Title:

Parametric Comparing for Local Inspection of Industrial Plants by Using As-built Model Acquired from Laser Scan Data

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Introduction:

Owing to the development of technology, industrial plants have become increasingly more complex, often including hundreds of thousands of components; therefore, performing inspection jobs has become more difficult in terms of both as-built inspection and maintenance. Laser scan measurement devices with the accuracy up to 1 cm provide a feasible solution which is fast and reliable; however, the number of studies undertaken in this field is very limited.

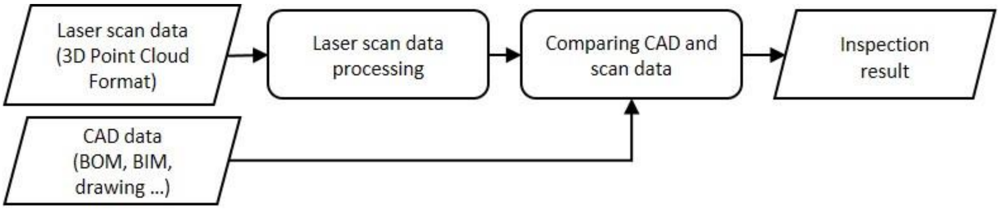

Fig. 1: General process to follow inspecting as-built plants.

Although the approach may differ, most methods that utilize laser scan data for inspecting as-built plants follow a general process as shown in Fig. 1. Because the as-built data acquired from laser scan devices is a 3D point cloud, a processing step is required to extract needed information for the inspection process. Several algorithms are available for this process, including the Random Sample Consensus (RANSAC)-based method, the Skeleton-based method and the normal-based region growing method. These methods are efficient and were validated by many test cases; however, they are limited in their application to real inspection problems. Although the inspection process step is crucial, only a few studies have been conducted in this field. The most common approach is the Iterative Closest Point (ICP)-based method.

Related works

Related works are divided into two main groups: works on as-built modeling of industrial plants by using laser scan data and works on inspection of as-built plants by using laser scan data. Most research on algorithms and methods for processing the laser scan data were applied for as-built modeling ([4-6],[8],[13],[14]). The utilization of laser scan data for as-built inspection of industrial plants is available in terms of dimensional quality control as well as building progress tracking ([1],[7],[9],[10],[11],[12]). Although a considerable amount of research has been conducted by other researchers, most of those works are separate and do not give engineers a complete solution for their real problems.

Main idea:
In this research, we apply a technique in the engineering problems solving method called "divide and conquer". Fig. 2 indicates the overview of our method.

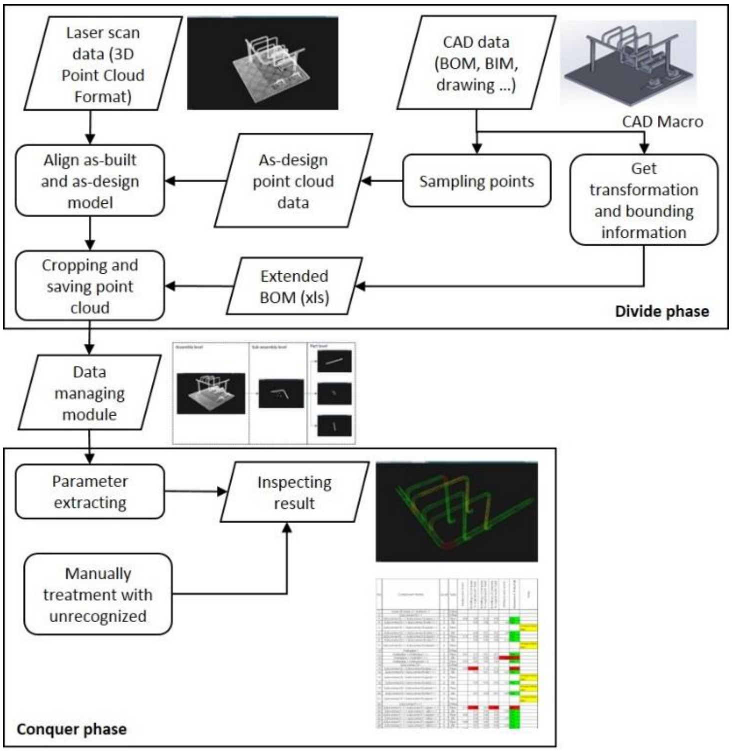

Fig. 2: Overview of our method.

Using this technique, our process is divided into two main part: "divide" part and "conquer" part. In the "divide" part. Firstly, the local region of interest (ROI) will be determined with both CAD and scan data. Both models then are aligned by using the "origin component". Based on the position and bounding information acquired from the CAD data via API, the point cloud data acquired from laser scan devices is segmented and saved into a data management module. This "divide" process not only splits the complex model into simpler models for easier processing but also creates a data structure that helps the later process to be executed systematically. In the "conquer" part, we mainly focus on two classes of components that belong to the piping system: the straight pipe class and the connecting component class. Therefore, two different algorithms are applied to deal with them. The RANSAC algorithm is applied to recognize and extract cylinder parameters of pipe components in the straight pipe class, and the ICP algorithm is utilized to deal with components in the connecting component class. In the comparison process, if wrong as-builts are detected, angle error values and translation error values are calculated to determine how different the as-built model and the as-designed are. Results are then written into an XLS format file to make it easier and more convenient for customers to use. In this work, we have implemented the solution by using the Points Cloud Library [2]. The approach is validated through two test cases.

Getting position and bounding information from CAD file using macro
Getting information needed from CAD file is one of the most important parts of this approach. Normally, parts' positions are defined by their transform matrix of their origin with the origin of assembly environment and parts' bounding boxes are defined in their own part environment. Therefore, to determine the position and bounding box of a part, which will be used to define cropping box in the

point cloud processing application, a macro was written to get this information and write to a table called "The Extended Bill of Material (BOM)" in XSL format. As mention above, a data management module similar with the data management structure of CAD software will be created, the level of each part and its corresponding parent sub-assembly will also be got and save to Extended BOM.

Cropping and saving point cloud

Using the information obtained from the CAD file, a cropping box is defined for each component in the extended BOM, and the points cloud in the cropping region is segmented. The point cloud data corresponding to each component is then saved into the data structure that has been created in the previous step, along with their inspection parameters (radius, direction parameters, etc.) As mentioned above, to process the point cloud data more efficiently and systematically, a data management module should also be created.

Extracting parameter and parametric comparing

After being cropped, the point cloud corresponding to each component will be sent to a processing process to extract the parameter needed for parametric comparing. If the component is classified as straight pipe component, sequential RANSAC algorithm will be utilized to extract cylinder parameter. Consequently, based on information got from extracting parameter process, transformation matrix between as-built and as-designed model will be calculated to determine how different in position as-built and as-designed models are and of course radius and length value will be used for size inspecting. In the case that component type is connecting component, ICP algorithm will be applied to deal with the parametric comparing problem. Firstly, CAD model will be transferred to Point cloud model by sampling points on part's surface. Consequently, CAD model and Point cloud model will be brought into the same environment at their own positions. ICP fitness score will tell us how match two models are and the ICP transform matrix will provide the information of difference in position. If fitness score is too high, it means that two models do not match and there must be a wrong installation of elbow components.

Dealing with wrong install components

After the completion of the automatic parametric comparing process, any remaining unrecognized components are treated manually. Because most of the piping components are "sweep"-type components, we suggest a skeleton-based method as presented in [3].

Experimental study:

Case study 1: Rapid prototype data

To validate the approach, a simple test data was generated by using a 3D printer to create the as-built model and using and a small laser scanner to generate the 3D point cloud. The method workflow was presented in Fig. 9. The advantage of this method is that we can acquire both scan and CAD data needed to test our approach. By observing the result indicated in Fig. 11, it can be seen that the proposed approach works very efficiently with 100% recognition of straight piping component (with direction angle error < 10°). However, the size of the model is small and its level of complexity is also low; therefore, a test case with larger dimensions and a higher level of complexity should be conducted to validate the approach.

Case study 2: Using method with simulated data

Because it is difficult to incorporate both laser scan data and CAD data of real complex industrial plants due to technology secrets, we used simulated data to validate our approach in a more complex term. First, the as-designed CAD model is converted into the point cloud model by sampling points on the components' surface. Then a stochastic process is performed to create simulated laser scan data. We assume that the laser scan technology tolerance fit the normal distribution error function; therefore, the coordinates of each point in the cloud are recalculated, as shown in Eqn. (4.1).

$$\begin{aligned} x_i &= x_i + N(0,\sigma^2) \\ y_i &= y_i + N(0,\sigma^2) \\ z_i &= z_i + N(0,\sigma^2) \end{aligned} \tag{4.1}$$

where (x_i, y_i, z_i) is the coordinate of each point in the Cartesian coordinate system and $N(0, \sigma^2)$ is the normal distribution error function.

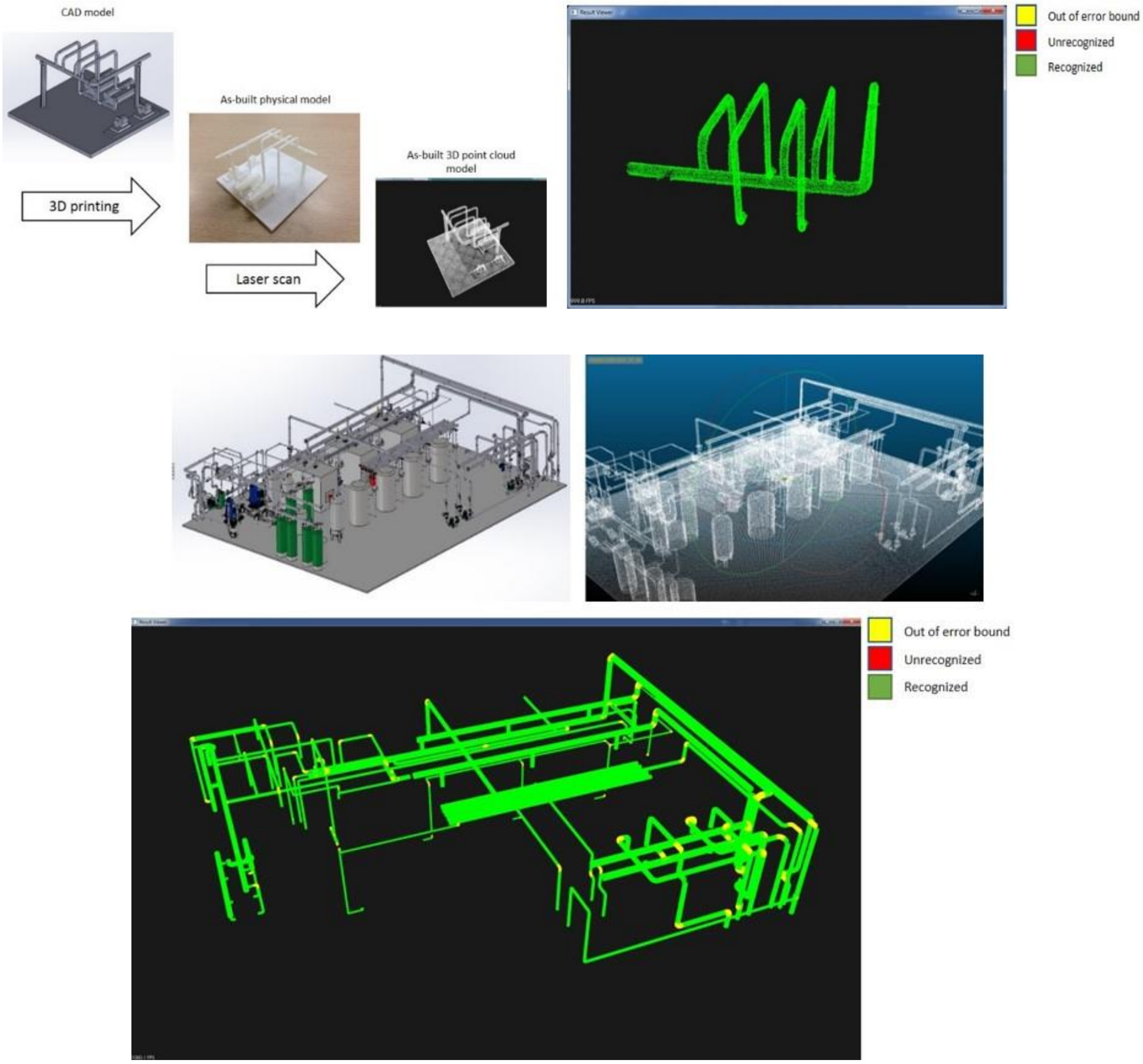

Fig. 3: An experimental study.

It is clear from the testing result that the percentage of correctly recognized piping components (direction angle error < 10°) is high (97.05%); however, there were still some cases wherein the algorithm could not recognize the piping part owing to a lack of data points (in the case wherein the piping part is too small) or the presence of multiple models in the same area (RANSAC algorithm is not robust when there is more than one model in estimation area). On the other hand, the ICP algorithm developed for standard connecting parts did not provide a stable result in the test case with simulated data. It can be seen from the testing result that even though the position of the part is correct, the testing result shows considerably more different magnitudes of translation than expected. This is due to the characteristics of the ICP algorithm. Firstly, the ICP algorithm is very sensitive to noisy data. In a large scale, as in the model in test case 2, we can observe that the effect of the noise level on the magnitude of the error is larger than that in test case 1. In addition, as the ICP algorithm is based on minimizing the error function, the choice of matching points also has an impact on the result. To solve this problem, better ICP variants should be used (point-to-mesh matching, point-to-surface matching) or a better match determination criterion should be applied. Finally, before applying the ICP algorithm, a calibration process can be executed to determine the level of error. Nevertheless, the result has proved that this approach is promising, reliable, and practical enough to be applied to real problems.

Conclusion:

This paper proposes a complete solution that uses laser scan data for inspecting complex industrial plants. In our approach, with the support from the CAD information obtained by using CAD's API, point cloud processing algorithms have worked very efficiently with high accuracy. Validation results have proved the practicality and reliability of the approach. However, there is still scope for developing a more robust variant of the ICP algorithm as well as studying the relationship between RANSAC's initialization threshold and the quality of input data; these will be considered in our future works.

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References:

[1] Bosche, F.: Automated recognition of 3D CAD model objects in laser scans and calculation of as-built dimensions for dimensional compliance control in construction, Advanced Engineering Informatics, 24(1), 2010, 107-118. https://doi.org/10.1016/j.aei.2009.08.006

[2] http://pointclouds.org/documentation:

[3] Huang, H.; Wu, S.; Cohen-Or, D.; Gong, M.; Zhang, H.; Li, G.; Chen, B.: L_1-Medial Skeleton of Point Cloud, ACM Trans Graph, 32(4), 2013, 1-8. https://doi.org/10.1145/2461912.2461913

[4] Kawashima, K.; Kanai, S.; Date, H.: As-built modeling of piping system from terrestrial laser-scanned point clouds using normal-based region growing, Journal of Computational Design and Engineering, 1(1), 2014, 13-26. https://doi.org/10.7315/JCDE.2014.002

[5] Kawashima, K.; Kanai, S.; Date, H.: Automatic recognition of a piping system from large-scale terrestrial laser scan data, Int Arch Photogramm Remote Sens Spatial Inf Sci, XXXVIII-5/W12(2012, 283-288. https://doi.org/10.5194/isprsarchives-XXXVIII-5-W12-283-2011

[6] Kawashima, K.; Kanai, S.; Date, H.: Automatic recognition of piping system from laser scanned point clouds using normal-based region growing, ISPRS Ann Photogramm Remote Sens Spatial Inf Sci, II-5/W2(2013, 121-126. https://doi.org/10.5194/isprsannals-II-5-W2-121-2013

[7] Kim, C.; Son, H.; Kim, C.: Automated construction progress measurement using a 4D building information model and 3D data, Automation in Construction, 31(2013, 75-82. https://doi.org/10.1016/j.autcon.2012.11.041

[8] Lee, J.; Son, H.; Kim, C.; Kim, C.: Skeleton-based 3D reconstruction of as-built pipelines from laser-scan data, Automation in Construction, 35(2013, 199-207. https://doi.org/10.1016/j.autcon.2013.05.009

[9] Nahangi, M.; Haas, C. T.: Automated 3D compliance checking in pipe spool fabrication, Advanced Engineering Informatics, 28(4), 2014, 360-369. https://doi.org/10.1016/j.aei.2014.04.001

[10] Shih, N. J.; Huang, S. T.: 3D scan information management system for construction management, Journal of Construction Engineering and Management-Asce, 132(2), 2006, 134-142. https://doi.org/10.1061/(ASCE)0733-9364(2006)132:2(134)

[11] Shih, N. J.; Wang, P.-H.: Point-Cloud-Based Comparison between Construction Schedule and As-Built Progress: Long-Range Three-Dimensional Laser Scanner's Approach, Journal of Architectural Engineering, 10(3), 2004, https://doi.org/10.1061/(ASCE)1076-0431(2004)10:3(98)

[12] Son, H.; Bosche, F.; Kim, C.: As-built data acquisition and its use in production monitoring and automated layout of civil infrastructure: A survey, Advanced Engineering Informatics, 29(2), 2015, 172-183. https://doi.org/10.1016/j.aei.2015.01.009

[13] Son, H.; Kim, C.; Kim, C.: 3D reconstruction of as-built industrial instrumentation models from laser-scan data and a 3D CAD database based on prior knowledge, Automation in Construction, 49(2015, 193-200. https://doi.org/10.1016/j.autcon.2014.08.007

[14] Son, H.; Kim, C.; Kim, C.: Fully Automated As-Built 3D Pipeline Extraction Method from Laser-Scanned Data Based on Curvature Computation, Journal of Computing in Civil Engineering, 29(4), 2015, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000401