Computer Vision Tools for Bridge Inspections and Reporting

CTIPS-017
Approved 6/17/2024

University

South Dakota State University

Principal Investigators

PI: Mostafa Tazarv, Ph.D., P.E.
Associate Professor
Dept. of Civil and Env. Eng.
South Dakota State University
326 Crothers Eng. Hall, Box 2219
Brookings, SD 57007
Phone: (605) 688-6526
Email: mostafa.tazarv@sdstate.edu
ORCID: 0000-0003-2115-3156

Co-PI: Kwanghee Won, Ph.D.
Assistant Professor
Dept. of Elec. Eng. & Comp. Science
South Dakota State University
Box 2222, DEH 127
Brookings, SD 57007
Phone: (605) 688-4346
Email: kwanghee.won@sdstate.edu
ORCID: 0000-0003-1717-6881

Research Needs

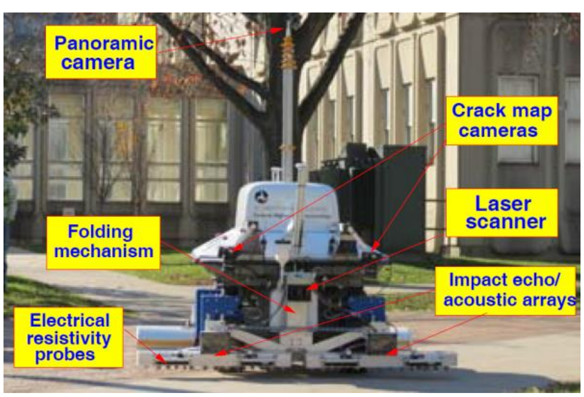
Nationwide, more than 300,000 bridges are annually inspected. For example, the Alaska Department of Transportation & Public Facilities (DOT&PF) is responsible for condition assessment of approximately 1,000 bridges in the state. Of which, approximately 44% are in good condition, 49% are in fair condition, and 7% are rated poor based on the 2021 National Bridge Inventory – NBI – data (Infobridge, 2024). **Figure 1** shows a few samples of element-level defects. Visual inspection is the common practice for inventory and routine inspections and is combined with other tools such as non-destructive evaluation (NDE) in other inspections for enhanced assessment. Inspectors usually complete both an NBI inspection (following the FHWA Recording and Coding Guide, 1995) and an element level inspection (based on the AASHTO Manual for Bridge Element Inspection, MBEI, 2019) per bridge. However, data collection and reporting are usually done manually, which are time consuming, error prone, and sometimes not consistent when repeated. For example, "deck damage mapping" requires manual detection and measurement of delaminated concrete, patch repairs, exposed reinforcing steel, and spalling. Such measurements often require traffic control for the safety of inspection crew.

(a) Deck Surface – Photo Courtesy: AKDOT

(b) Steel Girders – Photo Courtesy: AKDOT

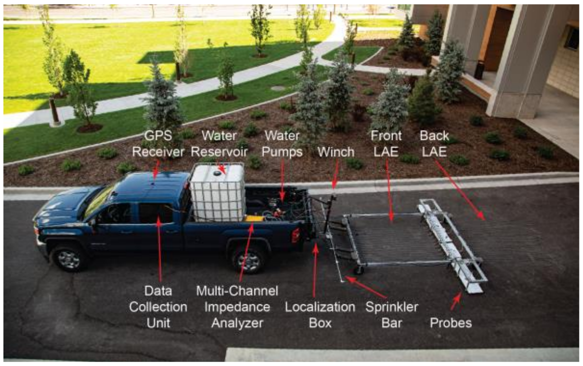
Figure 1. Sample Defects for Different Bridge Elements

Several studies have tried to expedite bridge inspection through emerging technologies such as robotics, drones, and artificial intelligence (AI). For example, La et al. (2013) developed a bridge deck inspection robot (**Fig. 2a**) equipped with several NDE techniques including GPS, laser scanner, ground penetrating radar, seismic sensors, electrical resistivity probes, and high-resolution cameras. The cost of this robot in 2014 was about $1 million (Zhorov, 2014). Drones equipped with depth, lidar, and/or infrared cameras can be used to generate 3D models of bridges (e.g., Lattanzi and Miller, 2015; Khaloo et al., 2018; Chen et al., 2019; Popescu et al., 2019; Jalinoos et al., 2019; Liu et al., 2020). A 3D reconstructed model (**Fig. 2b**) provides a virtual reality platform to remotely inspect a bridge. Nevertheless, data processing and storing are the challenges of this method due to the size of data ranging from 10 to 100 GB per inspection (Azari, 2021). A recent attempt to develop a mobile deck condition assessment system is a study by Pashoutani et al. (2020) sponsored by the Nebraska DOT in which four NDE methods were compared: vertical electrical impedance (**Fig. 2c**), ground penetrating radar, acoustic scanning system, and computer vision (**Fig. 2d**). All NDE methods were found viable for bridge deck damage assessment (**Fig. 2e**) and the crack map of the deck using computer vision showed a reasonable agreement with the damage maps developed using other NDE methods (e.g., **Fig. 2f**).



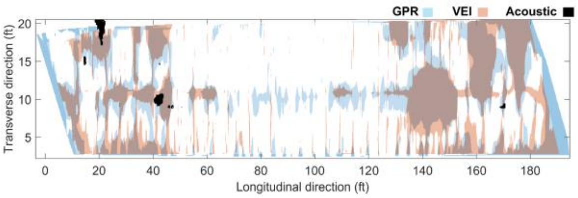
(a) Bridge Deck NDE Robot (La et al., 2013)

(b) 3D Reconstructed Bridge (Wells and Lovelace, 2018)

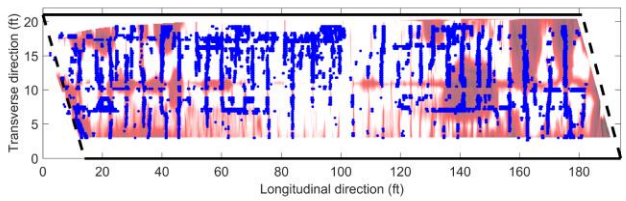


(c) NDE Truck (Pashoutani et al., 2020)

(d) Computer Vision Cameras (Pashoutani et al., 2020)



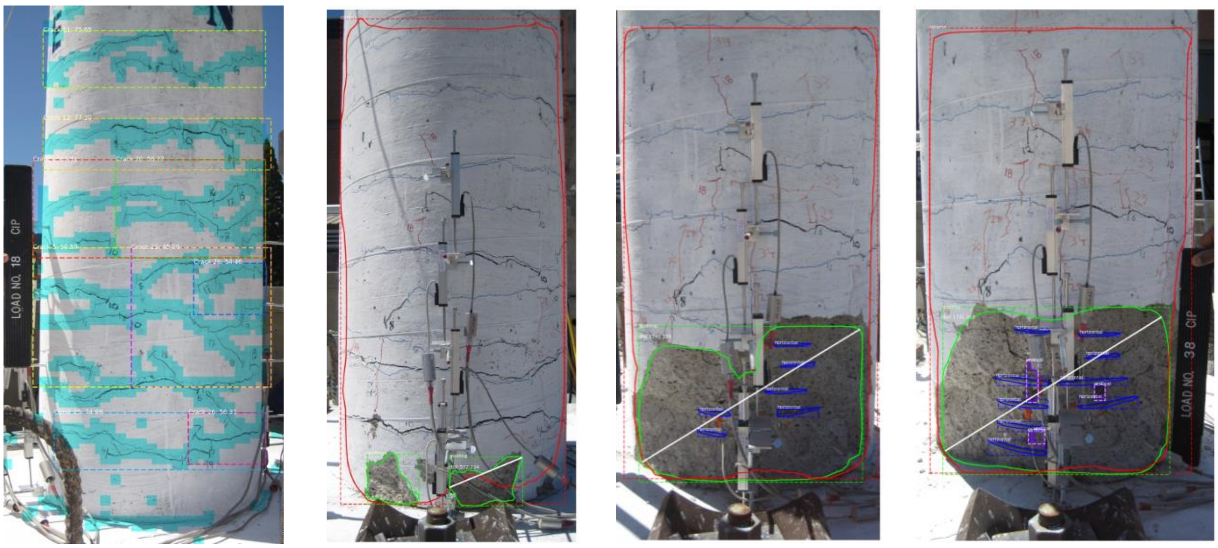
(e) Comparison of Tree NDE Methods for a Bridge Deck (Pashoutani et al., 2020)



(f) Comparison of Vertical Electrical Impedance Method with Computer Vision Cracking (Pashoutani et al., 2020)

Figure 2. Emerging Bridge Inspection Technologies

AI enabled computer vision techniques extract information from digital images, videos, and other media and interpret the information for the target applications such as object detection, instance segmentation, and prediction. The use of computer vision has been emphasized in various civil engineering applications such as detecting structural elements, damages, and reporting. For example, Zhu et al. (2010) used image stitching techniques to detect bridge columns to expedite inspection. Narazaki et al. (2020) used a convolutional neural network (CNN) designed for semantic segmentation to recognize bridge components from images. Zhu et al. (2011) used a percolation-based method to detect cracks in RC columns. German et al. (2012) used an image segmentation, template-matching, and morphological filtering to detect concrete spalling and rebars. Jahanshahi and Marsi (2012) proposed crack detection method using a 3D scene reconstruction, segmentation, and feature extraction. Torok et al. (2014) used a similar method and successfully detected cracks longer than 0.5 cm. Valença et al. (2017) combined image processing and point cloud data obtained from a terrestrial laser scanner to detect concrete cracks. Li and Zhao (2019) trained a deep CNN using 60,000 images to detect concrete cracks and developed a mobile application. Other recent studies (e.g., Dung and Anh, 2019; and Liu et al. 2020) used either deep CNN or U-Net (a CNN used for biomedical image segmentation) to detect concrete cracks and reported more than 90% precision. Furthermore, computer vision may be incorporated to expedite and automate post-event structural damage inspections. German et al. (2013) and later Paal et al. (2015) developed a framework to automatically detect RC building columns and their earthquake-caused damages, and to estimate the column damage state then the corresponding drift demand. Hoskere et al. (2018) utilized a pixel-wise deep CNN to detect concrete cracks, concrete spalling, exposed rebars, steel corrosion, steel fracture, steel fatigue cracks, and asphalt cracks. A 1695-image database cut from 339 photographs of 250 different structures was developed to label and train the network. The network was able to detect different types of damage, and the classification accuracy was more than 80%. Later, Hoskere et al. (2018) proposed a framework to generate vision-based condition-aware models to automate building inspection by detecting building, windows/doors, debris, sky, greenery, cracks, spalling, and exposed rebar with 80% detection accuracy.



(a) Damage State 2 (b) Damage State 3 (c) Damage State 4 (d) Damage State 5

Figure 3. Computer Vision Tools for Post-Earthquake Assessment of RC Bridge Columns

The research team of this proposal developed a framework and software that can evaluate the serviceability of RC bridge columns after strong earthquakes (Tazarv et al., 2022) in which computer vision tools were developed to detect the column earthquake-caused damages including cracking and crack angles, spalling, and exposed reinforcement (**Fig. 3**), to determine the column damage state, and to estimate the column displacement demand using damage-to-drift relationships. The AI-based computer vision tool for cracking can detect RC bridge column cracks with precision and recall of 97% and 96%, respectively. Furthermore, the precision and recall of the tool to detect concrete spalling was respectively more than 94% and 88%. The precision and recall for the rebar detection were more than 91%. Overall, the computer vision tools developed by the research team detect different damages of RC bridge columns quickly and with reasonable accuracy. Inspection software exists for bridges. For example, the mobile version of AASHTOWare has been recently developed (https://www.mayvue.com/). Another example is InspectX (https://www.bridge-intel.com/), which is a multi-asset management tool including bridges. In this software, NBI and MBEI bridge inspection requirements have been digitized for quick documentation. A few companies claim that AI has been implemented in their inspection software to detect damage. Examples are Intelligent Inspection (https://www.screeningeagle.com/) and Inspect (https://strucinspect.com/). The annual cost of Inspect only for damage detection is $1,438 per user and is $4,300/user when 3D damage mapping is included. With higher storage, their annual cost can be as high as $45,000.

Research Objectives

Computer vision can expediate bridge defect identification and quantification using images of bridge elements. The main goals of the present study are to:

1. Develop practical computer vision tools that help inspectors with the defect detection and quantifications
2. Develop tools that prepare inspection reports following NBI and MBEI requirements

Research Methods

To achieve the project objectives, a few bridge elements (e.g., concrete decks and steel girders) will be targeted for further investigation, inspection databases including images of the selected elements with/without damage will be compiled using different devices (iPhone and drones) and formats (RGB, lidar, and thermal), and computer vision tools will be developed for the selected elements to recognize the element defects, to quantify their damage state per NBI/MBEI, and to generate an inspection report following standard practices. The tools, which can be standalone or web-based software, will allow data acquisition using drones and mobile devices and will facilitate access, share, and reuse in future inspections.

Relevance to Strategic Goals

The expected outcomes of this project are directly related to the goals of "Transformation" and "Safety". This project incorporates cutting-edge technologies such as smartphones equipped with high-resolution RGB and lidar cameras, drones equipped with combined RGB and thermal sensors, and neural networks for quick damage identification and quantification. These technologies are either new or have not been widely used in bridge engineering. Furthermore, these technologies help with quick identification and quantification of bridge damages enhancing their safety.

Educational Benefits

This project will provide valuable learning experience to two Graduate Research Assistants (GRAs) at the PhD level, one at Civil and another at Computer departments. The two students will perform the tasks of the project under the supervision of the PIs. The student will have the opportunity to work on this multidisciplinary research project. A regular weekly meeting will be scheduled between the PIs and the students to better train them and to consistently monitor the project progress. Funds have been allocated to involve undergraduate students in data collection (e.g., drone pilots) and AI software development. A priority will be given to underrepresented students especially women and native Americans.

Outputs through Technology Transfer

Three main deliverables of the project will be: (1) a final report, (2) a set of verified opensource computer vision codes for damage detection and quantification from images, and (3) user-friendly software for routine inspection and reporting. A project webpage is designed under the PI's website (https://sites.google.com/view/mostafa-tazarv) in which the sponsors, personnel, and project goals are presented and the key findings are frequently updated. The final report (through the PI and CTIPS websites) and the opensource codes (through GitHub) will be publicly available at no cost for use by other researchers, DOTs, and software developers. The research findings will be further disseminated through journal publications and conference presentations. Furthermore, a presentation will be prepared for the CTIPS webinar series, which will be recorded and posted in public domains (e.g., YouTube). The research team will prepare a user guide and will organize in-person training sessions for the DOT engineers.

Expected Outcomes and Impacts

The main outcome of this project is a practical AI-based software package that can automatically detect bridge element (e.g., concrete deck and steel girder) damages and quantify their damage state. The impact of the work is a substantial reduction of time and cost in bridge inspection for these elements and automation in inspection data processing and reporting. The products of this project are expected to have national impacts as more than 300,000 bridges are annually inspected. Furthermore, the use of smartphones and drones allows transportation agencies to collect different information quickly and safely using cutting-edge technologies.

Work Plan

To achieve the project goal, the proposed work is divided into seven tasks.

1. Literature Review on Use of Computer Vision in Bridge Damage Detection (2 months)
2. Selection of Bridge Elements for Computer Vision Condition Assessment (1 month)
3. Inspection Data Collection for Bridge Elements (6 months)
4. Definition of Damage Conditions Suitable for Computer Programming (1 month)
5. Development of Computer Vision Condition Assessment Tools (10 months)
6. Field Validation of Computer Vision Condition Assessment Tools (2 months)
7. Project Deliverables including Final Report, Opensource Programs, and a User Guide (2 months)

Project Cost

Total Project Costs:	$144,223
CTIPS Funds Requested:	$ 71,650
Matching Funds:	$ 72,573
Source of Matching Funds:	Alaska Department of Transportation & Public Facilities

References

AASHTO MBEI. (2019). “Manual for Bridge Element Inspection, 2nd Edition,” American Association of State Highway and Transportation Officials (AASHTO), 406 pp.

Azari, H. (2021). “Effective Practices for Managing Bridge Inspection Data Captured by UAS,” Federal Highway Administration, FHWA, Publication No.: FHWA-HRT-21-043, 6 pp.

Chen, G., Liang, Q., Zhong, W., Gao, X. and Cui, F. (2021). “Homography-based Measurement of Bridge Vibration Using UAV and DIC method,” Measurement, Vol. 170, 16 pp.

Dung, C.V., and Anh, L.D. (2019) “Autonomous Concrete Crack Detection Using Deep Fully Convolutional Neural Network,” Automation in Construction, Vol. 99, pp. 52-58.

FHWA. (1995). “Recording and Coding Guide - Federal Highway Administration”, Federal Highway Administration, 124 pp.

German, S., Brilakis, I. and DesRoches, R. (2012). "Rapid Entropy-Based Detection and Properties Measurement of Concrete Spalling with Machine Vision for Post-Earthquake Safety Assessments." Advanced Engineering Informatics, 26(4), pp. 846-858.

German, S., Jeon, J.S., Zhu, Z., Bearman, C., Brilakis, I., DesRoches, R. and Lowes, L. (2013). "Machine Vision-Enhanced Postearthquake Inspection." Journal of Computing in Civil Engineering, 27(6), pp. 622-634.

Hoskere, V., Narazaki, Y., Hoang, T. and Spencer Jr, B. (2018). "Vision-Based Structural Inspection Using Multiscale Deep Convolutional Neural Networks." The 3rd Huixian International Forum on Earthquake Engineering for Young Researchers, arXiv preprint arXiv:1805.01055, 8 pp.

Hoskere, V., Narazaki, Y., Hoang, T.A., and Spencer B.F., (2018) "Towards Automated Post-Earthquake Inspections with Deep Learning-based Condition-Aware Models," in Proc., The 7th World Conference on Structural Control and Monitoring, 7WCSCM, 10 pp.

Infobridge. (2024). Federal Highway Administration, Retrieved on Jan. 15, 2024: <https://infobridge.fhwa.dot.gov/>.

Jahanshahi, M.R. and Masri, S.F. (2012). "Adaptive Vision-Based Crack Detection Using 3D Scene Reconstruction for Condition Assessment of Structures." Automation in Construction, 22, pp. 567-576.

Jalinoos, F., Agrawal, A.K., Brooks, C.N., Amjadian, M., Banach, D.M., Boren, E.J., and Ahlborn, T.M. (2019). "Post-hazard Engineering Assessment of Highway Structures Using Remote Sensing Technologies," Office of Infrastructure Research and Development, Federal Highway Administration, Report No. FHWA-HIF-20-004, 88 pp.

Khaloo, A., Lattanzi, D., Cunningham, K., Dell'Andrea, R., and Riley, M. (2018). "Unmanned Aerial Vehicle Inspection of the Placer River Trail Bridge through Image-based 3D Modelling," Structure and Infrastructure Engineering, Vol. 14, No. 1, pp. 124-136.

La, H.M., Lim, R.S., Basily, B., Gucunski, N., Yi, J., Maher, A., Romero, F.A. and Parvardeh, H. (2013). "Autonomous Robotic System for High-efficiency Non-destructive Bridge Deck Inspection and Evaluation," In 2013 IEEE International Conference on Automation Science and Engineering (CASE), pp. 1053-1058.

Lattanzi, D., and Miller, G.R. (2015). "3D Scene Reconstruction for Robotic Bridge Inspection," Journal of Infrastructure Systems, Vol. 21, No. 2, 04014041, 12 pp.

Li, S., and Zhao, X. (2019) "Image-Based Concrete Crack Detection Using Convolutional Neural Network and Exhaustive Search Technique," Advances in Civil Engineering, Vol. 2019, 12 pp.

Liu, Z., Cao, Y., Wang, Y. and Wang, W. (2019). "Computer Vision-Based Concrete Crack Detection using U-net Fully Convolutional Networks." Automation in Construction, 104, pp. 129-139.

Liu, Y.F., Nie, X., Fan, J.S., & Liu, X.G. (2020). "Image-based Crack Assessment of Bridge Piers Using Unmanned Aerial Vehicles and Three-Dimensional Scene Reconstruction," Computer-Aided Civil and Infrastructure Engineering, Vol. 35, No. 5, pp. 511-529.

Narazaki, Y., Hoskere, V., Hoang, T.A., Fujino, Y., Sakurai, A. and Spencer Jr, B.F. (2020). "Vision-Based Automated Bridge Component Recognition with High-Level Scene Consistency." Computer-Aided Civil and Infrastructure Engineering, 35(5), pp.465-482.

Paal, S.G., Jeon, J., Brilakis, I., DesRoches, R. (2015). "Automated Damage Index Estimation of Reinforced Concrete Columns for Post-Earthquake Evaluations," Journal of Structural Engineering, ASCE, Vol. 141, No. 9, 04014228, 13 pp.

Pashoutani, S., Zhu, J., Mazzeo, B., Guthrie, S. and Sim, C. (2020). “Development and Implementation of a Moving Nondestructive Evaluation Platform for Bridge Deck Inspection,” Nebraska Department of Transportation, Report No. M075, 71 pp.

Popescu, C., Täljsten, B., Blanksvärd, T., and Elfgren, L. (2019). “3D Reconstruction of Existing Concrete Bridges Using Optical Methods,” Structure and Infrastructure Engineering, Vol. 15, No. 7, pp. 912-924.

Tazarv, M., Won, K., Jang, Y., Hart, K. and Greeneway, E. (2022). “Post-earthquake serviceability assessment of standard RC bridge columns using computer vision and seismic analyses.” Engineering Structures, 272, p.115002.

Torok, M.M., Golparvar-Fard, M. and Kochersberger, K.B. (2014). Image-Based Automated 3D Crack Detection for Post-Disaster Building Assessment.” Journal of Computing in Civil Engineering, 28(5), pp. A4014004.

Valença, J., Puente, I., Júlio, E., González-Jorge, H. and Arias-Sánchez, P. (2017). “Assessment of Cracks on Concrete Bridges Using Image Processing Supported by Laser Scanning Survey.” Construction and Building Materials, 146, pp. 668-678.

Wells, J., and Lovelace, B. (2018). “Improving the Quality of Bridge Inspections Using Unmanned Aircraft Systems (UAS),” Minnesota Department of Transportation, Report No. MN/RC 2018-26, 345 pp.

Zhorov, I. (2014). “Robot could make bridge inspections quicker and easier,” <https://whyy.org/articles/robot-could-make-bridge-inspections-quicker-and-easier/>.

Zhu, Z., German, S. and Brilakis, I. (2010). “Detection of Large-Scale Concrete Columns for Automated Bridge Inspection.” Automation in construction, 19(8), pp. 1047-1055.

Zhu, Z., German, S. and Brilakis, I. (2011). “Visual Retrieval of Concrete Crack Properties for Automated Post-Earthquake Structural Safety Evaluation.” Automation in Construction, 20(7), pp. 874-883.