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AI-AR for Bridge Inspection by Drone*

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Abstract. Good and regular inspections of transportation infrastructures such as bridges and overpasses are necessary to maintain the safety of the public who uses them and the integrity of the structures. Until recently, these inspections were done entirely manually by using mainly visual inspection to detect defects on the structure. In the last few years, inspection by drone is an emerging way of achieving inspection that allows more efficient access to the structure. This paper describes a human-in-the-loop system that combines AI and AR for bridge inspection by drone.

Keywords: Bridge · Inspection · AI · Artificial intelligence · Deep learning · AR · Augmented reality · UAV · UAS · RPAS · Drone · Remote guidance.

1 Introduction

The recent tragedies caused by the collapses of the I-35W and Morandi bridges [4, 26] illustrate the importance to conduct regular inspections of such transportation infrastructures. Until recently, these inspections were done on site by teams of inspectors who used mainly visual inspection to monitor the state of those infrastructures. The emergence of flying drone technology (a.k.a. Unmanned Aerial Vehicles - UAVs or Remotely Piloted Aircraft Systems - RPAS or Unmanned Aerial Systems - UASs) for civilian applications [5, 10, 39] combined with computer vision-based inspection [6] allows for an easier access to parts of civil infrastructures such as bridges that are often difficult to inspect [8, 33, 34].

Though it is clear that using drones is a promising way for automatic bridge inspection, it remains important to design systems to collaborate humans and drones to perform the inspection task in an efficient way. That is to say, drones should be guided in a way that reduces the flying time and collision risks, while enabling to assess about potential defects through real-time image analysis. For

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this purpose, the combination of drone navigation with AI and AR technologies has a huge potential to increase the efficiency of the inspection. This combination will integrate the benefits of an easier access to the structure, automatic detection and classification of defects while facilitating drone remote navigation by a technician [18].

In this paper, we propose a remote guidance approach [18] toward realizing such a system, by enabling an open-loop and interactive collaboration between one or several remote experts and an onsite technician with pilots locally a drone. The drone is equipped with a camera sensor that will capture live video streams that are sent to a ground station to perform real-time image analysis for visual scene understating and defect detection. Then, an AR module will synthesize useful high-level information that will be superimposed to the view of the technician through and AR headset in order to give the technician crucial information about the presence of defects, the progress of the inspection mission and the drone navigation state (e.g., 3D position, speed, energy consumption, etc.). Finally, another, web-based AR module will provide to one or several remotely-located experts (the inspectors) the images relayed by the drone camera augmented with the AI-detected defects.The concept is illustrated in Figure 1 below.

This paper is organized as follows: Section (2) presents some related work about bridge inspection using drones. Section (3) presents the proposed inspection system. Section (4) presents a discussion about the proposed system.

2 Related works

Several method are used to inspect bridges [40] and they can be classified as non-visual and visual inspection methods. Also some research has been done already on the use of drones and augmented reality (AR) for bridge inspection.

2.1 Non-visual methods for bridge inspection

Different technique have been used to inspect bridges as an alternative for visual inspection. For example, acoustic techniques have been used to detect changes in sound pitch resulting from hitting the concrete surface with a hammer [11]. One of the advantages of these methods is cheapness, but they are less accurate in deep layer defect detection. They are also less applicable to non-concrete bridges [20]. Another group of bridge inspection techniques is ground-penetrating radar (GPR). In this method, inspectors use electromagnetic radiation to image the underlying layers and detect defects [7]. The disadvantage of this approach is its high energy consumption and the need for expertise to interpret the data. Another method is Half-Cell Potential which assesses the electrical potential difference between the reinforcement in concrete and a standard electrode for defect detection [29]. This method can detect corrosion in the early stages, but it incurs a high cost.

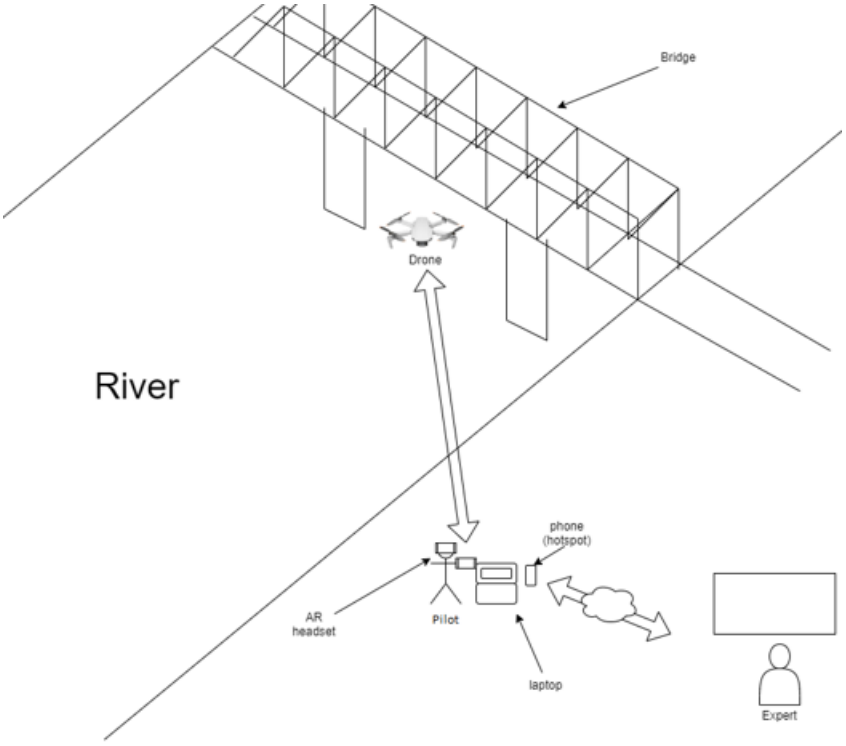

Fig. 1. Illustration of the concept

2.2 Visual methods for bridge inspection

For visual inspection, methods have been proposed using different modalities of visual data. Most of existing methods for visual inspection are based on he visible spectrum, although infrared / thermal imaging can be used for detecting special defects such as delamination [37]. Until recently, statistical methods were the most used to detect defects on images. Image features such as edges, color and texture are first extracted. Then, pattern recognition techniques including clustering and classification are in defect detection [15]. Abdel-Qader et al. compared four well-known image processing techniques: Fast Haar transform (FHT), Fast Fourier transform, Sobel edge detector, and Canny edge detector to detect bridge cracks [1]. They stated that the accuracy of the FHT in detecting cracks is much higher than other methods. Salman et al. provided an automated method for detecting cracks based on the Gabor filter [32]. Talab et al. used Sobel's filter and Otsu method [2] to detect cracks [36].

2.3 Drones and AR for bridge inspection

The use of Augmented reality (AR) and/or drones are emerging methods of inspecting bridges. Drones allow access to hard-to-reach areas, eliminating the need for physical presence. Wells et al. [39] used drones to inspect bridges. They used different types of drones on eight bridges with different sizes, locations, and conditions to evaluate the effectiveness of drones in inspecting bridges. Dam et al. [38] Measured the effect of AR cue types (none, bounding box, corner-bound box, and outline) on discrete levels in prominent places of the search location with a signal detection task. They concluded that different AR cue types differ greatly in false alarm rates while the terms hits and misses have no effect. Kilic et al. [17] Described the benefits of using AR with a visual inspection, Ground Penetrating Radar (GPR), Laser Distance Sensors (LDS), Infrared Thermography (IRT), and Telescopic Camera (TC). Hu et al. [12] proposed a method using a combination of AR and GPR to inspect concrete bridges.

Nowadays, with the expansion of artificial intelligence, these methods have been replaced with deep learning models. In most recent research, neural networks have been used to detect defects more accurately than previous methods. Among the deep learning algorithms, convolutional neural networks (CNNs) have been shown to effectively detect defects in concrete bridges and tunnels [19,28,35] along with U-net model [21]. This paper presents the result obtained so far in our research project aimed at improving bridge inspections by combining the technologies of AI, AR and drones.

3 The proposed system

The system is composed of a drone that flies nearby a bridge to inspect it, which is remotely piloted by an onsite pilot with a line-of-sight on it. The images relayed by the drone are analyzed by an AI module to detect potential defects and highlight them on the images seen by one or several remote experts (the inspectors) who can be located anywhere on the internet, thus providing an AR display. Finally, the pilot wears an AR headset which allows to augment the real view of the drone with relevant information (see Figure 1). The network connection is provided by a smartphone which acts as a Wi-Fi hotspot.

This paper describes the various modules of this system as illustrated on the system architecture (Figure 2). The architecture describes well the various modules of the system and their links with the actors (pilot, experts, drone).

3.1 The AI module

The AI module uses three computer vision techniques to inspect the defects that can be found on bridges, namely: object classification, detection, and segmentation. A level of gravity is then assigned to each defect. This process usually has six steps as illustrated by Hüthwohl et al. [14] in Figure 3.

The public datasets used to date are: CODEBRIM (COncrete DEfect BRidge IMage Dataset) and MCDS (Multi-Classifier DataSet for reinforced concrete

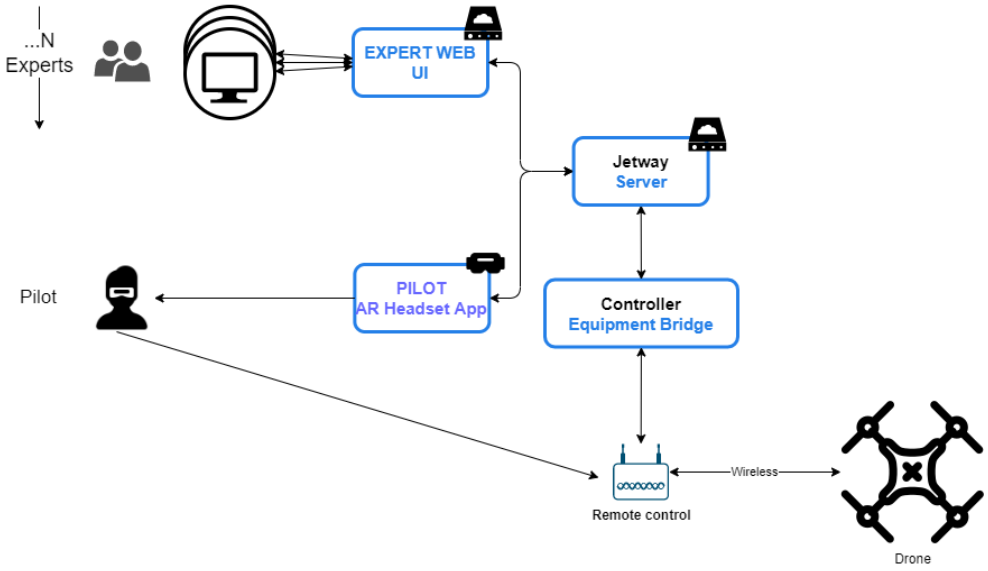

Fig. 2. System architecture

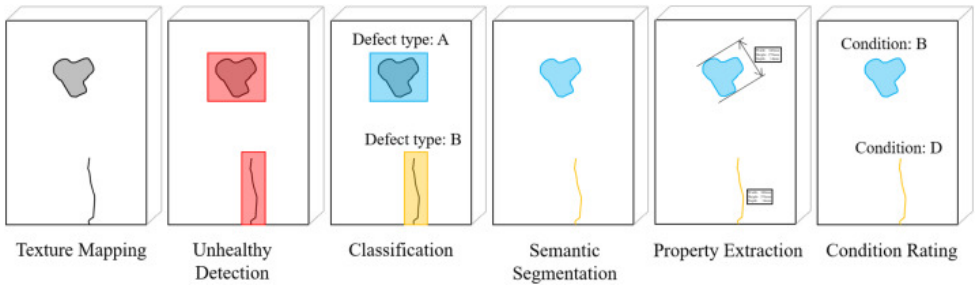

Fig. 3. Defects inspection steps [14].

bridge defects). CODEBRIM [25] is a multilabel dataset composed of six categories of defects: background (2490), crack (2507), spallation (1898), exposed bar (1507), efflorescence (833), and corrosion (1559). MCDS [14] is multilabel dataset defined by a hierarchy of classifiers which contains ten categories of defects: crack (789), efflorescence (311), scaling (168), spalling (427), general defects (264), no defects (452), exposed reinforcement (223), no exposed reinforcement (203), rust staining (355), and no rust staining (415).

A comparative study of current deep learning algorithms has been conducted to determine the most appropriate architecture for the classification and detection of defects from images. In particular, the ResNet, Inception, EfficientNet architectures and their variants are explored for classification. YOLO, SSD, Faster R-CNN and their variants are studied for detection. Finally, FCN, U-Net, and

their variants are compared for the segmentation. The method used for learning is transfer learning and the fine-tuning of models is conducted on tested models to optimize performance [3].

For the experiment's environment, we used Google Colab Pro+, which provides 52GB of RAM alongside 8 CPU cores and priority access to GPU P100. We split the dataset CODEBRIM into training, validation, and test set with a ratio of 70%, 20%, and 10% respectively.

To evaluate the performance of the fine-tuned classification models, we used AUC-ROC metric which is the area under the receiver operating characteristic curve. This metric is one of the most robust evaluation metrics for classification tasks having the problem of imbalanced data which is the case of CODEBRIM dataset. Table 1 shows the comparison of defect classification results obtained with tested models against those of a previous study. We observe that our result obtained by ResNet50 outperforms the state of the art, so we chose to select this classifier for defect classification.

Table 1. Comparison of defect classification results.

Models	**Our results**	**Previous results study [3]**
VGG16	0.88	0.88
ResNet50	**0.96**	0.90
Inception-v3	0.87	0.89
EfficientNet-B0	0.89	-
DenseNet-201	0.95	-
InceptionResNet-v2	0.93	-

In the case of defect detection, to evaluate the performance of the detectors and compare it to other studies, we used the mAP (mean Average Precision) metric representing the mean value of the AP of all classes. The AP is the area under the precision-recall curve. Table 2 shows the comparison of defect detection results obtained with tested models against those of previous studies. We observe that our result obtained by YOLOX outperforms the state of the art in terms of accuracy and speed, so we chose to select this detector for defect detection. YOLOX is the latest version of YOLO models, improving the limitation in terms of speed and accuracy, and most recently it won the Streaming Perception Challenge at CVPR 2021's Automatic Driving Workshop. Since CODEBRIM is multi-label dataset, we used YOLOX as a multi-label detector which assigns more than one label for each bounding box. The Figure 4 illustrates some early images from defect detection using YOLOX where we can see that the multi-label defects are represented by overlaid bounding boxes.

For the segmentation task, we plan in the future to create segmentation masks for the CODEBRIM dataset, and use semantic segmentation technique to label each pixel of an image with a corresponding defect.

Table 2. Comparison of defect detection results.

Studies	Method	mAP@0.5	Inference time (s)
Our study	**YOLOX**	**0.91**	**0.04**
	YOLOR	0.86	0.05
	SSD	0.41	0.06
	Faster R-CNN	0.36	0.14
Previous studies	Jiang et al. (YOLOv3) [16]	0.65	0.05
	Jiang et al. (SSD) [16]	0.64	0.06
	Zhang et al. (YOLOv3) [41]	0.80	0.05
	Zhang et al. (Faster R-CNN) [41]	0.74	0.14

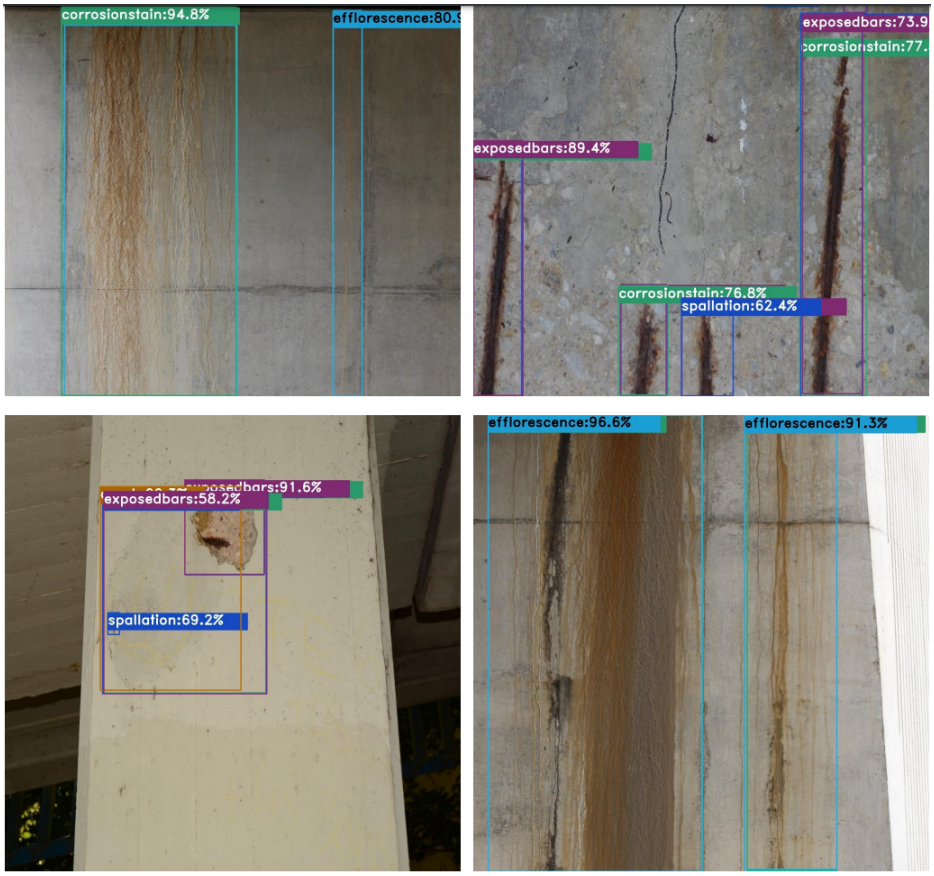

Fig. 4. Early images of defect detection using YOLOX

3.2 The AR modules

The system will include two AR modules. The first AR module will augment the images seen by the experts (the inspectors) by highlighting the defects detected by the AI module. An early prototype of this AR module for inspection is illustrated in Figure 5 that uses a YOLOv3 deep learning method to detect objects and people instead of bridge defects.

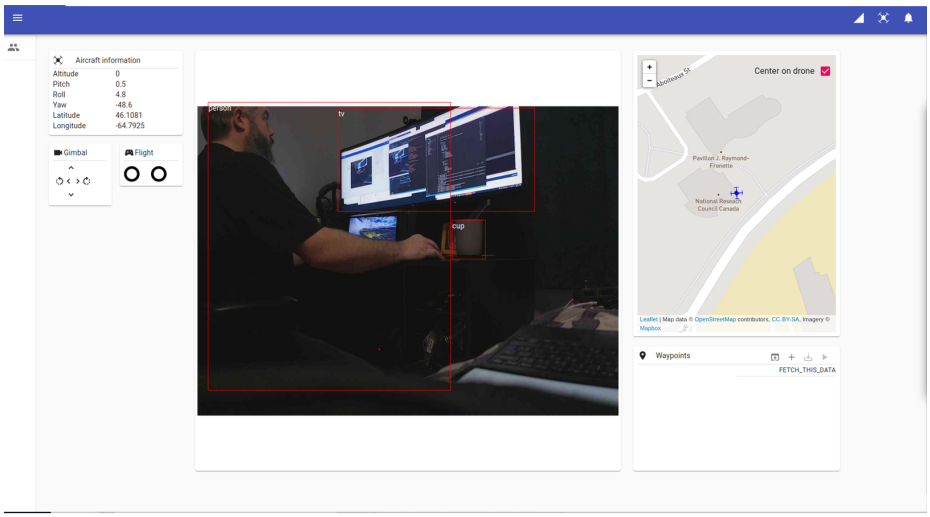

Fig. 5. Early prototype of the inspection AR module

Figure 5 also illustrates the possibility for the expert to control the yaw/pitch/roll parameters of the camera and to get some basic flight parameters such as the altitude. Finally, since many experts can be connected at once, the user interface allows each expert to request the control of the drone.

The second AR module will augment the images seen by the drone pilot with relevant information such as the video feed from the camera and battery life. This second module will try to palliate the current problem with drone remote guidance where the pilot must constantly share his/her visual attention between keeping a line of sight with the drone and looking at the remote control to gather useful flight information as well as the video feed from the drone's, a problem commonly referred as *head down time* [31]. As a result, the pilot will constantly keep a line-of-sight with the drone. Finally, additional information will be overlaid on this real view in the AR headset to improve the pilot's situational awareness [30].

3.3 Depth estimation and drone trajectory module

Estimating jointly depth map and motion cues, known by SLAM (Simultaneous Localization and Mapping) in the robotic community and by Structure-From-Motion (SFM) in the computer vision community, starts to attract attention in recent learning methods. The use of monocular SLAM by deep learning is explored in our work to provide both motion trajectory of the mounted sensor on the drone and depth map of the scene. Using a single camera is less constrained whether to the weight or to the occlusions related to stereo or multiple cameras. However, depth inference is more challenging in the case of monocular than methods using stereo cameras or RGB-D in SLAM. Also, using unsupervised methods has the advantage to avoid using labeled dataset especially in the context of uncommon environments like bridges.

In recent years, deep learning has overcome some of the shortcomings that classical geometrical methods fail to solve in the monocular visual SLAM. Good surveys by Huang et al. [13] and recently by Metan et al. [23], present the most recent DL-based SLAM methods and the challenges that face them in the future. We have explored a new paradigm to solve the unsupervised monocular SLAM. The method couples the spatio-temporal variations in image sequence to the scene geometry with the goal to supervise both camera motion and depth in an elegant new learning framework. Two CNNs networks are used to learn motion and depth, and are trained using KITTI dataset [9, 22]. Early results indicate that we outperform existing methods even if only camera motion is modeled in the learning process. Other moving objects in the scene can appear and disappear, like cars and pedestrians, and their motion should be taking into account to model correctly all existing motion in the scene. In this work only egomotion was considered, but the framework can be easily extended to moving objects and that will be tackled in the future.

4 Discussion

The purpose of the system described here is to assist, not replace, inspectors in performing their tasks so that they can achieve it in a better and faster way. Given their ability to quickly scan and acquire images of surfaces that can be hard to reach otherwise, drones are well suited to this task. In order to better understand the task itself and thus find better ways to fit the technology to the users, a task analysis is planned. Because of the current pandemic situation however, it is not completed yet. In fact, discussions with some bridge management authorities allowed us to collect some documentation on the task [24, 27] but direct field interviews with inspectors have been delayed. Nonetheless, as discussed in section (2) we already know that the inspection task itself is not always visual and that sometimes non-visual inspection methods are used.

Lab and field trials will allow to observe the performance of the whole system, including the possible image resolution and frame rate that can be transmitted in real-time over a cell phone connection. The available bandwidth at the inspected bridge site will mainly dictate those parameters. Also, field trials will allow

us to compare the usability of the AR headset for the pilot as compared to the traditional way of flying the drone without an headset. Once assessed and optimized the system could be demonstrated to real bridge inspectors for further feedback, development and validation.

5 Conclusion

This paper described an advanced human-in-the loop system that combines AI and AR for bridge inspection by drone. Although still in development, this system is really promising and the multidisciplinary nature of the project team enriches it. Future works will be to complete user and system requirements by conducting a task analysis of the inspection task itself, as well as lab and field trials to test and refine the system usefulness and usability. We also plan to explore image segmentation for the detection of defects, in order to better characterize them. Finally, the possibility to automatically locate and document the defects also has a lot of potential to allow bridge inspectors to better perform their task and avoid other tragedies.

References

1. Abdel-Qader, I., Abudayyeh, O., Kelly, M.E.: Analysis of edge-detection techniques for crack identification in bridges. Journal of Computing in Civil Engineering **17**(4), 255–263 (2003). https://doi.org/10.1061/(ASCE)0887-3801(2003)17:4(255)
2. Boulmerka, A., Allili, M.S., Ait-Aoudia, S.: A generalized multiclass histogram thresholding approach based on mixture modelling. Pattern Recognition **47**(3), 1330–1348 (2014), `https://arxiv.org/abs/2104.06456`
3. Bukhsh, Z.A., Jansen, N., Saeed, A.: Damage detection using in-domain and cross-domain transfer learning. Neural Computing and Applications pp. 1–16 (2021). https://doi.org/10.1007/s00521-021-06279-x
4. Calvi, G.M., Matteo, M., O'Reilly, G.J., Scattarreggia, N., Monteiro, R., Malomo, D., Calvi, M.P., Pinho, R.: Once upon a time in italy: The tale of the morandi bridge. Structural Engineering International **29**, 198-217 (2019). https://doi.org/10.1080/10168664.2018.1558033
5. Chen, S., Laefer, D.F., Mangina, E.: State of technology review of civilian UAVs. Recent Patents on Engineering **10**(3), 160–174 (2016). https://doi.org/10.2174/1872212110666160712230039
6. Dam, J.V., Krasner, A., Gabbard, J.L.: Drone-based augmented reality platform for bridge inspection: Effect of AR cue design on visual search tasks. In: 2020 IEEE Conference on Virtual reality and 3D User Interfaces Abstracts and Workshops (VRW). pp. 201–204 (2020). https://doi.org/10.1109/VRW50115.2020.00043
7. Diamanti, N., Annan, A.P., Redman, J.D.: Concrete bridge deck deterioration assessment using ground penetrating radar (gpr). Journal of Environmental and Engineering Geophysics **22**(2), 121–132 (2017). https://doi.org/10.2113/JEEG22.2.121
8. Feroz, S., Dabous, S.A.: UAV-based remote sensing applications for bridge condition assessment. Remote Sensing **13**(9), 1809 (2021). https://doi.org/10.3390/rs13091809

9. Geiger, A., Lenz, P., Urtasun, R.: Are we ready for autonomous driving? the KITTI vision benchmark suite. In: 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 3354–3361 (2012). https://doi.org/10.1109/CVPR.2012.6248074
10. Hassanalian, M., Abdelkefi, A.: Classifications, applications, and design challenges of drones: A review. Progress in Aerospace Sciences **91**, 99–131 (2017). https://doi.org/10.1016/j.paerosci.2017.04.003
11. Hendricks, L.J., Baxter, J.S., Chou, Y., Thomas, M., Boekweg, E., Guthrie, W.S., Mazzeo, B.A.: High-speed acoustic impact-echo sounding of concrete bridge decks. Journal of Nondestructive Evaluation **39**(3), 1–12 (2020). https://doi.org/10.1007/s10921-020-00695-0
12. Hu, D., Hou, F., Blakely, J., Li, S.: Augmented reality based visualization for concrete bridge deck deterioration characterized by ground penetrating radar. In: Construction Research Congress 2020: Computer Applications. pp. 1156–1164. American Society of Civil Engineers Reston, VA (2020). https://doi.org/10.1061/9780784482865.122
13. Huang, B., Zhao, J., Liu, J.: A survey of simultaneous localization and mapping. ArXiv (2019), `https://arxiv.org/pdf/1909.05214v1.pdf`
14. Hüthwohl, P., Lu, R., Brilakis, I.: Multi-classifier for reinforced concrete bridge defects. Automation in Construction **105**, 1–15 (2019). https://doi.org/10.1016/j.autcon.2019.04.019
15. Jahanshahi, M.R., Kelly, J.S., Masri, S.F., Sukhatme, G.S.: A survey and evaluation of promising approaches for automatic image-based defect detection of bridge structures. Structure and Infrastructure Engineering **5**(6), 455–486 (2009). https://doi.org/10.1080/15732470801945930
16. Jiang, Y., Pang, D., Li, C.: A deep learning approach for fast detection and classification of concrete damage. Automation in Construction **128**, 103785 (2021). https://doi.org/10.1016/j.autcon.2021.103785
17. Kilic, G., Caner, A.: Augmented reality for bridge condition assessment using advanced non-destructive techniques. Structure and Infrastructure Engineering **17**(7), 977–989 (2021). https://doi.org/10.1080/15732479.2020.1782947
18. Lapointe, J.F., Molyneaux, H., Allili, M.S.: A literature review of AR-based remote guidance tasks with user studies. In: Chen, J.Y.C., Fragomeni, G. (eds.) Virtual, Augmented and Mixed Reality. Industrial and Everyday Life Applications. pp. 111–120. Springer International Publishing, Cham (2020). https://doi.org/10.1007/978-3-030-49698-2_8
19. Li, S., Zhao, X.: Image-based concrete crack detection using convolutional neural network and exhaustive search technique. Advances in Civil Engineering **2019**, 1–12 (2019). https://doi.org/10.1155/2019/6520620
20. Lin, S., Meng, D., Choi, H., Shams, S., Azari, H.: Laboratory assessment of nine methods for nondestructive evaluation of concrete bridge decks with overlays. Construction and Building Materials **188**, 966–982 (2018). https://doi.org/10.1016/j.conbuildmat.2018.08.127
21. Liu, Z., Cao, Y., Wang, Y., Wang, W.: Computer vision-based concrete crack detection using U-net fully convolutional networks. Automation in Construction **104**, 129–139 (2019). https://doi.org/10.1016/j.autcon.2019.04.005
22. Menze, M., Geiger, A.: Object scene flow for autonomous vehicles. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 3061–3070 (2015). https://doi.org/10.1109/CVPR.2015.7298925
23. Mertan, A., Duff, D.J., Unal, G.: Single image depth estimation: An overview. ArXiv (2021), `https://arxiv.org/abs/2104.06456`

24. Ministère des Transports, de la Mobilité durable et de l'Électrification des transports: Manuel d'inspection des structures. Gouvernement du Québec (2017), http://www3.publicationsduquebec.gouv.qc.ca/produits/ouvrage_routier/guides/guide24.fr.html
25. Mundt, M., Majumder, S., Murali, S., Panetsos, P., Ramesh, V.: Meta-learning convolutional neural architectures for multi-target concrete defect classification with the COncrete DEfect BRidge IMage dataset. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2019). pp. 11196–11205 (2019). https://doi.org/10.1109/CVPR.2019.01145
26. National Transportation Safety Board: Collapse of I-35W highway bridge, minneapolis, minnesota, august 1, 2007 (2008), http://www.dot.state.mn.us/i35wbridge/pdf/ntsb-report.pdf
27. Public Works and Government Services Canada: Bridge inspection manual. Government of Canada (2010)
28. Ren, Y., Huang, J., Hong, Z., Lu, W., Yin, J., Zou, L., Shen, X.: Image-based concrete crack detection in tunnels using deep fully convolutional networks. Construction and Building Materials **234**, 1–12 (2020). https://doi.org/10.1016/j.conbuildmat.2019.117367
29. Rhazi, J.O.: Half-cell potential test from the upper-side and the lower-side of reinforced concrete slabs: a comparative study. NDTCE'09, Non-Destructive Testing in Civil Engineering (2009)
30. Ruano, S., Cuevas, C., Gallego, G., Garcia, N.: Augmented reality tool for the situational awareness improvement of UAV operators. Sensors **171**(2), 297–313 (2017). https://doi.org/10.3390/s17020297
31. Safi, M., Chung, J., Pradhan, P.: Review of augmented reality in aerospace industry. Aircraft Engineering and Aerospace Technology **91**(9), 1187–1194 (2019). https://doi.org/10.1108/AEAT-09-2018-0241
32. Salman, M., Mathavan, S., Kamal, K., Rahman, M.: Pavement crack detection using the Gabor filter. In: Proceedings of the IEEE Conference on intelligent transportation systems (ITSC 2013). pp. 2039–2044 (2013)
33. Seo, J., Duque, L., Wacker, J.: Drone-enabled bridge inspection methodology and application. Automation in Construction **94**, 112–126 (2018). https://doi.org/https://doi.org/10.1016/j.autcon.2018.06.006
34. Spencer Jr., B., Hoskere, V., Narazaki, Y.: Advances in computer vision-based civil infrastructure inspection and monitoring. Engineering **5**, 199–222 (2019). https://doi.org/10.1155/2019/6520620
35. Słoński, M.: A comparison of deep convolutional neural networks for image-based detection of concrete surface cracks. Computer Assisted Methods in Engineering and Science **26**, 105–112 (2019). https://doi.org/10.24423/cames.267
36. Talab, A.M.A., Huang, Z., Xi, F., HaiMing, L.: Detection crack in image using Otsu method and multiple filtering in image processing techniques. Optik **127**, 1030–1033 (2016). https://doi.org/10.1016/j.ijleo.2015.09.147
37. Vaghefi, K., Melo e Silva, H., Harris, D., Ahlborn, R.: Application of thermal ir imagery for concrete bridge inspection. In: PCI National Bridge Conference, PCI/NBC, Salt Lake City: UT (USA). pp. 1–12 (2011)
38. Van Dam, J., Krasne, A., Gabbard, J.L.: Drone-based augmented reality platform for bridge inspection: Effect of ar cue design on visual search tasks. In: 2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW). pp. 201–204. IEEE (2020). https://doi.org/10.1109/VRW50115.2020.00043

39. Wells, J.L., Lovelace, B., Kalar, T.: Use of unmanned aircraft systems for bridge inspections. Transportation Research Record **2612**(1), 60–66 (2017). https://doi.org/10.3141/2612-07
40. Yaghi, S.R., Dabous, S.A.: State-of-the art practices in bridge inspection. International Journal of Civil and Environmental Engineering **9**(10), 1344–1347 (2015). https://doi.org/10.5281/zenodo.1109619
41. Zhang, C., chen Chang, C., Jamshidi, M.: Concrete bridge surface damage detection using a single-stage detector. Computer-Aided Civil and Infrastructure Engineering **35**(4), 389–409 (2020). https://doi.org/10.1111/mice.12500