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Methods for Graph Conversion and Pattern Recognition for P&IDs

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ABSTRACT

In this study, we developed a method to simplify the analysis of complex Piping and Instrumentation Diagrams (P&IDs) on ships. By converting P&IDs into a graph format, we extracted lines and symbols from the original DXF files, enabling easier identification of connections between ship systems. Utilizing the graph, we can intuitively understand complex P&ID and easily apply it to research such as pipe routing optimization. This approach enhances the understanding of ship systems and has potential applications in recommending similar systems within existing ships, streamlining the design and analysis process.

KEY WORDS

P&ID; Pattern Recognition; Deep Learning; Arrangement Design; Connection relationships Analysis

INTRODUCTION

A piping and instrumentation diagram (P&ID) is a drawing that uses simple symbols to represent the connections of equipment and piping within systems on a ship. Understanding the connections within the P&ID is important for designers to comprehend the systems on the ship. However, this process is difficult because various systems on the ship are complexly connected. In addition, since the P&ID represents the connection relationships as a line, it is inconvenient to find and follow the connection lines between the equipment among many complex lines. Therefore, we proposed a method to analyze the existing P&ID by converting it into a graph. Lines and strings were extracted from the original P&ID in DXF (Drawing eXchange Format), and symbols were recognized using the connections between the extracted lines. We could identify their connections with the extracted lines and the recognized symbols and convert them into a graph. The converted graph can represent the complex connection relationships of P&ID in a simplified form. Using this, we can obtain connection relationships between equipment and utilize it for the pipe auto-routing. With the method proposed in this study, P&IDs can be automatically converted into a graph and utilized for various applications. This graph format is specialized for representing connection relationships; it can help with topological analysis, such as recommending similar systems within existing ships.

THEORETICAL BACKGROUND

The P&ID targeted for recognition in this study has the form shown in Figure 1. There are various objects in a P&ID, such as pumps, valves, and instruments. Objects in the drawing are represented by symbols that briefly represent the characteristics of the equipment. These symbols are composed of basic elements such as lines and are difficult to recognize because they are relatively small compared to the large size of the drawing. Additionally, because the types of objects are very diverse and mixed

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with strings containing information about the objects, it is not easy even for experts to check them. Therefore, research on recognizing or extracting specific objects from P&ID is being conducted in many fields. Table 1 shows a summary of related studies for recognizing various elements in drawings such as P&ID and the method proposed in this study.

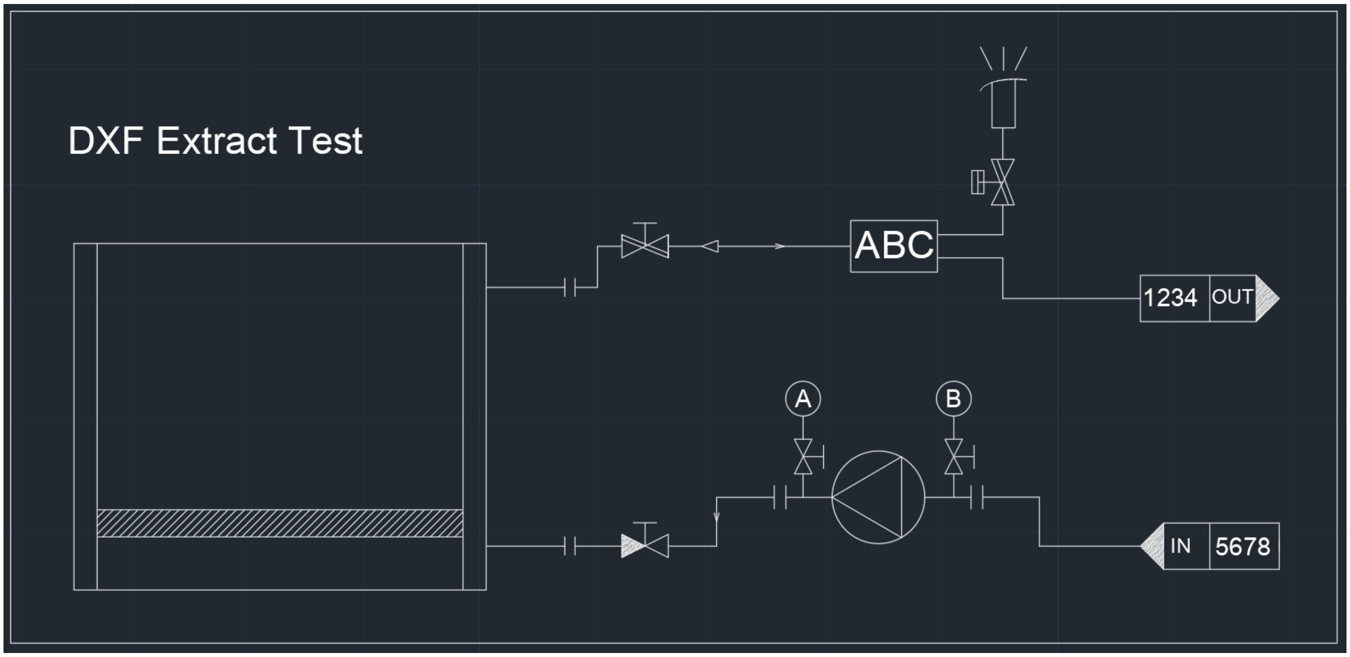


Figure 1: Example of P&ID (expressed briefly for security reasons)

Table 1: Summary of the related studies and comparison with this study

Studies	Application field	Recognition algorithms/model	Recognition target
Luo & Liu (2003)	Schematic	X	Schematic symbol
Yu et al. (2019)	P&ID	CNN (modified AlexNet)	P&ID symbol
Rahul et al. (2019)	P&ID	CPTN & FCN	P&ID symbol, text
WAN et al. (2019)	Mathematical formula	CNN	Math symbol
Kim et al. (2022)	P&ID	GFL, Tesseract	P&ID symbol, text
Moon et al. (2023)	P&ID	Modified hough transform	Line
This study	P&ID	Cascade R-CNN, DXF extraction tool	P&ID symbol, text, line, connection relation

As we can see from the table, there are two main ways to recognize objects in P&ID. The first method is to extract elements from a drawing and specify objects from their relationships. This method has the advantage of being able to accurately find an object under the condition that the drawing contains various information and can be extracted. Luo & Liu (2003) used a case-based recognition method to specify symbols from relationships such as points and lines. Additionally, Moon et al. (2023) used an image-based line recognition algorithm to find connecting lines in P&ID. Conversely, if the drawing is not created accurately and the creator makes a mistake when drawing some objects, there is a disadvantage in that the corresponding part cannot be found. In addition, the work process is complicated because users have to specify what the object looks like and find the corresponding characteristics.

The second method is a deep learning-based recognition method that has been popular recently. Convert the drawing into an image, and users directly label the objects they want to learn within the image. Afterward, a deep learning model for object recognition is built and trained to find objects in the image. Yu et al. (2019) and WAN et al. (2019) used a convolutional neural network (CNN) to recognize symbols in images. CNN is the most basic model among deep learning models for image recognition and is used to extract and classify image features using 2D images as input. Rahul et al. (2019) were able to extract more detailed features of equipment within P&ID by combining two deep learning-based object recognition models and text recognition models. In this method, because the deep learning model itself learns the characteristics of the object, there is a possibility of finding it well, even if there are slight errors or variations in the drawing. However, the disadvantage is that learning a deep learning model requires a large amount of data, and the user must label it. Therefore, it is crucial to understand the advantages and disadvantages of the two methods for recognizing objects within drawings in order to utilize them appropriately. For example, Kim et al. (2022) were able to achieve more accurate recognition results by leveraging the strengths of both the Tesseract (Smith, 2007) model, which recognizes characters from extracted images in drawings, and a deep learning-based image recognition model. Therefore, in this study, these two methods were appropriately combined to select the optimal recognition method suited to the characteristics of objects in the drawing.

Another important piece of information that P&ID contains is the connection relationships. Objects in the drawing represent equipment, and the pipes connecting them are expressed as lines. Therefore, the user can check this and know how the equipment is connected by referring to the drawing. Humans can easily understand connections by following lines, but in order to automate this process, lines must be recognized accurately. There are many elements in a drawing that make it difficult to construct a recognition algorithm, such as lines representing objects and lines representing pipes being mixed and intersecting, with one line being cut off in the middle. In this study, information was extracted from a common drawing format called drawing interchange format (DXF), and connection lines were recognized through a preprocessing process.

If the equipment and connection relationships in the drawing are extracted through the above process, this information can be used to analyze the characteristics of the P&ID. In this study, the recognition results were converted into data using the concept of a graph. As shown in Figure 2, the graph is composed of nodes and edges, with nodes expressed as points and edges expressed as lines. We converted P&ID into a graph by representing equipment as nodes and connection relationships as edges. The converted graph is easy to analyze topology and connectivity because it excludes unnecessary elements and only has connections. Therefore, we proposed a method to convert P&ID into a graph automatically. As a result, this graph can be used for research, such as creating piping routes or analyzing similar systems.

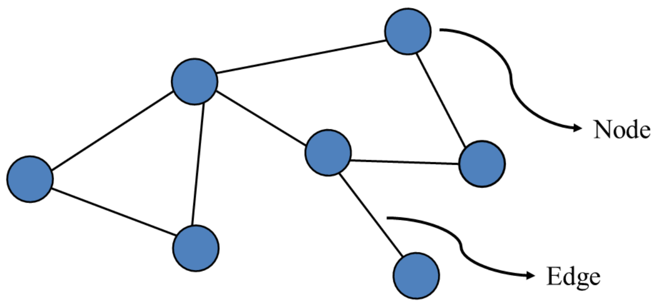


Figure 2: Components of a graph

APPLICATIONS

We used a deep learning model to recognize objects in P&ID. Deep learning allows us to find objects in drawings quickly; it is suitable for large-sized P&IDs. However, deep learning models require a large amount of training data. Because P&ID is large and contains various types of objects, the labeling process takes much time and labor. Therefore, we designed a model that can automatically generate training data. First, select an image that will become the background. At this time, several noises were added to the base image to increase the diversity of training data. Next, various objects are placed in random positions on the base. We called the placed objects as material. Material also went through the process of adding noise, such as rotation and scaling, to ensure diversity in the training data. The drawing created by this method is shown in Figure 3. Since we know where the materials are placed, we can automatically generate labeled data. Using this, we were able to generate a large amount of training data and train a deep-learning model for object recognition.

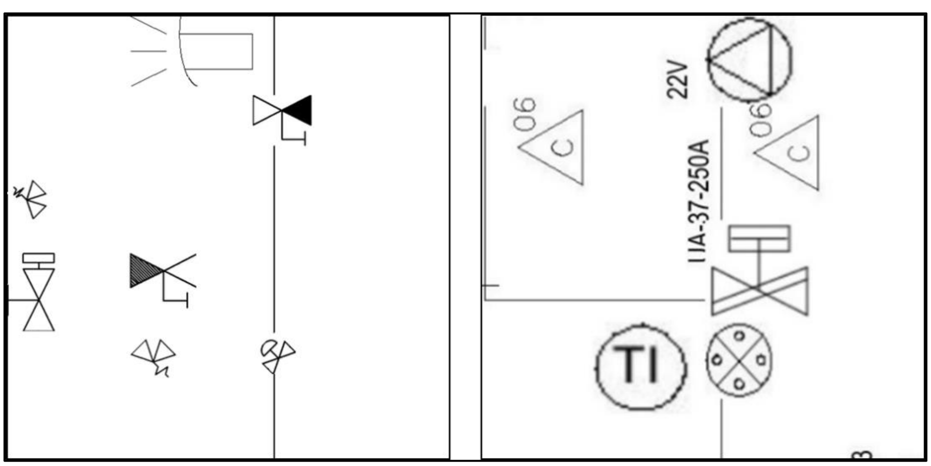


Figure 3: Example of the generated training data

Two-stage models generally showed better accuracy than one-stage models when recognizing objects in drawings (Kong et al., 2022). In this study, we used a two-stage CNN model called Cascade R-CNN (Cai & Vasconcelos, 2018) as a deep learning model to recognize objects. This model is known to have a high recognition rate for multiple overlapping objects. As shown in Table 2, we trained several two-stage models to find 26 types of objects and measured recognition accuracy on 11 actual drawings. Each model was trained using the same 120,000 pieces of virtually generated data. We trained the models using RTX 4070 Ti in a Windows 10 environment, and each parameter used the default values of each model. As a result, Cascade R-CNN showed the best performance among them. It took an average of 90 seconds to recognize each drawing, and most objects were recognized with F1-score=0.9863. Figure 4 shows some of the results of object recognition with the Cascade R-CNN model. We confirmed that the types, sizes, and locations of objects in the P&ID were accurately recognized.

Table 2: Accuracy analysis between the detection models

	Cascade R-CNN	Faster R-CNN	Sparse R-CNN
Elapsed time (s)	90	89	94
Precision (%)	99.29	97.19	96.06
Recall (%)	97.99	98.63	45.83
F1-score (%)	98.63	97.88	58.11

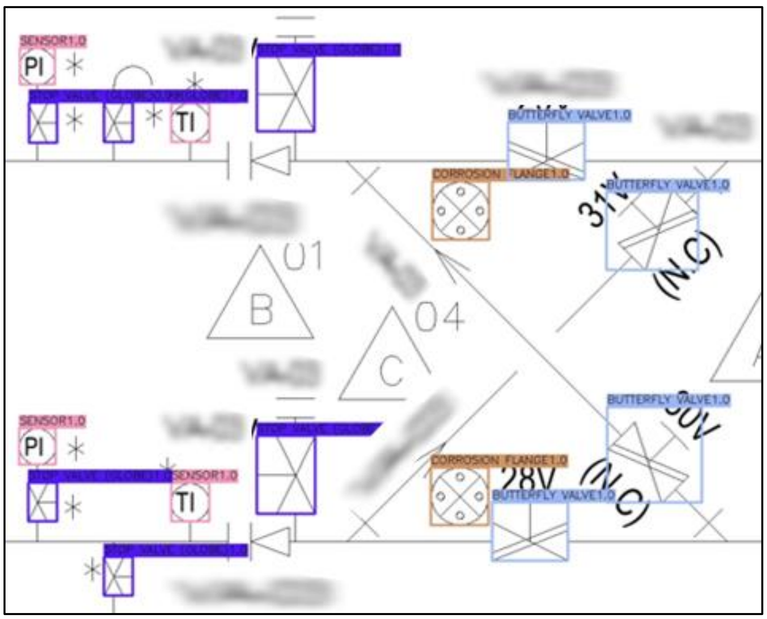


Figure 4: Example of P&ID recognition results with Cascade R-CNN model (text blurred for security reasons)

Deep learning models have the advantage of recognizing objects with distinct features, but they are known to have relative difficulty in recognizing simple elements such as lines. Therefore, we devised a method to extract lines directly from the drawing and preprocess them to find connecting lines between objects.

The DXF format converts drawings created with a computer-aided design (CAD) program into a highly compatible format. Elements that can be extracted from the DXF format include lines and strings. Figure 5 shows the types of elements that can be extracted from the DXF format. We analyzed the extractable elements and extracted only the lines representing the connecting lines. Lines extracted from the DXF format have both their start and end points. By using these, line elements in the object recognition results can be removed.

Furthermore, by sequentially linking the end points from the line connected to the object, a connecting line can be identified (Figure 6). Combining this result with the object recognition result is shown in Figure 7 (a). Since each extracted line has a starting point and an ending point, connecting lines between objects can be found by continuously extracting adjacent lines based on these points. As a result, it is possible to find all connections within the drawing, shown in Figure 7 (b). This result can again be expressed in graph form, as shown in Figure 7 (c).

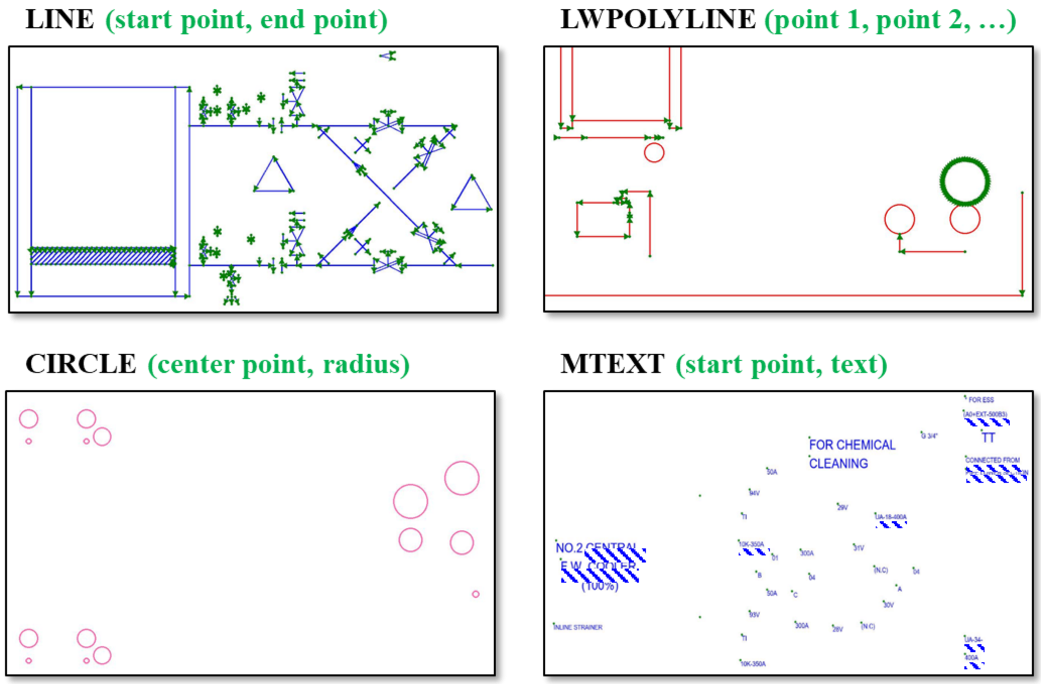


Figure 5: Examples of elements that can be extracted from files in the DXF format (text blurred for security reasons)

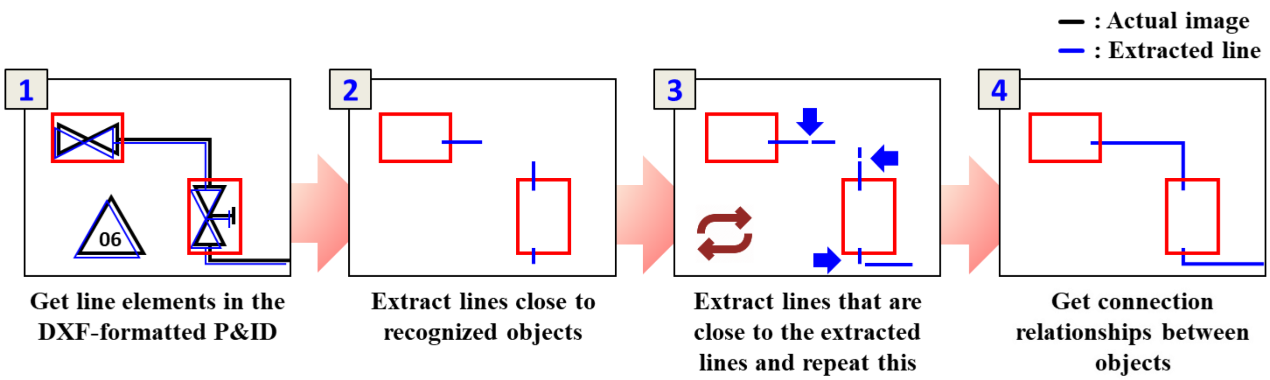
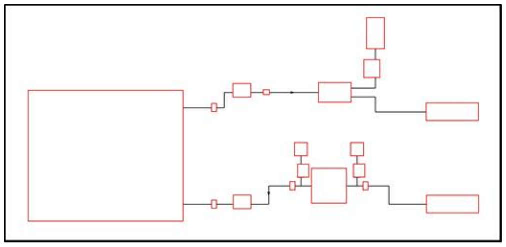
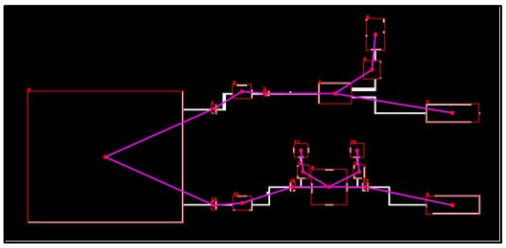


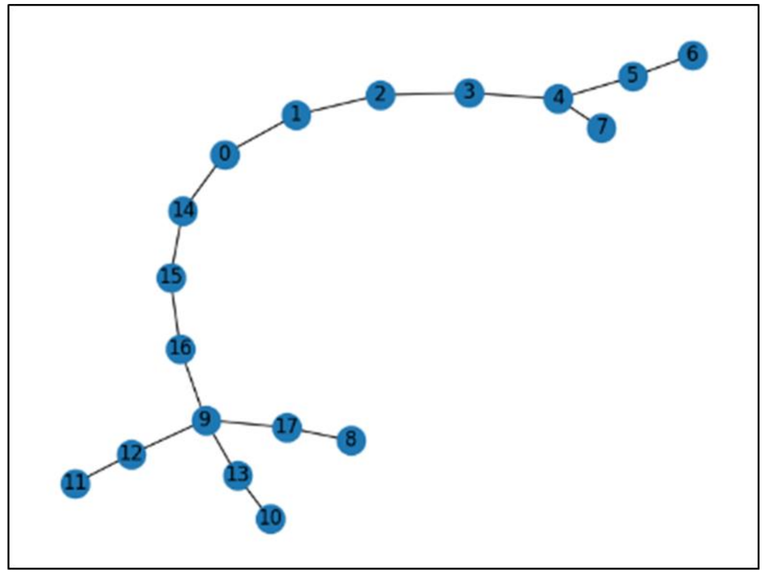
Figure 6: Process of obtaining connection relationships between objects using extracted line elements



(a) Pre-processed elements



(b) Defined connectivity



(c) Converted to a graph

Figure 7: Conversion process of the P&ID to a graph (expressed briefly for security reasons)

As mentioned above, P&ID represents the connection relationships between equipment in the form of a line. When the P&ID is converted into a graph form, we can use the connection relationships of the graph to check how the pipe is connected between each equipment. Each piece of equipment has a specific location for the part connected to the pipe, that is, the nozzle. Therefore, if we only determine the location of each equipment, we can automatically create pipes utilizing the graph. Even if they look like different P&IDs, if the recognized graph (so-called pattern) is the same, they can be considered the same system.

Ha et al. (2023) established measures for evaluating layouts of pipe by quantifying the expertise of professionals and, based on this, devised an algorithm to generate the optimal pipe routes. Utilizing this study, we designed a method that automatically creates pipes from the connection relationships of each piece of equipment. Figure 8 shows the results of creating pipe routes by adding the locations of equipment based on the graph extracted from P&ID. In the eyes of humans, the two results may appear as different systems, but from a graph perspective, they represent the same system. Therefore, an analysis from a graph perspective is necessary to recognize the patterns inherent in P&IDs.

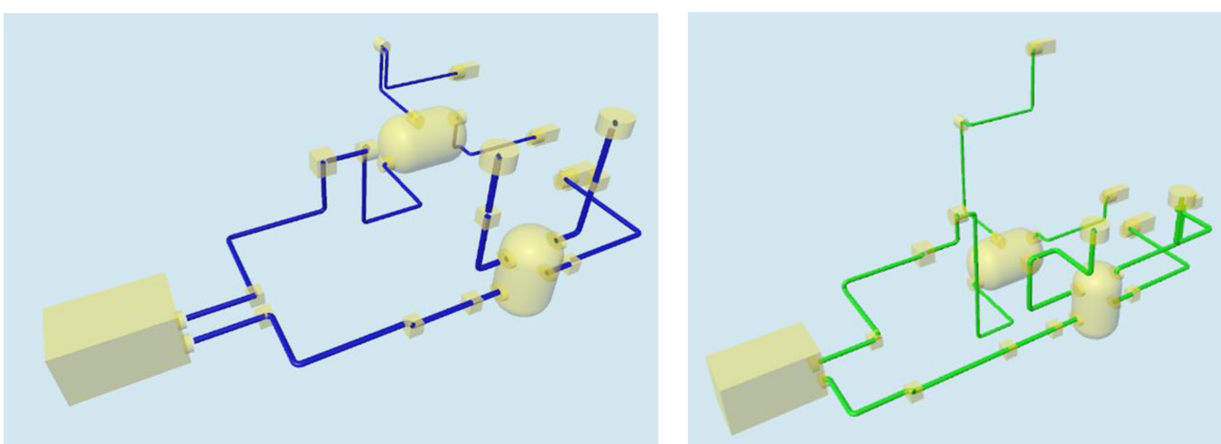


Figure 8: Results of creating different pipe routes from the same P&ID

Moreover, through the proposed process, we can convert many P&IDs into a graph form and train a deep learning model on the graph structure itself. In the future, we can train a deep learning model with a graph neural net (GNN; Scarselli et al., 2009) structure and create a model that classifies which system the input graph is similar to the database. As a result, we plan to build an automated process that takes P&ID as input, finds objects, interprets connection relationships, converts them into a graph, and recommends the one most similar to the existing system.

CONCLUSIONS

This study proposed an automated process for object recognition and connection relationships analysis targeting P&ID. P&ID consists of various objects such as pumps, valves, and instruments. So, precisely recognizing them is a difficult task. We trained the two-stage based CNN model with virtual images generated with our algorithm and were able to recognize objects in the drawing with high accuracy. Additionally, we extracted elements like lines or circles in the DXF format and obtained connection relationships between the recognized objects. We represented the results in a graph format. As a result, the proposed process could build an automated system. It receives P&ID as input, finds objects, and interprets the connection relationships. Then, it converts them into a graph and can be utilized in various studies. We applied the converted graph to the study for pipe auto-routing. Consequently, we confirmed that we could automatically place pipes by extracting the connection relationships between equipment from the P&ID. Due to the use of deep learning models and innovative application of training data generation methods, most objects were able to be recognized, and the characteristics of the system were successfully inferred through graph analysis.

We plan to convert more P&IDs into graphs and analyze additional features that can be learned from them. To confirm the practicality of the method proposed in this study, we must verify it on more diverse data. Additionally, the features of the converted graph must be labeled to train deep learning models in the future. We plan to research ways to create virtual data in DXF format, just as we created virtual data for object recognition. There are also many ways to utilize the graph, such as embedding the characteristics of each node and edge in addition to the characteristics of the structure itself used in this study. Therefore, we plan to investigate various possibilities that can be applied using the above process.

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