A 3D Automatic Optical Inspection (3D-AOI) System for Architecture Inspection

Yu-Hsiang Chen, Po-Ru Chiu, Meng-Hung Ho, Ching-Yuan Chang, Kuang-Yen Liu, and Po Ting Lin

***Abstract*—Most architecture inspections, that were traditionally relied on human operations by professionals or experts, could be dangerous and time-costly. With the recent developments of unmanned aerial and ground vehicles, some visual inspections were done based on image acquisitions from the camera on an unmanned vehicle. This paper presented a 3D Automatic Optical Inspection (3D-AOI) system for bridge inspection. A stereovision camera that was installed on top of an unmanned aerial vehicle (UAV) acquired a 3D point cloud of the inspected area of the bridge's cap beam. Image processing steps were used to recognize the bridge crack pattern. Finally, the voxels of the crack pattern were transformed to the plane that was perpendicular to the camera direction for the measurements of the geometrical features of the crack. In our implementation, the measurement error was less than 5% as the normal of the inspected plane had a 40°-angular difference between the camera direction.**

***Index Terms*—Bridge Inspection, Stereovision, 3D Point Cloud, Least Squared Approximation, Crack Measurement.**

I. INTRODUCTION

BASED on the information from the Ministry of Transportation and Communications, Taiwan [2], there are around 11 thousand highway bridges in Taiwan. Each bridge requires regular visual inspections which are mostly done by human workers. They sometimes are carried by bridge trucks, mechanical platforms or cables to reach closer to the inspection area. Therefore, visual inspection could be dangerous, costly and time-consuming.

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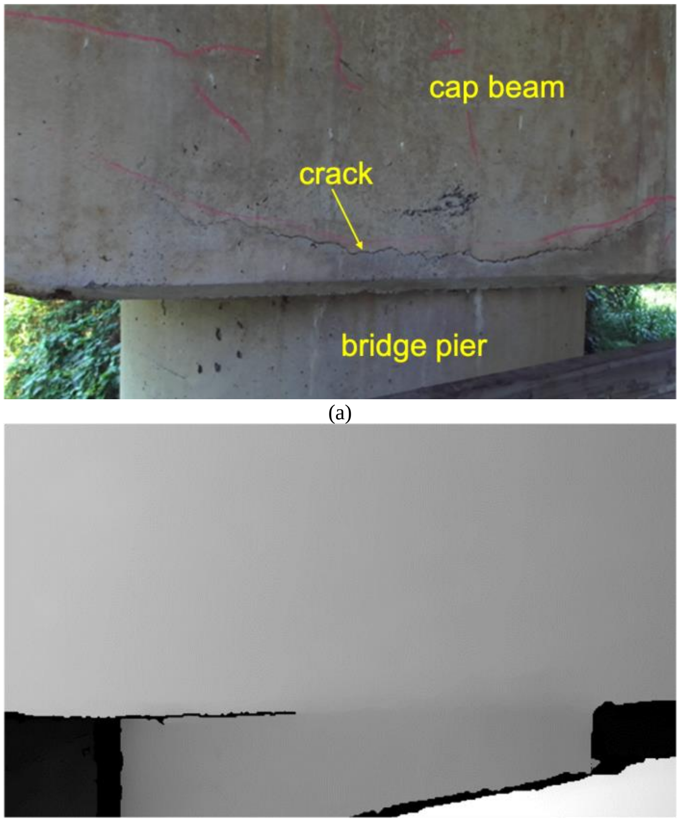
With the rapid development of unmanned aerial and ground vehicles, they have been used to do visual inspections [3, 4] with greater safety. An unmanned aerial vehicle (UAV) can carry a camera and fly closer to the inspection area of a bridge for visual inspections. Image processing techniques could then be used to identify the crack patterns and measure their geometrical features, such as type, length and width of the crack. However, the flying condition of the UAV may be stable all the time and the camera direction may not always be perpendicular to the surface of the bridge. The crack dimensions determined from an image that is not taken along the perpendicular direction may not be accurate, thus leading to failure of visual inspection. A proper methodology is desired to ensure the accuracy of visual inspection based on images taken from the camera on a UAV.

Kuo, et al. [5] used a laser beam to measure the distance between the camera on the UAV and the surface of the bridge. As the angular difference between the camera direction and the normal vector of the bridge surface, also known as the heading error, could be measured by laser, a tilting correction was made to the inspection image. Kuo, et al. [6] used a contrast enhancement method to increase the quality of the inspection image for better accuracy of the inspection result. These methods didn't provide a general solution to correct the angular difference between the camera direction and the normal vector of the inspected area.

On the other hand, Lin, et al. [7] installed a stereovision camera on the UAV and studied the normal vector field of the inspection area. By comparing the local normal vectors in the acquired 3D point cloud, the voxels of the inspected area could be automatically identified for further inspection processes. Chen [1] has developed a 3D Automatic Optical Inspection (3D-AOI) system for detection and measurement of bridge cracks. This paper will provide the details of the 3D-AOI system. It was desired that the proposed method could automatically correct the heading error in the acquired inspection data and determine the geometrical features of bridge cracks.

II. THE PROPOSED 3D AUTOMATIC OPTICAL INSPECTION (3D-AOI) SYSTEM FOR BRIDGE INSPECTION

In this paper, a 3D camera (ZED stereovision camera by Stereolabs Inc.) was installed on a UAV and used to acquire the 3D point cloud from the inspection area of a concrete bridge. Fig. 1 (a) shows an image of the cap beam. A crack pattern could be seen in the image; however, the image may not be taken along the normal direction of the bridge surface. The image cannot be directly used for pattern recognition and measurement of the crack length if the heading error exists. Fig. 1 (b) shows the 3D point cloud acquired from the stereovision camera. The color of the depth map represents the distance between the object and the camera. The darker the voxel, the further the distance from the camera.



(a)

(b)

Fig. 1. Inspection of the pier cap of a concrete bridge: (a) RGB image, (b) depth map.

Fig. 2 shows the process flow of the proposed 3D-AOI system for architecture inspection. The stereovision camera on the UAV was used to capture the 3D point cloud (X, Y, Z) of an inspected area on the concrete bridge. Since the camera direction may not be perpendicular to the inspected plane, geometrical information of the acquired 3D point cloud was used to transform the inspected area to a view perpendicular to the camera direction. Image processing and pattern recognition techniques were used to identify the existence of cracks on the inspected area. Therefore, the crack features could be properly measured in the transformed image patterns.

A. Determination of the Points on the Inspected Plane

Point Cloud Library (PCL) [8] was used to process the acquired 3D point cloud of the inspected area. An illustrative example could be seen in Fig. 3. First, an outlier filter [9] was used to remove the 3D points in the background, highlighted by the red boxes in Fig. 3 (a). The filtered point cloud could be seen in Fig. 3 (b). Next, a VoxelGrid filter [10] was used to downsample the point cloud, as shown in Fig. 3 (c). Downsmapling could shorten the computation time. The step (b) in Fig. 2 was then completed as the point cloud of the inspected area could be determined.

B. Estimation of the Inspection Plane

The step (c) in Fig. 2 was to estimate the plane of the inspected area. A K-dimensional tree [11] was used to build the

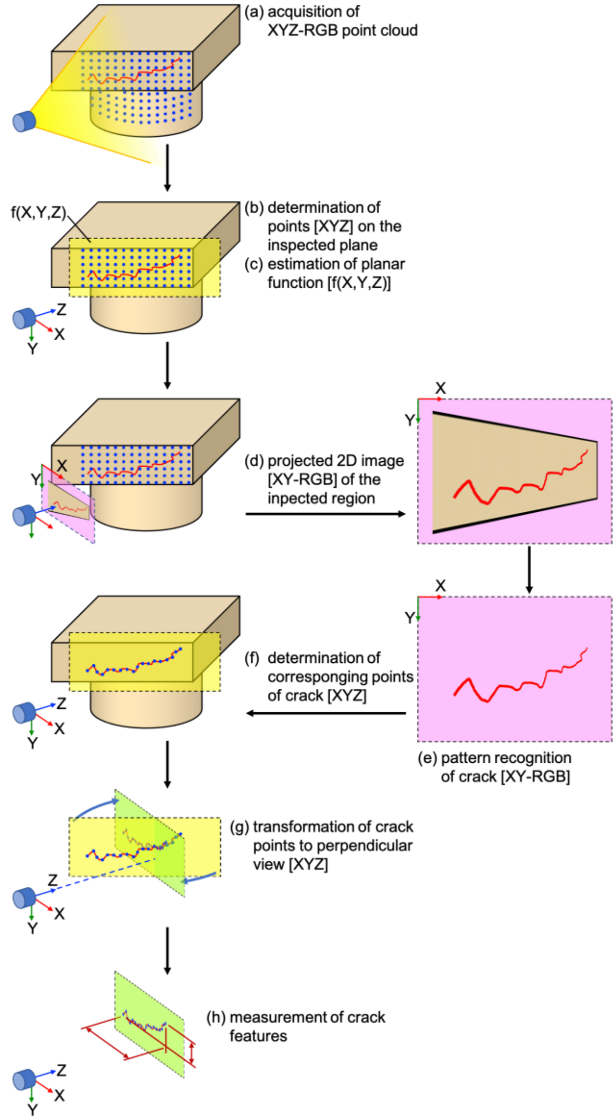
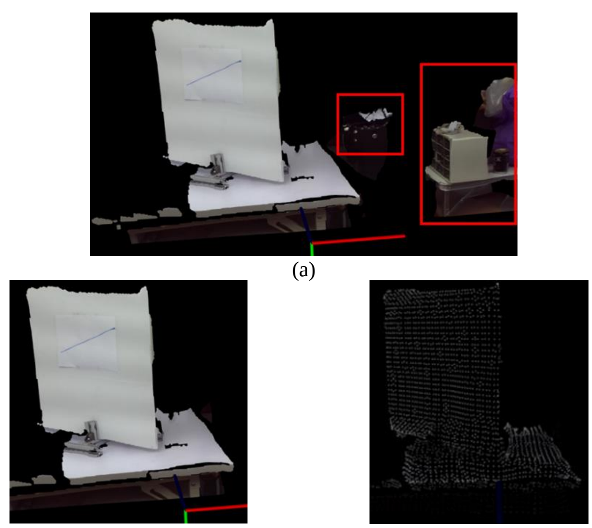


Fig. 2. Process of the proposed 3D-AOI system.



(a)

(b) (c)

Fig. 3. Determination of the points on the inspected plane in the laboratory: (a) original point cloud, (b) filtered point cloud after removing the outliers, (c) downsampled point cloud.

connectivity of voxels based on searching for the K nearest neighbors of voxels. The local normal vector of each voxel was estimated [12]. Random Sample Consensus (RANSAC) method was used to randomly select some voxels from the point cloud and estimate the plane passed through the selected voxels. An iterative process was executed until the closest estimation of the plane that passed through the inspected area was determined. Fig. 4 showed the estimated local normal vectors on the inspected area and the estimated plane that passed through the voxels of the inspected area, illustrated by the gray plane. The mathematical function f(X, Y, Z) of the estimated plane was finally obtained.

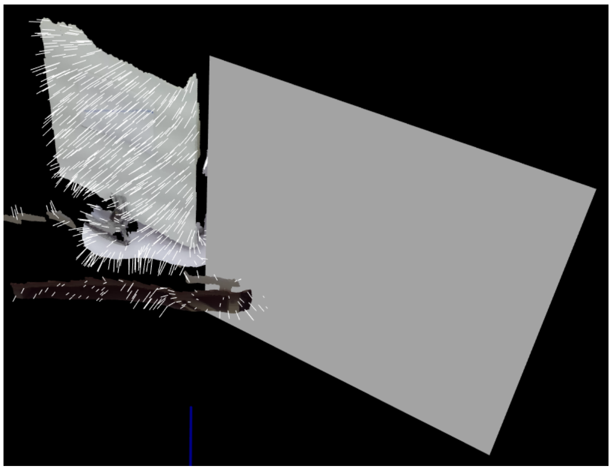


Fig. 4. Estimation of the plane that passed through the inspected area.

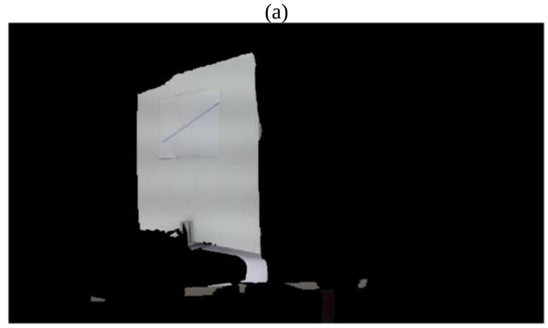
C. Image Processing and Pattern Recognition of Crack

The corresponding pixels of the inspected area in the 2D projected view of the camera were then selected for the following image processing. The original 2D image that was acquired by the camera could be seen in Fig. 5 (a) and the selected pixels of the inspected area could be seen in Fig. 5 (b). First, the quality of the image was increased by Contrast-Limited Adaptive Histogram Equalization (CLAHE) [13]. A closing operation was used to obtain the background patterns. The crack patterns could then be determined by subtracting the background patterns from the original image patterns. In order to remove the noises in the background, the crack patterns were binarized adaptively [14]. The aspect ratio of the oriented bounding box (OBB) of each crack pattern was investigated. Linear crack patterns had greater OBB aspect ratios. Furthermore, the ratio of the crack pattern area and the OBB area would be investigated. Linear crack patterns had greater area ratio than curved patterns. With the above image processing techniques, the linear crack pattern was finally determined in the 2D projected view, as shown in Fig. 5 (c). The step (e) in Fig. 2 was then completed.

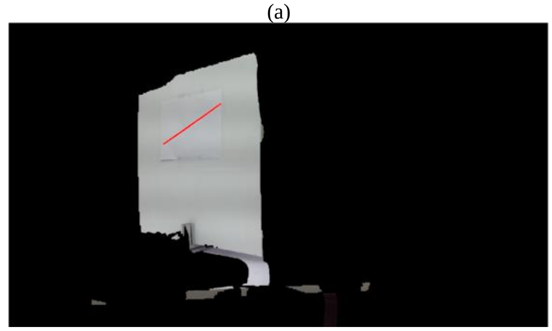
D. Transformation of Crack Points to Perpendicular View

The final step of the process flow of the 3D-AOI system was to transform the determined crack voxels to a plane that was perpendicular to the camera direction so that the geometrical features of the crack could be properly measured. Based on the information of the estimated plane f(X, Y, Z) in step (c) of Fig. 2 and the corresponding voxel of the identified crack pattern in step (e) of Fig. 2, the crack voxels were transformed to the perpendicular plane. The rational angle from the unit normal vector of f(X, Y, Z) and Z-directional unit vector (i.e. camera direction) was computed by the arccosine of the dot product of the above two vectors. The rotational axis could be determined by the cross product of the two vectors. Rodrigues rotation formula [15] was then used to transform the crack voxels to the perpendicular plane.

(a)



(a)



(a)

Fig. 5. Determination of the points on the inspected plane in the laboratory: (a) original point cloud, (b) filtered point cloud after removing the outliers, (c) downsampled point cloud.

III. Experimental Results and Discussions

Eight experiments were done in the laboratory to verify the accuracy of the proposed 3D-AOI system. The experimental results were shown in Table I. In the first four experiments, the distance from the camera to the inspected object was 1 m. The first two experiments had heading errors of 20 degree. The experiments No. 3 and 4 had heading errors of 40 degree. The measurement method of "3D-AOI" represented the solution process of Fig. 2 and the "Direct measure" indicated the procedure without estimation of the planar function and transformation to the perpendicular plane. As a result, the measurement errors of the 3D-AOI were less than 2%. The measurement error of No. 4 was 15.3% due to large heading error. In the experiment Nos. 5-8, the distance from the camera to the inspected object was 2 m. The rest of the experimental arrangements was the same. The experimental results showed that the 3D-AOI was able to measure the crack length with error less than 5% in all cases. The measurement error of No. 8 was 10.7% because of the large heading error. Therefore, it was essential to estimate the planar function of the inspected area and transform the crack voxels to the perpendicular plane for measurements of geometrical features.

TABLE I
EXPERIMENTAL RESULTS OF 3D-AOI OF LINEAR PATTERNS

No.	Distance from inspected object (m)	Heading error (degree)	Measurement method	Measured crack length (mm)	Correct crack length (mm)	Error
1	1	20	3D-AOI	304	300	1.3%
2	1	20	Direct measure	294	300	2%
3	1	40	3D-AOI	304	300	1.3%
4	1	40	Direct measure	254	300	15.3%
5	2	20	3D-AOI	308	300	2.7%
6	2	20	Direct measure	306	300	2%
7	2	40	3D-AOI	286	300	4.7%
8	2	40	Direct measure	268	300	10.7%

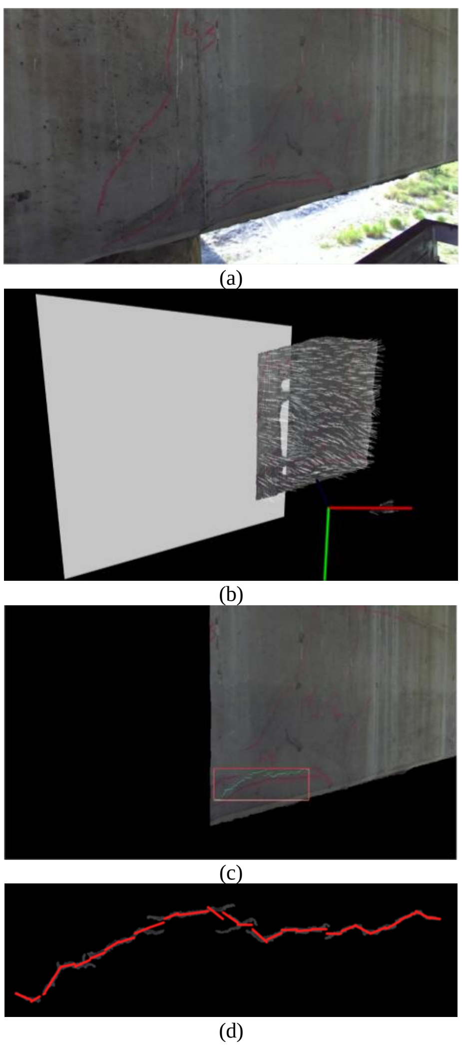


Fig. 6. Case 1 of 3D-AOI of crack patterns on the cap beam: (a) original image, (b) normal vectors of the inspected area and the estimated planar function, (c) identified crack pattern, (d) crack pattern transformed to the perpendicular plane.

In this paper, 2 different cases of 3D-AOI on the cap beam were demonstrated. Fig. 6 showed the Case 1 of the 3D-AOI of crack patterns on the cap beam of a concrete bridge. The original image shown in Fig. 6 (a) was not perpendicular to the camera direction. The 3D point cloud of the inspected area was identified and the estimated planar function of the inspected area was determined, as shown in Fig. 6 (b). The crack patterns were determined by the proposed image processing methods, as shown in Fig. 6 (c), and then transformed to the perpendicular plane, as shown in Fig. 6 (d). The measurement of the crack length without the correction of the heading error was 430 mm. After transforming the crack voxels to the perpendicular plane, the measurement of the crack length was 497 mm (corrected 13.5% of error).

In the case 2, a crack pattern was found at the edge of the cap beam, as shown in Fig. 7 (a). The proposed 3D-AOI identified two planar regions with different normal vectors, as indicated in

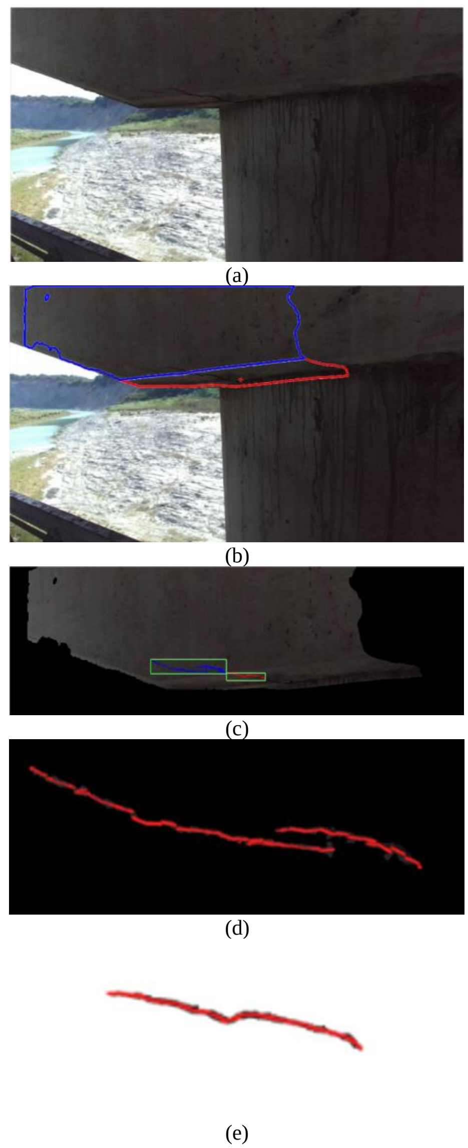


Fig. 7. Case 2 of 3D-AOI of crack patterns on the cap beam: (a) original image, (b) identification of two different planar regions, (c) identification of crack patterns in the two inspected planes, (d) crack pattern of the upper part transformed to the perpendicular plane, (e) crack pattern of the lower part transformed to the perpendicular plane.

Fig. 7 (b). As shown in Fig. 7 (c), the crack pattern was separated into two parts: an upper part in the blue planar region and a lower part in the red planar region. The upper crack pattern was transformed to the perpendicular plane, as shown in Fig. 7 (d). Similarly, the lower crack pattern was transformed to the perpendicular plane, as shown in Fig. 7 (e). The transformations of the upper and lower crack patterns were different because of the different normal vectors of the identified planar regions. As a result, the measurement of crack length without the transformations to the perpendicular plane was 639 mm as the corrected measurement of the crack length based on the proposed 3D-AOI method was 734 mm (corrected 12.9% of error).

IV. Conclusions

In this paper, a 3D-AOI system was proposed for bridge inspection. A stereovision camera was installed on a UAV. The 3D point cloud of the inspected area was identified based on the proposed point cloud processing methods. The planar function of the inspected area was determined based on the estimations of local normal vectors. The crack patterns were identified using several image processing techniques in the projected 2D view. The corresponding crack voxels were transformed to the plane that was perpendicular to the camera direction using Rodrigues rotation formula. The geometrical features of the crack patterns were then measured. The measurement error was less than 5% as the heading error was 40 degree. The proposed method could even identify the crack patterns that were located on multiple planar regions with different normal vectors. The crack pattern was then cut into multiple parts and processed separately. Each crack pattern would be transformed to the perpendicular plane for more accurate measurement of the crack features. The experimental results showed that the proposed 3D-AOI system was general and could be applied to various kinds of architecture inspections.

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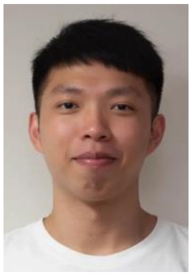

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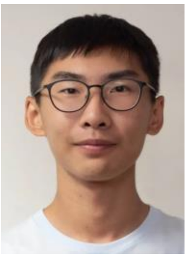

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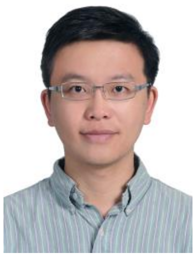

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