Manhattan-World Assumption for As-built Modeling Industrial Plant

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Abstract. As industrial plants such as chemical and power plants continue to age, their CAD models are increasingly required for model-based planning and simulation. However, in the case of old plants, the original CAD models rarely exist, and hand-drawings do not precisely match the present states of the plants due to repeated remodeling. It is therefore becoming a common approach to reconstruct CAD models from the point cloud of such plants captured by terrestrial laser scanning and use these models for the above purposes. Such a reconstruction process is usually called “as-built modeling”. However, existing methods for as-built modeling come with such problems as the need for many human operations and computational cost. In this paper, we propose an automatic and efficient method for as-built modeling industrial plants using Manhattan-world assumption which states that there exist three dominant axes orthogonal to each other in artificial buildings and the internal parts are arranged so that they are parallel or orthogonal to one of them. In the case of industrial plants, it is reasonable to consider that long pipes and shaped steels are arranged so that they follow this assumption. In addition, plant parts are supposed to be designed as long linear sweep surfaces on CAD system or hand drawings. Our method can automatically recognize such sweep parts and their cross sectional shape which follow the assumption, as well as efficiently recognize them even from a large point cloud which may contain as many as one hundred million points in a few minutes. We demonstrate the effectiveness of our proposed method from various experiments on real scanned data.

1 Introduction

Recently, as industrial plants such as chemical and power plants continue to age, their CAD models are increasingly required for model-based planning and simulation. However, in the case of old plants, the original CAD models rarely exist, and hand-drawings do not precisely match the present states of the plants due to repeated remodeling. On the other hand, the performance of long-distance terrestrial laser scanner has been improved considerably and it is now possible to quickly capture the point cloud of large industrial plants. It is therefore becoming a common approach to reconstruct CAD models from the point cloud of the plants captured by terrestrial laser scanning and to use these models for the above purposes. Such a reconstruction process of CAD models from scanned point clouds is usually called “as-built modeling”. Plants usually contain numerous pipes and shaped steels arranged in a complex manner. It is therefore very important to detect point subsets corresponding to each of them separately and convert them to CAD models.

CAD model reconstruction from scanned points have been well studied in mechanical CAD

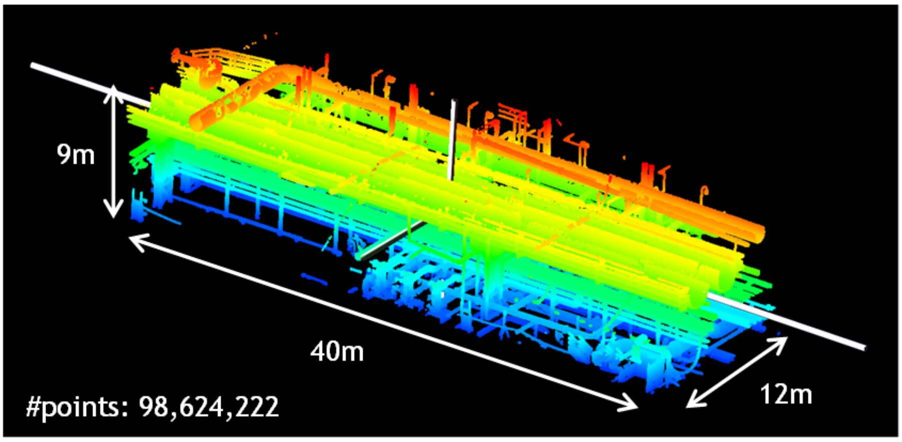


Figure 1. Example of laser scanned point clouds of industrial plants

field and is called "reverse engineering" [1,2]. However, the data being processed in this work is very poor in quality compared to those in mechanical CAD, *i.e.*, huge data size up to one billion, heavy noise, many outliers, and occlusions due to the positional limitations of scanning. Thus the methods developed in mechanical CAD cannot be directly applied.

In recent years, various studies on the as-built modeling of industrial facilities have been reported. Masuda *et al*. proposed an interactive modeling system combining 3D laser scanned point cloud and its spherical projection image [3,4]. However, given that large plants consists of tens of thousands parts, it is desirable to automate the modeling process. Kawashima *et al*. proposed an automatic method for detecting piping systems from the point cloud of large industrial plants [5]. However, this method requires the computation of the local shape descriptor at each scanned point, therefore the total computational time is considerably long.

In this paper, we propose an automatic method for as-built modeling industrial plants using the Manhattan-world assumption. This assumption states that there exist three dominant axes orthogonal to each other in artificial buildings, and internal parts, such as posts and walls, are arranged so that they are parallel or orthogonal to one of them [6]. In the case of industrial plants, it is reasonable to consider that long pipes and shaped steels are arranged so that they follow the assumption. In addition, plant parts are supposed to be designed as long linear sweep surfaces on CAD system or hand drawings. Our method can automatically recognize such sweep parts and their cross sectional shape which follow the assumption, as well as efficiently recognize them from a large point cloud which may contain as many as one hundred million points in a few minutes. We demonstrate the effectiveness of our proposed method from experiments on real scanned data.

2 Our Proposed Method

2.1 Overview

Our proposed method deals with a large point cloud captured by scanning an industrial plant using terrestrial laser scanner as shown in Figure 1. This data is obtained by merging multiple data captured from different positions into single data and contains 98,624,222 points in total. Color represents the z-coordinates of each point. Given such a point cloud, our method outputs point subsets each of which corresponds to a single sweep parts. Our method first recognizes three dominant axes orthogonal to each other and transforms the point cloud so that internal sweep parts can be aligned to them (step 1). Then it converts the point cloud to its cubic voxel representation

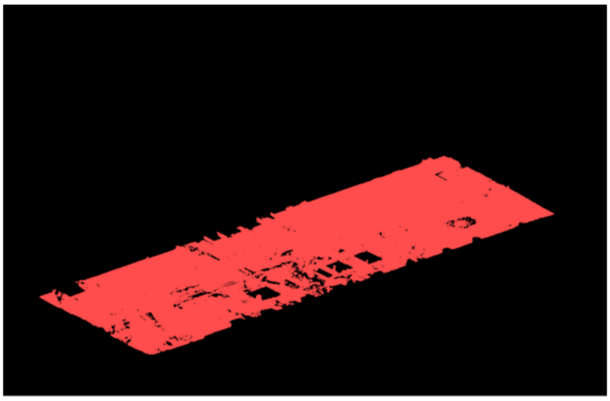


Figure 2. Points on the floor

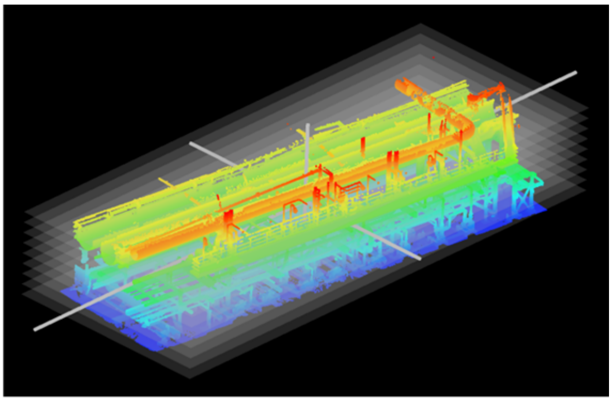


Figure 3. Cross-sectional planes

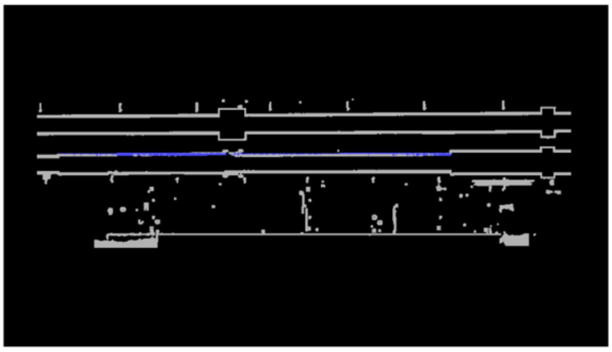


Figure 4. Points on a cross sectional plane and a detected line (blue)

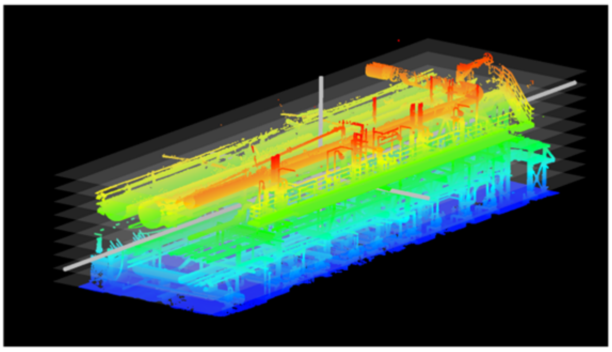
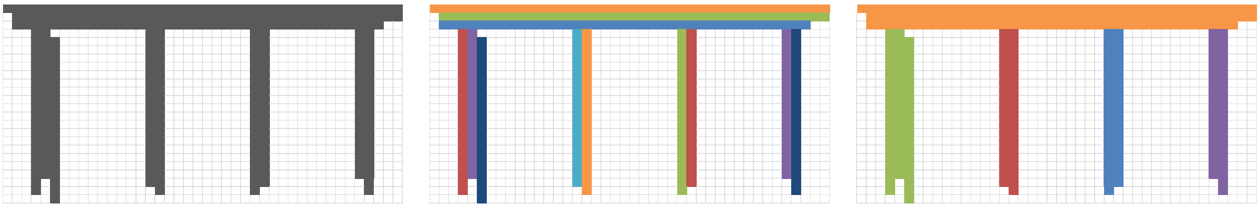


Figure 5. Transformed points

(step 2), detects line elements in the voxel data exhaustively (step 3), and finally detects sweep parts by grouping the topologically connected line elements (step 4).

2.2 Detection of dominant axes and transformation (step1)

Given a point cloud captured by scanning an industrial plant, our method first recognizes three dominant axes orthogonal to each other and transforms a point cloud so that the internal sweep parts can be aligned to them. To recognize the z-direction, we make two natural assumptions. The first is that the floor of the plant is flat, and the second is that the floor area is larger than those of other internal parts or equipment. Under these assumptions, our method detects a point subset corresponding to the floor by plane-based RANSAC algorithm [7], and recognizes an upward vertical direction as a new z-direction from the normal vector of the least-squares plane to the detected point subset. Figure 2 shows the detected point subsets corresponding to the floor. Next, our method recognizes the x- and y-directions. In plants, many long sweep parts are arranged so that they are orthogonal to the floor direction. For this reason, long lines appear on the cross sections of these parts and the planes parallel to the z-direction. With this observation, as shown in Figure 3, our method sets M planes parallel to z-direction at a constant interval, finds the largest point subset among the points being on these planes by the line-based RANSAC algorithm, and recognizes a new x-direction as the direction of the least-squares line to the subset. We set M=9 for the examples in this paper. Figure 4 shows an example of the points on a cross sectional plane and the largest point subset being on the long line. Finally, our method computes a new y-direction using the x- and z-directions and transforms a point cloud. Figure 5 shows the point cloud after the transformation.



Voxel representation converted from point cloud in step 2

Line elements detected in step 3

Sweep parts detected by grouping line elements in step 4

Figure 6. An overview of our proposed method from step 2 to step 4

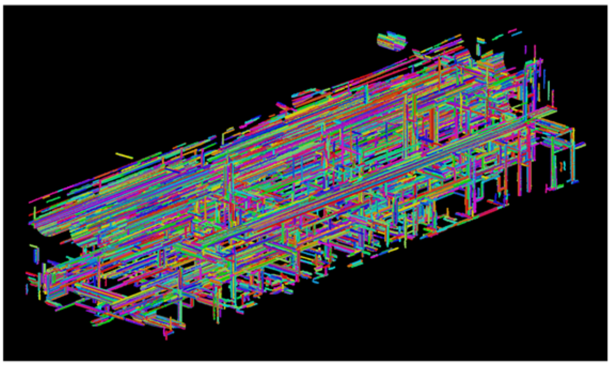


Figure 7. Detected line elements

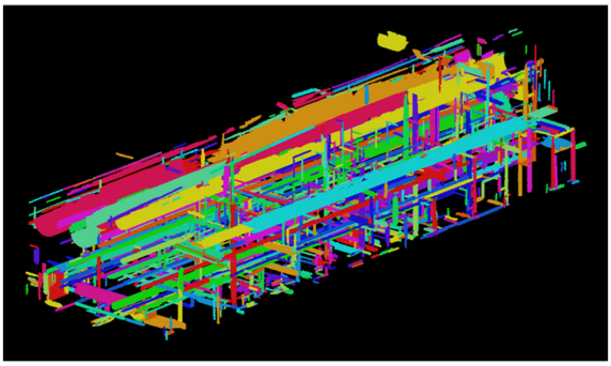


Figure 8. Detected sweep parts

2.3 Voxelization (step2)

In the second step, our method converts the point cloud to its cubic voxel representation. We set the voxel size 50mm×50mm×50mm for the examples in this paper. The voxelization enables easy data processing using connectivity. In the case of the data in Figure 1, the total number of cells is 39,053,170 and the number of active cells which contains at least one point is 1,015,036, which leads to data reduction and makes computation much faster. The illustration of the voxel representation is shown in Figure 6(left).

2.4 Detection of line elements (step3)

In the third step, multiple line elements are exhaustively detected from voxel data by iterating the RANSAC algorithm. With our method, an active cell and a search direction are randomly selected, and then the largest number of connected active cells is found recursively by searching along the selected direction from the selected cell. This process is stopped if more than N cells cannot be found. By iterating the above process, all line elements more than N cells can be exhaustively detected. We set N=10, which corresponds to 500mm, for the examples in this paper. Figure 7 shows the detected line elements where each color represents a line label. Intuitively, the longest line elements can be found first, then the second longest, and the process is continued until elements more than N cannot be found. The result is illustrated in Figure 6(center).

2.5 Detection of sweep parts by grouping line elements (step4)

In the final step of our algorithm, sweep parts can be detected by grouping the line elements which are topologically connected to each other and whose directions are the same as illustrated in Figure 6(right). Figure 8 shows the detected sweep parts where each color represents a part label.

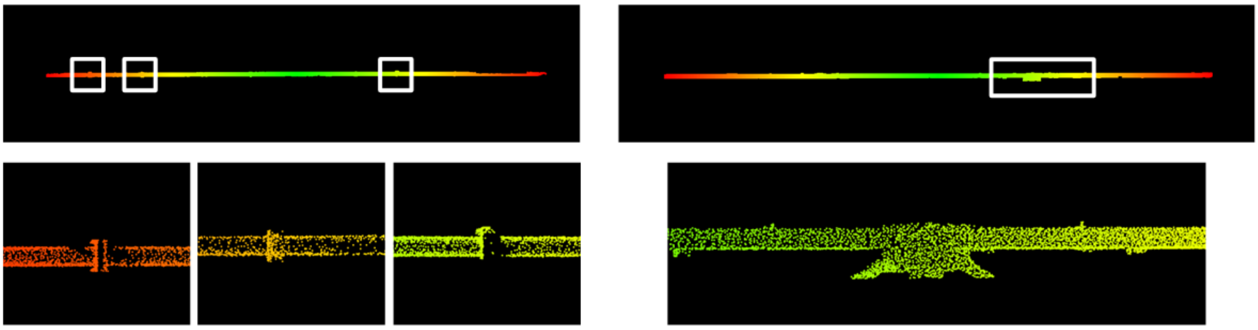


Figure 9. Examples of correctly detected parts

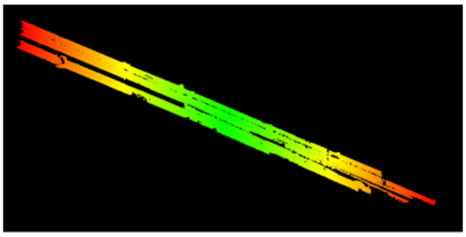


Figure 10. Examples of incorrectly detected parts

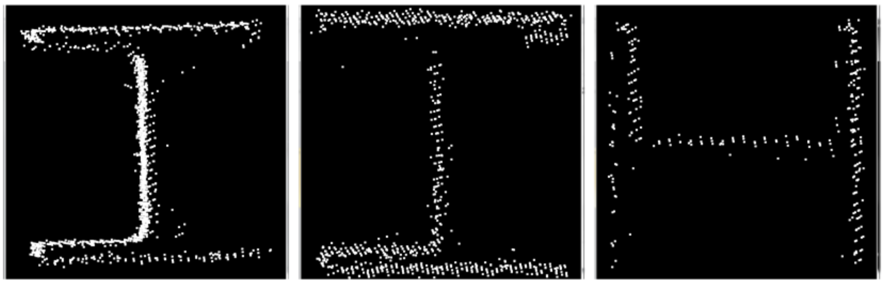


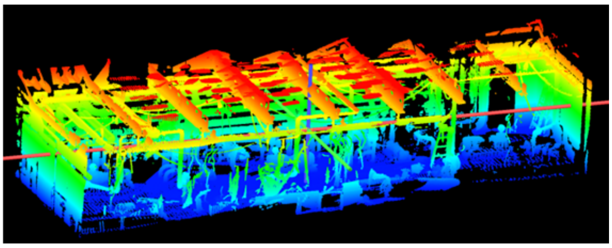
Figure 11. Cross sectional shape of H steel

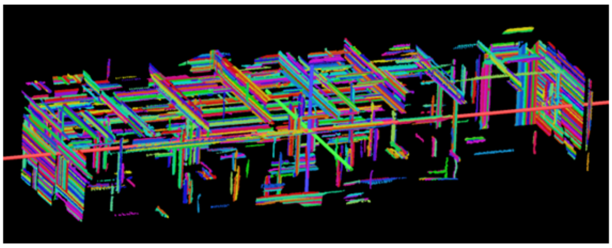
3 Results

Figures 2, 3, 4, 5, 7, and 8 show some of the experimental results obtained. All the experiments were run on PC with Core i5 3.33GHz and 8GB RAM and the total computational time was 65 seconds. Figure 9 shows examples of detected point subsets corresponding to sweep parts where each point is colored according to the distance to the point barycenter. As shown in these figures, we found that most of sweep parts can be correctly detected by our method. However in some parts, small portions of neighboring connected parts, such as elbows, are detected as a part of the pipes. Figure 10 shows an example of incorrect detections, where multiple pipes are detected together as a single part. Figure 11 shows examples of the cross sectional shape of H steels, which confirm that our method can correctly detect the cross sectional shape of a part designed using sweep operations on a CAD system.

Figure 12 shows the results for the mechanical room data. The total number of points was 4,524,324. Figures 12(b) and (c) show the detected line elements which are colored according to the line labels and z coordinates respectively, and Figure 12(d) shows the detected sweep parts. The running time was about eight seconds.

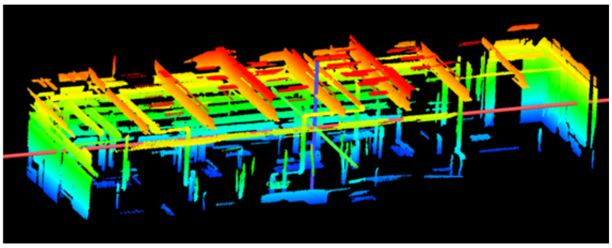
These results show that our method can efficiently and correctly detect sweep parts from large point clouds of industrial facilities.

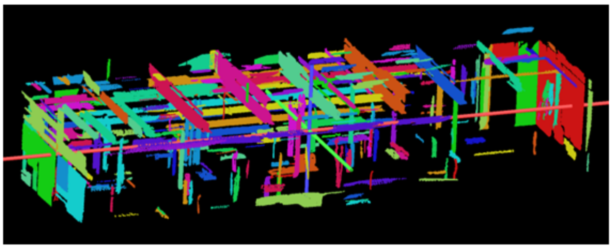




(a) Scanned point cloud

(b) Recognized line elements (part label)





(c) Detected line elements (z coordinates)

(d) Detected parts

Figure 12. Results for oil rig data

4 Conclusion and Future Works

In this paper, we proposed a new method for as-built modeling of industrial plants and verified its effectiveness. In future work, we plan to conduct part type classification, precise modeling of parts and their cross sectional shapes at the point level, and interpolation of areas missing data.

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