

YOLO-DCD: A YOLO-Based Framework for Dam Damage Change Detection and 3D Model Updating

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ABSTRACT

Dam health monitoring is a critical component of dam management, requiring regular inspection, assessment, and maintenance to ensure structural integrity and operational safety. While 3D models of dams can be constructed given sufficient data, maintaining their up-to-date accuracy is challenging. Constructing an entirely new 3D model is typically resource-intensive due to the need for extensive data acquisition and computational effort. To improve efficiency, it is preferable to update only the regions of the model that exhibit actual changes, as unnecessary updates may introduce additional uncertainty. This paper proposes a novel change detection method, YOLO-DCD (YOLO-based Damage Change Detection), designed to support efficient 3D model updating using a single input image. A real image is first acquired, and its spatial location within the existing 3D model is estimated using a pixel-level localization technique. Based on the established pixel correspondences, the camera pose is computed using the Perspective-n-Point (PnP) algorithm combined with Random Sample Consensus (RANSAC) for robustness. A rendered image is then generated within the 3D model using a refined camera pose, adjusted to ensure complete coverage of the observed region in the real image. Damage detection is subsequently performed on both the real and rendered images using a YOLO(You Only Look Once)-based detection model. The comparison between the two detection results enables the identification of potential damage-related changes, which are categorized as unchanged regions, newly formed cracks, or new spalling. The proposed YOLO-DCD framework is evaluated using the Upriver Dam dataset, with experimental results demonstrating that the method achieves accurate and reliable detection of structural changes, facilitating efficient and targeted 3D model updates.

INTRODUCTION

As vital components of a nation's infrastructure, dams play a crucial role in public safety, and their structural integrity is essential for national resilience and risk manage-

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ment [1]. By capturing and storing detailed structural features, a 3D model of a dam serves as a valuable tool for efficient monitoring, analysis, and decision-making in dam management [2]. However, maintaining the up-to-date accuracy of a 3D model is often costly and resource-intensive, highlighting the need for an effective model updating strategy. Rather than reconstructing the entire 3D model, which requires extensive data acquisition and substantial computational resources, it is more efficient and reliable to update only the regions where structural changes have occurred [3, 4]. Updating unchanged areas may unnecessarily introduce uncertainty and degrade the overall accuracy of the model. Therefore, an effective change detection method that compares the current condition of the dam with an existing 3D model is essential for timely and accurate model updating.

Infrastructure change detection has been extensively studied using remote sensing and photogrammetric sensors, including optical cameras and LiDAR scanners [5, 6]. However, LiDAR scanners are primarily effective for detecting major structural changes—such as alterations in walls, staircases, or ceilings—and objects with substantial geometric presence, like furniture. They are limited in detecting subtle surface changes that do not involve noticeable depth variation, such as cracks, and are ineffective in capturing transparent or reflective surfaces, including water flows and glass [7, 8].

Given that cracks serve as important indicators of potential structural issues in dams, image-based change detection methods offer a more appropriate solution for monitoring dam health, as they are capable of capturing fine surface details [9]. The use of imagery for detecting changes in building changes has been widely studied, particularly in the contexts of remote sensing, urban monitoring, and structural analysis [10, 11]. Such image-based infrastructure change detection methods primarily focus on major structural alterations—such as changes in walls, facades, or interior spaces—or the presence or absence of entire infrastructure buildings. Moreover, these approaches typically require large-scale image datasets to effectively train deep learning models, which can limit their applicability in scenarios with limited data availability [12–14]. Image-based dam damage detection has been explored [15]; however, existing methods primarily focus on identifying the presence of damage, without the capability to distinguish between newly emerged and pre-existing damage.

In summary, LiDAR scanners are limited in detecting minor cracks in dam walls, and existing crack detection methods fail to identify changes over time. Furthermore, existing change detection methods do not focus on wall damage. To address these gaps, this paper proposes a novel damage change detection method, YOLO-DCD. The proposed method integrates change detection between a single image and a 3D model, along with a YOLO-based damage detection model, enabling the identification of subtle new damage variations. A case study based on the Upriver Dam dataset has been conducted, with experimental results provided in the Results section.

METHODOLOGY

Framework

Figure 1 illustrates the overall framework of YOLO-DCD. A real image (after change) representing the current condition of the dam is provided as input to the system. The cor-

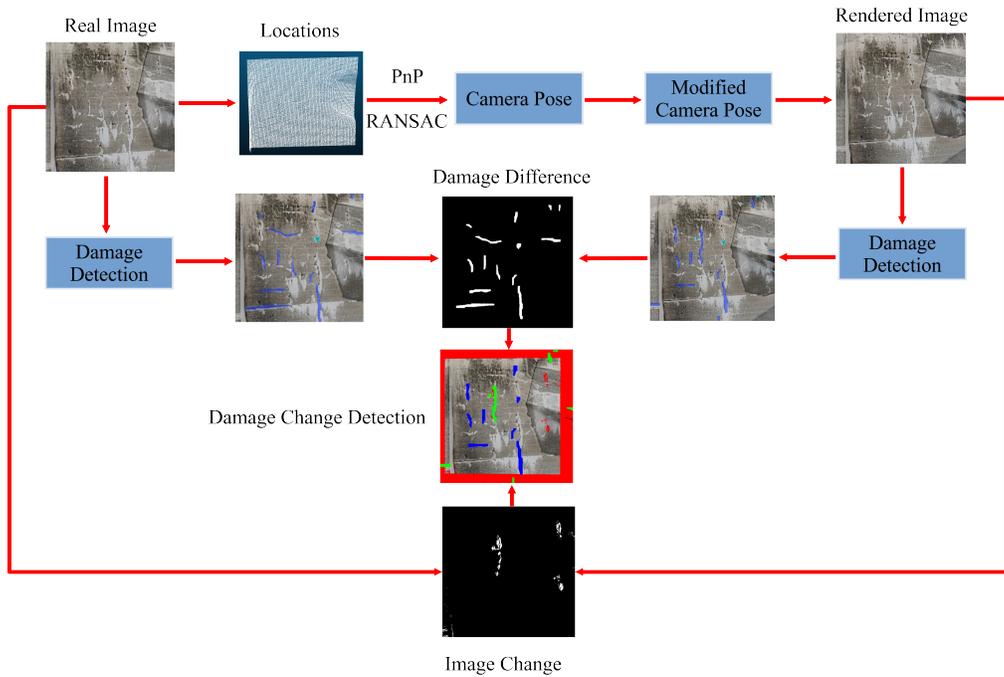


Figure 1. The framework of YOLO-DCD. In the final output, red highlights the image-level differences between the real image and the rendered image, clearly visible within the marked square region. Blue indicates the damage differences detected between the two images. The green areas represent the final damage changes—i.e., regions where both damage and image-level changes intersect. The square region is the primary area of interest for identifying these changes.

responding 3D locations of pixels in the image are estimated using a deep learning-based localization method. Based on these pixel-to-model correspondences and the known intrinsic parameters of the camera, the Perspective-n-Point (PnP) algorithm combined with Random Sample Consensus (RANSAC) [16] is employed to estimate the camera’s relative pose within the 3D model’s coordinate system. However, since the localization is inferred rather than ground truth, the resulting pose may be imprecise. To ensure the rendered image (after change) fully encompasses the region observed in the real image, the estimated pose is adjusted by minimizing the observation region. As a result, the rendered image effectively represents the 3D model and fully overlaps with the area captured in the input image.

The real image and the corresponding rendered image are subsequently fed into a YOLO-based damage detection model to identify potential damages. To determine damage changes, the detected results from both images are compared. However, due to the minimized field of view in the rendered image, the spatial scale and size of detected damages may differ from those in the real image. To account for this discrepancy, a classical image-based change detection method is employed to capture structural changes between the two images. The final detected damage changes are determined by comput-

ing the intersection between the YOLO-identified damage differences and the changes identified by the classical method, ensuring robustness and consistency in the damage change detection process.

Render Image

To enable change detection, the dam's condition as represented by the 3D model is simulated through a rendered image, which serves as an input for both crack detection and change detection. Given a real image of the dam, pixel-wise 3D locations are estimated using the localization algorithm PIL3D, which achieves accurate pixel-level mapping within the 3D model by training a Wavelet neural network with paired images and their corresponding 3D coordinates. With the established 2D-3D correspondences between image pixels and 3D coordinates, Perspective-n-Point (PnP) combined with RANSAC is employed to estimate the relative camera pose within the coordinate system of the 3D model. However, the estimated pose is not the ground truth, so the camera pose is further adjusted to enlarge the observable area. To achieve this, the average distance between the estimated camera position and the point cloud is first computed based on their spatial locations, as follows:

$$Dist = \beta \times \frac{1}{N} \sum_{i=1}^n \|X_i - t\| \quad (1)$$

Where X_i represents the i -th point, t is the location of the camera and β is the ratio for controlling the backward (camera) movement distance.

Then, the unit vector \vec{v} pointing from the camera to the center of the visible point cloud (as calculated earlier) can be determined, and the camera position is updated as:

$$t_{new} = t - Dist \times \vec{v} \quad (2)$$

With the updated camera position, a rendered image was generated in the 3D model using a camera simulator Blender [17].

Damage Detection and Simulation

Both the real image and the rendered image undergo damage detection to identify defects such as cracks and spalling. A YOLO-based damage detection model is employed for this purpose. This model is capable of accurately detecting cracks and spalling without requiring additional fine-tuning. For each input image, a corresponding damage map is generated, highlighting the detected damage regions.

To simulate damage changes, Photoshop was used to manually add cracks and spalling features to the newly acquired image [18]. As illustrated in Figure 2 (a), new cracks were manually added within the red rectangles, aiming to be detected by YOLO-DCD.

Change Detection

The change detection process consists of two stages: damage change detection and image change detection. In the first stage, damage masks generated from the YOLO-based detection for both the real image and the rendered image are compared to identify

differing regions, indicating potential new or missing damages. To enhance the accuracy of image change detection and reduce the influence of lighting variations and shadows, several strategies are applied. First, the images are converted from RGB to HSV color space. Then, a combination of CLASH (Contrast Limited Adaptive Histogram Equalization), SSIM (Structural Similarity Index), Canny edge detection, and Gamma correction is employed to emphasize structural differences while suppressing irrelevant variations in an automated way [19–21]. The final damage change detection is determined by identifying the intersection between the damage change detection and image change detection results.

To ensure accurate spatial alignment, Scale-Invariant Feature Transform (SIFT) [22] and the Fast Library for Approximate Nearest Neighbors (FLANN) [23] are first employed to establish feature correspondences between the real and rendered images. These matched features are then used to determine the overlapping observation region for subsequent analysis.

EXPERIMENTAL RESULT



(a) Real image

(b) 3D model image

(c) Rendered image

Figure 2. Real image and corresponding image in the 3D model and rendered image generated with a modified camera pose to match the area. (a): The acquired real image with new cracks. (b): the rendered image in the 3D model. (c): The rendered image in the 3D model using the adjusted camera pose, covering a larger area, with the matched region depicted.

The proposed YOLO-DCD method was tested using the Upriver Dam, located in Spokane, Washington, United States. Figure 2 (c) illustrates the rendered image generated with a matched region based on the real image, which was subsequently used to evaluate the YOLO-DCD method. YOLO-DCD relies on image localization and camera pose estimation. To reduce uncertainty, we adjust the estimated camera poses to cover a broader area of the scene, ensuring that the observations encompass most of the image content. As shown, the rendered image in Figure 2 (c) covers a larger area compared to the original image shown in Figure 2 (b) and the same observation region can be accurately determined. The real image in Figure 2 (a) has new crack features for damage detection purpose. In rare cases, PIL3D may not perform well, and additional images

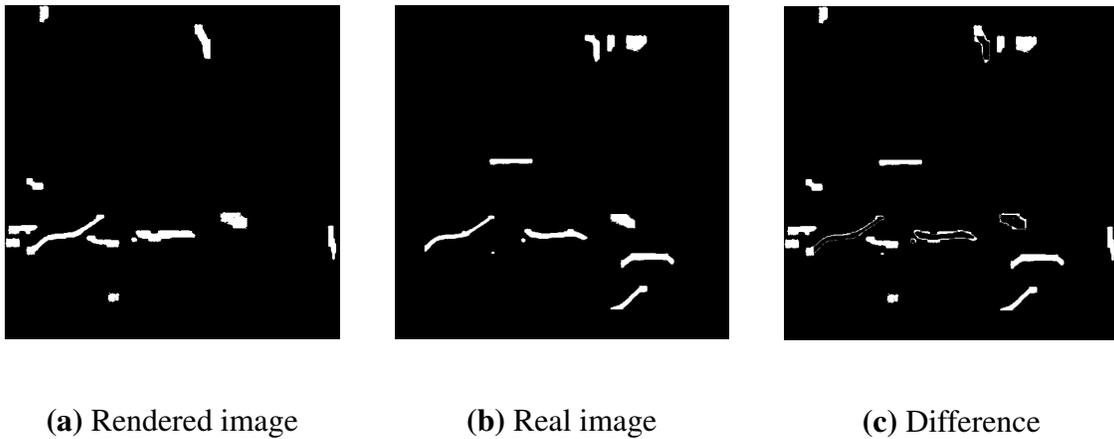


Figure 3. Masks of damage detection by YOLO model and results of damage change detection. (a): the damage mask of the rendered image; (b): the damage mask of the real image. (c): the damage change mask by comparing two masks.

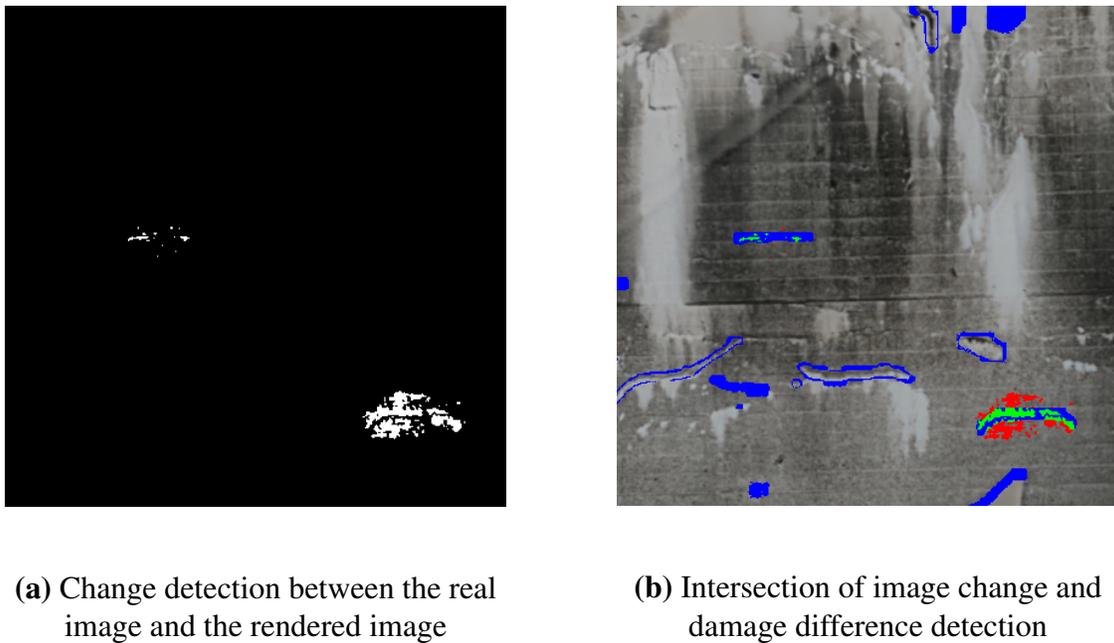


Figure 4. Change detection of the real image and rendered image, and the intersection of image change detection and damage difference detection. Red: detected changes; Blue: detected damage difference; Green: damage changes.

from different viewpoints may be required. However, since PIL3D currently achieves centimeter-level accuracy, it performs well across all images in our experiments.

Figure 3 illustrates the masks generated using the YOLO-based damage detection model, along with the results of the damage change detection. As shown, damage in both the real image and the rendered image is successfully detected, and the differences between them can be clearly identified based on the matching information presented in Figure 2. Figure 4 shows the final damage change detection result, obtained by combining damage difference detection and image difference detection. Integrating image

difference detection helps eliminate false positives that may arise from varying object appearances due to different camera observation poses.

CONCLUSIONS AND DISCUSSIONS

This paper proposes a novel damage change detection method, YOLO-DCD, which enables the detection of new damage—such as newly formed cracks and spalling—on dams. A single 2D image is compared with an image rendered from an existing 3D model. Damage detection is first performed independently on both images using a YOLO-based model, and damage differences are then identified by comparing the resulting label maps. The proposed YOLO-DCD offers a practical solution for damage change detection by combining damage and image-based change detection, without relying on deep learning models specifically trained for change detection—whose training data are often difficult to obtain. YOLO-DCD relies on the accuracy of image localization, but the centimeter-level precision of PIL3D ensures reliable performance of YOLO-DCD.

The performance of YOLO-DCD heavily depends on the accuracy of both the YOLO-based damage detection and the image difference detection methods. Any missed detections in either stage will result in incomplete final outputs. Zooming in or out on images can affect the accuracy of YOLO-based damage detection, potentially leading to increased false positives. Moreover, when the appearance of new damage is visually similar to its surrounding pixels, the detected damage regions may appear sparser than the actual damage. In future work, we plan to incorporate deep learning-based change detection methods to improve the robustness and accuracy of the proposed framework.

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