AutoCIS: An Automated Construction Inspection System for Quality Inspection of Buildings

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Abstract –

Quality inspection of existing buildings is a task currently performed by human inspectors. In general, these inspections consist of assessing the different elements of a building as they are being constructed, checking that they are within acceptable tolerances, and meeting industry standards. Typically, this process is carried out by doing a visual inspection, taking photographs, and using measuring tools to identify deficiencies for further comparison with the BIM model. The acquired data must be analyzed by different specialists such as civil, electrical, and mechanical engineers, looking for defects or substandard installations. This process is time-consuming and dependent on the human factor, leading to errors and inconsistencies.

To counteract that, we propose a methodology based on a multi-robot system that works synergistically to automatically collect data and analyze it for the further generation of a quality report. By automating the process, we are making the quality inspection more reliable, robust, and time-efficient.

The master robot will collect general data and identify specific regions of interest (ROI) (e.g., potentially defective areas). When additional information is needed, the master robot will command the slave robot to approach the ROI to collect more detailed data. This can be used to inspect some of the most prevalent defects in construction sites, such as cracks, hollowness in walls (i.e., lack of insulation or incomplete concrete fillings), surface finishing defects, alignment errors, evenness, inclination deviations, and possibly more.

Keywords –

Maintenance management; Quality assessment; Autonomous Robot; Master-Slave Robotic System.

1 Introduction

Automated processes have increasingly become more popular during the last decade in most industry-related fields. However, the construction field has not progressed at the same rhythm despite multiple studies proving that automation in construction would significantly improve the efficiency and productivity of the process [1]–[3]. Part of this slow adoption can be attributed to the unstructured nature of construction sites and their constantly transforming character.

Automation can significantly optimize tasks that need to be performed periodically and require repeatability. The construction progress monitoring and quality assessment are good examples of tasks that can be automated. Currently, those tasks are usually tackled by multiple experts that need to inspect the construction site visually, in most cases with the help of measuring tools. Unfortunately, this can lead to inconsistencies between consecutive reports because of the heavy reliance on the human factor.

In this study, we propose an automated construction inspection system (AutoCIS) for the quality inspection of buildings. The system consists of a multi-robot approach that, acquiring data from multiple sources (3D Scanners, visible and infrared cameras, environmental sensors, etc.), will provide, in an autonomous way, robust and reliable quality assessment during the construction progress. An overview of the proposed process is shown in Figure 1.

There are different quality assessment-related elements that could be automated. For this study, the focus will be limited to the task to identify specific elements, such as cracks, hollowness in walls (i.e., lack of insulation or incomplete concrete fillings), surface finishing defects, alignment errors, evenness, and inclination deviations.

The rest of the paper is structured as follows: Section 2 introduces the state-of-the-art on the two main areas of this research (i.e., multi-robot systems and Automation in the construction field). Section 3 presents the details and main features of the autonomous robotic platform. Section 4 explains the methodology and the data processing. Finally, Section 5 summarizes the conclusions and provides an outlook for future work.

2 Previous work

2.1 Master-slave robotic approaches

Research has proven that developing a multi-robot system (MRS) is more cost-effective than developing a single costly robotic platform with all the capabilities [4]. When it comes to defining the taxonomy and architecture that different MRS can adopt, there are systems where the workload and task assignment are equally distributed between the different agents inside the MRS, and systems where there is a hierarchy between the different agents and one of them is acting in command [5]. With systems where the number of agents is minimal, the latter approach is more efficient and robust.

The master-slave denomination refers to systems where there are at least two agents with two different roles, one of them being in charge of assigning tasks (master) and the other one that would follow said commands (slave). This architecture has been widely used in the medical field, where surgical robots act as the slave component in a system where a human operator manually commands the movements through a master device. In the construction field, there are few approaches where MRS have been used for applications such as mapping the environment, block placing, or 3D concrete printing coordination [6]–[8]. Most of these approaches present an equally distributed task allocation between the different agents inside the MRS, making them suitable for repetitive and simple tasks.

The system proposed in this study uses a master-slave MRS, making it a robust system that can deal with the unpredictability and harshness present in the construction environment. To the authors' knowledge, this is the first study in which a master-slave MRS is considered for high-level tasks in the construction field.

2.2 Automation in the construction field

The current state of the use of robotic systems in construction sites is far from having autonomous robots performing specific task-oriented procedures, such as high-level construction assignments (e.g., bolting, painting, tiling, or bricklaying) [9]–[11]. This requires high precision and robustness to ensure that these platforms are safe working side-by-side with humans. However, this directly conflicts with the high complexity of the construction environment and the constant movement of assets.

In contrast with the high-level construction assignments that require human collaboration, robots and autonomous processes can be integrated into tasks where no human interaction is needed, and there is not as much movement of assets across the site. Examples of suitable tasks are progress monitoring and quality assessment since these can be done when the construction works are paused. Automating these procedures can provide results with higher accuracy than those performed by skilled workers [10].

One of the steppingstones in the automation of construction is the BIM model. Many studies have shown that having a reliable and updated BIM model is the first step to increase efficiency and productivity in the overall construction process [12]. Therefore, a significant amount of research has been dedicated to creating as-built models from the data collected at the site [13], [14]. This process is commonly referred to as scan-to-BIM, and it is especially useful for both progress monitoring and quality assessment since the elements to be compared with the BIM model need to be segmented and identified.

2.2.1 Progress monitoring

Progress monitoring is usually based on the manual comparison of as-planned and as-built schedules. However, as-built schedules are often not maintained and updated throughout the entire life of the project but generated at the final stage [15].

Most of the progress monitoring approaches, even if they are updated during the construction process, do not consider the quality of the achieved progress [16], [17], which is something that can help prevent smaller problems from becoming bigger issues that might create rework, delay the construction process, and even affect the quality of the final product. By assessing the quality of the progress being made during the construction process, the generated report will be more accurate according to the current state of the construction and provide information for on-time actions to prevent defects in the final product.

2.2.2 Quality assessment

There is some research done regarding the quality assessment of construction [18]–[24]. When it comes to quality assessment of construction elements, there are two main approaches, namely destructive and non-destructive evaluation methods [25], based on the nature of the sensing element. Since this study aims to have an autonomous robotic system performing quality inspection during the construction process, a non-destructive evaluation method is preferred that allows for unsupervised and autonomous operation. The sensors used for non-destructive evaluation methods vary from 3D scanners to DSLR and RGB-D cameras to thermal infrared cameras or sensing probes to measure temperatures.

In [18], they developed an autonomous platform for the quality assessment for some of the most common defects present in the construction environment (e.g., hollowness, crack evenness, alignment, and inclination defects). The proposed robot was equipped with a thermal camera, a color camera, a 2D laser scanner, and an inclinometer. The system was meant to be operated in finished buildings, and therefore is not suitable for a construction environment.

A semi-autonomous system was proposed in [19]. The approach used manually taken photographs in order to reconstruct a 3D point cloud from the environment. Measurements were taken manually from the point cloud to later be compared with the stats present in the BIM model. They present an improvement on fully manual quality assessment, but the process still relies on the human factor, and it is also meant for post-construction assessments.

Another post-construction quality assessment approach is developed in [20]. The authors proposed the robotic platform as an assistant to accelerate the process rather than performing the inspections on its own. The platform was equipped with a thermal camera and a 3D scanner. The acquired data was used to detect some of the most prominent defects present in floors, walls, ceilings, doors, and windows.

Some approaches focus on specific elements of the building, such as pipes [22] or cracks [25], to provide an assessment regarding the proper geometric position of said elements and the deviation they present concerning the BIM model.

As can be seen from the literature review, most progress-monitoring and quality assessment approaches do not deal with the quality and completeness of the collected data since it is usually not being processed in real-time. It has been proven that timely and accurate information collected from the construction site must have proper quality reports [26]. For the approaches that focus on quality assessment, all the current research revolves around post-construction assessment. In addition, most of the current approaches are not fully autonomous, relying in one way or another on the human factor for its normal operation. Therefore, the methodology presented here aims to fill in the gap for the current state-of-the-art, proposing a system that assesses the quality of the progress being made during the construction process autonomously and processing the data in real-time to collect accurate information.

3 The robotic system

The Automated Construction Inspection System (AutoCIS) proposed for this study consists of three modules: (1) the Master Unmanned Ground Vehicle (M-UGV) robot, (2) the Slave UGV (S-UGV) robot, and (3) the Command Station. The UGVs (Figure 1) are equipped with different hardware with different capabilities. The reason for having two (or more) different UGVs is to distribute the responsibilities of the building inspection based on the capabilities of each robot. This architecture is scalable; therefore, additional robots can collaborate to perform inspection tasks (e.g., they can cover larger spaces or reduce the duration of the inspection).

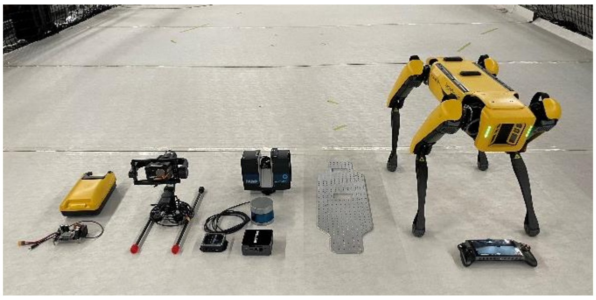


Figure 1. Unmanned Ground Vehicle and sensors. Photo taken at the KINESIS lab at NYUAD

3.1 Command Station

The Command Station is fixed on-site or off-site. It consists of a server and a communication device responsible for collecting data from the UGVs and displaying them in a human-readable format. Therefore, the Command Station also serves as the main interface between human operators and the UGVs. For example, the operators give “high-level” commands, such as perform a 3D scan in a specific area of the construction site, start-stop the inspection, set a new inspection protocol, etc.

3.2 Master UGV

The M-UGV robot is responsible for allocating tasks and collecting the data from all the S-UGVs, merging 3D scans, creating 3D models of the construction, analyzing the collected data, and sending comprehensive reports to the Control Station.

The M-UGV is a four-legged robot capable of navigating in a dynamic construction environment, for example, obstacles, narrow pathways, stairs, etc. The payloads of the Master UGV robot include a high-performance Computing Unit based on x64 architecture CPU and a CUDA capable GPU. The main data collection instrument is a 3D scanner to acquire detailed 3D point cloud data with color information. The robot is also equipped with five short-range depth cameras needed for perception and a communication device.

3.3 Slave UGV

The S-UGV is responsible for creating a local 3D map of the current environment (which it shares with the M-UGV), navigating to predefined local coordinates by avoiding obstacles, interacting with the physical world (turn valves, flip levers, open doors, etc.), and collecting data from a variety of sensors.

The S-UGV is the same four-legged robot as the M-UGV but with different payloads. In order to interact with the physical world, the robot is equipped with a six DOF Robotic Arm with an end effector and a two-finger Gripper with a high-resolution Visible Camera. For navigation, a fusion of long-range LiDAR, five short-range depth cameras, and encoders are used to perceive the environment. For data collection related to the inspection, the S-UGV is equipped with a high-resolution double spectrum camera (visible, thermal) mounted on a three-axis gimbal. The robot is also equipped with a Computing Unit to run the local algorithms and a communication device.

3.4 Communication

All the modules of the AutoCIS are interconnected through a mobile ad hoc network (MANET) capable of transferring data with speeds up to 120 Mbit/s operating in a Mesh topology. Through this network, the robots and Control Station exchange data for Telemetry, 3D maps, Sensors Measurements, etc. The Mesh architecture will allow for future expansion of the network when multiple robots are used, in both range and number of nodes.

4 Methodology

The main stages of the proposed system are shown in Figure 2. It consists of two basic elements: Data acquisition (for the M-UGV and S-UGV) and data processing. To effectively monitor and perform the quality assessment, the AutoCIS needs to autonomously navigate through the construction site, collect information from different sources, and process said information in real-time to ensure there is no missing information [27]. To simplify and facilitate the communication between the BIM workflow and the AutoCIS, we propose the BIM model as the only input to the process. Therefore, the M-UGV needs to fully understand the information present in the BIM model and interact with it to further retrieve the required data.

4.1 Data acquisition

The M-UGV and S-UGV fulfill an important part of the process as a whole. The data will come from various

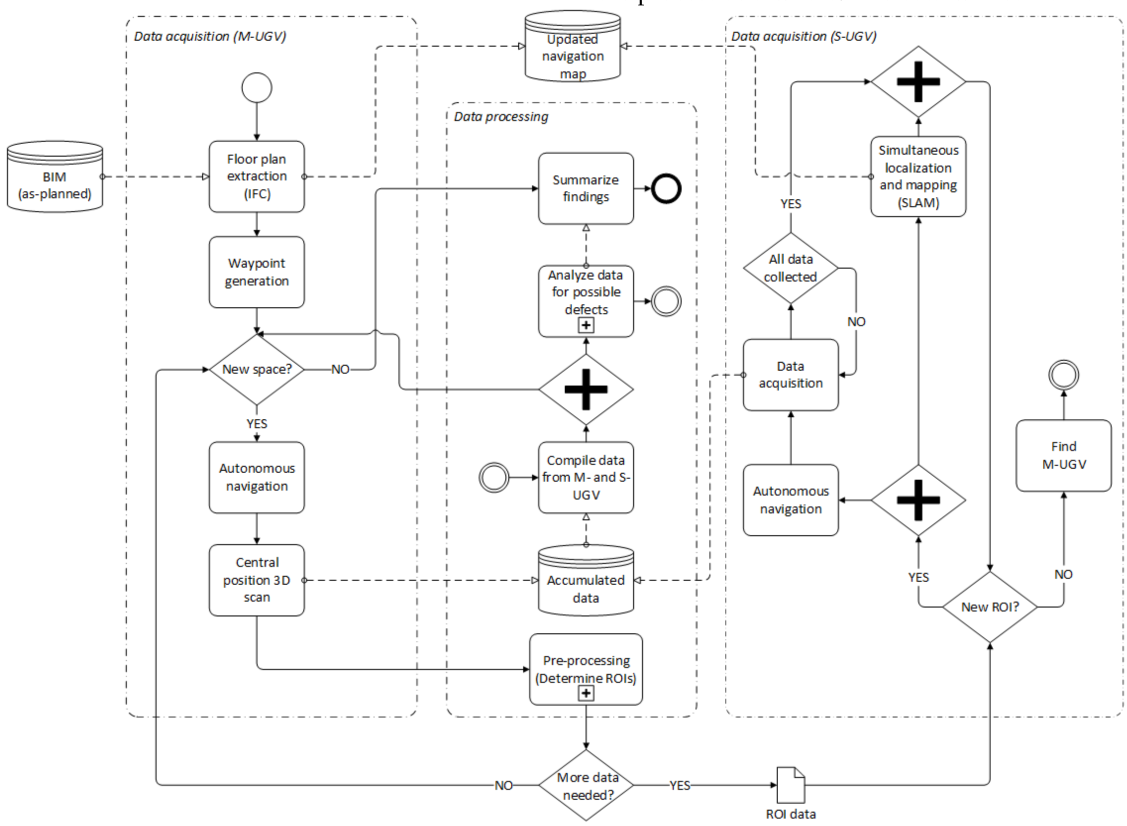


Figure 2. Flowchart of the overall methodology.

sources and sensors, mainly categorized in long-range and short-range, distributed between the M-UGV and the S-UGV, as indicated in Section 3.

4.1.1 M-UGV

The M-UGV is going to collect long-range data. The 3D scanner provides long-range information. The point cloud obtained will be used to build the general model of the construction site, obtaining the overall structure and geometry. The RGB information will help to determine regions where more data collection is needed. From now on, these regions will be called Regions of Interest (ROI).

In the proposed system, an initial floor map is extracted from the BIM model (using the IFC format). This floor map is used to generate a set of waypoints in each of the different planned spaces to ensure complete coverage of the scenario.

Waypoint-based navigation has been proven to be the most efficient way to collect as much data as possible from the construction site [28]. A set of waypoints located in the center of each space defined in the BIM model is automatically extracted from the initial floor map. The M-UGV will autonomously go from one position to the next, stopping on said waypoints to collect a 3D point cloud from the long-range 3D scanner. Plenty of solutions already exist for indoor positioning and autonomous path planning [29]. In this platform, we used an Adaptive Monte-Carlo Localization algorithm [30] and a Dijkstra-based planner approach [31].

4.1.2 S-UGV

The S-UGV is equipped mainly with short-range sensors, as indicated in Section 3. Although thermal information would be used as long-range to get an initial idea of the thermal characteristics of the different construction elements, it will also be used in a short-range approach whenever the S-UGV moves towards different ROIs to collect higher resolution images.

Before the AutoCIS moves towards the next waypoint in a different space, the S-UGV receives a set of local waypoints corresponding to the different ROIs detected in the pre-processing stage during the data processing part. The S-UGV then moves towards said waypoints in order to collect better quality data from those regions. The data collected is put together with the data taken by the M-UGV for further processing.

The constantly changing aspect of a construction environment makes it extremely hard for an autonomous robotic platform to navigate the construction site [32]. The presence of temporal obstacles and the rapidly evolving scenario requires a constant update of the maps used for autonomous navigation, making unreliable an approach entirely based on the initial maps obtained from the IFC file. That is why a multi-robot approach such as the one presented in this study increases the sources of information and allows for a complete obstacle map updated in real-time. As the S-UGV moves around the construction site, it runs a Simultaneous Localization and Mapping (SLAM) [33] approach used to update real-time the maps generated from the IFC file. This information is being used by the navigation algorithms of both the S-UGV and the M-UGV.

4.2 Data processing

4.2.1 Pre-processing stage

A set of ROIs is generated in real-time after each 3D scan is taken. In order to do that, a mix of geometric, RGB, and thermal information is being processed before the AutoCIS moves to the next waypoint. Every time the M-UGV takes a scan, a pre-processing stage is being applied to the collected data. During pre-processing, data collected from different sources (3D geometry, RGB and infrared), discontinuities, and interesting features are used to detect two types of areas: 1) areas where not enough data has been collected, for example, due to occlusions or because they are hard to reach (Figure 3), and 2) areas in which data of higher resolution needs to be collected. These areas are tagged as ROIs for the S-UGV to explore.

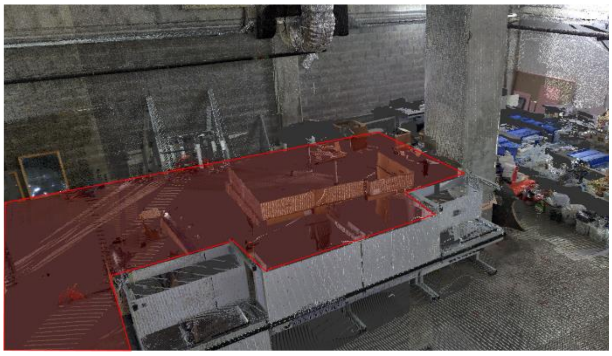


Figure 3. Example of a cluttered part of the point cloud where not enough data was collected.

Regarding the first type of areas, these can be detected in the 3D point cloud by analyzing its density (i.e., amount of points per surface unit) and big areas lacking points.

The second type of area can be detected by inspecting the RGB and thermal images. The RGB orthoimages corresponding to each structural element segmented from the point cloud are processed to look for discontinuities and defects, such as cracks or finishing defects. Higher-resolution data could be collected from the S-UGV for further quantifying the extension of said defect. Lastly, the collected thermal images are studied to look for discontinuity patches that could indicate the presence of different defects, such as hollowness or lack of insulation that could be properly detected with higher resolution data coming from the S-UGV.

4.2.2 Data analysis for possible defects

After the pre-processing stage and the data collection from the S-UGV have been done, all the information corresponding to each space is further registered with the accumulated point cloud using the localization data coming from the robot. An Iterative Closest Point algorithm [33] is then used in order to refine the alignment of these two data sets.

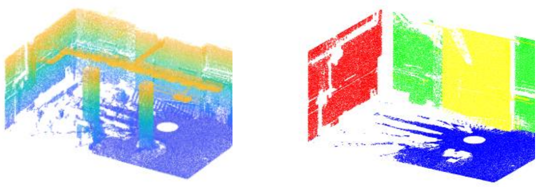
Some of the main defects to be identified in the processing stage are:

1. *Hollowness in walls, leaks, and insulation problems*. With the thermal information, the AutoCIS can detect incongruences inside the main structural elements. By studying the continuity of the structural element in the thermal space, a lack of insulation material or hollowness in the wall can be detected. The fact that the platform would be operating at the end of the working shift benefits the detection of these two features. This is because changes in the ambient temperature would be assimilated at different speeds by the construction elements, based on their structure behind the surface finishing. If there are noticeable problems with insulation, discontinuities in the thermal information can be expected due to how the internal structure follows the change of temperature, which would presumably decrease at the end of the working shift. Leaks would be difficult to detect in any of the two other data spaces, but the thermal information would provide a clear indicator of said defects by detecting the presence of humidity.
2. *Surface finishing defects*. By studying discontinuities in the RGB space, the system would be able to identify defects regarding the surface finishing of the construction element. Some of the most common defects regarding this category are surface roughness, paint discontinuities, and cracks. Cracks' overall position is being detected in the pre-processing stage from the RGB images using an Artificial Intelligence-based approach [34], tagging the location for further inspection. With the higher resolution images collected from the detected location, further image processing can be done to obtain quantitative data regarding the cracks. Some of the statistics obtainable from this stage are the cracks' length, width, and direction.
3. *Alignment, evenness, and inclination deviations*. Whenever two construction elements are concatenated with each other, the angle at which they join is measurable by studying the 3D geometry from the point cloud. When each construction element has been segmented (Figure 4), a theoretical plane representing a continuous space of said element can be computed. The system can accurately compare the alignment with the BIM model by inspecting the angle at which those two consecutive planes intersect. This can be done by obtaining the relative orientation (θ) between the normal vectors of said planes, $\vec{u}$ and $\vec{v}$ using Equation 1.

$$\cos\theta = \frac{\vec{u}\cdot\vec{v}}{\|\vec{u}\|\|\vec{v}\|} \tag{1}$$

Finally, the inclination of the floor can be assessed through the sensors onboard the robot and by inspecting the 3D point cloud.

The evenness of the wall can be assessed by studying the geometric distance of the 3D points belonging to a wall with respect to the theoretical plane computed for said wall. By doing this, the bumps and depressions in the wall are clearly visible (Figure 5). The results show the areas of the wall that are not completely even with the plane approximation.



(a) (b)

Figure 4. a) Original point cloud. Colors represent elevation (blue - low level; yellow - high level. b) Segmented point cloud. Colors represent different elements.

Once all data has been processed and assessed, it is presented in a structured and organized way to the user in the form of a quality report. This report will include a 3D representation of the space with color-coded information that will easily be accessible to the user. In addition, a list of all the discrepancies identified during the comparison will be available.

5 Conclusions and future work

Most of the research done regarding quality assessment focuses on the post-construction stage, where it might be too late to fix ongoing defects and would only imply additional work, time, and money to fix them. This study presents the preliminary work done to develop the AutoCIS, an automated construction inspection system consisting of a multi-robot approach for autonomous quality assessment and progress monitoring during the construction stage.

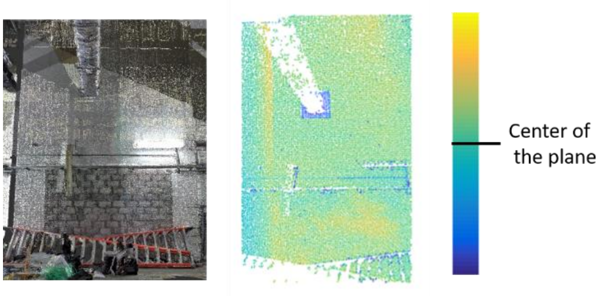


Figure 5 Left) Original point cloud. Right) Deviation of the wall with respect to the plane approximation of it.

The robotic system has been properly chosen to be efficient when navigating the harsh construction environment, collecting sufficient data to analyze some of the most common defects found in construction. With the M- and S-UGV onboard sensors, collected data from three different spaces (RGB, 3D point cloud, and infrared) can be processed, providing sufficient data to be analyzed and used to identify ongoing issues. Some of the current limitations of the proposed system rely on the presence of a complete and accurate BIM model. Segmenting each of the different elements in the construction site is not trivial. A wide variety of elements can be present (e.g., pipes, cables, columns of different shapes), and they can easily be mistaken by auxiliary elements such as scaffolding. Further robustness in order to prevent this is still needed.

Some individual parts have already been tested, but current work focuses on the scaling up of the experiment and validating the proposed AutoCIS as a whole. Once the platform is fully developed, the quality assessment can be easily extended into progress monitoring, including the 4D information from the BIM model.

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References

[1] G. Maas and F. Van Gassel, "The influence of automation and robotics on the performance construction," in *Automation in Construction*, 2005, vol. 14, no. 4, pp. 435–441.

[2] B. García de Soto *et al.*, "Productivity of digital fabrication in construction: Cost and time analysis of a robotically built wall," *Autom. Constr.*, vol. 92, pp. 297–311, Aug. 2018.

[3] A. Warszawski, "Economic Evaluation of Robotics in Building," *Proc. 1st Int. Symp. Autom. Robot. Constr.*, 1984.

[4] A. Gautam and S. Mohan, "A review of research in multi-robot systems," in *2012 IEEE 7th International Conference on Industrial and Information Systems, ICIIS 2012*, 2012.

[5] A. Farinelli, L. Iocchi, and D. Nardi, "Multirobot systems: A classification focused on coordination," *IEEE Trans. Syst. Man, Cybern. Part B Cybern.*, vol. 34, no. 5, pp. 2015–2028, 2004.

[6] B. Li, Z. Mi, Y. Guo, Y. Yang, and M. S. Obaidat, "A high efficient multi-robot simultaneous localization and mapping system using partial computing offloading assisted cloud point registration strategy," *J. Parallel Distrib. Comput.*, vol. 149, pp. 89–102, 2021.

[7] F. Real *et al.*, "Experimental Evaluation of a Team of Multiple Unmanned Aerial Vehicles for Cooperative Construction," *IEEE Access*, vol. 9, pp. 6817–6835, 2021.

[8] X. Zhang *et al.*, "Large-scale 3D printing by a team of mobile robots," *Autom. Constr.*, vol. 95, no. August, pp. 98–106, 2018.

[9] H. Ardiny, S. Witwicki, and F. Mondada, "Are Autonomous Mobile Robots Able to Take Over Construction? A Review," 2015.

[10] S. M. S. Elattar, "Automation and Robotics in Construction: Opportunities and Challenges," *Emirates J. Eng. Res.*, vol. 13, no. 2, pp. 21–26, 2008.

[11] T. Salmi, J. M. Ahola, T. Heikkilä, P. Kilpeläinen, and T. Malm, "Human-Robot Collaboration and Sensor-Based Robots in Industrial Applications and Construction," pp. 25–52, 2018.

[12] X. Yin, H. Liu, Y. Chen, and M. Al-Hussein, "Building information modelling for off-site construction: Review and future directions," *Automation in Construction*, vol. 101. Elsevier B.V., pp. 72–91, 2019.

[13] I. Armeni *et al.*, "3D Semantic Parsing of Large-Scale Indoor Spaces (a) Raw Point Cloud (b) Space Parsing and Alignment in Canonical 3D Space (c) Building Element Detection Enclosed Spaces."

[14] P. Tang, D. Huber, B. Akinci, R. Lipman, and A. Lytle, "Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques," *Automation in Construction*. 2010.

[15] K. J. Shrestha and H. D. Jeong, "Computational algorithm to automate as-built schedule development using digital daily work reports," *Autom. Constr.*, 2017.

[16] C. Kim, C. Kim, and H. Son, "Automated construction progress measurement using a 4D building information model and 3D data," *Autom. Constr.*, 2013.

[17] J. H. Lee, J. H. Park, and B. T. Jang, "Design of Robot based Work Progress Monitoring System for the Building Construction Site," *9th Int. Conf. Inf. Commun. Technol. Converg. ICT Converg. Powered by Smart Intell. ICTC 2018*, pp. 1420–1422, 2018.

[18] R. J. Yan, E. Kayacan, I. M. Chen, L. K. Tiong, and J. Wu, "QuicaBot: Quality Inspection and Assessment Robot," *IEEE Trans. Autom. Sci. Eng.*, vol. 16, no. 2, pp. 506–517, 2019.

[19] L. Klein, N. Li, and B. Becerik-Gerber, "Imaged-based verification of as-built documentation of operational buildings," *Autom. Constr.*, 2012.

[20] L. Liu, I. M. Chen, E. Kayacan, L. K. Tiong, and V. Maruvanchery, "Automated construction quality assessment: A review," *ISMA 2015 - 10th Int. Symp. Mechatronics its Appl.*, 2015.

[21] L. Liu, R. J. Yan, V. Maruvanchery, E. Kayacan, I. M. Chen, and L. K. Tiong, "Transfer learning on convolutional activation feature as applied to a building quality assessment robot," *Int. J. Adv. Robot. Syst.*, vol. 14, no. 3, 2017.

[22] C. H. P. Nguyen and Y. Choi, "Comparison of point cloud data and 3D CAD data for on-site dimensional inspection of industrial plant piping systems," *Autom. Constr.*, 2018.

[23] A. Adán, B. Quintana, S. A. Prieto, and F. Bosché, "Scan-to-BIM for 'secondary' building components," *Adv. Eng. Informatics*, 2018.

[24] R. Amhaz, S. Chambon, J. Idier, and V. Baltazart, "Automatic Crack Detection on Two-Dimensional Pavement Images: An Algorithm Based on Minimal Path Selection," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 10, pp. 2718–2729, Oct. 2016.

[25] T. Le, S. Gibb, N. Pham, H. M. La, L. Falk, and T. Berendsen, "Autonomous robotic system using non-destructive evaluation methods for bridge deck inspection," in *Proceedings - IEEE International Conference on Robotics and Automation*, 2017, pp. 3672–3677.

[26] D. Rebolj, Z. Pučko, N. Č. Babič, M. Bizjak, and D. Mongus, "Point cloud quality requirements for Scan-vs-BIM based automated construction progress monitoring," *Autom. Constr.*, 2017.

[27] K. Asadi *et al.*, "Vision-based integrated mobile robotic system for real-time applications in construction," *Autom. Constr.*, vol. 96, pp. 470–482, Dec. 2018.

[28] A. Ibrahim, A. Sabet, and M. Golparvar-Fard, "BIM-driven mission planning and navigation for automatic indoor construction progress detection using robotic ground platform," *Proc. 2019 Eur. Conf. Comput. Constr.*, vol. 1, pp. 182–189, 2019.

[29] F. Potortì, F. Palumbo, and A. Crivello, "Sensors and sensing technologies for indoor positioning and indoor navigation," *Sensors (Switzerland)*, vol. 20, no. 20. MDPI AG, pp. 1–6, 2020.

[30] D. Fox, W. Burgard, F. Dellaert, and S. Thrun, "Monte Carlo Localization: Efficient Position Estimation for Mobile Robots," *Aaai-99*, no. Handschin 1970, pp. 343–349, 1999.

[31] E. W. Dijkstra, "A note on two problems in connexion with graphs," *Numer. Math.*, vol. 1, no. 1, pp. 269–271, 1959.

[32] P. Kim, J. Chen, J. Kim, and Y. K. Cho, "SLAM-driven intelligent autonomous mobile robot navigation for construction applications," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2018, vol. 10863 LNCS, pp. 254–269.

[33] P. Besl and N. McKay, "A Method for Registration of 3-D Shapes," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 2. pp. 239–256, 1992.

[34] P. Ko, S. A. Prieto, and B. García de Soto, "ABECIS : an Automated Building Exterior Crack Inspection System using UAVs , Open-Source Deep Learning and Photogrammetry," in *Proceedings of the 38th International Symposium on Automation and Robotics in Construction (ISARC)*, 2021.