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Augmented reality-computer vision combination for automatic fatigue crack detection and localization

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ABSTRACT

Fatigue cracks in bridges are inspected visually by specialized bridge inspection professionals. Bridge inspectors conduct inspections in a limited amount of time, and at times small cracks may go unnoticed. Researchers have recently developed computer-based techniques to help overcome these issues. This study uses a computer vision algorithm combined with Augmented Reality (AR) to localize fatigue cracks during the visual inspection that otherwise may go unnoticed because of their size. The AR software utilizes a video processing algorithm for fatigue crack detection. Subsequently, the AR software generates a hologram using the algorithm's detection result and anchors it over the crack's location at the structure being inspected. The result of this new methodology is an automatic fatigue crack detection and localization AR software that provides holograms overlaid during the on-site visual inspection. This technique also provides the fatigue crack detection result in near-real-time. The method is verified using 2D and 3D benchmarks and a half-scale steel bridge girder specimen. The research team collected the feedback from bridge industry inspectors contextualized in real operations and their recommendations for integrating AR for inspections with the involvement of human resources and workforce development. This study is the first effort of holographic addressing the fatigue crack on the actual structure using AR headset.

1. Introduction

Aging infrastructure is associated with high maintenance costs necessary to ensure safety and functionality. Infrastructure managers traditionally employ inspectors who periodically conduct in-person visual inspection, to detect and evaluate structural defects, inform maintenance plans, and find any anomaly that may compromise safety. Inefficient or inopportune inspections may have significant consequences in terms of human life and/or economic impact (Zhu et al., 2010). A recent review reported in detail on the destructive effects of bridge failure on the human loss and economy underlined the importance of the frequent structural inspection (Zhang et al., 2022). Several factors influence the efficacy of periodic visual inspection (Phares et al., 2001; Megaw, 1979). These include, but are not limited to, human perception and sampling subjectivity. Marino et al. (2021) developed an AR tool to ease the design discrepancy detection for workers at the assembly line and to help them by merging holographic 3D annotations. In Structural Health Monitoring (SHM), researchers have recently proposed computer-based methods to assist human capabilities to improve the speed and efficacy of visual inspections. In these methods computer analysis power assists human for structural defects localization and quantification (Yasuda et al., 2022; Kot et al., 2021; Deng et al., 2022a; Spencer et al., 2019; Hu et al., 2021; Dong and Catbas, 2021; Zinno et al., 2022; He et al., 2022). Sabato et al. (2023) reviewed various non-contact sensing techniques and AI techniques, emphasizing on image-based methods for SHM highlighting their benefits and limitations. The authors aimed to conduct evaluations of various image-based SHM techniques and provide a comprehensive overview of their respective advantages and limitations.

Fatigue cracks can pose serious threats to the safety and performance

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of steel structures, and their detection and remediation, through monitoring, repair, and/or replacement, is of critical importance. Detection and monitoring can be accomplished by periodic field inspections. Although visual inspection is widely used for steel structural fatigue crack detection, this method is subjective. If fatigue crack growth goes unnoticed in a routine visual inspection, the structure's health is compromised. Therefore, it is significant to increase the ability of inspectors to objectively inspect fatigue cracks during their visual inspection.

Researchers have proposed various methods including vision and vibration-based techniques aimed at improving the speed and efficacy of structural damage detection with respect to crack localization and growth quantification. These methods can be divided into two general categories: (1) Vibration-based methods (Wang et al., 2021a, 2021b; Xiao et al., 2020; Liu et al., 2021; Chen et al., 2020) (2) Vision-bases methods. In the vibration-based approaches, researchers analyze signals acquired from installed sensors on a structure to locate and quantify structural damage based on the signal's variations. Sensors record the structural response under random or methodical excitation for further damage detection analysis using Artificial Intelligence (AI) techniques (Avci et al., 2021; Hou and Xia, 2021; Nick and Aziminejad, 2021). Amezquita-Sanchez and Adeli (2016) provided a comprehensive state-of-the-art for signal processing in SHM. While vibration-based techniques have been employed for various purposes in SHM, vision-based methods have recently gained attention from researchers. This is because of their advantageous features such as low cost, rapidity, non-contact nature, and minimal interference with infrastructure functionality (Dong and Necati Catbas, 2021).

Image or video-based computer vision methods use recorded videos or captured images from the damaged structure and analyze them through a variety of computer vision algorithms to find the location or extent of the structural damages (Deng et al., 2022b; Zhuang et al., 2022). Kong and Li (2018) proposed a crack detection and localization methodology based on analysis of short videos of the structure. They demonstrated that feature tracking technology of the developed algorithm was able to detect fatigue cracks with submillimeter accuracy in the presence of realistic factors such as dirt and welds. In another effort, Kong and Li (2019) proposed a new fatigue crack detection approach for steel structures utilizing image overlapping. Fatigue crack opening and closing behavior under cyclic loading was used as a detection indicator. Considering that approach fatigue cracks were successfully detected in the steel specimens by following the differential image features using image processing techniques. It is worth noting that the videos or images utilized in computer vision methods are typically obtained from fixed or handheld cameras, drones, or AR devices.

Numerous scholars have employed Unmanned Aerial Vehicles (UAVs) also known as drones, for inspection of infrastructures. By utilizing drones equipped with cameras, detailed images or videos of structures or infrastructures can be captured, which can aid in the identification of potential issues or damages. Dorafshan et al. (2018) examined the feasibility of fatigue crack detection in steel bridges using drones. In that study, they highlighted the importance of camera quality and surface illumination for fatigue crack detection and mentioned the challenges of using drones for visual inspection. Duan et al. (2023) proposed an accurate cost-effective method for full-scale bridge displacement measurement and damage detection using images captured via drone. Kumarapu et al. (2022) showed that UAV equipped with Digital Image Correlation (DIC) vision-based technique represents a rapid and cost-effective tool for bridges measuring deformations at inaccessible locations.

Although the utilization of drones in SHM offers several advantages, the application of AR for SHM has increasingly attract researchers' attention. Thus, they have conducted studies investigating applications of AR for infrastructure's inspection. Palmarini et al. (2018) investigated the use of AR as a practical tool to carry out administration, technical tasks, and decision-making for maintenance operations. They selected 30 AR-maintenance papers out of 732 published articles between 1997 and 2017 and pointed out that AR areas of improvement are comfortability, reconfigurability and authoring flexibility. More recently, AR advances have attracted attention for SHM applications. Li et al. (2018) published a critical review of the application of AR in construction safety, discussing the advantages that AR and Virtual Reality (VR) could bring to construction. Additionally, several researchers have deployed computer vision algorithms integrated within AR platforms and have utilized AR headsets as the interface of image-based methods for visual field inspection. Sadhu et al. (2023) published a critical review of the application of AR/VR in the inspection's industry, discussing the advantages that AR/VR could bring to construction. Additionally, several researchers have deployed computer vision algorithms integrated within AR platforms and have utilized AR headsets as the interface of image-based methods for visual field inspection. Wang et al. (2019) utilized a Deep Learning (DL) model in AR headsets for detecting structural behavior changes from an intact to damaged state caused by corrosion or fatigue. Moreu et al. (2017) discussed development and conceptual design of AR for structural inspection. In that study, they evaluated the AR's hologram generation capability and its impact on visual inspection in terms of defect visualization, virtual measuring, and documentation tasks. In another effort, Re et al. (2014) proposed an AR framework to visualize mechanical variations and crack growth in a real-time fatigue test. Malek and Moreu (2022) proposed an AR software deploying computer vision algorithm into the AR headset for crack detection and measurement. Thereby, they successfully applied AR-headset's limited analysis capacity for structural damage detection without requiring an external processing unit. A recent study proposes an AR and Artificial Intelligence (AI) based system emphasizing on some damage types in structures. The system achieves high accuracy in classifying and quantifying their severity and AR successfully implemented for in-situ visualization (Awadallah and Sadhu, 2023). Table 1 summarizes the advantages and limitations of AR in SHM.

Previous studies on the application of AR in SHM have demonstrated

Table 1
Advantages and limitations of AR in SHM.

Advantages	Limitations
• Enhanced visualization: AR can provide visual overlay of data and information in front of the inspector's eyes. • Enhance the inspector's perception: AR could improve human perception during the inspection by providing virtual information. • Hands-free: AR leaves the inspector's hands-free for climbing, writing, etc. • Cost-effective: Initial and further costs can be less than the traditional inspection methods. • Fast: Ability to provide real-time or semi-real-time information. • Processing: Ability to conduct simple processing. • Share data: Possibility to share the inspection results between the inspectors. • Training and education: Vast application in training new inspectors. • Documentation: AR could provide inspection evidence for proper inspection documentation.	• Cause fatigue: AR could cause neck fatigue for the inspectors after long term use due to its weight. • Distance: The inspector needs to stay close to the structure which may be dangerous in some specific situations. • Battery limitation: AR battery is limited and cannot withstand long term inspections. • Training: Inspectors who has no or low experience using AR need training or instruction manual. • Limited analysis capacity: The internal AR processing unit is unable to conduct complicated analysis. • Safety risks: AR may distract inspectors from the physical environment.

that AR can be a practical tool for enhancing the human's perception during visual inspection. Moreover, AR can generate real-time or near-real-time information based on computer analysis. This information can be delivered as text or shapes anchored or hovering in the virtual media in front of the user's vision. Malek et al. (2022). developed an AR crack detection technique that projects the crack's width with submillimeter accuracy in front of the inspector's vision in real-time.

The present study uses the orientation and hologram-generation capabilities of AR headsets to develop a new interface for computer vision techniques and fatigue crack inspection in steel bridges. Table 2 compares the advantages and limitations of the present study with other recent fatigue crack detection methods to disclose the authors motivation for implementing this methodology. In the current paper, the research team developed an AR software package to enhance inspector's perception during in-service fatigue crack inspections. The software's algorithm takes the following steps: (1) the inspector records a short video of a component suspected of having fatigue crack using AR developed software package through the Head Mounted Display's (HMD's) camera. This video should be recorded under ambient loading such as motoring traffic or train crossing event. (2) The software records the 3D coordinates of HMD's camera at the last video frame recorded as well as the direction of the inspector's vision. The 3D coordinates are the relative coordinates that AR spatial mapping records of the surrounding environment. (3) The AR developed software automatically transfers the video to a central processing unit through a prepared Structured Query Language (SQL) database (4) the software uses a video analysis fatigue crack detection method through a developed computer vision algorithm, creating feature points in the vicinity of the detected crack (5) then it transfers the feature points coordinates from the processing unit into the AR headset platform through the SQL database. (6) Digital hologram 3D-reconstruction using feature points received from the central processing unit by the HMD. (7) Hologram virtual anchoring and localization with a correct orientation using the last camera's position coordinates and vision direction information preserved in step 2 through innovative Auto Anchoring System (AAS) described herein.

Furthermore, the algorithm's complexity is optimized to achieve near-real-time results. The software presented in this manuscript automatically conducts the fatigue crack detection and localization: the AR headset records and uploads the video to the database; the computer vision algorithm automatically accesses the raw video, generates feature points through analysis, and uploads them back to database; finally, AR headset downloads the feature points result to project them on the

Table 2
Recent fatigue crack detection methodologies comparing with the present study.

Study	Methodology	Advantages	Disadvantages
(Dorafshan et al., 2018).	Fatigue crack detection using drones equipped by cameras.	• Out of reach inspections. • Keep the inspector in the safe zone.	• Difficult to use in adverse weathering conditions. • Hard to use in GPS[a] denied areas. • Fly limitations due to the privacy concerns and dangerous zones such as airports. • Drone certified pilot is needed.
(Quqa et al., 2022).	Fatigue crack detection using images analyzed by CNNs[b] and image processing techniques.	• Enhances the human's perception and their decision-making abilities. • Applicable to analyze the noisy images. • Off-grid application. • More result reliability due to the combination of two methods.	• Limited generalizability for different damage scenarios. • Depends on the quality of data. • Further computational analysis is needed after fatigue crack data acquisition. • Computationally intensive and time-consuming.
(Taher et al., 2022).	Fatigue crack growth monitoring and measurement using WLASS[c].	• Able to cover larger structural surface areas than traditional strain sensors. • Applicable for long term fatigue crack growth monitoring. • In-situ application.	• Pre-knowledge of the damage-prone area is needed. • Specialized data acquisition system.
(Zhang et al., 2021).	Develop a combined ML[d] and computer vision method for fatigue crack detection and growth calculation.	• Predict the fatigue crack growth. • Crack growth length and path calculation. • Semi-real-time result generation.	• Pre-knowledge of the damaged area is needed. • Prone to error and dataset bias. • A big database is needed for training and decrease the error. • Computationally intensive. • Sensitive to lightening condition.
(Zhai et al., 2022).	Solving the scarcity of fatigue crack detection training image by generating synthetic data.	• Doesn't depend on a big training set to provide accurate results. • Less sensitive to the lightning condition. • Applicable for different structural defect detection.	• Pre-knowledge of the damaged area is needed. • Depends on the amount and quality of the synthetic data to cover fatigue crack's full range of variation. • Needs training a deep fully convolutional network, which can be computationally intensive.
(Mojidra et al., 2023).	Computer vision video processing method under live loads for fatigue crack detection.	• Applicable for in-plane and out of plane fatigue cracks. • Robust against other crack-like surface features such as dirt, scratches, corrosion marks, etc. • In-situ application. • Time and cost effective.	• Depends on the resolution of the video. • Requires live load to trigger crack opening and closing during video acquisition.
The present study	Apply combination of computer vision video processing power and AR for near-real-time fatigue crack detection and localization.	• Semi-real-time hologram generation to virtually mark the fatigue crack's location on the structure. • Entirely automatized method that eliminate the inspectors need of computer knowledge. • Time and cost effective. • In-situ application.	• Needs calibration for each AR headset user. • Needs the inspectors in site and close to the structure for inspection.

[a] Global Positioning System
[b] Convolutional Neural Networks
[c] Wireless Large-Area Strain Sensor
[d] Machine Learning

Fig. 1. Microsoft HoloLens 2nd generation applied for this study.

Table 3
The AR headset's video recording camera specifications.

Resolution (Pixel[2])	Resolution (Megapixel)	FOVh[a] ()	Recording Rate (fps[1])
2272 × 1278	8	64.69	30

[a] Field Of View horizontal (degrees)

fatigue crack. The new algorithm is equipped with auto-awareness of the database, resulting on an uninterrupted inspection from the start of the video recording to the holographic crack detection and location. Finally, the method is verified using 2D and 3D fatigue crack's simulator benchmarks and a half-scale steel girder-to-cross frame specimen under out-of-plane cyclic loading.

2. Augmented reality (AR) headset

The research team utilized Microsoft HoloLens 2nd generation (HL2) for the current study purpose. This AR device can conduct 3D scanning (spatial mapping) of the surrounding environment, programming, and projection (Ungureanu et al., 2020). Spatial mapping, further described in the current paper, is utilized to find the correct place for hologram anchoring, which helps the software localize the structural fatigue crack. This device can satisfy this desire by generating and anchoring holographic information to the real world based on the user's needs in real or near-real time. Fig. 1 shows the device from two different angles labeling four depth cameras (two on each side), that enabling it to provide a high-quality 3D map of the surrounding environment.

Also, this device is equipped with two eye-tracking sensors for following the inspector's vision and a high-quality camera to capture photos or record videos of the real environment. Moreover, This AR headset is able to blend the real and virtual medias and provide photos and videos of surroundings, including the virtual information anchored. In this study, researchers benefit from the device's camera to feed the computer vision algorithm with high-quality videos. Table 3 provides this device's web camera specifications.

3. Architecture of the methodology

Fatigue crack growth occurs due to repeated loads exerted on the structure during its service life (Richard and Sander, 2016). Detecting fatigue crack opening with the naked eye is difficult during visual inspection so, this kind of crack could go unnoticed. Therefore, the research team developed a near-real-time method for fatigue crack detection and localization by generating holograms presented in AR. In addition, the research team utilizes the video stabilization method presented in Mojidra et al. (2022). to compensate the head movements while recording.

The authors provide an outline to achieve the goals mentioned in this paper. Fig. 2 schematically shows the researchers' outline. At the first step the inspector needs put on the HMD and run the software developed. Then, utilizing the software to record a short video from a fatigue crack suspected area and send the video to the developed computer vision algorithm for further analysis and detect the fatigue crack. The AR headset then holographically projects the algorithm's analysis result in front of the user's view. Meanwhile, the innovative projection method anchors the hologram in the correct position and direction which is further described in the section titled "Auto Anchoring System (AAS)" of the present study.

The AR software automatizes this procedure. Automatic workstream makes the software's application user-friendly for the users. The research team provided a SQL database to collect the information between all the components of the project. Also, Wi-Fi technology has been utilized to provide connection between all the proposed method's components. The inspection sequence is initiated by hitting a button in the AR's virtual media on the software's menu (Fig. 4).

Fatigue crack opening and closing under cyclic loading distinguishes this crack from the other types. Mojidra et al. (2022). developed a computer vision-based algorithm that uses feature point tracking to detect fatigue cracks opening and closing in a recorded video. The algorithm compensates for camera motion and distinguishes these motions from fatigue crack movement. Hence, the method is suitable for unstable recording situations, as is common with drones or HMDs. The fatigue crack detection algorithm was constructed using MATLAB software. More information about the algorithm is provided in Section 6 of the present study.

In addition, AR technology can provide real-time or near real-time information for the inspectors to improve their perception during the visual inspection. Therefore, the inspectors can see the computer vision algorithm's video analysis results in front of their eyes during visual inspection. Hence, the research group uses AR HMDs for both video recording of the structure under cyclic loading and holographic projection of the analysis result.

3.1. Software's design logic

To meet the goals of this study, it is imperative to construct (1) a

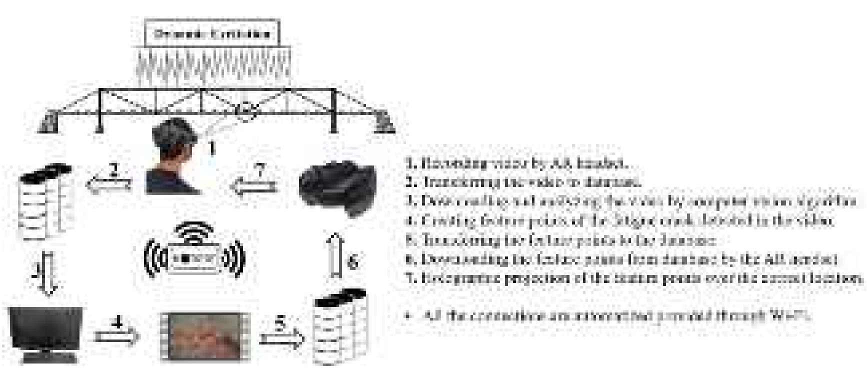


Fig. 2. Proposed method's architecture.

computer vision algorithm capable of video analysis for fatigue crack detection and localization, (2) an AR software to record the video and display holographic representations of the algorithm's analysis results, and a database to store data between the algorithm and AR software. Additionally, a dynamic connection is necessary to automate the process and create a user-friendly system. To this purpose, the development team utilized Wi-Fi technology, which is fast and applicable in areas without network connectivity. Fig. 3 illustrates the design logic of the software, depicting the three components, their functioning, and their interconnections.

As depicted in Fig. 3, the design logic starts and ends within the AR headset part, which implies that the user is not required to possess specialized expertise in computer vision algorithms to utilize the software. Additionally, the database serves as an intermediary connecting the AR and computer vision algorithm, necessitating a dynamic two-way connection with both components.

4. AR software

The research team used C-sharp (C#) programming language and Unity game engine to develop an AR software and deploy the application into the AR device. Fig. 4 shows the software's virtual menu from a view through the AR headset. The authors developed three virtual buttons, a virtual slider, a timer and one digital distance indicator related to inspector's need and software functionality. Each button is accessible by the inspector's virtual hit or hand tap in the AR virtual environment. Moreover, the virtual menu is programmed to pop up automatically when the user runs the software. In this way, the inspector doesn't need to take any action to bring up the virtual menu.

4.1. Floating menu button

The floating menu button shown in Fig. 4 switches the virtual menu between flying and hovering modes. The virtual flying menu refers to how the menu follows the inspector's movement during the inspection. The research team developed this button to improve the inspector's comfort during visual inspection, as the floating button eliminates the inspector's need to manually move the menu during the inspection and leaves the inspector's hands free for other tasks. The virtual menu's hovering mode is appropriate when the user is trying to inspect a specific part of the steel structure. By switching the virtual menu to the hovering mode, the inspector can manually put the virtual menu in the appropriate position.

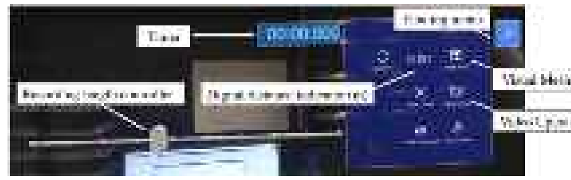


Fig. 4. Software's virtual menu (AR headset's view).

4.2. Visual mesh button

The "Visual Mesh" button is accessible on the top right part of the software's virtual menu (Fig. 4). The research team developed and added the visual mesh button to the virtual menu based on the headset's understanding of the surrounding environment, referred to as "spatial mapping." This button enables the user to see every object that the HMD analyzes as its 3D surrounding environment, enabling the inspector to verify that the AR headset is analyzing the appropriate surface during the inspection. Fig. 5 shows the spatial mapping of the half-scale steel bridge specimen utilized for the software's indoor testing. This figure shows the level of detail captured by AR device, which is well-suited for the spatial mapping of surfaces. In addition, the mesh generated in Fig. 5 shows the AR headset's ability to provide a detailed representation of the steel structural element surfaces.

Fig. 5. Visual mesh button shows the HMD's representation of real-world surfaces _ steel girder test setup.

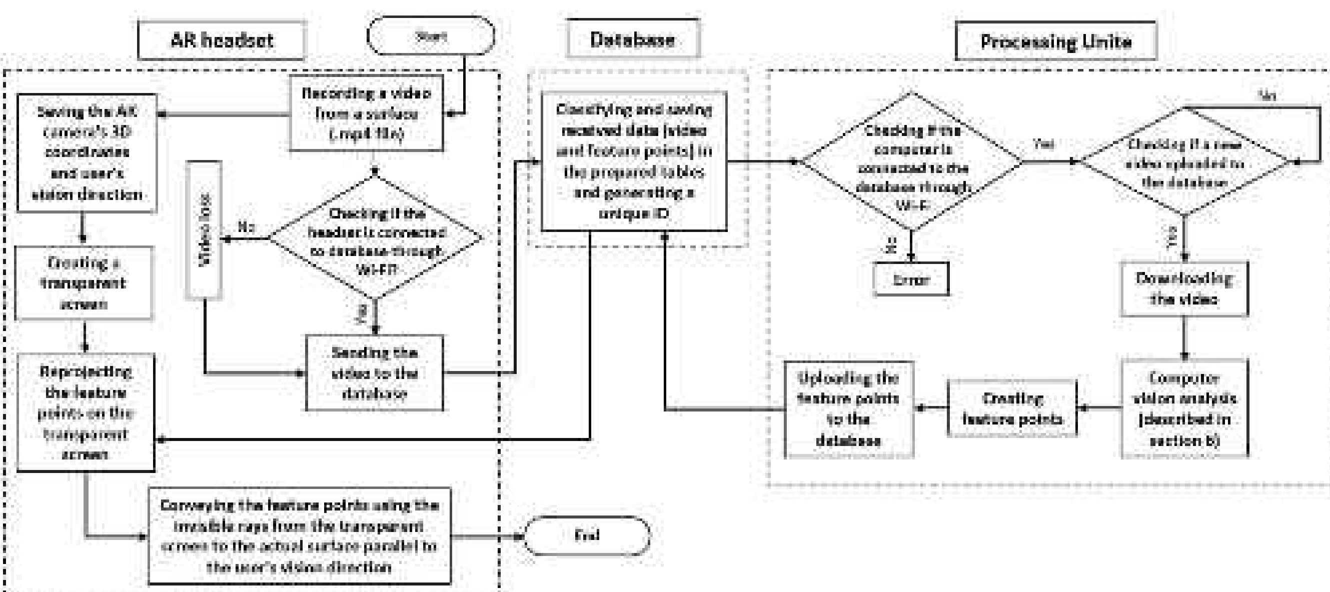


Fig. 3. System's components, their functionality, and interconnections.

4.3. Video upload button

Based on the software's outline (Fig. 2), the computer vision algorithm uses short videos to analyze and localize fatigue cracks. The AR device records a short video including camera 3D coordinates and the direction of the inspector's vision vector in the last video frame. These coordinates correspond to the headset's spatial mapping of the surrounding environment. These data are automatically saved in the AR software developed. Additionally, the research group automatized a connection between the computer vision algorithm and the database, so the algorithm automatically detects new videos uploaded to the database through the AR headset. The computer vision algorithm analyzes the recorded video and provides feature points of the detected fatigue crack, then uploads the feature point coordinates back to the database. This procedure is further described in the Section 6 (Video analysis algorithm).

At the next step the software automatically detects a new group of feature points uploaded by the algorithm to the database. The AR device creates a hologram using the grouped feature points and projects it based on the feature points coordinates over the fatigue crack in the correct location and orientation using the camera coordinates and the inspectors vision direction vectors. For this purpose, the software uses an innovative projection method called AAS, further described in the Section 7 (Auto Anchoring System (AAS)) of the present effort.

From the use perspective, the inspector therefore just needs to hit the video upload button in the AR's virtual media and look at the fatigue-prone area under active traffic loading. In this way, the inspector records a video for a short period of time while the structure or infrastructure is being loaded; then, the software takes care of the rest and projects a hologram over the fatigue crack if there is any.

4.4. Digital distance indicator

The research group developed a digital distance indicator, shown in Fig. 4, to represent the distance from the user to the closest perpendicular surface. This indicator helps the inspector maintain the appropriate distance from the surface, enabling recording of high-quality video for the analysis and providing the best holographic result possible in terms of the perpendicular distance to the surface described in Section 8.4.2 (Distance analysis). The digital distance indicator shows the user's perpendicular distance from the front surface in real-time.

The research team conducted several experiments to verify the digital distance indicator's accuracy and reliability. To ensure reliable results, the experiments were conducted at distances ranging from 0.25 m to 1.60 m in 0.05 m increments. The minimum distance of 0.25 m was chosen because it is difficult to read the digital distance indicator at closer distances. Each experiment was repeated three times, and the AR headset rebooted between each trial to recreate the spatial mesh. "Fig. 6 (a) provides a representative example of the experiments conducted. This figure depicts both the AR view and a third-person view from above, along with a tape measure used as the ground truth. To ensure the perpendicularity of the tape measurer to the surface, a triangle and a leveler were used. Fig. 6(b) displays the average error and standard deviation for all experiments. No error rates higher than 5% were observed, indicating a minimum of 95% accuracy for the digital distance indicator. It should be noted that the experiment was not carried out beyond 1.6 m due to the inadequacy of these distances for visual fatigue crack inspection.

4.5. Virtual recording length controller slider and timer

The research team developed a virtual slider enabling the user to control recorded video length. By means of this virtual slider, the inspector can modify the recording length in the range of 0–10 s. Although longer videos have a greater number of frames, which may result in more accurate outcomes, they also increase the processing time of the software to deliver the holographic result. Consequently, this study has examined the relationship between video length and processing time in the Section 8.4.1 (Time analysis).

Moreover, the virtual timer feature demonstrates the total processing time of the software from the moment the inspector virtually hits the "Video Upload" button until the hologram is visible. Thus, the inspector can monitor the time required for the software to provide the result on the crack and can adjust the processing time by adjusting the video length using the virtual slider.

5. Database and Wi-Fi connection

Databases have the capability to store thousands of Tera Bytes (TB) in several subjects and enable industrial managers and stakeholders to analyze, follow and decide based on the mined information from those data. In this study, the authors established an SQL database and used the Wi-Fi hotspot to connect each of the software components (algorithm, database, and AR device) as shown in Fig. 2. All connections provided are two-way connections, enabling the software to send and receive data from all of the components. For this purpose, the development group provided three different tables in the SQL database, as shown in Fig. 7, with each table performing a specific task. The “preprocessed_videos” table stores the short video recorded by the AR headset using the "Video Upload" virtual button. The software sends the video to the database through Wi-Fi. The video analysis algorithm downloads the video and analyzes it to detect a possible fatigue crack from the recorded video and generate feature points if any fatigue cracks are detected. Then, the developed algorithm sends the feature points' coordinates back to the database through the Wi-Fi connection. The “postprocessed_data” table (Fig. 7) receives the feature point's group to generate a hologram and project it laid over the actual fatigue crack in headset's view. The “lastframe_transform” table (Fig. 7) is a part of the innovative AAS,

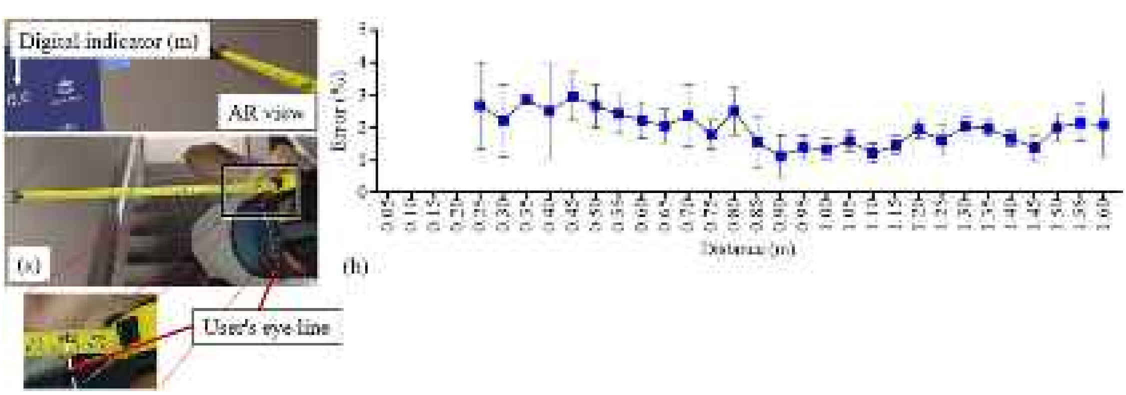


Fig. 6. (a) representative experiment and (b) error percentage versus distance graph for all the experiments.

Fig. 7. The SQL database established to connect different software's components.

which helps AR device to holographically project the hologram. It is worth noting that, all steps are done automatically without any need for user intervention.

6. Video analysis algorithm

The computer vision algorithm used in the current study uses feature points tracking approach for fatigue crack detection which is based on Mojidra et al. (2022) surface-motion-tracking-based fatigue crack detection methodology that is extended from the method by Kong et al. (Kong and Li, 2018) to compensate for camera movement. Also, Mojidra et al.'s method utilizes the Shi algorithm (Shi, 1994) to analyze the recorded first video frame for detecting the surface feature points based on the pixel intensity gradient change. Then, the Kanade-Lucas-Tomasi (KLT) (Suhr, 2009) method is utilized to track feature point displacements across the video frames. Finally, to localize the fatigue crack, the algorithm analyzes motion patterns of grouped feature points in Local Circular Regions (LCR) by computing the Standard Deviation (SD) of the displacement magnitudes of the feature points. When the obtained value exceeds a predefined threshold, it indicates the LCR contains differential motion patterns induced by opening and closing of the fatigue crack, and the algorithm keeps those feature points as a crack neighborhood area; otherwise, those points are eliminated by the algorithm. In this way, the algorithm keeps the feature points in the vicinity of the fatigue crack because the crack opens under cyclic loading. At this point, the LCR is predetermined by the developer team. So, the user cannot change the LCR and check and compare various hologram results created. It would be a further step for the prospective researchers to enable the user to toggle through different LCR results and choose desired one(s) for saving and documentation.

It is worth noting that, despite the numerous uses of deep learning techniques in detecting cracks and their extensive scope, the present study's objectives are better suited to the feature point tracking approach employed here, as it possesses the qualities of resilience and rapidity in identifying fatigue cracks and generating feature points (Mojidra et al., 2023). However, future research may explore the application of deep learning algorithms for the current approach instead of feature points tracking method and quantitatively and qualitatively compare the results.

Based on the needs of this project, the development team added two

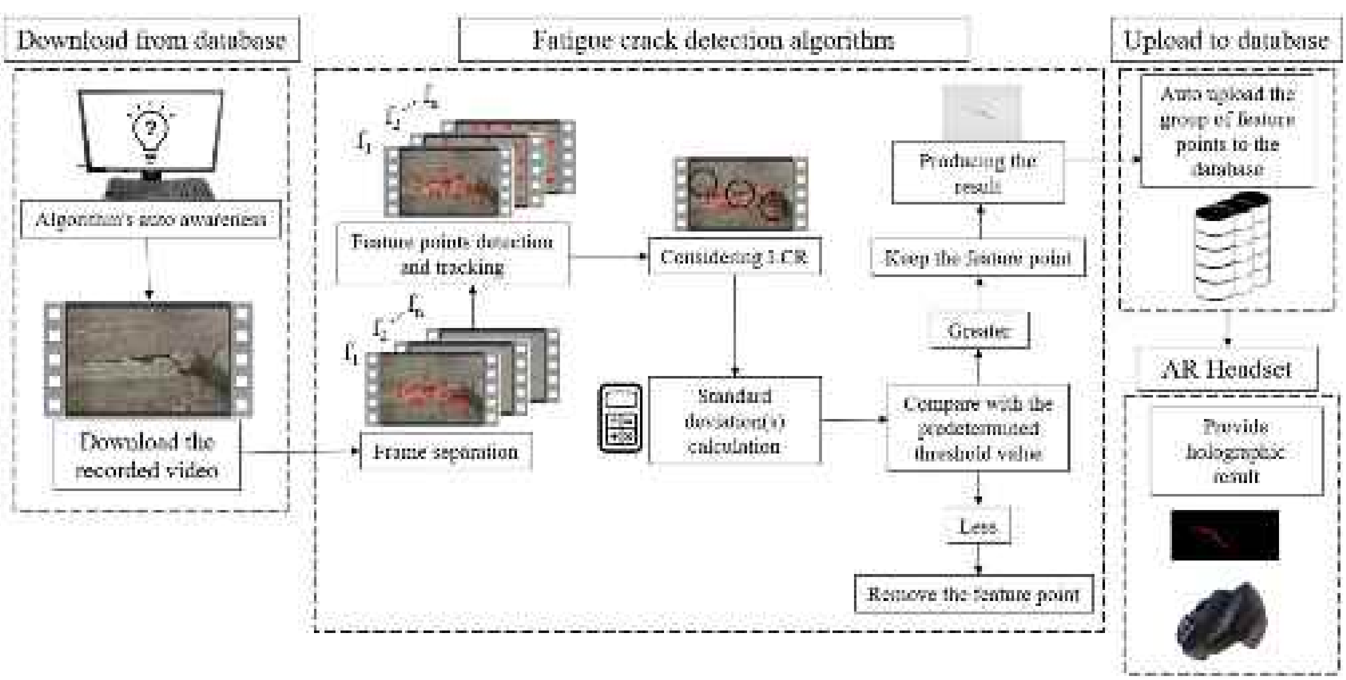


Fig. 8. Computer vision algorithm.

more features to the algorithm developed by Mojidra et al (2022).:

1. The algorithm's smart awareness of database to download the last video uploaded to the database through HMD.
2. Transferring the feature points to the database for further hologram generation in HMD and holographic projection.

Fig. 8 clarifies the entire computer vision algorithm and the automatized connection procedure schematically: the algorithm detects and downloads the video, analyzes it, provides feature points, and uploads it to the database.

7. Auto anchoring system (AAS)

The research team designed and developed an innovative AAS to achieve automated anchoring and hologram surface projection. For this purpose, the authors benefit from the innate ability of HL2 to conduct a 3D analysis of the surrounding area called spatial mapping. Fig. 5 represents spatial mapping, otherwise called "mesh" in both "on" and "off" modes. The software produces a hologram using the algorithm's feature points resulting from the video analysis and anchors it on the expected surface using the headset's spatial understanding of the surrounding environment. Although the AR device provides reasonable 3D mapping of the surrounding area, the development team still had two challenges:

1. Identification of the correct surface of the hologram's anchoring (crack's location), and
2. Anchoring the hologram directly over the crack in the correct position and orientation.

To solve these challenges, the research team developed a virtual transparent screen parallel to the surface that the last video frame has been recorded by the AR headset's camera. The research team prevents placement of the virtual transparent screen behind the cracked surface considering the camera 3D coordinates collected earlier. Therefore, the virtual transparent screen virtually hovers in a constant position parallel to the last video frame's surface somewhere between camera's 3D position and the actual cracked surface.

Fig. 9 shows the innovative AAS schematically. Fig. 9(a) displays the software's recorded data from the last video's frame, including the 3D coordinates of the camera position and the direction of the inspector's vision. Additionally, the Fig. 9(b) depicts the innovative anchoring method of the hologram on the surface using a virtual transparent screen, feature points, and invisible rays. The virtual transparent screen is the preliminary place for the holographic anchoring. Although this screen is the preliminary place for the hologram's projection, the user cannot see it, or hologram due to its transparency. In the next step, invisible rays are developed to convey each hologram feature points from the virtual transparent screen to the cracked surface. The start point of each invisible ray is the feature points on the virtual transparent screen and their endpoint is the hit-point with the first AR headset's spatial map surface detected noting that all of the invisible rays are parallel to the inspector's vision direction. Therefore, the software anchors the hologram on the crack in the correct direction and orientation. Moreover, if the inspector could clearly see the crack's opening and closing the hologram projection system may anchor the hologram in the right location because the projection system developed is independent of the user's angle. Similarly, the method can holographically localize out-of-plane fatigue cracks as well as in-plane ones.

8. Proof of concept evaluation of prototype

Proof-of-concept evaluation tests were first performed for 2D and 3D benchmark cases to evaluate, debug, and update the software. Subsequently, the team verified the prototype application with tests performed on a steel girder specimen with an actual fatigue crack occurring in a complex 3D geometry.

8.1. 2D and 3D proof-of-concept evaluations

Fig. 10(a) and (b) show a schematic and photographs of the preliminary 2D and 3D benchmark evaluations, which were conducted to support software development, debugging, and tests. These setups consisted of a simulated crack subjected to planar cyclic loading to mimic the fatigue crack's behavior. The software records a short video of the benchmark while the simulated crack is opening and closing under the cyclic loading, then the software automatically sends the video for further analysis to the developed algorithm. Fig. 10(a) represents the 2D benchmark and its simulated crack, feature points, and the result on the benchmark through the AR headset's view with the auto-generated hologram anchored over the simulated crack in the correct direction. The feature points are the preliminary fatigue crack detection algorithm's analysis result. The hologram is the product of those feature points made by the software and anchored over the simulated crack using AAS. In fact, AAS projects the feature points as a hologram and anchors it in the right surface over the simulated fatigue crack. This benchmark is called '2D' due to its planar surface. Therefore, the simulated crack opens and closes in-plane, and has no out-of-plane movement.

The research group prepared a similar 3D benchmark evaluation during software development to consider the performance of the software in an out-of-plane surface, as majority fatigue cracks in actual steel bridges occur at connected joints orthogonal surfaces. Fig. 10(b) shows a schematic and photographs of the 3D benchmark evaluation, configured using a folded surface with a simulated fatigue crack. Again, cyclic loading opens and closes the simulated crack to mimic fatigue's behavior. Fig. 10(b) represents the feature points generated by the fatigue crack detection algorithm and hologram laid over the simulated crack in the correct orientation through the AR headset's view. This figure shows that out-of-plane surfaces do not affect the software's

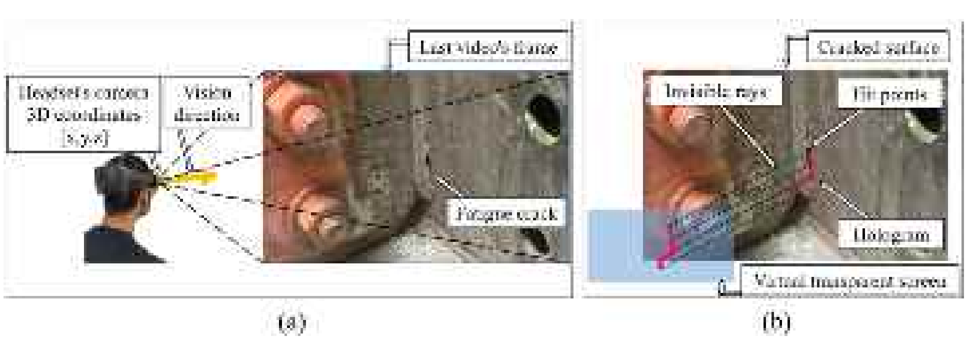


Fig. 9. Auto Anchoring System (AAS). (a) The 3D coordinates of the headset's camera and the direction of the inspector's vision from the last video frame are collected and transferred to the database. (b) innovative holographic anchoring method to anchor the hologram on a fixed position.

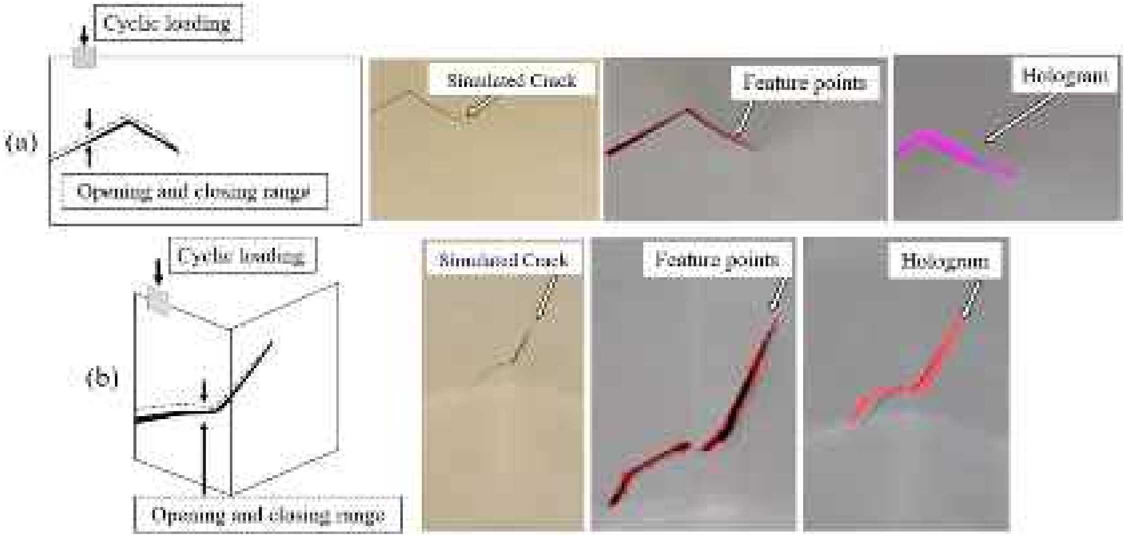


Fig. 10. Benchmarks (a) 2D (b) 3D. In both results, the first photo from the left, after the schematic figure is the actual simulated fatigue crack, and the next photo shows the video analysis algorithm's preliminary results (feature points), which detect the simulated fatigue crack's edge. Finally, the last one is the hologram anchored over the simulated crack in the correct orientation from AR headset's view.

ability to generate the feature points and anchor the hologram in the correct surface. Therefore, it means that the software is applicable for out-of-plane simulated crack situations.

8.2. Evaluation of the hologram anchoring in different distances

Researchers conducted an experiment to ensure the AAS's ability to fix the hologram on the simulated crack's surface. For this purpose, the research team conducted an AR crack detection test using a benchmark. Then after generating the hologram, the user moved back to evaluate the hologram's movement while getting further from the simulated crack's surface. Fig. 11 shows this test's result in 0.5–2.0 m distances from the benchmark. This figure shows the hologram's permanent location while the inspector moves back. Accordingly, the hologram keeps its fixed location based on the global coordinates that the AR headset scans by its spatial perception ability. Therefore, the user does not need to get close to the surface for seeing the hologram or be worried to look around before the holographic projection. Also, this ability enables inspectors who want to share their crack detection results using this software with others.

Additionally, it should be noted that the hologram produced through computer vision algorithm can maintain its stationary position regardless of whether it remains within the inspector's field of view or not, owing to the software's innovative anchoring method. This anchoring feature allows the hologram to remain fixed in its position as long as the headset retains the 3D map of its surroundings. Consequently, the inspector would be able to observe the hologram in its correct spatial orientation from any location offering a direct line of sight to the anchored surface.

8.3. Evaluation of software using half scaled steel girder specimen

After benchmarking both 2D and 3D developments in the laboratory, the research team evaluated the software performance on a realistic, half-scale steel bridge girder-to-cross frame specimen in the structural engineering laboratory. Fig. 12(a) represents the girder specimen includes a distortion-induced fatigue crack at the welded connection between the girder web and connection plate, similar to that found on

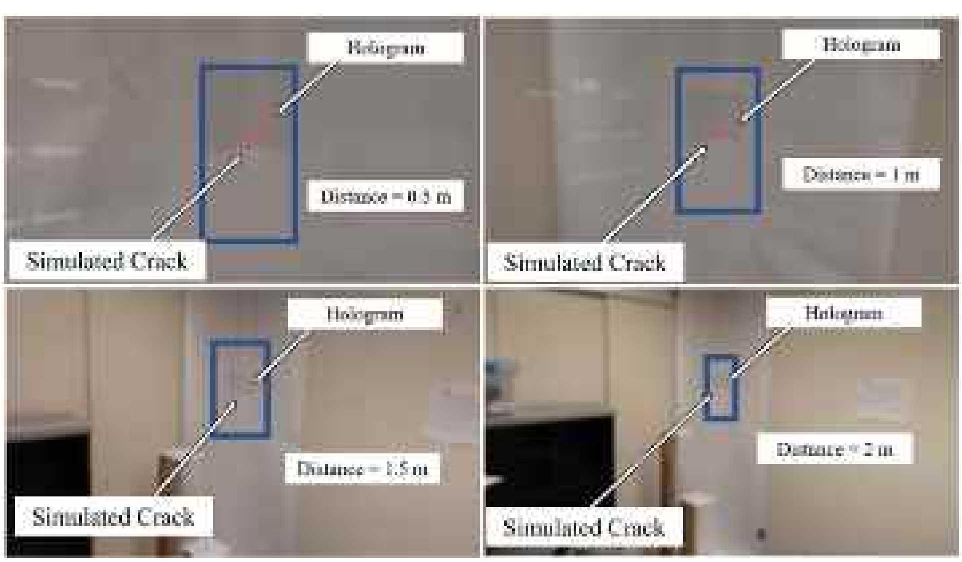


Fig. 11. Hologram anchoring test in different distances using 3D benchmark.

Fig. 12. (a) girder specimen, including an actuator (b) fatigue crack opening and closing under actuator's cyclic loading (c) indoor AR developed software testing.

many older steel highway bridges. The cyclic loading exerted by a hydraulic actuator connected at the far end of a cross-frame simulates ambient highway traffic or train excitation and creates realistic fatigue crack opening and closing. A detailed description of the test setup and girder geometry is provided in Al-Salih et al. (2021). Fig. 12(b) shows the fatigue crack opening and closing during applied cyclic loading; the loading was controlled to be a reasonable representation of fatigue crack opening displacements in practical applications. In this evaluation, the research team attempted to identify and locate the fatigue crack using the developed software. Fig. 12(c) shows the researcher testing the developed AR software wearing AR headset. Because of the fatigue crack openings were more realistic (smaller) in this application than in the 2D and 3D benchmark evaluations, the laboratory girder specimen is a more demanding application for the developed AR software.

Fig. 13 shows the holographic positioning of the experiment in two of the evaluations. The difference between the two cases is the inspector's head position distance to the cracked surface. Fig. 13 (a) depicts the fatigue crack placement in the steel specimen, (b) the inspector's head position distance is roughly 0.50 m, and in (c), it was approximately 0.30 m. In both cases, the AR software holographically addressed the crack's position in the specimen and detected some feature points which could be interpreted as a fatigue crack existence.

The holographic points correctly localize the fatigue crack on the steel specimen. The disparity of feature points in Fig. 13 (b) and (c) is caused by the surface anomalies. The holographic feature points projected out of the fatigue crack's margin are actually false positive points that caused by surface anomalies. Differentiating between surface anomalies and actual fatigue crack edges could be a potential further step for the prospective researchers.

8.4. Quantitative investigations

Quantitative analysis is necessary to validate the results and the variability of solutions. The following three sections quantify the success of crack detection by optimizing (1) video length; (2) best distance for simulated crack detection, and (3) simulated crack width. The fourth section of this investigation tests a complex simulated crack shape and its effect in the crack detection ability of the proposed methodology.

8.4.1. Time analysis

Fig. 14 presents an overview of the procedural duration necessary for the inspector, from the virtual activation of the "Video Upload" button in the software's menu until the moment of hologram overlay on the crack.

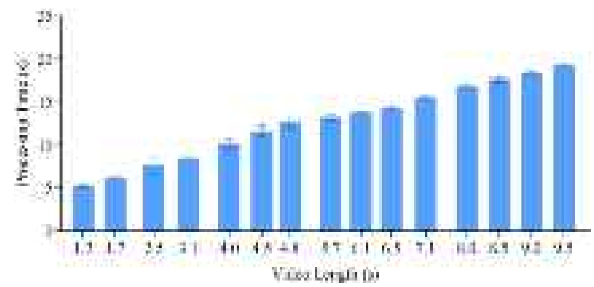


Fig. 14. Software's processing time versus video length in seconds.

The graph illustrates the processing time versus the recorded video length. Although, the processing time depicted in this figure highly depends on the number of video frames, other factors such as database query and transferring time, and the number of feature points detected in each test have direct effect on the software's processing time. That's why the result acquired in Fig. 14 is approximately linear. Noting that, Fig. 14 may be variable based on the central processing unit's capabilities and speed of analysis. It should be noted that the analysis was executed using a laptop with the following specifications: Intel(R) Core (TM) i7–9750 H CPU @ 2.60 GHz 2.59 GHz, NVIDIA GeForce RTX 2060, and 16 GB Ram.

Fig. 14 displays the mean of five experiments for each bar, which appears to be sufficient considering the low variability in the standard deviation (with maximum and minimum values of 0.97 and 0.09, respectively).

Fig. 15 shows the hologram result on the simulated crack related to

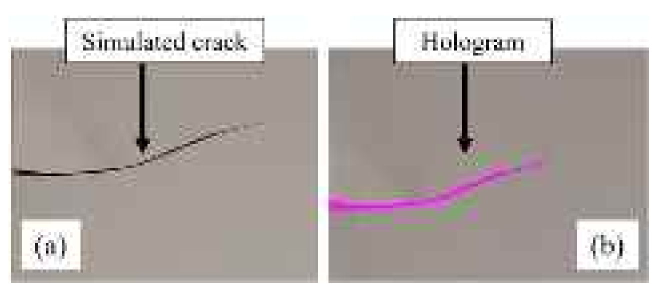


Fig. 15. The hologram anchored on the simulated crack for video length correspond to 4 s (a) actual simulated crack (b) virtual view.

Fig. 13. Holographic positioning of crack on the half-scale laboratory steel girder specimen (a) fatigue crack placement (b) hologram positioning of the fatigue crack with approximate head position distance of 0.50 m and (c) 0.30 m.

4 s video length. Based on the Fig. 14 approximately 10-second delay is needed for the inspector to see this result. In addition, the hologram in Fig. 15 shows most of the simulated crack is detected and could be considered as an acceptable result. Therefore, a video length of 4 s can achieve a trade-off between processing time and the quality of the hologram produced on the surface. As a result, an inspector would only need to allocate around 10 s to observe and record the hologram result. It is important to note that all subsequent quantitative analyses were based on a video length of 4 s.

8.4.2. Distance analysis

The inspector's proximity to the infrastructure is a crucial parameter in visual inspections due to safety concerns and the difficulty in reaching certain surfaces. In this section, the authors demonstrate the efficacy of the methodology in detecting and accurately placing holograms at different inspector to surface distances. Fig. 16 illustrates the experiment results obtained from varying distances. Notably, the results presented in this section differ from those in Section 8.2, which evaluate the software's ability to anchor the hologram in a fixed position after projection. In contrast, the present analysis focuses on the inspector's proximity to the cracked surface before conducting the experiment.

While Fig. 16 can assist the user in adjusting their distance to the cracked surface, more extensive quantitative analyses are required to establish the optimal distance for inspection purposes. As illustrated in Fig. 17, the quantitative analysis was conducted based on the score calculated through Formulas 1–3 initially proposed by Fawcett (2006). The values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are calculated through counting the number of the pixels through the length of the simulate crack and relative holographic result.

Considering Fig. 17, 0.5 m distance to the surface provides the best hologram result for the purpose of this study. Therefore, this distance has been considered for the following experiments.

8.4.3. Simulated crack's width detection ability

In this section, an evaluation of the proposed methodology's capability to identify minimum crack width is presented, using a simulated crack specimen. The effectiveness of the method to detect and generate a hologram for the thinnest simulated crack is assessed by creating benchmarks with different widths, starting from 0.25 mm (0.01 inch). Subsequently, a series of experiments were conducted by the research team on each simulated crack, using the aforementioned time and distance parameters (4 s and 0.5 m). The results indicate that the method was unable to detect 0.25 mm (0.01 inch) and 0.5 mm (0.02 inch) width simulated fatigue cracks but was able to holographically address 0.76 mm (0.03 inch) width simulated crack in majority of the experiments. The best holographic result for the 0.76 mm simulated crack is illustrated in Fig. 18(b).

8.4.4. Complex shaped simulated crack's benchmark

Previous quantitative and qualitative experiments have primarily focused on simple crack shapes, such as those depicted in Figs. 10, 11, 15, 16, and 18, which are representative of typical fatigue cracks. Nevertheless, evaluating the efficacy of the proposed method in detecting more complex-shaped cracks could be another evaluation criteria. Accordingly, the research team designed a benchmark crack with a complex shape that combined vertical, horizontal, and inclined simulated cracks (as illustrated in Fig. 19 (a)). The results of the holographic crack detection technique applied to this benchmark are presented in Fig. 19 (b). It is worth noting that this experiment represents the highest quality result of five attempts, conducted with a video length of 4 s, a surface distance of 0.5 m, and a minimum width of 0.76 mm (0.03 inch) for all parts of the benchmark.

8.5. Industry feedback

The research team has previous experience in sharing AR-developed software with infrastructural stakeholders (Maharjan et al., 2019) and has received responses about the application of AR in SHM in the context of industry implementation. The use of AR for field measurement has been tested by seven individuals involved in railroad infrastructural maintenance. Their experience ranged from a few months (entry level in engineering), 10–20 years in the railroad (seniors in the field inspection, with an emphasis on maintenance) and more than 20 years (engineering managers). They tested the use of AR for field inspection. The questionnaires asked them about their concern regarding the potential value to be used in the field. The new employees were interested in testing AR in field applications, whereas seniors in field inspection and engineering managers indicated that AR has limitations in the field and needs further testing, however they indicated AR can be an applicable tool for training new employees.

Regarding the method proposed in the present study the research team met with experienced bridge railroad industry inspectors and managers to collect their feedback about the applicability of the proposed AR fatigue crack detection method during visual inspections. Fig. 20 shows indoor and outdoor inspector's surveying the AR software. After testing in a mock visual inspection, the infrastructure managers and inspectors were optimistic about the possibility of enhancing the inspector's perception during the visual inspections using AR. They also made suggestions that provided practical guidance to the further direction of the research team.

The railroad industry identified that AR can be adopted to eventually train railroad workers to conduct new working duties. Railroad managers mentioned that AR as a training tool could improve the worker's safety in the railroad working environment. Furthermore, railroad managers appreciated the compatibility of HMD's hands-free experience with working tools at the job site, which is advantageous in comparison with AR using phone or tablet devices. When considering the applicability of this AR fatigue crack detection method, the researchers noted that due to the weight of the AR device and the concern that users may fatigue in the field wearing the headset, it is best suited for use on surfaces prone to fatigue cracks, such as welded connections and not during the entire visual inspection. They also suggested that the method could be used to differentiate fatigue cracks from other types of cracks.

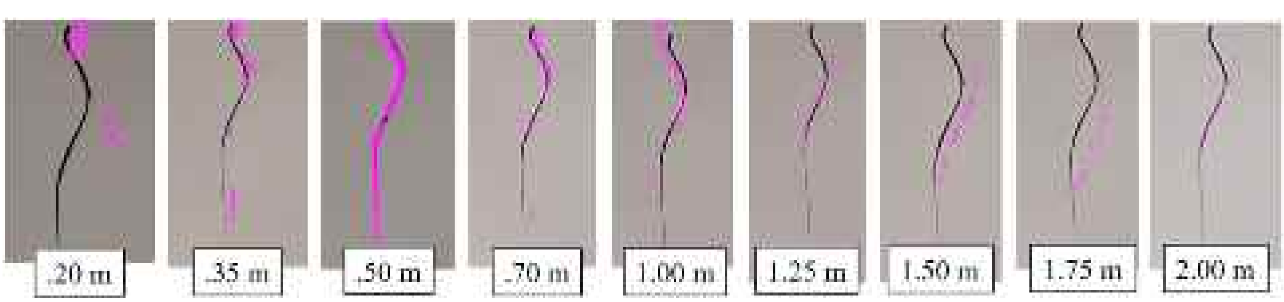
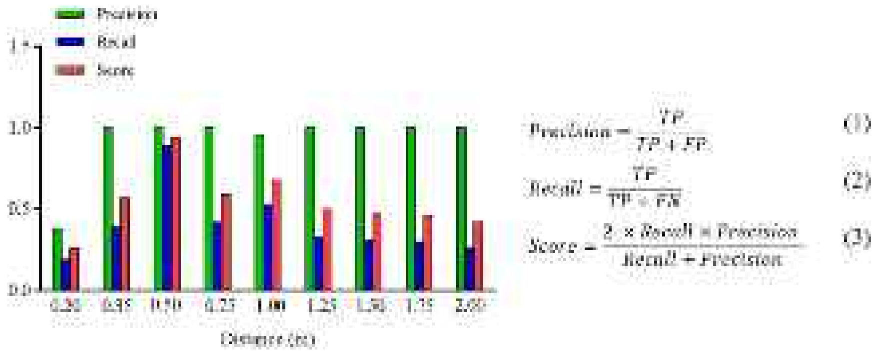


Fig. 16. The holographic results on the simulated crack from different distances.



$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (3)$$

Fig. 17. Precision, Recall and Score values for different crack to surface distances.

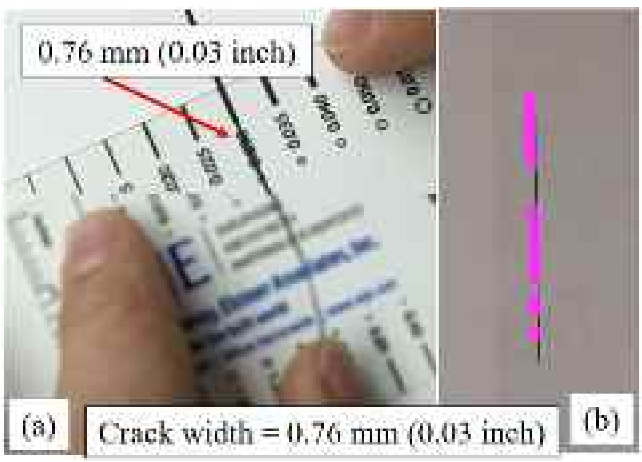


Fig. 18. (a) Measuring the simulated crack's width (b) 0.76 mm (0.03 inch) width simulated crack's detection hologram.

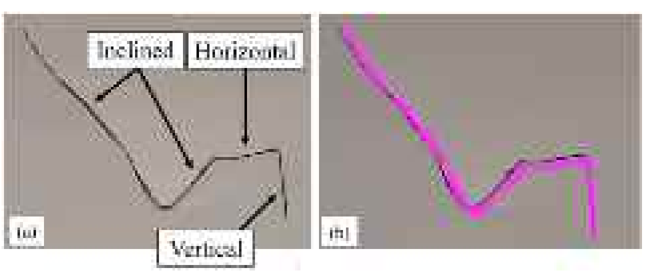


Fig. 19. (a) complex-shaped simulated crack benchmark (b) holographic result provided by the software.

Additionally, they provided recommendations for advancing this research, which can be found in the "Conclusions and future directions" section of this study.

9. Results and discussion

The authors conduct a comparative analysis between the results obtained from the proposed method and those of a previous study that explored a related topic. The aim of this comparison is to highlight the strengths and weaknesses of the present study relative to other recent methodologies for detecting cracks using AR technology.

Dorafshan et al. (2018). have successfully detected structural fatigue cracks measuring 0.04 mm in width by analyzing camera-to-surface distance using high-quality cameras mounted on drones. The maximum distance between the camera and the surface during their

Fig. 20. (a) Indoor and (b) In-field AR software experiment survey with infrastructural stakeholders.

study was 0.7 m. Similarly, Malek et al. (2022). have utilized a simplified Canny algorithm (Canny, 1986) deployed in an AR device positioned at a height of 1266 mm to detect cracks ranging in width from 0.59 mm to 2.15 mm, achieving AR crack detection in less than one second. Additionally, Wang et al. (2020). have proposed a computer vision method for fatigue crack detection that can detect cracks as small as 0.28 mm in width, and their method's crack width error was calculated to be 7.91%.

In summary, Malek et al. (2022) approach may be faster and eliminate the need for an external processing unit for data analysis, but it lacks the ability to distinguish fatigue cracks in the actual structure. On the other hand, the proposed methodology in this study is capable of detecting fatigue cracks from significantly greater distances. Additionally, while Dorafshan et al. (2018) method may be more applicable in terms of detecting crack width due to its reliance on human visual perception without the use of computer vision methods, the present study has the advantage of being able to detect and virtually localize fatigue cracks using computer vision and AR hologram generation technology, even at far distance. Wang et al. (2020). method appears to possess a similar level of crack width detection capability, yet it fails to address the issue of identifying fatigue cracks in the structure during visual inspection and requires a considerable amount of computational capacity for crack detection. Table 4 quantitatively and qualitatively compares the current proposed method, as well as those of the three previously mentioned fatigue crack detection studies.

10. Conclusions and future directions

This study has presented description and evaluation of an integrated AR-based inspection system for detecting and addressing fatigue cracks in steel bridges. The AR software described here uses feature points hologram generated by a computer vision algorithm to virtually address fatigue crack on the infrastructure. A new AR capability called "AAS" was designed and developed to place the hologram on the fatigue crack within the virtual headset's environment. The research team qualitatively and quantitatively evaluated the new AR system through benchmark 2D and 3D proof-of-concept, and a half-scale steel girder specimen with realistic distortion-induced fatigue cracks. The developed AR software helps inspectors to automatically detect, visualize and digitally

Table 4
Quantitative and qualitative comparison with recent fatigue crack detection methodologies.

Study	Quantitative comparison			Qualitative comparison					
				Limitations			Advantages		
	Minimum crack width detection ability (mm)	Camera to crack distance (mm)	Analysis time (s)	Prior awareness of crack's presence required	External processing unit needed	Computationally intensive	Computer vision method utilized	Automatic crack localization	Ability to detect fatigue cracks
Malek et al. [40]	0.59	1266	<1	Yes	No	No	Yes	Yes	No
Dorafshan et al. [29]	0.04	700	-	Yes	No	No	No	No	Yes
Wang et al. [55]	0.028	-	-	No	Yes	Yes	Yes	No	Yes
Current study	0.3	2000	4	No	Yes	No	Yes	Yes	Yes

Highlights indicate the strengths of the proposed methodology.
(Malek et al., 2022; Dorafshan et al., 2018; Wang et al., 2020)

mark fatigue cracks during their visual inspection.

As mentioned, earlier, several abilities have been developed for the AR fatigue crack detection software to assist the inspectors during their visual inspections. The digital distance indicator helps the inspector to monitor and manage the distance from the inspector's eyes to the surface of inspection helping to produce the most accurate results possible. Additionally, the software can provide fatigue crack detection and localization results in near-real-time, improving inspection speed and reliability benefiting from innovative AAS and AR device's spatial understanding.

Moreover, the authors conducted a series of indoor experiments to evaluate the performance of the proposed method in detecting and localizing simulated fatigue crack benchmarks of varying shapes and orientations, with a minimum width of 0.76 mm (0.03 inch). Results indicate that the method is capable of successfully detecting and localizing such cracks. Additionally, the author conducted several time experiments, which showed that a 4-second video length provides a balanced trade-off between obtaining an acceptable hologram result and the time required to overlay it onto the simulated crack, with a total processing time of 10 s. It should be noted that while the proposed method can detect simulated fatigue cracks from distances of up to 2 m, the optimal distance for obtaining the highest quality results, as assessed through a pixel-by-pixel analysis, is 0.5 m.

Considering the potential future directions for this research one could be to add different degrees of anomalies or dirt on the benchmark to evaluate the detection ability of the method existing different degrees of anomalies and dirt to mimic the realistic situations. Additionally, the algorithm's ability to automatically distinguish between the anomalies and fatigue crack could be enhanced, or a human could be added in the loop to choose between the variety of holographic results, increasing the method's ability to differentiate between actual fatigue cracks and anomalies.

Furthermore, given the extensive utilization of deep learning-based algorithms in crack detection, it may be beneficial to explore the feasibility of employing such algorithms as an alternative to the feature point tracking approach utilized in the current study for the purpose of fatigue crack detection from recorded structural videos. Subsequently, a comparative analysis, both qualitative and quantitative, of the results obtained from the deep learning-based algorithms and the feature point tracking algorithm employed in this study can be conducted to assess each method's pros and cons.

Another possible avenue for future research is to conduct indoor and outdoor experiments in different illuminations (synthetic and natural), to assess the robustness of the method in various lighting conditions. Additionally, it may be beneficial to consider the crack opening and closing frequency in testing, as this may impact the method's ability to detect fatigue crack. After all, validating the applicability of the proposed method on the actual steel bridges could be considered an ultimate goal for this research to move it one step further to come to the practice for visual inspections.

CRediT authorship contribution statement

Ali Mohammadkhorasani: Methodology, Software, Validation, Investigation, Writing – original draft, Visualization. **Kaveh Malek:** Methodology, Writing – review & editing. **Rushil Mojidra:** Validation, Writing – review & editing, Visualization. **Jian Li:** Conceptualization, Validation, Resources, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Caroline Bennett:** Resources, Writing – review & editing. **William Collins:** Resources, Writing – review & editing. **Fernando Moreu:** Conceptualization, Methodology, Resources, Data curation, Writing – review & editing, Supervision, Project administration.

Data Availability

Data will be made available on request.

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Deceleration of competing interest

The authors declare that there are no personal relationships or competing financial interests that could affect the study conducted in this paper.

References

Al-Salih, Hayder, Bennett, Caroline, Matamoros, Adolfo, 2021. Evaluation of novel combined CFRP-steel retrofit for repairing distortion-induced fatigue. J. Constr. Steel Res. 182, 106642 https://doi.org/10.1016/j.jcsr.2021.106642.

Amezquita-Sanchez, Juan Pablo, Adeli, Hojjat, 2016. Signal processing techniques for vibration-based health monitoring of smart structures. Arch. Comput. Methods Eng. 23 (1), 1–15. https://doi.org/10.1007/s11831-014-9135-7.

Avci, Onur, Abdeljaber, Osama, Kiranyaz, Serkan, Hussein, Mohammed, Gabbouj, Moncef, Inman, Daniel J., 2021. A review of vibration-based damage detection in civil structures: from traditional methods to Machine Learning and Deep Learning applications. Mech. Syst. Signal Process. 147, 107077 https://doi.org/10.1016/j.ymssp.2020.107077.

Awadallah, Omar, Sadhu, Ayan, 2023. Automated multiclass structural damage detection and quantification using augmented reality. J. Infrastruct. Intell. Resil. 2 (1), 100024 https://doi.org/10.1016/j.iintel.2022.100024.

Canny, John, 1986. A computational approach to edge detection. IEEE Trans. Pattern Anal. Mach. Intell. 6, 679–698. https://doi.org/10.1109/TPAMI.1986.4767851.

Chen, Hanxin, Zhang, Guangyu, Fan, Dongliang, Fang, Lu, Huang, Lang, 2020. Nonlinear lamb wave analysis for microdefect identification in mechanical structural health assessment. Measurement 164, 108026. https://doi.org/10.1016/j.measurement.2020.108026.

Deng, Jianghua, Singh, Amardeep, Zhou, Yiyi, Lu, Ye, Lee, Vincent Cheng-Siong, 2022a. Review on computer vision-based crack detection and quantification methodologies for civil structures. Constr. Build. Mater. 356, 129238 https://doi.org/10.1016/j.conbuildmat.2022.129238.

Deng, Jianghua, Singh, Amardeep, Zhou, Yiyi, Lu, Ye, Lee, Vincent Cheng-Siong, 2022b. Review on computer vision-based crack detection and quantification methodologies for civil structures. Constr. Build. Mater. 356, 129238 https://doi.org/10.1016/j.conbuildmat.2022.129238.

Dong, Chuan-Zhi, Catbas, F.Necati, 2021. A review of computer vision–based structural health monitoring at local and global levels. Struct. Health Monit. 20 (2), 692–743. https://doi.org/10.1177/147592172093558.

Dong, Chuan-Zhi, Necati Catbas, F., 2021. A review of computer vision–based structural health monitoring at local and global levels. Struct. Health Monit. 20 (2), 692–743. https://doi.org/10.1177/1475921720935585.

Dorafshan, Sattar, Thomas, Robert J., Maguire, Marc, 2018. Fatigue crack detection using unmanned aerial systems in fracture critical inspection of steel bridges. J. Bridge Eng. 23 (10), 04018078. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001291.

Duan, Xin, Chu, Xi, Zhu, Weizhu, Zhou, Zhixiang, Luo, Rui, Meng, Junhao, 2023. Novel method for bridge structural full-field displacement monitoring and damage identification. Appl. Sci. 13 (3), 1756. https://doi.org/10.3390/app13031756.

Fawcett, Tom, 2006. An introduction to ROC analysis. Pattern Recognit. Lett. 27 (8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010.

He, Zhiguo, Li, Wentao, Salehi, Hadi, Zhang, Hao, Zhou, Haiyi, Jiao, Pengcheng, 2022. Integrated structural health monitoring in bridge engineering. Autom. Constr. 136, 104168 https://doi.org/10.1016/j.autcon.2022.104168.

Hou, Rongrong, Xia, Yong, 2021. Review on the new development of vibration-based damage identification for civil engineering structures: 2010–2019. J. Sound Vib. 491, 115741 https://doi.org/10.1016/j.jsv.2020.115741.

Hu, Wenbo, Wang, Weidong, Ai, Chengbo, Wang, Jin, Wang, Wenjuan, Meng, Xuefei, Liu, Jun, Tao, Haowen, Qiu, Shi, 2021. Machine vision-based surface crack analysis for transportation infrastructure. Autom. Constr. 132, 103973 https://doi.org/10.1016/j.autcon.2021.103973.

Kong, Xiangxiong, Li, Jian, 2018. Vision-based fatigue crack detection of steel structures using video feature tracking. Comput. Civ. Infrastruct. Eng. 33 (9), 783–799. https://doi.org/10.12783/shm2019/32477.

Kong, Xiangxiong, Li, Jian, 2019. Non-contact fatigue crack detection in civil infrastructure through image overlapping and crack breathing sensing. Autom. Constr. 99, 125–139. https://doi.org/10.1016/j.autcon.2018.12.011.

Kot, Patryk, Muradov, Magomed, Gkantou, Michaela, Kamaris, George S., Hashim, Khalid, Yeboah, David, 2021. Recent advancements in non-destructive testing techniques for structural health monitoring. Appl. Sci. 11 (6), 2750. https://doi.org/10.3390/app11062750.

Kumarapu, Kumar, Mesapam, Shashi, Keesara, Venkat Reddy, Shukla, Anoop Kumar, Manapragada, Naga Venkata Sai Kumar, Javed, Babar, 2022. RCC Structural deformation and damage quantification using unmanned aerial vehicle image correlation technique. Appl. Sci. 12 (13), 6574. https://doi.org/10.3390/app12136574.

Li, Xiao, Yi, Wen, Chi, Hung-Lin, Wang, Xiangyu, Chan, Albert P.C., 2018. A critical review of virtual and augmented reality (VR/AR) applications in construction safety. Autom. Constr. 86, 150–162.

Liu, Han, Laflamme, Simon, Li, Jian, Bennett, Caroline, Collins, William, Downey, Austin, Ziehl, Paul, Jo, Hongki, 2021. Investigation of surface textured sensing skin for fatigue crack localization and quantification. Smart Mater. Struct. 30 (10), 105030 https://doi.org/10.1088/1361-665X/ac221a.

Maharjan, Dilendra, Agüero, Marlon, Lippitt, Chris, Moreu, Fernando, 2019. Infrastructure stakeholders' perspective in development and implementation of new structural health monitoring (SHM) technologies for maintenance and management of transportation infrastructure. In: MATEC web of conferences, vol. 271. EDP Sciences,, p. 01010. https://doi.org/10.1051/matecconf/201927101010.

Malek, K., Mohammadkhorasani, A., Moreu, F., 2022. Integration of Augmented Reality and Pattern Recognition for Crack Detection. Computer-Aided Civil and Infrastructure Engineering, in press.

Malek, Kaveh, Moreu, Fernando, 2022. Realtime conversion of cracks from pixel to engineering scale using Augmented Reality. Autom. Constr. 143, 104542 https://doi.org/10.1016/j.autcon.2022.104542.

Marino, Emanuele, Barbieri, Loris, Colacino, Biagio, Fleri, Anna Kum, Bruno, Fabio, 2021. An Augmented Reality inspection tool to support workers in Industry 4.0 environments. Comput. Ind. 127, 103412 https://doi.org/10.1016/j.compind.2021.103412.

Megaw, E.D., 1979. Factors affecting visual inspection accuracy. Appl. Ergon. 10 (1), 27–32. https://doi.org/10.1016/0003-6870(79)90006-1.

Mojidra, Rushil, Li, Jian, Mohammadkhorasani, Ali, Moreu, Fernando, Collins, William, Bennett, Caroline, Taher, Sdiq Anwar, 2022. Vision-based inspection of out-of-plane fatigue cracks in steel structures. In: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems, vol. 12046. SPIE, 2022, pp. 145–151. https://doi.org/10.1117/12.2613188.

Mojidra, Rushil, Li, Jian, Mohammadkhorasani, Ali, Moreu, Fernando, Bennett, Caroline, Collins, William, 2023. Vision-based fatigue crack detection using global motion compensation and video feature tracking. Earthq. Eng. Eng. Vib. 1–21. https://doi.org/10.1007/s11803-023-2156-1.

Moreu, Fernando, Brian Bleck, Shreya Vemuganti, David Rogers, and David Mascarenas. Augmented reality tools for enhanced structural inspection. Structural Health Monitoring 2017 SHM (2017).

Nick, Hooman, Aziminejad, Armin, 2021. Vibration-based damage identification in steel girder bridges using artificial neural network under noisy conditions. J. Nondestruct. Eval. 40, 1–22. https://doi.org/10.1007/s10921-020-00744-8.

Palmarini, Riccardo, Erkoyuncu, John Ahmet, Roy, Rajkumar, Torabmostaedi, Hosein, 2018. A systematic review of augmented reality applications in maintenance. Robot. Comput. -Integr. Manuf. 49, 215–228. https://doi.org/10.1016/j.rcim.2017.06.002.

Phares, Brent M., Rolander, Dennis D., Graybeal, Benjamin A., Washer, Glenn A., 2001. "Reliability of visual bridge inspection. Public Roads 64 (5), 22–29.

Quqa, Said, Martakis, Panagiotis, Movsessian, Artur, Pai, Sai, Reuland, Yves, Chatzi, Eleni, 2022. Two-step approach for fatigue crack detection in steel bridges using convolutional neural networks. J. Civ. Struct. Health Monit. 12 (1), 127–140. https://doi.org/10.1007/s13349-021-00537-1.

Re, Guido Maria, Kharshiduzzaman, Md, Bordegoni, Monica, Bernasconi, Andrea, Anodio, Luca Francesco, Comolli, Lorenzo, Braghin, Francesco, 2014. A mobile augmented reality framework for inspection and visualization during fatigue tests. In: Engineering Systems Design and Analysis, vol. 45851. V003T10A017. American Society of Mechanical Engineers.

Richard, Hans Albert, Sander, Manuela, 2016. Fatigue crack growth. Springer, Berlin.

Sabato, Alessandro, Dabetwar, Shweta, Kulkarni, Nitin Nagesh, Fortino, Giancarlo, 2023. Non-contact sensing techniques for AI-aided structural health monitoring: a systematic review. IEEE Sens. J. https://doi.org/10.1109/JSEN.2023.3240092.

Sadhu, Ayan, Peplinski, Jack E., Mohammadkhorasani, Ali, Moreu, Fernando, 2023. A review of data management and visualization techniques for structural health monitoring using BIM and virtual or augmented reality. J. Struct. Eng. 149 (1), 03122006. https://doi.org/10.1061/(ASCE)ST.1943-541X.0003498.

Shi, Jianbo, 1994. Good features to track. Proceedings of IEEE conference on computer vision and pattern recognition. IEEE,, pp. 593–600.

Spencer Jr, Billie F., Hoskere, Vedhus, Narazaki, Yasutaka, 2019. Advances in computer vision-based civil infrastructure inspection and monitoring. Engineering 5 (2), 199–222. https://doi.org/10.1016/j.eng.2018.11.030.

Suhr, Jae Kyu. Kanade-lucas-tomasi (KLT) feature tracker. Computer vision (EEE6503) (2009): 9–18.

Taher, Sdiq Anwar, Li, Jian, Jeong, Jong-Hyun, Laflamme, Simon, Jo, Hongki, Bennett, Caroline, Collins, William N., Downey, Austin R.J., 2022. Structural health monitoring of fatigue cracks for steel bridges with wireless large-area strain sensors. Sensors 22 (14), 5076. https://doi.org/10.3390/s22145076.

Ungureanu, Dorin, Bogo, Federica, Galliani, Silvano, Sama, Pooja, Duan, Xin, Meekhof, Casey, Stühmer, Jan, et al., 2020. Hololens 2 research mode as a tool for computer vision research, 2008.11239 arXiv Prepr. arXiv, 2008.11239.

Wang, Dalei, Dong, Yiqing, Pan, Yue, Ma, Rujin, 2020. Machine vision-based monitoring methodology for the fatigue cracks in U-Rib-to-deck weld seams. IEEE Access 8, 94204–94219. https://doi.org/10.1109/ACCESS.2020.2995276.

Wang, Junzhen, Shen, Yanfeng, Rao, Danyu, Xu, Wu, 2021a. Physical-virtual time reversing of nonlinear Lamb waves for fatigue crack detection and quantification. Mech. Syst. Signal Process. 160, 107921 https://doi.org/10.1016/j.ymssp.2021.107921.

Wang, Junzhen, Shen, Yanfeng, Rao, Danyu, Xu, Wu, 2021b. An instantaneous-baseline multi-indicial nonlinear ultrasonic resonance spectral correlation technique for fatigue crack detection and quantification. Nonlinear Dyn. 103, 677–698. https://doi.org/10.1007/s11071-020-06128-x.

Wang, Shaohan, Zargar, Sakib Ashraf, Xu, Cheryl, Yuan, Fuh-gwo, 2019. An efficient augmented reality (AR) system for enhanced visual inspection. Struct. Health Monit. 2019 https://doi.org/10.12783/shm2019/32278.

Xiao, Wenfeng, Yu, Lingyu, Joseph, Roshan, Giurgiutiu, Victor, 2020. Fatigue-crack detection and monitoring through the scattered-wave two-dimensional cross-correlation imaging method using piezoelectric transducers. Sensors 20 (11), 3035. https://doi.org/10.3390/s20113035.

Yasuda, Yuri D.V., Cappabianco, Fabio A.M., Martins, Luiz Eduardo G., Gripp, Jorge A.B., 2022. Aircraft visual inspection: a systematic literature review. Comput. Ind. 141, 103695 https://doi.org/10.1016/j.compind.2022.103695.

Zhai, Guanghao, Narazaki, Yasutaka, Wang, Shuo, Shajihan, Shaik Althaf V., Spencer Jr., Billie F., 2022. "Synthetic data augmentation for pixel-wise steel fatigue crack identification using fully convolutional networks. Smart Struct. Syst. 29 (1), 237–250. https://doi.org/10.12989/sss.2022.29.1.237.

Zhang, Guojing, Yongjian, Liu, Jiang, Liu, Shiyong, Lan, Jian, Yang, 2022. Causes and statistical characteristics of bridge failures: a review. J. Traffic Transp. Eng. (Engl. Ed.). https://doi.org/10.1016/j.jtte.2021.12.003.

Zhang, Le, Wang, Zhichen, Wang, Lei, Zhang, Zhe, Chen, Xu, Meng, Lin, 2021. Machine learning-based real-time visible fatigue crack growth detection. Digit. Commun. Netw. 7 (4), 551–558. https://doi.org/10.1016/j.dcan.2021.03.003.

Zhu, S., Levinson, D., Liu, H.X., Harder, K., 2010. The traffic and behavioral effects of the I-35W Mississippi River bridge collapse. Transp. Res. Part A: Policy Pract. 44 (10), 771–784. https://doi.org/10.1016/j.tra.2010.07.001.

Zhuang, Yizhou, Chen, Weimin, Jin, Tao, Chen, Bin, Zhang, He, Zhang, Wen, 2022. A review of computer vision-based structural deformation monitoring in field environments. Sensors 22 (10), 3789. https://doi.org/10.3390/s22103789.

Zinno, Raffaele, Haghshenas, Sina Shaffiee, Guido, Giuseppe, Rashvand, Kaveh, Vitale, Alessandro, Sarhadi, Ali, 2022. The state of the art of artificial intelligence approaches and new technologies in structural health monitoring of bridges. Appl. Sci. 13 (1), 97. https://doi.org/10.3390/app13010097.

Glossary

AAS: Auto Anchoring System
AR: Augmented Reality
CNNs: Convolutional Neural Networks
DIC: Digital Image Correlation
DL: Deep Learning
FN: False Negative
FOVh: Field Of View horizontal
FP: False Positive
GPS: Global Positioning System
HL2: Microsoft HoloLens 2nd Generation
HMD: Head Mounted Display
KDOT: Kansas Department of Transportation
KLT: Kanade-Lucas-Tomasi
LCR: Local Circular Regions
ML: Machine learning
NMDOT: New Mexico Department of Transportation
SHM: Structural Health Monitoring
SQL: Structured Query Language
TB: Tera Bytes
TN: True Positive
TP: True Negative
TRB: Transportation Research Board
UAV: Unmanned Aerial Vehicle
VR: Virtual Reality
WLASS: Wireless Large-Area Strain Sensor