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UGV-Driven Indoor Damage Detection of Ceilings and Walls Using PatchCore

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Post-earthquake safety assessment of building interiors requires rapid detection of damage to nonstructural elements such as ceilings and walls, which may affect occupant safety and building usability even after moderate earthquakes. However, the lack of damaged image datasets limits the application of supervised deep learning methods. This study proposes an indoor damage detection system that combines PatchCore-based anomaly detection with autonomous image acquisition using an Unmanned Ground Vehicle (UGV). The method detects moderate-scale ceiling damage and wall cracks using only normal-condition images. To enable efficient inspection, a LiDAR-based navigation algorithm is developed that allows the UGV to travel along walls without prior maps or GNSS. Experiments conducted in a real building environment, with ceiling damage simulated by opening inspection hatches, demonstrate that the UGV achieves stable autonomous navigation and that PatchCore effectively detects ceiling and wall damage. The proposed system enables rapid and scalable post-earthquake indoor safety assessment.

Keywords: anomaly detection, PatchCore, UGV, ceiling element, wall surface.

1 Introduction

In recent years, the importance of safety inspection of nonstructural elements such as ceilings and partition walls has increased, not only after major earthquakes but also following small- to medium-scale seismic events. From the perspective of business continuity planning (BCP) for offices and factories, rapid post-earthquake safety confirmation of indoor environments has become essential. In addition, securing evacuation spaces and temporary shelters for stranded occupants also requires prompt safety inspection of indoor areas. For example, during the 2016 Kumamoto earthquake, damage to ceilings in public facilities such as gymnasiums prevented their immediate use as evacuation shelters (Building Research Institute 2016). Unlike structural members such as columns and beams, nonstructural elements are rarely instrumented with sensors such as accelerometers. Therefore, rapid damage detection for ceilings and partition walls is seldom performed after earthquakes. To address this issue, image-based inspection methods using deep learning and LiDAR-based approaches have recently been investigated.

For civil infrastructure such as bridges and dams, deep learning-based damage detection has been widely applied because large numbers of damaged images are publicly available through inspection records. As a result, supervised learning approaches such as object detection (e.g., YOLO) (Ge 2025, Lyu 2025, Saha 2024, Tse 2023) and semantic segmentation are commonly used. In contrast, building interiors are private properties, and damaged images are rarely available, making it difficult to prepare sufficient labeled datasets for supervised learning.

To address this limitation, this study proposes a damage detection method for ceilings and mortar wall surfaces based on PatchCore (Barusco 2025), which requires little or no damaged data for training. In image-based inspection, efficient image acquisition is also essential. Therefore, this study employs an Unmanned Ground Vehicle (UGV) that autonomously travels along walls while capturing images of inspection targets. A LiDAR-based navigation algorithm (Nitta 2023) is developed to detect walls and enable the UGV to move around the inspection area while maintaining a constant distance from the walls.

The effectiveness of the proposed method, which combines autonomous image acquisition using the UGV and PatchCore-based damage detection, is verified through experimental validation conducted in an actual university building.

2 Autonomous Inspection and Damage Detection Framework

To achieve this objective, an integrated framework is developed in which a UGV autonomously acquires indoor images and detects damage using anomaly detection. The overall process consists of two stages: (1) LiDAR-based autonomous navigation for systematic image acquisition and (2) PatchCore-based anomaly detection for damage identification.

2.1 *LiDAR-based navigation for image acquisition*

To enable autonomous operation without prior information such as floor plans, a navigation algorithm is developed that utilizes wall lines detected by LiDAR. Indoor environments are primarily composed of walls, and by traveling clockwise or counterclockwise along these walls, the UGV can systematically traverse inspection areas and capture images of ceilings and wall surfaces. In this study, a wide field-of-view camera is assumed, and the UGV is controlled to move along walls while maintaining a constant distance. During clockwise motion, the vehicle follows the wall on its left side, whereas during counterclockwise motion, it follows the wall on its right side. LiDAR measurements obtained in polar coordinates (r, θ) are first converted into Cartesian coordinates (x, y) using Eqs. (1a) and (1b).

$$x = r \times \cos(\theta) \tag{1a}$$

$$y = r \times \sin(\theta) \tag{1b}$$

To improve wall detection accuracy, Canny edge detection is applied to the converted point data to enhance structural boundaries. Since the detected edges are represented as discrete points, a Hough transform is further applied to extract line segments corresponding to wall surfaces. For each detected line segment with endpoints (x_1, y_1) and (x_2, y_2), the slope is calculated using Eq. (2).

$$k = \frac{y_2 - y_1}{x_2 - x_1} \tag{2}$$

Based on the slope, the segments are classified into side walls, along which the UGV moves in parallel, and front walls, which require a turning maneuver. For each category, the longest segment is selected as the reference wall for motion control. During straight motion, the distance and relative orientation between the UGV and the side wall are continuously monitored. The relative angle φ between the UGV heading and the wall is calculated using Eq. (3).

$$\varphi = arctan\,(k) \tag{3}$$

If the distance or orientation deviates from predefined tolerances due to factors such as floor friction, the vehicle posture is corrected using LiDAR feedback. When a front wall is detected and the distance falls within a specified threshold, the UGV performs a turning motion to continue wall-following navigation. This navigation strategy enables stable autonomous coverage of indoor spaces for visual inspection without prior information such as maps or floor plans.

2.2 *Damage detection using PatchCore*

Images acquired during autonomous navigation are analyzed to detect damage to ceilings and walls. In this study, the PatchCore method is employed as an anomaly detection approach that requires only normal-condition images for training. PatchCore constructs a memory bank by storing feature vectors extracted from normal images. For a target image, feature vectors are compared with those in the memory bank, and an anomaly score $S_{i,j}$ is computed for each pixel based on the degree of dissimilarity. In indoor environments, high anomaly responses may be caused by minor stains, lighting variations, or ceiling equipment. To reduce false detections, this study evaluates damage using the sum of anomaly scores exceeding a predefined threshold, as expressed in Eq. (4).

$$I_s = \sum S_{i,j} \; where \; S_{i,j} \geq T \tag{4}$$

Here, $S_{i,j}$ denotes the anomaly score at the pixel located at the i-th row and j-th column, T is the anomaly threshold, and I_S represents the image-level anomaly measure.

For model development, only normal images are used to construct the memory bank. However, both normal and damaged images are used for validation to determine appropriate thresholds and improve detection reliability. A pre-trained ResNet18 model is adopted as the feature extractor.

3 Experimental Verification

To evaluate the practical applicability of the proposed system, experimental verification was conducted in an actual building environment.

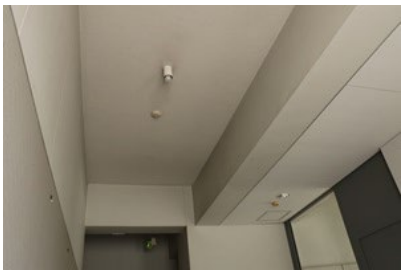
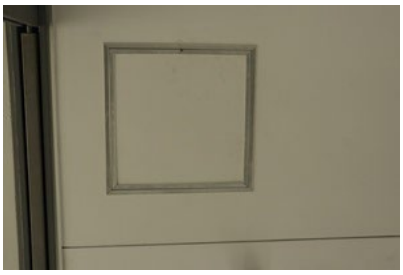
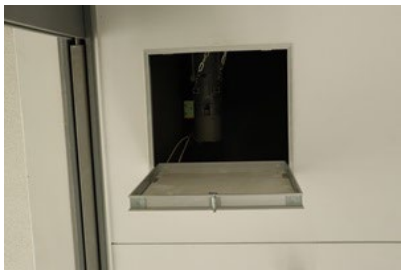


Figure 1. Inspection area for the ceiling.



(a) Closing



(b) Opening

Figure 2. Inspection hatch.

(a) South side

(b) North side

Figure 3. Inspection area for the cracks.

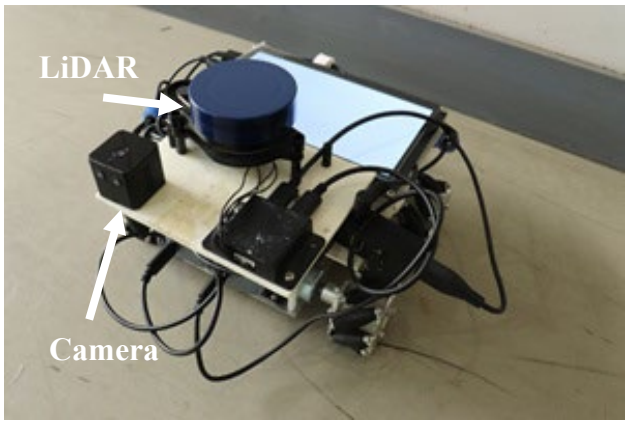


Figure 4. UGV.

The ceiling inspection area was a corridor section with a width of approximately 3.5 m and a depth of approximately 5.0 m, as shown in Figure 1. The inspection region was adjusted to a rectangular shape using poles. The ceiling included an inspection hatch shown in Figure 2, and ceiling damage was simulated by opening the hatch.

For wall inspection, a mortar wall in a storage room with dimensions of approximately 2.2 m × 2.2 m shown in Figure 3 was selected, and wall cracks were treated as damage.

Image acquisition was performed using a holonomic UGV equipped with a wide field-of-view compact camera and a LiDAR sensor, which was operated using the proposed navigation algorithm. The UGV is shown in Figure 4.

3.1 *Verification of ceiling damage detection*

First, the performance of the navigation algorithm for autonomous driving was evaluated. The UGV trajectory was reconstructed offline from recorded LiDAR data using Google Cartographer. This process also enabled the generation of a two-dimensional floor map of the inspection area. Figure 5 shows five recorded trajectories, and Figure 6 presents the corresponding 2D maps. As shown in Figure 5, the UGV was able to autonomously travel stably along the walls using the proposed navigation algorithm. Minor deviations in the trajectories were caused by the tolerance settings for the allowable distance from the wall. Figure 6 confirms that a rectangular floor map with dimensions close to the actual size (approximately 3.5 m × 5.0 m) can be generated, indicating that a simplified 2D layout of the inspection area can be obtained from Google Cartographer after the inspection.

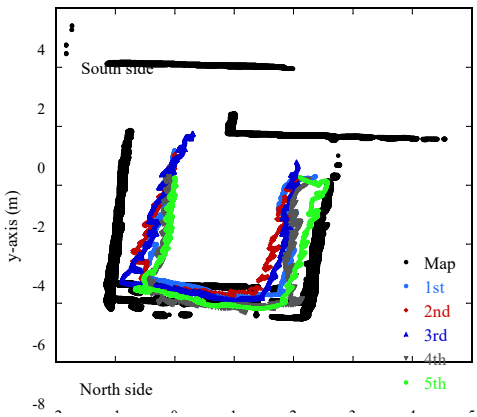


Figure 5. Trajectory of UGV.

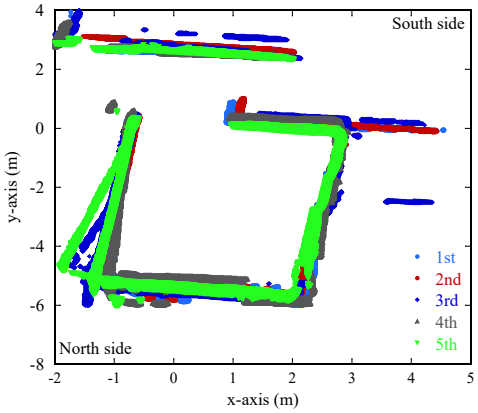


Figure 6. 2D map from Google Cartographer.

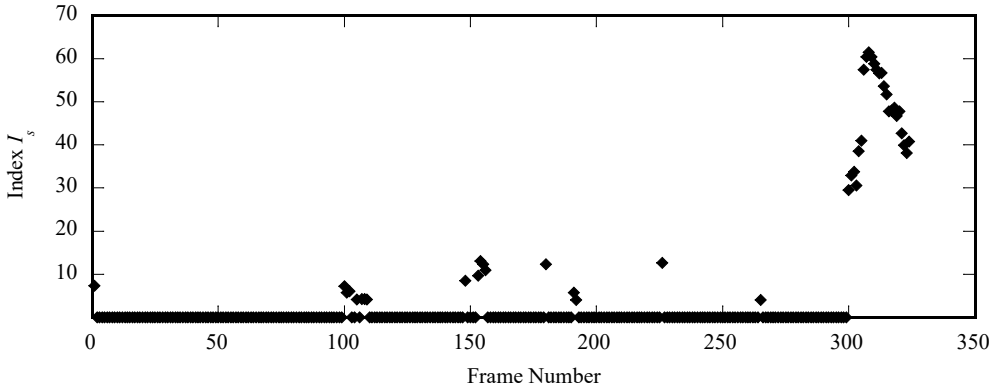
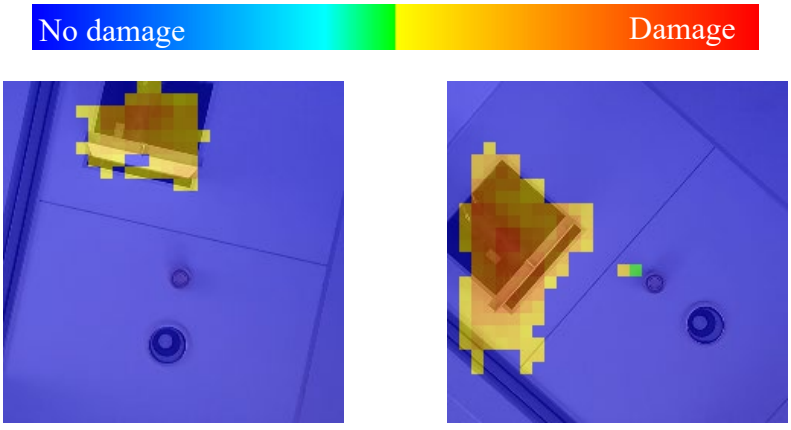


Figure 7. Sum of the anomaly scores.



(a) Frame number 304 (b) Frame number 308

Figure 8. Heatmap.

Next, ceiling damage detection using PatchCore was evaluated. A total of 324 images captured by the UGV were analyzed. The proposed evaluation metric, sum of the anomaly scores, is shown in Figure 7. The images containing simulated damage (open inspection hatch) correspond to Frame Numbers 300–324. The results show that the evaluation values are significantly higher for frames containing damage, clearly distinguishing damaged areas from normal regions. Figure 8 shows example heatmaps for the simulated damage. The heatmaps clearly localize the damaged regions. For example, in Frame 304, where the damaged area occupies a relatively small portion of the image, the anomaly score was 0.64 and the proposed evaluation value was 39. In Frame 308, where the damaged area was larger, the anomaly score was 0.74 and the evaluation value increased to 61. This indicates that the proposed evaluation metric reflects the extent of the damaged region more effectively than the anomaly score alone.

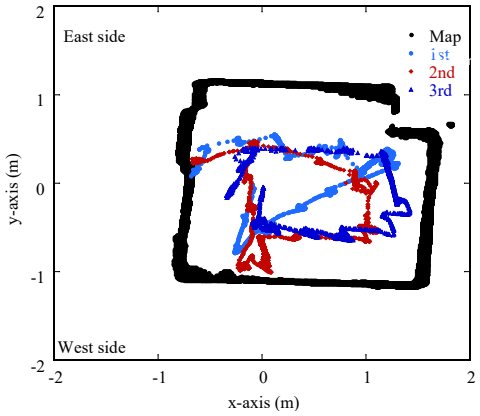


Figure 9. Trajectory of UGV.

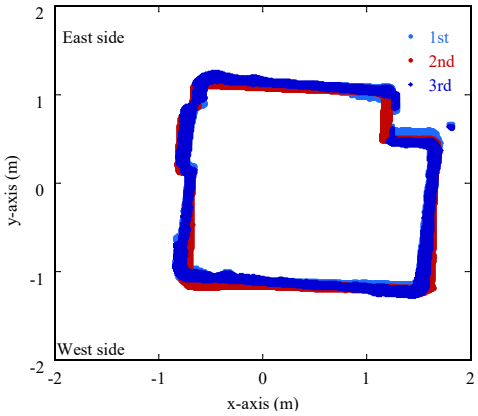


Figure 10. 2D map from Google Cartographer.

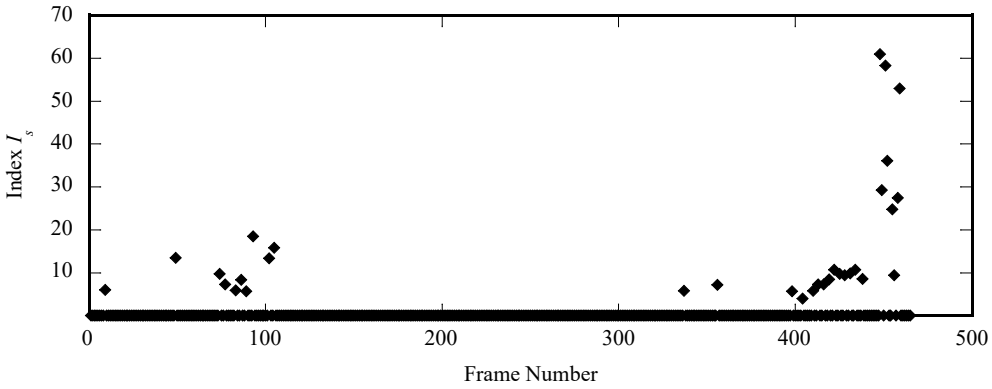
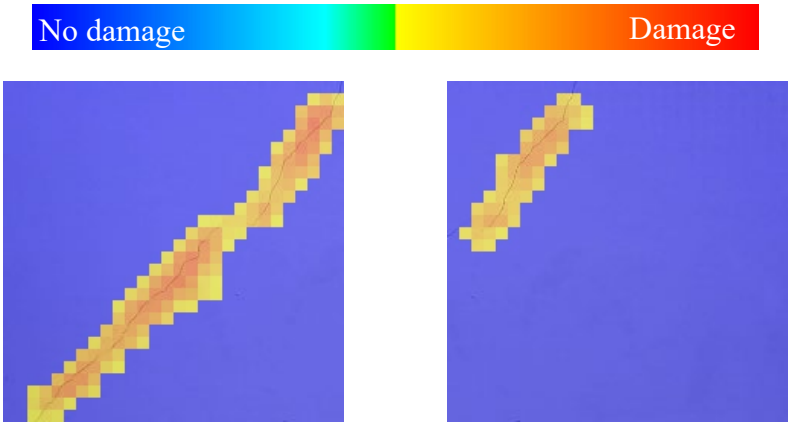


Figure 11. Sum of the anomaly scores.



(a) Frame number 450 (b) Frame number 454

Figure 12. Heatmap.

3.2 *Verification of crack detection on mortar walls*

For the mortar wall, the UGV trajectory and 2D maps were also generated using Google Cartographer, following the same procedure as for the ceiling experiment. Figure 9 shows three navigation trajectories, and Figure 10 presents the corresponding 2D maps. The results confirm stable wall-following navigation and successful generation of a floor map of the inspection area.

Figure 11 shows the crack detection results using PatchCore and the proposed evaluation metric. Frames 447–458 contain images with visible cracks. Similar to the ceiling experiment, cracks were efficiently detected. Example heatmaps are shown in Figure 12, demonstrating that the crack locations can be clearly visualized.

4 Conclusion

This study proposed an indoor damage detection method for ceilings and mortar wall surfaces in buildings, in which inspection images are acquired using an Unmanned Ground Vehicle (UGV) and damage is detected by applying PatchCore to the captured images. In addition, a LiDAR-based navigation algorithm was developed to enable efficient image acquisition by allowing the UGV to autonomously travel along walls while maintaining a constant distance.

Experimental verification conducted in an actual building confirmed the effectiveness of the proposed approach. The results demonstrated that the LiDAR-based navigation algorithm enables stable autonomous wall-following motion and efficient image acquisition without prior information about the inspection area. Furthermore, the use of Google Cartographer allows two-dimensional floor maps and UGV trajectories to be easily obtained after inspection. Damage detection for ceilings and mortar walls was successfully performed using PatchCore trained primarily with normal-condition images. In addition, the use of the sum of anomaly scores exceeding a predefined threshold as an evaluation metric was shown to provide an indicator related to the size of the damaged region.

The proposed system, which integrates autonomous UGV-based image acquisition and PatchCore-based anomaly detection, demonstrates the potential to support automated and labor-saving post-earthquake safety assessment of building interiors.

Acknowledgments

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