# KNOWLEDGE-BASED APPROACH FOR 3D RECONSTRUCTION OF AS-BUILT INDUSTRIAL PLANT MODELS FROM LASER-SCAN DATA

H. Son, C. Kim, and *C. Kim
*Chung-Ang University*
*221 Heukseok-dong, Dongjak-gu*
*Seoul, Korea 156-756*
*(*Corresponding author: changwan@cau.ac.kr)*

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## ABSTRACT

The three-dimensional (3D) reconstruction of as-built industrial plant models plays an important role in revamping planning, maintenance planning, and preparation for dismantling during the lifecycle of industrial plants. Recently, the 3D reconstruction of existing industrial plants was conducted using laser-scan data to make surveying processes more efficient. However, the current 3D reconstruction process from laser-scan data is still limited due to the need for significant human assistance. Although a great deal of effort has been made to efficiently reconstruct 3D as-built industrial plant models, the presence of objects—such as equipment, pipelines, and valves of different sizes and shapes—in existing industrial plants significantly increases the complexity of laser-scan data and makes automating the reconstruction process more challenging in practice. The purpose of this study is to propose a knowledge-based approach for the 3D reconstruction of as-built industrial plant models from unstructured laser-scan data. First, pipelines were extracted from laser-scan data based on surface curvature information and knowledge about pipelines' sizes from existing piping and instrumentation diagrams (P&ID). Once entire pipelines were extracted, they were modeled based on skeleton features. Then, the remaining objects were clustered and grouped separately via the region grouping process. Afterward, clustered objects were retrieved and modeled based on global feature-based matching from the 3D database. Finally, the resulting model was checked to ensure that it was well-reconstructed according to the information regarding the relationships among objects abstracted from the existing P&ID. The preliminary results on actual industrial plants show that integrating knowledge into the reconstruction steps played an important role in the proposed approach and that this approach obtained accurate as-built industrial plant models from unstructured laser-scan data. The proposed approach could be successfully utilized to assist in many applications during the lifecycle of industrial plants.



## KEYWORDS

As-built 3D model, Laser-scan data, Ping and instrumentation diagram, Plant database, Plant information model


## INTRODUCTION

The three-dimensional (3D) reconstruction of as-built industrial plant models is an important task in many fields of application, as it allows for the generation of digital representations of the current statuses of existing plant facilities. Various applications demand realistic as-built 3D industrial plant models (Veldhuis and Vosselman, 1998; Tangelder et al., 1999; Ermes, 2000). For revamping purposes, planning and analyzing in a 3D virtual reality world is much more efficient than relying on 2D information from drawings or photographs (Chunmei et al., 2009; Kawashima et al., 2011). For maintenance, accurate 3D industrial plant models are indispensable for developing strategies in operational situations. Preparations for dismantling also benefit from realistic 3D industrial plant models (Veldhuis and Vosselman, 1998).

Traditional approaches are largely based on manual interaction and interpretation because with the increasing complexity of objects, user understanding is inevitable and paramount for achieving reliable results. However, the manual creation of as-built industrial plant models is undoubtedly a rather slow and expensive process because of the enormous number of objects involved and the complexity of their shapes. With the increasing data complexity, an accurate validation of modeled objects, again, becomes more difficult, which is why traditional approaches tend to be impractical. Presently, most of the supporting algorithms are data-driven and concentrate on specific object features, being accessible to numerical models (see, for example, Rabbani et al., 2006). Using these models, which usually represent geometrical features, the laser-scan data can be analyzed successfully when deals with objects with low complexity, such as planes or cylinders, but this approach reaches its limits as objects become increasingly complex. At that point, purely numerical approaches cannot sufficiently model real-world applications.

This problem can be effectively solved with additional supplementary and guiding information. For example, if the types and numbers of equipment and the valves as well as sizes and numbers of pipelines to be modeled are known, the reconstruction process can proceed in an easier, faster, and more reliable manner. Whiles, if such information about the scene to be modeled is lacking, it is sometimes difficult to process and reconstruct each object in a fully automated manner. Integration of that information into the reconstruction process allows for the automated process to be supported instead of requiring one to rely merely on human interaction (Tang et al., 2010). In the case of industrial plants, such information can be derived from the piping and instrumentation diagrams (P&IDs) as well as from the given industrial plants' 3D databases. The P&ID is the overall document used to define the process; it contains an instrument list, a pipeline list, and information about their functional interrelationships. An industrial plants' 3D database allows the dimensions of each instrument to be drawn. During the reconstruction process, these types of knowledge provide relevant guiding information that helps to accelerate the analysis and identification processes.

The aim of this study is to propose a knowledge-based approach that automatically reconstructs as-built industrial plant models from unstructured laser-scan data. The remainder of the paper is organized as follows. An overview and details of the proposed approach for the 3D reconstruction of as-built industrial plant models are provided in Section 2. In Section 3, provided is an explanation about potentially helpful data sources for prior knowledge along with the reason for why looking for objects in the reconstruction process might still be necessary based on prior knowledge. In Section 4, experimental results are provided. Finally, conclusions and recommendations for future research are given in Section 5.

## INTEGRATION OF KNOWLEDGE INTO RECONSTRUCTION STRATEGY

Our approach aims to reconstruct detailed industrial plant models from laser-scanned industrial plants using a largely automatic process. Laser scanning systems can record industrial plants with a density of hundreds of laser points per square meter or more, which is obviously dense enough to recover small details. Laser-scanned data acquired from the plant facility can be incomplete because of complex occlusion (Johnson et al., 1997; Rabbani et al., 2006; Masuda and Tanaka, 2010), or they can be affected by noise due to the reflective surfaces of the instrument and the pipelines. In addition, some applications provide only single scans of data; thus, part—and at most half—of the objects' surface is acquired (Zheng and Moskal, 2012). In this situation, deciding where the equipment, valves, and pipelines are located and even reconstructing their geometry and topology is challenging.

The core idea employed in the proposed approach is that equipment, valves, and pipelines in the industrial plants have a relationship. The contextual constraints consider that the geometric relationships among each part can be extracted from the P&ID. By using this supplementary and guiding information, the proposed approach allows us to reconstruct as-built industrial plant models from laser-scan data in a practical manner. Object knowledge, which is used in the proposed approach, is classified into three categories: scene, geometric, and topologic knowledge. In our case, the knowledge information is drawn from the existing P&ID and the industrial plant' 3D database. First, the scene knowledge contains all relevant object elements that might be found within that scene. In the case of industrial plants, this comprises a list of elements such as equipment, valve, and pipeline. Geometric knowledge formulates geometrical characteristics of the object elements' physical properties. In our case, this information is represented by a few coordinates that express a bounding box containing the element. Topologic knowledge represents adjacency relationships among scene elements. In the case of an industrial plant, for example, a topological relationship between a davit and a pipeline can be defined, as both must be connected. The proposed approach for the 3D reconstruction of as-built industrial plant models, which is based on the scene knowledge, geometric knowledge, and topologic knowledge, is illustrated in Figure 1.

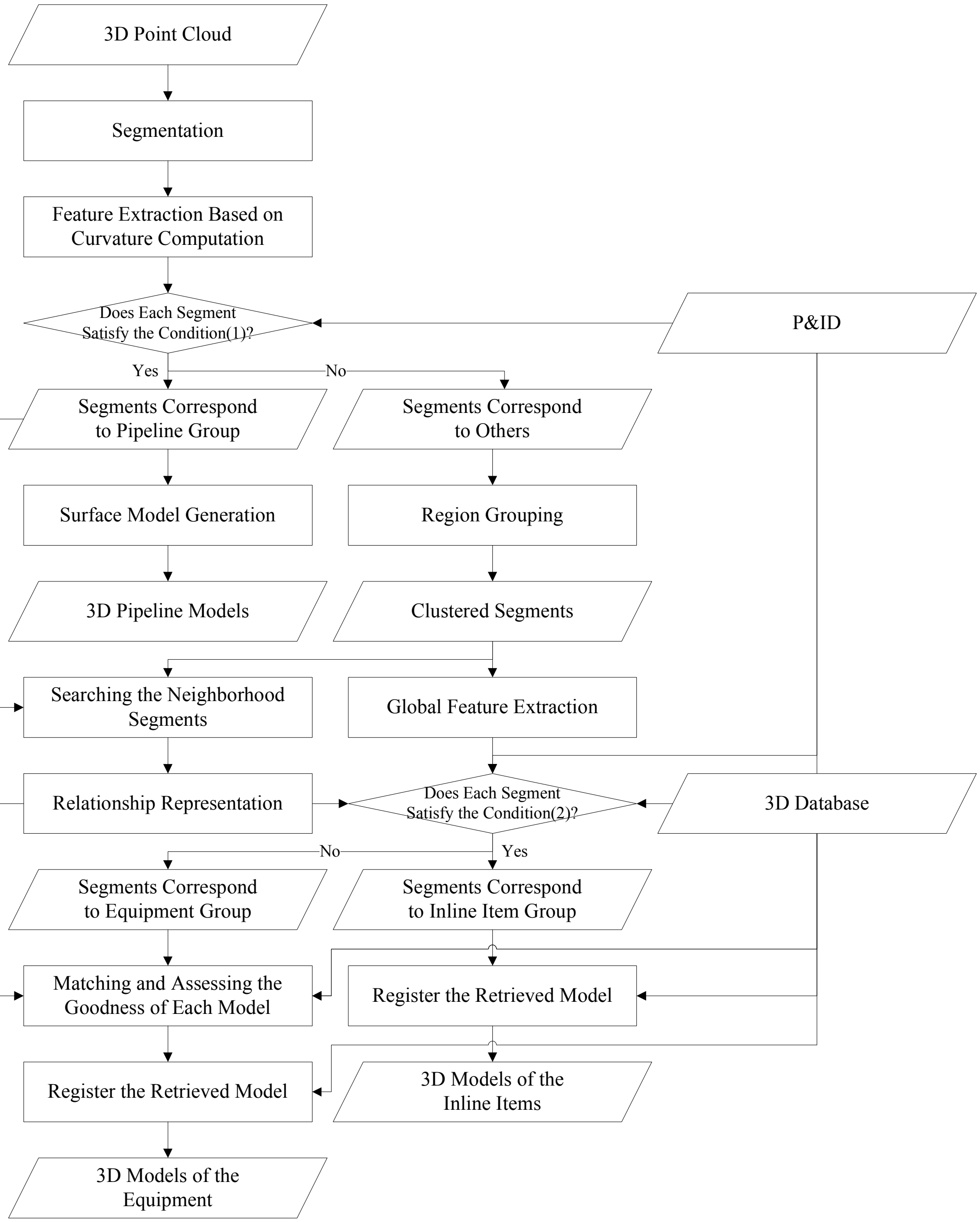



Figure 1 – Proposed knowledge-based approach for 3D reconstruction of as-built industrial plant models

The reconstruction of industrial plants begins with segmentation of the 3D data at the intersections of the pipelines and other industrial parts so as to first extract the pipelines. The segmentation step uses a criterion based on a combination of surface normal similarity and spatial connectivity, which is defined by Rabbani et al. (2006) as a smoothness constraint. Usually, the extracted pipelines have cylindrical surfaces. The pipeline extraction step is based on computing curvature at certain points on the objects' surfaces in order to decide if they have cylindrical surfaces with the pipelines' geometric knowledge (radii) drawn from the P&ID. This method requires only one-third of an object's surface for computing its radius. Then, based on the results of the curvature computation, the objects that belong to the pipelines are identified, and all others are regarded as equipment or valves. For details regarding the as-built 3D pipeline extraction step, please see Son et al. (2013).

Once classification is completed, pipelines are modeled based on skeleton features, and others are clustered and grouped separately through the region grouping process. When grouped, each cluster represents equipment or valve groups. Then, the modeling process begins in an effort to model the valves, which are also called inline items and are located between pipelines. In the 3D database, a number of types of valves exist; even the same type of valve has several dimensions according to the adjacent pipelines' radii. In order to efficiently model the valves, two types of knowledge—geometric knowledge (dimensions) drawn from the 3D database and topologic knowledge (what the valve types are and the number of valves located in the pipeline)—are used. If a cluster satisfies the condition, the cluster is classified as belonging to the valve group. Then, the valve models are matched and retrieved based on this knowledge.

Afterward, the remaining clusters represent the equipment group. In the 3D database, a number of types of equipment are also present, and with respect to their use, the dimensions of several pieces of equipment slightly differ from one another. In order to efficiently model the equipment, two types of knowledge—geometric knowledge (dimensions) drawn from the 3D database and topologic knowledge (what type of pipelines are connected)—are used. By matching and retrieving data based on this knowledge, a cluster that corresponds to a particular type of equipment is modeled.

## REPRESENTATION AND USE OF KNOWLEDGE

The representation and use of knowledge have already been suggested as a possible solution for reconstructing objects from a 3D point cloud (Cantzler et al., 2002; Boochs et al., 2011). Recently, there is a growing consensus about such prior knowledge can assist the 3D reconstruction process of an existing large-scale facility, as this knowledge can serve as guidance in the construction industry (Tang et al., 2010). This chapter provides a detailed description and example of the use and representation of knowledge that is used in our approach for the 3D reconstruction of as-built industrial plant models. The chapter focuses on where the knowledge comes from, what knowledge is drawn, and how the knowledge is represented.

### Scene Knowledge

From the existing P&ID, we can extract an instrument list consisting of equipment and valves (also called inline items) and a pipeline list. With respect to the plant facilities' sizes, the instrument and the pipeline lists can be several hundreds to hundreds of thousands of lines. Table 1 reveals a short example that comes from part of the existing P&ID. By using this information, we can understand which objects might be recognized and modeled. In addition, as a starting point, we can extract more detailed information about the objects listed in the scene, such as the objects' dimensions or the relationships among the objects.

Table 1 – Grouping of scene elements in the case of an industrial plant

| | Tag |
|---|---|
| Equipment | DV-2101 |
| | PU-2101A |
| | PU-2101S |
| | ⋮ |
| Inline Items | Check Valve 1-10” |
| | Gate Valve 1-10” |
| | Gate Valve 2-10” |
| | Globe Valve 2-10” |
| | Glove Valve 1-14” |
| | ⋮ |
| Pipelines | 10”-EC-21006-A26 |
| | 10”-EC-21008-A26 |
| | 10”-EC-21039-A26 |
| | 14”-EC-21007-A26 |
| | 14”-EC-21038-A26 |
| | ⋮ |

## Geometric Knowledge

From the existing 3D database, we can extract the dimensions (height, width, and depth) of each instrument (equipment and inline items). The bounding surfaces of the computer-aided design (CAD) file are represented in a simple file that denotes the coordinates of each vertex of the triangle. From this file, we can compute and store each instrument's dimensions with its tagged name. For the pipelines, the first two letters of the tagged names indicate their radii information in inches. Table 2 provides a short example that comes from part of the existing P&ID and 3D database. The geometric knowledge is used to decide each segment that belongs to the pipeline group as well as the groups of equipment or inline items to which each cluster belongs following the region grouping step. Then, this geometric knowledge is used for matching and retrieving steps in the equipment and inline item modeling.

Table 2 – Dimensions of each scene element extracted from the P&ID and 3D database

| | Tag | Dimension (mm) |
|---|---|---|
| Equipment | DV-2101 | 2,600*7,700*5,200 |
| | PU-2101A | 1,750*750*1,200 |
| | PU-2101S | 1,750*750*1,200 |
| | ⋮ | |
| Inline Items | Gate Valve 1-10” | 400*400*1,400 |
| | Gate Valve 2-10” | 400*400*1,400 |
| | Globe Valve 2-10” | 600*650*1,100 |
| | Check Valve 1-10” | 600*550*600 |
| | Glove Valve 1-14” | 650*850*950 |
| | ⋮ | |
| Pipelines | 10”-EC-21006 | 127 |
| | 10”-EC-21008 | 127 |
| | 10”-EC-21039 | 127 |
| | 14”-EC-21007 | 177.8 |
| | 14”-EC-21038 | 177.8 |
| | ⋮ | |

## Topologic Knowledge

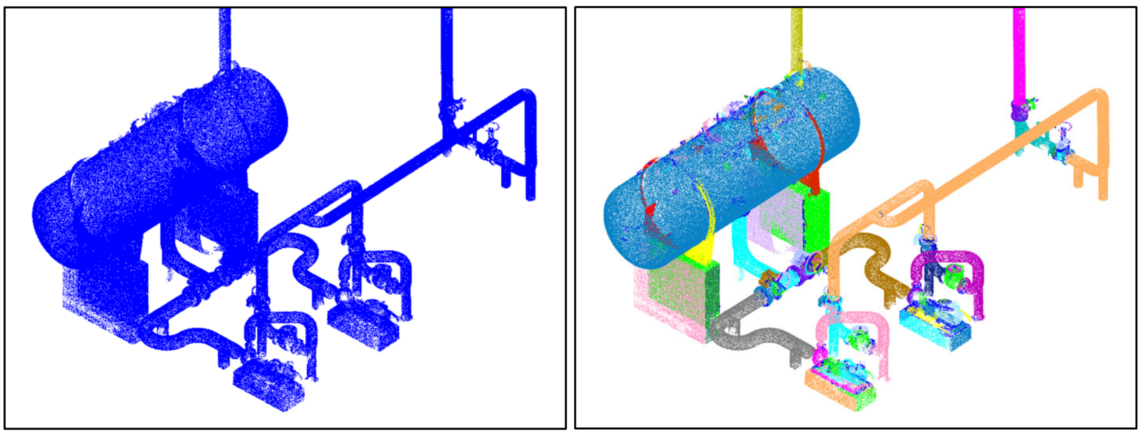
From a semantic view, topological properties describe adjacency relationships among objects. A computer-aided system is developed to execute the analysis automatically by encoding knowledge that is related to process control engineering (PCE) in rules so that they can be applied to a given set of P&ID in order to produce the corresponding cause & effect (C&E) diagram (An et al., 2009). By exporting the P&ID as a form of the C&E diagram, we can figure that the spatial relationship (connectivity and adjacency) between objects is that they are “connected from A to B.” This information is helpful for characterizing each cluster as well as for directly identifying the clusters, as each cluster has a unique relationship.

Table 3 – Cause and effect table in Excel for P&ID example

| Tag | To | From | Inline Items |
|---|---|---|---|
| 10”-EC-21006 | DV-2101 | HE-2101 | |
| 10”-EC-21008 | RE-2101 | PU-2101A | Check Valve 1-10”<br>Gate Valve 1-10”<br>Gate Valve 2-10”<br>Globe Valve 2-10” |
| 10”-EC-21039 | 10”-EC-21008-A26 | PU-2101S | Check Valve 1-10”<br>Globe Valve 2-10” |
| 14”-EC-21007 | PU-2101A | DV-2101 | Glove Valve 1-14” |
| 14”-EC-21038 | PU-2101S | 14”-EC-21007 | Glove Valve 1-14” |

## CASE STUDY/EXPERIMENTAL RESULTS

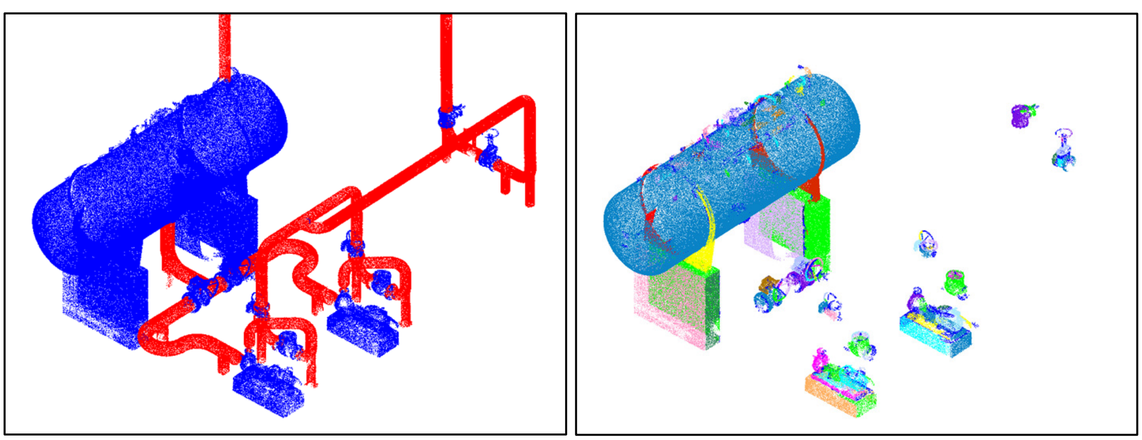
The proposed approach described was applied to real experimental data, including cases of partially occluded parts. Laser-scanned data was acquired from the chemical plant located in Yeosu, South Korea (Figure 2). ScanStation C10 by Leica Geosystems was used to acquire a 3D point cloud. Figure 2(a) shows the laser-scanned data of the test scene. This scene includes two types of equipment (a davit and two pumps), three types of valves (two check valves, two gate valves, and four glove valves), and two types of pipelines (which have radii of 127 mm [a total of three pipelines] and 177.8 mm [a total of two pipelines]). Figure 2(b) shows the result of the segmentation of the point cloud in Figure 2(a). In this figure, different segments are displayed using different colors. This figure shows that the segmentation approach based on a smoothness constraint actually divided the point cloud at intersections among pipelines and other industrial parts, while a pipeline is preserved as one segment.



(a) (b)

Figure 2 – (a) Laser-scan data; (b) Segmentation of the point cloud

Figure 3(a) shows the result of the pipeline classification. In this figure, red-colored points indicate the extracted pipelines, while blue-colored points indicate how the point cloud corresponds with equipment and valves. This step was validated for the precision rate, and the precision rate shows that the percentage of extracted pipelines is calculated as the number of true pipelines over extracted pipelines. The precision rate of the proposed pipeline extraction was observed as being 100%. Figure 3(b) shows that the segments correspond with others by deleting the segments that were classified as pipelines in the previous step. As shown in Figure 3(b), we can find the over-segmentation problem. In order to resolve this over-segmentation problem, region grouping is performed to merge adjacent segments.

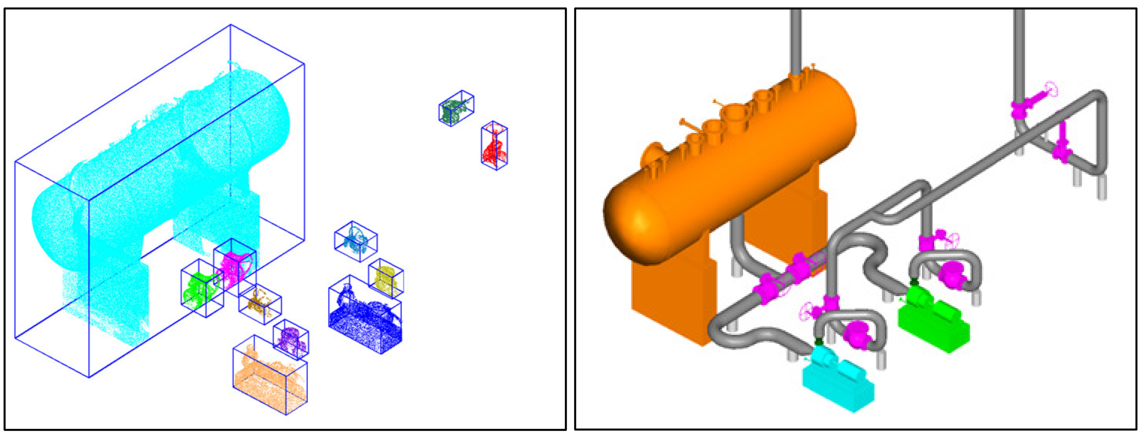


(a) (b)

Figure 3 – (a) Pipeline classification; (b) Segments correspond with others

Figure 4(a) shows the results of clustered segments by region grouping. Here, each of the combined segments is displayed using different colors. As shown in Figure 4(a), two types of equipment (a davit and two pumps) and three types of valves (two check valves, two gate valves, and four glove valves) were accurately grouped together by merging over-segmented parts. For each cluster, the neighborhood segments that corresponded with the pipeline groups were then searched. Afterward, their relationship was represented for the purpose of comparing the 3D point cloud and the topologic knowledge extracted from the P&ID. The blue-colored bounding boxes in the Figure 4(a) shows the results of global feature computation. Based on the geometric and topologic knowledge, each cluster can be modeled by matching and retrieving CAD models from the 3D database.

Figure 4(b) shows the results of the proposed approach for the 3D reconstruction of as-built industrial plant models. From the experimental result, one can conclude that the proposed approach can be used to automatically model the as-built industrial plants without any manual intervention. The knowledge used in the reconstruction process is helpful for characterizing and identifying the various objects in the laser-scan data. In addition, the reconstructed as-built industrial plant models not only have geometric properties but also their semantic information can be used for various purposes in revamping planning, maintenance planning, and preparation for dismantling during the lifecycle of industrial plants.



(a) (b)

Figure 4 – (a) Clustered segments by region grouping; (b) 3D reconstruction result

## CONCLUSIONS

This paper proposes a knowledge-based approach to automatically reconstructing as-built industrial plant models from unstructured laser-scan data. The proposed approach makes use of available knowledge in the reconstruction of as-built industrial plant models—for example, knowledge that is extracted from the existing P&ID. This prior knowledge was modeled, representing a basis for the decisions made during the reconstruction process. Scene, geometric, and topologic knowledge was used to characterize and identify objects in the laser-scan data. The feasibility of the proposed approach was validated in an experiment using real laser-scanned data obtained from an operating industrial plant.

The results demonstrated that the proposed approach can successfully model the as-built 3D industrial plant from laser-scanned data, with knowledge being present. In other words, the proposed approach offers a practical solution for 3D as-built industrial plants reconstruction. During this process, all object models were tagged with their information predefined in the P&ID. Thus, the reconstructed model can be used for various managerial purposes. Nevertheless, the proposed approach was validated and tested for a rather simple case. For the purposes of practical uses, future research will focus on the validation of more complex scenes as well as on improvement of the proposed approach.

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