Automated Crack Detection for Underwater Inspection of Miter Gates with Unmanned Underwater Vehicle

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ABSTRACT

The emergence of Unmanned Underwater Vehicles (UUVs) as tools for underwater inspection tasks presents promising potential. This study presents a novel automatic damage detection framework in large-scale underwater structures using a physics-based graphics model (PBGM). A high-fidelity finite element model of the Greenup Miter gate on the Ohio River is utilized to provide the fundamental information for the graphical model development. An open-source software is used as a graphic-based observational system to render images given different inspection distances and environmental conditions, such as light conditions and water quality. A deep neural network for crack detection with segmentation from the existing literature is adopted and then trained using transfer learning, adapting it to the unique conditions of underwater circumstances. Results indicate that the proposed method provides high-accuracy damage detection amidst the unique background noise and uncertainties presented in the underwater environment, contributing significantly to the field of UUV inspection of large-scale structures.

1. INTRODUCTION

The emergence of Unmanned Underwater Vehicles (UUVs) as tools for underwater inspection tasks has gained increasing attention recently [1-2]. Equipped with an array of sensors, including lidar and/or video/photogrammetry, UUVs can significantly augment our ability to inspect and understand large-scale, complex structures with substantial underwater footprints, such as miter gates. However, the interpretation of video/photo-based inspection data taken underwater presents significant difficulties. The scattering effect and turbulence in the water, as well as variable lighting conditions, often complicate the visual identification of damage. Moreover, the complex geometry of these structures, coupled with underwater obstructions, poses further challenges in scanning all surfaces and areas of interest with adequate resolution.

To address these challenges, this study proposes a novel automated damage detection framework for large-scale underwater structures using a physics-based graphics model (PBGM). The proposed framework counteracts the challenges presented by damage detection with UUV images, such as the scattering effect, water turbulence, and complex geometries. This innovative approach aims to provide effective and reliable crack detection on images with high uncertainty and background noise.

For the demonstration of this proposed framework, a high-fidelity finite element (FE) model of the Greenup Miter gate on the Ohio River is used in this paper for geometry information of the PBGM. Blender 3.4 is then used as a graphic-based observational system to simulate underwater images with different inspection distances and environmental conditions, such as light conditions and water quality. To further enhance the process, we adopt a deep neural network for crack detection with segmentation from existing literature [3]. The model is then trained on a synthetically generated dataset from Blender using transfer learning, adapting it to the unique conditions of underwater circumstances. A diagram of the proposed framework is shown in Figure 1. The rest of the paper is constructed as follows. Section 2 introduces the development of PBGM from a validated FE model of the miter gate. Section 3 describes the architecture of the convolutional neural network (CNN) model used in this paper and the corresponding training process. Section 4 shows the performance of the proposed framework, followed by conclusions in Section 5.

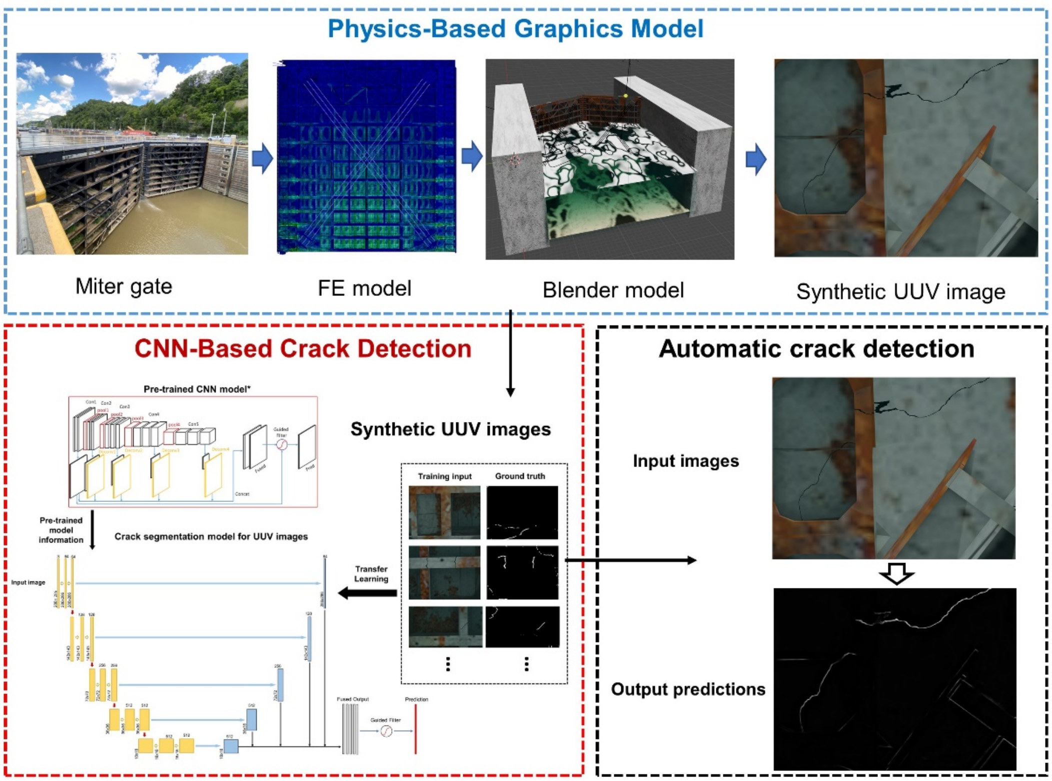


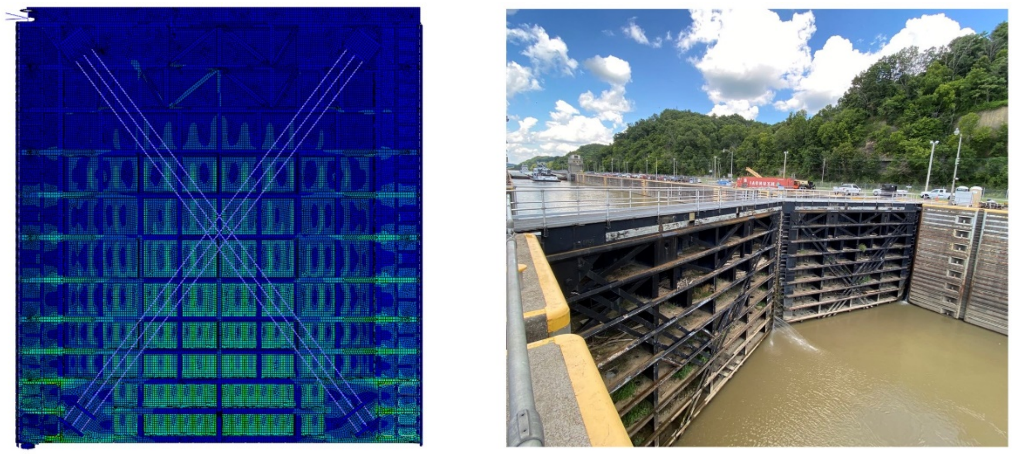
Figure 1. Overview of the proposed framework

2. PHYSICS-BASED GRAPHICS MODEL DEVELOPMENT

Generating Unmanned Underwater Vehicle (UUV) images from physics-based graphic models requires an accurate representation of the real-world structure and its surrounding environment, accounting for the complexity of the geometry, the variability of environmental conditions, and the uniqueness of underwater optics.

In this work, we focus on the Greenup miter gate located on the Ohio River. The FE model of this miter gate, built in Abaqus 2021 from design drawings, provides the fundamental information for the graphical model development as shown in Figure 2 a).

The FE model, which has been validated to provide accurate responses of the miter gate under various conditions, captures the structural information needed to translate into a graphical model. Detailed information and validation of the FE model can refer to our previous work [4-6]. The first step is the extraction of the geometrical information from the FE model, including its mesh, nodal coordinates, and element connectivity. This data is then imported into Blender 3.4, an open-source 3D graphics software. The raw structural data is transferred into a detailed graphics model that closely resembles the real miter gate, as shown in Figure 2 b).

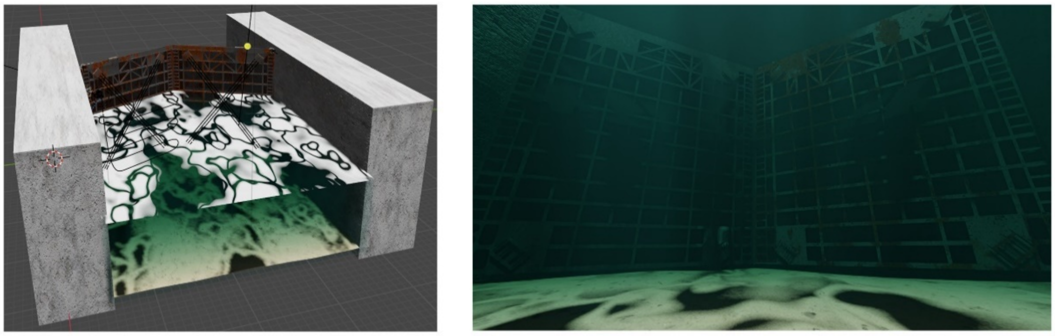


a) b)

Figure 2. a) FE model, and b) Field collected photo.

As shown in Figure 3 a), to reproduce the physical appearance of the (underwater) structure, we employ Blender's principled bidirectional scattering distribution function (BSDF), which enables image textures to the surface of the graphics model, mimicking the real structure's material and surface properties. For the underwater environment, a cubic volume in Blender is introduced to emulate the water effects, which considers various water conditions and turbidity levels. The sunlight is added and modified as another essential control of underwater imaging. Cracks, as one of the most dominant structural failures, are implemented according to different geometry drawing techniques in Blender, covering a wide range of potential failure conditions.

Once the graphics model of the structure and its surroundings is complete, a movable virtual camera is set to mimic the UUV's behavior. The camera can take photos underwater at any location and orientation, with parameters such as focal length, light beam power, and image resolution adjusted to the desired values. The rendered image shown in Figure 3 b) demonstrates the physics-based graphics model with an accurate representation of the underwater environment surrounding the real miter gate, enabling the generation of realistic UUV photos under specific field scenarios.



a) b)

Figure 3. a) Blender model, and b) rendered underwater image example.

3. CRACK DETECTION WITH TRANSFER LEARNING

Convolutional Neural Network Architecture

The Convolutional Neural Network (CNN) architecture used for automated crack detection from UUV images in this study was adopted from a previous work [3], which formulates crack segmentation as a binary image per-pixel classification problem. In this context, "0" represents "non-crack" region and "1" corresponding to "crack" areas. As shown in Figure 4, the architecture consists of 13 convolutional layers, mirrors the first 13 layers in the VGG-16 network, each incorporating convolution, batch normalization, and a Rectified Linear Unit (ReLU).

The architecture uses a filter bank for producing feature maps, while batch normalization is utilized to reduce internal covariate shift. The ReLU layer applies the activation function $max(0, x)$, enabling the network to learn non-linear functions. Spatial pooling is executed through four max-pooling layers, following specific convolutional layers which perform plane size reduction using a stride 2 block with a 2×2 kernel filter max-pooling.

The architecture further includes side-output layers and a refinement module. The side-output features are obtained via a convolutional layer, with the feature maps upsampled by deconvolutional layers to match the input image size. These upsampled feature maps are concatenated together, followed by a convolutional layer and a softmax layer, which generates an N-channel probability map (where $N = 2$, corresponding to the two classes, i.e., "crack" and "non-crack"). A final predicted label for each pixel is acquired via a fixed threshold, and the model refines the fused prediction by applying guided filtering. The model is composed of three main parts: the convolutional layers, the side-output layers, and the refinement module. Utilizing the principle of transfer learning, we adapted the pre-trained model for the task of underwater crack detection.

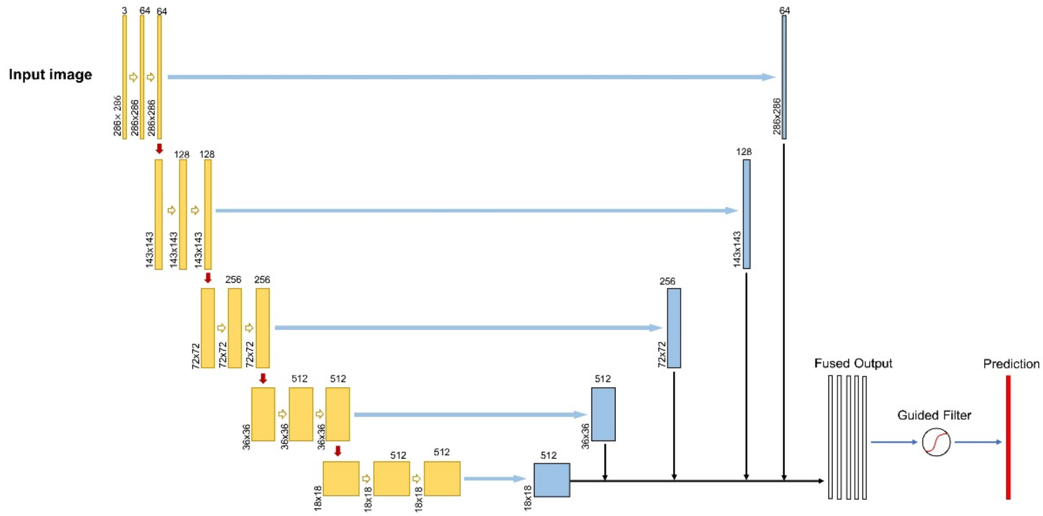


Figure 4. CNN architecture.

Data Preparation and Training Configuration

Detecting cracks using images captured by UUVs often yields suboptimal results due to the unique properties of the underwater environment, including water turbidity, lighting conditions, and complex structure geometry. Recognizing the lack of underwater crack images in existing literature, a new dataset was developed. This dataset contains photos of a miter gate underwater, created using the 3D computer graphics software, Blender. The generated images authentically reflect the intricate structural geometry, diverse crack types, and variable lighting conditions characteristic of the underwater environment.

An example of the training image is shown in Figure 5 a). This image highlights the challenges of crack identification due to factors such as the corrosion on the steel surface, and the less visible cracks located further from the camera (on the back face of the gate). To produce a ground truth dataset suitable for transfer learning in this context, a duplicate of the photo was rendered, maintaining the original location and angle of view, but excluding all surface texturing as shown in Figure 5 b). Subsequently, gradient-based post-processing was applied to generate binary ground truth images. In these images, the intact regions were represented by “0” (“non-crack” region), while “1” corresponded to areas with cracks. In Figure 5 c), by eliminating the potentially misleading complex structure geometry from the images, the transfer learning process effectively reduced the occurrence of "false positives".

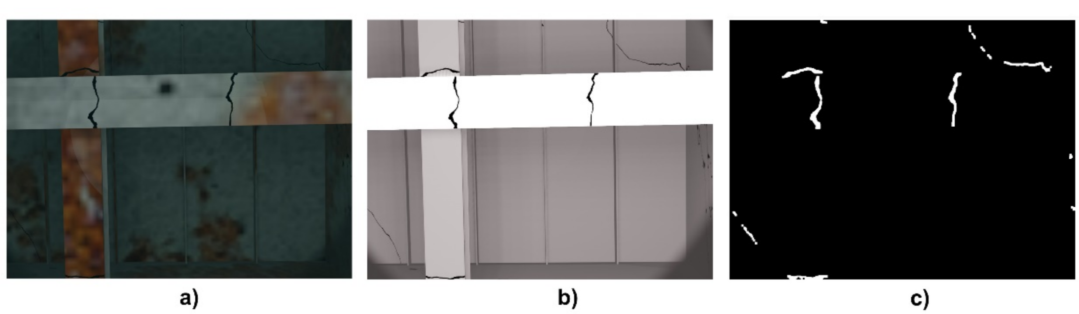


Figure 5. Training image example: a) synthetic UUV image, b) Blender model without texturing, and c) synthetic ground truth by post-processing

Figure 6 illustrates the transfer learning configuration, which utilizes approximately 100 samples to recalibrate the weights of the original CNN model to accommodate the unique circumstances of the UUV case.

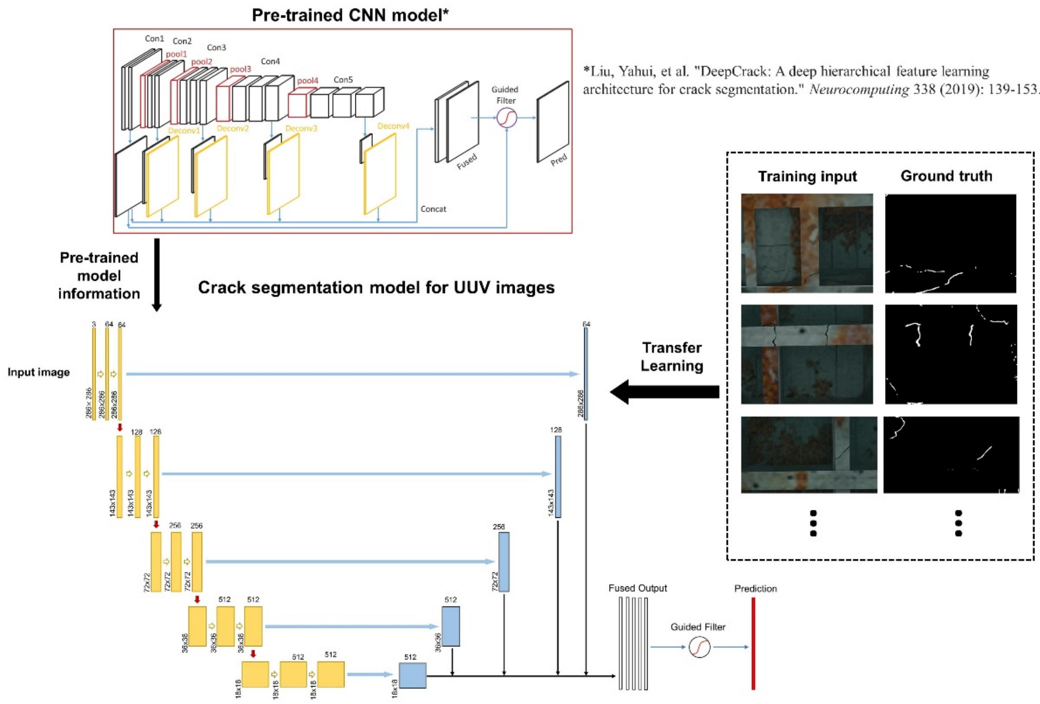


Figure 6. Training configuration.

4. RESULTS AND DISCUSSIONS

The efficacy of the proposed framework is evaluated by studying its performance across three outstanding scenarios encountered in the UUV task. These scenarios include: 1. The presence of cracks against a geometrically intricate surface. 2. Obscure cracks appearing on a similarly complex structural surface. 3. Cracks located on the structure's reverse face, observed from a skewed viewing angle. The framework successfully detected the cracks in the first scenario, affirming its capability in identifying substantial defects. In the second scenario, while it was able to detect the less apparent cracks, it also misidentified certain structural boundaries as defects. This indicates a degree of difficulty in distinguishing genuine flaws from the surface irregularities inherent in complex structures. In the third scenario, the cracks were again successfully identified. However, the framework falsely recognized the beam boundaries as defects, like the second scenario. This suggests that an oblique viewing angle and complex geometry can both potentially increase detection error. Additionally, it's worth noting that increasing the viewing angle—while potentially reducing the UUV's path distance—could compromise the reliability of the structure's inspection. This highlights a trade-off between the efficiency of the inspection process and the accuracy of defect detection.

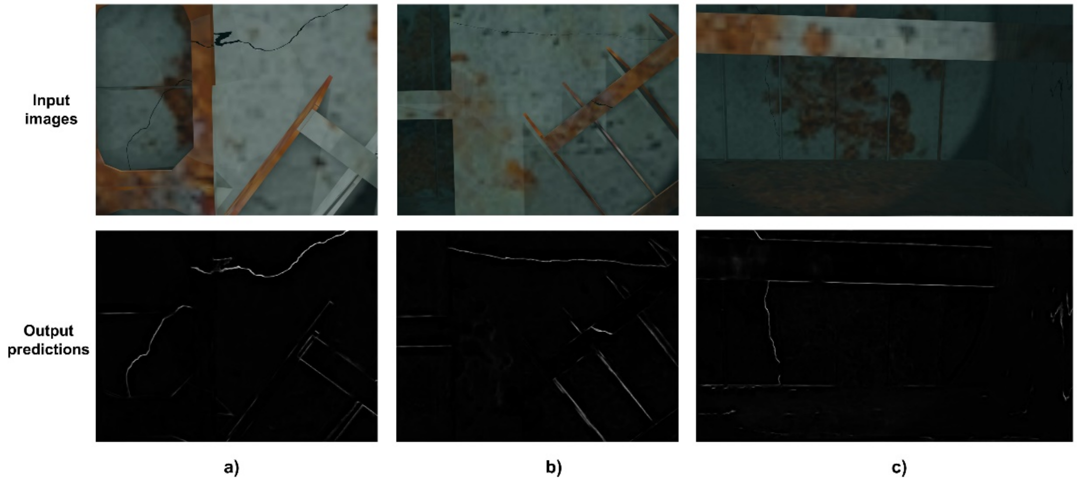


Figure 7. Results for three different outstanding scenarios: a) synthetic UUV image, b) Blender model without texturing, and c) synthetic ground truth by post-processing

5. CONCLUSIONS

This paper proposed a deep learning-based automatic damage detection framework which accommodates the challenges presented during the UUV inspection of large-scale structures. The proposed framework can effectively evaluate the potential consequences of different UUV inspection strategies. Notably, it can optimize UUV trajectories, given the presence of multiple environmental noise and uncertainty sources. In essence, this study introduces a practical solution that improves inspection efficiency and detection accuracy, which essentially enables the optimization of UUV inspection task. Overall, it represents a significant contribution to the field of UUV inspection of large-scale structures.

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