Automated Generation of Inspection Reports for Construction Operations

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Abstract

This paper introduces a newly developed framework for the automated generation of inspection reports in construction. The method utilizes earlier published developments by the authors on object recognition and localization. Inspection reports in this paper are documents that monitor and record the progress of installed project components and their targeted locations. Components in this research are also referred to as objects, which include installed piping systems, tanks, and mechanical equipment. The reports identify the deviations of the installed components by comparing their as-built status to the as-planned ones. The framework integrates the data acquired by a Real-Time Location System (RTLS) and a computer vision-based LiDar technology to generate the reports using object identification and localization. While considerable work has been reported using such technologies, the contribution of the framework presented here lies in the efficient integration of these technologies to acquire as-built 3D coordinates of the installed components. The framework has been validated through laboratory experiments, demonstrating an accuracy of approximately 27 centimetres for the installations' coordinates in the inspection reports. The framework presented here can be used for project commissioning to ascertain the precise locations of the project's installations.

Keywords

RTLS; LiDar; Computer vision; Indoor localization; Inspection reports

1 Introduction

Tracking a project's progress and the quality of the activities' execution are critical for project control. This process provides a large amount of as-built information related to various activities on site. Such reporting, however, is not simple due to the challenges associated with real-time data acquisition and processing. Onsite object tracking is an important part of a progress reporting system that necessitates identifying and localizing the installed objects. These objects include project components such as mechanical equipment and piping systems.

1.1 Related Works in Literature

Automated localization and tracking of objects have found many applications in the construction industry, including but not limited to timely progress reporting, inventory planning and management, and productivity analysis [1,2]. By digitizing and automating the processes involved, many objects related to various project activities are localized and tracked in a digital environment. It also enables us to track a project activity in a desired timespan, enhancing onsite project control. There is a wide range of Remote Sensing (RS) technologies for tracking resources on site. Real-time Location Systems (RTLSs) are a group of these technologies that provide localization and identification information of the tagged objects on site. Examples of these technologies include Global Positioning System (GPS), Sensor-Aided GPS (SA-GPS), Ultra Wide-Band (UWB), Bluetooth Low Energy (BLE), and Radio Frequency Identification Device (RFID), which have various indoor and outdoor applications for object tracking [1]. Several researchers have investigated using these technologies for location identification of objects to track onsite construction operations. Most of their efforts are focused on evaluating real-time tracking of workers, equipment, and materials in indoor and outdoor environments [2,3-12].

Integrating these technologies also provides more capabilities and helps overcome the limitations of individual use of each technology [1]. Studies have been conducted on the integrated use of RS technologies to overcome the limitations of each individual technology and achieve a more reliable and economical system in which many objects can be tracked and localized. While the reasonable price of RFID tags makes them a good choice for indoor object tracking, the sole use of RFID tags for indoor object localization needs to employ many RFID reference tags to enhance localization accuracy [13]. For outdoor tracking of objects, an integrated system of RFID and GPS-based sensors was developed, eliminating the need for reference tags [13-14]. It was basically based on finding the location of the RFID reader (s) by a GPS receiver and then finding the tag's location through the trilateration technique. In another example, GPS was integrated with RFID to improve positioning and identification capabilities. To localize the RFID tags, a boundary condition-based algorithm was used in which the maximum reading range of a hand-held RFID reader helps to localize the objects within the radius of the trilateration circles [15-16]. In [17], a low-cost integrated GPS-barcode system was designed to track objects in a storage yard. Furthermore, an integrated use of GPS with RFID technologies demonstrated a better performance for tracking onsite resources [2,13-15,18]. Unfortunately, in an indoor environment, the performance of the GPS sensors is highly degraded since they need direct access to the sky to receive signals from satellites. In this case, the UWB system can replace GPS to localize the RFID reader within a defined period. For indoor applications, an integrated RFID and UWB system was developed in [19], providing a low-cost and efficient Indoor Positioning System (IPS) using passive RFID tags.

There are various levels of automation in generating 3D models out of the point cloud data. In a manual approach, the point cloud data are used to manually model the objects by visual inspection. Also, supplementary tools for 3D modelling (i.e., as-built modeler) are used to facilitate the modelling of objects out of the point cloud data. In another approach, AI-based supervised algorithms are implemented in which the as-planned 3D model of the project corresponds to the acquired point cloud data. In these techniques, the supervised classifiers or AI techniques are used to relate every project object in the generated model to a corresponding element in the planned model. The planned model is used as a reference to help identify the objects in the point cloud data. These techniques are semi-automated, however, manual inspection of the generated models is still inevitable. Furthermore, it assumes that the as-planned 3D model is accurate enough, while it was shown that it might need to be corrected in many cases [20]. The AI-based Deep Neural Network (DNN) techniques are also used to model the objects out of point cloud data. These techniques directly use the point cloud data and are trained once for various classes of objects available in the tracked scene. After that, the DNN could detect or segment the objects accordingly. These techniques are categorized as fully automated techniques. However, the accuracy of the DNN in detecting the objects in the scene needs to be improved [20-21].

Sensory data achieved by RTLS and 3D imaging technologies such as laser scanners and depth cameras can be used to enhance the project's Level of development (LOD) through a digital twin platform. Lean 4.0 and Industry 4.0 are two new concepts that can be implemented through a digital twin. The RTLS-based digital twin was investigated in [21-25] to facilitate the practice of Lean 4.0 for object tracking. That study introduced three levels of digitalization and communication between the physical and digital twins. In level 1, only a 3D representation model of the physical object or site is available. In level 2, a one-way data flow from the physical object (s) to the digital object (s) in the model is initialized. In level 3, an integrated and bi-directional connection between the physical object (s) in the field and digital object (s) in the model is fully automated [22-23]. Information about the scheduling of the activities and the objects assigned to each activity can be added to the Building Information Modelling (BIM) to enrich the information about the onsite objects. For this purpose, various RS technologies are used to obtain different types of required information. For example, the RTLS sensors attached to these objects on site, including mechanical equipment and plumbing systems, are acquired information about the location of objects. Transferring these captured raw data to a BIM-based model and updating it in a defined time resolution depends on the type of project activities on site. Every change in the objects' location and status are updated in the BIM model. This information is then processed, and the required actions are taken accordingly and reflected again on the BIM model. The constant communication between the physical environment and the digital model of the project environment through the sensory data communication and the 3D project representation on site help to enhance project inspection and progress reporting through a digital twin platform.

1.2 Research Objectives

This research introduces an innovative framework for the automated generation of inspection reports, leveraging an integrated use of

Real-Time Location System (RTLS), 3D digital imaging, and web-enabled computer vision technologies. These integrations help to bring more visibility into project's operation by tracking actual progress on the job site through efficient use of the mentioned technologies. They also reduce the manual effort required for data collection and generation of inspection reports. The framework will enhance the efficiency of construction project delivery by boosting productivity and facilitating timely decision-making through an improved inspection process.

2 Developed Framework for Generating Inspection Reports

In this study, a sensory-based framework is developed to identify and localize onsite installations for generating inspection reports that comprise the installations' progress and their targeted coordinates. Figure 1 illustrates the framework, including the data collection technologies, data processing algorithms, and generated inspection reports. The framework comprises three methods: (1) an RTLS-based tracking method that utilizes a joint application of RFID and UWB technologies to improve the localization of the tagged objects, (2) a 3D object detection and localization point cloud-based method that utilizes a computer vision algorithm, PointNet, and a ready-to-use platform, Vercator Cloud, and (3) a method that integrates the output of the first two methods.

The first method was developed earlier by the authors to provide location identification information about indoor objects' locations [19]. The second method was also developed earlier by the authors to detect and localize objects using a computer vision algorithm and 3D point cloud data [25]. These two types of data are then integrated using the third method to improve the 3D localization of the RTLS while giving ID to the objects detected by the computer vision algorithms. This integration is performed by mapping the coordinates of the objects realized by these two technologies

Integrated technologies are used in the framework to enhance the coordinates' accuracy of the identified objects (i.e., chairs), along with information about the quantity of the objects. Inspection reports are then generated using the collected data mapped to the digital environment, considering the quantities and locations of the objects. The coordinates' deviation illustrates the difference between the installations' as-built and as-planned locations, including the ± localization error of the integrated RTLS and 3D imaging technologies. The as-planned coordinates are derived from the tie-points on the ground in the laboratory.

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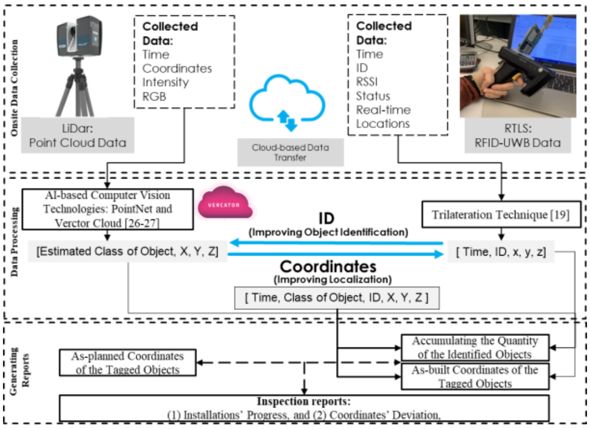


Figure 1. Developed framework for data collection and integration using RTLS and LiDar data.

2.1 RTLS for Object Identification and Localization

Here, an integrated system of RFID and UWB sensors is used. This integration helps to avoid the high cost of UWB implementation for object tracking while benefiting the medium-range capability of the RFID tags [19]. This method aims to provide near real-time localization data of indoor objects. An integrated use of RFID and UWB sensors benefits from the accurate positioning capability of UWB sensors for localizing the hand-held RFID reader in an indoor environment [19, 28-30]. The system can localize the tagged objects using less expensive passive RFID tags while transferring the collected data through cloud-based data collection tools. As illustrated in Figure 1, the RTLS method assigns unique IDs to identified objects, thereby compensating for the limitations of computer vision in distinguishing identical objects.

The input data for this system are gathered using a hand-held RFID reader, which is equipped with an UWB tag. The data are collected in the form of two .txt files, corresponding to the RFID and UWB devices. The RFID file contains the ID and Received Signal Strength Index (RSSI) values, while the UWB file captures real-time 3D coordinates of the roving RFID reader. The system's output includes the estimated 3D coordinates of the RFID tags attached to various objects. The authors' experimental work showed an accuracy of around 1.5 meters for 3D localization of the tagged objects, while 90 percent of the objects are identified and localized by the integrated RFID-UWB technologies.

2.2 LiDar-based Computer Vision for Object Detection and Localization

This study uses a point cloud-based algorithm, PointNet, to detect and localize objects. An available benchmark is used to train and test the model [25, 28]. The acquired point cloud data collected in the laboratory are fed into the model to validate the algorithm. The algorithm used has an acceptable classification accuracy. However, the results for 3D scene object segmentation and detection, which is required for detecting the target objects in the scene, are unsatisfactory. Only four out of ten target objects are correctly identified by the network. However, the localization accuracy of the detected objects increased to a few centimeters. This problem was reported in [26] and is compensated by integrating the RFID technology in this study. Also, for comparison purposes, object segmentation and detection have been done by a ready-to-use platform in the market, Vercator Cloud, to improve the 3D scene object segmentation and detection [27].

As illustrated in Figure 1, the detected point cloud data obtained through the computer vision algorithm compensates for the low accuracy of the 3D coordinates provided by the RTLS. This enhancement improves the 3D localization of the tagged objects, which is essential for accurately measuring the location of installed components.

2.3 Integrated RTLS and LiDar Data for 3D Object Identification and Localization

Integrating RTLS data with point cloud data enhances the localization and identification of the objects by benefiting the capabilities of these two types of data [20]. Assigning IDs to identical objects through RTLS ensures accurate identification, which is not possible with computer vision algorithms due to their limitations in differentiating identical objects from the same class. Additionally, RTLS is useful in Non-Line-of-Sight (NLoS) scenarios where the LiDAR device cannot collect point cloud data (i.e., in the covered area or invisible objects behind a panel). However, point cloud-based computer vision algorithms provide more accurate localization information with centimetre-level accuracy, which is crucial for many use cases on job sites, such as for automated inspection of the Mechanical, Electrical, and Plumbing (MEP) installations.

For integration, all objects recognized and localized by the RTLS and point cloud data are first derived. Then, for any object tagged by the RFID tag, the objects detected by the point cloud data in the vicinity of the tagged object that belong to the same class of object are selected. For example, if an object (i.e., chairs in this study) is tagged and identified with the RFID tag, the point cloud data detected as a chair by the DNN algorithms are assigned to that chair. The accurate coordinates of the detected objects by point cloud data are then replaced with the location information of the RTLS system. Figure 2 shows the flowchart of the steps for individual use of these technologies and their integration for generating inspection reports.

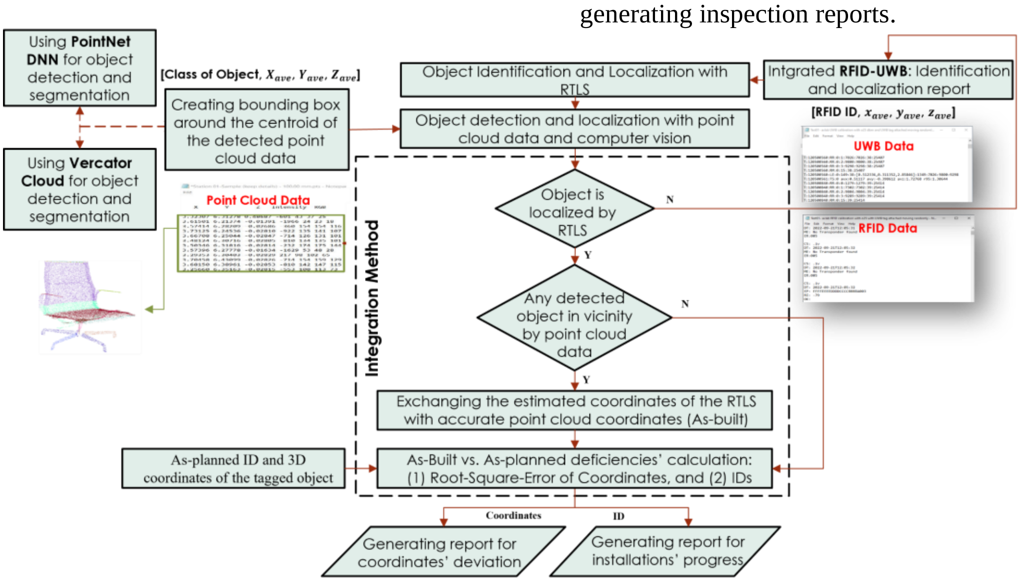
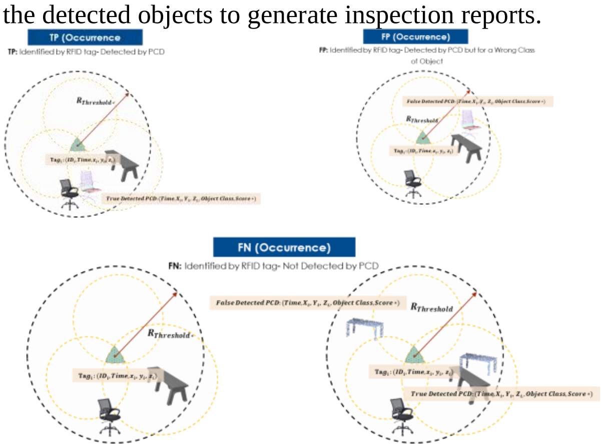


Figure 2. Flowchart of the developed method for integrating RTLS and point cloud data.

The integration enhances the localization accuracy of the RTLS within the coordinates' accuracy of the point cloud data. However, the experiment results show that the occurrence rate for this improvement is only 30-40 percent of the tagged objects when using the PointNet algorithm and available datasets as a benchmark [20]. For the other 60-70 percent of the tagged objects, the identification and localization information achieved by the RTLS is still used to generate the inspection reports. In this study, the computer vision results achieved with PointNet are compared with those achieved by the Vercator cloud platform. Vector Cloud uses optimized computer vision-based algorithms to detect objects from point cloud data and for various classes of objects. Also, it enables us to export the labelled point cloud data for further analysis and integration with RTLS data [27].

Figure 3 illustrates various scenarios for integrating RTLS and point cloud data to detect chairs in the laboratory. Integrating the RTLS data with computer vision data ensures higher accuracy of the objects' 3D coordinates while assigning IDs to the detected objects to generate inspection reports.



$R_{Threshold}$: In Range of the RTLS Localization Error
Score: The score of DNN for a specific Class of Object

Figure 3. Various scenarios in integrating RTLS and point cloud data.

3 Validation of the Developed Framework

The developed framework is validated through an experimental study conducted in a laboratory environment, in which identical chairs are used as the sample class of objects to be identified and localized through the developed framework. The chairs are labelled with passive RFID tags on their top back at a height of one meter and put on the targeted tie points on the ground (Figures 4 and 5). The laboratory is also scanned with a LiDar device to calibrate the RTLS system and collect point cloud data required for the DNN algorithms. Table 1 shows the as-planned coordinates of the chairs on the designated tie-points on the ground, along with information about the assigned RFID ID to each chair. Ten tie-points are selected from a total of 65, where each chair is located on the tie-points.

The tagged chairs are identified and localized by the RTLS technologies, RFID-UWB. At the same time, the chairs are detected and localized by the computer vision algorithms. The integrated method is then used to exchange information to generate inspection reports and identify coordinates' deviation. Table 2 illustrates the estimated coordinates of the chairs as determined by the integrated method used in this study in two scenarios: (1) using the PointNet algorithm and (2) using the Vercator cloud platform to refine RTLS coordinates. The coordinates deviation is calculated using the Root-Mean-Square-Error (RMSE) between the as-built coordinates and the as-planned coordinates of the chair in each tie-point. In a real scenario on the job site, this value is a sum of the deviations from the as-planned coordinates and the integrated method's error in estimating the chairs' coordinates. However, in this experiment, all chairs are precisely located on the as-planned coordinates to identify the integrated method error in estimating the as-built coordinates, as provided in the last column of Table 2. This error could result by various factors that affect the performance of the technologies used on the laboratory or job site environments. For instance, the presence of the metal objects, occlusions and obstacles decrease the localization accuracy of the integrated method. Additionally, the process of mapping RFID-based data to point cloud data reduces the precision of the coordinates detected and localized by the computer vision algorithm. Nevertheless, this integration is essential to improve the detection rate of the integrated method.

To calculate the progress of the chair installations, the number of identified chairs is divided by the total number of planned tie points. In this study, only one chair was not identified and localized by the integrated method. Since all chairs are available at the targeted tie-points, the estimated progress should be 100 percent. However, due to the integrated method error in object identification, this value has a 10 percent error from the actual progress.

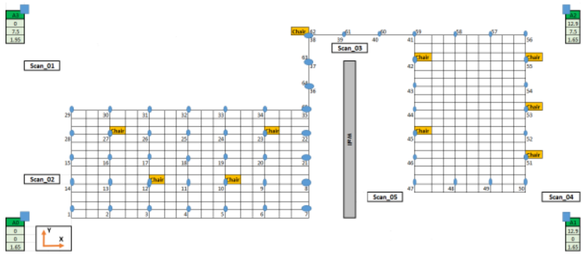


Figure 4. Layout of the tie-points in the lab.

Figure 5. Registered point cloud data of the laboratory.

Table 1. Chairs' targeted coordinates in the tie-points (as-planned status).

No.	Tie-point	ID	X_p(m)	Y_p(m)	Z_p(m)
1	10	A001	4.8	1.2	1
2	12	A002	3	1.2	1
3	23	A003	5.7	3	1
4	27	A004	2.1	3	1
5	38	A005	6.6	6.6	1
6	42	A005	9.3	5.7	1
7	45	A007	9.3	3	1
8	51	A008	12	2.1	1
9	53	A009	12	3.9	1
10	55	A010	12	5.7	1

Table 2. Tagged chairs' estimated coordinates using the integrated method and coordinates' deviations from as-planned status.

No.	Tie-point	X_e(m)	Y_e(m)	Z_e(m)	Coordinates' deviation (RMSE)
Using PointNet Algorithm					
1	10	3.5	1.9	1.8	0.97
2	12*	3.2	1.4	1.5	0.33
3	23*	5.9	3.3	1.2	0.24
4	27	3.5	3.2	2.6	1.23
5	38	6.1	7.4	1.9	0.75
6	42	8.5	6.9	1.7	0.46
7	45*	9.1	3.1	1.2	0.17
8	51	-	-	-	-
9	53*	11.7	3.6	1.5	0.38
10	55	13.4	4.8	1.7	1.042
Average Deviation (m)					0.62
Detection Rate					40%
Estimated Progress					90%
Using Vercator Cloud Platform					
1	10*	4.6	1.1	1.2	0.17
2	12*	3.1	1.2	0.9	0.08
3	23*	5.5	3.2	1	0.16
4	27*	2.2	3.1	1.2	0.14
5	38*	6.7	6.5	0.8	0.14
6	42	8.5	6.9	1.7	0.46
7	45*	9.2	3	1.1	0.14
8	51	-	-	-	-
9	53*	11.8	3.9	0.9	0.13
10	55	13.4	4.8	1.7	1.042
Average Deviation (m)					0.27
Detection Rate					70%
Estimated Progress					90%

* The refined RTLS locations by integrated method using DNN algorithm.

As illustrated in Table 2, the use of Vercator Cloud enhances the detection rate of the chairs from 40 percents to 70 percents. This is due to optimized algorithms used in this platform and with a larger dataset than the PointNet algorithm. Also, that results in more accurate coordinates for the chairs identified through the integrated method. As provided in the table, the chairs are localized more accurately with an average accuracy of 62 centimeters to the 27 centimeters by using Vercator Cloud platform instead of PointNet algorithm. This is close to the required accuracy for approving the installed project's components, which is around 15 centimeters. However, one of the chairs is still not identified through the integrated method, and with RTLS tags (chair number eight in Table 2).

3.1.1 Contributions and limitations

The framework presented in this study automates the generation of inspection reports for construction operations during the construction phase. Integrating the RTLS data with point cloud data enhances indoor object localization by refining the estimated coordinates of the installed project components using the object segmentation capability of the DNN algorithms and accurate coordinates of the point cloud data.

While the developed method automates the generation of inspection reports, it also presents certain limitations. For experimental purposes, the target objects were positioned at the same height and maintained a clear line of sight (LoS). Future studies could explore the challenges of tag placement at varying elevations and in congested environments, which would provide valuable insights for practical applications on job sites.

The application of the computer vision algorithm used in this study should be extended to more construction components, such as MEPs, which are among the most challenging components to track and report on the job sites. Available point cloud data benchmarks assist in detecting some of these objects without the need for manually creating annotated datasets. However, object detection accuracy is not acceptable for the class of objects with small datasets due to the imbalance in the training dataset size for these objects compared to others. Future investigations are needed to improve object detection with computer vision and to automate the integration of RTLS and point cloud data. This will result in more accuracy in location identification of the detected objects required for approving the installation of the projects' components. Also, the object detection capability of the DNN algorithms could be used to improve the object identification of the RTLS. However, identical objects still cannot be distinguished by DNN algorithms. Further integration with BIM compensates for this limitation.

4 Summery and Concluding Remarks

The framework developed in this study supports the automated generation of inspection reports. The inspection reports include the progress of the installed components and their targeted coordinates on the construction sites. These reports are used to identify deviations from the targeted coordinates of the installed project components by comparing their as-built locations to their as-planned ones. The digital solution technologies employed in the framework are utilized for data capturing, analysis, and reporting, leveraging the developed integration capabilities. These digital solutions include: (1) an RTLS based on integrated RFID-UWB for location identification of tagged objects in an indoor environment, (2) computer vision and deep learning models for object detection and localization of the installed project components using point cloud data, and (3) an integrated method that enables automated generation of the inspection reports through refined localization and recognition of the components. Further integration of the developed method with a project's planned data (i.e., planning and scheduling data) enhances the method's cohesion in automated data acquisition, site inspection, and progress reporting. Additionally, the method has the potential to be further integrated into various quality aspects of a project, including material quality, waste management, and the execution quality of construction operations.

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