USER REQUIREMENTS FOR AN AUTOMATED BRIDGE INSPECTION SYSTEM

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Abstract

Forty two percent of bridges in the USA are at least 50 years old, and 46,000 bridges are in poor condition. A predictive maintenance program can help extend the bridges' life, thereby minimizing the need to replace the majority of bridges within a short time. The technological needs of inspectors in the state of Florida were analyzed after reviewing federal highway standards for designing an automated inspection system. This work presents the synthesis of technical knowledge required to conduct bridge inspections and user requirements which will serve as guidelines for the development of a prototype system targeted to expedite the inspection process by data collection, 3D model generation, and report processing.

Introduction

There are more than 617,000 bridges across the United States, out of which 42% of bridges are at least 50 years old and 7.5% of the existing bridges, i.e., 46,154, are considered structurally deficient (**?**). As the average age of the nation's bridges grows to 45 years in 2022, the backlog of bridge repair needs is estimated to reach $125 billion. In 2021, the Congress announced an investment plan that includes $26.5 billion for bridge repair, replacement, and rehabilitation (**?**). A systematic bridge maintenance program that prioritizes existing damage and emphasizes on preventive maintenance is suggested.

Inspection of bridges is the first step for monitoring and maintaining these complex structures. It entails frequent safety evaluations and documentation of existing conditions, considering maintenance measures required to address faults such as cracks, corrosion, and spalling. To locate and evaluate existing bridge deficiencies, the National Bridge Inspection Standards (NBIS) (**?**) was established by the US Department of Transportation after the collapse of the Silver Bridge in West Virginia in 1968 to ensure the safety of the moving traffic.

Federal, State, and local transportation authorities convey great importance to heavily invested bridge inspection activities. Federal Highway Administration (FHWA) guidelines mandate that public road bridges with a distance over 20 feet to be inspected every two years. This involves a thorough inspection of all accessible bridge parts, as well as the implementation of appropriate access and traffic management measures. The National Bridge Inventory (NBI) 0 to 9 rating scale is an FHWA requirement for evaluating bridge conditions, where 0 denotes a failed condition, and 9 denotes an excellent condition. The components (namely deck, superstructure, or substructure) are assigned an NBI rating by the bridge inspectors, and the overall rating for a bridge is the lowest rating assigned to any component observed through visual bridge inspection (**?**). Additional recording items and their descriptions can be found in the coding guide (**?**).

This work presents the user requirements of bridge inspectors for an automated bridge inspection system, which will accelerate the inspection process so that the system is tailored to the needs of inspectors. After reviewing the current inspection practices and state-of-the-art (SOTA) research for all the steps of the bridge inspection process, we conducted surveys and interviews with bridge inspectors in the state of Florida and then synthesized the results to derive the software and hardware requirements of an automated inspection system based on their needs. The development of such an automated system is out of scope of this paper and is part of future work.

State of practice review

After reviewing FHWA guidelines, this paper divides the bridge inspection process into the following steps:

1. Bridges are visually inspected, and significant defects are measured and tested.
2. Findings are documented by bridge inspectors in an inspection report.
3. Inspectors, based on their training and experience, assign elements a condition rating.
4. And finally, that report is updated in a bridge management system for engineers to review and give out work orders for maintenance.

A detailed literature review of the current bridge inspection practices is presented in the following sections.

Visual Inspection

The bridge inspection process begins with reviewing the previous inspection reports, planning the inspection, and identifying areas of old defects. When conducting the visual inspection, inspectors find out whether the identified defects earlier have been fixed or whether their size and severity have increased, along with coordinating traffic control and access equipment. There are multiple inspection types: NBI, Element, Fracture critical, Underwater, and Other special types, which are performed for AASHTO elements or National Bridge Elements (NBE). These commonly recognized components are the deck, superstructure, substructure, culvert, bridge rail, joint, bearing, Wearing Surfaces and Protective Coatings. The inspection cost can include crew, flagger, and helper hours, along with equipment costs like a snooper truck, watercraft, and other special equipment. Special inspection teams are required for movable bridges.

The bridge inspection and reporting guide suggests that whenever practical, inspection should proceed from substructure to superstructure then to the deck. The cause of superstructure and deck deficiencies might be more evident if the substructure was inspected initially. Based on the type of bridge under inspection, the actual order of its inspection will differ.

Defect assessment can be categorized based on its relevance of directly affecting safety, severity, and urgency to address the defect. Routine issues include asphalt raveling, hairline concrete cracking, damage to curbing faces. Non-Routine issues can be a significant deflection of girders, Medium to wide flexural or shear cracks, loss of material under spread footing. Defects such as scaling and concrete spalling are low relevancy defects. On the other hand, loose concrete on overhang, unevenly loaded bearing, or sagging of members can be medium relevancy defects. Defects that directly affect safety today or immediate future like impact damaged girders, medium and wide flexural or shear cracks (cracks exposing the steel to corrosion), missing sidewalk joint cover plates, the disintegration of abutment near girder bearing are examples of high relevancy defects.

The next paragraph reviews the inspection practices for NBE elements. Deck and parapet are sounded for delamination. Delamination occurs when corroding reinforced steel in concrete expands causing subsurface fracture. Wearing surface is also inspected to identify potholes, cracking, and excessive wear. Deck joints should be properly functioning to allow expansion and contraction at temperature changes. They are looked at for evidence of seepage and loose armor angles. Debris is also a typical issue with joints. The superstructure is inspected with close attention to areas of high stress and those prone to deterioration. Concrete is inspected for cracking, spalling and hollow areas. In timber bridges, inspectors try to identify wood rot, crushing, splitting, and cracking in timber. Steel members are inspected for paint peeling, corrosion, and cracking. FHWA recommends Ultrasonic Testing (UT) for thickness measurements of single plate gusseted connections to check for corrosion. The Function of bearings is to allow the movements of the bridge due to temperature changes; they should not be excessively deformed. Typically, items such as bearing areas, fatigue-prone details, areas where debris accumulates, and other areas known to be prone to deterioration should be inspected at arm's length. As the condition of the structure deteriorates, the effort required for the inspection will increase.

Bridges with underwater piers need a special inspection. When the depth of the water is less than three feet, an underwater inspection will not be required. In other cases, underwater inspection at arm's length includes looking for evidence of scour or settlement, deterioration of foundations' bearing capacity, and the exposure of normally buried portions of the structure. Another important consideration for underwater piers is a settlement. Structures can undergo settlement over time; however, uneven settlement can cause damage to the structure. Scour is when water currents erode the soil around the hidden foundation members and expose them, leaving scour holes behind. Problems arising from visibility, wildlife, and polluted waters can also affect underwater inspection.

In the US, the inspection frequency depends on the NBI ratings. For example, if a component of a bridge namely deck, superstructure or substructure has a condition rating of 5 or more, it is inspected every 24 months; if the rating is 4, then the frequency is 12 months and six months for rating 3 or less.

Inspection Report Generation

The findings from the visual inspection step are documented in the Bridge Management System (BMS) in the following format. Inventory data such as location, bridge name, roadway, facility crossed, geometric, and other inventory data are mentioned in the report, followed by verbal descriptions of the inspectors' findings, including the size and severity of identified defects. Pictures and sketches of bridge sections are also included to justify the verbal descriptions. Inspector recommendations and evaluation of work performed on the bridge since the last inspection are noted. Inspectors assign numerical ratings to various bridge components. There are four defined condition states for each element. The intensity of various distress paths or deficiencies is defined for each condition state in the AASHTO Manual, with the following general intent: Condition State 1 Good, Condition State 2 Fair, Condition State 3 Poor, Condition State 4 Severe. Quantities reported to the FHWA in Condition State 4 for primary load bearing elements indicate that a structural review has been completed, as described in the AASHTO Manual, and defects that are discovered have an impact on the strength or serviceability of the element. Sufficiency Rating and Health Index are automatically calculated in the BMS based on condition ratings.

Performance Measures

Ratio-based methods assign a bridge condition index (BCI) or number (BCN) based on the ratio of the current condition to the condition of the structure when it was built. The objective of this method is to calculate the remaining life of the bridge. The California Bridge Health Index (BHI) and the health index method used by AASHTO-WARE Bridge Management software (**?**), BrM (formerly Pontis), are software examples of the ratio-based method. The index assesses the current condition of a bridge by aggregating the current condition value of all the elements of the bridge and comparing it to the total value of the bridge elements when they were in their best possible state. The value of each element is proportional to the number of elements in the present condition and the economic consequence of the element's failure. The element's failure cost (FC) can be seen as a weight emphasizing the importance of the element to the overall health of the bridge. The weighted average approach is suitable for planning bridge maintenance and rehabilitation activities. The approach estimates the condition of the whole structure by combining condition ratings of all individual bridge elements weighted by their significance or contribution to the structural integrity of the bridge. A summary of BHI methods is included in Table 1.

Table 1: Summary of BHI and their calculation approaches

Index name	Calculation Approach
California BHI	Ratio based
United Kingdom's BCI	Weighted average
Austria's Qualitative Bridge Rating	Qualitative method
Finnish Bridge Condition Rating	Weighted average
Germany's BCI	Worst Conditioned Component
Bridge Sufficiency Rating	Formulaic combination of many parameters
Risk-Based Assessment Framework	Formulaic combination of risk scores

The worst-conditioned component approach is common in systems that carry out inspections on key bridge components. In this approach, the BCI is approximated to the rating of the component in the worst condition. Some States also use the worst (lowest) National Bridge Inventory (NBI) rating to report bridge conditions at performance dashboards.

Qualitative methods do not report the condition of the bridge on a numerical scale. They describe a structure as either "Poor," "Fair," or "Good," based on the condition state and importance of the elements under investigation. Washington, Florida, and other States use NBI condition ratings to classify bridges as "Good," "Fair," or "Poor." A risk-based prioritization method is currently being tested by the New Jersey Department of Transportation (NJDOT). This approach combines different performance limit states to calculate the perceived relative risk for each bridge.

Bridge Management System

Classification of the bridge inventory is performed based on characteristics, conditions, and comparison of relative construction costs of bridges by structure type. The characteristics of the classification include the number of bridges, their age, structure types, and deck areas, as well as conditions such as the overall structural condition, structurally deficient bridges, posted and closed bridges, and functionally obsolete bridges.

Structurally deficient bridges (SD) are bridges that have been confined to light vehicles, closed to traffic, or need rehabilitation and are therefore considered structurally deficient. When a bridge is “structurally deficient”, it does not mean it will collapse, or it is unsafe. It implies that the bridge should be carefully monitored, examined, and maintained. The condition rating of at least one component of an SD bridge is four or less.

Functionally obsolete bridges (FO) are bridges that were built to standards that are no longer in use. Bridges that are FO are those with insufficient lane widths, shoulder widths, or vertical clearances to meet contemporary traffic demand or those that are occasionally flooded. The term ”Functionally Obsolete” is no longer used by FHWA. Fracture-critical bridges (FC) are fracture-critical bridges that lack redundant supporting parts. The bridges would be in jeopardy of collapse if those vital supports failed. Currently, FHWA does not allow the use of innovative inspection techniques such as small Unmanned Aerial Vehicles (sUAVs) for fracture critical inspections.

Automated Visual Inspection

Data collection Methods

In the last decade, the use of UAS for structural inspections has increased, but significant technological developments have not been evident, which makes this field a relevant subject for research as well as analyzing potential technology applications. A UAS is considered a system that integrates three subsystems: i) the unmanned aircraft, ii) the ground control station, and iii) the communications link between the aircraft and the ground station.

Among the data collection techniques for bridge inspection using UAVs, a significant challenge is manual remote control. To address issues like ceiling effect, drifting in a GPS denied environment, a vision-based control system for the hybrid flying and climbing robot for bridge inspection was developed by Reven et al. (2019) in which the UAV clamps under a girder to transverse along using visual-inertial odometry (VIO) in GPS denied areas. Usability issues may arise in segmental bridges. Rodriguez et al. (2021) reviewed equipment required to acquire data and images mounted on UAS and techniques used to create models from images, such as 3D reconstruction, infrared thermography, Structure From Motion (SFM), Convolutional Neural Network (CNN), and others in order to detect failures. The paper also mentioned the software required to apply the techniques. For structural inspection, a drone can be equipped with payloads like high-resolution digital cameras, thermographic cameras, Light Detection and Ranging or Laser Imaging (LIDAR) devices for terrain characterization, radiation detectors, and humidity and temperature sensors. Cost and accuracy of UAS mountable LIDAR's is currently the pain point. Inspectors can use these aspects to gather the information that will help them find and assess various types of faults and discontinuities in the structural components and materials. High-quality images that cannot be acquired at wind speeds of higher than 15mph can be one of the limitations of this method.

The current UAS implementation has challenges, such as the need for a trained operator and/or the need for a UAS to function in a crowded, GPS-denied environment. A solution to these challenges was presented by Whitley et al. (2020) using commercial off-the-shelf (COTS) gear such as laser rangefinders, optical flow sensors, and live video telemetry. The system includes a drone with obstacle avoidance capabilities and a ground station manned by a pilot and bridge inspector. During inspections, the suggested custom-fabricated UAS was able to travel under GPS-denied and obstacle-laden bridge decks. The use of the proposed UAS offers an innovative strategy that could eventually allow inexperienced pilots to effectively navigate bridge and other structure inspections, improving safety and lowering costs.

Photogrammetry from unmanned aerial vehicles (UAVs) and Terrestrial Laser Scanning (TLS) are two of the most common advanced technologies for creating qualitative digital models in the case of bridge monitoring. Mohammadi et al. (2021) examined point clouds generated using several approaches in terms of point distribution, outlier noise, data completeness, surface deviation, and geometric precision. TLS-based point clouds were proven to have a higher level of point density and better agreement with as-is measurements when it came to exact 3D model reconstruction for detailed quality inspections of bridges. However, concerns remain, including the implementation time, the high equipment cost, and the limited/restricted access of TLS, which can all be compensated by using UAV-based photogrammetry techniques.

Damage assessment

A great proportion of the research publications covering automated inspections focus on damage detection and a lesser portion on assessment. Solutions for detection normally address only a single class of damage (usually cracks) or at most two. For instance, Son et al. (2014) proposed a method for detecting rust stains, which are distinguished by their specific color, with a success rate of 97.5%. Determining other damage types is not feasible on the basis of images alone, even when attempted by an experienced inspector; additional information such as location on the structure, orientation with respect to elements, or type of elements is needed. Some structural defects, such as cracks, might also extend across several sides. For correct classification, a complete defect has to be assessed, even if it spreads over on more than one side. Such detail cannot be easily captured by automated systems unless the assessment is performed with the help of an accurate 3D model.

Bridge condition rating

By representing high-dimensional data in dataset abstractions, Liu & Zhang (2020) predicted the NBI bridge condition ratings, applying a Natural Language Processing algorithm to predict future conditions of bridge parts from historical inspection data that can surpass conventional mathematical models. The research achieved 85% prediction accuracy for data-driven condition forecasting by using NBI ratings from 1992-2017. When studying some of the inspection reports, it was identified that there could be instances where notes related to damage during repair or renovation work on the existing structure can mislead the algorithm. The damages done during renovation work do not necessarily mean that the defect is structural.

The Artificial Neural Network (ANN) - based methods are considered as the most common AI method. For example, Li & Burgueño (2010) compared multiple ANN techniques for predicting bridge abutment condition ratings in Michigan, and their models had an averaged prediction accuracy of about 73% in recognizing the true condition rating of damaged bridge abutments (with condition rating </= 4). Huang (2010) used an ANN model to assess historical concrete deck maintenance and inspection data in Wisconsin, with a claimed accuracy of 75% in determining the true condition rating. YAMANE et al. (2021) focused on the use of object detection-based deep learning to extract data from past inspection records. This technique was used to automatically extract the bridge element numbering from structural drawings whose extraction was challenging using the approach of general optical character recognition (OCR). The research goal was to automatically generate a database from past inspection records. Li et al. (2021) proposed a method that has the capacity of detecting the change in the condition of the bridge compared to the last inspection record, which can also assist on the bridge condition forecasting and automated bridge inspection. Their study formalizes structural conditions as the central topic of inspection and maintenance. For the context-aware condition mapping, the use of dependency-based word embeddings, bidirectional Long Short-term method, and the use of Conditional Random Field model was employed. Word Embedding was performed by the skip-gram model, which trains a simple three-layered network that predicts the semantic (contextual) meaning of the word. A Recurrent Neural Network (RNN) was used for the Bi-directional LSTM. LSTM is used to organize the information through gate and cell operations, which prevents the forgetting of important long-term knowledge. The RNN processes the input sequence one by one and computes the output (O_t) of the current input (I_t) based on the hidden state of the previous input (O_{t-1}). Conditional Random Field was used as the last layer of the network to jointly model the label sequence such that the prediction of each label depends on its contextual labels instead of decoding each label independently. The output from the bi-directional LSTM network was first mapped to the labels space using a feed-forward neural network layer. The CRF layer maintained a transition score matrix as parameters that recorded the likeliness of transitioning from one label to another for two consecutive inputs.

Combining the CRF transition score with the

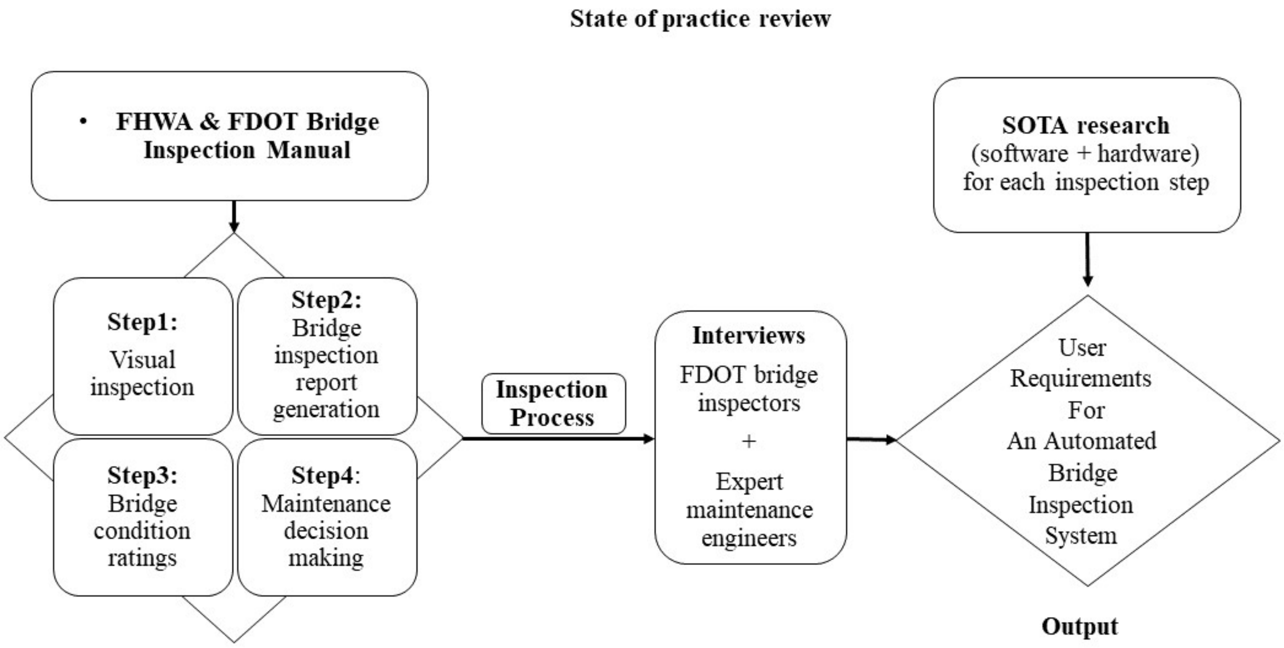

Figure 1: Research Methodology

predictions from the bi-directional LSTM network, the final score of the label was computed using an equation. The model Performance was 94.12%. The limitations of their study are: the extracted segments can be automatically matched where there is only one segment for each category in the sentence but can become confusing when multiple segments are from the same category.

Previous research has primarily focused on bridge damage recognition and inspection systems without first assessing the current inspectors practices. To introduce automation in the process, we first want to understand the needs of our working bridge inspectors and consider how they feel about the use of different techniques.

Research Methodology

Based on the presented systematic literature review, the following knowledge gaps were identified: (1) theoretical or commercialized systems that effectively overcome the limitations of traditional visual bridge inspection do not exist, and (2) the existing systems automate parts of the complex bridge inspection process without necessarily addressing the inspectors' needs. This work targets on addressing these knowledge gaps by achieving the core objective: to elicit the user requirements for an automated bridge inspection system that will, later on, be used on a novel approach to integrate system components. To achieve this goal, the following research questions need to be answered:

1. In practice, what are inspectors workflows when performing a visual bridge inspection in the state of Florida?
2. How do the inspector workflows translate to hardware and software requirements?
3. How can computer vision and Artificial Intelligence (AI) facilitate the most critical inspection processes?

The theoretical framework of this study is what makes it unique, from which a user-centered system is specified through collaboration between future users (inspectors) and the analyst (the authors) that explored user workflows (user needs) and technological possibilities. Instead of specifying the key components upfront, those are derived after gaining a clear understanding of both ends of the spectrum.

The research methodology was developed to both operate within this framework and address the research objectives (Figure 1). This plan is centered around establishing a human-centered design process for an automated bridge inspection system. To understand the current practices and future technological needs of inspectors in the visual field inspection, the collection of user requirements was divided into two phases. In the first phase, an anonymous survey within the seven districts of the Florida Department of Transportation (FDOT) was conducted, and for the second phase, a series of interviews with bridge inspectors and maintenance engineers in FDOT were conduced. When this work was submitted, the second phase was yet to be commenced.

The first phase of data gathering had 14 respondents with roles ranging from inspection program managers, bridge inspectors, report reviewers, and underwater bridge inspectors. Eighty percent of respondents had ten plus years of experience in field inspections.

Before leaving for the field inspection, inspectors review previous inspection reports, structure plans, maintenance and repair records, inventory reports, and the bridge record file.

This is when the inspector will determine if any special equipment or maintenance of traffic is needed for the

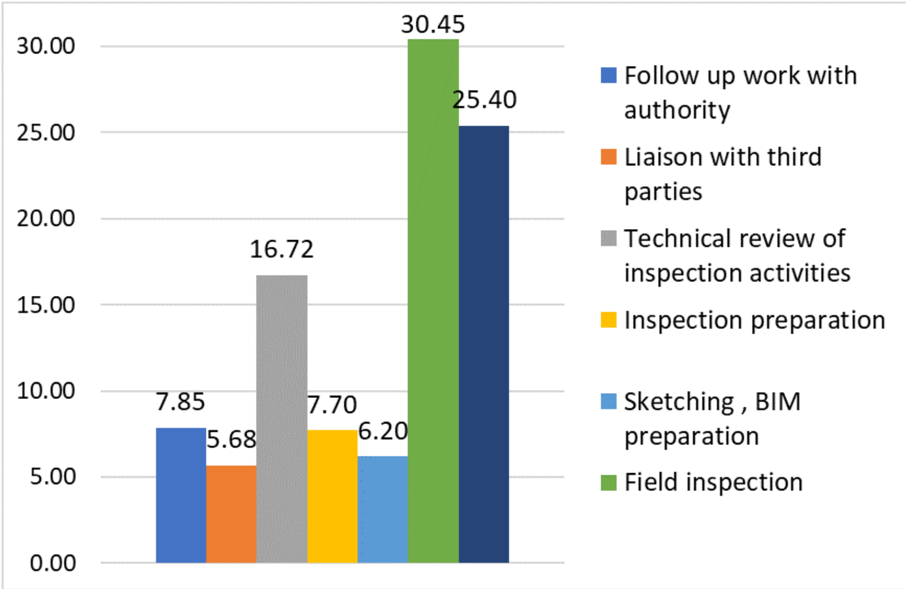

Figure 2: Time split of inspection activities for all respondents

specific bridge. Table 2 shows the importance of the information sources during this process based on the inspectors' responses.

All respondents reported that during the inspection, documents are referred through a set of printed documents or their personal handheld devices. FDOT is yet to provide inspectors with dedicated digital devices. The same channels are used to take notes based on inspection observations. The observations in the previous inspection reports are checked if they have been rectified, and new observations are noted down on the previous report for ease during field inspections.

During the inspection process, we identified different activities that inspectors perform while reporting the bridge condition, and the distribution of time spent on each activity is shown in Figure 2. The report is created in BMS to input data gathered and recommendations for repair. FHWA requires that the date the inspection is performed should be entered into BMS within 30 days after the inspection and the inspection report should be completed within 60 days. For all respondents, the highest time is spent on field inspection (30.45%) followed by reporting (25.4%). This clarifies the need for automation in both activities.

Inspectors reported that they perform multiple inspections in a day, which also includes High Mast Light Poles (HMLPs), TSMAs, overhead signs. Table 3 shows the maximum number of inspections performed simultaneously.

We also asked the inspectors when they convert the observations gathered during visual field inspections into assessment to determine the condition rating of elements. The duration varies from two weeks after inspection to seven weeks, depending on the number of inspections performed in the tour. Inspectors revealed that multiple inspections and time elapsed between inspection and reporting sometimes causes mental confusion between observations, difficulty in remembering relevance of defect, sometimes just omission of observation due to depleted severity compared to other prominent defects. This gives researchers a scope that an automated system should be developed which can keep track of observations in real-time, by virtue of having an inspection report in edit mode in the field with access to Bridge Management System (BrM), which can help to save time by eliminating paper redundancy. 70% of inspectors reported that some degree of automation needs to be introduced in the reporting process. All-purpose, weatherproof tablets with glare screens and a support strap system for practical field use are needed. That software should be compatible with BMS, which is capable of compiling comments, photos, and sketches.

The survey also revealed that inspectors would like to have modern tools such as drones to narrow down the areas of defects so that the entire bridge should not be inspected physically and access requirements, as well as traffic closure requirements, can be limited to only areas with defects identified by drone inspection. Also, when asked which part of the visual field inspection process needs automation, inspectors reported channel measurements, clearance measurements, average daily traffic count, measurement of deficiencies, bridge and roadway geometry. Table 4 presents the prioritized list of defects in response to the question asked to inspectors on using an automated system to supplement their needs.

Inspectors preferred touchpad and voice input methods over gaze (eye-tracking), gestures, remote controller for the automated system. 80% of inspectors are inclined towards the use of drones for the inspection process; however, skepticism comes from the need to pilot the UAV. The predefined flight path, obstacle avoidance, and autonomously flying drone can eliminate the need for extensive training for the equipment. However, to autonomously

Table 2: Importance of information sources

Field	Mean	Std Deviation	Variation
Photographic records	4.86	0.29	0.09
Inspection records	4.64	0.69	0.48
Structure plans	4.00	1.09	1.18
Maintenance & repair records	3.86	0.77	0.59
Guidelines to define severity	4.36	0.83	0.69
Inventory reports	3.75	1.15	1.31

detect and quantify defects, as discussed in the literature, and in order to maintain the relevancy of the defect, data gathering using UAV should be able to create a scanned 3D model of the bridge so that the root of the defect can be identified. 78% of inspectors reported that they dont have access to 3D models of the bridge, which is another exploration channel for researchers to improve usability of photogrammetry which includes taking measurements from images.

Along with data collection, data assessment, and condition rating generation, Table 5 shows the list of functional features and their usability as the outcome of the questionnaire.

Conclusions

With the findings from this study, a complete automated system combining data collection, data assessment, and condition rating prediction can be developed based on the needs of working bridge inspectors with the help of the proposed guidelines. This study can be extended to other states and countries given local inspection requirements are met. The vision of the project is to overcome the substantial limitations of manual visual inspection by designing an automated system improving value for money in the maintenance of the aging bridge stock. This next generation bridge inspection system in contrast to previous research that focused on automating parts of the process can provide DOTs with a tool based on Artificial intelligence, equipping inspectors with an automated software and hardware system, which accelerates data collection, 3D model generation, and report processing. Capabilities like multi-user collaboration at the time of need will help to arrive at the decision-making phase at a much faster rate and give out work orders for repair. A predictive maintenance program can be used to extend the useful life of the bridges, thereby minimizing the need to replace a large number of bridges within a short time.

Table 3: Maximum number of inspections performed on the same day or tour

Inspection component	Maximum number of inspections
Single Span Bridge	10
Multi Span Bridge	3
HMLP	20
TSMA	10
Overhead sign	12
Culverts	8

Table 4: Prioritized list of defect identification

Damage type	Mean	Std Deviation	Variation
Cracks	3.71	1.80	3.24
Spalling	3.32	1.69	2.84
Corrosion	3.71	1.66	2.74
Delamination	3.29	1.66	2.74
Paint defect	2.54	1.55	2.41
Discoloration	2.04	1.48	2.19
Section Loss	3.00	1.64	2.68

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Table 5: *Usefulness of automated inspection features*

Feature	Not at all useful	Slightly useful	Useful
Multiuser collaboration	7.14%	28.57%	64.29%
Reviewing documents	0.00%	21.43%	78.57%
Defect detection	7.14%	35.71%	57.14%
3D Model	14.29%	28.57%	57.14%
Image collection	0.00%	28.57%	71.43%
Field Measurements	0.00%	0.00%	100.00%
Member identification	7.14%	42.86%	50.00%
Stationing	7.14%	35.71%	57.14%

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