations that can result in issues, such as adhesion and distortion of the 3D model [26]. Recent studies have also shown that the quality of inspection images, including resolution and shooting conditions, can significantly influence vision-based damage interpretation and subsequent data-driven structural assessment results [27]. Furthermore, in practical engineering applications, UAVs fre-

quently encounter challenges, such as low-altitude flight restrictions, the need to optimize the relationship between image resolution and ground sampling distance (GSD), and difficulties in reconstructing weakly textured surfaces, particularly over water surfaces.

Models reconstructed from TLS data generally demonstrate higher accuracy compared with those generated from UAV images. 3D laser scanning technology, also known as reality replication technology, rapidly acquires precise 3D coordinate information of object surfaces through high-speed laser scanning, resulting in a detailed point cloud representation. This technology is characterized by high efficiency, good compatibility, strong initiative, elevated data acquisition rates, and superior data quality [28]. Olsen et al. [29] developed a methodology utilizing TLS for damage detection and volumetric change analysis in a full-scale structural test specimen. Lague et al. [30] introduced a method called the multiscale model to model cloud comparison (M3C2), which enables direct comparison of 3D point clouds by calculating orthogonal distances between them to measure surface changes, as demonstrated in the Rangitikei River Canyon, New Zealand. However, TLS also presents certain limitations. Equipment constraints and the impact of bridge height on scanning angles can hinder the capture of detailed information on the upper sections of bridges, resulting in models that lack associated texture features [31]. Additionally, in practical engineering scenarios, TLS is susceptible to registration errors during multi-station scanning and is highly susceptible to occlusions in complex environments. These challenges are particularly significant when inspecting structurally intricate bridges, substantially limiting the completeness and accuracy of data acquisition.

The integration of multi-source data represents a significant advancement in bridge inspection and safety assessment, as UAV and TLS provide complementary capabilities that effectively mitigate their various limitations [16]. Although research in this domain remains limited, notable contributions have been made. Moon et al. [32] proposed a method for generating and merging hybrid point cloud data obtained from both laser scanning and UAV-based image processing, enabling diverse applications, such as the creation of 3D surface modeling, field surveys, and volumetric earth computations. Han et al. [33] introduced a practical UAV flight planning approach for oblique photography using feature waypoints, alongside an efficient framework for the automatic extraction of bridge alignment from point cloud data. Their study compared the accuracy of bridge alignment obtained from TLS and UAV point clouds, using total station data as a reference. Mohammadi et al. [34] proposed a comprehensive methodology that leverages bridge information modeling to enhance the efficiency and functionality of bridge management systems (BMS). In a related study, Mohammadi et al. [35] presented a detailed case analysis of two digital point clouds, generated through UAV-based photogrammetry and TLS, from an existing Australian heritage bridge. Despite these advancements, there remains, to the best of our knowledge, no existing algorithm or methodology that effectively integrates point cloud data from multiple sources, such as UAVs and TLSs, for comprehensive 3D DT model reconstruction and damage inspection, particularly for large cable-stayed bridges. The integration of multi-source data fusion within the DT technology facilitates the development of real-time, interactive virtual bridge systems, significantly enhancing the accuracy of real-time replication, structural evaluation, and the capabilities of intelligent inspection methodologies [36].

Given the limitations of current research methodologies and inspection equipment, the principal innovations and contributions of this study are summarized as follows: ① the development of a novel framework that integrates UAV and TLS data for bridge 3D reconstruction and damage inspection, enabling informed

assessments and maintenance decisions throughout the life-cycle of the bridge; ② the establishment of a technical workflow that incorporates a two-step UAV flight path planning strategy and a seasonal TLS scanning scheme, significantly enhancing data acquisition efficiency and ensuring high data quality under complex field conditions; ③ the implementation of three point cloud registration methods, manual, semi-automatic, and automatic registration to achieve precise registration of UAV and TLS point clouds; ④ the introduction and application of three quantitative evaluation metrics, including absolute accuracy, relative accuracy, and completeness, to comprehensively evaluate and validate the performance of the reconstructed DT model; and ⑤ the facilitation of comprehensive DT model construction, enabling effective application to critical inspection tasks, such as surface damage detection and structural alignment control. The effectiveness and robustness of the proposed framework are demonstrated and validated through field test investigations on a large cable-stayed prestressed concrete bridge in Jiamusi, northeast of China. This framework addresses prevailing challenges in bridge inspection and maintenance, particularly for large cable-stayed bridges, by enhancing data accuracy, enabling more comprehensive assessments of structural integrity, and enhancing overall efficiency and labor savings.

2. Framework for 3D digital twin reconstruction and damage inspections of large cable-stayed bridges using point cloud registration from UAV and TLS techniques

The framework for 3D DT model reconstruction and damage inspections of large cable-stayed bridges, utilizing point cloud registration methods based on UAV and TLS techniques, is shown in Fig. 1. The process begins with the collection and registration of bridge point cloud data. Specifically, Fig. 1(a-i) details the acquisi-

tion of two primary data types: UAV-based images acquired through oblique photography and TLS-based point cloud obtained through laser scanning. Further information on these data collection methods is provided in Section 3.1. Subsequently, noise reduction is applied to the raw data using a combination of radius outlier removal (ROR) and statistical outlier removal (SOR) filters, as shown in Fig. 1(a-ii) and discussed in Section 3.2.

A key innovation and challenge of this research lies in the registration of multi-source datasets, particularly the integration of UAV imagery and TLS point clouds, using manual, semi-automatic, and automatic techniques, as shown in Fig. 1(a-iii) and further elaborated in Section 3.3. The distinct advantages of UAV oblique photography and TLS 3D scanning are shown in Table 1. UAVs are highly effective for rapid, large-area coverage, particularly in hard-to-reach locations, whereas TLS offers superior accuracy and detail, making it ideal for precise measurements. The complementary deployment of UAVs and TLSs, where UAVs primarily capture the upper and middle sections of bridges (such as towers, cables, and decks), and TLSs focus on lower sections (including girder bottoms, bearings, and piers), eliminates the need for deck-based measurement stations and avoids traffic disruptions, thereby enhancing inspection efficiency. This integrated approach also addresses the limitations of UAVs in acquiring detailed data from lower structural components, enhances the quality of 3D model reconstruction, and underscores the importance of multi-source data registration in fulfilling the diverse 3D spatial information requirements in bridge life-cycle management.

The field test performed to validate this technical framework was conducted on an extra-large cable-stayed concrete bridge in Jiamusi, China, with location details provided in Fig. 1(b-i) and Section 4.1. For data acquisition, the DJI Mavic 3E UAV (SZ DJI Technology Co., Ltd., China) and the Trimble SX12 TLS (Trimble Inc., USA) were employed, as described in Sections 4.2 and 4.3. As shown in

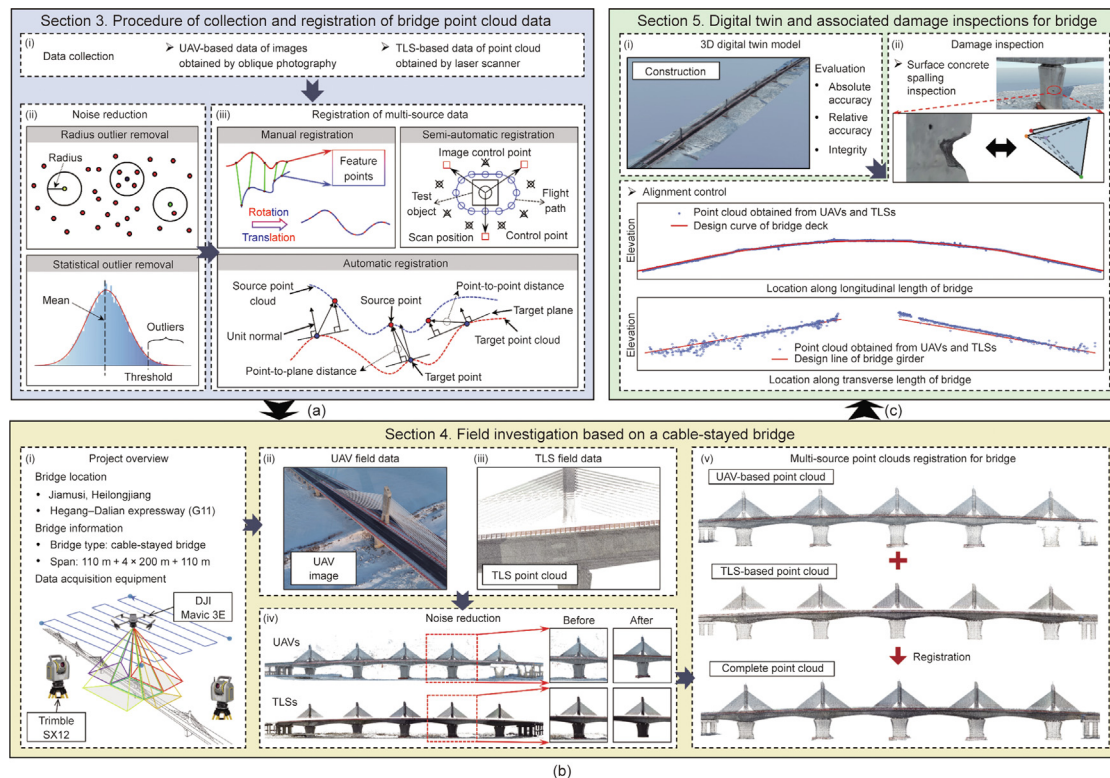


Fig. 1. Framework for (c) 3D geometric DT model reconstruction and damage inspection for (b) large cable-stayed bridges using (a) UAV- and TLS-based point cloud registration. DJI Mavic 3E: SZ DJI Technology Co., Ltd., China; Trimble SX12: Trimble Inc., USA.

Table 1

Comparison of UAVs and TLSs for data collection in the reconstruction of 3D DT bridge models.

Compared item	Data quality and detail	Data collection speed	Accessibility	Safety	Cost
Oblique photography by UAVs	High-resolution aerial imagery	Large area coverage and rapid data collection	High flexibility and remote access for large and open areas	Less risk	More cost-effective owing to less expensive UAV equipment, faster data collection, and less labor
3D scanning by TLSs	Extremely detailed point cloud	Slower owing to multiple scanning setups	Ideal for interior spaces in which great detail is required	Higher risk	More expensive considering TLS equipment, need for skilled operators, more time-consuming data collection, and road closures

Figs. 1(b-ii) and (b-iii), oblique aerial imagery was captured by UAVs following a planned flight path, whereas the TLSs collected point clouds based on a predefined scan strategy. The noise reduction process applied to the field data is shown in Fig. 1(b-iv) and detailed in Section 4.4. The registration of multi-source point clouds, along with a comparative analysis of registration accuracy using different methods, is shown in Fig. 1(b-v) and discussed in detail in Section 4.5.

Section 5.1 presents a comparison between the 3D DT models generated by fusing point clouds using various methods and the model constructed exclusively from UAV imagery. To evaluate the model, three key indicators are introduced: absolute accuracy, relative accuracy, and model integrity, as outlined in Fig. 1(c-i). Finally, the two applications of this technical framework for damage detection are shown in Fig. 1(c-ii), comprising the following: ① surface concrete spalling identification and volume calculation (Section 5.2.1) and ② alignment control through comparison of point cloud-fitted curves with corresponding design curves (Section 5.2.2).

3. Collection and registration of bridge point cloud data

This section discusses the methodologies for collecting, processing, and registering multi-source point cloud data from both aerial platforms (UAVs) and terrestrial systems (TLSs). The workflow encompasses UAV and TLS data acquisition, preprocessing steps, such as single-source point cloud data registration and noise reduction, and the registration of multi-source point clouds from both UAVs and TLSs. The corresponding processing efficiency and scalability for practical engineering applications are evaluated based on the case study of the investigated cable-stayed bridge, as detailed in Section 5.

3.1. Collection of point cloud data

The data acquisition procedures utilizing UAV-based oblique photography technology and TLS-based 3D laser scanning are shown in Figs. 2(a) and (b), respectively. The determination of GSD and the configuration of front (R_{FO}) and side (R_{SO}) overlap ratios for UAV missions are shown in Figs. 3(a) and (b), respectively. Both UAVs and TLSs are equipped with global navigation satellite system (GNSS) and real-time kinematic (RTK) modules, enabling real-time data registration with centimeter-level accuracy. Unlike TLSs, which directly generate point clouds through 3D laser scanning, UAV-based oblique photogrammetry produces overlapping two-dimensional (2D) images that require subsequent reconstruction into 3D point cloud models, as shown in Fig. 2(a-iii). The resulting 3D point clouds, generated from oblique aerial imagery, acquired from multiple perspectives, are subsequently aligned to a global coordinate system using ground control points (GCPs), as shown in Fig. 4 [37]. Similarly, GCPs established through GNSS-RTK technology are employed in TLS workflows to align and register point cloud data from multiple scan positions (SPs) into a unified coordinate system.

3.2. Preprocessing of point cloud data (noise reduction)

Point clouds are composed of scattered, unstructured data points lacking explicit topological relationships, which present significant challenges for effective noise reduction. To address these challenges, both ROR and SOR filters are employed to produce a cleaner point cloud, as shown in Fig. 1(a-ii).

The set of inliers points identified in ROR (U_{ROR}) is obtained as follows [38]:

$$U_{ROR} = \{p | c[U_r(p, q)] \geq \text{Min}_{PNT}\} \quad (1)$$

in which

$$U_r(p, q) = \{q | d_{pq} \leq r \text{ and } (p, q) \in P_c\} \quad (2)$$

where p represents the considered point, P_c represents the set of all points in the point cloud, Min_{PNT} represents the minimum number of neighbors, $c[\cdot]$ represents the number of elements in set $[\cdot]$, $U_r(p, q)$ represents the set of neighbors q for point p within a certain radius r , and d_{pq} represents the distance between p and its neighbor q . In SOR, the set of identified inlier U_{SOR} in Eq. (3) will not be removed as outliers [38]:

$$U_{SOR} = \left\{ p \left| \frac{1}{k} \sum_{q=1}^k d_{pq} \leq \mu + \delta \sigma \right. \right\} \quad (3)$$

in which

$$\mu = \frac{1}{mk} \sum_{p=1}^m \sum_{q=1}^k d_{pq} \quad (4)$$

$$\sigma = \sqrt{\frac{1}{mk} \sum_{p=1}^m \sum_{q=1}^k \left(d_{pq} - \frac{1}{mk} \sum_{p=1}^m \sum_{q=1}^k d_{pq} \right)^2} \quad (5)$$

where μ represents the mean, σ represents the standard deviation; m represents the number of points in the point cloud, k represents the number of neighboring points for each point, and δ represents the standard deviation multiplier.

The selection of filter parameters is crucial to achieving an optimal balance between outlier removal and the preservation of geometric features, while minimizing the risk of discarding valid points during the noise reduction process. Reliability and sensitivity analyses should be performed to ensure achieving the optimal balance [39,40]. For ROR, the parameter r should be set based on the average point spacing, and Min_{PNT} should be adjusted according to the overall point density. In the case of SOR, the parameter k is closely related to point density, whereas δ controls the sensitivity of outlier detection. A higher δ value results in a more conservative filter. These parameter settings should be optimized through visual validation to ensure that both model integrity and accuracy are maintained after filtering. When appropriate, empirical values can serve as initial references for parameter selection [41].

Finally, the points in the intersection (U_{PC}) of the U_{ROR} and U_{SOR} sets are retained for subsequent data registration and DT model reconstruction.

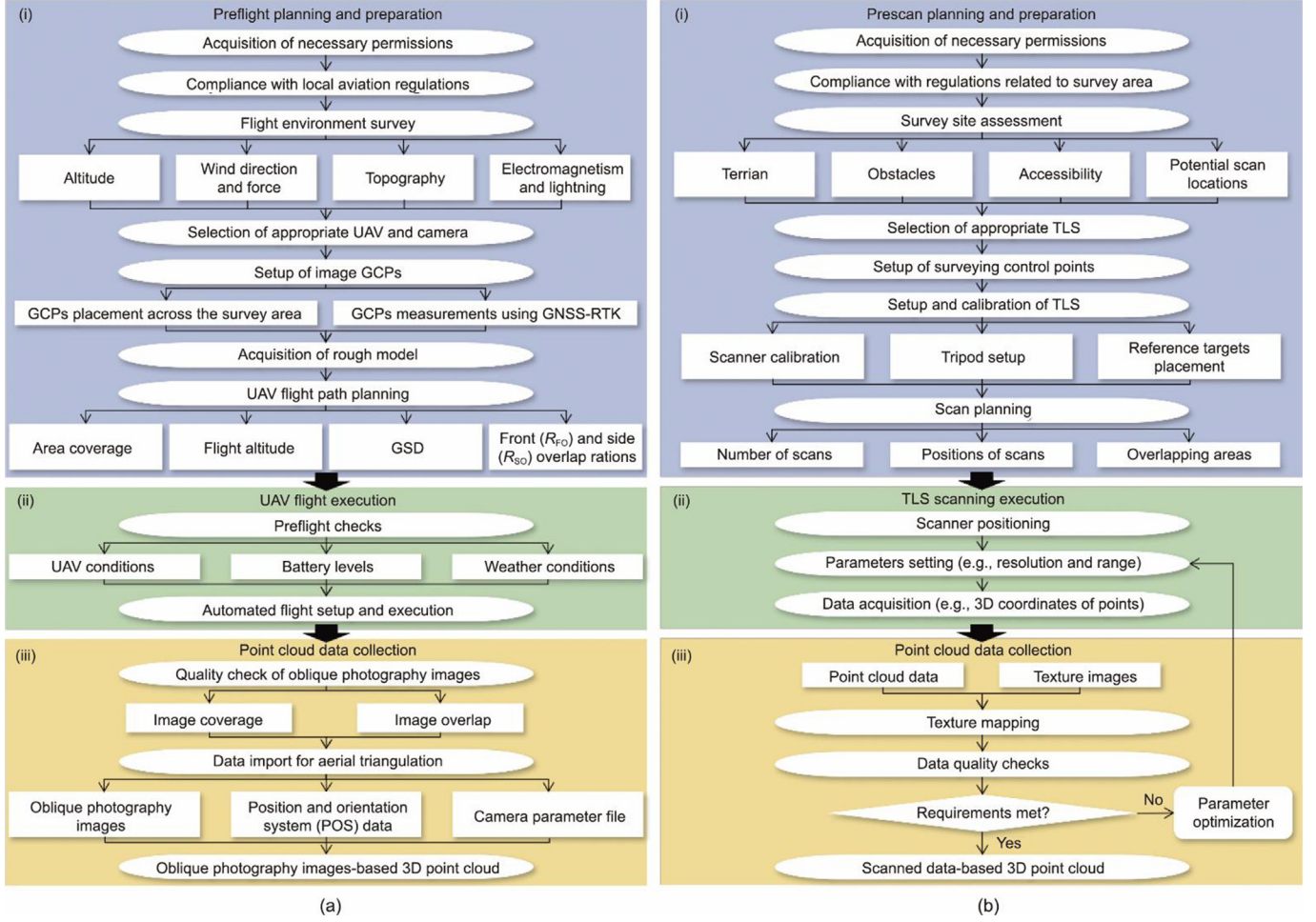


Fig. 2. Procedures for field work associated with collecting point cloud data utilizing (a) UAVs and (b) TLSs.

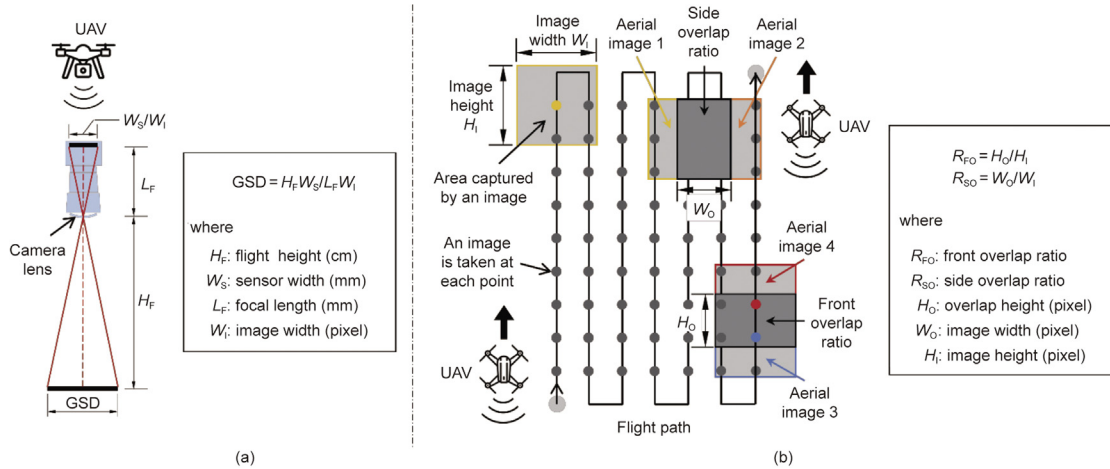


Fig. 3. Illustration of flight path planning associated with (a) GSD and (b) front and side overlap ratio.

$$U_{PC} = U_{ROR} \cap U_{SOR}$$

(6)

3.3. Registration of multi-source data

The integration of UAV and TLS technologies enables high-quality data acquisition and rapid processing for complex bridge models. The registration procedure for UAV and TLS-based point clouds is shown in Fig. 5. This section outlines the three registration

methods employed in this study: manual, semi-automatic, and automatic approaches.

3.3.1. Manual registration

Manual registration involves selecting at least three pairs of homologous feature points (FPs) with clear visibility and stability, such as distinct environmental features or architectural details. Notably, while manual registration is straightforward, it is

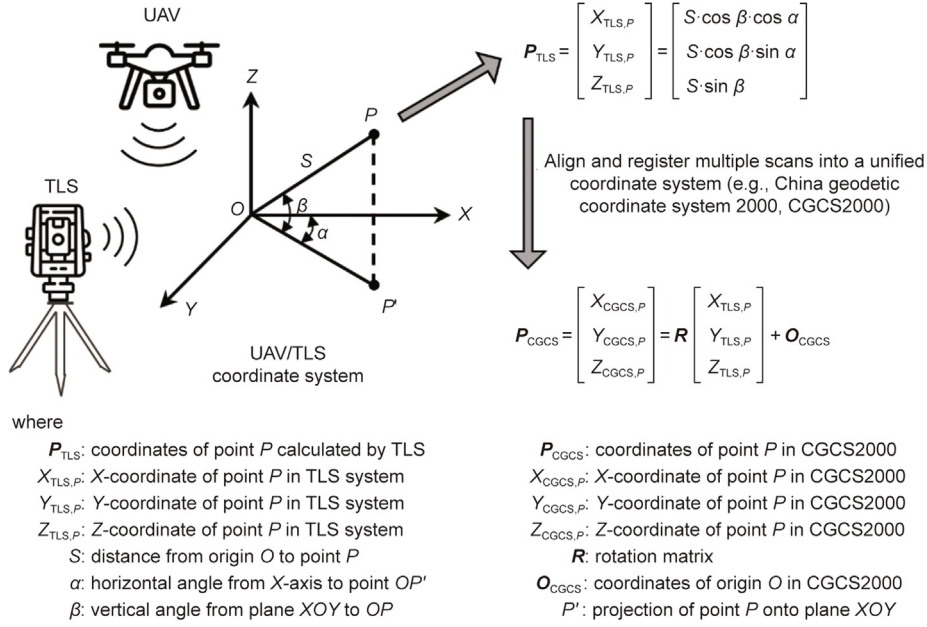


Fig. 4. Process of obtaining coordinates of 3D point cloud by TLS [38].

labor-intensive and susceptible to human error. The primary objective in manual registration is to use Eq. (7) to establish the rotation and translation relationships between coordinate systems, thereby registering multi-source point clouds.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \mathbf{R}_{\text{man}} \begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} + \mathbf{t}_{\text{man}} \quad (7)$$

where x_0 , y_0 , and z_0 represent the coordinates of points along the x -, y -, and z -axes, respectively, $\mathbf{R}_{\text{man}}$ represents the rotation matrix for manual registration, and $\mathbf{t}_{\text{man}}$ represents the translation matrix for manual registration.

3.3.2. Semi-automatic registration

Multi-source point cloud registration can be enhanced by incorporating GNSS-RTK technology, which enables the manual unification of data coordinate systems in the field and facilitates automatic point cloud registration post-processing. This approach establishes a semi-automatic registration workflow. UAV and TLS datasets are aligned within a unified target coordinate system by equipping UAVs with GNSS-RTK modules and utilizing GCPs for TLS data. However, the accuracy of the semi-automatic registration process depends on the precision and reliability of GNSS-RTK posi-

tioning, as well as the quantity, spatial distribution, and accuracy of the control points.

3.3.3. Automatic registration

Automatic point cloud registration algorithms are generally classified into three categories: optimization-based, feature-based, and deep learning-based methods. However, owing to the limited availability of bridge-specific point cloud datasets, deep learning-based algorithms are not considered in this study [42]. Among feature-based methods, point cloud registration using fast point feature histograms for feature matching typically yields lower accuracy and is primarily used for coarse registration [43]. In contrast, the iterative closest point (ICP) algorithm is widely recognized as an effective method for fine registration; however, its performance is highly sensitive to the quality of the initial alignment. Without a sufficiently accurate initiation position, ICP is susceptible to convergence to local optima [38]. To address this limitation, manual registration can be employed to provide an initial coarse alignment, followed by ICP-based fine registration to achieve higher accuracy and robustness in the automatic registration process.

The core of the ICP algorithm involves the iterative optimization of rotation and translation matrices to achieve a rigid transformation

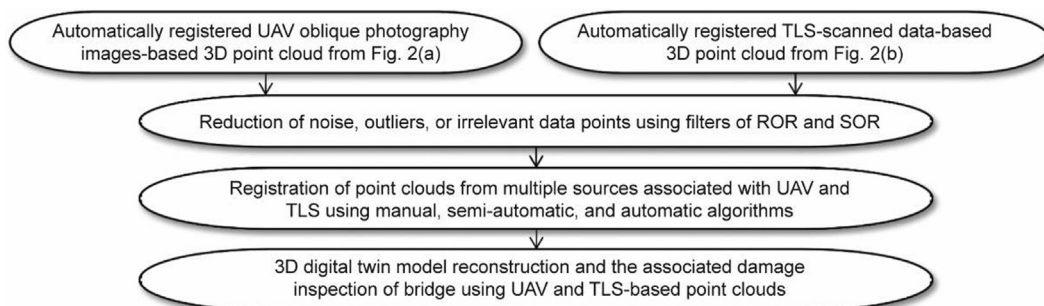


Fig. 5. Procedure for registering multi-source point clouds from UAVs and TLSs.

between the source and target point clouds. This process minimizes the error function $E(\mathbf{R}_{\text{icp}}, \mathbf{t}_{\text{icp}})$, as shown in Eq. (8) [44]:

$$E(\mathbf{R}_{\text{icp}}, \mathbf{t}_{\text{icp}}) = \operatorname{argmin}_{\mathbf{R}_{\text{icp}}, \mathbf{t}_{\text{icp}}} \frac{1}{|P_s|} \sum_{i=1}^{|P_s|} \|p_t^i - (\mathbf{R}_{\text{icp}} \cdot p_s^i + \mathbf{t}_{\text{icp}})\|^2 \quad (8)$$

where $\mathbf{R}_{\text{icp}}$ represents the rotation matrix for ICP automatic registration, $\mathbf{t}_{\text{icp}}$ represents the translation matrix for ICP automatic registration, $|P_s|$ represents the point number of source point cloud P_s , p_t^i represents the set of points extracted from the target point cloud P_t , and p_s^i represents the i th point extracted from the source point cloud P_s .

4. Field investigation based on a cable-stayed bridge

4.1. Project overview

This study focuses on the extra-large cable-stayed bridge, built in 2022, which is a critical part of the Hegang–Dalian Expressway (G11). The bridge is situated in Jiamusi City, Heilongjiang Province, China, along the Songhua River. Jiamusi experiences a monsoon-influenced humid continental climate, with extreme temperatures ranging from -41.1 to 38.1 °C. The top and bottom views of the bridge are shown in Fig. 6, whereas the detailed prestressed concrete structure, featuring five towers, each 26.5 m tall, with a total length of 1020 m and a deck width of 28 m, is shown in Fig. 7.

Data collection using UAV and TLS was conducted in January 2024, during winter conditions when the river surface was frozen. At the time, environmental temperatures reached as low as -26 °C, with wind speeds corresponding to 3 to 4 on the Beaufort scale. This period was strategically selected to avoid capturing large water surfaces with UAVs, which can result in weakly textured scenes and insufficient FP, thereby compromising modeling accuracy. Consequently, UAVs effectively captured data from the upper bridge structures without the need for additional TLS stations on the bridge. This approach not only reduced inspection risk and costs but also enhanced overall inspection efficiency. Furthermore, the frozen river provided a stable platform for deploying TLS equipment, enabling the acquisition of more precise and detailed data. This contributed to an overall improvement in the quality

of the information for the entire bridge structure. Additionally, the winter conditions helped mitigate the effects of extreme weather, such as strong winds, on UAV flight stability and sensor accuracy.

Data processing tasks, including noise reduction, multi-source point cloud registration, and 3D geometric DT model reconstruction of the cable-stayed bridge, were performed on a high-performance workstation equipped with two NVIDIA GeForce RTX 4090 GPUs (24 GB each; NVIDIA, USA), two Intel® Xeon® Platinum 8352 V CPUs (2.10 GHz; Intel, USA), and 512 GB of RAM (Samsung, Republic of Korea).

4.2. UAV field data

UAV field data collection was conducted using two UAVs: the Feima D2000S and DJI Mavic 3E, as shown in Figs. 8(a) and (b), respectively.

(1) Feima D2000S: This UAV can ascend to altitudes of up to 6000 m, cruising at $7 \text{ m}\cdot\text{s}^{-1}$, and offers an endurance of 74 min. It is equipped with both photogrammetric ortho module and oblique modules, making it well-suited for extensive area operations and enhancing data collection efficiency. However, the absence of an orbit flight mode can result in data redundancy when surveying individual buildings [45].

(2) DJI Mavic 3E: This UAV compensates for the limitations of the Feima D2000S by supporting both orbit and facade flight modes, making it well-suited for detailed modeling of individual buildings or small areas. It features a 24 mm lens, can withstand wind speeds of up to $12 \text{ m}\cdot\text{s}^{-1}$, has a flight time of 45 min, and supports RTK for centimeter-level precision data acquisition [46].

4.2.1. Preliminary model construction using Feima

To address the challenges associated with modeling complex bridge structures, such as cable-stayed bridges, a two-step UAV-based flight planning methodology is proposed. The intricate geometry and limited distinguishing features of these structures often render a single UAV insufficient for accurate modeling. Therefore, an initial flight is conducted using a UAV, such as the Feima D2000S, to capture imagery for generating a preliminary 3D model using software, such as Soarscape Smart3D [47], as shown in Fig. 9. However, factors, such as flight altitude and camera angles can result in incomplete acquisition of geometric and texture data, particularly over water surfaces with weak textures (Fig. 9(a), resolution: 3144×1812) and slender structural elements such as cable-stays (Fig. 9(b), resolution: 15794×9054). These challenges may result in texture adhesion and data loss, thereby compromising the overall completeness and accuracy of the model. To address these limitations, a more detailed, component-based flight planning strategy is introduced in the following section.

4.2.2. Flight path planning using DJI

This methodology segments the bridge into key structural components, including the deck, piers, girders, stay cables, and towers, with dedicated flight paths assigned to each element to ensure comprehensive coverage and high-quality data acquisition using a DJI Mavic 3E UAV. For example, orbit flight paths are recommended for the bridge deck (Fig. 10(a)), whereas facade flight paths are designed to capture detailed data of stay cables and towers (Fig. 10(b)). Facade flights are also optimal for capturing the geometry of piers and girders, as shown in Fig. 10(c). Across all flight paths, the parameters introduced in Fig. 3 are recommended as follows: a GSD of less than $1 \text{ cm}\cdot\text{pixel}^{-1}$, a side overlap ratio of 70%, and a front overlap ratio of 80%, to ensure the acquisition of high-resolution imagery and comprehensive data for accurate modeling.



Fig. 6. Two examples associated with the investigated large cable-stayed bridge in Jiamusi: (a) bottom view in summer and (b) top view in winter.

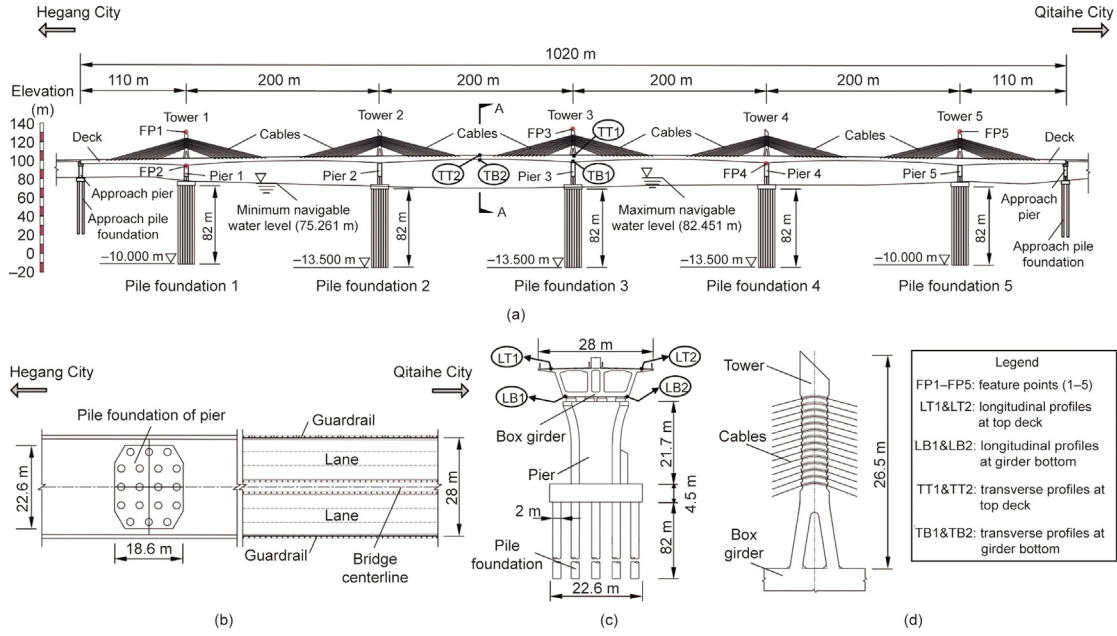


Fig. 7. Detailed information associated with the investigated cable-stayed bridge: (a) front view of main bridge, (b) top view of pile foundation and bridge deck, (c) cross-section of A-A, and (d) cross-section of tower.



Fig. 8. Two models of UAVs used for collecting point clouds of the investigated large cable-stayed bridge. (a) Feima D2000S; (b) DJI Mavic 3E.

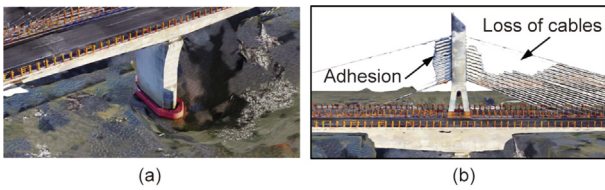


Fig. 9. Deficiencies of the preliminary model associated with (a) large water surfaces with weak textures and (b) slender structures of cable stays.

4.2.3. Image collection

The detailed flight operation described in Section 4.2.2 resulted in the collection of 5451 images, comprising 1045 overall aerial

images from the main flight path and 3563 close-up supplemental images from the circling flight path. Representative oblique photographs are presented below, with Figs. 11(a)–(c) corresponding to the flight paths shown in Figs. 10(a)–(c), respectively.

4.3. TLS field data

For the bridge substructure, data collection primarily utilizes 3D TLS with the Trimble SX12. This TLS system is equipped with three major components: ① a laser scanning module, ② an overview camera, and ③ a primary camera, as shown in Fig. 12 [48]. The overview and primary cameras are employed to capture photographs that facilitate point cloud colorization and support comprehensive image data documentation. The laser scanning module is utilized to acquire point cloud data for precise measurements of the bridge structure. Additionally, the TLS is equipped with Trimble's newly introduced lightning 3D measurement technology, which enables the capture of high-precision data at a rate of 26 600 points per second, with a range of up to 600 m. The system provides vertical and horizontal fields of view of 300° and 360°, respectively.

4.3.1. Point cloud data

To ensure the accuracy and completeness of the point cloud dataset, seven SPs were established: four on the upstream side of the bridge (SP1–SP4) and three on the downstream side

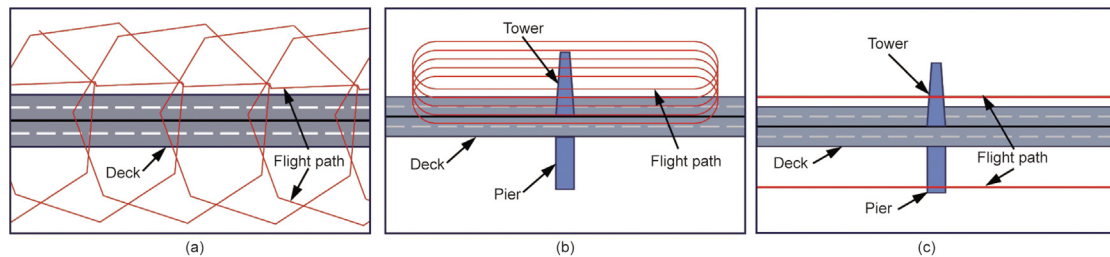


Fig. 10. Schematic of the flight path associated with (a) orbit flights, (b) and (c) facade flights.

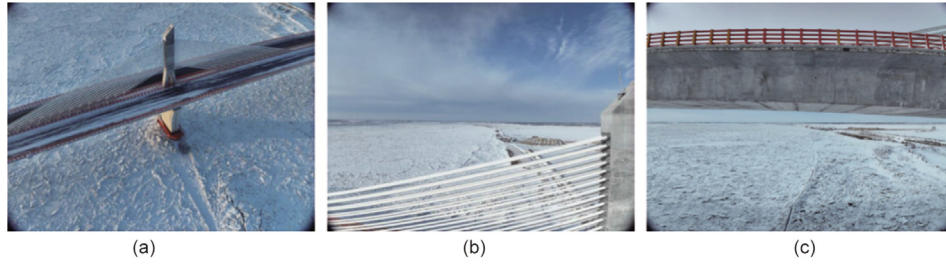


Fig. 11. Images captured by UAVs at (a) bridge tower, (b) cables, and (c) bridge girder.

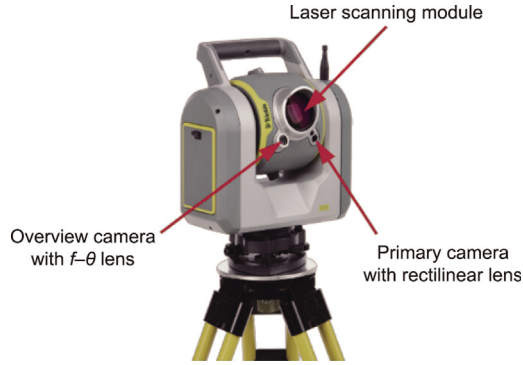


Fig. 12. Trimble SX12 scanning total station used for collecting TLS-based point cloud of the investigated large cable-stayed bridge [48]. f : effective focal length; θ : scan angle.

(SP5–SP7), as shown in Fig. 13(a). For example, scanning data acquired from SP2 can be visualized and reviewed in real time using the Trimble TSC7 controller (Trimble Inc., USA), as shown in Figs. 13(b)–(d). To mitigate the adverse effects of extreme cold on equipment performance, all data collection devices were equipped with thermal insulation and protective accessories, as also shown in Fig. 13(b). This approach facilitates high-quality, high-precision, and efficient automatic continuous acquisition of point cloud data, along with automated data registration and point cloud quality assurance processes. In total, 13 255 337 data points associated with the bridge point cloud were collected during this TLS scanning. However, raw 3D point cloud data inherently lacked color information, which is essential for the realistic and intuitive visualization of the measured object. To address this, corresponding texture images are captured and mapped onto the point cloud through texture mapping techniques. This process overlays color data onto the point cloud, significantly enhancing both the visual fidelity and structural realism.

4.3.2. Texture images

In addition to the point cloud acquired by the laser scanning module, texture images containing corresponding red-green-blue (RGB) information were captured using the overview or primary cameras. During the TLS scanning process, 79 texture images were obtained with the overview camera, providing detailed representations of the objective attributes of the bridge. These texture images are integral to enhancing the realism and completeness of the reconstructed model through texture mapping. A selection of texture images associated with the bridge captured from different scan locations is shown in Fig. 14.

4.3.3. Texture mapping

The TLS system, equipped with built-in cameras, simultaneously captured coaxially rotating texture images during point cloud data acquisition. The spatial positions of the cameras relative

to the origin of the TLS internal coordinate system remain fixed, ensuring a consistent and reliable mapping relationship between the texture images and point cloud data. Utilizing the collected point cloud data and corresponding texture images, texture mapping was performed to assign RGB values to each data point, as shown in Fig. 15. This process ensures that each data point contains both 3D positional and RGB color information. The complementary nature of point cloud data and texture images enables the detailed capture of both structural geometry and visual attributes, thereby significantly enhancing the overall representation of the bridge.

4.4. Noise reduction

The distinct noise characteristics in UAV-based point clouds are shown in Fig. 16(a). The UAV dataset contains both large- and small-scale noise interspersed with the target data, which complicates comprehensive noise reduction using a single algorithm. To address this, the ROR and SOR filters introduced in Section 3.3 were applied to effectively mitigate both types of noise, as shown in Fig. 16(b). Notably, the parameters of Min_{PNT} and r in Eqs. (1) and (2) for ROR were set at 15 and 0.5, respectively, whereas the SOR filter (Eq. (3)) utilized $k = 15$ and $\delta = 3$. In contrast, TLS data predominantly displays large-scale, isolated noise points, as shown in Fig. 17(a). Consequently, manual intervention is preferred for noise removal to preserve critical structural data. The efficiency of manual noise reduction, particularly in removing non-relevant objects, such as vehicles and pedestrians, while ensuring the integrity of the bridge model, is shown in Fig. 17.

The detailed views in Figs. 16 and 17 demonstrate significant improvements in noise reduction achieved through the implemented filtering strategy. Notably, the UAV point cloud was reduced from 45 704 932 to 26 239 781 points, representing a reduction of approximately 42.6%. Similarly, the TLS point cloud decreased from 13 255 337 to 12 313 615 points, corresponding to a reduction of approximately 7.1%.

4.5. Multi-source point clouds registration for bridges

4.5.1. Point cloud registration based on different algorithms

For multi-source point cloud registration, three different multi-source point cloud registration algorithms were employed: ① a manual method based on FP, ② a semi-automatic method utilizing GCP, and ③ automatic methods using the ICP algorithm, initialized with the results from the manual method. During manual registration, five pairs of corresponding feature points (i.e., FP1, FP2, FP3, FP4, and FP5) were selected, as shown in Fig. 7(a), in accordance with the criteria specified in Eq. (7). The rotation matrix $\mathbf{R}_{\text{man}}$ and translation matrix $\mathbf{t}_{\text{man}}$ are calculated as follows:

$$\mathbf{R}_{\text{man}} = \begin{bmatrix} 1.000 & 0.000 & -0.004 \\ 0.000 & 1.000 & 0.001 \\ 0.004 & -0.001 & 1.000 \end{bmatrix} \quad (9)$$

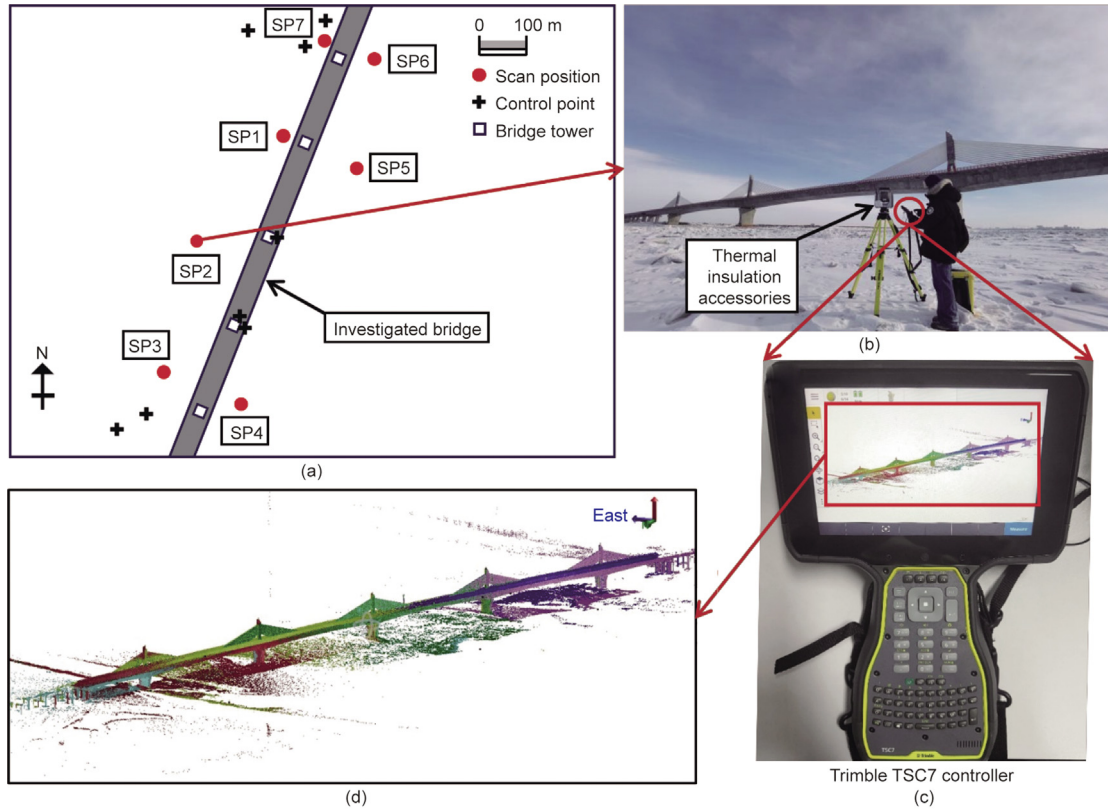


Fig. 13. Procedures of (a) scanner positioning and control point, (b) scanning execution, (c) point cloud quality checks using controller, and (d) data automatic registration, acquisition, and documentation for collecting bridge point cloud with the aid of TLS.

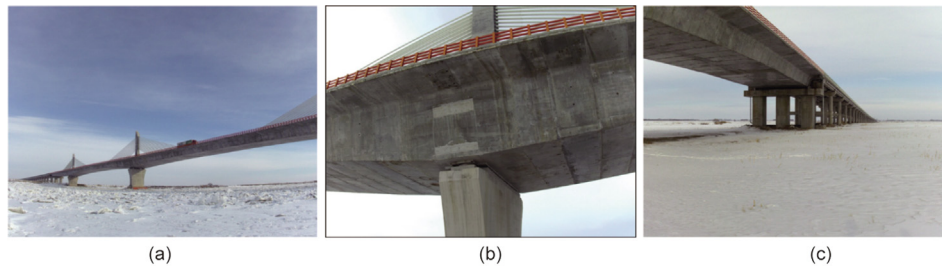


Fig. 14. Three examples of texture images obtained using the overview camera of TLS. (a) General view of the main bridge; (b) detailed view of the girder; (c) view of the bridge piers.

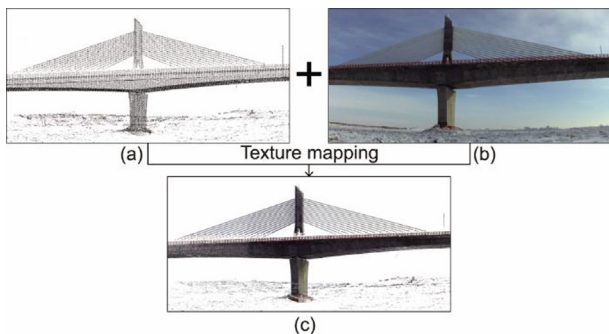


Fig. 15. Texture mapping process using (a) point cloud data collected by laser scanning module with only 3D positional information and (b) texture image collected by overview cameras with only RGB color information to obtain (c) point cloud data integrated with color information.

$$\mathbf{t}_{\text{man}} = \begin{bmatrix} 100.567 \\ 279.677 \\ -0.094 \end{bmatrix} \quad (10)$$

In the semi-automatic registration process, GCPs were incorporated using GNSS-RTK technology to align the point clouds within the China Geodetic Coordinate System 2000 (CGCS2000). The UAV GNSS-RTK modules provide a horizontal positioning accuracy of $1 \text{ cm} + 1 \text{ ppm}$ and vertical accuracy of $1.5 \text{ cm} + 1 \text{ ppm}$ [46]. For TLS, the RTK positioning accuracy of the control points is $\pm (8 + 1 \times 10^{-6}D) \text{ mm}$ horizontally and $\pm (15 + 1 \times 10^{-6}D) \text{ mm}$ vertically, where D represents the distance (km) between the rover and base station [49]. During data processing, all point clouds were transformed into the CGCS2000 reference frame, enabling automatic registration.

Building on the manual registration results, automatic registration algorithms (optimization-based ICP) were subsequently employed in this study. In the implementation of Eq. (8), the

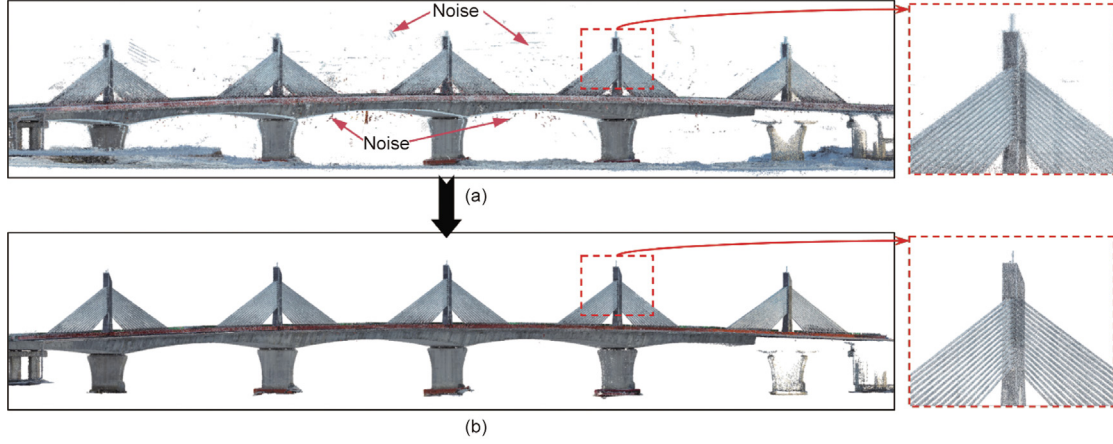


Fig. 16. (a) Before and (b) after noise reduction for the point cloud obtained from UAVs.

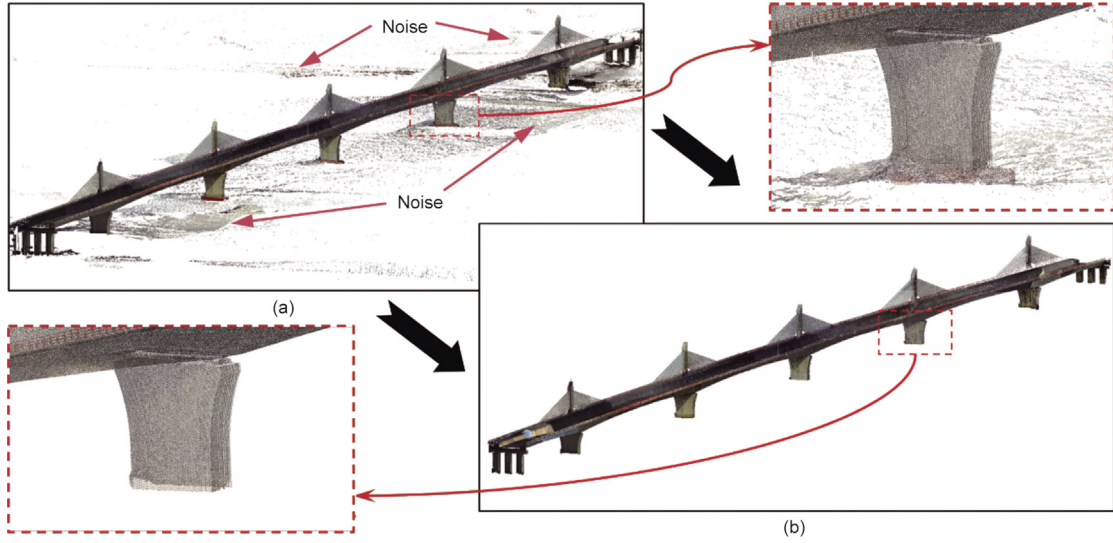


Fig. 17. (a) Before and (b) after noise reduction for the point cloud obtained from TLSs.

TLS- and UAV-based point clouds were designated as the source (P_s) and target point cloud (P_t), respectively. The number of points in the source point cloud ($|P_s|$) and target point cloud ($|P_t|$) is 12 313 615 and 26 239 781, respectively, resulting in a total of 38 553 396 points after integration, ($|P_s| + |P_t|$). The threshold of the root mean square difference for the iterative process is set to 1×10^{-5} . The resulting rotation matrix R_{icp} and translation matrix t_{icp} are derived as follows:

$$R_{icp} = \begin{bmatrix} 1.000 & 0.000 & 0.002 \\ 0.000 & 1.000 & 0.005 \\ -0.002 & -0.005 & 1.000 \end{bmatrix} \quad (11)$$

$$t_{icp} = \begin{bmatrix} -0.278 \\ -0.626 \\ 0.916 \end{bmatrix} \quad (12)$$

A comparative analysis of three registration methods demonstrates their effectiveness in addressing the inherent limitations of data from TLSs and UAVs. As shown in Fig. 18, the ICP algorithm effectively compensates for the coverage gaps present in both TLS and UAV datasets. Specifically, the integration of UAV data from Fig. 18(a) mitigates the limitations of TLS in capturing the upper

bridge components, such as towers, cables, and bridge deck, as shown in Fig. 18(b). Conversely, TLS data from Fig. 18(b) compensates for UAV deficiencies in acquiring detailed information from lower bridge components, including the undersides of girders and piers, as shown in Fig. 18(a). This complementary approach ensures comprehensive spatial coverage and enhances registration accuracy.

4.5.2. Accuracy comparison of point cloud

The root mean square error (RMSE) is employed as a metric to evaluate the model accuracy associated with the point cloud [50]:

$$\begin{aligned} RMSE_{PC} &= \sqrt{RMSE_{PC,x}^2 + RMSE_{PC,y}^2 + RMSE_{PC,z}^2} \\ &= \sqrt{\frac{1}{n} \left[\sum_{j=1}^n (x_{j,PC} - x_{j,BP})^2 + \sum_{j=1}^n (y_{j,PC} - y_{j,BP})^2 + \sum_{j=1}^n (z_{j,PC} - z_{j,BP})^2 \right]} \end{aligned} \quad (13)$$

where $RMSE_{PC}$ represents the RMSE associated with the point cloud model, $RMSE_{PC,x}$, $RMSE_{PC,y}$, and $RMSE_{PC,z}$ represent the RMSE components along the x -, y -, and z -axes, respectively, n represents the number of points considered, $x_{j,PC}$, $y_{j,PC}$, and $z_{j,PC}$ represent the coordinates of point j in the point cloud along the x -, y -, and z -axes, respectively, and $x_{j,BP}$, $y_{j,BP}$, and $z_{j,BP}$ represent the coordinates of

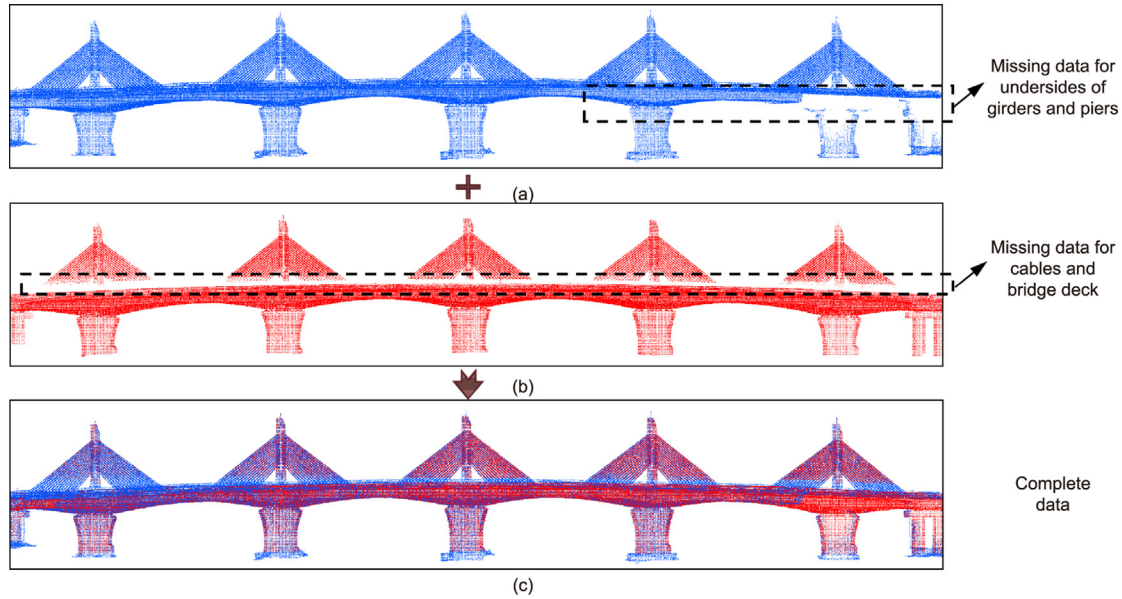


Fig. 18. Bridge point cloud based on (a) UAV and (b) TLS before registration and (c) after registration.

the corresponding bridge point j along the x -, y -, and z -axes, respectively, obtained using the GNSS-RTK technology.

The accuracies of point cloud models derived from single-source and multi-source data utilizing various registration algorithms are listed in Table 2. While single-source point clouds, such as those derived from TLS, demonstrate higher accuracy, they suffer from significant deficiencies in spatial integrity compared with multi-source models. Among the evaluated registration methods, manually registered multi-source point clouds achieved the highest accuracy. Notably, single-source point clouds displayed relatively high accuracy but significantly lower integrity, as shown in Fig. 18. This trade-off between accuracy and integrity is a crucial consideration and will be further examined in the subsequent section, particularly in relation to the bridge DT model.

5. Digital twin and associated damage inspections for bridges

5.1. Construction and evaluation of a 3D DT model

5.1.1. Construction of a DT model

The point cloud model developed in Section 4.5 provides precise spatial data at the individual point level, making it well-suited for accurate measurements and serving as a foundational dataset for further modeling. However, it lacks the visual detail, surface smoothness, and textual information required for realistic rendering, which limits its applicability for detailed inspections of bridge damage. To overcome these limitations, a 3D DT model with highly

detailed, smooth surfaces and realistic textures is essential. Accordingly, both point clouds and images were imported into Soarscape Smart3D software [47], allowing for the reconstruction of a 3D realistic DT model of the cable-stayed bridge. As shown in Fig. 19, the resulting 3D DT model, reconstructed from registered point clouds and tie points obtained through aerial triangulation, provides more enhanced textural accuracy and a more comprehensive structural representation.

This test focuses on a kilometer-scale cable-stayed bridge, for which comprehensive field data acquisition was completed within approximately 4 h and 30 min, ensuring comprehensive and efficient coverage of the entire structure. Utilizing the high-performance workstation detailed in Section 4.1, data processing required approximately 48 h to fully reconstruct the DT model. In comparison, conventional bridge inspection methods primarily depend on manual visual assessments. For large and complex structures, such as kilometer-scale cable-stayed bridges, accessing critical components, such as pylons and pier tops, typically necessitates the use of specialized equipment, such as bridge inspection vehicles. Conservative estimates indicate that conventional field data collection generally requires between five and eight days. Furthermore, during periods of river navigation, conducting inspection tasks in such challenging environments presents significant safety risks, particularly when inspecting components, such as mid-span piers, even with specialized equipment. Additionally, compared with the approach proposed in this study, conventional techniques often result in incomplete field data acquisition, thereby hindering

Table 2

Accuracy comparison associated with point clouds utilizing different registration algorithms.

Type of point cloud	Registration algorithm	RMSE _{PC,x}	RMSE _{PC,y}	RMSE _{PC,z}	RMSE _{PC}
Single source	GNSS-RTK	0.0946	0.0649	0.0713	0.1350
	GNSS-RTK	0.0505	0.0440	0.0408	0.0784
Multiple sources	MFP	0.0631	0.0482	0.0587	0.0987
	GCP	0.0652	0.0486	0.0638	0.1034
	ICP	0.0837	0.0520	0.0727	0.1225

MFP refers to manual registration based on feature points.

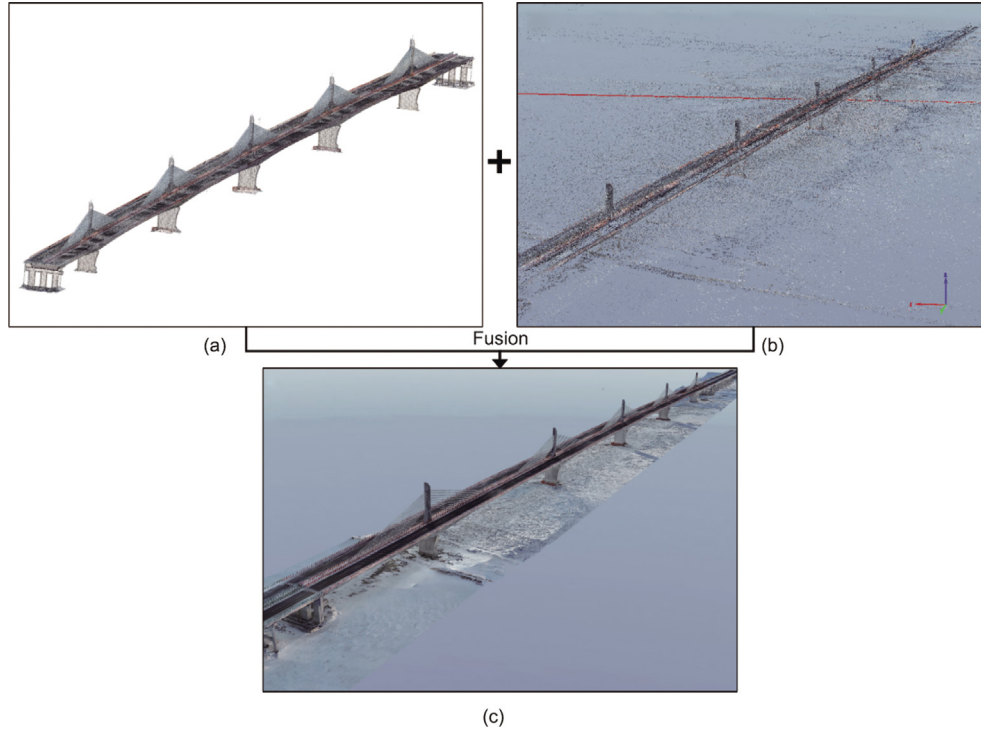


Fig. 19. Construction of (a) registered point clouds, (b) tie points from aerial triangulation, and (c) 3D DT model by fusing.

the ability to perform systematic and comprehensive inspections of the entire bridge during subsequent data processing.

5.1.2. Absolute accuracy of the DT model

To validate the effectiveness of the proposed modeling approach, which fuses point clouds registered through various methods, the resulting models were compared with those generated exclusively from UAV-based oblique photography. Owing to the absence of TLS data, modeling based solely on single TLS data was not included in the subsequent quality evaluation and comparison. Measurement accuracy was evaluated from two distinct perspectives: absolute and relative accuracy. Absolute accuracy was quantified using RMSE, which assesses the planar and elevation accuracy of the reconstructed models [50].

Based on the absolute accuracy evaluated in both planar and elevation dimensions, as defined by Eq. (14), a comparative analysis of the absolute accuracy of DT constructed using exclusively UAV data versus those constructed by integrating UAV and TLS data is presented in Table 3. The results demonstrate that integrating UAV and TLS data significantly enhances model accuracy. Specifically, the model utilizing ICP-registered point clouds achieved a 24.7% (calculated based on the combined RMSE of x - and y -axes) and 41.6% improvement in planar and elevation accuracies, respectively, compared with the model constructed exclusively on UAV data. The Kolmogorov-Smirnov test results validate that the error distributions for both ICP-based and UAV-based models conform to a normal distribution. Although the observed improvements in absolute accuracy may appear relatively modest and the absolute error differences are relatively small, these enhancements are nonetheless meaningful. The increased accuracy is expected to facilitate the detection of finer-scale structural defects, potentially enabling millimeter-level identification of concrete cracks in bridge structures. These findings suggest the effectiveness of the proposed framework in producing highly accurate 3D realistic models.

$$\begin{aligned} \text{RMSE}_{\text{DT}} &= \sqrt{\text{RMSE}_{\text{DT},x}^2 + \text{RMSE}_{\text{DT},y}^2 + \text{RMSE}_{\text{DT},z}^2} \\ &= \sqrt{\frac{1}{n} \left[\sum_{j=1}^n (x_{j,\text{DT}} - x_{j,\text{BP}})^2 + \sum_{j=1}^n (y_{j,\text{DT}} - y_{j,\text{BP}})^2 + \sum_{j=1}^n (z_{j,\text{DT}} - z_{j,\text{BP}})^2 \right]} \end{aligned} \quad (14)$$

where RMSE_{DT} represents the RMSE associated with the DT model, $\text{RMSE}_{\text{DT},x}$, $\text{RMSE}_{\text{DT},y}$, and $\text{RMSE}_{\text{DT},z}$ represent the RMSE components along the x -, y -, and z -axes, respectively, $x_{j,\text{DT}}$, $y_{j,\text{DT}}$, and $z_{j,\text{DT}}$ represent the coordinates of point j in the DT model along the x -, y -, and z -axes, respectively.

Additionally, this study examines the influence of point cloud resolution, quantified by the number of points, on the accuracy of the resulting DT model. Analysis based on the ICP registration algorithm reveals that RMSE increases as the point count decreases, emphasizing the importance of high-resolution point clouds for achieving optimal model accuracy. Meanwhile, the potential loss of a small proportion of valid points owing to noise reduction is negligible, given the overall scale of the point cloud, which comprises tens of millions of points.

5.1.3. Relative accuracy of the DT model

To evaluate the relative accuracy of the realistic models, measurements derived from the models were compared with on-site ground-truth values. This evaluation utilized thirty checkpoints, from which eight distance discrepancies (H1–H8) and ten height deviations (V1–V10) were calculated to quantify the relative accuracy. The results of this analysis are shown in Fig. 20 and Table 4, providing a comprehensive assessment of model performance against actual measurements.

As shown in Table 4, point cloud modeling based on fused registration significantly outperforms modeling using data from a single UAV. In terms of mean relative accuracy, the model constructed with manually registered point clouds demonstrated significant improvements, with the ICP-registered point cloud model achieving a distance discrepancy and height difference of 0.028 and 0.030 m, respectively. Furthermore, the analysis revealed that the

Table 3

Absolute accuracy comparison of the bridge DT model utilizing different point cloud registration algorithms.

Type of data	Registration algorithm	Number of points	RMSE _{DT,x}	RMSE _{DT,y}	RMSE _{DT,z}	RMSE _{DT}
UAVs	GNSS-RTK	$ P_t $	0.0939	0.0627	0.0606	0.1282
UAVs and TLSs	MFP	$ P_s + P_t $	0.0652	0.0537	0.0500	0.0982
	GCP	$ P_s + P_t $	0.0694	0.0583	0.0528	0.1049
	ICP	$ P_s + P_t $	0.0660	0.0536	0.0354	0.0921
	ICP	$0.75(P_s + P_t)$	0.0808	0.0571	0.0312	0.1037
	ICP	$0.50(P_s + P_t)$	0.0909	0.0657	0.0409	0.1194
	ICP	$0.25(P_s + P_t)$	0.0976	0.0625	0.0422	0.1234

mean values of both distance discrepancy and height deviation increased as the number of point clouds decreased.

Currently, no established standard defining geometric accuracy specifically for bridge models exists [51], underscoring the urgent need for a dedicated technical code to standardize and guide 3D bridge modeling in practical applications. However, the Technical Code for 3D City Modeling (CJJ/T 157–2010) [52] published by the Ministry of Housing and Urban-Rural Development of China is widely referenced for 3D urban modeling and smart city development, despite being originally intended for city-scale applications. In this study, the specification is referenced solely as a conceptual benchmark for evaluating the level of detail in bridge models. According to this specification, models are qualified as level of detail (LOD) 4 if both planar and elevation accuracy exceed 0.2 m [52]. The models constructed using the proposed framework exceed the established threshold and can be classified as high-detail models, consistent with the LOD 4 specifications. Notably, the absence of dedicated LOD standards for bridges constitutes a significant gap in industry practice. This study provides an initial contribution toward addressing this deficiency and highlights the necessity for collaborative efforts among industry, academia, and

standardization organizations to formulate bridge-specific LOD definitions. Such standards should be established to ensure consistency, accuracy, and applicability of 3D bridge DT models across diverse engineering and management domains.

5.1.4. Integrity of the DT model

Model integrity is defined as the completeness of the structural representation and the clarity of its textures, both of which are essential for accurately reflecting real-world conditions. Integrity can be quantitatively assessed as the ratio of the complete mesh to the total mesh considered within the model. The evaluation process is shown in Fig. 21. As illustrated, the piers of the cable-stayed bridge are segmented into planar meshes for the front, top, and bottom views, as well as ten cross-sections. Red meshes represent incomplete regions characterized by structural omissions or unclear textures that do not correspond to actual conditions, whereas gray meshes are excluded from the evaluation owing to the absence of realistic model elements.

The model integrity (I_{DT}) was evaluated using Eq. (15), with results listed in Table 5.

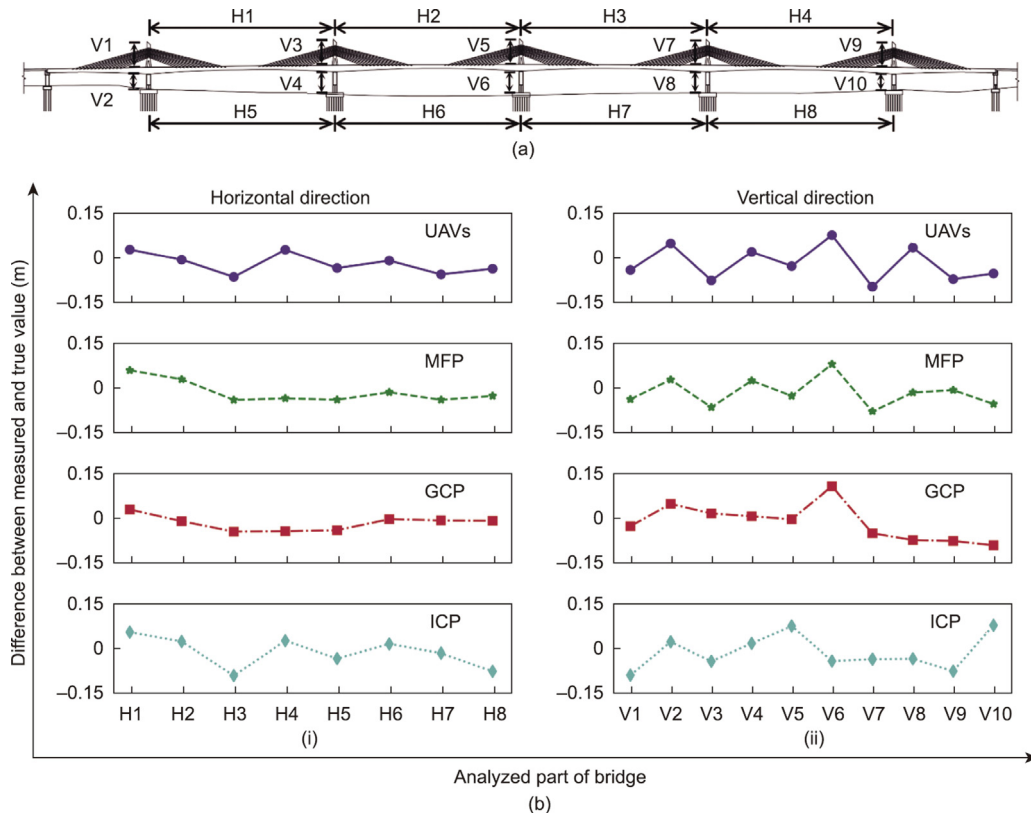
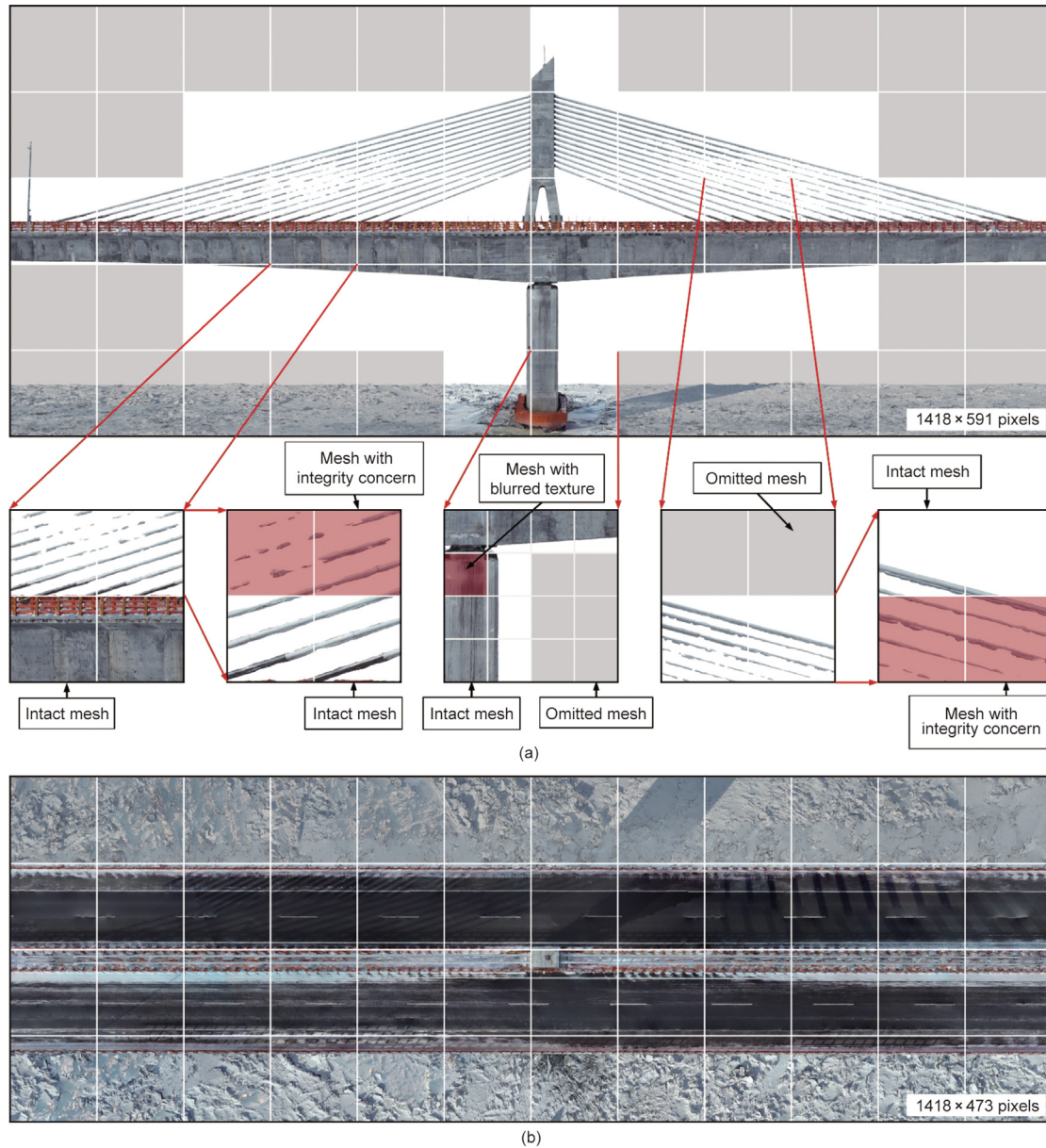


Fig. 20. Evaluation of the relative accuracy through checkpoints based on different point cloud registration algorithms. (a) Distribution of checkpoints H1–H8 and V1–V10 on the bridge; (b) calculated difference in horizontal and vertical directions.

Table 4

Comparison of the relative accuracy of the bridge DT model.

Accuracy indicator	Source of data	Number of points	Maximum difference	Minimum difference	Mean	Standard deviation
Distance discrepancy (m)	UAVs	$ P_t $	0.059	0.009	0.032	0.019
	MFP	$ P_s + P_t $	0.046	0.016	0.027	0.010
	GCP	$ P_s + P_t $	0.054	0.007	0.030	0.018
	ICP	$ P_s + P_t $	0.052	0.009	0.028	0.017
	ICP	$0.75(P_s + P_t)$	0.085	0.009	0.029	0.024
	ICP	$0.5(P_s + P_t)$	0.090	0.008	0.030	0.029
	ICP	$0.25(P_s + P_t)$	0.071	0.008	0.031	0.019
Height deviation (m)	UAVs	$ P_t $	0.077	0.009	0.033	0.023
	MFP	$ P_s + P_t $	0.069	0.008	0.029	0.021
	GCP	$ P_s + P_t $	0.081	0.008	0.030	0.026
	ICP	$ P_s + P_t $	0.075	0.008	0.030	0.020
	ICP	$0.75(P_s + P_t)$	0.096	0.008	0.031	0.026
	ICP	$0.5(P_s + P_t)$	0.105	0.009	0.032	0.028
	ICP	$0.25(P_s + P_t)$	0.108	0.009	0.033	0.028

**Fig. 21.** Schematic of integrity quantification through uniform meshing for (a) front view and (b) top view.

$$I_{DT} = \frac{n_f + n_t + n_b + n_c}{N_{f,t,b,c}} \times 100\% \quad (15)$$

where n_f , n_t , n_b , and n_c represent the counts of intact meshes in the front view, top view, bottom view, and pier cross-sections, respectively, and $N_{f,t,b,c}$ represents the total number of meshes evaluated in the front view, top view, bottom view, and pier cross-sections.

Multi-source data integration significantly enhances the integrity of DT compared with single-data approaches. Specifically, DT generated from ICP-registered point clouds achieved a model integrity of up to 93.73%. As shown in Table 5, a reduction in the number of point cloud data points correlates with a decline in model integrity. A comparative analysis of model quality based on UAV data, registered point cloud, 3D DT, and field-captured images is shown in Fig. 22.

The results clearly demonstrate that fusion modeling yields DT models with superior completeness and enhanced texture clarity. This enhancement addresses several issues observed in the UAV-based model shown in Fig. 22(a), such as missing structural elements in cables and the deck, the absence of texture on the girder, texture blurring on the bottom of the girder, and structural adhesion anomalies at the bearing locations. These findings underscore the advantages of employing semi-automatic (GCP) or optimization-based (ICP) registration methods for constructing DT of large-scale outdoor environments, as they significantly enhance both the accuracy and integrity of the DT model. Component-level inspection, as detailed in Fig. 22, identifies several issues: seepage on towers and piers, corrosion and turbidity on beams, minor rusting on bearings, and construction imprints on girders. Notably, concrete spalling on piers highlights the necessity for protective measures during navigation and ice-melting periods. These observations are corroborated by UAV imagery and on-site field inspections, validating the observed conditions.

While the proposed framework presents certain limitations and incurs inspection costs during practical deployment, it offers significant advantages in detection efficiency and accuracy, particularly for bridges situated in extreme environments or featuring complex structures and long spans. Therefore, its adoption in real-world engineering applications should be carefully evaluated based on the specific structural configuration and environmental conditions of the bridge. For example, the framework is particularly well-suited for extra-large bridges with spans exceeding 1000 m, critical transportation hubs, such as highway bridges, and those situated in challenging settings, including cold climates, coastal regions with high winds, mountainous terrain, and canyon crossings. In these scenarios, the framework is highly recommended owing to its substantial advantages in long-term inspection efficiency, safety, and life-cycle management.

Although the initial investment in equipment may be relatively high, the long-term advantages, such as improved inspection accuracy, reduced dependence on manual intervention, and enhanced operational safety, justify the upfront costs. Moreover, the equipment is versatile and can be applied beyond bridge inspections to a wide range of civil engineering structures across diverse geo-

graphic contexts. Specifically, the framework demonstrates robust capabilities in two critical aspects of damage assessment: surface distress inspection and alignment control, as detailed in the subsequent section.

5.2. Damage inspection based on digital twin

5.2.1. Surface spalling inspection

As shown in Fig. 22, the surface concrete spalling can be observed in the DT model of the cable-stayed bridge. In this section, the volume of the spalled concrete was quantified and compared using both point cloud and DT models, respectively, as shown in Fig. 23. As illustrated, the mean value of the spalled concrete volume is $1.76 \times 10^{-2} \text{ m}^3$, with a prediction error of 4.886%.

5.2.2. Alignment control

Representative profiles were selected from the bridge deck (LT1 and LT2 in Fig. 7(c)) and the girder bottom (LB1 and LB2 in Fig. 7(c)) to compare point cloud-fitted curves with the corresponding design vertical curves along the longitudinal direction. Analysis of the bridge deck profiles, shown in Fig. 24(a) and (b), and the girder bottom profiles in Fig. 24(c) and (d), reveals that the point cloud data for the bridge deck (LT1 and LT2) closely align with the design curve, with the coefficient of determination (R^2) values of 0.9968 and 0.9965, respectively. In contrast, the box girder bottom profiles near the side spans demonstrated greater deviations compared with those near the midspan. For example, the R^2 values for Span #1 and Span #6 at LB1 are lower than those observed in other spans. This indicates that the side-span experiences more pronounced deformation than the mid-span, which may be attributed to the structural configuration, specifically, the tower-girder consolidation at the mid-span versus the pier-girder separation at the side-span, as well as variable loading conditions, including impact loads at bridge heads, which are more prevalent in the side-span region. These findings highlight the importance of monitoring profile changes in the girder bottom and side spans during the operation and maintenance phases to mitigate structural uncertainties and ensure the safety and timely maintenance of the bridge throughout its life-cycle.

Similarly, a comparison between the profiles of the bridge deck top (TT1 and TT2 in Fig. 7(a)) and the box girder bottom (TB1 and TB2 in Fig. 7(a)) with the corresponding design vertical lines in the transverse direction is shown in Fig. 25. The obtained point cloud data accurately captured the actual transverse alignment of the bridge, further validating the effectiveness of point cloud technology in representing the structural geometry of the bridge.

Considering the minor surface distresses identified in Section 5.2.1 and the precise point cloud alignment in Section 5.2.2, the overall condition rating of the investigated bridge is evaluated as 7, indicating good condition [53]. Conventional methods for construction profile control and bridge span monitoring during operation are typically limited to discrete point measurements, resulting in inefficiencies and reduced accuracy. In contrast, this study utilizes wide-area, high-density precision point clouds for profile comparison and control, providing an efficient and accurate approach that fulfills engineering requirements for bridge span profiling during both construction management and operational maintenance. This approach significantly enhances the reliability and effectiveness of bridge monitoring throughout its life-cycle.

6. Conclusions

This study introduced a framework for integrating UAV and TLS data to reconstruct a DT of large-scale bridges, such as cable-stayed bridges. In the field, UAVs capture image data, whereas TLS collects point cloud data. Subsequent data preprocessing in the office

Table 5

Integrity comparison associated with the DT model based on different point cloud registration algorithms.

Type of data	Registration algorithm	Number of points	Integrity (%)
UAVs	GNSS-RTK	$ P_f $	78.90
UAVs and TLSs	MFP	$ P_s + P_t $	88.61
	GCP	$ P_s + P_t $	90.02
	ICP	$ P_s + P_t $	93.73
	ICP	$0.75(P_s + P_t)$	89.74
	ICP	$0.5(P_s + P_t)$	85.74
	ICP	$0.25(P_s + P_t)$	80.56

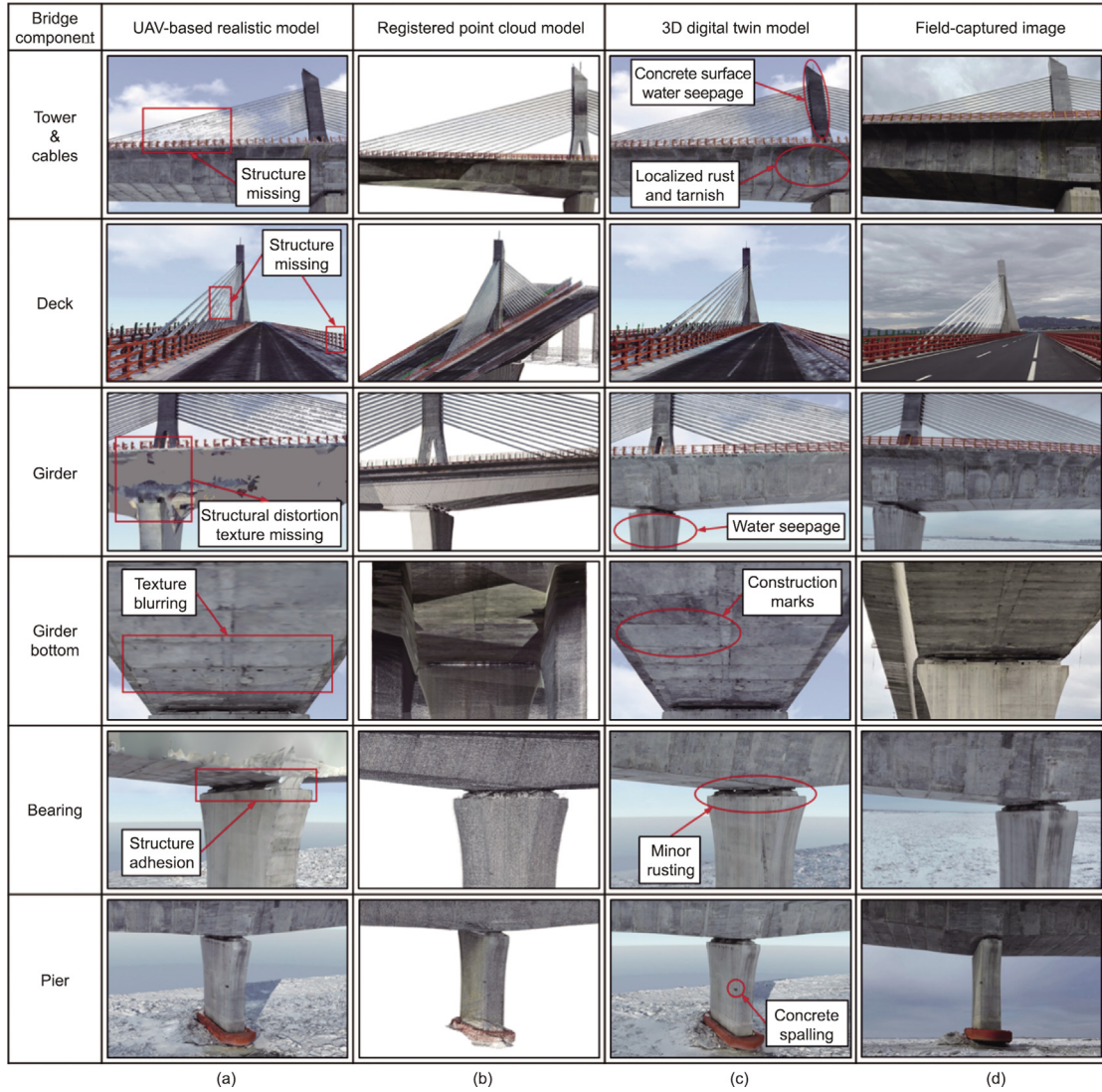


Fig. 22. Comparison of bridge components among models associated with (a) UAV photography, (b) registered point cloud, (c) 3D DT, and (d) field-captured image.

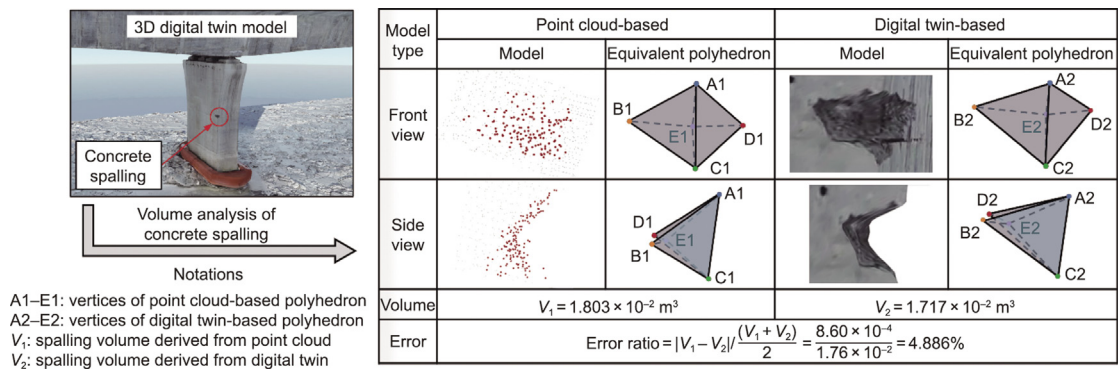


Fig. 23. Comparison of the volume of concrete spalling between point cloud-based and DT-based models.

ensures the applicability of the integrated aerial and terrestrial point cloud data. The integration of these multi-source, heterogeneous data was achieved through two primary approaches: first, three different registration methods were applied to generate a

complete bridge point cloud; second, UAV image data was integrated with the point cloud to construct the DT. Subsequently, both qualitative and quantitative assessments were conducted on the 3D point cloud model and DT (3D realistic model) to validate the

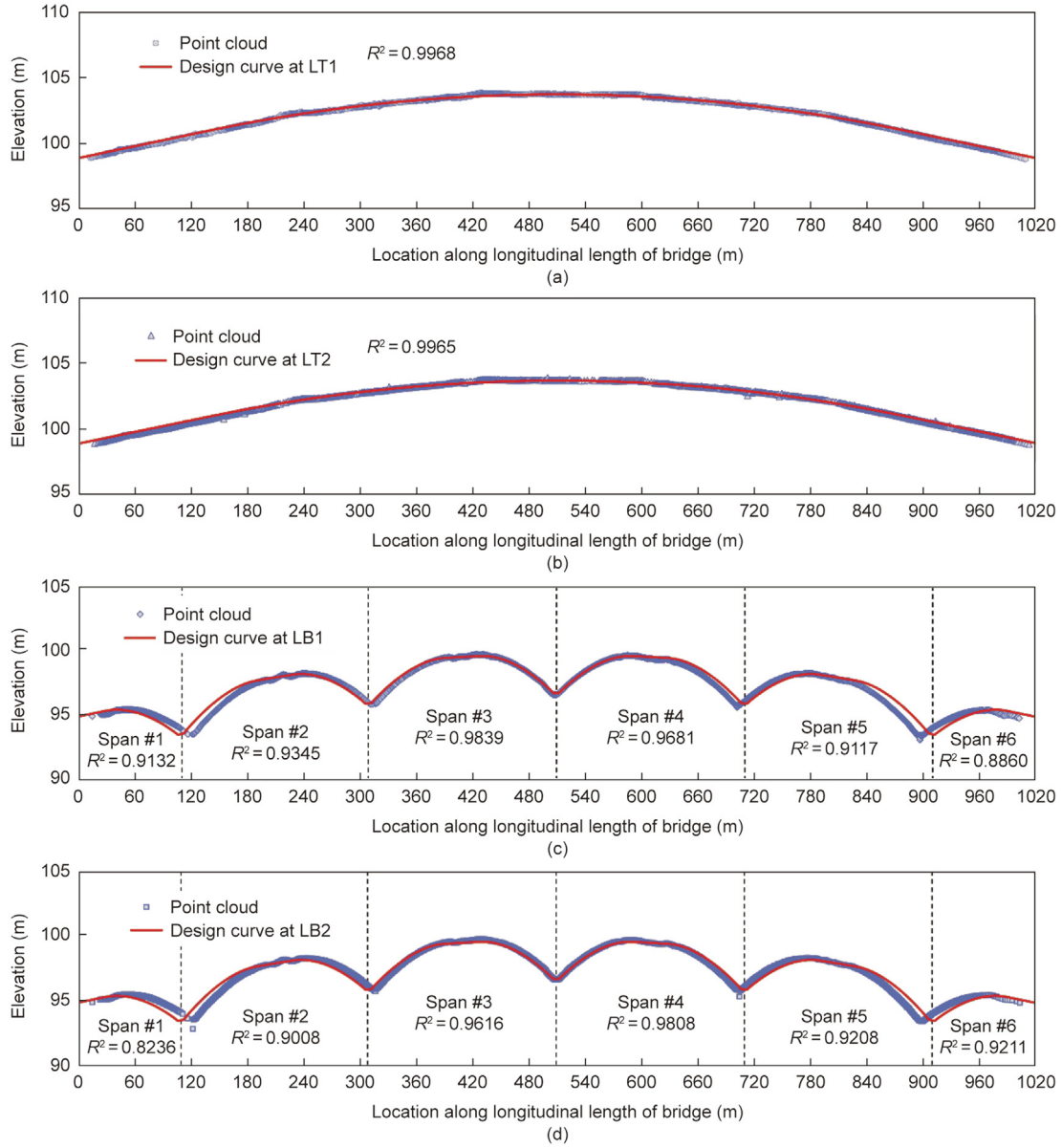


Fig. 24. Comparison between the point cloud and designed alignment in the longitudinal direction associated with locations of (a) T1, (b) T2, (c) B1, and (d) B2, as shown in Fig. 7.

proposed framework. The richness, accuracy, and versatility of point cloud data established it as a valuable resource across various applications, providing significant advantages in precision, efficiency, and analytical capabilities. The key conclusions of this study are:

(1) In contrast to conventional DT construction methods that rely on single-source data, this study introduced an innovative technical framework that integrates multi-source data from UAV and TLS, leveraging their strengths to enhance bridge inspection efficiency and safety. This approach enables the integration of aerial and terrestrial-based data into a unified network, introducing a novel methodology, thereby broadening the application scope for DT construction.

(2) Point cloud registration techniques have progressed through three primary stages: manual, semi-automatic, and automatic methods. Qualitative results demonstrated that these methods significantly enhanced the integrity of bridge point cloud models.

Quantitative evaluation further validated that all three registration methods yielded high-accuracy results.

(3) The application of the proposed framework to an extra-large cable-stayed bridge in a cold region demonstrated its effectiveness. By leveraging the seasonal characteristics of cold environments to acquire high-quality data, GCP-based semi-automatic or optimization-based automatic point cloud registration is recommended for outdoor heterogeneous (multi-source) data. This strategy is particularly effective for constructing bridge DTs.

(4) A comprehensive comparison demonstrated that the DT developed using this technical framework outperformed models constructed from single-source data. Quantitatively, it achieved an accuracy level consistent with LOD 4, significantly surpassing the 0.2 m threshold, and meeting the requirements for high-quality modeling. Qualitatively, the model delivered enhanced texture clarity and a more complete structural representation.

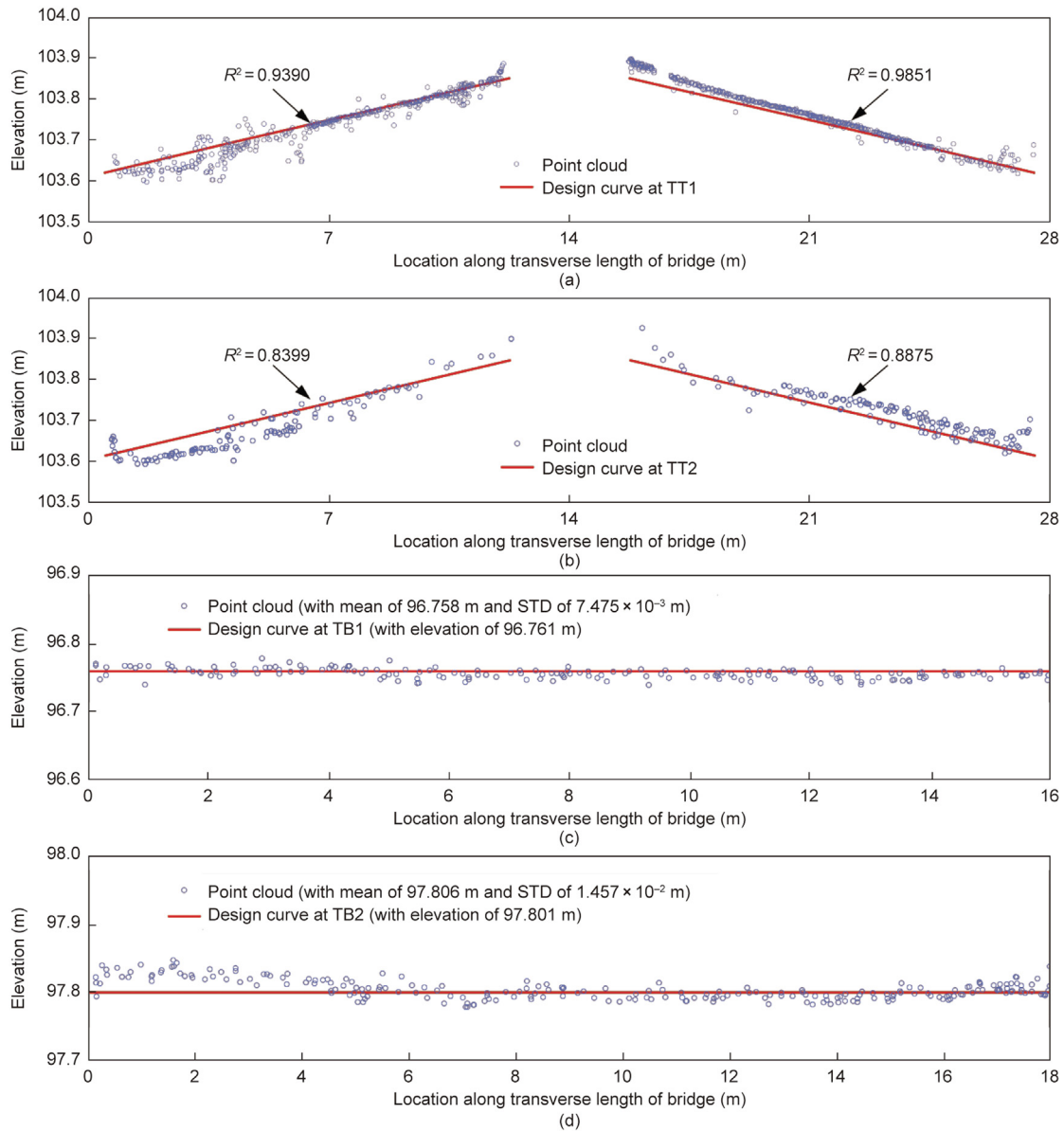


Fig. 25. Comparison between the point cloud and designed alignment in the transverse direction associated with locations of (a) TT1, (b) TT2, (c) TB1, and (d) TB2, as shown in Fig. 7. STD: standard deviation.

(5) To comprehensively evaluate the reconstructed DT model, three novel indicators, absolute accuracy, relative accuracy, and integrity, were introduced. Generally, the point cloud resolution exhibits a negative relationship with absolute and relative accuracy but a positive relationship with integrity.

(6) The DT generated through this framework provided significant support for bridge inspection and condition assessment, particularly in detecting structural issues such as concrete spalling and alignment control. This capability facilitated more efficient and informed decision-making for maintenance strategies, ultimately enhancing bridge management and sustainability.

The application of DT technology into bridge inspection and SHM represents a significant advancement. Although the initial investment in equipment may be considerable, the proposed framework offered substantial long-term advantages in terms of inspection efficiency and operational safety, particularly for extra-large bridges (e.g., those with total span lengths exceeding 1000 m) located in challenging or hard-to-access environments,

such as mountainous regions. Despite its demonstrated potential, DT-assisted bridge inspection is still in its infancy and still requires a certain degree of subjective human intervention. Therefore, future research should prioritize the following areas:

(1) The development of fully automated and highly efficient inspection technologies, leveraging advancements in deep learning and the increasing availability of high-quality bridge datasets.

(2) The enhancement of data processing capabilities through cloud-based platforms and integration with on-site inspection equipment, thereby improving computational efficiency and system responsiveness.

(3) The deeper integration of DT technology with finite element models to validate geometric reconstruction accuracy and damage detection, thereby strengthening the understanding of structural behavior.

(4) The design of next-generation equipment that integrates the complementary advantages of UAV and TLS data acquisition,

enhancing both the cost-effectiveness and scalability of the proposed framework.

(5) The establishment of dedicated evaluation standards for 3D bridge DT modeling to ensure consistency, accuracy, and interoperability across diverse applications.

Collectively, these research directions will facilitate the realization of real-time, interactive, and intelligent bridge inspection and SHM systems, delivering enduring value for both academic research and engineering practice.

CRedit authorship contribution statement

Lianzhen Zhang: Writing – review & editing, Funding acquisition, Conceptualization. **Kaizhong Deng:** Writing – original draft, Software, Methodology, Investigation. **Yanliang Du:** Writing – review & editing, Project administration. **Mitsuyoshi Akiyama:** Writing – review & editing, Supervision, Resources, Project administration. **Jiyou Xin:** Writing – original draft, Software, Methodology, Investigation, Conceptualization.

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.

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