STRUCTURAL HEALTH MONITORING 2021

Enabling Next-generation SHM for Cyber-Physical Systems

Edited by

Saman Farhangdoust

Department of Aeronautics and Astronautics
Stanford University, Stanford, CA 94305

Alfredo Guemes

ETSI Aeronautics, Madrid, Spain

Fu-Kuo Chang

Department of Aeronautics and Astronautics
Stanford University, Stanford, CA 94305

Proceedings of the 13th International Workshop on Structural Health Monitoring
Stanford University, Stanford, CA
March 15-17, 2022 (formerly December 7-9, 2021)

Sponsors:
• Office of Naval Research Science & Technology • Air Force Office of Scientific Research, United States Air Force • Boeing • U.S. Department of Transportation • Transportation Research Board • IABMAS U.S.A. • Energies • Aerospace • Sensors • DEStech Publications, Inc.

DEStech Publications, Inc.

Use of Deep Encoder-Decoder Network for Sub-Surface Inspection and Evaluation of Bridge Decks

HABIB AHMED, HUNG MANH LA and ALIREZA TAVAKOLLI

ABSTRACT

The automation of various processes underlying maintenance and inspection of bridges using different robots have gained considerable attention in recent literature. For the development of effective methods to automate existing manual processes, a number of different solutions have been proposed. In this paper, the automation of rebar detection and localization will be discussed, which is one of the process for sub-surface health inspection of bridges. This study explores the utilization of Deep Encoder-Decoder Networks for the segmentation of GPR data in the form of B-scan images to extract parabolic rebar profiles. This research area is problematic, as the B-scan image data is fraught with noise, signal reflection and other artefacts that hinder the effective extraction of these rebar profiles. The data is collected in this study using Ground Penetrating Radar (GPR) sensor, which is employed in this study consist of data from 8 different bridges from different parts of the United States. A “leave-one-out” approach was used for the training and validation of the performance of the proposed system; the data from seven bridges was used for training and validation was performed on the remaining single bridge data. A number of different encoder modules have been trained and evaluated using SegNet as the backbone architecture. The performance of the proposed rebar detection and localization system has been evaluated in terms of different qualitative and quantitative metrics. On average, for the different encoder modules, the mean intersection-over-union (mIOU) values range between 60%-70%. The qualitative examination has highlighted the level of similarity between the ground truth and outputs from the different encoder modules within the SegNet framework.

INTRODUCTION

The monitoring, maintenance and rehabilitation of bridges is of paramount importance at the national and international level with different robots and automation solutions being developed in the recent past [1-25]. Of the different types of civil infrastructure, the need for maintenance and evaluation of bridges has been stressed by studies in the recent past [26-29]. At the national level within the United States, in particular for the bridges, there are a large number of disasters, which have occurred in the past fifty-year history. Based on the recent statistics outlined by the National Bridge Inventory (NBI) statistics, there are more than 307,000 bridges in the entirety of the

United States [26]. Another recent report revealed that out of every ten bridges within the United States, one can be classified as structurally deficient in nature [28, 29].

The existing studies have utilized block-based approach for learning and classification between rebar and non-rebar regions within the larger B-scan images. The block-based approach examines portions of images for the presence or absence of rebar hyperbolic signatures. At the same time, variations in the intensity of hyperbolic signatures, presence of noise artefacts and reflective signals cause challenges towards effective rebar detection and localization within existing block-based approaches [33]. Consequently, leveraging Deep Encoder-Decoder framework will allow an effective pixel-level rebar and non-rebar classification. This study will examine the superior performance of pixel-level frameworks in comparison with their counterparts that leverage block-based learning approaches.

RELATED WORKS

Research by Gibb and La [34] proposed a method for rebar detection using Naïve Bayesian classifier trained on HOG features for the detection and classification of GPR-based B-scan images. Support Vector Machines (SVM) has also been used in the prior studies [10] [11]. Kaur et al. [35] developed an automated system for rebar analysis using HOG features and SVM for rebar classification using data from 3 bridges. A number of neural network frameworks have also been used for rebar classification [36-39]. However, many of the methods fail to effectively leverage the capabilities of neural network models by the use of edge features [36] [37] [40]. Some recent studies have made use of Deep Convolutional Neural Networks (CNNs) for rebar detection [36-40]. Study by Dinh et al. [33] proposed the usage of 24-layer deep CNN model for rebar classification. Masked R-CNN with distance-guided intersection over union (IoU) was used for performance evaluation of the developed method in another study [34].

There are other studies that focus on development of rebar detection and localization systems in a collective fashion [35, 35-37]. The study by Wang et al. [35] made use of partial differential equations and template matching technique with sum of square similarity index for hyperbola localization. The template matching techniques for rebar localization can result in high false positive and low true positive rates [10]. Yuan et al. [21] proposed the drop-flow algorithm using edge features to extract individual hyperbolas and cater to over-segmentation. However, the edge-feature-based localization methods suffer from lack of generalizability to rebar size, dimensions and location as well as variations in the noise levels. An expectation-maximization algorithm was proposed by Chen and Cohn [37], which has various limitations for implementation in real-time systems, in terms of computational complexity, difficulty in convergence and sensitivity to the variations in configuration points. A column-connecting clustering algorithm with orthogonal hyperbola fitting was developed in [23]. Another study proposed a precise hyperbola localization algorithm [34], which made use of hyperbola fitting and local maxima. However, this method cannot provide real-time results, especially for large-size GPR radargrams. The proposed study will rely on large-scaled B-scan images for training and validation. As, in real-time data collection using GPR sensor, the B-scan output is saved into the sensor or robot system as large-scale images.

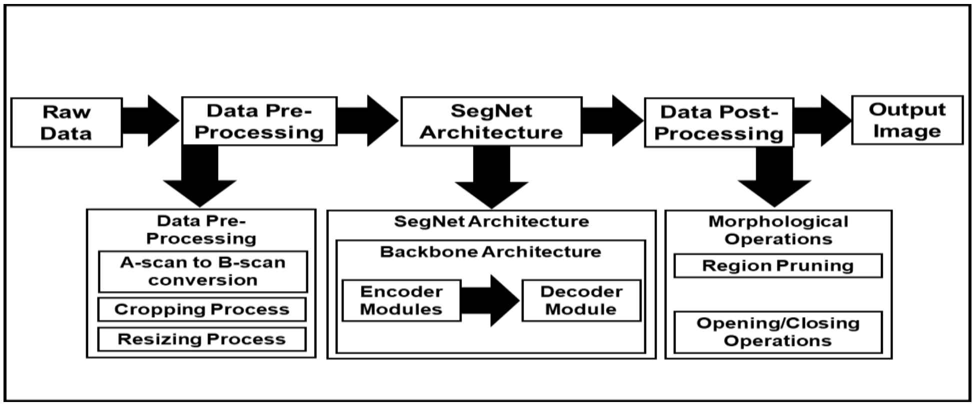

Figure I. The proposed system for rebar detection and localization.

METHODOLOGY

In this section, the particular details of the proposed method will be discussed. The building blocks for the proposed system for rebar detection and localization has been outlined in figure 1. The original raw data is in the form of one-dimensional A-scan signals, which is converted to GPR B-scan images with varying dimensions. Before SegNet is able to train on the GPR image data, different pre-processing techniques (e.g. editing, cropping and resizing) are used to convert the raw GPR B-scan image data from different bridges each of varying dimensions to image data with fixed dimensions. In contrast to most of the existing studies in this research area [35-39, 41-43, 45-50], which utilize the bounding box approach of annotation, this study employs the pixel-level annotation technique. This allows the system to train the different model parameters to enable the pixel-level classification of input data into either belonging to foreground (e.g. rebar signatures) or background (e.g. non-rebar regions, noise, signal reflection). With the different encoder modules, the decoder module used is this study employs the original native SegNet decoder that has been used in the original seminal study [51], which includes 13 consecutive decoding and up-sampling layers from the original VGG16 network. The data is divided between training and validation sets based on "leave-one- out" approach, such that out of the total data from nine bridges, training of SegNet [51] is conducted on eight bridges and validation is performed on data from one bridge. This process is used to perform validation on all of the bridges to assess the performance of the proposed system for rebar detection and localization.

The usage of Deep Encoder-Decoder Networks has gained increased importance within diverse fields in the past few years. SegNet was first introduced for semantic segmentation in a seminal work by [51]. Figure 2 outlines the basic overview of the architectural details of SegNet. The GPR B-scan images, after undergoing different pre-processing functions are given as input to the SegNet for training with seven bridge data and the performance is validated using data from the other remaining bridge. This ensures that the training and validation are performed on completely different data. There are different encoder modules (e.g. Vanilla-CNN, VGG16, VGG19, ResNet50, and ResNet-Xception modules) that have been used within the framework of SegNet. After the B-scan images are segmented using SegNet, a number of different post-processing operations (e.g. region pruning, removal of erroneous segmented artefacts

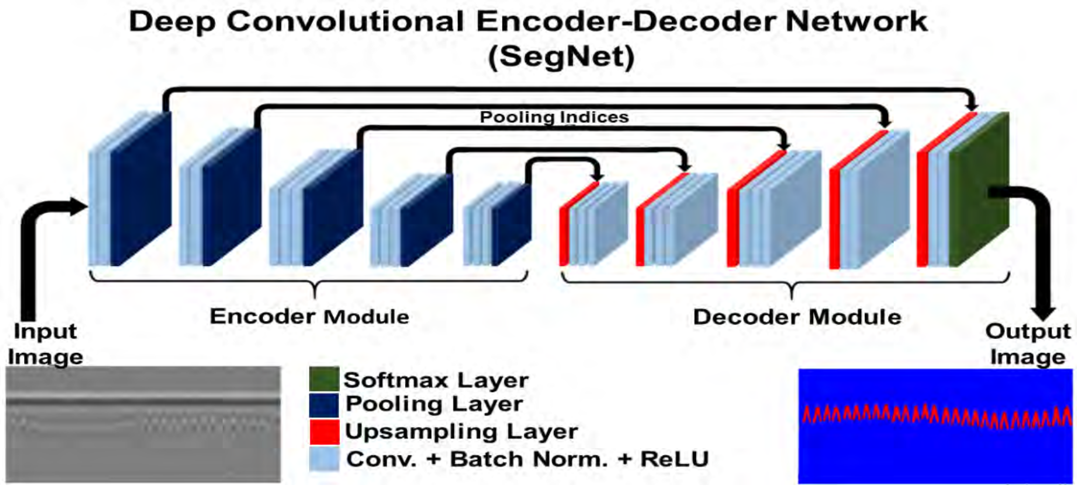

Figure II. Architectural Details of the SegNet [51].

and noise) are performed to remove noise, reflection and other artefacts from the segmented image. The detailed specifications of the computer system used for the training and validation of the proposed rebar detection and localization system are given as follows: Ubuntu 18.04 LTS, 32 GB memory, 350 GB hard disk, Intel ® Core i7–8700 CPU with 3.2 GHz clock speed and NVIDIA® GeForce® GTX 1080 TI Graphical Processing Unit (GPU). For the purpose of training and validation of the proposed system for rebar detection and localization, Tensorflow and Keras libraries have been used within Python programming language framework.

DATASET

For the development of the proposed system for rebar detection and localization, GPR data was acquired from a number of different bridges in the US. It can be seen from table 1 that the bridge data has been taken from different type of bridges (e.g. suspension, beam, truss, girder). Table 1 outlines the important properties of the different bridges in terms of the bridge name, geographical location, and physical properties of the different bridges. Table 1 also highlights the quantity of images acquired from the different bridges. The GPR data used in this research is one segment of the overall GPR data collected from the inspection and evaluation performed on 40 different bridges in the United States between the time period of 2013 and 2014 [52, 53].

All of the data was collected using the RABIT platform (for details regarding data collection, see [52, 53]). A portion of the GPR data has also been used in previous studies [41, 42, 54]. In contrast with existing studies in this research area, this research will utilize pixel-level annotation for data annotation of B-scan images that utilize all visual information given in large-sized B-scan images (dimensions of 768 × 768 × 3), instead of using small-sized bounding-box images for rebar and non-rebar regions. It is for this reason, the size of the current dataset cannot be compared with existing studies, which contain small-sized images (typically ranging in dimensions between 50 × 50 to 100 ×100 pixels). The next part of the paper will examine results and discuss the implications.

TABLE I. DETAILS REGARDING DATASET USED IN THIS STUDY.

Bridge Location	Bridge Type	Bridge Dimensions	No. of Images
1. Galena Creek Bridge, NV	Twin Span Arch Bridge	1726.5 × 62.0	133
2. East Helena Bridge, MT	Concrete Tee-Beam Bridge	66.9 × 40.0	55
3. Kendall Pond Rd. Bridge, NH	Girder Bridge	78.1 × 44.0	65
4. Piscataqua Bridge, ME	Through-Arch Bridge	4503 × 98	90
5. Broadway Bridge, AR	Arch Bridge	2786 × 40	165
6. Fordway Bridge, NH	Beam Bridge	131 × 23	93
7. Dove Creek Rd Bridge	BC Beam Bridge	50 × 45	50
8. Baxterville Bridge, CO	Lost-through Truss Bridge	117 × 15.4	114

RESULTS AND DISCUSSION

QUANTITATIVE RESULTS

For the quantitative aspect of performance, the performance will be examined in terms of mean intersection-over-union (mIOU), which highlights the level of difference between the masks obtained for the ground-truth and output from trained SegNet. Table 2 outlines the performance of the different Architecture-Encoder pairs from a quantitative aspect. Different encoder modules have been used for the training of SegNet for rebar detection and localization. For each encoder module (e.g. Vanilla-CNN, VGG16, VGG19, ResNet-50, and ResNet-Xception modules), the results obtained for the validation for different bridges have been classified in terms of the minimum, maximum and average values. Training time is another quantitative metric used in table 2.

Figure 3 outlines the average, minimum and maximum values for the training time for the different Architecture-Encoder pairs. Out of the different encoder modules, SegNet framework utilizing ResNet-Xception module is able to provide the highest performance in terms of mIoU. However, the slight increase in the maximum value for

TABLE II. QUANTITATVE RESULTS.

Model	**Encoder Backbone**		**mIoU(%)**	**Train Time (s)**
SegNet	Vanilla-CNN	Min.	62.1	**12,600**
		Max.	71.8	12,700
		Avg.	66.9	12,600
	VGG-16	Min.	**51.8**	24,300
		Max.	72.0	47,100
		Avg.	63.6	35,800
	VGG-19	Min.	52.8	27,400
		Max.	71.9	27,500
		Avg.	62.6	27,500
	ResNet-50	Min.	53.7	38,100
		Max.	71.5	38,200
		Avg.	65.1	38,100
	Xception	Min.	62.4	39,400
		Max.	**73.9**	**77,600**
		Avg.	67.2	60,200
Overall Average (Max.)			72.2	40,620

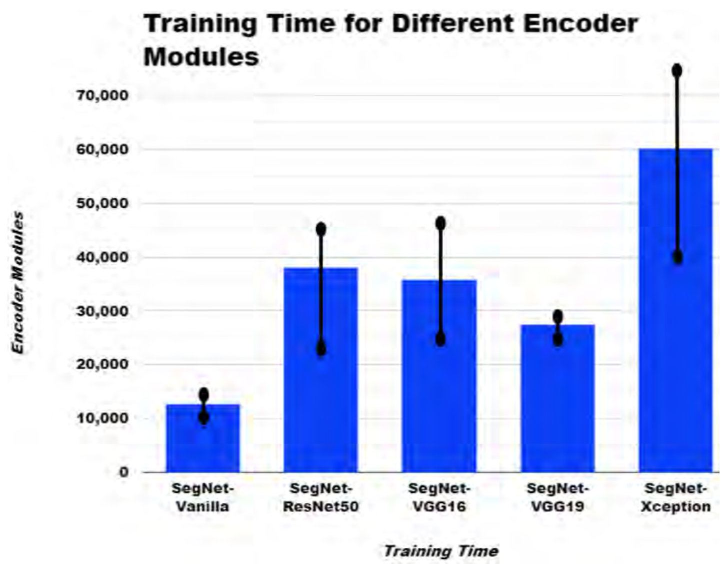

Figure III. Training Time for Different Encoder Modules.

mIOU is followed with an exponential increase in the overall average training time.

Apart from that, there is varying difference in the maximum and minimum values of mIOU for the different encoder modules. For majority cases, the lower values of the mIOU remain between 60%-70%. The values of mIOU greater than 50% are considered as reliable results. There are also various issues in the dataset, which have been adequately discussed in [54]. These issues provide challenges towards effective detection and localization of rebar profiles by increasing the number of false positives and addition of noise artefact.

The comparison between the training time of the different encoder modules can be better appreciated in figure 3. It can be seen in figure 3 that the SegNet with Vanilla CNN provides the lowest amount of training time as compared to other encoder-modules with average training time slightly above 12,000 s. The highest training time has been obtained by Xception encoder module with an average training time around 60,000 s.

QUALITATIVE RESULTS

For the qualitative performance of the proposed system, the quality of the rebar signatures obtained from system validation will be discussed. Figure 4 outlines a comparison between bridge 4 and 5 with results from different Encoder modules within the SegNet architecture. It can be seen in figure 4 that out of the different results obtained using different encoder modules within the SegNet framework, ResNet--Xception module has shown the most promising results. The data from bridges 4 is challenging, as the distance between individual rebar profiles is small, which can lead to merger between adjacent rebar profiles. Figure 4 shows that in comparison with bridge 4, the data from bridge 5 contains separated rebar signatures. Out of the different encoder modules, Vanilla-CNN, VGG-16 and VGG- 19 modules demonstrate considerable degradations. The results obtained from ResNet-50 and ResNet-Xception have a higher quality of rebar profiles obtained from noisy and challenging dataset.

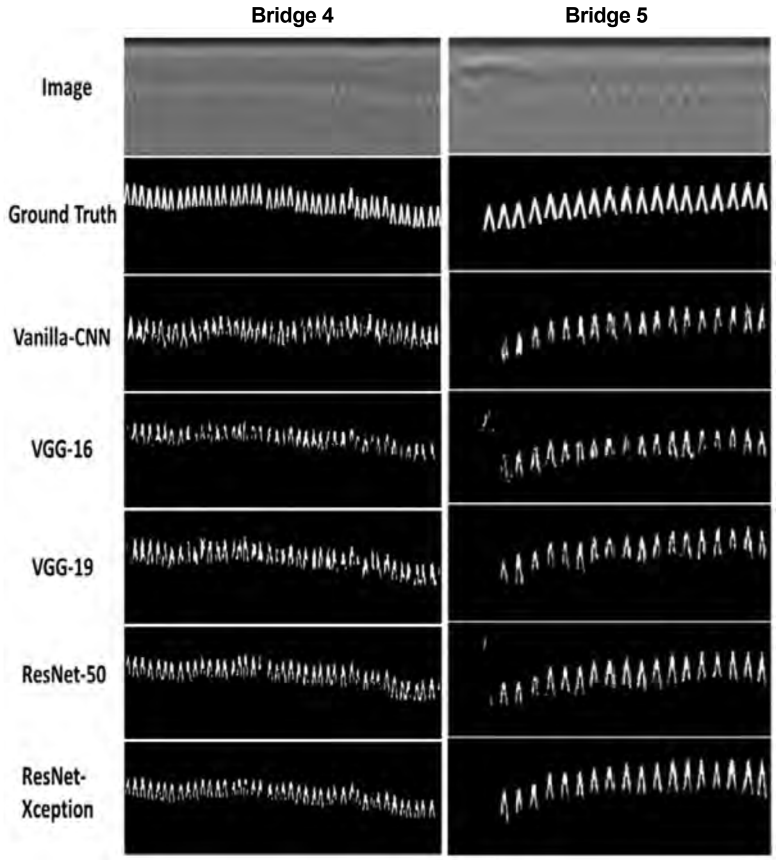

Figure IV. Qualitative results for Different Encoder Modules with data from bridges 4 and 5.

CONCLUSION AND FUTURE WORKS

The infrastructural evaluation and inspection of bridges has led to the development of efficient method for rebar detection and localization, which has been discussed in this study. In order to rectify some of the challenges of the existing research, a preliminary evaluation towards the use SegNet has been used in this study. The dataset has been acquired from 8 real bridges. The use of different encoder modules has also been discussed with SegNet. For quantitative aspect of the performance of proposed system, the average value of mIOU for different encoder modules range between 60% -70%. There are large variations in the training time for the different encoder modules. The qualitative aspect of performance and comparison between the different encoder modules has also been discussed.

ACKNOWLEDGEMENT

This work is supported by the U.S. National Science Foundation (NSF) under grants NSF-CAREER: 1846513 and NSF-PFI-TT: 1919127, the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (USDOT/OST-R) under Grant No. 69A3551747126 through INSPIRE University Transportation Center, and the Vingroup Joint Stock Company (Vietnam)’s Vingroup

Innovation Foundation (VINIF) under project code VINIF.2020.NCUD.DA094. The views, opinions, findings and conclusions reflected in this publication are solely those of the authors and do not represent the official policy or position of the NSF and USDOT/OSTR.

REFERENCES

1. S. Nguyen and H. M. La. A Climbing Robot for Steel Bridge Inspection. Journal of Intelligent & Robotic Systems, Springer Publisher, July 2021. https://doi.org/10.1007/s10846-020-01266-1.
2. H. Ahmed and H. M. La, and N. Gucunski. Review of Non-Destructive Civil Infrastructure Evaluation for Bridges: State-of-the-art Robotic Platforms, Sensors and Algorithms. Sensors, 20 (2954):1-38. http://dx.doi.org/10.3390/s20143954,
3. H. M. La, T. Dinh, N. Pham, Q. Ha, and A. Pham. Automated robotic monitoring and inspection of steel structures and bridges. Robotica, 37(5): 947-967,
4. S. Gibb, H. M. La, T. Le, L. Nguyen, R. Schmid, and H. Pham. Non-Destructive Evaluation Sensor Fusion with Autonomous Robotic System for Civil Infrastructure Inspection. Journal of Field Robotics, 35(6): 988-1004. September 2018, DOI:10.1002/rob.21791.
5. H. M. La, N. Gucunski, K. Dana, and S. H. Kee. Development of an Autonomous Bridge Deck Inspection Robotic System. Journal of Field Robotics, 34(8) :1489-1504,
6. P. Prasanna, K. J. Dana, N. Gucunski, B. B. Basily, H. M. La, R. S. Lim, and H. Parvardeh, Automated crack detection on concrete bridges, IEEE Transactions on Automation Science and Engineering, 13(2): 591 – 599.
7. H. M. La, N. Gucunski, S. H. Kee, and L. V. Nguyen, Data analysis and visualization for the bridge deck inspection and evaluation robotic system. Journal of Visualization in Engineering,
8. N. Gucunski, A. Maher, B. B. Basily, H. M. La, R. S. Lim, H. Parvardeh, and S. H. Kee, “Robotic Platform RABIT for Condition Assessment of Concrete Bridge Decks Using Multiple NDE Technologies,” Journal of Croatian Society for Non Destructive Testing, 12: 5-12, 2013.
9. H. M. La, R. S. Lim, B. B. Basily, N. Gucunski, J. Yi, A. Maher, F. A. Romero, and H. Parvardeh, Mechatronic and control systems design for an autonomous robotic system for high-efficiency bridge deck inspection and evaluation, IEEE Transactions on Mechatronics, pp. 18(6): 1655-1664, 2013.
10. H-D. Bui, S. T. Nguyen, U-H. Billah, C. Le, A. Tavakkoli, H. M. La. Control Framework for a Hybrid-steel Bridge Inspection Robot. In Proceedings of the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Las Vegas, Nevada, USA, October 25 – 29, 2020.
11. S. T. Nguyen, A. Q. Pham, C. Motley and H. M. La. A Practical Climbing Robot for Steel Bridge Inspection. In Proceedings of the 2020 IEEE International Conference on Robotics and Automation (ICRA), May 31-June 4, 2020, Paris, France.
12. S. T. Nguyen, H. M. La. Development of a Steel Bridge Climbing Robot. In Proceedings of the 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macau, China, November 3 – 8, 2019.
13. N. Harris, S. Liu, S. Louis, H. M. La. Optimizing Routes for Safe Robot-Automated Bridge Inspection. In Proceedings of the 2019 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), Würzburg, Germany, September 2-4, 2019.
14. N. Harris, S. Liu, S. Louis, and H. M. La. A Genetic Algorithm for Multi-Robot Routing in Automated Bridge Inspection. The Genetic and Evolutionary Computation Conference (GECCO), July 13th-17th 2019, Prague, Czech Republic.
15. S. T. Nguyen, and H. M. La. Roller Chain-Like Robot For Steel Bridge Inspection. In proceedings of the 9th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII-9), August 4-7, St. Louis, Missouri, 2019
16. H. Ahmed, and H. M. La. Education-Robotics Symbiosis: An Evaluation of Challenges and Proposed Recommendations. In: Proceedings of the 9th IEEE Integrated STEM Education Conference (ISEC), March 16, 2019, Princeton University, New Jersey, USA
17. L. Nguyen, S. Gibb, H. X. Pham, and H. M. La. A Mobile Robot for Automated Civil Infrastructure Inspection and Evaluation. In Proceedings of the 16th IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), August 6-8, 2018, Philadelphia, PA, USA.

18. N. Gucunski, S. H. Kee, H. M. La , B. Basily, A. Maher, and H. Ghasemi, Implementation of a Fully Autonomous Platform for Assessment of Concrete Bridge Decks RABIT, Structures Congress, pages 367-378, April 23-25, 2015, Portland, Oregon, USA.
19. K. Dinh, N. Gucunski, J. Y. Kim, T. Duong, and H. M. La, Attenuation-based Methodology for Condition Assessment of Concrete Bridge Decks using GPR, The 32nd International Symposium on Automation and Robotics in Construction and Mining (ISARC), pages 1-8, June 15-18, 2015, Oulu, Finland.
20. N. Gucunski, B. Basily, S. H. Kee, H. M. La, H. Pavardeh, A. Maher, and H. Gashemi. Multi NDE Technology Condition Assessment of Concrete Bridge Decks by RABITTM Platform, NDE/NDT for Structural Materials Technology for Highway & Bridges, August 25, 2014.
21. H. M. La, N. Gucunski, S. H. Kee, J. Yi, T. Senlet, and L. Nguyen, Autonomous Robotic System for Bridge Deck Data Collection and Analysis, IEEE International Conference on Intelligent Robots and Systems (IROS), September 14-18, 2014, Chicago, USA.
22. H. M. La, N. Gucunski, S. H. Kee, and L. Nguyen, Visual and Acoustic Data Analysis for the Bridge Deck Inspection Robotic System, The 31st International Symposium on Automation and Robotics in Construction and Mining (ISARC), July 9-11, 2014, Sydney, Australia.
23. H. M. La, R. S. Lim, B. B. Basily, N. Gucunski, J. Yi, A. Maher, F. A. Romero, and H. Parvardeh, Autonomous Robotic System for High-Efficiency Non-Destructive Bridge Deck Inspection and Evaluation, IEEE International Conference on Automation Science and Engineering (CASE), August 17 – 21, 2013, Madison, WI, USA.
24. H. M. La, R. S. Lim J. Du, W. Sheng, G. Li, S. Zhang, and H. Chen, A small-scale research platform for intelligent transportation systems, IEEE International Conference on Robotics and Biomimetics (ROBIO), December 7-11, 2011, Phuket, Thailand
25. [25] R. S. Lim, H. M. La, Z. Shan, and W. Sheng, Developing a crack inspection robot for bridge maintenance, IEEE International Conference on Robotics and Automation (ICRA), May 9 – 13, 2011, Shanghai, China.
26. A. Penn, "The deadliest bridge collapses in the US in the last 50 years," CNN, 15 March 2018.
27. R. S. Kirk and W. J. Mallett, Highway Bridge Conditions: Issues for Congress, Washington, DC: US Congressional Research Service, 2013.
28. L. Wright et al., "Estimated effect of climate change on flood vulnerability of US bridges," Mitigation and Adaptation Strategies for Global Change, vol. 17, no. 8, pp. 939-955, 2012.
29. J.-L. Briaud, L. Brandimarte, and J. Wang, "Probability of scour depth exceedance owing to hydrologic uncertainty," Georisk, vol. 2, no. 77-88, p. 1, 2014.
30. US Department of Transportation Report, Status of the Nation’s Highways, Bridges, and Transit: Conditions and Performance, Washington, DC: US Department of Transportation, 2010.
31. D. Schaper, "10 Years After Bridge Collapse, America is Still Crumbling," 1 August 2017. [Online]. Retrieved from: https://www.npr.org/2017/08/01/540669701/10-years-after-bridge-collapse-america-is-still-crumbling.
32. American Society of Civil Engineers Report, 2017 Infrastructure Report Card. Reston, VA: American Society of Civil Engineers, 2017.
33. R.S. Lim, H. M. La, Z. Shan, and W. Sheng, “Developing a crack inspection robot for bridge maintenance”. In Proceedings of the 2011 IEEE International Conference on Robotics and Automation, Shanghai, China, 9–13 May 2011; 2011; pp. 6288–6293.
34. S. Gibb and H. M. La, "Automated Rebar Detection for Ground Penetrating Radar," In: Proceedings of the 12th International Symposium on Visual Computing, pp. 815-825, 2016.
35. P. Kaur, K. J. Dana, F. A. Romero, N. Gucunski, “Automated GPR Rebar Analysis for Robotic Bridge Deck Evaluation”. IEEE Transactions on Cybernetics. 2016, 46, 2265–2276
36. E. Passoli, F. Melgani and M. Donelli, "Automatic analysis of GPR Images: A Pattern-Recognition Approach," IEEE Transactions on Geosciences and Remote Sensing, vol. 47, no. 7, pp. 2206-2217, 2009.
37. P. Gamba and S. Lossani, "Neural detection of pipe signatures in ground penetrating radar images," IEEE Transactions on Geosciences and Remote Sensing, vol. 38, no. 2, pp. 790-797, 2000.
38. W. Al-Nuaimy, Y. Huang, M. Nakhkash, M. T. C. Fang, V. T. Nguyen and A. Eriksen, "Automatic detection of buried utilities and solid objects with GPR using neural networks and pattern recognition," Journal of Applied Geophysics, vol. 43, no. 2, pp. 157-165, 2000.
39. S. Birkenfeld, "Automatic detection of reflexion hyperbolas in GPR data with neural networks," In: Proceedings of World Automation Congress, pp. 1-6, 2010.

40. M. R. Shaw, S. G. Millard, T. C. K. Molyneaux, M. J. Taylor and J. H. Bungey, "Location of steel reinforcement in concrete using ground penetrating radar and neural networks," NDT&E International, vol. 38, no. 3, pp. 203-212, 2005.
41. H. Ahmed, H. M. La and N. Gucunski, "Rebar Detection using Ground Penetrating Radar with State-of-the-Art Convolutional Neural Networks," In: Proceedings of the 9th International Conference on Structural Health Monitoring of Intelligent infrastructure, pp. 1-6, 2019.
42. H. Ahmed, H. M. La and G. Pekcan, "Rebar Detection and Localization for Non-Destructive Infrastructure Evaluation using Deep Residual Networks," In: Proceedings of the 14th International Symposium on Visual Computing, pp. 1-6, 2019.
43. K. Dinh, N. Gucunski and T. H. Doung, "An algorithm for automatic localization and detection of rebars from GPR data of concrete bridge decks," Automation in Construction, vol. 89, pp. 292-298, 2018.
44. F. Hou, W. Lei, S. Li, J. Xi, M. Xu, and J. Luo, "Improved Mask R-CNN with distance guided intersection over union for GPR signature detection and segmentation" Automation in Construction, 121, pp. 1-14. 2021
45. Z. W. Wang, M. Zhou, G. G. Slabaugh, J. Zhai and T. Fang, "Automatic Detection of Bridge Deck Condition from Ground Penetrating Radar Images," IEEE Transactions on Automation Science and Engineering, vol. 8, no. 3, pp. 633-640, 2011.
46. C. Yuan, S. Li, H. Cai and V. R. Kamat, "GPR Signature Detection and Decomposition for Mapping Buried Utilities with Complex Spatial Configuration," Journal of Computer and Civil Engineering, vol. 32, no. 4, pp. 1-15, 2018.
47. H. Chen and A. G. Cohn, "Probabilistic robust hyperbola mixture model for interpreting ground penetrating radar data," In: Proceedings of IEEE World Congress on Computing Intelligence, pp. 3367-3374, 2010.
48. Q. Dou, L. Wei, D. R. Magee and A. G. Cohn, "Real-Time Hyperbola Recognition and Fitting in GPR Data," IEEE Transactions on Geosciences and Remote Sensing, vol. 55, no. 1, pp. 51-63, 2017
49. H. Harkat, A. E. Ruano, M. G. Ruano and S. D. Bennani, "GPR target detection using a neural network classifier designed by a multi-objective genetic algorithm," Applied Soft Computing Journal, vol. 79, pp. 310-325, 2019.
50. A. Simi, G. Manacorda and A. Benedetto, "Bridge deck survey with high resolution ground penetrating radar," In: Proceedings of 14th International Conference on Ground Penetrating Radar, pp. 489-495, 2012.
51. V. Badrinarayanan, A. Kendall and R. Cipolla, "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation," IEEE Transactions on Pattern Recognition and Machine Intelligence, vol. 39, no. 12, pp. 2481-2496, 2017
52. N.H. Pham, and H.M. La, "Design and implementation of an autonomous robot for steel bridge inspection". In Proceedings of the 2016 54th Annual Allerton Conference on Communication, Control, and Computing (Allerton), Monticello, IL, USA, 27–30 September 2016; pp. 556–562.
53. T. Le, S. Gibb, N. Pham, H. M. La, L. Falk, and T. Berendsen, "Autonomous robotic system using non-destructive evaluation methods for bridge deck inspection". In Proceedings of the 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, 29 May–3 June 2017; pp. 3672–3677
54. H. Ahmed, H. M. La, and K. Tran. "Rebar Detection and Localization for Bridge Deck Inspection and Evaluation using Deep Residual Network". Automation in Construction, vol. 120: 1-18.