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RAILWAY BRIDGE CONDITION ASSESSMENT BASED ON STATE-OF-THE-ART REALITY CAPTURE TECHNOLOGIES: APPLICATION TO A CASE STUDY

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Abstract

Structural visual inspection documentation is essential for monitoring, maintaining, rehabilitating, and reinforcing structures. Close-Range Photogrammetry (CRP) and Terrestrial Laser Scanners (TLS) are cutting-edge technologies that are commonly used in surveying. In this article, these technologies were integrated to capture a railway bridge. The lower deck and lateral deck surfaces were captured using TLS, while the upper deck, track and laterals of the deck were captured using CRP-UAV photogrammetry. Post-processing techniques allowed the fusion of TLS and CRP models to produce a precise 3D model of the entire railway bridge deck.

Introduction

Railway infrastructure is crucial for economic growth, low-carbon emission, and energy-efficient transport. Framed on the railway infrastructure, bridges, and viaducts face problems due to aging, overloading, lack of maintenance, and poor inspection. To remain competitive in comparison to other means of transport, digitalization in railway infrastructure is a crucial aspect, particularly in what concerns the structural condition assessment. The traditional human-dependent inspection methods are typically costly and time-consuming. Advances in robotics and remote sensing technologies provide non-destructive, contact-free ways to capture the 3D state of the infrastructure and improve inspection efficiency.

Digital three-dimensional reconstruction models are representations of assets that may be developed using active or passive vision systems. In general, active systems employ their own source of illumination for measurements, whereas passive systems use ambient light in the scene (Popescu et al., 2019). Each method has benefits and limitations in terms of resolution, speed, and scene depth. In a hybrid system, the benefits of both systems may be combined.

Active systems are then divided into two types: methods based on triangulation (Atif & Lee, 2017; El-etriby, 2015; Spectra, 2019) and Time-of-Flight based technologies (ToF) (Foix et al., 2011; Görüm, 2019; Zhong et al., 2019). Passive approaches include Multi View Stereo (MVS) and Structure-from-Motion (SfM) technologies. Overall, the emphasis has been placed on LiDAR and SfM. LiDAR is simply an extension of the notions of the ToF sensor. It measures the time it takes for the reflected light to return when a laser is used to illuminate the target item; however, the laser emitter and receiver are placed in the same sensor. To deal with occlusion issues, terrestrial LiDAR, also known as Terrestrial Laser Scanning (TLS), requires a complex setup and must scan an object from many locations. This approach has proven its worthiness in surveying applications for instance in landslide characterization (Görüm, 2019; Zhong et al., 2019). LiDAR has the advantage of precisely measuring any target volume for geometry monitoring. This approach, however, is more costly, has a higher cost, is time-consuming, and laborious when compared to passive systems, making it less suitable for geometry monitoring.

Passive systems implement the multiple point of object view , using imaging cameras and geometry to reconstruct the scene, covering all digital photogrammetry techniques (Chiabrando et al., 2013). The process of reconstructing a 3D scene using Close-Range Photogrammetry (CRP) includes camera calibration, sequential image acquisition, feature correspondences, geometry, dense matching, surface modeling and texture matching (Khaloo et al., 2018; Popescu et al., 2019). SfM generates a 3D model of the target by combining a series of 2D images acquired by a sensor camera at various locations and estimating the relative camera's positions and orientations (Siddique et al., 2021). To merge the images and build the 3D model, corresponding points in the images are retrieved and matched. Depending on the camera sensor used, the 3D point cloud contains color and intensity information. Essentially, triangulation can compute the 3D coordinates of each point in the scene if they are shared by two or more photographs of known camera position and orientation. In the case of unknown position and orientation, there is a geometric restriction that must be satisfied to estimate them, called epipolar constraint (Khaloo et al., 2018; Masoumian et al., 2022). In contrast with active systems, which require more time for acquisition and the direct result is the point cloud, SfM requires less time for acquiring the images; but needs more time for reconstruction (Popescu et al., 2019). The point resolution achieved from SfM may be comparable to laser triangulation. However, it depends on the camera's resolution and number of images used for 3D modelling.

The advent and evolution of new technologies, such as TLS and CRP-based on Unmanned Aerial Vehicles

(UAV), aid in the acquisition of data, which leads to accurate and exact 3D representations of complex objects after processing. Even if numerous multi-surveys are used, no single sensor can provide comprehensive information on large and complex items. The combination of TLS and CRP-based on UAV techniques (Chatzistamatis et al., 2018; Luhmann et al., 2020) enables the creation of models of complex objects by employing each technology using specific settings that provide the best operating performance. The raw data received from these technologies may be used to produce point-clouds dense enough to provide a digital representation of the real object.

Popescu et al. (2019) assessed the performance of three imaging methods for 3D geometric modelling of existing concrete railway bridges: TLS, CRP-based on UAV, and infrared scanning integrated in a 3D camera. The findings showed that all the tested approaches can be used to produce 3D models, although at varying degrees of completeness. TLS and photogrammetry produced substantially denser data than infrared scanning. Denser point clouds improve visualization but need more processing time and storage. They conclude that photogrammetry is the best technology regarding cost-efficiency. Khaloo et al. (2018) created a 3D model of a bridge using CRP-based on UAV technique. This methodology enables inspection surveys as well as the precise anomalies monitoring. The results are compared to models created using TLS. The findings show that the UAV inspection approach surpassed TLS in terms of completeness and resolution, giving superior 3D models with the precision needed to fix problems and satisfy the infrastructure managers' demands. TLS has the advantage of capturing consistent point clouds without needing specialized engineering knowledge, if stable positioning and mutual overlaps are guaranteed. On the other hand, CRP-based on UAV can measure remote locations not accessible by TLS or terrestrial images and can fill gaps in point clouds if parts of objects are only visible from one measurement system. The high resolution of images compared to LiDAR can result in a higher quality textured 3D model.

Luhmann et al. (2020) and Chatzistamatis et al. (2018) developed a hybrid technique combining UAV photogrammetry and LiDAR to build an accurate 3D model of a historic church envisaging the damage assessment. However, the high precision of TLS in scanning civil engineering assets suggest it has a higher accuracy (geometry) than CRP-based on UAV. Currently, there is no work available on the application of hybrid processing techniques on railway bridges.

The data acquisition for railway bridges has a unique aspect in comparison to buildings concerning the UAV photogrammetry, namely the requirement of an upward camera to collect images under the bridge's deck. The number of UAVs with this specification is quite restricted. On the other hand, a TLS sensor does not have this limitation since it has ground support under a bridge and works within the data acquisition range. However, for security considerations, it is usually not permitted to operate over the deck.

Thus, this work intends to give innovative contributions to the thematic of the structural condition assessment of concrete railway bridges using advanced reality capture technologies, with special emphasis on the following aspects:

- The development of a reality capture framework in railway bridges employing a hybrid vision system, for which pratically no applications were found in the existing bibliography. Typically, the railway environment presents significant challenges to reality capture due to rigorous safety requirements as well as limited accessibility to bridge components and railway corridor.

- The establishment of a precise geometric and high-quality 3D image-based model of the condition state of an existing railway bridge using a CRP-based UAV and TLS, leveraging the capability of both technologies.

Methodology

The proposed methodology for railway bridge inspection uses a fusion of both active and passive vision systems to collect data, and is divided in four phases, as depicted in Figure 1.

The first phase, recognition and preparation, requires the collection of project details and a review of the target structure's inspection history. This phase also involves visiting the site to identify any potential risks, selecting technical staff and equipment such as TLS and UAV, and creating an acquisition plan that outlines procedures and permissions required.

In a second phase, data acquisition, a precision topographic survey of the structure's control points should be performed. This step is crucial for georeferencing and calibrating the point cloud data. Control points must be placed along the entire structure and can be marked with auxiliary targets or using significant points of the structure. The coordinates of these control points are obtained using GNSS receivers with RTK support and an electronic theodolite. To conclude phase two, the point cloud is captured using TLS and images are captured using an UAV. The TLS must meet specific requirements to provide high-quality point clouds and images, while the UAV shall preferably have high autonomy, obstacle proximity sensors, RTK positioning accuracy, and high-resolution cameras. Both data acquisitions must be done as close to the structure as possible for higher image resolution and should be performed safely.

The third phase, digital railway bridge, involves aligning the TLS point clouds and reconstructing a 3D geometric model of the structure using SfM techniques on georeferenced images captured by the UAV. The derived point cloud should be registered and exported to the desired format, with the removal of neighboring objects or background noise.

Finally, the fourth phase involves the condition assessment of the railway bridge by specialized experts. Surface anomalies can be easily visualized, and a virtual

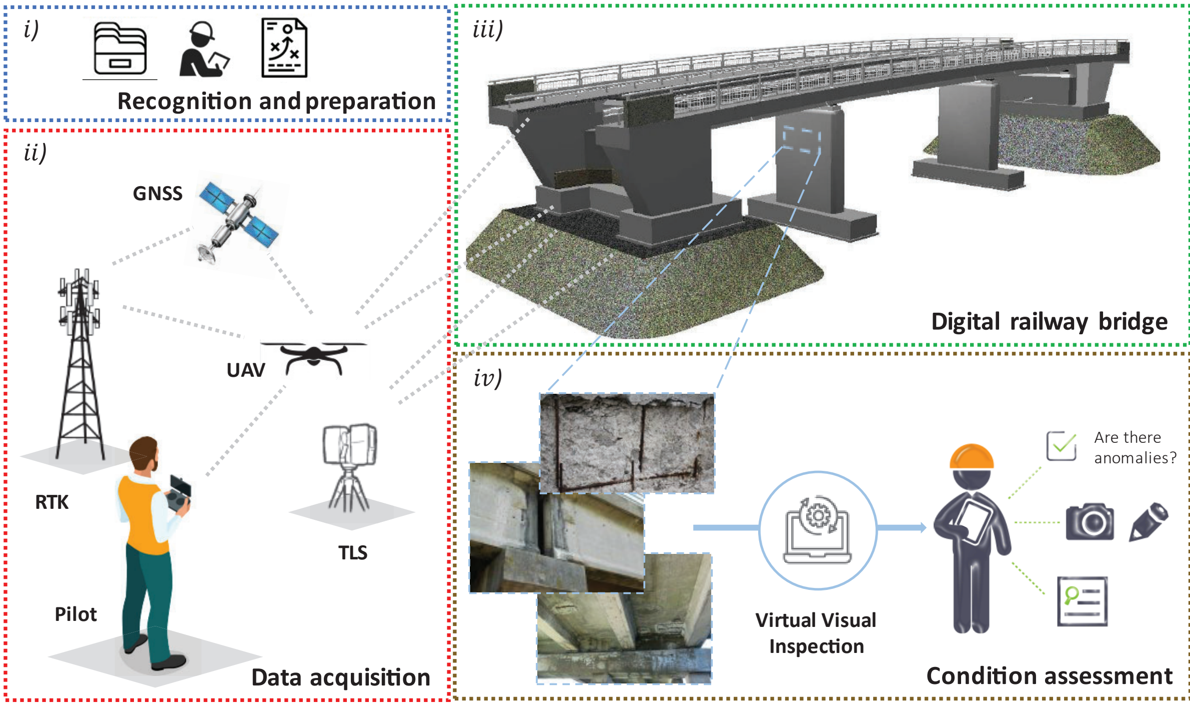


Figure 1: Methodology for railway bridge virtual visual inspection

inspection is performed over the digital model of the railway bridge. Also, the final report is created.

Technologies

This section discusses the technologies used for the reality capture adopting a data fusion process based on active and passive vision systems. In terms of hardware, TLS (active) and CRP-UAV (passive) devices were used, whereas the dedicated required software is discussed.

The TLS employed was BLK360 from Leica Geosystems. It has an integrated spherical imaging system and thermography panoramic sensor system. It allows to take photos and point clouds, which are then transferred by Wi-Fi protocol to a mobile device running Leica Cyclone Field 360 or locally saved to be later synchronized with Leica Cyclone Register 360. It is important to note that the Leica does not permit data to be synchronized outside Leica's software solutions. Leica Cyclone Field 360 is a mobile device app available for iOS and Android platforms, that is used to collect data from the LiDAR and process it into Leica Cyclone Register 360. The software manages the scanner's capture settings, examines scans and images data, and includes capabilities like tagging measurements, text, or audio files. The desktop solution for point cloud processing is Leica Cyclone Register 360, which gets the point cloud data either collected from the mobile app or scanning device and performs the synchronization by sharing the same IP address and network Port. This desktop software allows the user to handle projects with hundreds of scans without reducing performance and includes capabilities such as automated alignment (registration), measuring, and noise clean-up.

In terms of UAVs, the DJI Mavic 2 Enterprise Advanced (M2EA) equipped with a ½" CMOS sensor and a true focal length of 9 mm from DJI company, was used. This UAV includes a camera with enhanced quality, is lighter, and can avoid obstructions, allowing a safer flight. The outputs desired in this phase are images covering all structural components from all directions to be able to reconstruct the full structure. Being a passive vision system, it does not generate point clouds automatically. As a result, the photos captured by the UAV mounted sensor are used to perform a SfM technique for point clouds generation.

SfM technique may be used with a variety of commercial and open-source software packages capable of reconstructing scenes. ContextCapture, Pix4Dmapper, Agisoft Photoscan, and Recap are some examples of commercial software. The commercial software used for point cloud data fusion was ContextCapture from Bentley. It enables hybrid processing for the development of meshes, dense point cloud, orthophoto, as well as some AI detection tools that combine the best of both technologies, the versatility and convenience of high-resolution images, reinforced by the increased precision of point clouds.

Case Study

For the application of the methodology developed to railway bridge inspection, an extremity module of the west access viaduct to the Pirâmides bridge in Aveiro, in Portugal, inserted in the railway extension of access to the port of Aveiro, is the object of study. The module consists of four 25-m continuously supported spans for a total length of 100 m.

The bridge deck has a U-shaped cross section, with the bottom slab being 0.45 m thick in the center part, and 0.40 m thick at either laterals and connecting two main prestressed girders of 1.60 m high and 0.60 m wide. Each girder has a 0.60 m wide and 0.50 m height cantilever on the deck's wings serving as walkways.

Figure 2: Extremity module of the west access viaduct to the Pirâmides bridge in Aveiro, in Portugal

Data Acquisition

The railway bridge was marked with 50 Ground Control Points (GCPs) and 8 Automatic Tie Points (ATPs) for georeferencing and photogrammetry, respectively. These targets were placed mostly on the columns and deck directly on the concrete surface, as shown in Figure 3. The GCPs were measured using topographic support, while the ATPs allowed for automated image detection in ContextCapture.

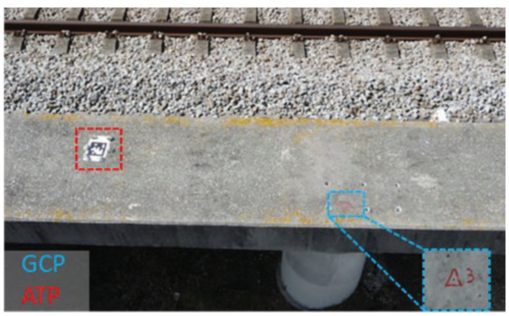


Figure 3: GCP and ATP marked over the railway bridge

The laser scanning was performed in high density mode, which results in a point spacing of 5 mm at a distance of 10 m. A complete scan, including panoramic image capture, takes about 5 min in this specific mode. Figure 4 shows the LiDAR system in operation. Table 1 provides an overview about the collected data.

Figure 4: LiDAR system in operation

The registration was done manually, followed by an optimization using the Iterative Closest Point (ICP) algorithm. The ICP algorithm is a traditional approach for rigid registration. It alternates between nearest point query in the target set and distance minimization between related points, and it is guaranteed to converge to a locally optimum alignment. The final registration had an average mean error of about 17 mm. Figure 5 shows the registered point cloud with the scan stations distribution.

Table 1: Laser Scan data

Parameter	**BLK360**
Stations	113
3D points (bill.)	2.9
Scan duration (h)	12
Mean resolution (mm)	9
Registration precision (mm)	17
Data Size (GB)	60.1

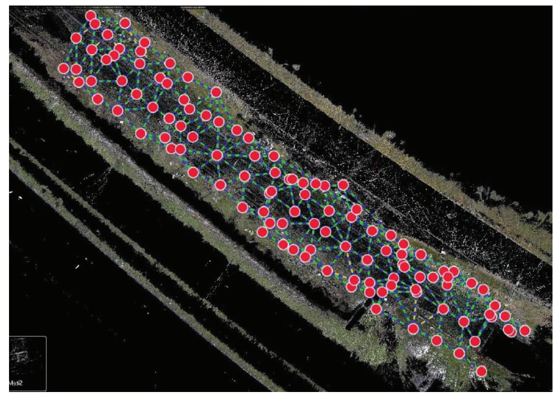


Figure 5: TLS station distribution (in red)

The M2EA has a maximum flight time of around 30 min and was operated by an experienced pilot in a stop-and-go mode, which allowed for stable image recording. A flight path with nadir photographs and oblique views was performed. Figure 6 shows the UAV in operation. Table 2 provides a summary of the essential flight data.

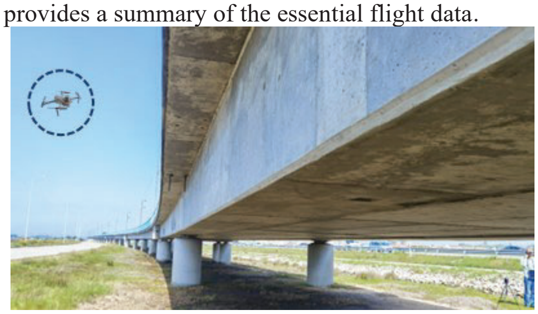


Figure 6: UAV in operation

In general, the image quality from the UAV flights was good in terms of sharpness and exposure, as demonstrated in Figure 7. However, some of the images were overexposed, especially on surfaces with high contrast, particularly the lower bridge deck surface. Despite this, the photogrammetric processing went smoothly, which can be verified by the good image quality.

Figure 7: Sample images from the aerial survey

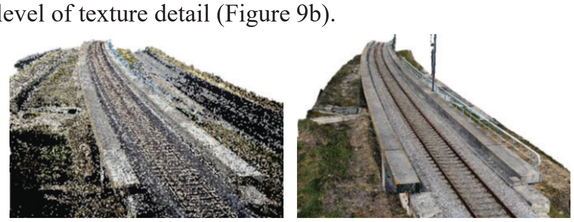
Table 2: UAV data

Parameter	M2EA
Images	3533
Focal length (mm)	9
Sensor size (mm)	6.4
Flight duration (h)	8
`Ground coverage (ha)	2.77
Mean GSD (mm/px)	1.04
Data size JPEG (GB)	45.9

Results

The data processing result in both a dense point cloud (Figure 8a) and a texture mapping (Figure 8b). Texture map allows to incorporate components in the scene reconstruction that are smaller than the distance between points in the dense point cloud. To carry out data fusion, a high-performance computer is necessary. In this case, an Intel i7-11700 8-core with 32 GB RAM and a Nvidia GeForce RTX 3090 24GB graphics card were used.

The model generated using TLS data in Context Capture encompasses the lateral and bottom deck parts of the railway bridge and features a high Level Of Accuracy (LOA) including the reconstruction of the catenary wires. However, the texture may not be as visually appealing compared to the results produced using high resolution images (Figure 9a). In contrast, the model created in Context Capture using UAV image data encompasses the lateral and upper deck components and presents a high level of texture detail (Figure 9b).

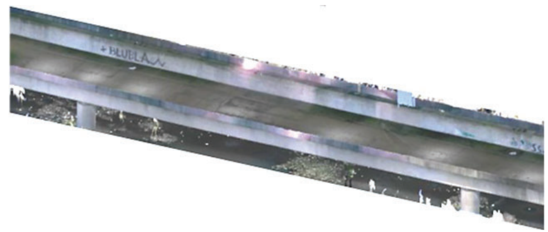


a) b)

Figure 8: Outputs: a) dense point cloud b) texture map

As a result, the goal was to develop a model that incorporates both types of data collection to create a fusion with information about the entire deck. LiDAR technology provided a detailed point cloud of the railway bridge's lateral and bottom deck portions, as well as the ground beneath the deck with mean resolution of 9 mm, equivalent to LOA30, while photogrammetry technology produced highly detailed lateral and upper deck portions with mean resolution (GSD) of 1.04 mm/px, corresponding to LOA40.

The integration of information from both collection techniques has been proven to be highly effective, with the potential to build a coherent georeferenced model. To validate the geometric survey, a comparison between the design (as-designed) and real geometry (as-is) of the deck's cross-section was performed as presented in Figure 10 with mean absolute error (MAE) calculated to be 2.73 mm, which shows the accuracy of the methodology and technologies used in this study. Figure 11 show the achieved results using Context Capture software, and some close images are presented in Figure 12 . It is important to highlight that the results of this study have significant implications for the industry, as they provide a powerful tool for surveying and monitoring large infrastructure projects such as railway bridges.



a)

b)

Figure 9: Model of Span's Railway Bridge: a)TLS data b)CRP-based on UAV data

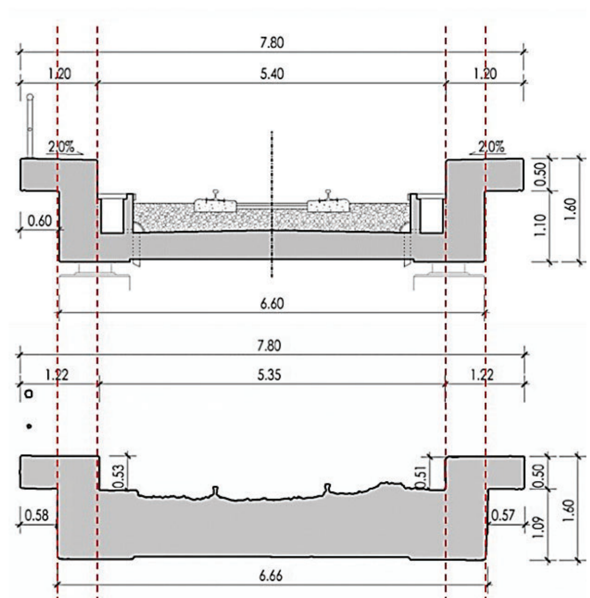


Figure 10: Cross-section comparison of the as-designed (top) and as-is (bottom)

Such a digital model could be used further for inspection purposes to identify single and multiple anomalies, typically related to concrete cracks and delamination; loss of material, water damage; corrosion, and degradation of bearings. All experimental information can be used further for the development, updating, and validation of numerical models of the bridges under service trains, envisaging the development of a reliable and accurate

Digital Twin (DT). DT allows a dynamic representation of the bridge, which includes a management model that acts as a link between the physical and virtual counterparts (Adibfar & Costin, 2022; Chiachío et al., 2022; Jeong et al., 2016). Alternatively, visual inspection or structural repair can be considered, although they require offline involvement (VanDerHorn & Mahadevan, 2021). A functional DT should be capable of simulation, learning, and management (Chiachío et al., 2022) and allow practical applications for Bridge Management Systems (BMS) (Jiang et al., 2021).

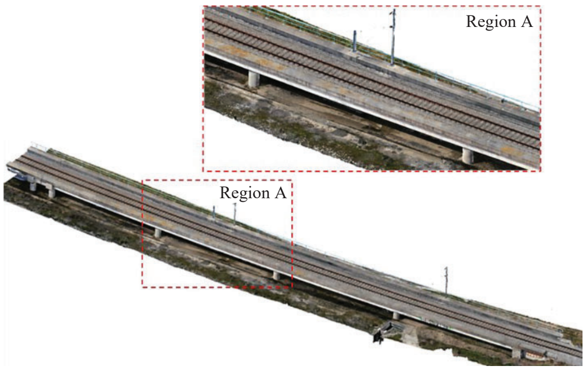


Figure 11: Reality capture of the extremity module of the west access viaduct to the Pirâmides bridge in Aveiro, in Portugal

Figure 12: Example images of 3D state output

Conclusions

This research article detailed all the procedures and challenges faced in conducting a survey and 3D modeling of a railway bridge through the integration of TLS and UAV-photogrammetry technologies. The aim was to generate a precise and realistic 3D representation of the railway infrastructure to be used on structural inspection and assessment of surface damages. The TLS method was used to collect data on the bridge's lower and lateral deck surfaces, while the UAV mounted camera was used to characterize the upper surface and laterals of the deck. The integration of the TLS and photogrammetric models, which is possible due to recent advancements in processing algorithms, resulted in a highly accurate 3D model of the entire railway bridge deck. As future investigations, the authors propose several areas for further research, including evaluating automat-ed UAV flights, automating tie points to speed up the registration process, and incorporating artificial intelligence for local automated damage identification. These research efforts aim to improve the accuracy and efficiency of the survey and 3D modeling of railway bridges using TLS and CRP-based UAV technology.

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