2025 European Conference on Computing in Construction

CIB W78 Conference on IT in Construction

Porto, Portugal
July 14-17, 2025

TOWARDS DAMAGE PREDICTION: MAPPING INSPECTION HISTORY OF CONCRETE BRIDGES

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Abstract

The analog nature of bridge inspections hinders long term prognosis of structural health. Accordingly, we propose a comprehensive digitization concept to enhance the effectiveness of bridge inspections: historical inspection data is consolidated into digital damage models with machine learning. These models can then be combined with a BIM model for the creation of a digital twin, which paves the way for an evaluation of damage progression. The model furthermore enables inspectors to easily locate existing damage via images and point clouds, and to record changes into a new damage model. This significantly improves maintenance and retrofitting efforts.

Introduction

More than 2,200 highway bridges in Germany are in poor condition due to age and excessive wear (Bundesanstalt für Straßenwesen (BASt), 2024). Efficient repair and retrofitting measures are essential to prevent infrastructural and economic consequences, such as highway closures, costly repairs or even collapse. Bridge operators must therefore evaluate the current bridge condition and estimate probable future deterioration using up-to-date and accurate information, particularly damage data, to formulate an economical and timely maintenance strategy. For example, analyzing and potentially forecasting damage progression based on damage documentation is essential to estimate repair timings.

In Germany, this damage data is collected during regular, standardized inspections as defined in DIN 1076 (Deutsches Institut für Normung e.V., 1999) and RI-EBW-PRÜF (Bundesministerium für Verkehr und digitale Infrastruktur, 2017). These inspections require a high degree of accuracy to provide useful information, but the process also needs to be efficient to enable frequent inspections and thereby maintain up-to-date damage data. Currently, bridge inspections are conducted by specially trained inspectors at a low frequency and in a long, labor-intensive, and mostly analog process.

The inspection process faces several challenges that conflict with the requirements of bridge maintenance. Damage has to be assessed accurately, uniformly, and reproducibly, which is essential for evaluating damage progression and planning maintenance. However, Bennetts et al. (2018) found "significant uncertainty" when comparing the evaluation of the same damage instances by different inspectors. Similarly, Martins et al. (2024b) found that current inspection practices are limited by the subjectivity of the process among other factors. Also, the low frequency of inspections makes early damage detection and the evaluation of damage progression difficult. And furthermore, damage found in a previous inspection is often hard to locate again, as its positions is rarely documented in detail, and bridge structures are often large and self-similar. This complicates the evaluation of damage progression additionally. Making the inspection process more efficient has economic benefits, too, as the inspections require expensive technology and personnel whose skill and experience is currently not utilized optimally.

Technologies such as Artificial Intelligence (AI), Building Information Modeling (BIM) and Augmented Reality (AR) have shown great potential for addressing these challenges (Jeon et al., 2023). AI analyzes large amounts of data to find patterns indicating damage and can assist in predicting damage progression. BIM enables efficient data collection and sharing for analysis and informed decision-making. AR lets inspectors easily locate, analyze, and evaluate damage. It has been shown repeatedly that these digital technologies can significantly improve the on-site inspection process as well as the off-site decision making (Embers et al., 2022; Martins et al., 2024b), thereby increasing the effectiveness of maintenance strategies. However, using all three technologies to optimize the inspection process requires a comprehensive concept that covers the entire inspection process and is based on best practices while considering relevant legal requirements. Such a concept should include the usage of historical damage information and and assist users with damage forecasts, which have a high potential of increasing accuracy and effectiveness of maintenance strategy. The project BRIX aims to develop such a concept on behalf of Federal Highway Research Institute by building upon the results of the research project FE69.0008 ("BridgeInspect") by Embers et al. (2022). This involves analyzing and evaluating current research trends, conducting a requirement analysis based on expert interviews, and validation of the concept. The following sections review related literature, explain the methodology in detail, summarize the results of the literature and the requirement analysis, propose the resulting concept, and finishes with a discussion and conclusion.

Related Works and Research Gap

Due to its importance, the field of bridge inspection and maintenance has garnered significant research attention in recent years. Many studies explore various opportunities for digitization and other improvements, with only the works most relevant to this study examined below. Saback et al. (2022) analyze recent research trends for the management of existing concrete bridges and find that the creation of 3D-models for existing structures is often often difficult with standard libraries due to the bridges' complex geometries. Furthermore, most of the papers reviewed bySaback et al. (2022) seem to disregard the use of historical inspection data, as knowledge transfer between inspections is identified as a critical issue. For example, Bridge Management Systems (BMSs) are often not available for remote access. The authors also note that photogrammetry and laser scanning are commonly investigated inspection methods, and that there is a lack of Life-cycle Cost Analysis (LCA) incorporation. Jrade et al. (2023) review recent works considering LCA with Bridge Information Modeling (BrIM), and note that most works focus on new rather than existing structures.

Hüthwohl et al. (2018) extract damage information from bridge inspection reports, model it, and map it to IFC entities. Similarly, Heise et al. (2024) develop a graph-based representation of legacy data for both bridges and roads, mapping damage data with relative location information from inspection reports. While both works consider the German bridge inspection system, neither considers additional information such as images or prognosis, or explicitly assists with the inspection process. In the work by Martins et al. (2024a), the inspection process is improved with BIM and AR. Damage is located into a BIM model during the inspection, and a 3D model of the structure can be viewed and overlaid over the structure with AR. The authors note difficulties with localization of the digital model and, therefore, the damage. Lin et al. (2021) use images collected by drones for the construction of a point cloud in which damage is mapped and visualized for virtual inspections. They enable the comparison of the current and previous recordings of the bridges conditions and include the automatic generation of inspection reports. Jeon et al. (2023) map inspection data into a 3D model using a reference point, with images collected by a drone. Operators are supported with inspection information and condition comparison graphs, among others, in a BrIM model.

Li et al. (2023) use a BrIM model for damage data management, with maintenance suggestions provided based on input damage types. John Samuel et al. (2022) combine BIM and AR to give on-site inspectors access to mapped historical damage information, but only if this information has been entered and localized in a previous inspection.

In summary, most works combine BIM, usually using an existing 3D model, and AR, reinforcing the importance of these technologies. While a lack of usage of historical data was noted by Saback et al. (2022), some researchers have investigated different methods of organizing and mapping this data. However, none of the available works map historical image data to 3D models, and make this legacy data available for inspectors to more accurately assess long term damage progression using AR. Furthermore, the potential of analyzing historical damage data and evaluating additional information entered by inspectors in a more efficient system remains under-explored. Therefore, next to evaluating current research trends in bridge inspections under consideration of legal requirements in Germany, this work furthermore considers 3D mapping and analysis of historical data in the context of the bridge inspection process.

Methodology

The aim of this study is to develop a concept guided by technological best practices for bridge inspections that takes into account practical requirements of bridge inspectors as well as the advantages inherent in utilizing historical damage data.

The technological best practices are obtained from a literature review of works considering individual components of the inspection process, works related to the whole process, as discussed previously, and previous research projects. The results provide an overview of the current opportunities and limitations of AR-, BrIM-, and AI-based applications in the inspection process, and are then compared to current requirements and practices as defined in the inspection guidelines.

To ensure that the developed concept optimally supports bridge inspectors, it is necessary to identify relevant practical requirements. To this end, bridge inspectors were interviewed regarding their perspectives and experiences with current maintenance practices, as well as their views on potential for improvement. Additionally, technological and legal requirements are investigated.

The best practices and requirements are then used to identify the steps within the inspection process with the highest potential for improvement. Particular attention is paid to considerations of effectiveness and feasibility, the latter of which is evaluated based on literature and experts.

The contribution of this study are as follows: a literature review regarding current technological advancements for individual steps of the inspection process, an analysis of current practical requirements of bridge inspectors, and a methodical concept for the improvement of the inspection process which serves as a foundation for further research and practically oriented application.

State of the Art

According to the DIN 1076 standard (Deutsches Institut für Normung e.V., 1999), the inspection process is divided into inspection preparation, on-site data gathering, and data processing. This study evaluates improvements for all three process part, with a focus on on-site data gathering. Among the numerous technological advancements in the inspection process explored in the literature, only the most relevant are discussed here, with others summarized for brevity. Emphasis is placed on works utilizing visual and textual historical data.

Inspectors first receive previous inspection reports, which include images, rule-based descriptions, and sometimes free-text damage descriptions, matched to a damage instance with a unique identifier (UID). During the inspection, known damage is located and checked for changes, and the structure is inspected for new damage during a main inspection. Identifying new damage requires up-close visual checks of all parts of the structure. Damage is documented using images, notes, and sometimes sketches, and evaluated concerning their impact on durability, stability, and traffic safety. This information is transferred into the BMS after the inspection. The data is then processed to algorithmically calculate the bridge's condition rating and inspectors estimate the urgency of maintenance measures. Finally, an inspection report is generated and submitted to the bridge operators.

Data Sharing. Bridge data is typically stored in a BMS-like database. BIM models or Digital Twin (DT) of existing structures must be specifically created, as demonstrated by Martins et al. (2024a) or Jeon et al. (2023). Damage information is available either on a desktop computer or as an inspection report, which is then used for planning the inspection.

Localization. During an inspection, previously located damage must be checked. Currently, damage locations are provided in rule-based descriptions or, in rare cases, in sketches. Finding known damage and especially the part of a damage where the corresponding image was taken can be challenging depending on the quality of the description. Additionally, images are re-used and can be outdated.

Embers et al. (2022) identify spatial mapping methods, such as Structure from Motion (SfM) and depth cameras, as the best for orientation in known environments during bridge inspections. However, they also note challenges with repetitive and self-similar geometry, common in longer bridges. Additionally, the proposed method only localizes the user and thereby newly found damage and doesn't consider known damage. The mapping of the latter requires a 3D model, which often has to be created first. There are many possible methods for the creation of such models with mapped damage, e.g., UAV-based (Zhao et al., 2022), or reconstruction using sequential image pairing and photogrammetry (Bartczak et al., 2023). However, these methods still do not map historical damage data.

Detection. Bridge inspectors identify damage based on experience, while research focuses on using computer vision to support the detection process. Damage detection models for, e.g., cracks, achieve performances between 75%-99% (Munawar et al., 2021). Damage segmentation also remains an active research topic, as damage masks enable downstream processes such as measurements. Both disciplines struggles with the number of possible classes and noise (Embers et al., 2022). As an example for segmentation performance, Çelik et al. (2024) use a Feature Pyramid Network with the EfficientNetb0-Backbone to segment four types of concrete damage with an mIoU of 58.72%.

Measurement. Damage measurements are crucial for severity assessment (Munawar et al., 2021), with an accuracy of 0.1 mm required in some cases. The object-distance method achieves the best results in transforming measurements from images to physical units (Tian et al., 2019). Kim and Cho (2019) achieve an accuracy of less than 0.1 mm for concrete cracks wider than 0.3 mm. Using an image resolution of 0.02 mm/px, Song et al. (2022) achieve a mean relative error of 3.87% (22.57 µm) when measuring fine cracks. Such high image resolution is usually not available under inspection conditions. Furthermore, transforming the measurements from pixels to millimeters requires an accurate camera distance measurement, for example, using a depth sensor. The camera distance is unknown for historical images and can be challenging to acquire for more distant damage.

Evaluation. Damage is evaluated concerning its impact on durability, stability, and traffic safety, with a score ranging from 0 to 4 (Bundesministerium für Verkehr und digitale Infrastruktur, 2017). Scores may be predefined or limited to a specific scale depending on the damage class. This class in return depends on the type of damage, its size, and the component it affects, but is also highly dependent on the inspector's experience (Bennetts et al., 2018). A similar issue has been found for the scoring, which leads to subjective results (Martins et al., 2024b). Bai et al. (2023) classify images of earthquake damage into four hazard levels based on the depicted components and damage, achieving an accuracy of 89.5%. While this work partially aligns with the requirements of bridge inspectors, damage classification and evaluation require more detail than currently achieved in the literature. Vardanega et al. (2024) similarly notes that even with AI, inspectors are needed to assess the extent and severity of damage.

Prognosis. Inspectors do not explicitly forecast damage developments, but time-based effects of damage are considered as part of the durability score. Correctly assessing damage changes is difficult due to long intervals between inspections (Bennetts et al., 2021). Text- and image-based approaches are considered in this study. Common text-based approaches, such as the prediction of bridge condition ratings (Zhang et al., 2024), provide limited information about individual damage instances, which is necessary for better maintenance planning. An image-based approach is investigated by Bianchi et al. (2023), where old and new images of the same damage are matched, transformed to align in perspective, and differences in a damage mask are calculated in pixels, as shown in Fig. 1.

AR. The use of AR is not standardized for bridge inspections, but can support inspectors during multiple steps of the process. Embers et al. (2022) demonstrate that overlay-

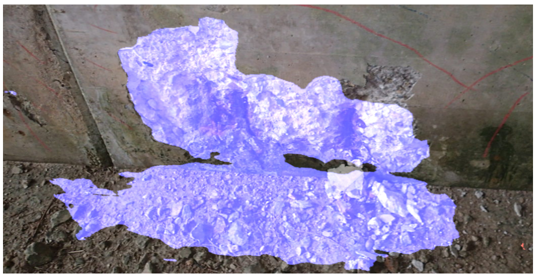

Figure 1: Spalling damage in 2017. Overlaid with a segmentation mask (blue) from the same damage in 2005, transformed to the same perspective.

ing damage masks for easier localization receives positive feedback from inspectors. Riedlinger et al. (2021) use AR to strengthen teamwork during bridge inspections.

Requirements Analysis

To develop a framework for our concept, we performed a requirement analysis based on the State of the Art and previous research projects by conducting interviews with experts. We focus on four core aspects: **Guidelines**, **Processes**, **Technology**, and **People**. In the following, we will describe the resulting requirements for our concept.

Guidelines. To summarize the German guidelines, every damage is evaluated on three impact criteria: stability, traffic safety, and durability. Criteria are given a score from 0 (lowest impact) to 4 (highest impact) based on the RI-EBW-PRÜF guideline (Bundesministerium für Verkehr und digitale Infrastruktur, 2017). Referred to as the SVD scores, these values are the defining factor for planning future measures. Federal buildings and infrastructure are required to use a central database called SiB-BW to manage inspection reports. Any digitization concept is required to work within this framework, adhering to the relevant guidelines and keeping continuity.

Processes. The building inspection process focuses on capturing the current state of the structure. The inspectors currently perform no comprehensive prognosis of damage. Interviews with inspectors conclude that the assessment of damage is often a subjective process based on individual experience and estimations from the inspector. This subjectivity can lead to diverging interpretations and proposed measures being ignored by later inspectors. Digital tools can give more objectivity to analysis and provide a basis for damage prognosis.

Furthermore, a timely response to damage is central to avoiding critical failure or costly maintenance. Recognizing damage early and providing a prognosis can thus improve longevity. Interviewees have also emphasized financial constraints threatening an effective maintenance process.

Past inspection reports are used for planning the inspection and analyzing damage progression. Currently, this is done using written reports as printed documents or on tablets. Giving better access and visualization would speed up the inspection process, and gives the inspectors more data for damage evaluation.

Technology. While the inspection process is still manual, inspectors often use digital tools at their own discretion. Tablets and smartphones are often used for documentation, while photos are mainly captured with high resolution digital cameras. Which digital tools are used is not defined in any guideline. A concept for damage prognosis should therefore include the devices already in use by inspectors. Since it is required in Germany to store damage data for federal structures in the SiB-BW database, a large amount of data is present in digital form. Currently, accessing this database during inspections is cumbersome, as there is no mobile application and the internet connection can be unreliable. Interfacing with this data source between inspections is therefore a requirement.

People. Usability is an important factor when designing a new concept, as considering the needs of the end users is critical for a successful transition. Previous research projects on AR have shown that devices must not hinder the mobility of inspectors, as structures are usually difficult to traverse. At the same time, the safety of the inspectors must be ensured. Thus, devices must comply with safety regulations and withstand harsh environments.

The experience and knowledge of inspectors are an important factor for structural health assessment. Unfortunately, the reasons for a decision is rarely documented during inspections. These interpretations often include a prognosis of the structural health, resulting in a different grade based on implicit knowledge. Documenting these predictions allows other inspectors and stakeholders to better understand decisions and plan measures.

Many of the identified requirements are supported by the state of the art analysis. The expert interviews additionally show that there is a high demand for digital solutions, especially regarding data sharing.

BRIX Concept

Based on the state of the art and the requirement analysis, we present a concept for a digitized bridge inspection process that enables damage prognosis through data col-

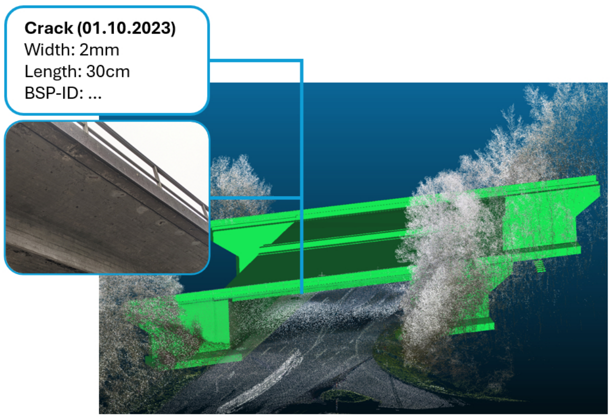

Figure 2: A 3D model of a bridge with a registered point cloud and localized damage information.

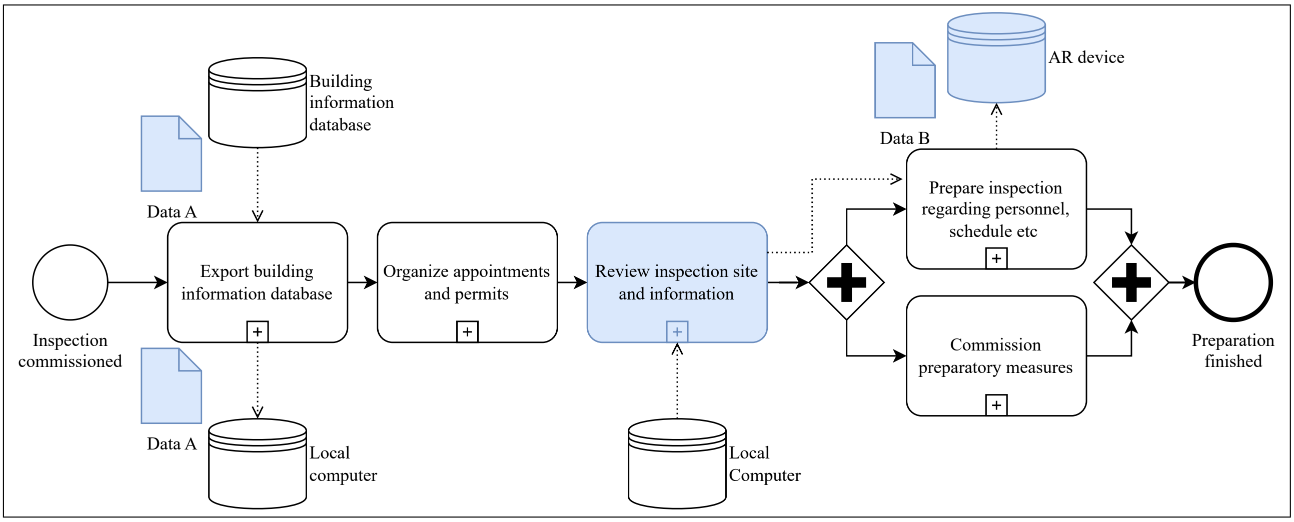

Figure 3: Simplified process diagram of inspection preparation during a bridge inspection. Process steps changed as part of the BRIX concept are marked in blue. Data A refers to all relevant data of the bridge that is to be inspected (3D model, structural information, data from previous inspections etc). Data B refers to all information relevant to the current inspection and is a subset of Data A.

lection and visualization. The requirement analysis shows that on-site access to past inspection data such as impact scores and images is essential for informed decisions about future damage progression. Enabling efficient localization of damage and comparison with past data is therefore a central element of our concept.

Our concept spans the whole inspection process, namely **Inspection preparation, On-Site Data Gathering, and Data Processing**, as well as a module for the creation of a 3D model with mapped damage (see Fig. 2).

The 3D model provides a basis for analysis, inspection, and prognosis by collating historical data into a database for a DT of the structure. While damage is currently mapped to a building component by a rule-based description, images may be of different parts of the damage, or from different perspectives. To allow precise localization of an image for structural analysis and comparison, the exact location of the damage should be mapped in a 3D model.

The implementation of the mapping module uses key point matching in combination with laser scanning to map each damage to a 3D position. A one-time laser scan with panoramic has to be recorded of the structure. Damage images are then matched to the panoramic image of the laser scans. For key point extraction, XFeat (Potje et al., 2024) is used, a learned key point extractor, as it responds well to the imperfections of concrete surfaces. The key point matching is performed with LightGlue (Lindenberger et al., 2023). If a match has been found, the 2D location of the damage can be projected onto the point cloud from the view of the laser scanner. This results in a 3D position for damage images in reference to the point cloud. If the point cloud is registered to the 3D model, the damage positions can be translated to the model space in geo-coordinates.

In the following, we will introduce how our concept fits into the three inspection process steps.

Inspection Preparation

The step of inspection preparation considers all sub-steps necessary to plan and prepare the inspection, such as finding an appointment and planning the inspection schedule, see Fig. 3. In the BRIX concept, the 3D model created as described above enables inspectors to make informed decisions and plans about downstream steps. Location and accessibility of known damage and bridge components is readily visible in the model, while less easily seen in, e.g., 2D plans. Therefore, preparatory measures such as cutting back vegetation can be planned more accurately, and necessary technical equipment can be estimated more easily.

On-Site Data Gathering

The proposed concept is a part of every sub-step of on-site data gathering, as shown in Fig. 4. For brevity, only the process of a main inspection is considered here, but the concept is applicable to all inspection types.

Until all damage has been processed, inspectors keep searching for damage instances. They are supported by AR tablets, which detect damage in real time and mark them clearly onscreen. There are two changes in comparison to the previous projects (see Embers et al. (2022)). First, damage is detected as opposed to segmented, as segmentation is not necessary at this point. Second, only tablets are used as AR devices, because of usability and safety concerns regarding head-mounted displays as well as performance issues.

Using the AR device, the inspector can overlay images from previous inspections when a known damage instance has been found. This is implemented in a similar way to the laser scan mapping using key point matching described above. Fig. 5 shows an example of a visual match. Since both XFeat (Potje et al., 2024) and LightGlue (Lindenberger et al., 2023) utilize a lightweight neural network for feature matching, the overlay can be calculated in real time on the device. This is a key feature for damage prognosis: The inspector can immediately see the changes in

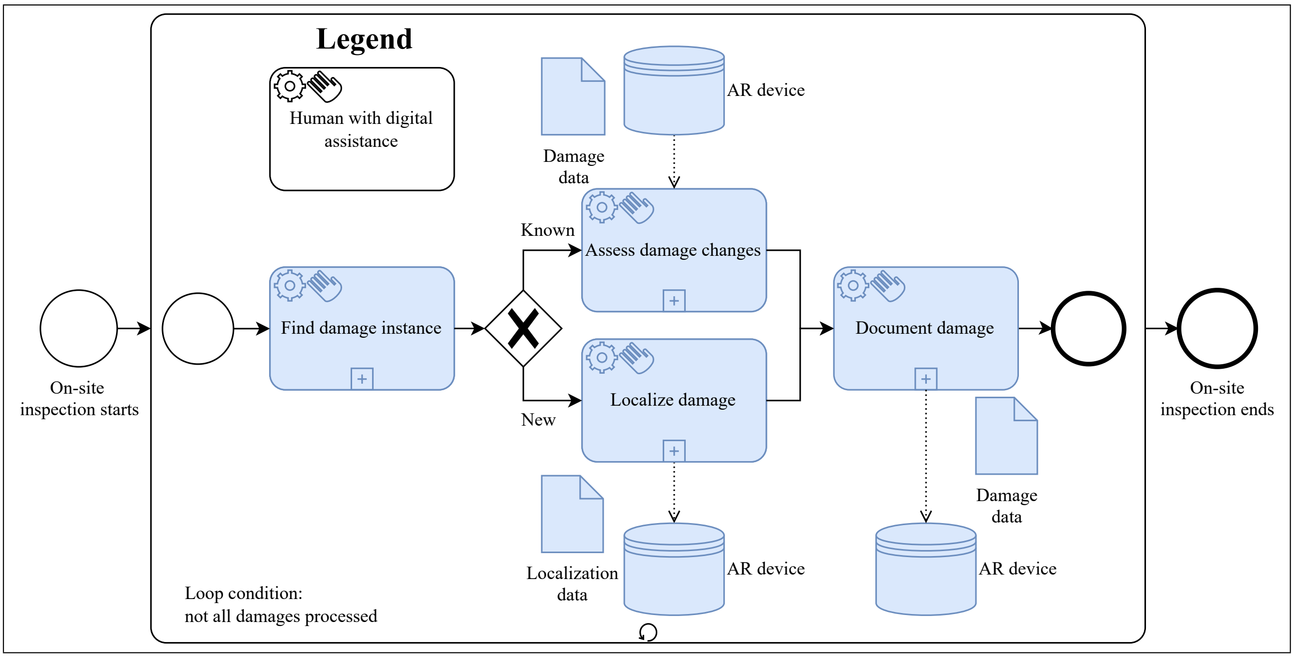

Figure 4: Simplified process diagram of on-site data gathering during a bridge inspection. Process steps changed as part of the BRIX concept are marked in blue.

the structure of the damage, aiding their decision making for impact.

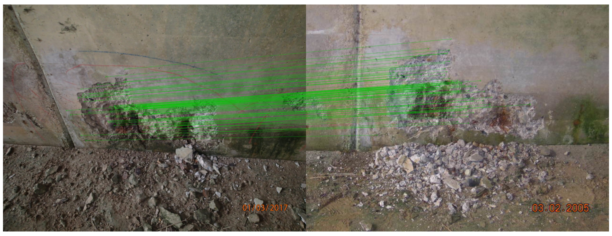

Figure 5: Key point matching between two inspection photos of spalling damage with a time difference of three years.

The state-of-the-art analysis indicates that few feasible methods exist for prognosis in the context of inspections. The requirement analysis revealed that inspectors have limited capacity for forecasting damage evolution. Therefore, the most effective way to support inspectors is by assisting with decision-making. Two methods were identified: Firstly, overlaying new and old images and segmentation masks as described by Bianchi et al. (2023) and shown in Fig. 1. Secondly, forecasting changes in numerical values such as the text/number-based approaches described in the state of the art section. The former method assists inspectors in visually comparing the previous and current condition. Additionally, masks could be compared numerically by calculating differences and even rates of change if enough data is available. The latter methods requires measurements of a damage over a few inspections. These measurements, such as width and length of a crack, could be fitted with a function to give an idea of damage progression in the future, taking uncertainties into account with a safety factor.

If the damage is new, the inspector enters the location manually by selecting it in the 3D model. Similar to above, the images can also be localized automatically if a suitable match has been found.

Finally, the current damage instance is documented. All information, such as measurements, images and masks, damage type, and severity assessment, are entered into the tablet application and saved. For measurements, a high resolution image is taken, segmented, and the mask is measured. Pixel values are transformed to meters based on the camera's distance to the damaged surface, and the inspector can compare these values to their own measurements. The inspector chooses the damage type from a list of the available classes, with context given by the localization in the 3D model. Severity scores and other info is entered, and for existing damage, the captured images can be matched to previous photos.

Data Processing

The data processing step involves evaluating the inspection results to assess the necessity of special inspections, recommending maintenance measures and their urgency, and calculating the bridges condition grade. Usually, this step also involves entering all the data that has been collected into the building information database as an inspection report. An advantage of the BRIX concept is removing the necessity of manually creating a report. All data has already been entered digitally during the data gathering step and can now easily be transferred from the AR devices to a local computer and then be integrated into the building information database.

The data construct is designed to be modular and BIM-based and can be added to a DT of the bridge, which, in combination with other information in the DT, allows for an improved overview over the current bridge condition.

The availability of timely and accurate information allows operators to make quick and informed decisions with regards to maintenance measures.

Discussion

A strength of the BRIX concept is that it builds upon the feedback gained from Embers et al. (2022). Furthermore, many of the individual methods combined into the BRIX concept have been tested successfully by other researchers, such as the comparison of segmentation masks by Bianchi et al. (2023). We are currently evaluating other methods, such as the localization of damage images by key point matching, with promising preliminary results.

However, the concept has to be evaluated as a complete process in regards to usability and accuracy. While previous research indicates the BRIX concept's benefits, it must be compared to the classical process in future research to quantify the resulting improvements. E.g., the methods proposed in literature have to be validated for the specific application of bridge inspection in Germany. And while the concept was developed based on expert interviews with inspectors, it might have to be adjusted based on feedback in case of changing requirements. Furthermore, due to a lack of available data, it is possible that some methods cannot be evaluated to their full extent within the project.

Therefore, the next step is implementing the BRIX concept on an exemplary bridge to assess its functionality, strengths, and limitations. Each method will be evaluated with regards to feasibility and resilience.

Lastly, the BRIX concept was developed based on previous experience, a state of the art review, and a requirement analysis. While this process can be expected to yield quality results, the state of the art review was thorough, but not explicitly systematic.

Conclusion and Outlook

The digitization of bridge inspections is an essential tool for improving the efficiency and quality of bridge maintenance measures. As part of the BRIX project, this study conducted a literature review to analyze the state of the art and a requirement analysis based on interviews with bridge inspection experts. A comprehensive concept covering all three inspection steps was developed from these analyses. This concept enables inspectors to assess and document damage more quickly, uniformly, and with consideration of more information. Inspectors are supported with information visualization via AR and tools for improved data gathering and sharing. Information is evaluated with the assistance of AI to provide optimal information density, such as the segmentation of damage to provide a chronology and measurements. Additionally, the three-dimensional mapping of damage lets inspection personnel locate damage easily and thereby save time.

There are further aspects that can be considered in future work. If damage types are predicted or measured incorrectly and the correct information is entered by an inspector, this can be used to train the underlying AI. Furthermore, the 3D model can be extended with environmental and structural information, such as weather data and material types, to allow for better inspection planning, damage analysis, and prognosis.

Acknowledgment

This research was funded by the mFUND research programme of the Federal Ministry for Digital and Transport (BMDV) (funding code: 01FV2067B). The paper is based on parts of a research project carried out at the request of the BMDV, represented by the Federal Highway Research Institute, under research project No. 69.0017/2023. The authors are solely responsible for the content.

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