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# Parametric comparing for local inspection of industrial plants by using as-built model acquired from laser scan data

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**ABSTRACT**

Owing to the increasing complexity of modern industrial plants such as naval and ocean plants and industrial factories, it is very urgent to have an efficient method for inspecting such structures in terms of as-built inspection and maintenance. In this paper, we propose a method called 'parametric comparing' which utilizes laser scan technology to support the inspection process of industrial plants. In our approach, component parameters are extracted from laser scan data and then compared with their as-designed parameters. The results of this process can support engineers to assess the quality of the as-built model. Because most components in an industrial plant could be classified as piping elements, we focus on two classes of components: straight pipes and connecting components. Validations on two prototype data sets have proved that our approach is practical and fit for industrial application.

## 1. 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. Son et al. [17] have reported that laser scan technology can support engineers in both progress tracking and dimensional quality control of MEP (Mechanical, Electrical, and Plumbing) work, which is the main part of industrial plants construction. However, the number of studies undertaken in this field is very limited.

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, there are limited

in the number of works which conduct those method to solve inspection problems.

In term of inspection by utilizing laser scan technology. although it is crucial, only few studies have been made. The most common approach is the Iterative Closest Point (ICP)-based method. Overall, it can be observed that a fully developed solution to deal with as-built inspection problems is not available; therefore, the creation of a practical solution which is the purpose of this research is needed.

## 2. Related works

### 2.1. As-built modeling of industrial plants by using laser scan data

Most research on algorithms and methods for processing the laser scan data were applied for as-built modeling. Son and his colleagues in a series of research studies ([11],[18],[19]) have proposed several methods for automatic reconstruction of as-built pipelines, such as the Skeleton-based method or a method based on the combination of 3D point cloud data with 3D CAD database. Another notable work is a series of research studies on laser scan data processing, performed by Kawashima and his colleagues ([7–9]). In this series, the authors proposed
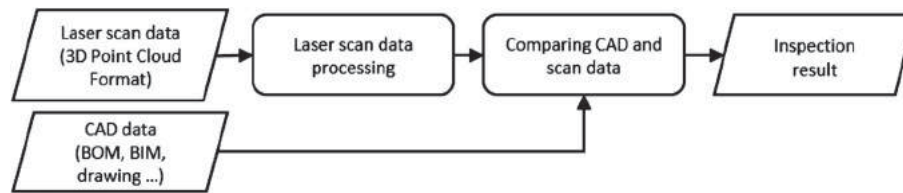
**Figure 1.** Inspection of industrial plants using laser scan data process overview.

an as-built modeling method based on the normal region growing algorithm. A few such similar methods are the works conducted by Patil et al. [13] and Holi et al. [3] with the combination between normal-based region growing, segmentation, and cylinder fitting algorithms. Last but not least, Chaperon et al. [2] suggested a random sampling method in combination with the utilization of the gaussian image which is also very effective in recognizing and extracting cylinder parameters. Overall, although the main purpose of these works is reconstruction for inspection, the term "inspection" was not mentioned, and their work needs to be extended.

### 2.2. Inspection of as-built plants by using laser scan data

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 [17]. In order to track the construction progress of the industrial plant, the 4D model (3D Point Cloud + time) was mostly used ([10],[15],[16]). Shin et al. in [16] used laser scan devices to acquire 3D point cloud data and bring it to a time-based 3D monitor process. Another approach involves using 4D BIM and 3D Point Cloud as in the work by Kim et al. [10]. In this work, along with utilizing matching algorithms to determine the as-built status, the authors also examined the as-built status of each component to validate the tracking result.

With regard to dimensional quality control of piping systems, Nahangi et al. [12] have dealt with the problems by using the ICP algorithm for registration and then assessing the pipe condition by detecting and quantifying existing deviations. Another approach was proposed by Bosche et al. in [1]. In this approach, the authors mainly used a registration algorithm to deal with inspection problems. First, CAD and scan models were aligned using ICP algorithms. After the object recognition process, the difference between the CAD and as-built fine registration model of each component was estimated. The result of this process provides the information about the difference between the as-built and the as-designed model.

Despite of a considerable amount of research conducted by other researchers providing reliable solutions for as-built inspection problems of industrial plants, works in term of utilizing laser scan technology for inspecting such huge and complex industrial plan are separate; therefore, they do not give engineers a complete solution for their problems.

## 3. Methodology

### 3.1. Overview

An overview of proposed method is given in Fig. 2. In this research, we apply a technique in the engineering problems solving method called "divide and conquer". 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 incorrect 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 [4]. The approach is validated through two test cases mentioned in 4.2 and 4.3.
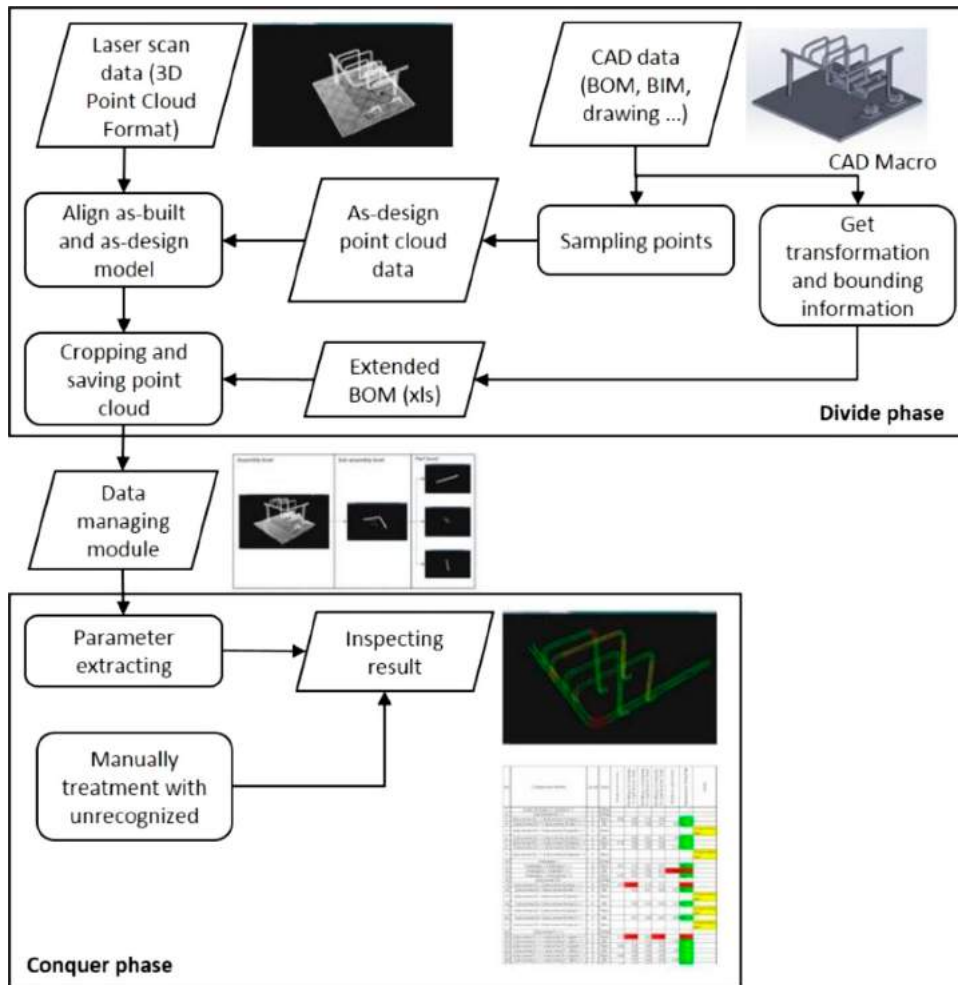
**Figure 2.** Overview of the proposed method.

### 3.2. Divide phase

#### 3.2.1. Obtaining position and bounding information from CAD file using macro

Obtaining information needed from the CAD file is an essential part of this approach. Generally, in a CAD system, parts' positions are defined by the transform matrix of their origin with the origin of the assembly document, and parts' bounding boxes are defined in their own part documents. Therefore, to determine the position and bounding box of a part, which is used to define cropping box in the points cloud processing application, it is needed to obtain this information from the CAD model. The API provided in most of the common CAD systems allows us to access the CAD data structure directly to obtain this information. In this work, a macro was written using API to obtain this information and write it to a table called "the extended Bill of Material (BOM)" in XLS format (Fig. 3.).

#### 3.2.2. Cropping and saving points 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 (see Fig. 4 for more details). 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 be created. The data structure of the point cloud processing application is also presented in Fig. 3.

### 3.3. Conquer phase

After being cropped, the point cloud corresponding to each component is processed to extract the parameter
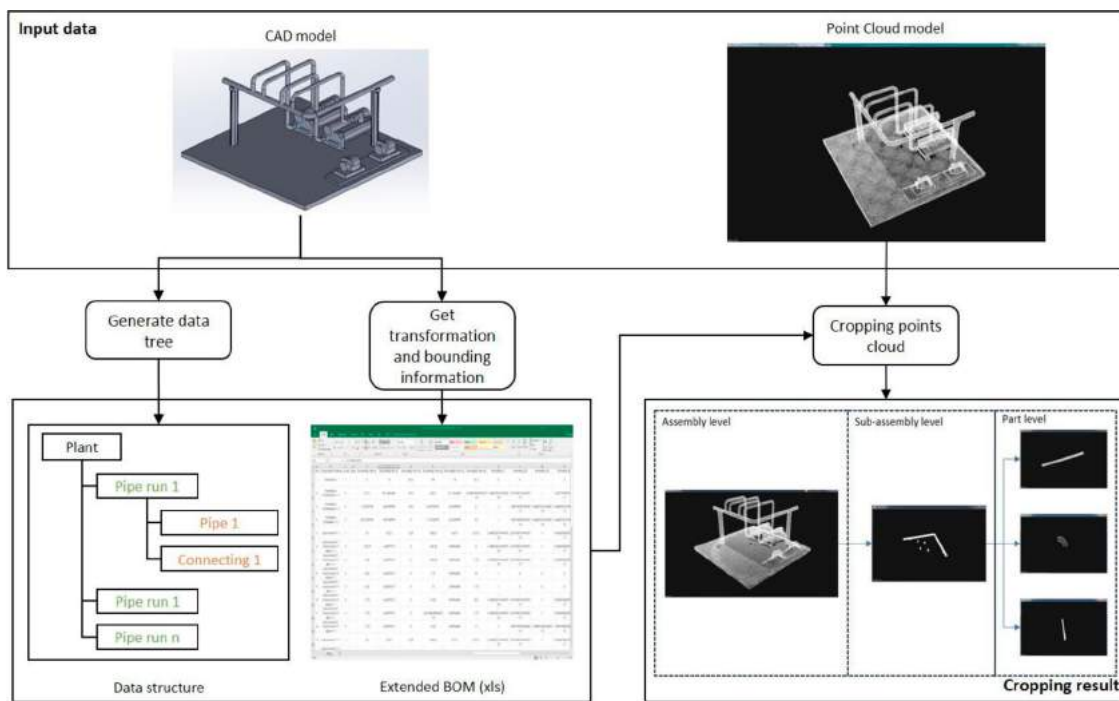
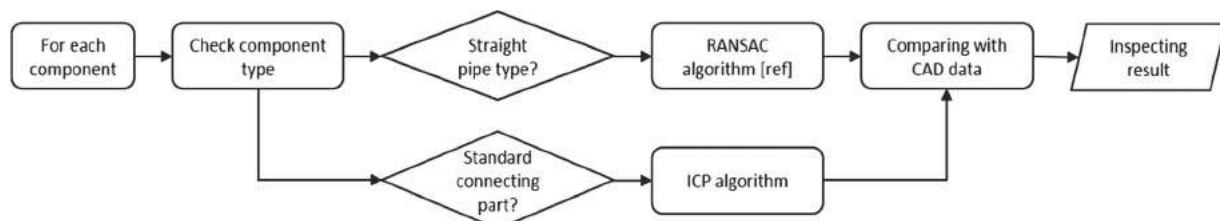**Figure 3.** Cropping and saving corresponding point cloud.



**Figure 4.** "Conquer" phase workflow.

needed for parametric comparing. An overview of the workflow is illustrated in Fig. 4.

### 3.3.1. More efficient RANSAC algorithm

If the component is classified as "straight pipe component", the RANSAC algorithm, proposed by Schnabel et al. [14], is utilized to extract cylinder parameters (Fig. 5.). After applying the RANSAC algorithm to obtain cylinder parameters (centerline direction vector, points on the centerline, radius), the direction vector is compared with that of the as-designed model for direction inspection, and the radius information will be used for checking radius.

### 3.3.2. Utilization of ICP algorithm to find difference matrix

In the case that the component type is "connecting component", the ICP algorithm is applied to deal with the parametric comparing problem. Firstly, CAD models are transformed into point cloud models by sampling points
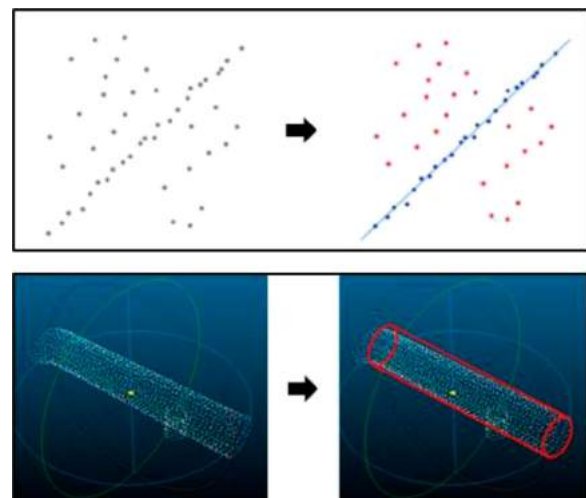


**Figure 5.** RANSAC algorithm applied for cylinder model fitting.

on components' surface. Consequently, the CAD model and the point cloud model are brought into the same environment. The ICP algorithm is then applied to check
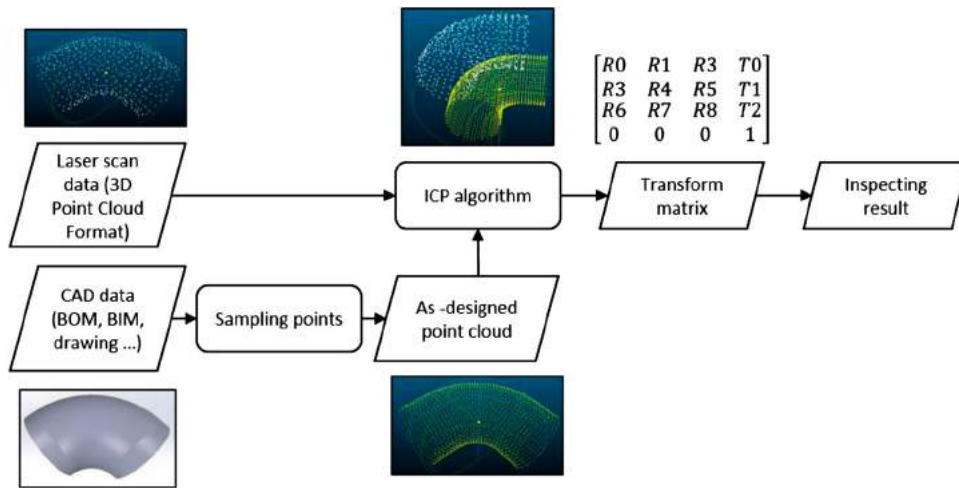
**Figure 6.** Applying ICP algorithm to estimate the difference in position of connecting components.
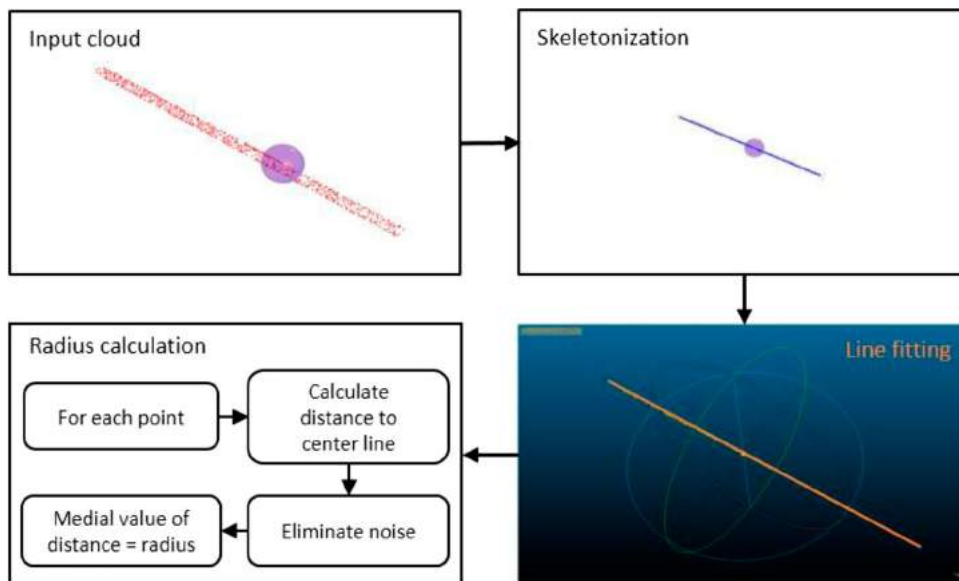


**Figure 7.** Manual treatment process for unrecognized and incorrectly recognized components.

the matching of both models. The result ICP transformation matrix, which includes rotation and translation magnitudes, provides the information regarding the difference in positions of the two models. If the fitness score is over a threshold, defined by users, it implies that the two models do not match and there must be an incorrect installation of connecting components. Fig. 6 shows the workflow of utilizing the ICP algorithm in the parametric comparing process.

### 3.4. Manual treatment of unrecognized piping 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 shown in Fig. 7.

First, the skeleton of point cloud is estimated using the $L_1$ - Medial Skeleton method proposed in [6]. Consequently, 3D line fitting algorithms (RANSAC, Least Square Fitting Method, etc.) are applied to estimate the centerline of the component. After eliminating noisy data, the radius of the piping component is estimated by Eqn. (3.1) and Eqn. (3.2).

$$r = \frac{\sum_{i=1}^{n} d_i}{n} \tag{3.1}$$

$$d_i = \frac{|ax_i + by_i + cz_i + d|}{\sqrt{(a^2 + b^2 + c^2)}} \tag{3.2}$$

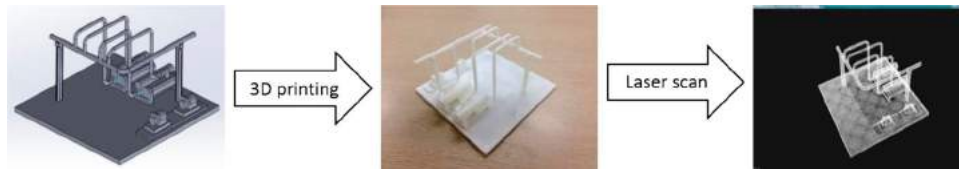where $ax + by + cz + d = 0$ is the equation of the plane which includes the estimate centerline, having the

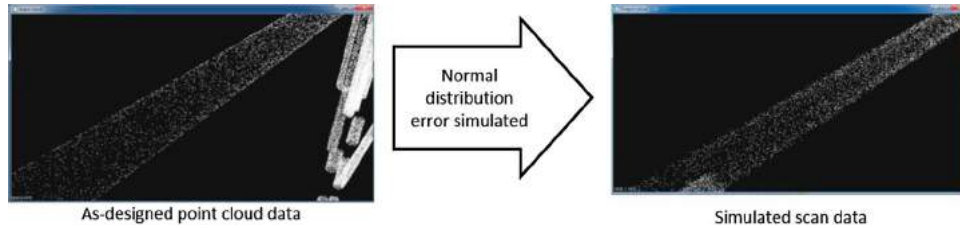**Figure 8.** Small-scale scan data generation process.



**Figure 9.** Simulated data generation process.

greatest distance to the candidate point and $(x_i, y_i, z_i)$ is the coordinate of each candidate point in the Cartesian coordinate system.

The direction and radius parameters are then used to compare with those of the as-designed model to assess the dimensional quality of the piping components.

## 4. Experimental study

### 4.1. Testing data

#### 4.1.1. Scan data of a small-scale piping system
In order to validate the approach, a simple test data was generated by using a 3D printer to create the as-built model and using a small laser scanner to generate 3D point cloud. The method workflow was presented in Fig. 8. The advantage of this method is that we can acquire both scan and CAD data needed to test our approach.

#### 4.1.2. 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. The method for generating testing data is shown in Fig. 10.

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).

$$x_i = x_i + N(0, \sigma^2)$$
$$y_i = y_i + N(0, \sigma^2) \qquad (4.1)$$
$$z_i = z_i + N(0, \sigma^2)$$

**Table 1.** Properties of the test case 1 model.

| Properties | Value |
|---|---|
| Model dimensions | $150 \times 150 \times 85$ *(mm)* |
| Number of components | 45 |
| Number of straight pipe components | 18 |
| Number of connecting components | 13 |
| Number of points in cloud | $\sim 200{,}000$ points |

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.

The result of this process is shown in Fig. 9. This simulated data provides us with a test data set that is quite close to the real data and can be used for validating our approach.

### 4.2. Case study 1: validating with small-scale piping system

To validate the efficiency of the approach, we first applied it to small-scale data generated by the method presented in 4.1.1. The characteristics of the model are shown in Tab. 1.

By observing the result indicated in Fig. 10, it can be seen that the proposed approach works very efficiently



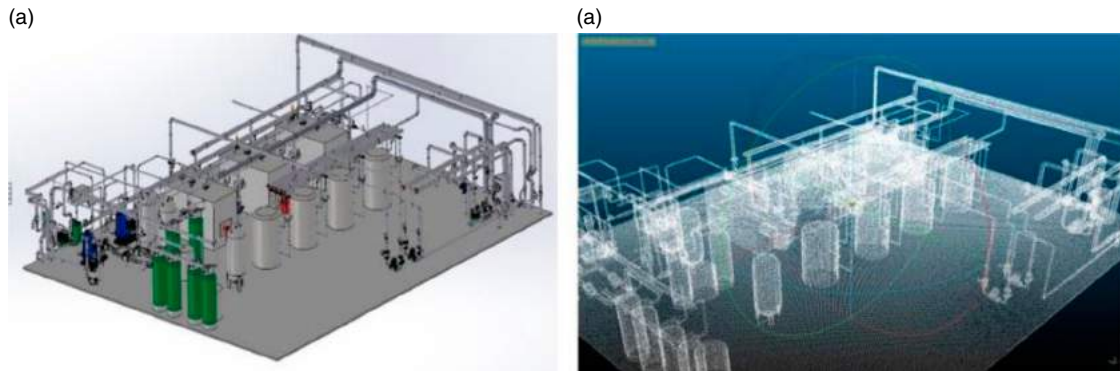**Figure 10.** Validating result with the rapid-prototype-based model.

(a)                                    (a)



**Figure 11.** Simulated data used for validating the approach: (a) CAD model, (b) Scan model.

**Table 2.** Properties of simulated model.

| Properties | Value |
| --- | --- |
| Model's dimension | $14 \times 11 \times 2$ (m) |
| Deviation of error function | 1 (cm.) |
| Number of components | 2080 |
| Number of straight pipe components | 408 |
| Number of connecting components | 266 |
| Number of points in cloud | ∼ 3,000,000 points |



**Figure 12.** Inspection result obtained from simulated data.

**Table 3.** Results of essential parameters after validating the approach with simulated data.

| Observed parameters | Value |
| --- | --- |
| Number of straight piping components | 408 |
| Number of unrecognized pipes | 0 (0%) |
| Number of incorrectly recognized pipes | 12 (2.85%) |
| Number of correctly recognized pipes | 396(97.05%) |
| Number of connecting components | 185 |
| Mean translation error | 186.225 (mm) |
| Mean rotation angle error around x-axis | 0.0007° |
| Mean rotation angle error around y-axis | 0.0002° |
| Mean rotation angle error around z-axis | 0.001° |

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 higher level of complexity should be conducted to validate the approach. Overall, the testing result showed that the approach is promising and practical.

### 4.3. Case study 2: validating with simulated data

In order to check if the approach can be applied to solve real problems, we applied it to a fairly complex boiler plant model obtained from [5]. Fig. 11 and Tab. 2 indicate the properties of the simulated model.

The validating result is presented in Fig. 12 and Tab. 3. 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 or recognize incorrectly 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). In addition, the RANSAC algorithm is highly affected by the pre-set threshold (distance threshold $\tau$ and the angle threshold $\theta$), and the determination of these values depends on the quality of input data (density, level of noise,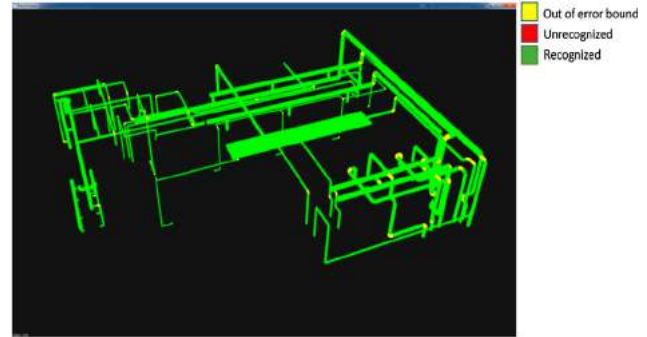 etc.). Therefore, pre-setting similar values for every component seems unsuitable. However, the relationship between the quality of input data and the initialization threshold values of the RANSAC algorithm was not studied completely. Hence, a future work in this subject should be conducted to make the algorithm more robust.

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 (the mean translation error is 186.225 (mm) (Tab. 3) while the expected is lower than 50 (mm)).

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; this leads to the instability in the calculation result. In addition, as the ICP algorithm is based on minimizing the error function (Eqn. (4.2).), the choice of matching points (the pair of $p_i$ and $y_i$) also has an impact on the rotation matrix $\boldsymbol{R}$ and the translation vector $\boldsymbol{t}$.

$$e(R, t) = \frac{1}{N_p} \sum_{i=1}^{N_p} (\|(Rp_i + t) - y_i)\|)^2 \qquad (4.2)$$

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. Another solution could be increasing the density of the point cloud; however, this will lead to longer processing times and would not be suitable for applying to a real situation. 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.

## 5. 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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