AUTOMATIC RECOGNITION OF A PIPING SYSTEM FROM LARGE-SCALE TERRESTRIAL LASER SCAN DATA

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ABSTRACT:

Recently, changes in plant equipment have been becoming more frequent because of the short lifetime of the products, and constructing 3D shape models of existing plants (as-built models) from large-scale laser scanned data is expected to make their rebuilding processes more efficient. However, the laser scanned data of the existing plant has massive points, captures tangled objects and includes a large amount of noises, so that the manual reconstruction of a 3D model is very time-consuming and costs a lot. Piping systems especially, account for the greatest proportion of plant equipment. Therefore, the purpose of this research was to propose an algorithm which can automatically recognize a piping system from terrestrial laser scan data of the plant equipment. The straight portion of pipes, connecting parts and connection relationship of the piping system can be recognized in this algorithm. Eigenvalue analysis of the point clouds and of the normal vectors allows for the recognition. Using only point clouds, the recognition algorithm can be applied to registered point clouds and can be performed in a fully automatic way. The preliminary results of the recognition for large-scale scanned data from an oil rig plant have shown the effectiveness of the algorithm.

1. INTRODUCTION

Recently, in chemical, material and food plants, because of the short life cycle of the products in the market, changes in the plants' equipment have been becoming more frequent. However, the former changes are not necessarily recorded in the plant drawings in many cases in Japan. For this reason, unintended collisions between the existing equipment and the designed ones often occur in the construction stage, and this causes delays of the work and additional costs.

On the other hand, with improvement of terrestrial laser scanner performance, massive point clouds of real objects have been acquired very easily and quickly. Also, there is a strong possibility that 3D models of production facilities and plant equipment could be reconstructed from these point clouds. Once the models are built, the unintended collisions between the existing equipment and the designed ones can be efficiently checked and avoided before the construction stage.

Therefore, 3D modelling of existing plants from scanned point clouds is considered to be an imperative process in the recent plant rebuilding process. However, the laser scanned data of the existing plant has a huge number of points, captures very tangled sets of objects and includes a large amount of noises. Therefore, recognizing each individual object from these tangled, enormous and noisy point clouds and building 3D models of them becomes nearly impossible or very time consuming when doing it in a manual way. Thus, automating recognition and construction of the 3D models from the point clouds needs to be strongly promoted in plant engineering.

Chemical, material, and food plants consist of many types of objects. Among them, the piping system especially accounts for the greatest proportion. As shown in Fig.1 and 2, a piping system consists of various piping elements and connection relationships; straight pipes, connecting parts, such as T-junctions and elbows, indicators, valves, etc. Also, the connection relationship defines the logical connectivity between these piping elements.

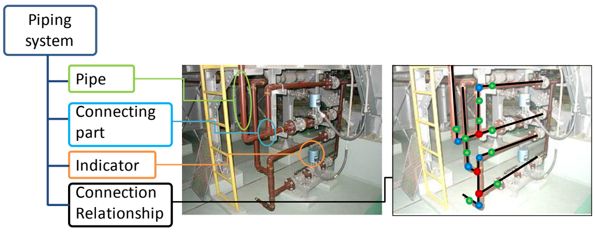


Fig.1 Elements of a piping system

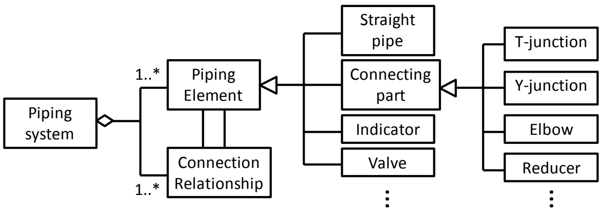


Fig.2 UML class diagram of a piping system

Several research studies have been proposed for algorithms of recognizing a piping system from laser scanned point clouds. However, these algorithms could not recognize pipes in a fully automatic way, or could not be applied to a registered point cloud, or could not recognize pipe parameters such as radii or length.

Therefore, the purpose of our research was to propose a new algorithm that can automatically recognize piping elements and their connection relationships from a registered laser scanned point of a plant. In addition, the algorithm can recognize pipe

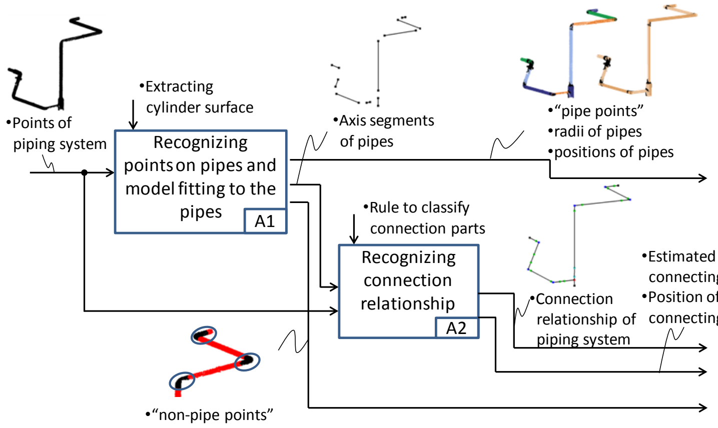


Fig.3 Recognition Algorithm Overview

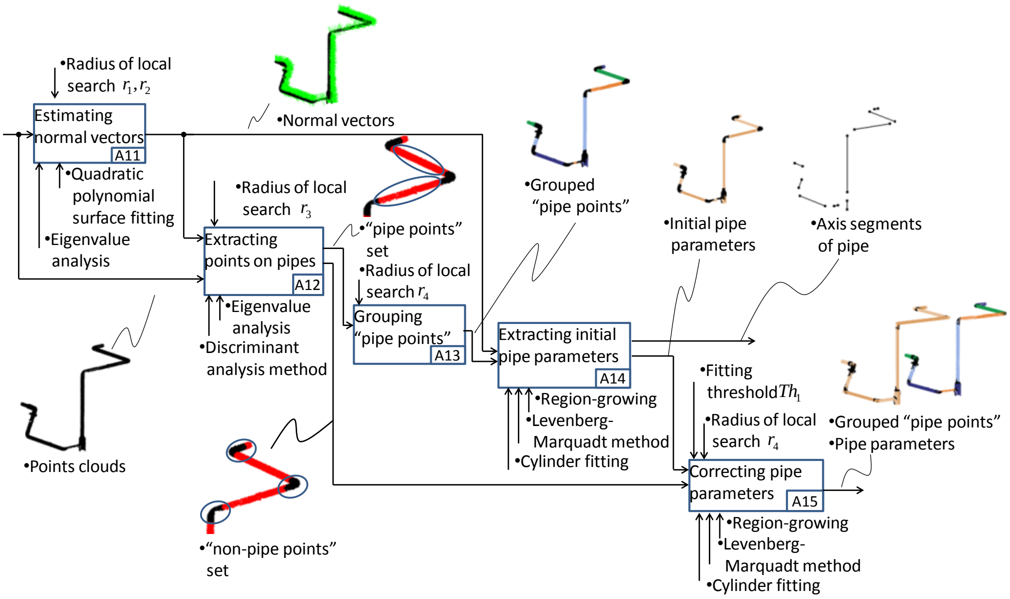


Fig.4 The detailed process of recognizing points on pipes and model fitting to the pipes

radii and their positions, and the orientations of them as pipe parameters with high accuracy.
The algorithm was tested for a large-scale laser scanned point cloud of a real plant, and the accuracy of the radii and their connection relationships were verified.

2. RELATED WORKS

So far, several research studies have been done for developing algorithms to recognize objects from terrestrial laser scanned point clouds. Binert proposed an algorithm which can recognize tree trunks from a point cloud measured from forests (Binert et.al 2006). Luo proposed one which recognizes pillars from a point cloud of building indoor environments (Luo et.al 2008). In both of these, objects are recognized by fitting circles to the points projected onto a horizontal plane. However their algorithms can only recognize column-like objects whose inclination was limited to nearly only the vertical one.
Several research studies have also been done to recognize objects from laser scanned data of plant equipment. Masuda proposed an algorithm which can recognize planes and cylinders from the data of plants (Masuda et.al 2009). However, a region to be recognized has to be selected manually in advance. Matsunuma also proposed an algorithm similar to Masuda's (Matsunuma et.al 2010), but it requires the combination of measured point clouds, range imageries and brightness imageries. Rabbani also proposed an algorithm which reconstructs a 3D plant model from the combination of point cloud data and a photographic image which are taken from a single measuring location (Rabbani et.al 2004). However, the recognition algorithms can only be applied to the combination of the point cloud and the image generated by a single scan. Piping systems usually occupy a large-space in factories and multiple scans must be taken and each be registered to collect the point cloud which can cover the existing space of all the pipes. Unfortunately, it is hard for the above algorithms to be applied to a huge point cloud which is created as a result of the registration of the points generated by multiple scans. Andrew proposed an algorithm which can semi-automatically build a 3D model by matching a point cloud to a CAD model using spin images (Andrew et.al 1997). However, the matching is inefficient because it uses an exhaustive search, and an experimental verification was not done. Bucksch proposed a skeletonization algorithm which classifies the scanned point cloud into several groups, each of which corresponds to a single skeleton. It can be used to extract the feature structure and to recognize the connection relationship in a piping system (Bucksch et.al 2010). However, it is hard for this algorithm to recognize straight portions of the pipe from the point cloud.

3. ALGORITHM OVERVIEW

As shown in Fig.3, our algorithm consists of two steps.
In the first step (A1), points on straight pipes, here after referred to "pipe points," are extracted, and their radii and the positions of the pipes are recognized as pipe parameters from a point cloud. Also, axis segments of the pipes are calculated from the extracted points and from the parameters.
Then, in the second step (A2), the connection relationships among the extracted straight pipes are recognized using the positions of the axis segments.
The point clouds from the laser scan in a plant generally include, not only the points on the piping system, but also those on many other classes of objects, such as building columns, supporting brackets, containers, etc. However, in this research, in order to simplify the recognition, it is assumed that the points measured from objects other than the piping system are roughly removed by manual pre-processing and that the input point cloud to the recognition algorithm only includes the points of the piping system.
The detailed processes of steps (A1) and (A2) are shown in sections 4 and 5.

4. RECOGNIZING POINTS ON PIPES AND MODEL FITTING TO PIPES

In this section, the detailed process of the recognizing points on pipes and fitting models to pipes are described. The flow of the process is shown in Fig.4.

4.1 Estimating normal vectors (A11)

A scanned point cloud consists of a set of vertices. In order to estimate the normal vector at a vertex i, first, the covariance matrix S_i is calculated by equation (1) (Qian et.al 2008), (Leo et.al 2007) .

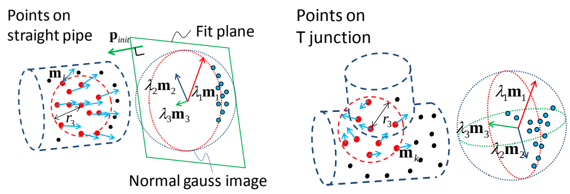
$$S_i = \frac{1}{|N(i,r_1)|} \sum_{j \in N(i,r_1)} (\mathbf{v}_j - \mathbf{v}_i)^T (\mathbf{v}_j - \mathbf{v}_i) \qquad (1)$$

where $N(i,r_1) =$ a set of neighbouring vertices contained in the sphere of radius r_1 centred at i.
$\mathbf{v}_i =$ a position vector of i.

Then, the eigenvalues $\lambda_1, \lambda_2, \lambda_3 (|\lambda_1| \geq |\lambda_2| \geq |\lambda_3| \geq 0)$ and corresponding eigenvectors $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3$ are obtained by eigenvalue analysis of S_i. If we set r_1 to smaller than the radius of pipe R, the vector $\mathbf{e}_3$ will approximate the normal at i. Thus, $\mathbf{e}_3$ is determined to be the initial normal vector $\mathbf{n}'_i$ at vertex i. Then, another set of points $N(i,r_2)$ are projected to a plane $u-v$ whose normal is $\mathbf{n}'_i$. Also a quadratic polynomial surface $w = h(u,v)$ of equation (2) is fit to $N(i,r_2)$. Finally, the normal vector $\mathbf{n}_i$ at vertex i is calculated as a normal of $h(u,v)$ at vertex i in the original coordinate frame $x-y-z$ (Mizoguchi et.al 2007).

$$w = h(u,v) = a_0 u^2 + a_1 v^2 + a_2 uv + a_3 u + a_4 v + a_5 \quad (2)$$

where $(u,v,w) =$ a local coordinate frame whose origin is at i, and w axis parallel to $\mathbf{n}'_i$.



(a) "pipe point" (b) "non-pipe point"

Fig.5 Normal gauss image and eigenvectors of normal tensor

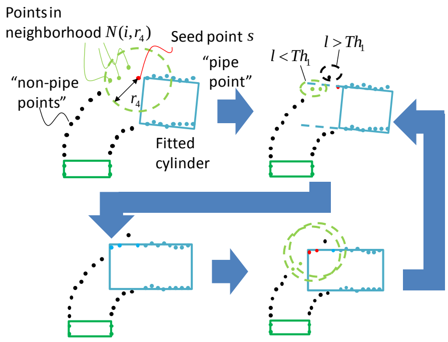


Fig.6 Cylinder fitting using region-growing

4.2 Extracting points on pipes (A12)

First, a normal tensor T_i at vertex i is calculated by equation (3) from a set of points $N(i,r_3)$ (Qian et.al 2008), (Leo et.al 2007).

$$T_i = \frac{1}{|N(i,r_3)|} \sum_{k \in N(i,r_3)} \mathbf{n}_k{}^T \cdot \mathbf{n}_k \qquad (3)$$

Then, the eigenvalues $\hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3 (|\hat{\lambda}_1| \geq |\hat{\lambda}_2| \geq |\hat{\lambda}_3| \geq 0)$ and corresponding eigenvectors $\mathbf{m}_1, \mathbf{m}_2, \mathbf{m}_3$ are obtained by eigenvalue analysis of T_i. These eigenvalues and eigenvectors show spatial distributions of the normal gauss image as shown in Fig 5. For example, at a vertex i on a straight portion of pipe, the normal vectors in $N(i,r_3)$ exist almost on one plane. Then $\hat{\lambda}_3$ becomes much smaller than $\hat{\lambda}_1$ and $\hat{\lambda}_2$. While at a vertex on an elbow or a T,Y junction, the normal vectors are distributed three-dimensionally. Then, $\hat{\lambda}_3$ becomes larger than that of the former case. Thus, limiting $\hat{\lambda}_3$ enables whole scanned points to be classified into "pipe points" and "non-pipe points". The threshold value is determined by the discriminant analysis method [William et.al 1980].

4.3 Grouping "pipe points" (A13)

After finding the pipe points, the points on one straight portion of a pipe are integrated into a single region by applying the region growing method. First, a seed point s of a region is chosen from "pipe points" at random. Then, other pipe points contained in a set of neighbouring points $N(s,r_4)$ centred at s are added to the region. Each of these added points are then chosen as a new seed point, and other "pipe points" adjacent to each seed point are added to the region.
The above steps are repeated until "pipe points" exists in neighbourhoods of the seed points.