ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-4-2024
ISPRS TC IV Mid-term Symposium “Spatial Information to Empower the Metaverse”, 22–25 October 2024, Fremantle, Perth, Australia

Acquiring Semantic Information of Precast Concrete Pipe Using Geometric Feature Extraction from Mobile Laser Scanning Point Cloud

Kartika Nur Rahma Putri[1,2], Xuesong Shen[1], Mitko Aleksandrov[1], Khalegh Barati[1], James Linke[3]

[1]School of Civil and Environmental Engineering, The University of New South Wales, Sydney, Australia – (k.putri, x.shen, mitko.aleksandrov, khalegh.barati)@unsw.edu.au
[2]Department of Civil and Environmental Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia – kartikanurrahmaputri@ugm.ac.id
[3]Linke & Linke Surveys, Sydney, New South Wales, Australia – j.linke@llsurveys.com.au

Keywords: Material Tracking, Point Cloud, Mobile Laser Scanning, Digital Twin, Geometric Feature Extraction, Object Detection

Abstract

In a construction project, the need to conduct effective and efficient material management is urgent since it takes up to 60% of the project budget. Most of the material tracking uses tag-based technology by attaching RFID, GPS, or UWB to the materials. This method is found to be effective in tracking the material in construction projects. However, there is still a manual job of putting the tag into each of the materials and problems related to the signal quality and infrastructure requirements. As an alternative way to do material tracking, point cloud processing can be used. This paper aims to develop an efficient approach to accurately detect concrete pipe precast material, calculate its numbers, and produce valuable data for material inventory management. The data was taken by a mobile laser scanner of a site-specific infrastructure project in Sydney. The resulting data was sparse and occluded because it was taken only from one side to replicate the actual scanning process in a construction project. The automated process has been conducted by matching the material based on its geometric feature of the 3D material model. The proposed approach can provide some spatial information such as location (x, y, z global coordinate), orientation of each material, and the number of materials. The result can detect up to 78.5% of the material. The difference between actual and predicted global coordinates is 0.75m which is acceptable for material location in a large infrastructure project. This data can be reconstructed in a 3D detail of the site project in the Building Information Modeling (BIM) platform in its actual location. The implementation of this method serves as an initial stage toward achieving synchronization between the physical construction and its corresponding digital twin in the field of construction.

1. INTRODUCTION

1.1 Background

In a construction project, the cost of materials took around 60% of the project budget (Kar & Jha, 2020). Therefore, material management is crucial to be managed effectively. A closer look at the construction industry shows that a considerable amount of waste produced is rooted in poor management of the material supply chain (e.g. delivery services, inventory, communications). In this regard, the use of information technology (IT) is suggested to achieve better logistics processes and avoid delays (Irizarry et al., 2013). Moreover, based on (Lin and Golparvar-Fard, 2021), stable working assignments can be achieved when information regarding the location of the worker, the progress of previous work, and the availability of material can be provided by location-task visualization. Currently, the assessment of materials present on-site heavily relies on manual inspections, which can be labor-intensive, time-consuming, and prone to human error (Cheng and Teizer, 2013).

Some previous well-known technologies for construction resources tracking include the usage of Ultra-Wide Band (UWB) technology (Alarifi et al., 2016), Radio Frequency Identification (RFID) (Shin et al., 2011), and Global Positioning System (GPS) (Lee and Lee, 2021). Each technology has its advantages and weaknesses. Previous technological solutions for material detection primarily revolved around tag-based methods. To be able to use tagging technology, each resource needs to be tagged first before we can track it. The flagging activities of the material onsite this activity still need manual human-involvement (Grau et al., 2009). Moreover, a specific infrastructure is needed to support the tagging technology such as Wifi, cellular-based, and Bluetooth (Alarifi et al., 2016).

The tagging technology has been proven to be effective in tracking valuable materials like prefabricated concrete decks, heavy equipment, and personnel. However, these methods have not adequately addressed the detection and tracking of other types of materials, particularly bulk materials and big precast items such as concrete pipes, which are commonly found on construction sites and require a wider area in a construction site (Teizer, 2015). As a result, there is a significant gap in the existing technology when it comes to detecting and monitoring these specific types of materials. The application of tracking technology to support inventory management systems and supply chains also lacks exploration.

In order to fill the gap, a new approach for material tracking systems is proposed in this research. Moving from tag-based technology which needs manual tagging to the resources and its need to build a specific infrastructure in the construction site, the proposed technology used to solve the material tracking problem is by using laser scanning and Point Cloud (PC) data. Nowadays, three-dimensional point clouds generated from laser scanning are adopted in the construction industry (Q. Wang et al., 2018). Numerous applications of point cloud technology exist within the construction industry. Nevertheless, the majority of these applications are concentrated on construction progress monitoring (Ibrahimkhil et al., 2023), quality inspection (M. Wang et al., 2021), and operation safety (Cheng and Teizer, 2013).

1.2 Contribution

This research focuses on answering the research question of how to make the precast concrete pipe material onsite be automatically detected, recognized, quantified, and reconstructed from mobile laser scanning data in a construction site project. Moreover, there is a need to extract the volume, specific location, and orientation of the materials as basis data for material inventory. The project manager can get information on material needs by synchronizing the material inventory and schedule of the project. The result will of this object detection will be visualized in the digital model as the basis for the construction digital twin model.

2. LITERATURE REVIEW

Some positioning technologies such as RFID, UWB, infrared, ultrasonic, and ZigBee require building infrastructure technology such as Wi-Fi, cellular-based, and Bluetooth. Meanwhile, some technologies such as image-based technology and point cloud processing do not need dedicated technologies in the building (Alarifi et al., 2016). Therefore, this technology is gaining much attention nowadays. For instance, Kamari and Ham, (2021) have proposed an automated method for measuring the volume of bulk materials. This approach integrates point cloud data obtained from both photogrammetry and computer vision technologies to identify various types of bulk materials. Li and Chen, (2022) have also developed a computer vision-based system capable of automatically quantifying the quantity of densely packed steel pipes at a construction site from image data. While it achieves a detection rate of up to 95.8% for the pipes, it necessitates a substantial volume of data for training, which poses a challenge given the current scarcity of available construction site data. Despite these limitations, the adoption of vision-based and point cloud technologies has gained traction in addressing the shortcomings of scan-based methods, as they reduce the need for manual tagging and scanning, and do not require specialized infrastructure for data transfer.

To retrieve an object detection from a 3D point cloud, generally, there are 3 different methods used currently i.e. simple geometric models, feature descriptors, and deep learning (Chen et al., 2019). The first method is by detecting objects using simple geometric shapes such as planes and cylinders from point cloud data. The second method includes the utilization of feature descriptors from an object. A descriptor is a vector of information/features that enables algorithms for shape retrieval or correspondence finding to identify a key point of an object uniquely. It can be divided into local descriptors and global descriptors. The local descriptor tries to summarize statistics of the object feature such as curvature, density, and normal to describe the neighborhoods around interest points. Meanwhile, the global descriptors define objects by their lengths, area, and angle in a single feature vector. The third method is using deep learning for object detection. This method requires a large number of objects to be trained before it can predict the correct type of object to be detected.

Previous work has been made to identify cylinder objects from point cloud data. Bosché et al. (2014) tried to align the as-built 3D point cloud of pipes scanned using TLS from the site project with its coordinate system in the as-planned model. An object is considered detected if at least 500 points from the as-built PC are matched with the as-planned model. The objects that are not matched with the 3D model are identified as occluders. For this method, the 3D model of as-design point cloud with its location is needed. Meanwhile, for material in the site project, the location of material is unknown.

Patil et al. (2017) detect cylinder pipelines by using area-based adaptive Hough transform. Hough transform was used to detect geometric shapes such as cylinders by using a set of parameters such as axis direction, axis position, and radius. In this research, pipeline plants can be detected and automatically reconstructed to produce the as-built drawing. Since the algorithm needs to detect the edge of the point cloud and use a voting mechanism to determine the best fit of the cylinder, a dense and complete point cloud is needed to make sure that the pipes can be segmented and detected. While Czerniawski et al. (2016) filter pipe spool from cluttered point cloud by using curvature-based shape descriptor and Bag of Features (BoF) to compare the 3D 3D model point cloud with the actual point cloud. The algorithm can extract pipe spools and differentiate between similar pipes from the same point cloud. In both of this research, the point cloud was scanned by TLS resulting in a dense and complete point cloud. Meanwhile, the data resulting from mobile laser scanning is usually not complete and occluded.

Current research on point cloud processing mostly uses Terrestrial Laser Scanning (TLS) from more than one angle which results in a dense and complete point cloud. Meanwhile, the data from the actual construction site taken by a mobile laser scanner is sparser and more occluded (Bienert et al., 2018). In addition, current point cloud research is more focused on object detection from a computer science point of view. The evaluation criteria mostly rely on recall (count accurately identified objects belonging to a specific class of interest), precision (correct identification of objects within all data predicted for a particular class) and mean average precision. Meanwhile, a new parameter of point cloud processing which is more related to construction project management is needed (Xu & Stilla, 2021). Other semantic data such as location, number of materials, and orientation also need to be tracked for material tracking and visualization purposes.

3. METHODOLOGY

The proposed methodology aimed to achieve material tracking DT in construction projects. This approach leverages construction-specific point cloud data and is projected as a viable substitute for material tracking that does not rely on tag-based techniques. A Fast Point Feature Histogram (FPFH) combined with the Random Sample Consensus (RANSAC) method was used to extract the feature from concrete pipe material and evaluate the geometric feature of the detected object. This method was chosen to balance a simple algorithm to detect the pipes and calculate their number to support material tracking.

Figure 1 illustrates the framework of the material detection from construction site and material reconstruction into 3D digital model. A mobile laser scanning system traveled through the construction site to capture data, resulting in the creation of a

https://doi.org/10.5194/isprs-annals-X-4-2024-263-2024 | © Author(s) 2024. CC BY 4.0 License.

point cloud. Subsequently, this construction site point cloud served as input for a geometric feature detection algorithm. The algorithm can determine both the quantity of materials and their respective locations from GPS. This data, presented in spreadsheet format, then was used as input to visualize the materials within the Building Information Model (BIM). Since the generated locations were specified in terms of global positioning, the BIM model must be synchronized with its global coordinates. The result of this methodology is a 3D visualization of the material in 3D BIM format.

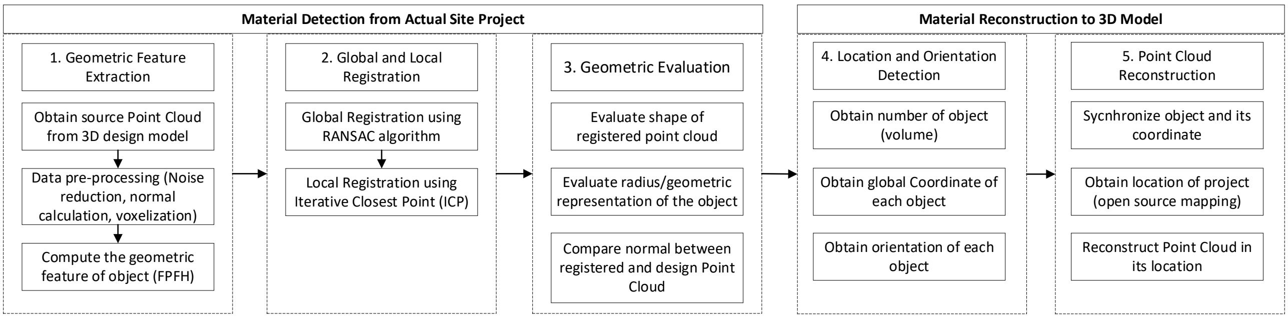


Figure 1. Framework of Material DT

To obtain material tracking from point cloud data, the proposed workflow consists of five modules as follows: (1) geometric feature extractions of the material from the 3D object, (2) global and local registration of the material, (3) geometric evaluation of the registered object, (4) location and orientation detection of the material, and (5) reconstruction of the point cloud into a 3D model.

3.1 Geometric feature extractions of the material from a 3D model

A 3D point cloud data was taken from mobile laser scanning to provide us with the actual condition of the site project. The retrieved data is large, noisy, and mostly occluded. This data served as a location to search for the construction material and further will be mentioned as ‘target’ point cloud in Figure 2. From the actual site condition, the objective of this study is to find an object of interest material to be detected without knowing prior information about the material location. A 3D model of the construction material will be used as the source data for the registration step and will be further mentioned as ‘source’ point cloud in Figure 2.

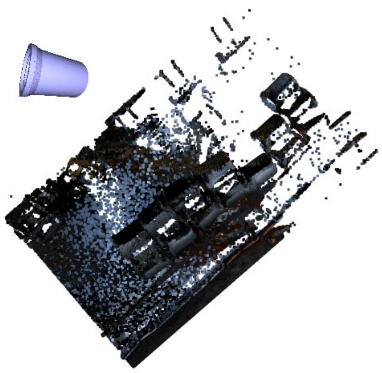


Figure 2. 3D pipe as a source point cloud (above-left) and construction area as a target point cloud (below-right)

Since the material was expected to be above the ground, removing the ground point was the first preprocessing step conducted to reduce the number of point clouds. This was done to decrease the volume of point cloud information. Subsequently, a down-sampling technique was employed to achieve a uniform distribution of the point cloud data. Down-sampling is a method utilized to reduce the data volume while retaining the geometric and semantic characteristics of the point cloud (Qiu et al., 2022). The point cloud was sampled by using voxel-based method. The size of the voxel was 8 cm. The result of downsampling made the point cloud data becomes uniformly distributed.

For geometric feature extraction, a robust method called Fast Point Feature Histograms (FPFH) (Rusu et al., 2009) was employed to characterize the local geometric properties surrounding a given point p in the source point cloud. Through the nearest neighbour query in the 33-dimensional space, points with similar local geometric structures are retrieved. The computation of these structures was based on a combination of specific geometric relationships among p's closest k neighbours. These relationships encompass the (x, y, z) 3D point coordinates and the estimated surface normal (nx, ny, nz) of the points, but they can be expanded to accommodate other properties like curvature, 2nd order moment invariants, and other properties.

3.2 Global and local registration of the material

Registration is a process to find a transformation estimation between two-point cloud (Huang et al., 2021). In order to find the object of material in a noisy point cloud, a registration process was used to match the object from a source point cloud in the target point cloud. A global registration process was used as this method does not require a rough alignment as the initialization. The global registration process usually produces less tight alignment results and is used as the initialization data for the local registration process.

For the global registration stage, a Random Sample Consensus (RANSAC) iteration was used (Fischler & Bolles, 1981). This is a popular algorithm for robust estimation in computer vision problems (Raguram et al., 2008). In each RANSAC iteration, 3 random points were picked from the source point cloud. Their corresponding points in the target point cloud were detected by querying the nearest neighbor in the 33-dimensional FPFH feature space. A pruning step took fast pruning algorithms to quickly reject false matches early. There are two pruning algorithms used. The first one was a correspondence checker based on distance. This algorithm checks if the aligned point clouds are close to each other in less than a threshold which is 1.5*voxel size = 12 cm. The second algorithms were correspondence checker based on edge length. This algorithm checks if the length of any two lines formed by two vertices individually drawn from source and target point cloud are similar. The algorithm checked that $||edge_{source}|| > 0.9*||edge_{target}||$ and $||edge_{target}|| > 0.9*||edge_{source}||$. Only matches that passed the pruning step were used to compute a transformation, which was validated on the entire point cloud.

For performance reasons, the global registration was only performed on a heavily down-sampled point cloud. The results were also not tight. We used Point-to-plane Iterative Closest Point (ICP) (Rusinkiewicz & Levoy, 2001) to further refine the alignment and call this stage as local registration. The result from global registration was used as the initial pose for the ICP Step. The ICP algorithm found correspondence for each point in the source point cloud into the closest point in target point cloud by using nearest neighbor search. Then, it computed the transformation (rotation and translation) that minimize the mean squared error between the matched points. After the least mean squared error found, the algorithm applied transformation to all points in the source point cloud. By conducting the global and local registration process, a pipe would be matched between the source and the target point cloud and would be referred to as a registered object or detected pipe.

3.3 Geometric evaluation of the registered object

Once the pipe has been detected, some steps were be conducted to check if the registered object matches the dimension of the concrete pipe in the object of interest. The registered object was evaluated individually by separating it from the rest point cloud data. Firstly, for each registered point cloud, a RANSAC-based cylinder fitting was done to check the radius, center point, and axis of the cylinder. The second important geometric evaluation is to check the normal angle differences of the detected pipe with its 3D model. The procedure started by extracting the detected pipes and finding k-nearest neighbors (KNN) for each point in the detected pipe and the 3D model. For each point and its corresponding point detected, we calculate the angle difference between them. This step aimed to determine if the detected point cloud has the same shape as the 3D model.

3.4 Location and orientation detection of the material

From various iterations, not all point clouds can be classified as pipes based on the previous geometry evaluation. For the group of point clouds that have successfully passed all the thresholds, we designate them as detected pipes and calculate their properties. Through cylinder fitting, each pipe is assigned its center coordinate and axis/orientation. The center coordinates are considered local coordinates. The mobile laser scanner plays a crucial role in providing accurate GPS coordinates for each point cloud. By having a global coordinate of one reference point, we can have the global coordinate of the material center point by calculating its distance difference.

3.5 Reconstruction of the point cloud to the 3D model

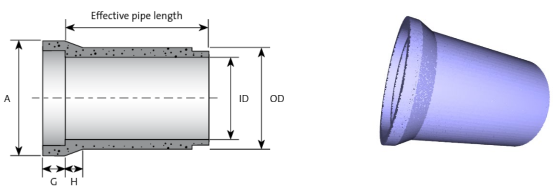
The concrete pipe detection process yields valuable information, including the number of pipes, their orientation (axis), and their global coordinates. Additionally, it captures the crucial timestamp of each scanning operation, which is essential for the reconstruction process. This timestamp ensures that data confusion between successive scan results is avoided, guaranteeing the accuracy and integrity of the reconstructed data. Since each material has its global coordinate, the visualization can be done by using the actual coordinate in BIM-based visualization software. The actual site project location obtained from open-source mapping data and the material can be placed in its real location. The visualization of material aimed to give information to the project manager about the location and inventory of material available on the site project.

4. CASE STUDY

As a case study, a construction site from the Sydney Gateway project was selected to implement the proposed methodology. The data collection was conducted using the Green Valley International Mobile Laser Scanner with the specification mentioned in Table 1. The described methodology was implemented in a Python environment on a PC with the Processor Intel(R) Core (TM) i9-7940X and installed RAM 128 GB. The primary library utilized for 3D processing was Open3D library (Zhou et al., 2018). For this case study, a precast pipe concrete was used to check the robustness of the methodology. As a source point cloud, a 3D model of the material that will be detected can be seen in Figure 3.

Criteria	Specification
Laser Sensor	XT32
Range Accuracy	±3cm
Vertical Field of View	-16° ~ 15°
Horizontal Field of View	0° – 360°
Maximum Range	120 m

Table 1. Mobile Laser Scanner Specification



(a) (b)

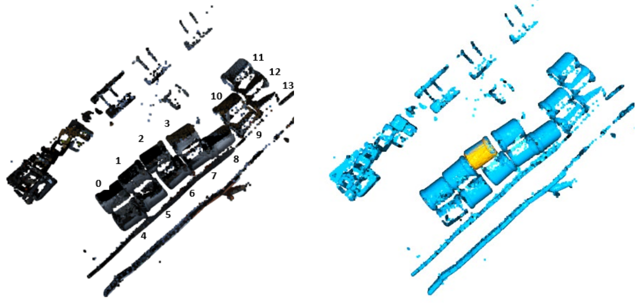
Figure 3. Model of concrete pipe. (a) Size of 3D pipe, ID = 1.74 m (r = 0.87 m), OD = 1.96 m (r = 0.98 m), A = 2.18 m (r = 1.09 m); (b) 3D model of the concrete pipe as source point cloud

4.1 Preprocessing

The first preprocessing step was by removing the source ground points (Figure 2) as most of the material onsite will be located above the ground. The result of ground point removal and the pipe numbering can be seen in Figure 4a. This process was conducted using open access PDAL library for ground filtering (Butler et al., 2021). The next step is to do a down sampling and normal estimation. Down sampling is a process to reduce the amount of data without losing point cloud geometric and semantic features (Qiu et al., 2022). The point cloud is sampled by using voxel-based method with 8 cm voxel size. The proper voxel size should be determined based on the project characteristics. If the project contains many small components, a smaller voxel size should be taken to avoid losing object characteristics. The result of down sampling makes the point cloud data becomes uniformly distributed.

4.2 Material Detection from Actual Site Project

This step was started by calculating the geometric feature of the concrete pipe. To find the matching pipe, the RANSAC iteration for global registration was set to be done into maximum 5 million iterations with the threshold fitness 0.7. If the maximum iteration is achieved but the threshold of fitness is below the target, the algorithm will continue to ICP local registration. This is because the point cloud data is sparse and not all the object has enough point cloud to reach 70% of the source point cloud. The result of this stage is a detected pipe from a target area (Figure 4b).

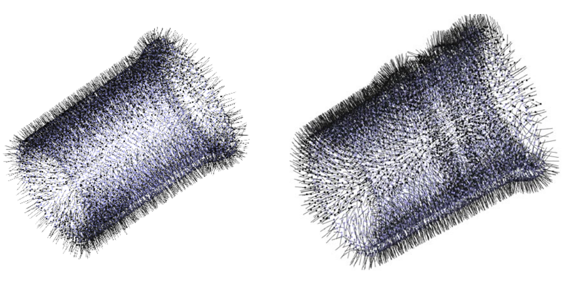


(a) Ground point removal, voxelization, and geometric feature extraction

(b) Detected pipe from global and local registration

Figure 4. Stages of concrete pipe detection.

If the fitted cylinder had a radius between 0.8 to 1.4 meter, the cylinder is counted as well-aligned. The actual radius of inner diameter (ID) of the pipe is 0.87 meter, and the radius of outer diameter (OD) is 0.98 meter, it also has a bigger diameter (A) in one side of the pipe which has a 1.09-meter radius (Figure 2). Since the RANSAC algorithm will estimate the radius from random points in the point cloud, it can detect the inner, outer, or even the bigger diameter on one side of the pipe. Therefore, the threshold was made not too tight, namely 0.8 meters to 1.4 meters. To get this threshold, a visual check was carried out to ensure that the detected pipe was indeed the desired pipe.

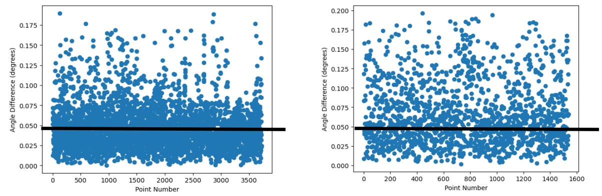


(a) Example of normal of well-aligned pipe

(b) Example of normal of not well-aligned pipe

Figure 5. Geometric evaluation of the registered object.

The next step was a calculation of the normal between the registered point cloud and comparing it with the normal of the 3D model. Figure 5a shows normal from a well-aligned pipe and Figure 5b shows an example of normal from a not well-aligned pipe. The angle differences between both were then calculated and plotted to a graphic in Figure 6a. Since the angle differences were mostly dense at 0.05 degrees, this value becomes the threshold. If the registered point cloud had angle differences more than 0.05 degrees below 55%, the point can be categorized as the pipe of interest. The smaller the angle difference means that the two-point clouds have high similarity. Figure 6a shows the plot of the angle difference for each point in the object. When the object has many similarities, the plot of the angle difference is denser below the 0.05-degree axis (black line). Two groups of clouds that were not too similar resulted in a sparse normal angle difference plot as shown in Figure 6b.



(a) Angle differences more than 0.05 degrees = 37.24%

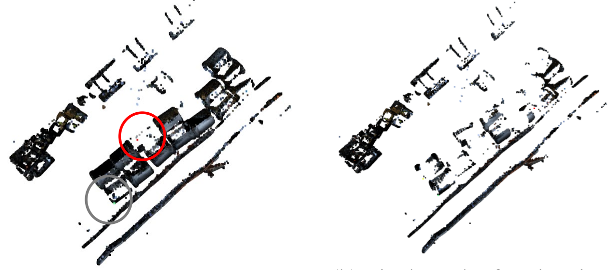
(b) Angle differences more than 0.05 degrees = 56.05%

Figure 6. Angle differences between detected pipe with the 3D model.

4.3 Material Reconstruction to 3D Model

To obtain the global coordinates of each pipe, a reference point with a known global coordinate was utilized as a reference plot. The grid coordinate of the reference point was verified using Cloud Compare software. To achieve accurate location data, the coordinates were then transformed into geographic coordinates through the service provided at https://geodesyapps.ga.gov.au/grid-to-geographic. The distance between the center point of the pipe and the reference point was subsequently measured. By combining this distance with the global coordinate of the reference point, the global coordinate of the registered point cloud could be determined (Figure 7a).

After validating the identified pipe, the radius, center, and orientation (axis) of the pipe were computed. Subsequently, the group of registered pipe points was removed to minimize the chances of detecting the same pipe twice and to simplify the subsequent processing stage. This removal of registered pipe points was marked as the ending of each iteration in the material detection process. The entire process was then repeated, starting from global and local registration and geometric evaluation to detect any remaining pipes until no more pipes were detected. Figure 7b displays the outcome at the completion of the looping process. The visual observation of the point cloud reveals that multiple detected pipes have been intentionally removed from the data.



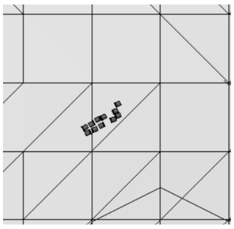
(a) Reference point (green) and the center of detected pipe (red)

(b) Final result after the pipes have been detected.

Figure 7. Point Cloud after Processing Material Visualization

Once the algorithm completed its looping process, it successfully acquired the data for each pipe, including the global coordinates and axis orientation. In Figure 8a, the actual construction site location was obtained using CAD Mapper software. This data was then imported into Revit 2022 software, which serves as the primary tool for visualization. To streamline and automate the visualization process, the global coordinate and axis data for each pipe were exported into an Excel file. This Excel file served as the data source for Dynamo BIM, a visual programming tool used within Revit software. The result of visualization can be seen in Figure 8b.

(a)



(b)

Figure 8. Visualization of the Material. (a) Actual location of site project; (b) Material in its exact location

Pipe	Radius (m)	Axis (Orientation)			Average Angle Differences	Centre (Local coordinate)		
		x	y	z		x	y	z
0	1.380977	-0.0562	-0.25555	0.965161	42.38%	-49.7177	-0.50305	-3.0284
1	1.354678	-0.06786	-0.16869	0.98333	44.28%	-47.4277	1.521852	-3.01216
2	1.345363	-0.05313	0.034081	0.998006	50.83%	-45.2677	3.572	-2.53198
3	1.116988	-0.11806	-0.47721	0.870821	52.03%	-42.1649	5.56079	-2.66903
4	1.263662	-0.04407	-0.21597	0.975404	42.75%	-48.3572	-2.28964	-2.69179
5	0.940128	-0.03167	-0.9776	0.208072	37.74%	-45.3789	0.722186	-3.51405
6	0.975571	-0.08493	-0.5567	0.368885	36.65%	-42.7072	2.59464	-3.32187
7	-	-	-	-	-	-	-	-
8	1.019584	-0.11785	-0.1735	0.977757	47.99%	-39.4431	5.416842	-3.79305
9	1.048815	0.204384	0.926148	-0.31698	53.98%	-37.1102	6.997075	-3.48407
10	1.028002	0.000838	-0.30389	-0.95271	47.12%	-37.7862	9.172892	-2.95918
11	1.085812	-0.29927	-0.67632	0.673076	50.98%	-36.5032	12.93058	-3.23763
12	-	-	-	-	-	-	-	-
13	-	-	-	-	-	-	-	-

Table 2. Radius, axis, angle differences, and center of each detected pipe

Pipe	Actual Global Coordinate			Predicted Global Coordinate			Difference (m)
	x	y	z	x	y	z	
0	331181.6375	6245073.845	25.569137	331181.6823	6245073.717	25.9816	0.43
1	331183.8625	6245075.937	25.633137	331183.9723	6245075.742	25.9978391	0.43
2	331185.9905	6245078.204	25.645137	331186.1323	6245077.792	26.4780203	0.94
3	331188.9005	6245080.269	25.628137	331189.2351	6245079.781	26.3409679	0.93
4	331183.0955	6245072.014	25.601137	331183.0428	6245071.93	26.3182103	0.72
5	331185.5275	6245074.146	25.610137	331186.0211	6245074.942	25.4959464	0.94
6	331188.0765	6245076.492	25.602137	331188.6928	6245076.815	25.688128	0.70
7	331190.3185	6245078.252	25.451137	-	-	-	-
8	331192.5545	6245080.055	25.522137	331191.9569	6245079.637	25.2169512	0.79
9	331195.2565	6245082.137	25.502137	331194.2898	6245081.217	25.52592626	1.33
10	331193.7565	6245083.575	25.507137	331193.6138	6245083.393	26.0508212	0.59
11	331194.6135	6245087.133	25.419137	331194.8968	6245087.151	25.77236719	0.45
12	331196.1565	6245085.856	25.431137	-	-	-	-
13	331197.4995	6245084.415	25.404137	-	-	-	-
	Average Difference (m)						0.75

Table 3. Difference between Actual Global Coordinate and Predicted Global Coordinate

4.4 Result

The performance and accuracy of the proposed object detection method were assessed using real experimental data from one construction site. The area contains concrete pipes of the same size. From 14 pipes presented, there were 11 pipes (i.e., 78.5%) detected using the proposed methodology. Additionally, the number of pipes, their radius, axis, angle differences and center were automatically detected and are summarized in Table 2. Pipes number 7, 12 and 13 were not detected as the point cloud is very sparse. The results, in the form of an Excel file, served as the foundation for 3D reconstruction and data for material inventory purposes.

The prediction of the global coordinate was taken by transforming the center of each pipe which is a local coordinate into the global coordinate using the transformation matrix from a known reference point. To check the precision, a difference between predicted and actual global coordinates was presented in Table 3. For pipe location tracking, a high degree of precision in the order of millimeters or centimeters is not essential. Detecting and visualizing the pipe's location in the 3D virtual model with an accuracy within a range of 1 meter is deemed adequate. In this study, the average disparity between the actual and predicted coordinates of the pipe was found to be 0.75 meters. Project managers can effectively utilize this information, including the material's location and volume, to facilitate their tasks. This finding aligns with the conclusions of prior research by Cheng et al., (2011), which emphasized that meter-level accuracy is generally sufficient for the majority of construction project tasks.

The use of geometric feature extraction for material tracking in construction projects presents a promising alternative to traditional tag-based methods. By offering advantages over its predecessor, this approach addresses the limitations of tag-based tracking particularly for less valuable precast materials like concrete pipes and boxes, which require a large storage area and have a substantial impact on the success of project activity. By processing the point cloud, one can acquire the number of the precast material, its orientation, and actual coordinates which helps to locate the materials. Although obtaining point cloud data can be expensive, this approach offers significant benefits for a large construction project that already uses point cloud technology for monitoring progress. Furthermore, it takes advantage of additional surrounding point cloud data that is usually overlooked, enhancing the tracking process.

In comparison to conventional tag-based approaches, utilizing 3D point cloud data processing for material tracking presents several advantages. Notably, it eliminates the dependence on specific building infrastructure technologies like Wi-Fi, cellular-based, and Bluetooth, thereby offering a more flexible and adaptable solution. Additionally, this method alleviates the need for manual tagging to the material during a construction project, streamlining the tracking process. It is therefore suitable for both indoor and outdoor use.

5. CONCLUSION

This research focuses on the application of 3D point cloud technology for onsite precast concrete pipe object detection from a mobile laser scanner. The study proposes a material tracking method as an alternative to the conventional tag-based approach commonly employed in current construction projects. A case study was conducted on a site containing concrete pipes, where the proposed method successfully detected 11 out of 14 pipes with a precision rate of 78.5%. Some objects that were not detected are not complete and occluded. Therefore, they cannot be detected as a pipe. Moreover, the predicted location of the pipes was within 0.75 meters of their actual positions, which is acceptable for material tracking in a large construction project.

The newly developed method effectively eliminates the manual labor involved in tagging materials. It eradicates the need for scanning tagged items and significantly reduces the necessity for supporting infrastructure to facilitate signal transfer from the tags. By conducting scans of a construction site using a mobile laser scanner, 3D point cloud data is generated. The proposed method employs geometric feature-based algorithms for object detection to extract meaningful information. It enables the determination of material characteristics such as quantity, real-world location, and orientation in a timely manner. These findings hold significant value for inventory updates and offer valuable insights to project managers for efficient material management. It forms a low-level Digital Twin, capable of converting the construction site conditions into a virtual 3D model. This information can further be incorporated into a 4D model that encompasses both the 3D site project details and the timing of the scans. This data plays a crucial role in controlling on-site materials inventory within the construction site. Additionally, when integrated with the construction progress, this data can be employed to forecast material requirements to support the material ordering process.

Despite the effectiveness of this method, using point cloud data as a material tracking method also has several disadvantages. The point cloud data cannot identify which objects should be in which positions in the main structure. Additionally, some post-processing step required after the scanning makes the proposed method not categorized as real-time. This method also has a high dependency on data quality. If the resulting point cloud is not complete and occluded, then the object cannot be detected properly. The quality of data has a significant role in the success of the method.

For future research direction, there is an option to use a machine learning-based method to complete the point cloud and conduct material detection. However, one particular problem that arises from this approach is the need to have enough data for training. Unfortunately, the construction industry does not have much data for training, especially from the actual construction site data that is usually occluded and sparse. Therefore, the usage of learning transfer from other machine learning training might be useful for construction case studies.

6. ACKNOWLEDGEMENT

The authors are grateful to BPPT (Center for Higher Education Funding), Ministry of Education, Culture, Research, and Technology, Republic of Indonesia, LPDP (Indonesia Endowment Fund for Education) [Grant No. 1253/J5/KM.01.00/2021], and Research Technology and Resilient Intelligent Infrastructure System (RIIS) Hub for funding this research. The laser scanning data provided by the Linke & Linke Surveys are greatly appreciated.

REFERENCE

Alarifi, A., Al-Salman, A., Alsaleh, M., Alnafessah, A., Al-Hadhrami, S., Al-Ammar, M. A., & Al-Khalifa, H. S. (2016). Ultra wideband indoor positioning technologies: Analysis and recent advances. *Sensors (Switzerland)*, *16*(5), 1–36. https://doi.org/10.3390/s16050707

Bienert, A., Georgi, L., Kunz, M., Maas, H. G., & von Oheimb, G. (2018). Comparison and combination of mobile and terrestrial laser scanning for natural forest inventories. *Forests*, *8*(2), 1–25. https://doi.org/10.3390/f9070395

Bosché, F., Guillemet, A., Turkan, Y., Haas, C. T., & Haas, R. (2014). Tracking the Built Status of MEP Works: Assessing the Value of a Scan-vs-BIM System. *Journal of Computing in Civil Engineering*, *28*(4), 1–13. https://doi.org/10.1061/(asce)cp.1943-5487.0000343

Butler, H., Chambers, B., Hartzell, P., & Glennie, C. (2021). PDAL: An open source library for the processing and analysis of point clouds. *Computers and Geosciences*, *148*(August 2020), 104680. https://doi.org/10.1016/j.cageo.2020.104680

Chen, J., Kira, Z., & Cho, Y. K. (2019). Deep Learning Approach to Point Cloud Scene Understanding for Automated Scan to 3D Reconstruction. *Journal of Computing* *in Civil Engineering*, *33*(4), 1–10. https://doi.org/10.1061/(asce)cp.1943-5487.0000842

Cheng, T., & Teizer, J. (2013). Real-time resource location data collection and visualization technology for construction safety and activity monitoring applications. *Automation in Construction*, *34*, 3–15. https://doi.org/10.1016/j.autcon.2012.10.017

Cheng, T., Venugopal, M., Teizer, J., & Vela, P. A. (2011). Performance evaluation of ultra wideband technology for construction resource location tracking in harsh environments. *Automation in Construction*, *20*(8), 1173–1184. https://doi.org/10.1016/j.autcon.2011.05.001

Czerniawski, T., Nahangi, M., Haas, C., & Walbridge, S. (2016). Pipe spool recognition in cluttered point clouds using a curvature-based shape descriptor. *Automation in Construction*, *71*(Part 2), 346–358. https://doi.org/10.1016/j.autcon.2016.08.011

Fischler, M. A., & Bolles, R. C. (1981). Random sample consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography. *Communications of the ACM*, *24*(6), 381–395. https://doi.org/10.1145/358669.358692

Grau, D., Caldas, C. H., Haas, C. T., Goodrum, P. M., & Gong, J. (2009). Assessing the impact of materials tracking technologies on construction craft productivity. *Automation in Construction*, *18*(7), 903–911. https://doi.org/10.1016/j.autcon.2009.04.001

Huang, X., Mei, G., Zhang, J., & Abbas, R. (2021). *A comprehensive survey on point cloud registration*. 1–17. http://arxiv.org/abs/2103.02690

Ibrahimkhil, M. H., Shen, X., Barati, K., & Wang, C. C. (2023). Dynamic Progress Monitoring of Masonry Construction through Mobile SLAM Mapping and As-Built Modeling. *Buildings*, *13*(4). https://doi.org/10.3390/buildings13040930

Irizarry, J., Karan, E. P., & Jalaei, F. (2013). Integrating BIM and GIS to improve the visual monitoring of construction supply chain management. *Automation in Construction*, *31*, 241–254. https://doi.org/10.1016/j.autcon.2012.12.005

Kamari, M., & Ham, Y. (2021). Vision-based volumetric measurements via deep learning-based point cloud segmentation for material management in jobsites. *Automation in Construction*, *121*(October 2020), 103430. https://doi.org/10.1016/j.autcon.2020.103430

Kar, S., & Jha, K. N. (2020). Assessing criticality of construction materials for prioritizing their procurement using ANP-TOPSIS. *International Journal of Construction Management*, *22*(10), 1852–1862. https://doi.org/10.1080/15623599.2020.1742637

Lee, D., & Lee, S. (2021). Digital twin for supply chain coordination in modular construction. *Applied Sciences (Switzerland)*, *11*(13). https://doi.org/10.3390/app11135909

Li, Y., & Chen, J. (2022). Computer Vision–Based Counting Model for Dense Steel Pipe on Construction Sites. *Journal of Construction Engineering and Management*, *148*(1), 1–16. https://doi.org/10.1061/(asce)co.1943-7862.0002217

Lin, J. J., & Golparvar-Fard, M. (2021). Visual and Virtual Production Management System for Proactive Project Management. *Journal of Construction Engineering and Management*, *147*(7). https://doi.org/https://doi.org/10.1061/(ASCE)CO.1943-7862.0002045

Patil, A. K., Holi, P., Lee, S. K., & Chai, Y. H. (2017). An adaptive approach for the reconstruction and modeling of as-built 3D pipelines from point clouds. *Automation in Construction*, *75*, 65–78. https://doi.org/10.1016/j.autcon.2016.12.002

Qiu, Q., Wang, M., Guo, J., Liu, Z., & Wang, Q. (2022). An adaptive down-sampling method of laser scan data for scan-to-BIM. *Automation in Construction*, *135*(April 2021), 104135. https://doi.org/10.1016/j.autcon.2022.104135

Raguram, R., Frahm, J. M., & Pollefeys, M. (2008). A comparative analysis of RANSAC techniques leading to adaptive real-time random sample consensus. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5303 LNCS*(PART 2), 500–513. https://doi.org/10.1007/978-3-540-88688-4_37

Rusinkiewicz, S., & Levoy, M. (2001). Efficient variants of the ICP algorithm. *Proceedings of International Conference on 3-D Digital Imaging and Modeling, 3DIM*, 145–152. https://doi.org/10.1109/IM.2001.924423

Rusu, R. B., Blodow, N., & Beetz, M. (2009). Fast Point Feature Histograms (FPFH) for 3D Registration. *Proceedings - IEEE International Conference on Robotics and Automation*, 3212–3217. https://doi.org/10.1109/ROBOT.2009.5152473

Shin, T. H., Chin, S., Yoon, S. W., & Kwon, S. W. (2011). A service-oriented integrated information framework for RFID/WSN-based intelligent construction supply chain management. *Automation in Construction*, *20*(6), 706–715. https://doi.org/10.1016/j.autcon.2010.12.002

Teizer, J. (2015). Status quo and open challenges in vision-based sensing and tracking of temporary resources on infrastructure construction sites. *Advanced Engineering Informatics*, *29*(2), 225–238. https://doi.org/10.1016/j.aei.2015.03.006

Wang, M., Wang, C. C., Zlatanova, S., Sepasgozar, S., & Aleksandrov, M. (2021). Onsite quality check for installation of prefabricated wall panels using laser scanning. *Buildings*, *11*(9). https://doi.org/10.3390/buildings11090412

Wang, Q., Sohn, H., & Cheng, J. C. P. (2018). Automatic As-Built BIM Creation of Precast Concrete Bridge Deck Panels Using Laser Scan Data. *Journal of Computing in Civil Engineering*, *32*(3), 04018011. https://doi.org/10.1061/(asce)cp.1943-5487.0000754

Xu, Y., & Stilla, U. (2021). Toward Building and Civil Infrastructure Reconstruction from Point Clouds: A Review on Data and Key Techniques. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *14*, 2857–2885. https://doi.org/10.1109/JSTARS.2021.3060568

Zhou, Q.-Y., Park, J., & Koltun, V. (2018). *Open3D: A Modern Library for 3D Data Processing*. http://arxiv.org/abs/1801.09847