Automating the Expansion of Instrument Typicals in Piping and Instrumentation Diagrams (P&IDs)

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Abstract

Within the Engineering, Procurement, and Construction (EPC) industry, engineers manually create documents based on engineering drawings, which can be time-consuming and prone to human error. For example, the expansion of typical assemblies of instrument items (Instrument Typicals) in Piping and Instrumentation Diagrams (P&IDs) is a labor-intensive task. Each Instrument Typical assembly is depicted in the P&IDs via a simplified representation showing only a subset of the utilized instruments. The expansion activity involves recording all utilized instruments to create an instrument item list document based on the P&IDs for a particular EPC project. Fortunately, Artificial Intelligence (AI) could help automate this process.

In this paper, we propose the first method for automating the process of Instrument Typical expansion in P&IDs. The method utilizes computer vision techniques and domain knowledge rules to extract information about the Instrument Typicals from a project's P&IDs and legend sheets. Subsequently, the extracted information is used to automatically generate the listing of all utilized instruments. The effectiveness of our method is evaluated on P&IDs from large industrial EPC projects, resulting in precision rates exceeding 98% and recall rates surpassing 99%. These results demonstrate the suitability of our method for industrial deployment. The successful application of our method has the potential to reduce engineering costs and increase the efficiency of EPC projects. Furthermore, the method could be adapted for additional applications in the EPC industry, which highlights the method's industrial value.

Introduction

The Engineering, Procurement, and Construction (EPC) industry executes projects involving the construction of infrastructure installations with a capital cost exceeding $500 million (Berends 2007). During the execution of EPC projects, engineers need to analyze numerous engineering drawings to produce project deliverables. However, these activities can be time-consuming and prone to errors (Mani et al. 2020). Therefore, the use of artificial intelligence in the EPC industry holds immense potential to increase the efficiency of engineers (Dzhusupova, Bosch, and Olsson 2024). Particularly, deep learning methods for computer vision could automate the analysis of engineering drawings (Dzhusupova et al. 2022).

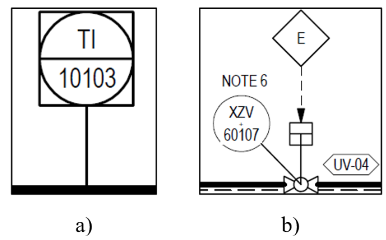

Figure 1: An example of a regular instrument (a), and a simplified representation of an Instrument Typical assembly indicated by typical number "UV-04" (b).

A type of engineering drawing heavily used in the EPC industry is the Piping and Instrumentation Diagram (P&ID). P&IDs depict the interconnection of process equipment and the instrumentation devices necessary for controlling processes (Theisen et al. 2023). The instruments are depicted using squares or circle shapes in these diagrams, where their type and tag number are indicated inside the shapes. Figure 1 a) showcases an example of an instrument of type "TI" (temperature instrument) with tag number "10103".

The P&IDs are important as many project deliverables are based on them. An example of such a deliverable is the "Instrument Index" document (Process Industry Practices 2015). This document lists all instrument devices depicted in the P&IDs in a table format. It records the instrument type, the tag number, and other relevant data for each instrument. This document is used for cost estimation and the generation of other project deliverables.

When P&IDs are only available in PDF format, engineers must manually create the "Instrument Index" document. This involves analyzing the P&IDs and recording the instruments shown in these drawings. P&IDs often depict simplified schematic representations of the actual instruments, without implied components. Instead, there are references to the standard assemblies of instrument items known as "Instrument Typicals" (Process Industry Practices 2023). The reference to the Instrument Typical is indicated by a typical number and is shown next to the simplified P&ID instrument schematic representation. Figure 1 b) showcases an example of a simplified P&ID representation of an Instrument Typical assembly with the typical number “UV-04”. The simplified P&ID representation depicts only the instrument “XZV” with tag number “60107”. However, engineers need to record all instruments in the Instrument Index document, not just the instruments shown in the simplified schematic representations. This is done by referring to a project’s legend sheet depicting all instruments for each typical. An example of a legend is shown in Figure 2. This activity is known as “Instrument Typical Expansion”, which is time-consuming and error-prone. Thus, the EPC industry would benefit from its automation.

In this paper, we propose a novel method combining computer vision techniques and domain knowledge rules to automate the manual process of “Instrument Typical Expansion”. The method detects the simplified representations and the typical numbers indicated in the P&IDs. Furthermore, it extracts the Instrument Typicals information from the P&ID legends. Finally, a procedure based on engineering practices is applied to automatically generate the complete set of instruments for each Instrument Typical detected in the P&IDs. The method was evaluated on three multibillion EPC projects for the petrochemical industry executed by McDermott, a global EPC company. This research holds the potential to reduce the need for manual P&ID analysis and enable engineers to create an “Instrument Index” document automatically.

To summarize, our main contribution is the following: We propose the very first method for automating the expansion of Instrument Typicals indicated in P&IDs. The method combines deep learning text recognition, line detection techniques, and domain knowledge rules. It achieves impressive overall rates of 98% recall and 99% precision.

The remainder of the paper reviews the manual Instrument Typical Expansion process and existing literature on information extraction from engineering drawings, followed by the research objective and methodology of this research. Subsequently, we present the method for automatic Instrument Typical Expansion, along with the evaluation method and results. The applicability of the method and the path to deployment are then discussed, leading to a conclusion summarizing the findings.

Problem Background

During the tendering phase of EPC projects, P&IDs are predominantly available in PDF format due to intellectual property concerns (Dzhusupova, Bosch, and Olsson 2022). This is also applicable to legacy drawings that do not have a digital version. In these cases, engineers are required to analyze hundreds of P&IDs and extract the instruments depicted on these drawings to create the “Instrument Index” document.

As mentioned previously, an additional challenge arises from the fact that P&IDs often show only a few of the utilized instruments by depicting simplified schematic representations of common instrument assemblies, which are known as “Instrument Typicals” (Process Industry Practices 2023). The Instrument Typicals are depicted in the legend sheets of a project. Figure 2 shows an excerpt from a legend sheet depicting two Instrument Typicals by specifying

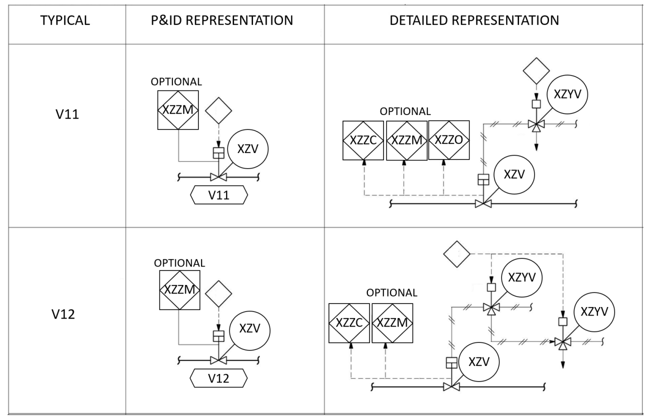

Figure 2: A legend sheet excerpt depicting the typical numbers, the simplified representation shown in the P&IDs, and the detailed representation of all utilized instruments.

their typical numbers (V11, V12), their simplified representation shown in the P&IDs, and their detailed representation showing all utilized instruments.

The simplified P&ID representations are used to improve the readability of P&IDs as these drawings contain a substantial amount of information (Process Industry Practices 2023). However, engineers must manually record all utilized instruments, rather than only the instruments shown in the P&ID representations. This activity is known as “Instrument Typical Expansion”. Engineers need to refer to the project’s legend sheet for each Instrument Typical indicated in the P&IDs based on the typical number and manually record all instruments listed in the legend’s detailed representation of the Instrument Typical assembly. Furthermore, each typical may have optional instruments. For example, in Figure 2 the two typicals have an optional instrument “XZZM”, which may not be present in the P&ID. If it is not present, then the corresponding “XZZM” instrument in the detailed representation should be ignored. Moreover, it should be noted that every EPC project defines its unique Instrument Typicals. Due to all these factors, the process of “Instrument Typical Expansion” in the P&IDs consumes many engineering hours and is susceptible to errors. Therefore, automating this process can save costs for the EPC industry and increase the efficiency of engineers.

Although there is existing work on P&ID information extraction, to our knowledge the problem of automatically expanding Instrument Typicals in P&IDs based on the detailed representations in the legend sheets has not been studied previously. In this research, we investigate a novel industrial application of AI. We propose a method combining computer vision techniques and domain knowledge rules to automate this process and aid instrumentation engineers.

Related Work

In recent years, computer vision methods have been actively applied for detecting regions of interest and extracting text from documents and engineering drawings. This is due to the potential of these methods to automate the analysis of documents and enable efficient information extraction. A common computer vision technique is Hough Transform, which was primarily used for diagram detection (Illingworth and Kittler 1987) and has been applied to detect lines in P&IDs (Kim et al. 2022; Rahul et al. 2019). Chu 2023 presents a fully automated pipeline for key-value pair information extraction in unstructured documents, where regions of interest are identified using OCR methods. Studies focusing on P&ID information extraction have used the EAST network (Zhou et al. 2017) to detect text on P&IDs (Jamieson, Moreno-Garcia, and Elyan 2020; Saba, Hantach, and Benslimane 2023; Francois, Eglin, and Biou 2022). While this network is reported to achieve high overall detection results, it is also reported that it can truncate long text or merge multiple text instances into one (Jamieson, Moreno-Garcia, and Elyan 2020; Francois, Eglin, and Biou 2022). Kim et al. 2022 employ a pre-trained CRAFT text detector (Baek et al. 2019), but one drawback of this approach is that the detector is not fine-tuned to the domain data. Furthermore, these studies utilize either Tesseract OCR (Smith 2007) or EasyOCR (Jaided.AI 2021) to recognize the detected text regions in the drawings. Although to our knowledge there is currently no published work on P&ID Instrument Typical Expansion, the existing research on P&ID text extraction and document region-of-interest detection serves as an inspiration for our proposed method.

Research Objective and Methodology

The research was executed at McDermott, an international EPC company undertaking construction projects in the energy sector. The problem explored in this study is based on the workflow of instrumentation engineers. As mentioned previously, when P&IDs are only available in PDF format, engineers need to manually expand the Instrument Typicals indicated in the P&IDs to create an Instrument Index document. Therefore, the research question explored in this study is the following: **"How can computer vision be applied to automate the manual process of Instrument Typical Expansion and reduce engineering costs?"**.

The research was performed by members of McDermott's AI team. The first author served as the AI Engineer of the method presented in this paper, while the second author is the lead of the AI team. As the authors are industry practitioners, the Action Research methodology is followed, where the researchers investigate a problem while developing a solution (Easterbrook et al. 2008). Despite potential bias concerns due to the authors' involvement (Walsham 1995), this methodology grants exclusive access to industrial data unavailable to external observers. The following activities follow established action research workflow (Coughlan and Coghlan 2002). Initially, problem identification and research planning were conducted through discussions with the company's instrumentation engineers to understand their challenges. Subsequently, data collection, text detection model training, and the development of the proposed method were executed. The company's instrumentation engineers supported the evaluation of the proposed method.

Automatic Instrument Expansion Method

The method for automated Instrument Typical Expansion involves the use of computer vision techniques and domain knowledge rules. The overall method is shown in Figure 3. As can be seen, text detection and recognition models are used to extract all the text and its location from a project's P&IDs and legend sheets. Furthermore, a line detection method is used to identify the border lines in the legend sheets. These border lines separate the typical numbers, the simplified representation of the Instrument Typicals in the P&IDs, and the detailed representation of the Instrument Typicals. By identifying these lines, the recognized text in the legend can be organized into groups, with each group indicating an Instrument Typical. Each group consists of a typical number, the instruments in the simplified P&ID representation, and the actual utilized instruments in the detailed representation. Subsequently, the extracted groups and the P&ID text are passed to a method that generates all the utilized instruments for each Instrument Typical indicated in the P&ID. This method is based on the practices followed by instrumentation engineers. The text detection and recognition models, legend information extraction approach, and the method generating the utilized instruments for each typical indicated in the P&ID are presented in more detail in the following subsections.

Text Detection and Recognition Methods

The Progressive Scale Expansion Network (PSENet) (Wang et al. 2019) is used to detect the text in the P&IDs and the legend sheets. According to (Wang et al. 2019), PSENet is capable of detecting text in densely populated regions, as well as text with various orientations. These characteristics make the model applicable for detecting typical numbers, types of instruments, and tag numbers, which are commonly found in densely populated P&ID areas and have vertical or horizontal orientations. Furthermore, the pre-trained PP-OCR recognizer (Li et al. 2022) is utilized to recognize the text detected by the PSENet text detector.

The PSENet model training data consists of 315 industrial P&IDs from projects executed by McDermott. The model is trained using a tiling approach (Ozge Unel, Ozkalayci, and Cigla 2019), where each training P&ID is split into overlapping sub-regions, called "tiles". More specifically, each P&ID is split into 16 regions with 200 pixels overlap. The tiling method is used to improve the detection of small text in the P&ID, such as the typical numbers. The tiling approach produced 4338 training tiles. The training is performed using the Adam optimizer with a learning rate of 0.001 for 40 epochs with a batch size of 8 tiles.

The process of text detection and recognition is executed in the following manner. Initially, the images are divided into overlapping tiles, and each tile is fed into the trained PSENet model as input. The predicted detections for each tile are then mapped to their corresponding positions in the full image. Subsequently, any overlapping detections are merged to obtain the final text detection results. Lastly, the detected texts are cropped and fed as input to the pre-trained PP-OCR text recognizer.

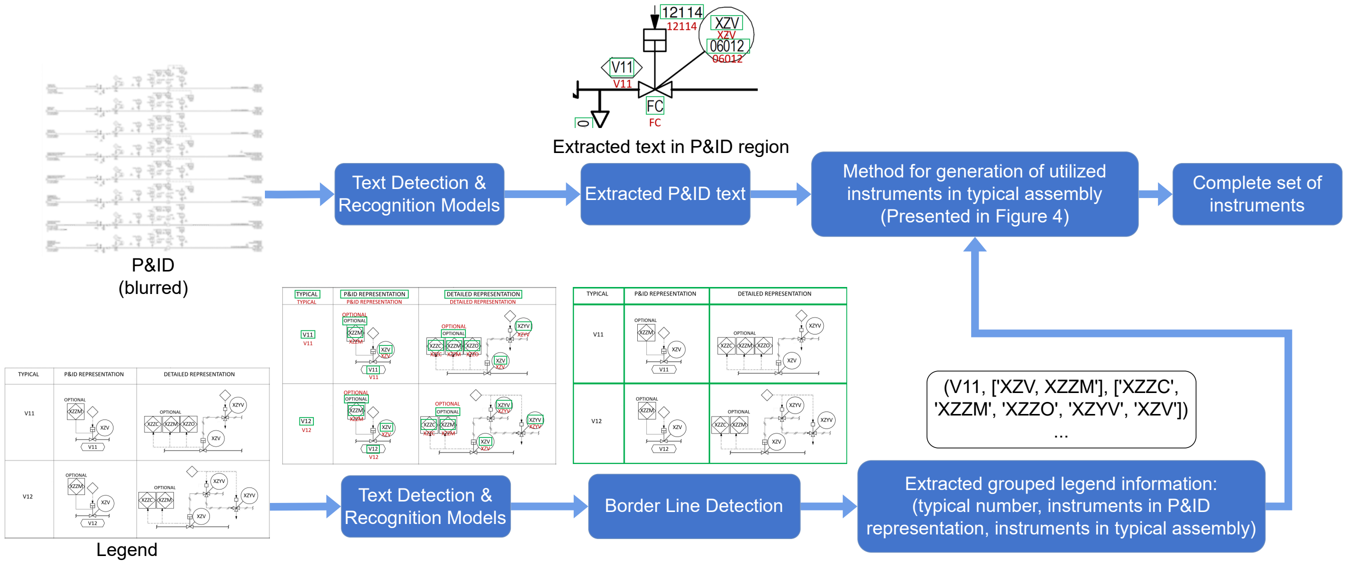

Figure 3: A visualization of the proposed method for automatic Instrument Typical Expansion in P&IDs.

Legend Information Extraction

The PSENet text detector and PP-OCR text recognizer are also used to extract the text from the legend sheets. As not all text present in the legend sheets is relevant, we preserve only the text related to the instrument type based on domain knowledge rules regarding the naming of these instruments. The extracted text is divided into groups, where each group corresponds to an Instrument Typical. The grouping is based on the structure of McDermott's legend sheets, where the typical numbers, simplified P&ID representation, and detailed representation of the Instrument Typicals are separated by border lines. To detect the lines, first, we convert the legend images to grayscale and apply Canny edge detection (Canny 1986). Next, we apply Probabilistic Hough Transform (Kiryati, Eldar, and Bruckstein 1991) to obtain all the lines in the legends. Finally, these lines are filtered based on their length to preserve only the border lines. Using the coordinates of these lines and the coordinates of the extracted instrument type text, we produce a group for each Instrument Typical in the legend sheets.

Generation of Utilized Instruments

The process of generating the list of the utilized instruments indicated in the Instrument Typical's detailed representation is visualized in Figure 4. The process assumes the extracted P&ID text and the extracted legend sheet typical information as input. The first step is to identify all typical numbers extracted from the legend sheet, which appear in the extracted text from the P&ID. In the second step, the process identifies the instrument types associated with each identified typical number. The identification is done by locating the k closest texts to the typical number using Euclidean distance. Furthermore, only the texts matching the instrument types extracted from the legend's simplified P&ID representation are preserved. As previously mentioned, some simplified representations may have optional instruments. If an optional instrument in the legend's P&ID representation is not identified during the second step of the process, the same instrument from the legend's detailed representation should be excluded from the generation. In the third step, the process identifies the tag number of these instruments. As each typical's instruments share the same tag number, it is sufficient to identify the tag number of a single instrument. The tag number identification is done by finding the closest text to one of the identified instrument types using Euclidean distance. Additionally, domain knowledge rules are applied to check if the text follows the tag number formatting. Finally, the utilized instruments in the Instrument Typical are obtained by associating the identified instrument tag number from the third step to the non-excluded instruments from the legend's detailed representation of that typical.

Evaluation Setup

The evaluation dataset was collected from 3 large EPC projects for the onshore petrochemical industry executed by McDermott with a total EPC budget exceeding a billion dollars. In the following sections, we will refer to these projects as A, B, and C. In total, the dataset consists of 4 legend sheets and 55 P&IDs. The P&IDs were randomly selected from each of the 3 projects, with the condition that they contain at least one Instrument Typical. None of the evaluation images were used in the training data of the PSENet text detection model. The distribution of the legends and the P&IDs per project is shown in Table 1. Project C has fewer P&IDs as it is a smaller project.

To our knowledge, no published research exists on automatically expanding Instrument Typicals in P&IDs. Nevertheless, prior research on text detection in P&IDs has utilized evaluation sets comprised of 5 to 30 P&IDs (Kim et al. 2022; Francois, Eglin, and Biou 2022; Jamieson, Moreno-Garcia, and Elyan 2020). Thus, our evaluation set aligns with the methodologies used in those studies and should en-

	Project A	Project B	Project C	Total
Legends	1	2	1	4
P&IDs	20	20	15	55

Table 1: The per-project distribution of the legend sheets and the P&IDs.

Expanded Instruments	Project A	Project B	Project C	Total
Correct	456	893	225	1574
Missed	20	8	0	28
Wrong	4	8	0	12
Recall	95.80%	99.11%	100.00%	98.25%
Precision	99.13%	99.11%	100.00%	99.24%

Table 2: The results of the proposed Instrument Typical Expansion method for each project.

able us to effectively evaluate our method.

The evaluation of the legend sheet information extraction approach is done by calculating the percentage of correctly extracted Instrument Typical groups out of all ground truth groups. Each group consists of a typical number, the instruments in the simplified P&ID representation of the typical, and the actual utilized instruments in the typical's detailed representation. Furthermore, the method for automating the Instrument Typical Expansion process is evaluated by calculating the precision and recall of generated instruments, i.e. the percentage of correctly generated instruments out of all generated instruments and the percentage of correctly generated instruments out of all ground truth utilized instruments.

Results

Our legend information extraction approach extracted all typical groups with 100% accuracy in all evaluation projects. Furthermore, the Instrument Typical Expansion method's overall and per-project results are detailed in Table 2. The expansion method achieved a recall of above 95% and a precision above 99% on all projects. These results demonstrate our method's ability to expand Instrument Typicals accurately across projects and its potential for the EPC industry. Moreover, they confirm the text detection and recognition models' reliability. The method's PSENet text detector accurately detected all text of interest except 2 typical numbers and 1 optional instrument. Furthermore, the PP-OCR recognition model correctly recognized all properly detected text.

As previously stated, the text detector missed 2 typical numbers and 1 optional instrument. These errors resulted in 15 missed instruments in Project A. An incorrectly detected typical number and optional instrument are shown in Figure 5 a) and b), respectively. The remaining missed and erroneously generated instruments in projects A and B were attributed to incorrect associations of the typical numbers with wrong instruments due to closer proximity. This scenario is exemplified in Figure 5 c). Despite these errors, our method correctly generated the majority of the instruments in the typical assemblies indicated in the P&IDs.

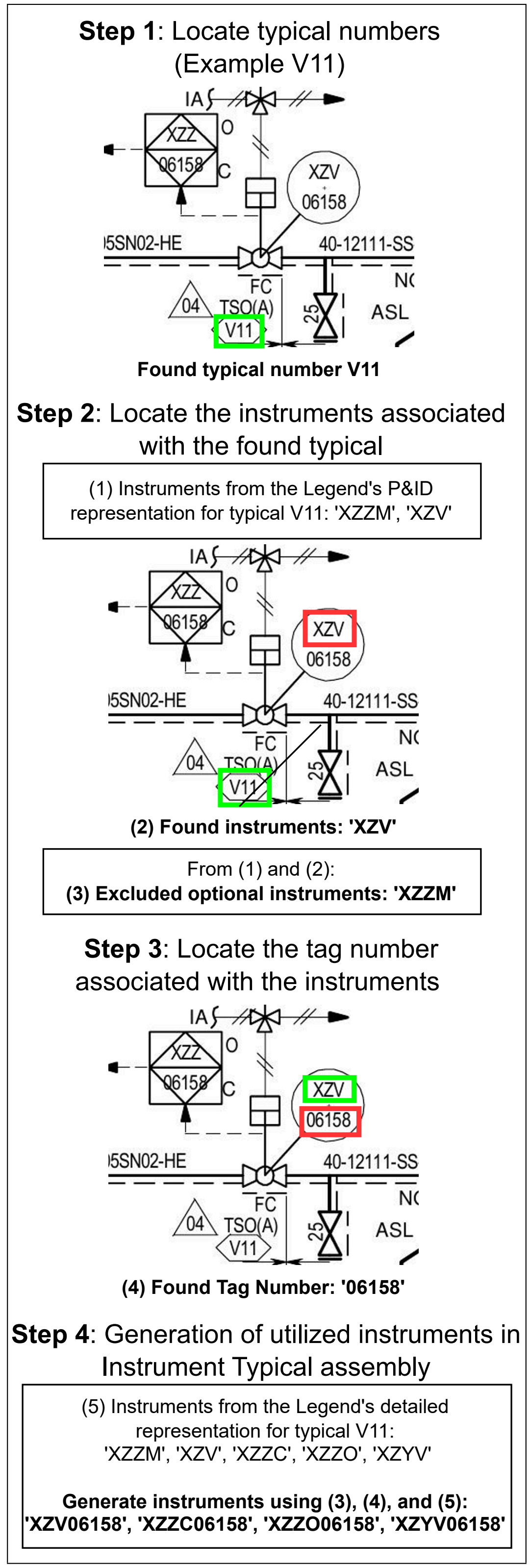

Figure 4: A visualization of the generation of all utilized instruments for a single Instrument Typical in a P&ID.

a) b) c)

Figure 5: Examples of errors: (a) the detection for typical number “V22” captured additional text, (b) the optional instrument “XZZM” was not fully detected, (c) the typical number “V11” was associated with instrument “XZV06194” instead of “XZV06160”.

Discussion and Future Work

Based on the evaluation results, our Instrument Typical Expansion method is suitable for adoption in the EPC industry. While the method exhibits some errors, error margins could be set to mitigate their effect on the specific application’s objectives. For example, when a manually generated Instrument Index document is used for cost estimation, an error margin is added to the cost estimates. Similarly, an appropriate error margin could be applied to documents generated using our method. Additionally, these documents undergo multiple reviews throughout project execution, ensuring the mitigation of errors.

It should be noted that the legend information extraction approach was customized to McDermott’s Instrument Typical legend format. However, other EPC companies might utilize different legend formats. Consequently, the approach may necessitate adjustment to address such variations. Alternatively, a potential solution would involve converting the legends to adhere to McDermott’s format, which separates the typical numbers, the instruments in the typicals’ simplified schematic representation, and the instruments in the detailed representation via border lines. Given that EPC projects typically feature a limited number of Instrument Typical legends, the feasibility of this conversion is viable.

Although the proposed method has shown promising results, the research efforts are ongoing. Further research should focus on the following areas:

- Improving the text detection and recognition models to prevent the errors observed in our analysis and comparing with alternative established models.
- Investigating additional domain knowledge rules to prevent errors related to Euclidean distance association.
- Evaluating the robustness of our proposed Instrument Typical Expansion method to the presence of occlusions, such as markups.
- Implementing a format-agnostic approach for extracting P&ID legend Instrument Typical information.
- Adapting the method for additional applications, such as expanding piping items similarly to instrument items.

Path to Deployment

Our proposed method was evaluated by a limited group of instrumentation engineers with very promising results. This prompted the decision to deploy the method. At the moment of writing this paper, the proposed method is being integrated as a new feature in an internal McDermott application generating Instrument Index documents.

The existing application extracts only regular instruments and does not handle Instrument Typicals. As it does not utilize deep learning techniques, it does not require intensive computational resources. However, our proposed method utilizes deep-learning text detection and recognition. Therefore, the method would require the use of GPUs to achieve fast processing time. Based on this requirement, modifications are being made to the application to support GPU utilization. Preliminary testing has demonstrated that the method can process a hundred P&IDs in under an hour. The efficiency of the method could be improved with further optimizations.

Based on McDermott’s industrial experience, the Instrument Typical Expansion for a single P&ID throughout a project’s entire execution cycle, involving multiple revisions, is on average 3 hours. Furthermore, a single McDermott engineering office executes 5 projects per year on average. Additionally, a single McDermott project typically consists of 1000 P&IDs (Dzhusupova et al. 2024). Assuming that an engineer’s hourly expense is 100 dollars, we can calculate the potential **yearly cost savings for a single McDermott office**:

$$5 \; projects \; * 1000 \; P\&IDs \; * 3 \; h \; * 100\$ = 1,500,000\$ \quad (1)$$

When the method’s deployment is finalized, it would be imperative to evaluate the performance of the application when it is utilized by a larger group of users. Furthermore, we would need to collect and analyze the users’ experience and quantify the application’s measurable benefits in terms of cost and time savings.

Conclusion

This study investigated the problem of manual Instrument Typical Expansion in P&IDs for the generation of Instrument Index documents, which list all instruments used in EPC projects. The manual expansion is a time-consuming and error-prone process. To address this issue, we proposed a novel method for automating Instrument Typical Expansion in P&IDs. The method’s overall 99% precision and 98% recall results highlight its potential for industrial use. This indicates that our method could minimize engineering hours and reduce costs in the EPC industry. As a result, the method is being integrated as a new feature in an application for Instrument Index generation within McDermott. The method could also be adapted for additional applications. Thus, this research offers substantial benefits to the EPC industry.

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