Mobile-robot and Cloud based Integrated Defect Inspection System for Indoor Environments

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Abstract –

Conventional defect inspections in newly constructed indoor environments still rely heavily on manual checking and judgement, which can be costly, time-consuming, superficial, and prone to human errors. In this paper, we have proposed a novel complete integrated system where a mobile-robot platform capable of autonomous navigation, performs data collection in indoor environments and transmits this data to a remote server on the cloud. Here, our AI and 3D fusion analysis software detect defects such as alignment, evenness, cracks, damages, and finishing defects as per the Construction Quality Assessment System (CONQUAS) standards. The results are then published to a well-designed web-based User-Interface system where stakeholders can view/track the defects. By integrating these core technologies and addressing most of the practical concerns, our proposed approach is able to conduct inspections with higher accuracy and efficiency compared to traditional manual assessments.

Keywords –

Mobile-robot; Defect Inspection; Cloud; Construction Quality, Alignment, Evenness, Crack, Damages, Stains, User Interface

Figure 1. Overview of the System: It consists of (i) Mobile-robot platform, (ii) 3D and AI Analysis software on the cloud, (iii) Web-based user interface for robot control and defect

1 Introduction

Conventional inspection tasks in many of the building construction processes, such as soil investigation, excavation, structural, architectural and mechanical and electrical inspection are conducted manually by skilled inspectors. Manual inspections have several associated problems such as inaccuracies (prone to subjectivity of inspection professionals), difficulty to find skilled inspectors or high cost to upskill existing inspectors to prevent incorrect use of tools and failure to spot defects, incompleteness (areas like external walls, facade, ceilings, etc. are difficult to be assessed and evaluated), physical fatigue and safety hazards due to long working hours and unsafe working environment. The data collected during an inspection is owned by the individual entities responsible for the inspection task and this data cannot be distributed across multiple stakeholders for further tracking or management of defects. For these reasons, it is imperative to consider automated solutions for inspection tasks using robots.

One of the common inspection tasks is the assessment of the quality of finishing in newly completed units such as unevenness, wall corner right-angleness, wall verticality, etc. In Singapore, this assessment is based on workmanship standards set in the Construction Quality Assessment System (CONQUAS), which is maintained by Building and Constuction Authority (BCA), a statutory board under the Ministry of National Development of the Government of Singapore. The latest revision to the standards was released in 2022 [1]. There is generally a higher demand for Quality Mark (QM®) tested residential units which are 100% thoroughly inspected (compared to sample tested units). Therefore, there is a real need to automate these tedious inspection tasks using mobile robots that overcome the disadvantages of conventional manual methods. The Government of Singapore is actively working towards the integration of digital technologies in various construction processes through its Integrated Digital Delivery (IDD) program. [2].

Based on our interviews with the building inspectors, 'architectural' inspections (which consider internal and external finishes, material & functional tests) constitute the major workload (more than two-thirds) compared to 'structural' and 'M&E (Mechanical and Electrical)' inspections. Therefore, we are considering primarily architectural inspection for this project. From our preliminary investigation, automating this inspection process called for a complete integrated solution that addressed several key concerns: (i) a portable and automated robot system with safe navigation, (ii) ease of control for a person with limited robotics skills, (iii) fast, thorough and accurate inspection, (iv) real-time analysis to detect defects such as cracks, stains and unevenness, and (v) render visualizations and generate reports of defects. Overall, the target is to achieve high accuracy and higher productivity compared to manual inspection.

In this paper, we introduce an autonomous mobile-robot-based inspection system to facilitate 'Accurate Construction Quality inspections' with an 'Intuitive User Interface'. The contributions of our work include:

1) Integrated mobile-robot inspection platform with safe autonomous navigation and data collection capabilities. The robot uses Building Information Model (BIM) or 2D floorplan drawing as a prior map for robot navigation and scanning position determination for data collection.

2) AI and 3D-based analytic engines for room structure understanding and defect inspection from 3D point-cloud and image data. AI semantic segmentation and 3D geometry analysis technologies are combined to facilitate analysis.

3) Intuitive user interface for robot control, inspection results visualization/editing, report generation and information sharing with multiple stakeholders.

In this paper, we have discussed the related works in Section 2, described the overview of our inspection system in Section 3, and the operations and methods in Section 4. We have provided the results from on-site testing in Section 5 and concluded in Section 6.

2 Related Works

Recently, many robotics related open-source software (such as ROS) have simplified the adoption of robot systems and it can be easily observed in the rise in the number of construction related research papers [3, 4, 5, 6, 7]. Paper [5] develop a scaffold scanning dog robot with all computation such as SLAM, scaffold detection algorithm running in an onboard PC. Paper [6] developed a mobile for point cloud scanning with SLAM and context awareness for navigation all on the on-board PC. For such an architecture, scaling the robot to larger area or more complex algorithms requires upgrading the computational capacity of the computer. This eventually increases the power-requirement, and thereby the battery weight. To avoid this problem, our method off-loads some of the computationally heavy tasks (that are not so time-sensitive) to the remote server on the cloud. This introduces new challenges such as network connectivity and data transmission efficiency, which we have also addressed in this paper.

In paper [7], the authors describe the development of an autonomous robot that performs data collection through autonomous navigation. The paper focuses on the data collection process and only for construction progress monitoring purpose. Data collection for an inspection operation needs to consider many other factors such as sensor characteristics, floor plan geometry, total inspection time, etc. In papers [8] and [9], the authors describe methods to find optimal scan positions that improve coverage and minimize data collection time. In paper [8], it simplifies the problem by considering only a discrete grid of candidate scan points on the floorplan for optimization. Our approach improves this method by considering an iterative approach to optimize over a continuous space. Although, many of these research techniques focus on the autonomous capability, construction workers mostly look forward to using a product that is easy-to-use and intuitive. We address this by providing multiple modes of operation of the robot through a simple user interface.

In recent years, we have seen an uptick in the number of technology companies that have started working in this domain. A Singapore start-up company, Transforma Robotics developed Quicabot, an autonomous wheeled robot used for 3D and visual data collection and defect detection [10, 11]. The robot has at least four types of sensors (a 2-D laser scanner, a colour camera, a thermal camera with heater, and an inclinometer) for detecting hollowness, alignment and evenness, crack and inclinations. While the system claims to cover many of the defect types to be inspected faster than manual, there is not much information on how the defect information is stored and reported to the user. Based on interviews, during defect rectification, the main pain points for most construction companies are miscommunication and non-traceability of defects. In this paper, we present solutions to address these pain-points through our defect visualization and report generation techniques.

A startup based in Barcelona, Naska.ai (previously Scaled Robotics), works on construction site data capture, analysis and reporting services for quality control and coordination [12]. Its software is not attached to any specific sensor or robot hardware. Doxel, a startup based in Silicon Valley, provides software services for automated progress tracking, cost scheduling and estimation. Another Silicon Valley startup company Holobuilder (developed the ‘Spotwalk’ robot), primarily uses a 360-degree camera for Construction Progress Monitoring. Naska, Doxel and Holobuilder do not work on defect detection and the robot hardware is not their primary focus. For defect inspection application, the accuracy and reliability of defect analysis depends a lot on the data acquisition process. Early defect detection can save significant time and money by avoiding rework. In this paper, we focus on problems and solutions with respect to defect inspection process and present methods to improve the data acquisition process.

Differing from existing players, our solution aims to provide a complete integrated solution with an autonomous mobile robot platform equipped with high-resolution 3D scanning and surround-view image capture, capable of traversing safely in a newly constructed unit, real-time defect detection (both structural and visual defects) with 3D and AI analytical engines. Our solution addresses practical concerns and aims to deliver superior accuracy and faster inspections compared to traditional manual methods.

3 Overview and Physical setup

The overall inspection system consists of 3 main components corresponding to (i) data collection (mobile robot platform with sensors), (ii) data analysis (remote server with AI/3D analysis engines), and (iii) data visualization (web-based UI). The connections between these components are shown in Figure 1.

The data collection platform mainly consists of a wheeled mobile robot platform fitted with a variety of sensors, computing platform and internet connectivity. The robot is built from scratch using mostly off-the-shelf components. The chassis is modified from Ubiquity Robotics Magni robot by replacing the non-driving caster wheels with two larger omni-wheels of 20 cm diameter. This makes the mobile platform capable of climbing small steps less than 5cm. This is to take care of the movement of the robot in and out of the toilet or balcony whose floor levels are usually lower than other rooms. The robot is not designed to climb stairs. However, we have designed the robot to be under 25kgs, allowing for manual lifting to different floor levels, if elevators are not available. Within the same floor level, the robot can be either remote-controlled or be pushed like a trolley to the testing site. The suspension design was modified to allow for the driving wheels to be always in contact with the floor to avoid slippage.

The robot uses a multitude of sensors such as Hokuyo UST-10LX 2D laser range scanner, Intel Real-sense D435 RGB Depth cameras, and Leica BLK360 3D

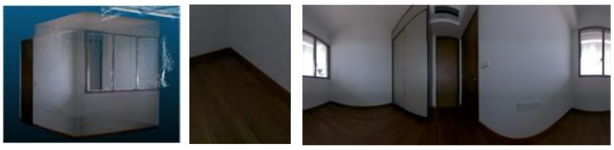


Figure 2. Data captured by scanner on the robot.

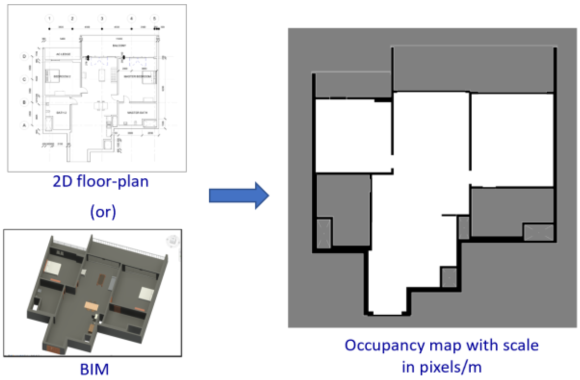


Figure 3. Occupancy map is created from 2D floor plan. The pixel colors represent free space (white), obstacles(black), keep-out region (grey).

terrestrial laser scanner. The 2D laser range scanner and the depth cameras are for navigation purposes (localization, safety and teleoperation). The terrestrial laser scanner is for collecting high resolution and high accuracy point cloud and image data. The robot is required to stop and then perform scanning (stop-scan-go) as BLK360 is a static laser scanner. The specification of this sensor is shown in Table 1.

Each scan takes less than two minutes to complete the scan and each scan captures high-resolution point cloud and 28 pictures covering 360° space, as well as generates a panoramic image, as shown in Figure 2. The laser scanner is mounted at a certain height on a pole and the robot connects to this sensor via Wi-Fi. The robot footprint dimensions are 63cm x 42cm and height is 50cm (with sensor pole folded) and 1.20m (with sensor pole upright). The battery life is above 6 hours for nominal usage (70% travel time) and further it supports hot-swapping to prolong the operation time. The entire robot is designed to be modular for easy development and troubleshooting.

As the computation power of the robot is limited, all

Table 1 BLK360 Specifications

Field-of-view	360° (horiz) / 300° (vert)
Scanning range	min. 0.6 - up to 60 m
Accuracy	6mm @ 10m
Camera system	15 MPixel 3-camera system, 150Mpx full dome capture, HDR

the scan data collected gets uploaded to the remote server on the cloud through the internet for 3D and AI analysis and defect report generation. At the remote server, the high computational power hardware is able to process the data very fast. Speed is very critical for inspections as the longer it takes to detect a defect, the more the rework that must be done. Apart from the scan data, other necessary information such as robot position in the map, calibration details and analysis results are also stored on the remote server. The data management software and intuitive user interface are also developed to share the information among multiple stakeholders to visualize the inspection data and check the reported defects.

4 Operation and Methods

In this section, we will first introduce three operation modes of the robot, the 3D and AI analysis flow and integrated robot control and data management UI.

4.1 Robot Operation

In a typical CONQUAS inspection, two inspectors are involved. However, our inspection routine is designed to streamline the process by combining the efforts of one robot and one human inspector. In this setup, a single inspector brings the robot to the test site. Using a hand-held tablet's user interface, the inspector selects the map corresponding to the residential unit number. They then set an approximate initial pose for the robot on the map by utilizing a click and drag action. The robot utilizes this information for localization, estimating its current position within the map.

Our localization algorithm (based on AMCL - Adaptive Monte-Carlo Localization) relies on odometry data from laser scan matching instead of the wheel encoders, and therefore, does not lose localization even if the map information is not very precise. We only use an approximate occupancy map image obtained from either BIM (IFC) model or 2D floor-plan map drawing (with some manual cleanup to ensure that the occupancy map is safely navigable by the robot) as shown in the Figure 3. This alleviates the necessity to conduct any prior mapping for autonomous navigation. This saves any time required for setting up the robot (at least 30% of the total time needed) and improves productivity compared to existing automated systems. Our navigation algorithms (based on open-source ROS Navigation stack) ensure that the robot does not enter the unknown areas or collide with obstacles. Once the inspector verifies that the robot has localized properly from the UI, then he/she can choose one of three modes of operation for the robot.

The robot has three modes of operation (Mode 1, Mode 2, and Mode 3). Mode 1 is the manual mode where the robot is controlled manually using a joystick button on the UI. It also allows the inspector to teach scan-routes

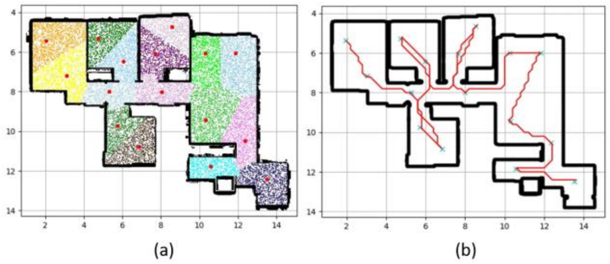


Figure 4. Mode 3 of the robot operation (a) Optimal computation of scan-points, (b) Shortest path through the scan points.

to the robot. Scan-route are made up of waypoints (where the robot passes through) and scan-points (where the robot stops to scan). Although we have the option to handcraft the scan-routes directly on the UI (without moving the robot), it is recommended to use the robot to ensure that the scan-route is navigable with high confidence. In the Mode 2, the user simply selects along one of the previously created scan-routes in the same or similar floorplan unit. This is very useful for high-rise buildings, where the same scan-route can be used for units with similar floorplans across different levels of the building. The robot then autonomously and safely navigates along this selected scan route and collects the scan data.

When the robot moves to the scan location, it triggers the scan command wirelessly to BLK360 sensor. The robot waits until the scan is complete and then navigates to the subsequent scan position. While the robot is working, the inspector is free to do other inspection tasks such as functionality tests and hollowness checking. As the robot is not capable of opening doors by itself, the inspector ensures that the doors are already open before starting autonomous navigation. This implies that surfaces behind the open doors will not be scanned by the robot.

Manually creating an optimal scan-route to maximize coverage and minimize inspection time, is very difficult without much experience and knowledge about the sensor and the robot. Therefore, we have developed Mode 3, where the robot does automatic selection of good scanning positions that guarantee full coverage with

Table 2 CONQUAS Inspection Requirements

Items	Description
Wall / floor evenness	No more than 3mm per 1.2m
Wall meet at right angles	No more than 4mm per 0.3m
Wall verticality	No more than 3mm per m
Wall / floor / ceiling / door finishing/damage defect	No stain marks. No rough / patchy surface No visible damage / defects
Floor level height	Minimum 2.8 m
Ramp slope	A gentle gradient of 1:20 to 1:15 is preferred

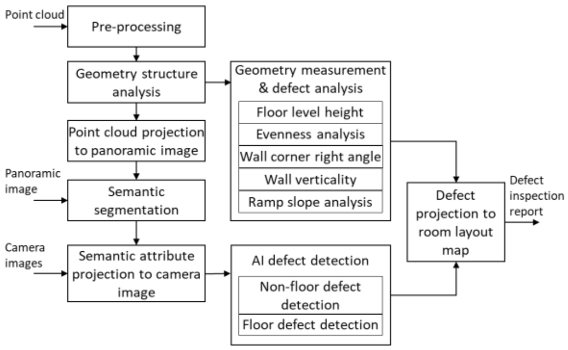


Figure 5. 3D/AI analysis flowchart

minimum number of scans, given a floorplan image. We observed that the noise of the measurement increases with the distance from the scanner and decreases with the incidence angle at the surface to be inspected. It also increases with the reflectivity of the material surface. Based on our experiments with BLK360, the nominal range could be set at 3 meters for achieving the required high inspection accuracy up to 3mm per 1.2m length as per CONQUAS standards. For a dense grid of points uniformly distributed on the navigable free space of the floor plan, we compute a score for each point that quantifies the scanning efficiency at that point based on the visibility, incidence angle and distance requirement from the walls. Given the floorplan area and scanner range we compute the required number of scan-points. The scan points are seeded at random positions in the floorplan and then we use these points as Voronoi centers for the Lloyd's algorithm to construct a weighted Centroidal Voronoi Tessellation. The weighting density function is obtained from the dense grid scores. Over several iterations, the scan-points (also Voronoi centers) converge to an optimal position that maximizes the scan scores. Figure 4 shows the resulting optimal scan positions for covering a sample unit. We then use an open-source Travelling Salesman Problem (TSP) solver to get the optimal path to these scan-points.

The robot can travel along the same path, stop at same locations and collect data whenever it sent for inspection. That provide the advantages of being able to compare images or point cloud from several inspections over a long period of time. It requires multiple scans to cover the entire apartment to handle occlusions and meet the accuracy requirement at all surface points. As the data size is humongous, we use MPEG point-cloud compression technique to compress the data by more than 80% before uploading. The raw images are compressed to lossy JPEG compression (85% quality). The final data size (including the point-cloud and the images per scan) is only about 12~15 Mb. All the scan data is further compressed to a zip file and then it becomes easier to transmit the data to the remote server via 4G/LTE modem on the robot.

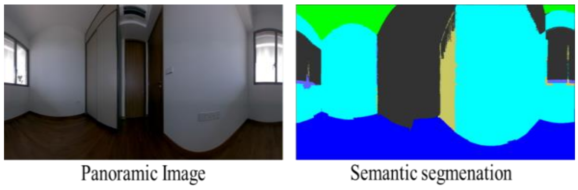


Figure 7. Room structure analysis

4.2 3D and AI analysis flow

Once all the scan data is uploaded, the remote server conducts the 3D and AI analysis on both the point cloud and image data. It is essential to link defects or non-compliances with the relevant structural components of the rooms, such as walls, floors, ceilings, doors, and windows (see Table 2). Therefore, the key step is to understand the room's structure.

A framework is devised to combine both point cloud and image data. In Figure 5, the process begins with point cloud cleanup, including de-noising and removal of low reflectance points. Geometric analysis is then employed to extract planes, eliminating objects unrelated to the room structure, such as the robot operator. Position and direction information for the floor, ceiling, and walls can be derived from the point cloud. Utilizing AI technique PointNet++ [13], we extract more semantic information like doors and windows in the point cloud. Semantic segmentation results of point cloud are then then further refined by projecting onto the panoramic image. This information is later used by visual defect detection system on camera images to remove false detections. A sample result of panoramic image is shown in Figure 7.

Defect inspection is conducted by 3D and AI analysis parallelly. 3D point cloud measurement is used for ceiling height measurement, evenness of walls, floor and ceiling, wall verticality, wall corner angle, and ramp slope. To reduce computation complexity, sampling method is used. For example, for unevenness analysis, the points on each plane are sampled and the up-down variance in the local area around the sampled point is

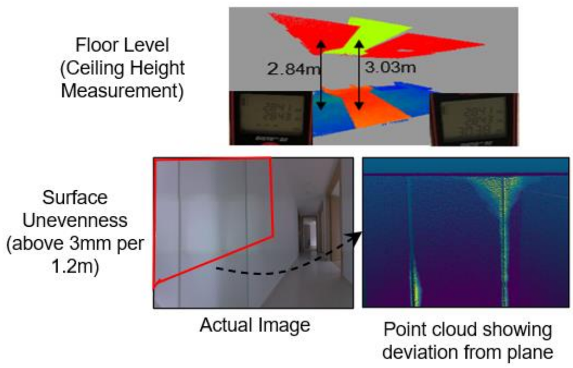


Figure 6. 3D analysis for structural defects

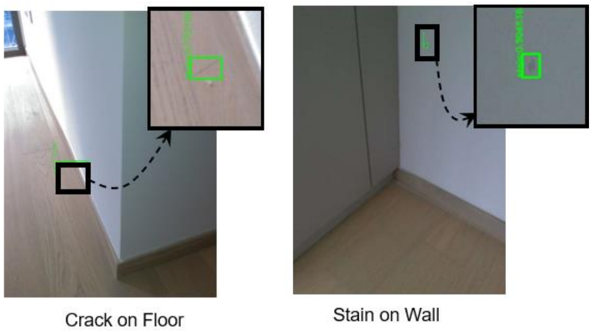


Figure 8. Visual defects at actual site

computed for evenness. The sampled measurements are interpolated to obtain the dense output for each point on the plane.

Figure 6 demonstrates the measurement of floor level height for individual points on the floor. Additionally, it illustrates the measurement of evenness for each point relative to its own plane surface. In the image, purple color indicates an even surface, green indicates unevenness of 3mm and yellow indicates unevenness of 4mm or higher. This example highlights the robot system's ability to easily detect door warpage that could be overlooked by inexperienced inspectors. In Figure 8, the sample visual defect detection results are shown for floor and non-floor part separately.

To detect finishing and damage defects, we project the semantic segmentation information onto camera images to distinguish between floor and non-floor components. The defect object detection is conducted separately because floor and non-floor parts are different in their characteristics. Non-floor components, like walls and ceiling, are usually white painted which lacks textures. On the contrary, floor contains more textures due to different materials such as wood, marble, and ceramic tiles. Therefore, detection methods and models are trained for floor and non-floor parts separately by using YOLOv5's architecture [14]. Our approach involves utilizing multiple public datasets for pre-training, followed by fine-tuning the model using a combination of both public datasets and our collected datasets. By employing this technique, we achieve a recall rate of up to 80%.

Defect analysis is performed on each scan independently. To facilitate accurate record-keeping and effective communication with stakeholders for necessary repairs, it is crucial to determine the precise defect positions relative to the entire unit. By leveraging the recorded robot position at the time of the scanning, we can register point-cloud of each scan to the map. Thus, the defect position identified in each scan can be transformed and mapped onto the floorplan layout and are linked to corresponding room segment (living room, kitchen, bedroom, etc.).

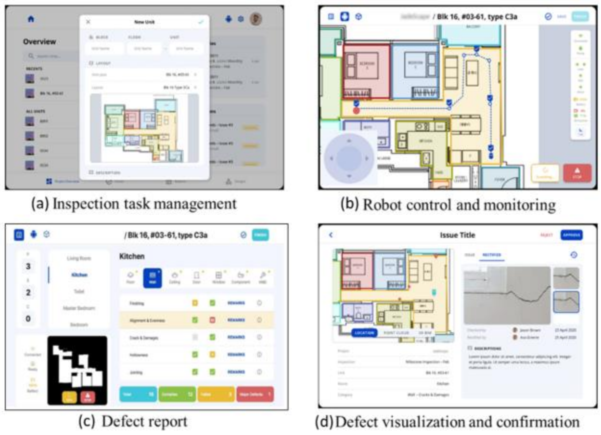


Figure 9. User interface

4.3 User interface

A web-based user interface (UI) is developed for robot control and visualization. The data is organized hierarchically, categorizing it based on the construction project, unit number, and inspection time. Each unit is associated with floorplan information and room segment details, represented by polygons on the floorplan image (refer to Figure 9(a)). To accommodate inspectors without robotics expertise, the UI only exposes essential controls, ensuring a user-friendly and intuitive experience. The UI also provides real-time updates on the robot's position and logging information, enabling inspectors to monitor the autonomous inspection process effectively. Following the analysis, the detected defects are displayed on the issue page, organized under the relevant room segment (refer to Figure 9(c)). The defect position is also visualized on the floorplan and the panorama viewer. The inspector has the option to add/modify the issues listed before generating the final report as a PDF file in the CONQUAS report format. The

Figure 10. A panoramic visualization showing accurate defect-positions with close-up image.

report also contains the exact pin-point location of the defects marked on a panoramic image as illustrated in Figure 10.

5 Results

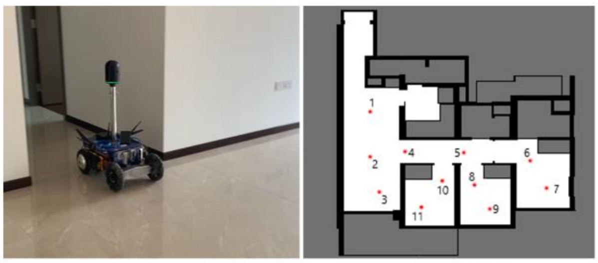
Tests were conducted in a newly constructed residential units, before the actual CONQUAS inspection by the inspection personnel. The floorplan was obtained from the brochure of the construction project and occupancy map image is prepared as seen in Figure 11. After the robot is brought to the construction unit, the initial position was set, the robot was observed to localize and navigate well just based on the approximate floorplan map and did not require prior mapping.

We have provided a comparison of timing and detection performance of the robot with a manual counterpart in Table 3 from one of our site tests. The inspection was carried out in a newly constructed three-bedroom apartment. With the assistance of a trained inspector, we identified a total of about 61 finishing defects in the whole unit. Subsequently, we evaluated and compared the performance of a robot against that of an actual inspector. For a total of 11 scans, robot takes roughly 22 minutes for the data collection for the entire unit. The raw data generated from these 11 scans amounts to approximately 1.6GB, but after compression, it reduces to around 150MB. For data downloading from the scanner and uploading to server (which highly depends on network connectivity), it takes another 18 minutes. Analysis takes around 5 minutes at the remote server. Altogether, the data collection, transmission and processing take a total of about 45 minutes. Initially, the inspection process carried out by our system may seem slightly slower compared to a human inspector team, which typically takes around 35 minutes to complete visual and structural defect detection in the same area. However, significant time savings are achieved during the photographic evidence capturing and report generation phase. This particular process can take several hours for a human inspector, whereas the robot is capable of producing location-referenced images within a few seconds.

In terms of inspection performance, the robot is able to detect at least two thirds of the total visual defects reported by human inspector team. the human inspector excels in identifying certain minute defects that are observed up close and may not be captured by the robot's camera due to factors such as poor lighting or significant distance (as shown in Figure 12). Lighting plays a critical role in determining the accuracy of visual defect detection results. The analysis indicates comparable performance between the robot and human inspectors in detecting larger defects measuring over 2 cm. However, further improvement is necessary for identifying smaller defects. As an improvement measure, we conducted tests by equipping additional lights on the robot, which led to enhanced inspection results, especially on cloudy days. In terms of structural defect inspection, our system surpasses manual inspection effortlessly. Human inspectors are limited to conducting sampling tests on reachable surfaces, whereas our system can examine every single point on the surface. Furthermore, we have observed instances where the robot successfully identifies new visual and structural defects that were previously unnoticed by human inspectors.

Table 3 Comparison of the Timing and Defect detection

Items	Mobile-Robot (+ 1 Inspector)	Manual (2 Inspectors)
Defects (numbers)	40	61
Set-up time	< 2 min	NA
Total Inspection Time	**46 min 51 sec**	**~35 min**
- Data Collection	22min 37 sec	
- Scanning Time (11 scans)	~18 min	NA
- Movement (Mode2)	~4 min	NA
- Data downloading from Scanner	15 min 15 sec	NA
- Data Upload to Server	3 min 24 sec	NA
- AI and 3D Analysis	5 min 35 sec	NA
Report generation	**15 sec**	**Several Hours**
Accurate location referencing	Yes	No
Digital photographic record for evidence and traceability	Yes	No



(a) Robot at test site (b) Scan locations

Figure 11. Testing at Actual Site

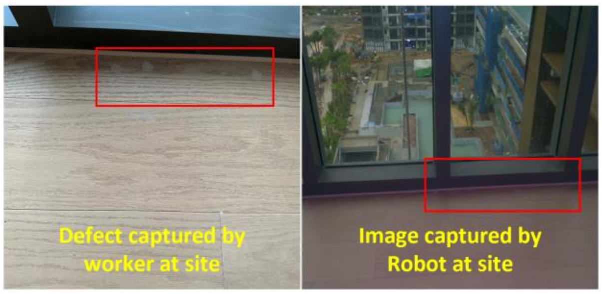


Figure 12. Some defects not observed from far distance with bad light conditions

6 Conclusion

In this paper, we introduce the integrated mobile-robot and cloud-based defect inspection system for indoor built environments and discuss the practical challenges that the system addresses. We present a complete system with a mobile-robot platform powered by advanced navigation technology, defect inspection using novel 3D and AI analytic engines, intuitive user interface for robot-system control and data management. Our system has been tested in actual construction sites for robot navigation and indoor building quality analysis. The results demonstrate that our system outperforms manual inspection methods in terms of accuracy and speed. Moving forward, we plan to enhance the defect detection rates by incorporating more training data and leveraging manual defect entries as feedback for the learning process. Additionally, we aim to reduce inspection time significantly by conducting tests with multiple robots. The global construction robotics industry is experiencing steady growth, and we are actively exploring opportunities for commercialization in this rapidly expanding market.

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