

3D Damage Quantification for Visual Inspection

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Abstract. We propose a method to segment and quantify visual damage in civil infrastructure. A new inspection pipeline is built where an on-site user equipped with a mixed reality headset (MRH) can obtain a quantitative measure of the volume, and size of damage in concrete. We define the volume of damage as the space enclosed within the concave defect and a hypothetical flat plane that would have been present on the undamaged surface. A deep learning-based interactive segmentation algorithm deployed in the MRH is used to segment the defect in the structure. Structure from Motion is applied to get a detailed point cloud reconstruction of the damage using a series of images captured by the MRH on-site. The segmentation mask is applied to categorize points in the point cloud inside and outside the damage. A dense three-dimensional mesh is created for the deformed region using the mask and selected points. We calibrate our meshed model to obtain the scale of damage by utilizing the built-in sensors in the MRH.

Keywords: visual inspection, remote inspection, damage quantification, computer vision

1 Introduction

Civil infrastructure is often prone to damage and deterioration over a period of extended use. Large structures such as bridges must be evaluated over a long period [1], [2]. A shift towards smarter technologies and integration of machine learning, vision-based inspection, and artificial intelligence has been observed in recent years [3]. Traditionally, surface changes such as spalling, segregation, formation of sand pockets, and scaling in addition to obvious cracks on concrete surfaces are signs of concrete distress and deterioration [4]. For example, the Ontario Structural Inspection Manual (OSIM) mentions that all bridges, retaining walls, and culverts should be inspected biennially within a recommended range of an arm's length of the element [5].

In this study, we propose a methodology to perform an image-based three-dimensional reconstruction of a damaged region in civil infrastructure components and quantify it in terms of its size, volume, and damage segmentation. The proposed

methodology requires images and camera poses as inputs. In the context of computer vision, a camera pose (or simply pose) contains information about the rotation and translation of the camera from the position an image is captured. It acts as a reference in terms of the placement of objects while performing reconstructions in 3D. Utilizing the workflow developed in this paper, structural inspectors on-site can measure and categorize damages as per OSIM [5] in a relatively fast and real-time mannerism. The method can be used to identify and measure a common type of damage, spalling, on any component in structures. The method is invariant to the material used for the facade. The method can be deployed in conditions where accessibility is a hindrance and reaching within arm's length distance is not a feasible option.

In this paper, testing and validation of the proposed procedure and technique were done by performing laboratory experiments. The proposed method was tested on artificial spalling damage which was 3D printed from a CAD model. The CAD model was prepared from depth-sensing data obtained from an actual spalling which was present on a bridge abutment. For evaluation purposes of the proposed method, the spalling was unevenly scaled in the depth direction (see Fig. 1).



Fig. 1. Spalling damage (left); 3D printed damage (right)

2 Proposed Approach

2.1 Overview

The objective of the proposed damage quantification technique is to make a reliable, repeatable, and robust measurement from 3D reconstruction using images and camera poses without the need for a dedicated sensor. A photogrammetry technique called structure from motion (SfM) is deployed to assist the reconstruction. A damaged component is reconstructed using SfM once multiple images along with poses are collected. Using existing interactive segmentation techniques that were developed previously in our lab [6], binary masks are created to isolate the region of interest (ROI) in the reconstructed scene. Our developed algorithm takes the 3D scene reconstructed using images and poses and the binary masks as inputs. The algorithm then performs operations on the scene to compute the volume based on these inputs and measures the size of the damage and the volume of the same. Using these metrics, spalling damage can be categorized as *Light*, *Medium*, *Severe*, or *Very Severe* as per OSIM recommendations.

2.2 3D pointcloud reconstruction using Structure from Motion

Structure from motion (SfM) is a photogrammetry technique that reconstructs a scene in 3D from a series of multiple images of the same scene taken from different viewpoints while also simultaneously obtaining the position of the camera (poses). SfM has been extensively used by researchers in the field of geomorphic studies [7], performing structural analysis of building components under different load states [8] even used to reconstruct entire cities [9]. It has also been used to perform visual inspections remotely [10], and large-scale aerial inspections in the field of agriculture, geosciences, and environmental disaster management among other uses. The underlying principle in SfM is that by capturing the same scene from multiple viewpoints sequentially, keypoints (which are common features across two or more images) can be detected. Once these keypoints are detected and matched in multiple images taken from different viewpoints, these keypoints (feature points) can be identified in three-dimensional space as point clouds by analyzing the relationships (change in position) between the feature points due to the different camera poses (rotation and translation) from which they were captured.

In this study, open-source software called openMVG [11] was used to generate 3D point clouds from the input images and poses. A point cloud is a collection of data points in 3D space, in our case, the output of the SfM is a colored point cloud of the damage. Hololens2 (HL2) which is an extended reality device from Microsoft was used to collect the images (with poses) of a damaged component for this study (see Fig. 2). In practice, an inspector on-site can use the HL2 to collect multiple images from different viewpoints of damage (see Fig. 3). Using the algorithm proposed in this article quantifies the defect to a high level of accuracy and categorizes them as per OSIM. Fig. 4 shows a colored point cloud of a scene reconstructed from 50 images collected from HL2.



Fig. 2. Microsoft Hololens2(HL2)



Fig. 3. Data collection using gesture control

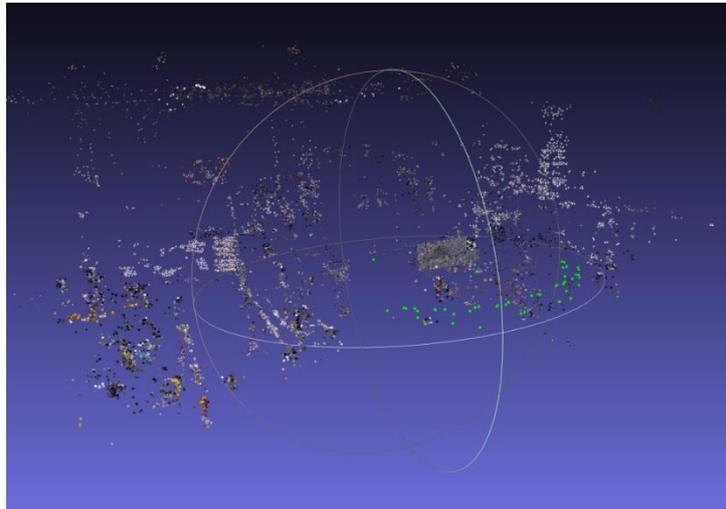


Fig. 4. Colorized pointcloud obtained by performing SfM on 50 images

2.3 Damage segmentation to get binary mask

To filter out the spalling region from the rest of the image, an image mask is used in the pipeline. A binary mask is an image that can be used to extract regions of interest for the damage. In the binary mask image, all the black pixels are filtered out and the white pixels are segmented (saved) to isolate the damage from the rest of the image (see Fig. 5). In practice, on-site, an inspector wearing HL2 can create this mask using interactive segmentation wherein the user (inspector) picks a few seed points inside and outside the damage and the artificial intelligence-enabled method can create a segmentation mask to separate the spalling damage. For more details, readers are referred to a previous paper [6] from our research group on interactive segmentation.

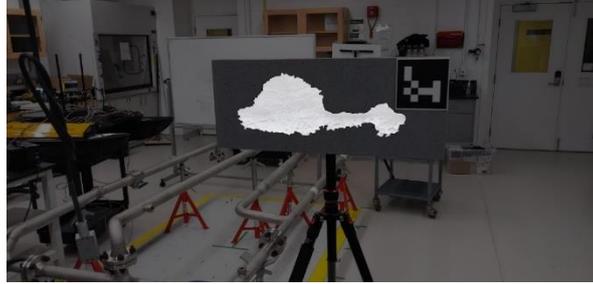


Fig. 5. Binary mask overlaid on the damage

For the sake of scientific analysis of the quantification method only, for the laboratory experiments, we used a ground truth segmentation mask which was generated manually for one image. Using ArUco markers the one mask can be distorted to fit all the images used in the point cloud generation. An algorithm in the OpenCV library [12], [13] was deployed which detects and recognizes the corners of the ArUco marker and accordingly distorts the ground truth mask to fit a given image (see Fig. 6). Using these binary masks, the point cloud region containing the spalling damage can be filtered from the whole reconstructed scene.

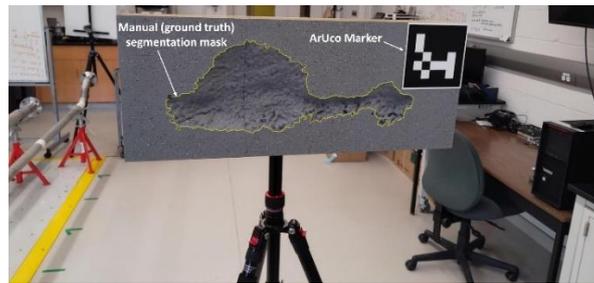


Fig. 6. Manual segmentation mask used to segment the damage

2.4 Volume estimation

From the point cloud obtained in section 2.2 and the binary masks obtained in section 2.3, a point cloud region of the spalling damage is segmented from the larger point cloud. Using an open-source library, open3D [14] for 3D data processing, a colorized point cloud can be converted to a triangular mesh solid which assists the quantification process. To facilitate the process of finding the volume of the damage, we first define the volume of the damage as the quantity of missing material (say, concrete) which has been detached from the rest of the component. Intuitively, this will be the volume between the triangular mesh that we create and the hypothetical undamaged flat surface plane (HUFPP) of the component. It is to be noted that in its current iteration, our method has been adapted to quantify spalling damages on flat surfaces only. To get the HUFPP, a few points are selected in the immediate exterior neighborhood of the damage. Theoretically, these points should lie on one plane. This plane can be

found by fitting a plane through the points selected in the exterior neighborhood using RANSAC [15] which is a random sampling-based method to fit data to a model, in our case, the plane model.

We propose the following volume calculation methodology. Since the mesh of the damage is a triangular mesh (Fig. 7), it is composed of triangles connected through common edges, and corners. The contribution of one of such triangles to the total volume of the damage can be viewed as the volume this triangle encloses between itself and the hypothetical undamaged flat plane (HUFPP) of the component in the form of a slender solid projection (see Fig. 8). Mathematically, this can be found by multiplying the area of the said triangle and the mean of the distance of its corners from the HUFPP. Once these steps are repeated for all the triangles comprising the damage mesh, the volumes can be summed up to get the total damage volume. This, of course, is an estimation but one which is within acceptable limits of error in terms of the intended applications of the method.

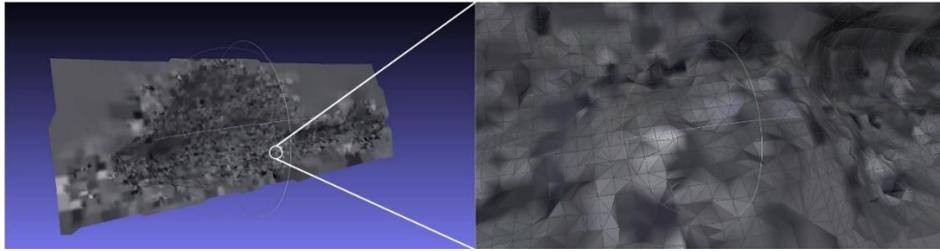


Fig. 7. 3D Mesh reconstruction of the mesh

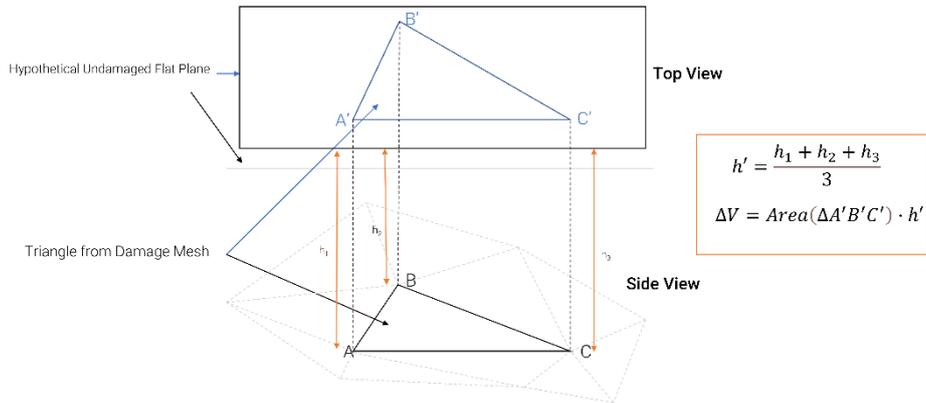


Fig. 8. Volume calculation for one triangle in the mesh

3 Experimental Validation

As mentioned in section 1, the method is evaluated on a 3D printed damage, this enables us to have the ground truth volume of the missing damage from Rhinoceros 3D software which can be used as an error metric for the proposed framework. For the laboratory experiments, 50 images were taken of the damage from different view-points, while moving in a circular arc around the damage. The experiment was repeated by taking images at average distances of 1, 2, 3, 4 and 5 m. Using these images, the colorized point cloud was obtained from SfM (section 2.2), and using the manual segmentation mentioned in section 2.3, the point cloud was segmented, the mesh was generated, and volume was obtained in real world units. Experiments for this paper were conducted 20 times for each distance range. Each iteration of the software produced slightly different volume results since the plane segmentation relies on RANSAC which is a random sampling-based method. The average error in volume computation when compared to the volume obtained from CAD model is within a range of 6.5% at the closest range of 1m to within 12% in the most unfavorable condition. As the inspector moves away from the defect, the results become more unrepeatable and deviated, this conclusion can be drawn from the categorical scatter plot presented in Fig. 9.

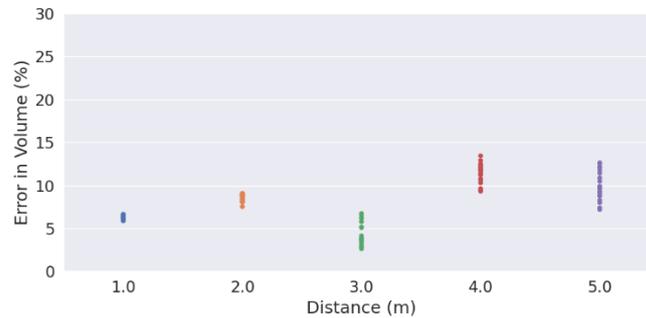


Fig. 9. Categorical scatter plots for average error evaluated at different distances

4 Conclusion

In this study, the authors propose a novel image-based, 3D modeling reconstruction of a structural spalling defect to automate the process of quantification. Utilizing the algorithms of Structure from Motion, the damage is reconstructed in three-dimensional space on real-world scale using images and camera pose information from an XR wearable device. The method has been tested on artificial damage to gauge its accuracy in computing the volume of damage. The results of the laboratory experiment show that the accuracy is within 6.5% in close range (1m) compared to the ground truth.

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