Automated pipeline extraction for modeling from laserscanned data

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Purpose Threedimensional (3D) as-built plant models are required for various purposes, such as plant operation, maintenance, and the expansion of existing facilities. The as-built plant model reconstruction process consists of as-built plant measurement and 3D plant model reconstruction. As-built plant measurement uses 3D laser scanning technology to efficiently acquire data. However, the current method used for 3D as-built plant model reconstruction from laser-scanned data is still labor-intensive. The objective of this study is to develop a fully-automated parametric reconstruction of the as-built pipe-line occupying a large portion of the area in an as-built plant. **Method** The proposed approach consists of three main steps. The first step is to extract the cylindrically- formed pipelines from laser-scanned data based on random sampling consensus (RANSAC). The second step is to segment the extracted pipelines into pipe components, such as straight pipe, elbow, and branch tee, based on medial axis extraction and curve skeletonization. The last step is to surface-model reconstruct the segmented pipe-lines using the parametric modeling method. **Results & Discussion** The experiment was performed at an operating plant to validate the proposed method. The experimental results revealed that the proposed method could contribute to automation for 3D as-built plant model reconstruction.

Keywords: *automation, as-built modeling, as-built pipe, parametric modeling, RANSAC*

INTRODUCTION

The pipelines of a plant play an important role in the operation, maintenance, and expansion phases of existing chemical, refinery, and power plants[6]. Much equipment and instruments are connected only by the pipelines to perform their functions, so they play a role as an intermediary[6, 10]. Therefore, 3D as-built pipeline models can be used for maintenance and operation phases and expansion or modification of existing plants[5, 10, 11]. For example, by using 3D as-built pipeline models for planning, expansion, and modification of existing plants, collisions between equipment can be detected[3, 7]. During the maintenance and operation phase, 3D as-built pipeline models can be used for efficient inspection and part replacement[11].

In practice, to generate 3D as-built pipeline models, laser scanners are used to measure plants, and then users manually generate 3D as-built models from laser-scanned data using commercial software packages[3]. To generate 3D as-built pipeline models using commercial software packages, the user must extract laser-scanned data corresponding to each pipeline to be modeled in large laser-scanned data sets[3]. After extraction of laser-scanned data corresponding to each pipeline, the user generates as-built pipeline models by using some functions in commercial software. However, manually identifying each pipeline is nearly impossible and is a very time-consuming and labor-intensive process because the laser-scanned data of the plant is huge and includes other objects such as structural components, containers, and equipment; the pipelines are also intricately entwined like a net[3, 7, 10]. Thus, to efficiently generate 3D as-built pipeline models, automated pipeline extraction must be performed.

Research has been done to effectively extract pipelines from laser-scanned data by extracting cylinder[1, 8]. Rabbani and Heuvel[8] proposed a method for extraction of cylinders in laser-scanned data using the Hough transform. Bey et al.[1] proposed a method for extraction of cylindrical objects in laser-scanned data using Bayesian formulation to generate a 3D as-built model. Previous research shows that cylindrical objects can be extracted from laser-scanned data to generate a 3D as-built model based on extracted cylindrical objects. However, cylindrical objects include straight pipes as well as other objects like equipment. Therefore, extraction of entire pipelines including straight pipes, elbows, and junctions from laser-scanned data is still a laborious and challenging problem.

The aim of this study is to propose a fully automated process that allows extraction of a 3D as-built pipeline for modeling from laser-scanned data. The rest of the paper is organized as follows. An overview and details of the proposed extraction process of as-built pipeline are provided in Section 2. In Section 3, experimental result is provided. Finally, conclusion and recommendation for future research are given in Section 4.

A PROPOSED PIPELINE EXTRACTION METHOD

In this section, the proposed pipeline extraction process from laser-scanned data is presented. The pipeline extraction for modeling method consists of three main steps. The first step is to segment the laser-scanned data of an industrial plant into subsets based on a smoothness constraint. The purpose of segmentation is to subdivide the laser-scanned data of an industrial plant into meaningful subsets in order to extract an as-built pipeline in this paper. The laser-scanned data does not include topology information of objects and only contains the points with color information. However, an industrial plant is composed of primitive-shaped objects, meaning that each primitive in the laser-scanned data represents an object. Therefore, segmentation is first performed based on the smoothness constraint that can segment the laser-scanned data into primitives. In this step, segments of the laser-scanned data are computed. The second step involves classifying pipelines from subsets of the laser-scanned data based on approximating medial axis extraction, skeletonization, and radius calculation. The purpose of pipeline classification is to classify the segments of laser-scanned data into either pipeline or non-pipeline in order to generate the pipeline model automatically. The approximating medial axis extraction and skeletonization extract features from each segment. The result of the extracted feature can be used as the principal axis of an object. Pipelines of an industrial plant that require the principal axis as a parameter are cylindrical in shape. Therefore, pipelines can be classified by means of their characteristics based on approximating medial axis extraction, skeletonization, and radius calculation. The result of this step is the classification of an as-built pipeline from laser-scanned data. Finally, a 3D as-built pipeline model is generated using the skeleton of pipeline segments and their radii.

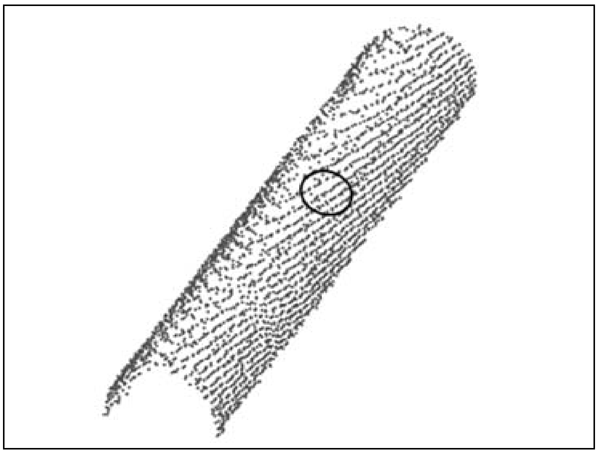
Laser-scanned data segmentation

Segmenting the laser-scanned data is performed using the smoothness constraint proposed by Rabbani et al.[9]. The smoothness constraint segments the laser-scanned data at the points that have high normal variances with neighboring points. The industrial plant is composed of primitive-shaped objects. Therefore, the laser-scanned data of an industrial plant can be subdivided into objects based on the smoothness constraint.

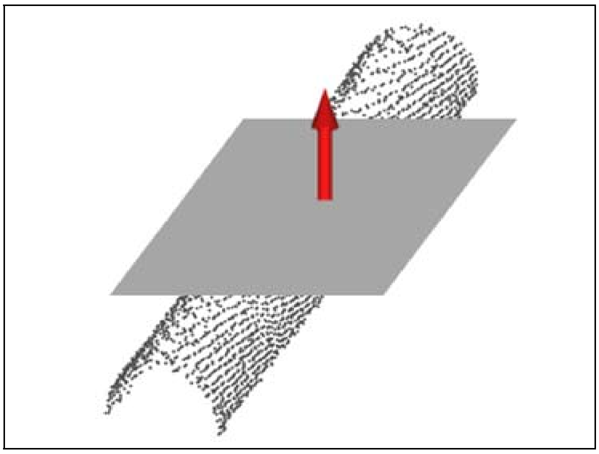
The segmentation method consists of normal estimation and region growing. The normal estimation is performed first, as the segmentation points are calculated using normals of points. After normal estimation, region growing is performed. Region growing makes groups of points that have a smooth surface with neighboring points using the estimated normals and their residuals.

Normal estimation

The segmentation method embarks on normal estimation for each point. To estimate normal for each point, plane fitting to some neighboring points is performed. Neighboring points are computed for each point using k nearest neighbors (KNN), which selects the k number of points having minimum distance (Fig. 1(a)). In this paper, the nearest neighbor number k is set to 30 for the original study. The plane fitting finds the best fit plane that minimizes the sum of orthogonal distances from neighboring points. The normal of the plane is taken as the estimated normal for a point, and the residuals of plane fitting are taken as indicator of areas of high curvature (Fig. 1(b)).



(a)



(b)

Fig. 1. (a) k nearest neighbors of a point; (b) Normal estimation by fitting a plane

Region growing

The region growing takes as input the estimated point normals and their residuals. The region growing is performed with two constraints. The first constraint is local connectivity. The constraint means that the points of a segment have to be locally connected. That would be enforced by using the k nearest neighbors. The second constraint is surface smoothness. The constraint means that the normals' variance has to be smooth. That would be enforced by using a threshold angle (θ_{th}) between a seed point and the added points to the region of the seed point.

The process of region growing is as follows.

1. Specify a residual threshold r_{th}.
2. Define a smoothness threshold in terms of the angle between the normals of the current seed and its neighbors. If the smoothness angle threshold is expressed in radians, it can be enforced through dot product as follows $\|n_p \cdot n_s\| > \cos(\theta_{th})$.
3. If all the points have been already segmented, go to step 7. Otherwise, select the point with the minimum residual as the current seed.
4. Select the neighboring points of the current seed. Use KNN with the specified parameters for this purpose. The points that satisfy condition 2 are added to the current region. The points whose residuals are less than r_{th} are added to the list of potential seed points.
5. If the potential seed point list is not empty, set the current seed to the next available seed, and go to step 4.
6. Add the current region to the segmentation and go to step 3.
7. Return the segmentation result.

Pipeline extraction

In order to classify a pipeline, the feature extraction is first performed using the approximating medial axis method proposed by Dey and Zhao[4] and the skeletonization method proposed by Cao et al.[2]. Skeletonization is a suitable feature by which to classify pipelines, as a pipeline is cylindrical in shape, and the approximating medial axis is used to generate an accurate skeleton. Thereafter, a simple classification is performed based on the radius estimation of the points of each segment, using skeleton points as a principal axis.

Pipeline feature extraction

In the pipeline feature extraction, the approximating medial axis is performed using Voronoi diagram. The Voronoi diagram of the laser-scanned data is filtered with the angle condition and ratio condition to extract an approximating medial axis using its dual Delaunay edges from the Delaunay triangulation of the sample points.

Angle condition θ can be described as follows:

$$\max_{ptu \in U_p} \angle n_{ptu}, t_{pq} < \frac{\pi}{2} - \theta$$

Where p and q are sample points of input data; U_p is an umbrella that is extracted from Delaunay triangulation; t_{pq} is a tangent vector from p to q; and n_{ptu} is a normal to a triangle ptu. Ratio condition ρ can be described as follows:

$$\min_{ptu \in U_p} \frac{\|p-q\|}{R_{ptu}} > \rho$$

Where R_{ptu} is the circumradius of a triangle.

After filtering, the Delaunay edges remaining are only those that satisfy both conditions. The remaining set of Voronoi facets from the Voronoi diagram creates the approximating medial axis[4].

After performing the approximating medial axis, skeletonization is performed. The skeletonization algorithm takes as input the vertices of the result of the previous step. The algorithm embarks on the geometric contraction of the vertices based on implicit Laplacian smoothing, which removes details of the input data along the normal directions. The algorithm automatically chooses some anchor points to maintain the original shape of input data during the contraction. After the contraction process, the skeletal shape of the input data remains the result.

The geometric contraction first constructs a one-ring structure for all vertices. It is needed to use the Laplacian matrix to compute the normal direction of the vertices. To define one-ring neighbors, therefore, an approximate neighborhood of the vertex as a point p_i is extracted by finding k nearest neighbors and projecting the neighbors on its tangent plane.The contraction process can be described as follows. Assume that the following equation is solved for P^{t+1}:

$$\begin{bmatrix} W_L^t L^t \\ W_H^t \end{bmatrix} P^{t+1} = \begin{bmatrix} 0 \\ W_H^t P^t \end{bmatrix}$$

Where superscript t is used to denote the t-th iteration; L is a $n \times n$ Laplacian matrix with cotangent weights; P is the input data; and W_L and W_H are the diagonal weight matrices balancing the contraction and attraction forces. Then, the diagonal weight matrices $W_L^{t+1} = S_L W_L^t$ and $W_{H,i}^{t+1} = W_{H,i}^0 S_i^0 / S_i^t$ are updated, where S_i^t and S_i^0 are the current and original neighborhood extents of point p_i, respectively. Finally, the new Laplacian matrix L^{t+1} is constructed with the new point cloud P^{t+1}. The contraction process stops when the solution converges. The input data becomes a skeletal shape C. The result of geometric contraction is not a 1D curve skeleton. Further steps are required to extract the 1D curve skeleton. The 1D curve skeleton is extracted by imposing an initial connectivity and computing edge contraction.

Pipeline classification

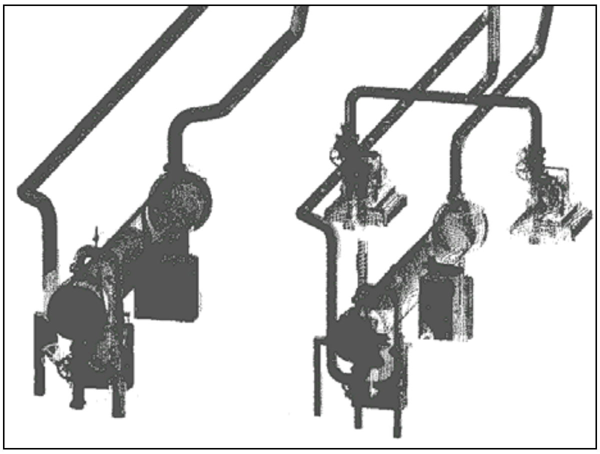
The pipeline classification method takes as inputs the segments and 1D curve skeletons of each segment. To classify pipelines, the distance from the 1D curve skeleton points to the surface points is computed for each segment. The surface points of a skeleton point are selected using k nearest neighbors. The nearest neighbor number k is set to 30. The radius of a segment is defined as the average distance from skeleton points to the segment surface, and standard deviations of the distances are computed for each segment. The classification is performed with the radii of segments and the standard deviations. The pipelines are roughly extracted using the radii of segments with a threshold (d_{th}) that defines the boundary between the minimum diameter of a pipe and the maximum diameter of a pipe. Finally, the pipeline is extracted to remove the segments that have a high standard deviation.

Skeleton based pipeline model generation

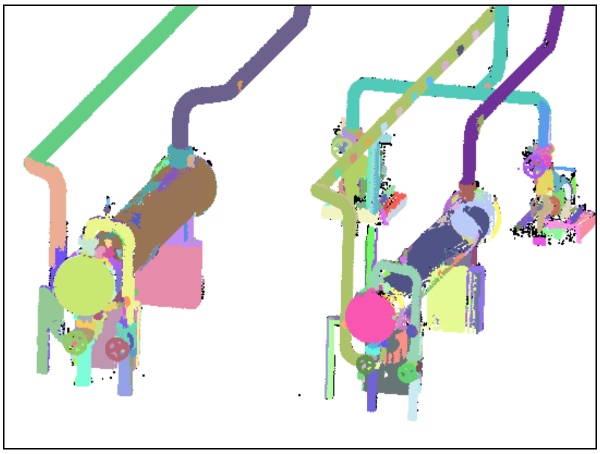
Once the skeleton points of extracted pipeline segments and their corresponding radii are obtained, the pipeline model is simply generated automatically by the parameters. The pipeline model is also classified by type of pipe components such as elbows, T-junctions, and straight pipes using the degree variation of skeleton points.

EXPERIMENTAL RESULT

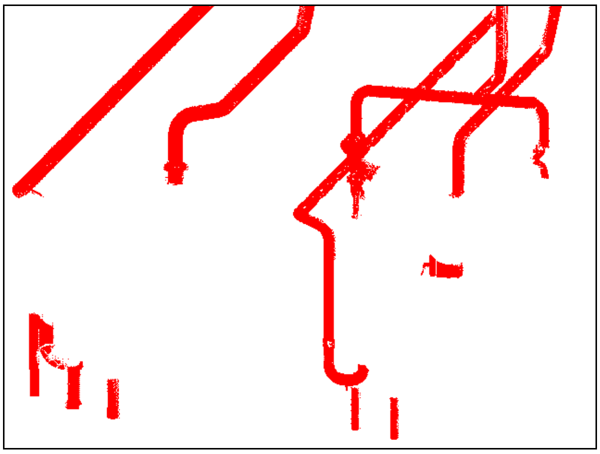
In this study, the performance of the proposed pipeline extraction for modeling from laser-scanned data was tested on actual laser-scanned data. The result of the test is shown in Fig. 2. Fig. 2(a) shows a laser-scanned data acquired from an operating industrial plant and Fig. 2(b) shows the result of segmentation based on smoothness constraint. The segmentation result shows that most segments, which are displayed using various colors, represent each object. Fig. 2(c) shows extracted pipeline and Fig. 2(d) shows the pipeline model. In Fig. 2(d), the gray-colored models denote the models of straight pipes, the green-colored models denote the models of elbows, and the red-colored models denote T-junction. The threshold angle (θ_{th}) was set to 15 ° for the original study and r_{th} was calculated by the 98^{th} percentile of the residuals for segmentation. The threshold (d_{th}) was set to 2–10 inches for the diameters that were used for this industrial plant in the scene.



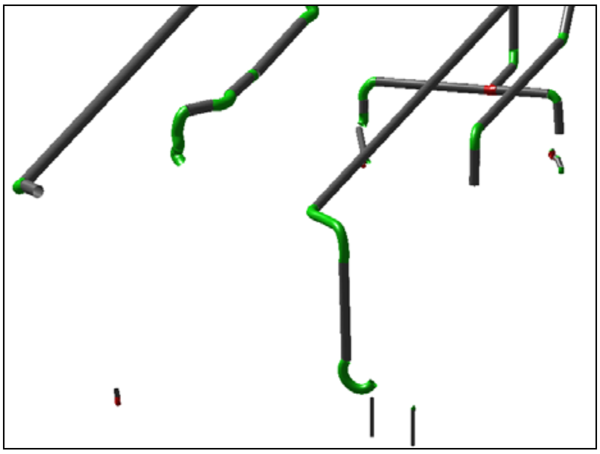
(a)



(b)



(c)



(d)

Fig. 2. Result of pipeline extraction and model generation; (a) Laser-scanned data; (b) Segmented laser-scanned data; (c) Extracted pipeline; (d) Generated pipeline model

The proposed pipeline extraction method was validated for precision rate, and the result is presented in Table 1. The precision rate shows that the percentage of extracted pipelines is calculated as the number of true pipelines over detected pipelines. It is observed that the precision rate of pipeline was 93.33%. Based on the experimental result, it can be concluded that the proposed method can be used to accurately extract the as-built pipeline for modeling by means of the automated process. The result shows a high precision rate, but the error occurred in incomplete data part due to occlusion or other visibility issues during acquiring laser-scanned data. The incomplete data leads to an under- or over-segmentation problem and that is the cause of the error.

Table 1. Performance of the proposed extraction method

	Detected Objects	True Objects	Precision rate
Pipelines	15	14	93.33%

CONCLUSION

This paper proposes a new method that can automatically extract an as-built pipeline for modeling from laser-scanned data. The segmentation of the pipelines is performed by the smoothness constraint. The segments of laser-scanned data are then classified into either pipeline or non-pipeline using medial axis extraction, skeletonization, and radius calculation. The pipeline model is simply generated based on the skeleton points of extracted pipeline segments and their corresponding radii. The feasibility of the proposed method was demonstrated in an experiment using real laser-scanned data obtained from an operating industrial plant. The result shows that the proposed method can successfully extract the 3D as-built pipelines for modeling. The proposed method is advantageous as it extracts pipeline and generates a model automatically. Thus, it could be successfully incorporated into the development of as-built plant information modeling. Nevertheless, the proposed pipeline extraction method for modeling has a limitation that may extract objects instead of pipelines because of incomplete data. In order to extract the entire pipeline without errors, complete data is required, which does not contain holes. Therefore, future research should focus on the reconstruction of the incomplete laser-scanned data acquired from an industrial plant.

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