Title:
Extraction and Recognition of Components from Point Clouds of Industrial Plants

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Introduction:
In recent years, rapid advances in laser scanning technology have made it easier to acquire dense point-clouds from large industrial plants. Since reliable 3D models or drawings of existing industrial plants are rarely obtained due to repeated renovation, point-clouds are very useful for planning renovation work.

However, it is difficult to acquire complete point clouds of industrial plants, because measurement positions are limited and occluded regions cannot be avoided when many components are densely placed. Therefore, in many cases, it is required to extract each component from incomplete point clouds. In industrial plants, standard components such as pipes and flanges are typically used. They consist mostly of primitive surfaces, such as planes, cylinders, cones, spheres, and tori. Therefore, existing methods in reverse engineering of industrial plants extracted standard components by extracting primitive surfaces. In order to accurately calculate dimensions from point clouds, many practical systems detect only planes and cylinders, which can be uniquely determined using a small number of parameters, and standard components with torus or conic surfaces are estimated using industry standards of connected pipes [4]. Fig. 1(a) shows standard components connecting to cylindrical pipes. These shapes can be uniquely determined according to the industrial standards if the radii of connecting pipes are given.

However, there may be non-standard components in industrial plants, such as valves and manometers. Such components cannot be identified from connecting cylinders or planes. In addition, there may be several variations on standard components. For example, the flange may be composed of a combination of multiple members connected by bolts. The pipe may be wrapped with thermal insulation.

Furthermore, as shown in Fig. 1(b), the existing method may not be able to estimate the component type. This is because component types are estimated using positional relationships between cylinders, and complex industrial plants allow for multiple interpretations of pipe routes.

In this research, we discuss methods for identifying component types using machine learning. Since point clouds captured using a terrestrial laser scanner can be mapped on the 2D grid, convolutional neural network (CNN) designed for images can be applied to points. In our method, cylinders and planes are detected from point-clouds and candidate component regions are extracted. Then component types are estimated using CNN. In our method, three types of images are generated from point clouds, and they are used for classification. In addition, we introduce a classifier that integrates the three types of classifiers.

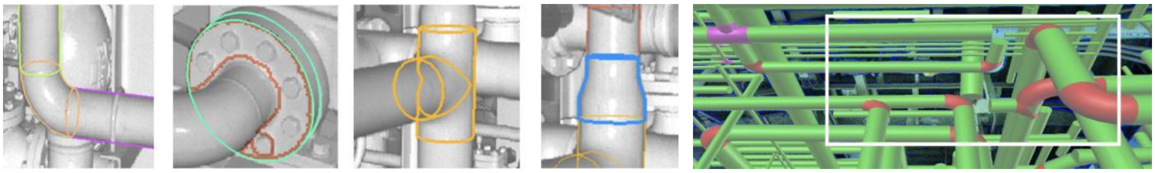

Fig. 1: Component detection using cylinder and plane: (a) Detection of standard parts from cylinders and planes, and (b) Ambiguous pipe routing.

Detection of Planes and Cylinders:

The terrestrial laser scanner emits laser beams, whose directions are determined by the azimuth angle θ and the zenith angle ϕ, as shown in Fig. 2. Since the angle intervals are constant, points can be mapped on the 2D grid defined by θ and ϕ. Therefore, each point clouds can be converted into a 2D image.

Planes and cylinders can be efficiently detected on the 2D grid using the method proposed by Masuda, et al. [3]. In this method, if the distance between adjacent points on the grid is smaller than a threshold, these points are segmented into the same region. Then, points are segmented into connected regions on the 2D grid, as shown in Fig. 3(b). Next, planes and cylinders are detected using the RANSAC method in each region. Since the performance of the RANSAC method [5] largely depends on the size of the search region, surfaces are searched only in each connected region. Each time a cylinder or a plane is detected, the remaining region is further subdivided into smaller regions. The detection and subdivision are repeated until region areas become smaller than a threshold. Fig. 3(c) shows detected planar and cylinder regions.

Detection of Regions Connecting to Cylinders:

In the previous research, component types were estimated using the positional relationship of cylinders and planes. However, this method limits the variations of detectable component types. In this research, we extract regions connecting to cylinders and identify component types using machine learning.

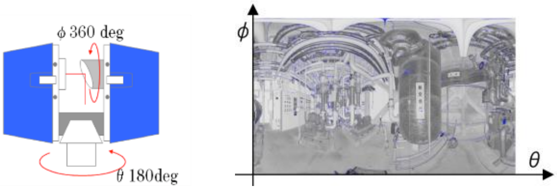

Fig. 2: Points arranged on the 2D plane.

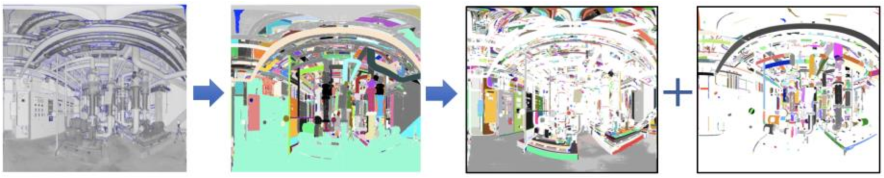

Fig. 3: Extraction of planes and cylinders: (a) Point cloud, (b) Segmentation, and (c) Planar and cylindrical regions.

Fig. 4: Regions that connect to cylinders.

By using detected planes, floors, ceilings, and walls are identified, and they are removed from point clouds. Then, regions connecting to cylinders are extracted. Fig. 4 shows pipe regions in green, planer regions in blue, and the detected regions in red.

Generating Images from Points:
Since a point cloud can be mapped on the 2D grid, the detected regions can also be mapped onto an image. However, the image defined by the azimuth angle θ and the zenith angle ϕ is distorted, and the linearity of the object is not preserved. Distortion is particularly large at the top and bottom of the 2D grid. To solve this problem, a virtual perspective projection plane is placed, and the angle coordinate (θ, φ) is converted to the coordinate (I, J) on the perspective projection plane, as shown in Fig. 5(a). As shown in Fig. 5(b), the perspective projection image preserves the linearity.

Each point captured using the terrestrial laser scanner typically has a 3D coordinate, an intensity value, and a RGB color. The intensity value represents the strength of a returned laser beam, and it is added as an attribute of each point. The intensity value may be an integer or a floating point number depending on the laser scanner type. In this research, the intensity value is normalized to an integer between 0 and 255. RGB colors are captured using a camera built in the laser scanner, and added to points as attributes in the post process. Each RGB color is represented by three integer values $[R, G, B]$ from 0 to 255. The depth value is calculated as the distance between a coordinate and the scanner origin. Therefore, three types of images can be generated by writing intensity values, RGB colors, or depth values to pixels of an image. Fig. 6(a) shows an RGB image generated from a point cloud. The normalization is required for the convergence of CNN. Therefore, Each attribute is nomalized between 0 to 1.

Data Augmentation:
To train a CNN classifier, a large number of images are required. However, it is difficult to obtain point clouds of many industrial plants. Therefore, data augmentation techniques are applied to images. Many variations of images are generated from the original image by rotating, changing the brightness values, adding black and white noises, and inverting.

To augment depth images, it is effective to transform points and obtain depth images on various positions and orientations. However, this approach cannot be applied to partially measured point clouds. Therefore, we create CAD models of typical components and generate depth images from the CAD models. By changing the position and orientation of the 3D model, a lot of depth images can be generated. Depth images are generated by projecting the CAD model onto the perspective projection plane. Fig. 6(b) shows a depth image generated from a CAD model.

Fig. 5: Generation of images from point clouds: a) Perspective projection, and (b) Conversion to the perspective image.

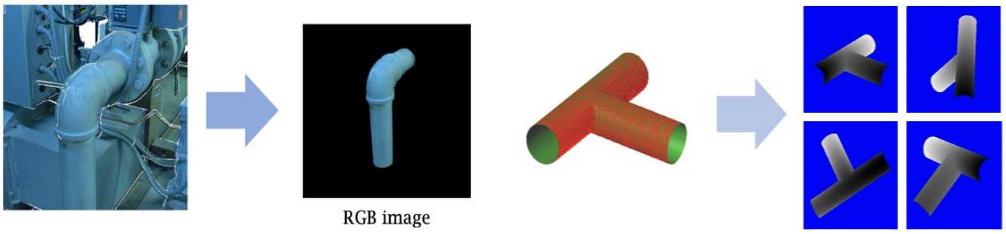

Fig. 6: Generation of images from point clouds: (a) RGB image, and (b) Depth image generated from CAD model.

Feature Extraction and Selection:

We used VGG16 trained by ImageNet for classification using images. We fine-tuned VGG16 using three types of images. Three types of images are separately added to VGG16, and therefore, three types of classifiers are obtained. In VGG16, the input image is processed in many layers, and the class type is output from the final layer. We extract 1024 features of each image from the fully connected layer immediately before the final layer. From the extracted features, effective features are selected using the method proposed by Boruta [2]. In this method, false features are generated, and the significance values of the true feature and the false feature are compared using Random Forest (RF) to determine whether the feature is important. Finally, we define the classifier for components by integrating important features extracted from three types of classifiers.

Experimental Results:

To evaluate our method, we extracted regions of components from point-clouds of industrial plants, and selected elbows, flanges, straight pipes, T-shaped pipes, valves, and pressure gauges, as shown in Fig. 7. The numbers of each class data are shown in Tab. 1. One half of the data were used for training the classifier, and the other half were used for evaluation.

We first evaluated single-input classifiers. For comparison, we also evaluated PointNet [1] using the same point clouds. Tab. 2 shows the results of single-input classifiers. In this evaluation, the classifier using depth images enhanced with CAD models has achieved the best score. This result shows that the use of CAD models has significantly improved the accuracy of tees, valves and pressure gauges, whose numbers were small. The score of PointNet was the lowest among five classifiers. This might be because data augmentation could not be applied to point clouds and the well-trained learned model was not available for the PointNet model.

We also evaluated the effectiveness of feature selection. In our method, features extracted from CNN models were reduced according to their effectiveness. Tab. 3 shows comparison between classification using all features and classification only using effective features. The result shows that effective features were effective for improving the recognition scores. In addition, as a result of using effective features

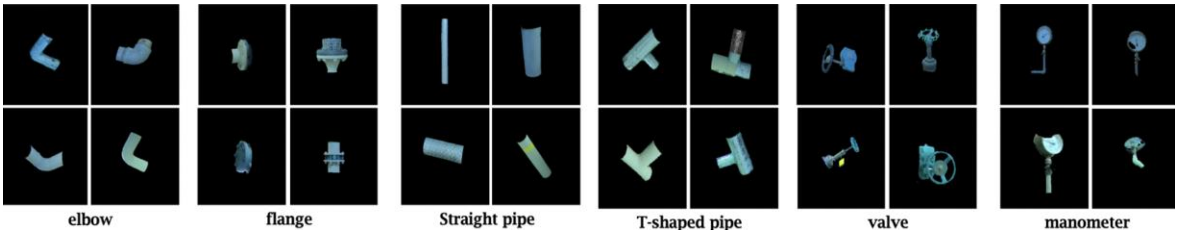

Fig. 7: Examples of components.

	Elbow	Flange	Straight	T	Valve	Manometer
Point Clouds	171	161	80	21	43	7
CAD Data	60	120	80	80	80	80

Tab. 1: Number of data for each class.

	RGB	Intensity	Depth	Depth & CAD	PointNet
Elbow	89.8 %	89.8 %	93.8 %	92.0 %	87.8 %
Flange	91.8 %	89.9 %	93.0 %	92.9 %	66.7 %
Straight	93.5 %	95.0 %	92.1 %	95.1 %	77.1 %
T	50.0 %	40.0 %	55.6 %	66.7 %	42.9 %
Valve	95.0 %	85.7 %	81.8 %	86.5 %	32.9 %
Manometer	80.0 %	80.0 %	75.0 %	85.7 %	16.7 %
Weighted Average	89.8 %	88.1 %	90.1 %	91.2 %	71.5 %

Tab. 2: F-measures of the single-input classifiers.

from CNN models, the accuracy is greatly improved compared to single-input classifiers. This result

	All Features	Effective Features
Elbow	95.3 %	96.5 %
Flange	97.5 %	96.3 %
Straight	96.2 %	96.2 %
T	60.0 %	73.7 %
Valve	93.0 %	95.0 %
Manometer	100.0 %	100.0
Weighted Average	94.6 %	95.3 %

Tab. 3: F-measures using all features and effective features.

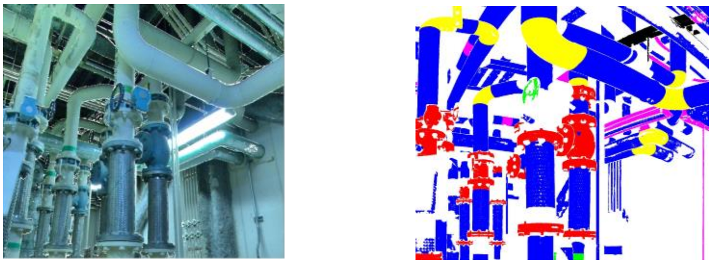

Fig. 8: Classification results: (a) Point cloud, and (b) Classification result.

shows that color and geometry are complementary results.

In industrial plants, there are component types other than those in Fig. 7. Therefore, we accepted the result only if the classifier output the result with a probability of 70 % or more. Otherwise, the result was rejected. Fig. 8 shows classification results. The blue regions indicate pipes extracted as cylinders. Points classified as straight pipes, flanges, elbows, and valves are shown in magenta, red, yellow, and green, respectively. Most components were correctly classified, but some distant components were incorrectly classified. This result indicates that the classifier requires a sufficient number of points on each component.

Conclusion:

In this research, we extracted components connected to pipes, and identified their component types using machine learning. We trained five types of single-input classifiers using either RGB images, intensity images, depth images, augmented depth images, or 3D coordinates. In our evaluation, the classifier using depth images augmented by CAD models was the best among the five classifiers. We also created multi-input classifiers by integrating features obtained from single-input classifiers. In our evaluation, the classifier using RGB, intensity and augmented depth images could achieve the best score.

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