Hardware-in-the-loop and Digital Twin Enabled Autonomous Robotics-assisted Environment Inspection*

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Abstract—**Empowered by the advanced 3D sensing, computer vision and AI algorithm, autonomous robotics provide an unprecedented possibility for close-up infrastructure environment inspection in an efficient and reliable fashion. Deep neural network (DNN) learning algorithms, pretrained on the large database can empower real-time object detection as well as fully autonomous, safe robotic navigation in unstructured environments while avoiding the potential obstacle. However, the development and deployment of the robots, inspection planning and operation procedures are still tedious and segmented with tremendous manual intervention during environmental inspection and anomaly monitoring. The proposed digital twin approach is able to provide a virtual representation model of the target environment either from a build-design or from 3D scanning of the real-world physical assets at high resolution in the Unity simulation environment, a transverse drone robot model and test its Robotics Operating System(ROS) autonomous navigation and obstacle avoidance software stack, and the hardware-in-the-loop test can thus be conducted for the flight control algorithm effectiveness and real-time object detection performance evaluation. The preliminary result shows that VGG16-UNet deep learning algorithm was able to use only a small amount of guidance and time from experienced inspection pilots to successfully identify the critical elements and defects and real-time navigate around the unstructured environment. The proposed digital twin framework and methodology is promising to be utilized for developing and testing fully autonomous inspection robots and its path planning and navigation and detection operation with greater cost- and time-efficiency.**

Key word: **Digital twin, Deep learning, Crack detection, hardware-in-the-loop, bridge inspection**

I. Introduction

There are approximately 600,000 highway bridges and 42% of them have exceeded their original 50 years of design life [1]. Currently the bridges in the U.S. National Bridge Inventory were biennial inspected and mainly with visual inspection, which requires a crew of two inspectors at any bridge site including one for inspection and paperwork and the other for photographing of bridge deterioration and areas of concern [2]. Expensive snooper truck was aided for inaccessible region inspection. Recently, as drone technology and climbing robot develops, the robot-assisted bridge inspection shows promise for autonomous navigation and structure defects around the bridge elements. The current practice is archaic and inefficient particularly as the deterioration of aging bridges accelerates, which is quite inconsistent among inspectors with its inspection data of limited use in bridge asset management. Magnetic climbing robot was able to crawl the steel bridge and navigation around for the bridge condition imaging [3]. Vacuum climbing robot that is able to perform non-destructive evaluation of the bridge elements [4]. A software called Simulation Training and Control System (STACS) to simulate multi-robot route planning and coverage control for bridge inspection purpose [5-6]. While digital representations of a physical bridge and defect propagation process and detected by the video feed from the drone or robots, which allows us to understand and model its real-time object detection performance and defect classification/segmentation as well as quantification accuracy. With hardware-in-the-loop approach, the bridge inspection and maintenance robot development, route planning and defect detection algorithm could be evaluated on the target robot and target bridge asset.

Cracks are one of the critical bridge defects and are often distributed irregularly, and the related indexes calculation of the of bridge cracks is important for bridge detection evaluation [7]. For example, if the crack is smaller than 0.2 mm, they may be interfered by surrounding obstacles, resulting in potential safety hazards of crack detection omission. Deep learning has attracted attention due to its advantageous for feature extraction and recognition in civil applications. However, classical deep learning are mainly classification or recognition models for datasets with large sizes and overall targets, such as AlexNet [8], GoogLeNet [9], UNet [7, 10-13] has been applied for bridge crack detection although they are prone to detection omission and misjudgment due to different shapes and linear topological structure of the cracks.

The current practice is archaic and inefficient particularly as the disparity of the robot development and defect detection, which is quite inefficient for the real-time bridge inspection and potential maintenance. Exploiting digital twin approach for bridge defect detection through high fidelity defects and its deep learning-based defect detection could accelerate the bridge inspection robot development and its online bridge condition detection and potential in-situ maintenance.

To increase the autonomous bridge inspection, robot development and online bridge condition assessment, this

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research is to synergy the autonomous robot navigation and real-time defect detection process to automate the robot navigation, defect detection and visualization, defects severity assessment and reporting. The digital twin framework was implemented based on the Simulation Training and Control System (STACS2) and the ROS interface was developed for the robot navigation stack development and hardware-in-the-loop simulation. The crack pattern was marked up into the bridge element based on the ASHTTO bridge inspection manual [2]. The VGG-16-Unet deep learning framework and pre-trained model was utilized for crack detection without training. The effect of lighting condition, imaging field of view and orientation as well as different crack size/pattern were investigated and compared. The unity simulation and image feed methodology and the deep learning framework implementation was introduced, and the crack detection performance was analyzed. The future work was outlooked for future real-time bridge inspection and defect detection practices.

II. Materials and Methods

The digital twin framework for robot-assisted bridge inspection and crack detection was implemented and consisted of (a) Simulation Training and Control System (STACS) for robot route planning and data acquisition of the defected embedded bridge asset, (b) a Robotics Operation System (ROS) navigation stack, and (c) VGG16-UNet deep learning based crack detection.

A. *Simulation Training and Control System for Bridge Inspection Simulation*

A Simulation Training and Control System (STACS) simulation was developed for bridge inspection [14-15]. It has capability to add bridge asset and robotics/swarm inspection with different data view (Figure.1). In this research, we create the crack patten and add it as materials in Unity3D and apply those materials to the bridge element (such as bridge column) for further crack detection.

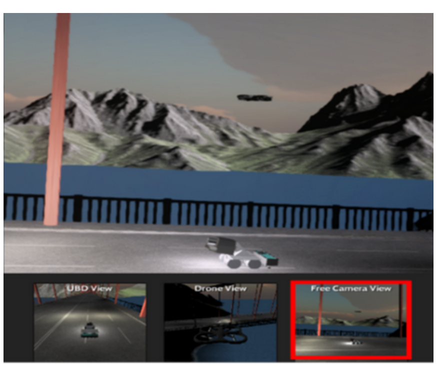

Figure 1. STACS Unity simulation software

B. *ROS Navigation Stack for Robot-assisted Bridge Inspection*

A ROS interface was further developed to integrate with the STACS simulation software so that the robotics navigation stack could be tested online. The training simulation for monitoring and controlling multiple simulated robots and then hooked up with the real robot and control software for hardware-in-the-loop testing. Thus, STACS can implement a training simulation, in Unity, for multi-robot bridge inspection and through a simple ROS bridge to monitor and control real robots. The crack detection node was added to stream the drone robotics camera view and conduct the deep learning-based crack detection in real time.

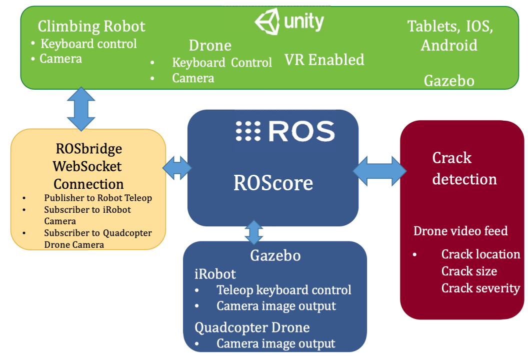

Figure 2. Digital twin of ROS navigation and crack detection

C. *VGG16-UNet Deep Learning for Crack Detection*

U-Net is an effective CNN architecture for image segmentation. We proposed to utilize a VGG16 model to reduce the layer and parameter of U-Net. VGG16 has similar contracted layer as U-Net but has less number of parameters than U-Net. Additionally, VGG16 has weights from parameters that are easily accessed, therefore we apply these weights directly to the new model. Typically models used for segmentation compose of contracting layer and the expansion layer. In this research, we resembled the U-Net architecture by modifying VGG16 with additional expansive layer consisting of up-sampling layers and convolution layers to the end of the VGG16 architecture. Thus the overall architecture of the model is becoming symmetrical and resembling the letter U shape. Therefore, the proposed UNet-VGG16 model architecture has contracting layer of VGG16, and the expansion layer to be added correpondingly [16-18]. The VGG16-UNet deep learning algorithm was implemented on an Ubuntu 22.04 with NVIDIA Corporation GP102 [GeForce GTX 1080 Ti] GPU graphics card machine with 6 CPU family of Intel(R) Core (TM) i7-8700K CPU @ 3.70GHz.

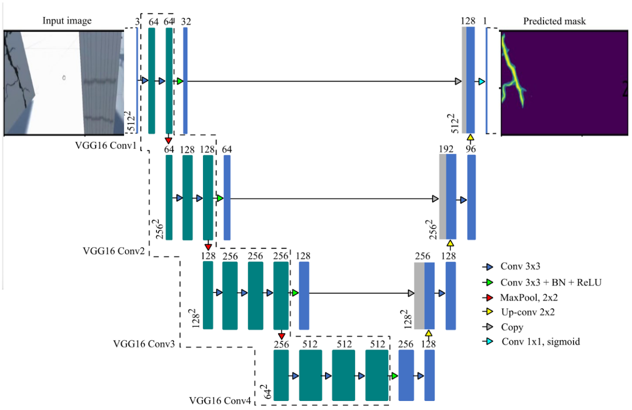

Figure 3 VGG16-UNet deep learning architecture

III. Results and Discussions

The Unity simulation software package was implemented in the previous study for the autonomous bridge inspection and drilling operation [19]. We added a crack image as material in Unity3D and applied that material to the bridge column as shown in Fig. 3 by dragging that image to the bridge column.

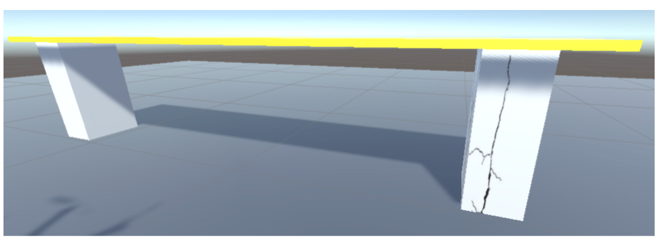

Figure. 3 Right column has a crack in the Unity3D scene (crack texture: https://www.seekpng.com/ima/u2e6y3e6r5i1e6r5/)

The VGG16-UNet deep learning algorithm was implemented for crack detection. The result shows that the proposed VGG16-UNet architecture is able to segment the crack on the bridge column (Figure 4b) and it overlaid onto the original bridge column (Figure 4c).

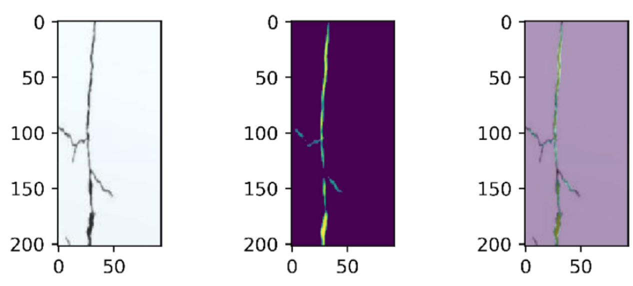

Figure. 4 Crack segmentation results (original image, crack mask, overlayer)

The training and validation accuracy from the proposed alogirthm was indicated in Figure 5. It shows that it reaches 99.3% accuracy for taining and 76.2% accruacy for validation after 9 epoches. The training and vlication loss was indicated correpondingly in Figure. 6.

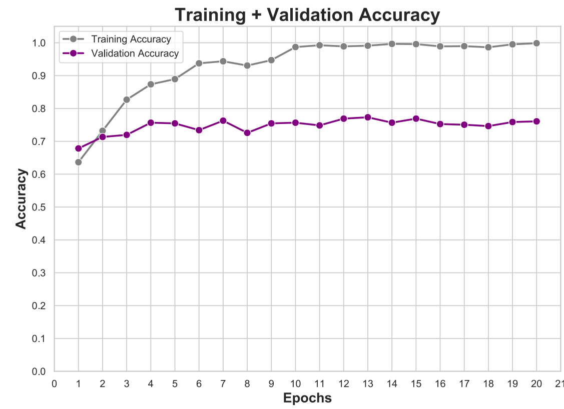

Figure 5. The training and validation accuracy from the proposed approach

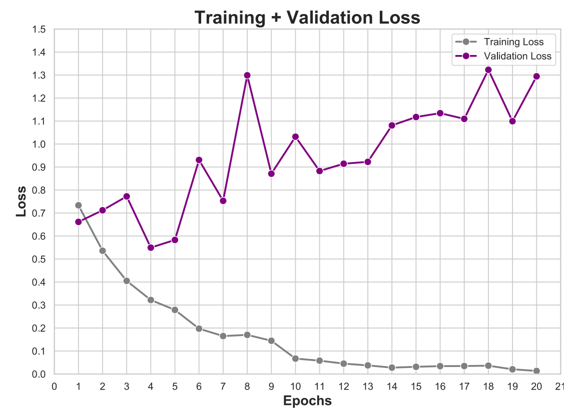

Figure 6. The training and validation loss from the proposed approach

In most case, the crack detection algorithm was able to accurately detect the crack and segment reasonaly for crack size estimation as in Figure 7.

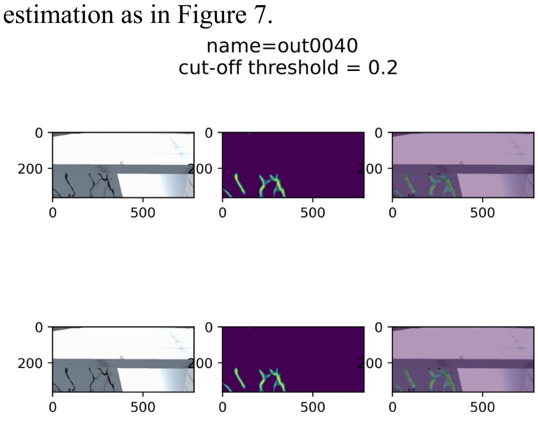

Figure 7. complex background crack detection result

The crack detedtion algirthm is also senstistive to the robotic imaging view angle and the lighting condition simulated, the crack detection failure are summarized in Figure 8 and Figure 9.

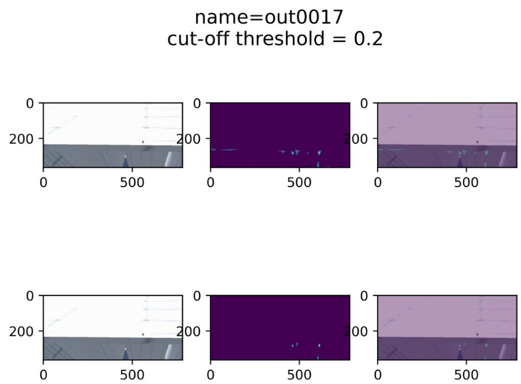

Figure 8. Complex background crack detection failture due to imaging view angle

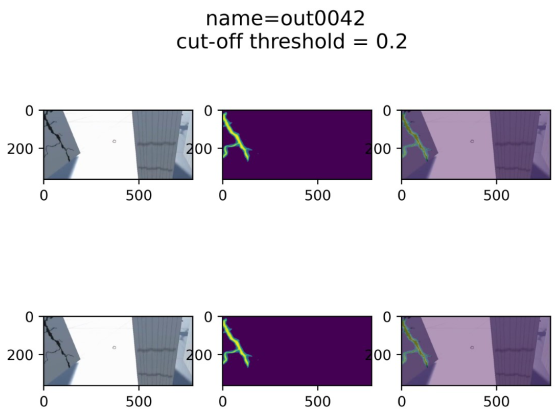

Figure 9. Complex background crack detection failture due to lighting condition

The result was summarized in Figure 8. The precision is 80%, the recall is 66.7%, the F1 score is 0.72. The overall crack detection is about 81.4%.

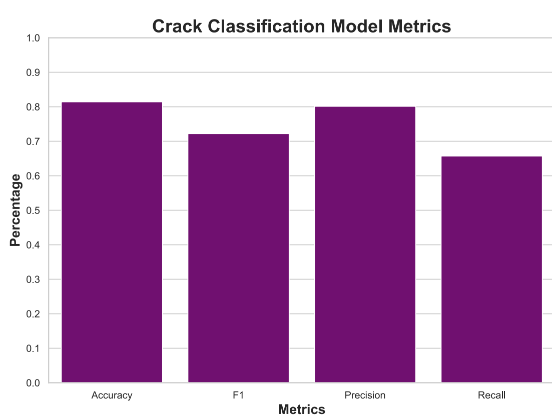

Figure 10. Crack classification model metrics

IV. Conclusion

This research explored how to incorporate Unity simulation engine and hardware-in-the-loop for digital twin enabled autonomous bridge inspection robot development and deep learning-based crack detection. The crack detection algorithm was able to detect the crack size at accuracy of 81.4% and at 10 fps. It also indicated that crack detection results are sensitive to lightning conditions and crack width. Crack width automatic estimation is challenging since cracks may go along different directions, which might require additional preprocessing to be added. Our future works will investigate optimal lighting strategies within Unity simulator to improve crack detection robustness, and further refine the deep learning-based crack classifier for distinguishing crack pattern categories based on crack width and severity as indicated in ASHTTO 2019 Bridge Inspection Manual.

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