

Towards an AI-driven Platform for Damage Detection in Civil Infrastructure: Understanding Benefits and Stakeholder Needs

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ABSTRACT

Federal and state departments of transportation, the U.S. Army Corps of Engineers, electric utility companies, and other decision-makers need accurate and timely information about the condition of infrastructure to prioritize investment decisions. Currently, there are no broadly applicable automated tools to provide timely information about structural health. Artificial intelligence (AI) provides a forward-looking perspective to conceptualize and implement a data-driven and physics-informed structural health monitoring (SHM) strategy to overcome some of the challenges in traditional approaches. In September 2020, the National Science Foundation funded a project to demonstrate the proof-of-concept of an AI-driven SHM platform. The project team interacted with potential end-users and decision-makers to identify important aspects to consider in an AI-driven SHM platform. This paper summarizes the feedback received from the stakeholders and presents the project's preliminary results that serve as proof of concept.

INTRODUCTION

Reliable methods for evaluating and monitoring structural conditions are necessary to support decisions regarding the maintenance, repair, or replacement of structures. Federal and state departments of transportation, the U.S. Army Corps of Engineers (USACE), electrical utility companies, and other decision-makers need accurate and timely data on structural health to inform and help prioritize investment decisions. Much research has been performed to develop automated tools to assess the condition of civil infrastructure; however, systems are usually designed for a very specific application, and there is not a standard system that has been deployed broadly.

The USACE defines structural health monitoring (SHM) as "the science of making accurate condition assessments about the current and future ability of an asset or system of assets, particularly infrastructure assets, to perform the intended design function(s), based on sensor and inspection data, numerical engineering models, and statistical analyses" (Smith 2018). Traditional contact sensor-based SHM approaches have limitations, such as high costs for installation and maintenance and data quality issues due to environmental and operational conditions. As the applicability of traditional contact sensor-based methods to large and complex structures has not yet been sufficiently

demonstrated at a broad scale, decision-makers remain highly skeptical of the accuracy and reliability of traditional SHM approaches.

Artificial intelligence (AI) provides a forward-looking perspective to conceptualize and implement a data-driven and physics-informed SHM strategy to overcome some of the challenges of traditional approaches. In September 2020, the National Science Foundation funded a project to demonstrate the proof-of-concept of an AI-driven SHM platform that uses video cameras as non-contact sensors. The project team conducted surveys and semi-structured interviews with potential end-users and decision-makers to identify important aspects to be considered in an AI-driven SHM platform. This paper summarizes the team's findings from these interactions and presents a proof-of-concept of the proposed platform.

STAKEHOLDER FEEDBACK ON AI-DRIVEN SHM PLATFORMS

The project team sought feedback from potential end-users and decision-makers regarding their needs and expectations from an AI-driven SHM platform. These interactions were in the form of semi-structured interviews and survey questions. Key findings from these interactions are summarized below.

Interview Overview and Results

The semi-structured interviews included questions that were customized based on the background of the interviewees. Feedback was requested on topics such as (a) current needs in damage detection and localization methods, (b) necessary demonstrations/evidence that would convince the skeptics on automated damage detection and condition monitoring of structures, (c) identification of candidate structures to be used for benchmarking, (d) data and information required to make critical decisions, and (e) anticipated obstacles for the implementation of the proposed AI-driven SHM platform.

Forty-two (42) semi-structured interviews were administered to personnel from the state and federal government (Department of Transportation, District Department of Transportation, The National Institute of Standards and Technology, Los Alamos National Laboratory, the United States Army Corps of Engineers, and the U.S. Department of Housing and Urban Development), experimental facilities (Insurance Institute for Business & Home Safety, Wall of Wind at Florida International University, and the NHERI Experimental Facility at the University of Florida), a nonprofit organization (Development Corporation of Columbia Heights), industry (Walter P Moore, Michael Baker International, Applied Research Associates, Inc., Structural Integrity Associates, Berkshire Hathaway Specialty Insurance, Washington Metropolitan Area Transit Authority, the Potomac Electric Power Company, among others), and academia (faculty from the University of Illinois at Urbana-Champaign, the University of Texas at Austin, University of California, Berkeley, among others).

The interviewees provided useful feedback on various aspects to consider in the development of an AI-driven SHM platform and offered new insight into potential uses of the platform that the team had not previously considered. The benefits of an AI-driven SHM platform for damage detection were evident to the interviewees. Below are the key takeaways from the interviews:

- Traditional monitoring approaches relying on a network of wired or wireless sensors for data collection offer limited damage detection capability due to the practical limitations on the number and placement of the sensors used.
- Collecting data on structures is less complicated today; what is lacking are reliable data analysis tools for decision-making.
- Existing damage detection algorithms are typically derived using simple laboratory models or numerical simulations. Their applicability rarely translates to real, in-service structures. An AI-driven platform should be validated and calibrated using field data from actual structures.
- Output-only damage detection approaches are desirable, as application of controlled input to civil engineering structures is a difficult and expensive task.
- AI-driven SHM platforms can offer great benefits for the monitoring of operations and maintenance.
- AI-driven SHM platforms would be of great value to property owners concerned with assessing the progression of damage.
- Many interviewees do not consider traditional SHM a decision-making tool due to the lack of data analysis tools that provide actionable insight.
- Interviewees emphasized the need for automated data analysis tools that provide quantitative metrics about the condition of the structure that are easy to interpret.
- AI-driven SHM platforms need to go beyond the cost-benefit assessment to be considered for adoption in practice.
- Existing vibration-based SHM tools can detect global stiffness changes but not local damages. AI-driven SHM tools that are able to detect local, minor damages are of interest.
- AI-driven SHM tools should not be generic; they should be customized to the structure and the damage type of concern.
- When vibration response is measured on actual structures, the influence of operational and environmental conditions must be considered.
- Inaccuracies due to numerical integration/differentiation errors must be adequately addressed when the measured response is converted to another type of response (e.g., from acceleration to displacement).
- Correlations between the responses measured at different points can be used to distinguish damage from the large-amplitude, elastic response.

The responses from the semi-structured interviews were used to help develop a stakeholder survey. The 20-question survey was administered to 89 stakeholders. The purpose of the survey was to gather additional data on the perceived need, usefulness, and feasibility of an AI-driven SHM platform.

Survey Overview and Results

Figure 1 shows the survey respondents' characteristics. A majority of the respondents were from the government sector (72%), industry (13%), or academia (10%). Of the respondents, 36% have roles in maintaining their organization's facilities, and 30% work as technical consultants. 72% of respondents have more than ten years of experience. Figure 2 provides some details of the roles of the respondents. More than half (53%) of respondents work in an organization overseeing more than a hundred structures; most use safety inspections at least once per year and need more than ten people to perform those inspections.

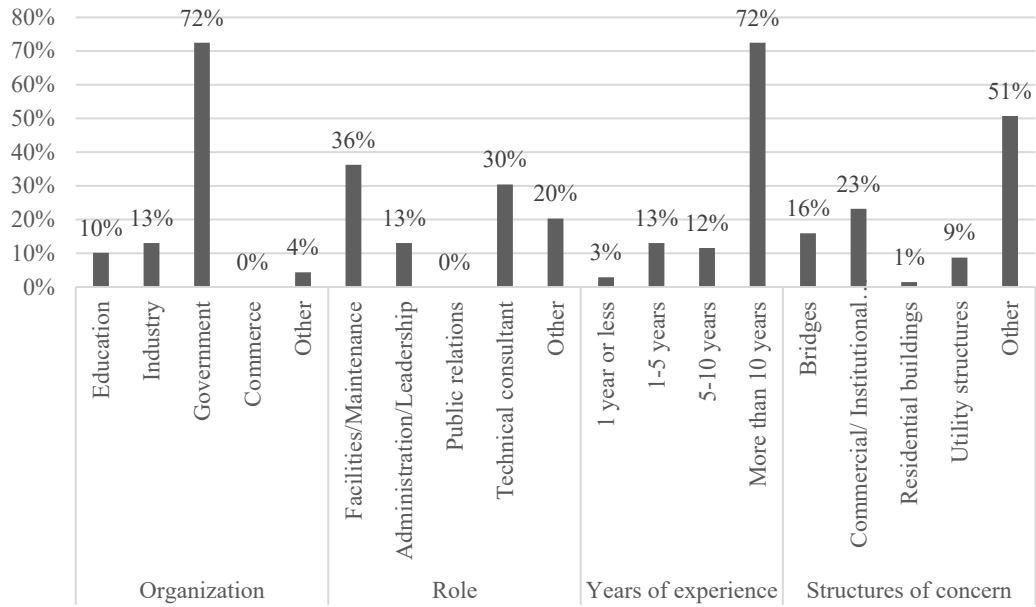


Figure 1. Survey respondent characteristics

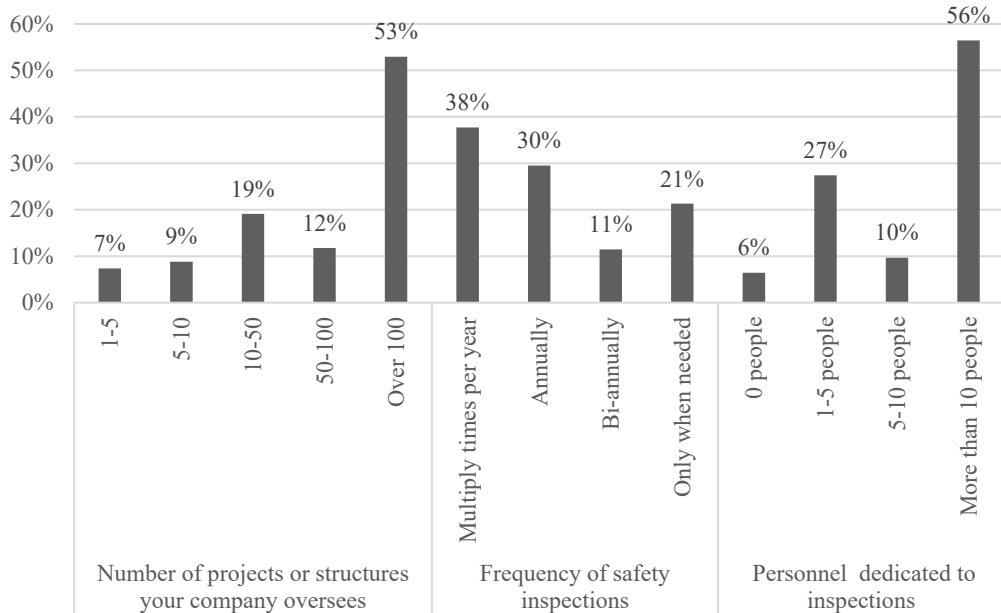


Figure 2. Roles of respondents

The survey data indicates the interviewed stakeholders are primarily interested in an AI driven SHM system to help inform the condition of structural elements and mechanical systems, as shown in Figure 3. A lack of data to support the practical value of SHM is the largest obstacle to the widespread implementation of any SHM platform, as seen in Figure 4. The American Society of Civil Engineers (ASCE) Structural Identification of Constructed Systems Committee (Çatbaş et al. 2013) identified the skepticism of the potential end-users as a major barrier to the widespread adoption of SHM in public and government sectors. This skepticism could be overcome by producing an accurate

system. A minimum level of accuracy of at least 80% would be needed to achieve buy-in for critical decisions from the majority of stakeholders surveyed in this study, as shown in Figure 5.

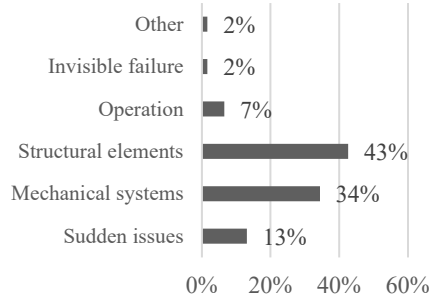


Figure 3. Desired uses of the platform

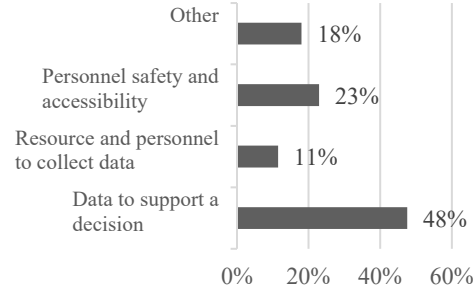


Figure 4. Primary concerns

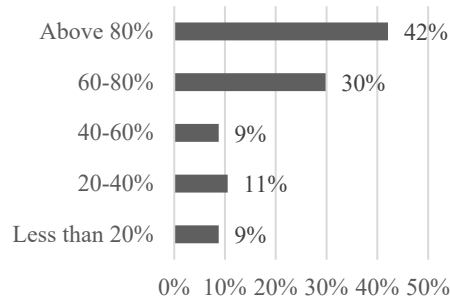


Figure 5. Minimum acceptable level of accuracy

PROTOTYPE DEVELOPMENT

Reduced technology costs and exponential increases in computational power have led to an increase in the research and development of computer vision-based tools for inspection and monitoring of infrastructure (Alexander et al. 2022). Using computer vision-based tools, each pixel of a frame acts as a sensor. The research team explored this technology in the development of a prototype platform consisting of video tracking and damage detection components, with the goal of achieving at least 80% accuracy to meet the accuracy desired for the highest level of buy-in. The video tracking component uses video cameras as non-contact sensors tracking points of interest at specific locations. The damage detection component uses machine learning algorithms to detect, locate, and quantify stiffness changes. It incorporates physical laws and constraints into the pretraining of machine learning algorithms to ensure the compatibility of the predictions with physical principles while reducing computational requirements. Figure 6 illustrates the general concept of the prototype integrating the video data and damage detection models.

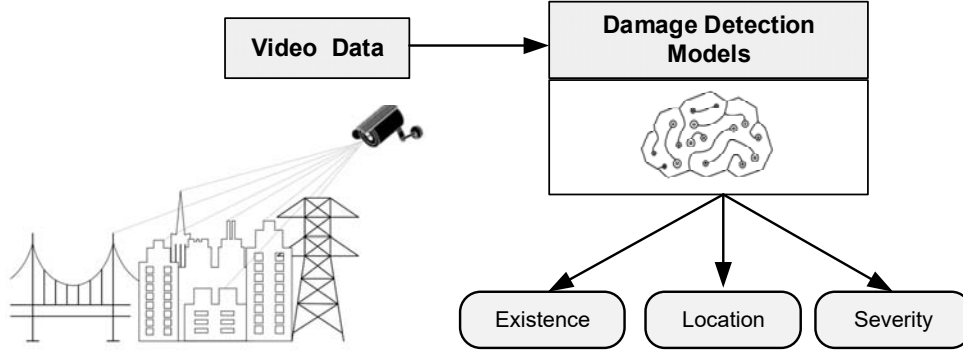


Figure 6. The general concept of the prototype integrating video data and damage detection

Video Tracking Prototype (VTP)

The team developed a video tracking prototype (VTP) to track points of interest across video frames. The prototype was tested using video footage recorded during shake table experiments for which experimental data was available, and the optical flow between subsequent frames when tracking visible pixels was determined (Whiteman et al. 2021). The VTP was also tested on a small-scale model of a five-story shear frame, which was placed on a shake table and subjected to a sinusoidal load exciting the first mode of the structure. Figure 7 shows the model frame, with accelerometers placed on the shake table at the base (Point 10) and the top of the frame (Point 11).

The acceleration data was used to determine the relative displacements using both cumulative trapezoidal numerical integration (Papazafeiropoulos 2021) and the least-squares support vector machine (LSSVM) method (Tezcan et al. 2018). Linear baseline correction was applied to the acceleration time history before the trapezoidal method to minimize the overall drift of the displacement obtained from double integration. The displacements calculated from the accelerations (i.e., using the trapezoidal method (Papazafeiropoulos 2021) and the LSSVM method (Tezcan et al. 2028)) are found to be in good agreement with the displacements predicted using the video tracking program.

The VTP estimated peak displacements are up to 20% smaller than those predicted by the trapezoidal integration and LSSVM methods; still, the overall histories of responses have similar trends to the LSSVM method. Previous assessments comparing the video predictions to sensor measurements were closer in magnitude when the sensors used provided displacements directly (i.e., from potentiometers) .

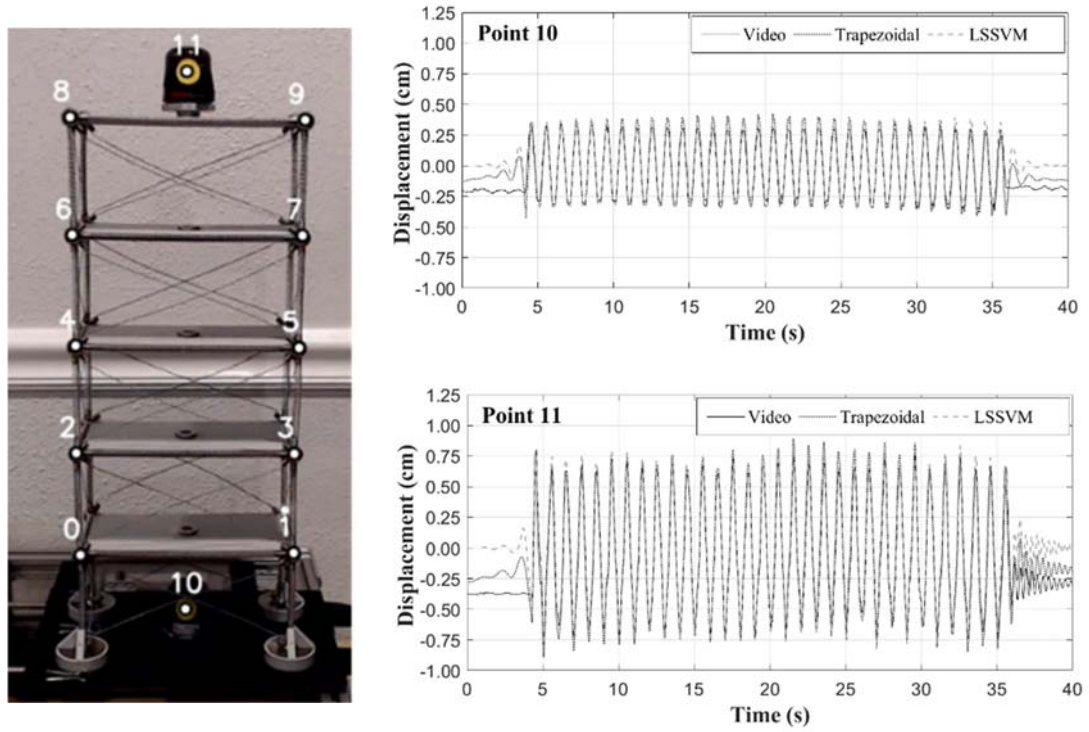


Figure 7. Five-story frame and displacements at the base (Point 10) and top of the frame (Point 11) predicted using the VTP and calculated from the acceleration data

Damage Identification Prototype (DIP)

An AI-based prototype was developed to identify linear damages, which appear as a sudden loss of stiffness. This prototype includes three successive levels of damage identification: Level 1: detection of the occurrence of damage, Level 2: estimation of the location of the damage, and Level 3: quantification of the damage severity.

Considering Level 1 damage identification (i.e., damage occurrence), it was found that in systems whose displacement behavior can be adequately described using a few degrees of freedom, time-frequency analysis of the vibration response at any of the degrees of freedom can reveal the occurrence of sudden damage along with the time instance(s) at which damage occurs. Figure 8a describes a damage scenario, depicting an 80% cumulative loss in stiffness occurring over three instances. This damage was imposed on the first floor of a 4-story shear building described in (Bernal et al. 2000). The wavelet synchrosqueezed transform (WSST) of the displacement of the first floor under the El Centro ground motion is shown in Figure 8b. The WSST ridge shown as a white line closely follows the damage scenario considered. The ridges obtained using the displacement of the other floors followed similar trends.

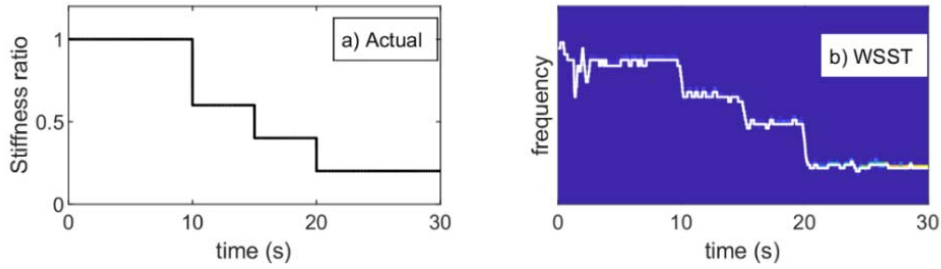


Figure 8. Detection of stiffness changes using wavelet synchrosqueezed transform

For Level 2 damage identification (i.e., damage location), independent component analysis (ICA) was explored as a tool to locate damages based on discrete wavelet coefficients of measured accelerations. Damage locations were estimated by examining the absolute values of the mixing coefficients corresponding to each spiky independent component. The method's performance was evaluated using the acceleration readings collected during the full-scale testing of a 5-story reinforced concrete building (Chen et al. 2016). Figure 9 shows the main steps of the damage location method. Damage locations indicated by the ICA algorithm matched, to a large extent, the damages observed during post-test inspections.

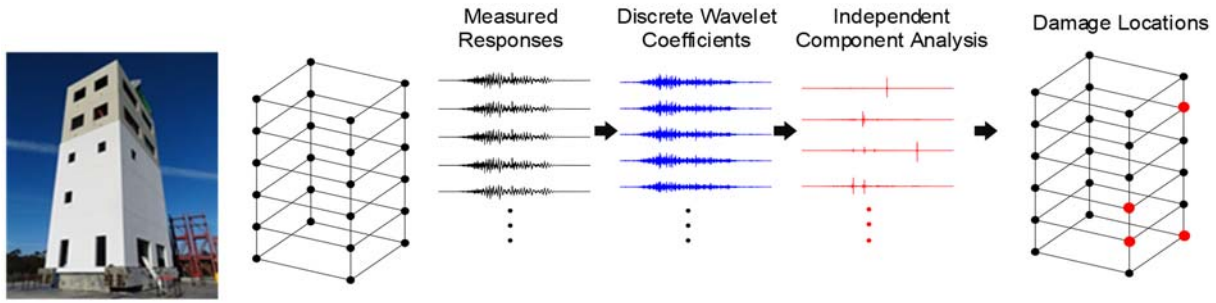


Figure 9. Finding damage locations on a test building using independent component analysis

For Level 3 damage identification (i.e., damage quantification), convolutional neural networks (CNNs) were investigated to classify the extent of damage to a 5-story reinforced concrete building (Chen et al. 2016) subjected to white noise base excitations and experimentally measured base excitations. The damage state of the structure is predicted using the Fourier amplitude spectra of floor acceleration or displacement time histories. The team used numerically simulated data to train the model. The results of the study were presented at the 2022 Natural Hazards Research Summit (Whiteman et al. 2022). The model achieved a probability distribution prediction with an accuracy of 99.98% for experimentally measured responses.

CONCLUSION

Interactions with potential end-users and decision-makers revealed the lack of data to support the practical value of SHM as a major obstacle to the widespread implementation of any SHM platform. Additionally, organizations were concerned about the safety associated with accessing the sensor locations, the resources associated with collecting the data, and the accuracy of the results. As such,

it is important to develop an automated SHM system that is simple to deploy, using sensors that do not have to be installed on the structure and that produce results with a high level of accuracy.

Preliminary results have shown that an AI-driven SHM platform can successfully detect and locate damage and quantify damage severity by tracking structural responses from video recordings. The team developed a small-scale prototype of a five-story shear frame to test the platform's components.

ACKNOWLEDGMENT

This project is supported by the National Science Foundation (NSF) under Grant No. 2040665. The research team is grateful for the feedback provided by potential end-users and decision-makers.

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