PhD Proposal

An Automatic Approach to Guaranteeing the Consistency between two Technical Drawings

Kaizen Solution
Laboratoire d'Informatique de Grenoble

May 2023

1 Subject

Historically, industrial revolutions have shaped global industry, with the fourth revolution underway. The second revolution, which took place in the early 1960s, greatly influenced the development of large-scale energy production systems built to withstand the test of time, eliminating the need for costly replacements. During that time, engineers created technical drawings on paper using drawing boards and ensured their compliance to standard guidelines. Consequently, the 2D technical drawing comprises multiple oriented views and an extensive material and machining data block. This unique document gathers all the knowledge of the part or assembly, in terms of machining requirements and functional needs.

The emergence of computers led to the third revolution, radically transforming the process of conception and construction of mechanical components. Computer-Aided Design (CAD) tools have greatly simplified the creation of technical drawings for large mechanical systems. These tools enable designers to digitally design mechanical components, validate design constraints, visualize three-dimensional representations, and automatically generate section views. However, despite technological advancements, the 2D technical drawing remains the primary medium where engineers can access all the necessary knowledge instantly.

The recent need for manufacturers to replace old mechanical components from the early 1960s led to a digitalization process. In order to manufacture the new components, it is essential to create 3D CAD models, which are required for configuring the manufacturing machines. Consequently, as part of this replacement process, engineers must ensure that all the information from the original 2D technical drawing is accurately preserved in the newly generated 2D technical drawing derived from the 3D CAD model. This verification becomes even more complex due to the introduction of new regulatory systems and evolved standard notations over time. Fig. 1 illustrates this digitalization process.

The comparison step is essential. If the 3D CAD model does not meet the original design requirements, the replacement part will not match the equipment. This can lead to considerable costs and delays, highlighting the necessity for caution regardless of the complexity of the drawings (cf. Fig. 2).

The process of digitalization is time-consuming and laborious, often requiring the dedicated work of 1 to 2 individuals for a week per drawing. With thousands of drawings awaiting processing in the coming years, the task ahead is significant. Consequently, companies are now exploring the possibility of automating the verification phase to enhance speed and to minimize errors while detecting discrepancies. Image analysis and artificial intelligence approaches appear to be the most suitable methods to achieving this goal.

2 State of the art

In recent years, deep learning methods have proved to be highly effective in image matching and similarity

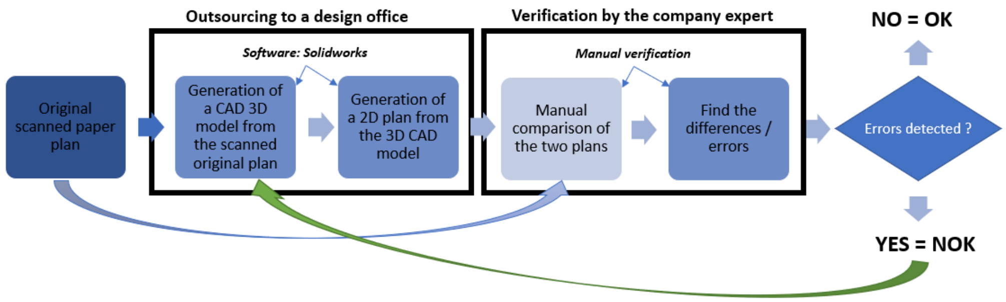

Figure 1: Overview of the digitalization process.

analysis tasks, with Siamese neural networks [2, 9] and triplet networks [1, 14] being among the most popular models [12, 13]. Other deep learning based methods like MatchNet [8] combine feature computation and similarity analysis for patch-based matching (e.g., [9, 21]). Although the classical Convolutional Neural Network (CNN)-based techniques mentioned in the literature review are mostly applied to general image matching and similarity analysis, some of them are adapted to match technical drawings [18]. However, CNN-based feature descriptors analyze images globally, which may be insufficient for similarity analysis of technical drawings that require capturing the structural similarity.

Graph Neural Networks (GNNs) are effective in capturing these structural relationships, unlike CNNs that only capture pixel-level similarities. Studies like Fey et al. (2020) [6], Chaudhur et al. (2019) [5], Shen et al. (2018) [17], and Patil et al. (2021) [15] have successfully used GNNs to find the similarity between two images. However, most GNN methods suffer from scalability [19] and explainability [20] issues. To overcome these issues, researchers proposed various techniques like graph coarsening [3] for scalability and attribution [16] for explainability. Despite these efforts, scalability and explainability remain significant challenges for GNNs. In addition, to our knowledge, both CNN- and GNN-based net-

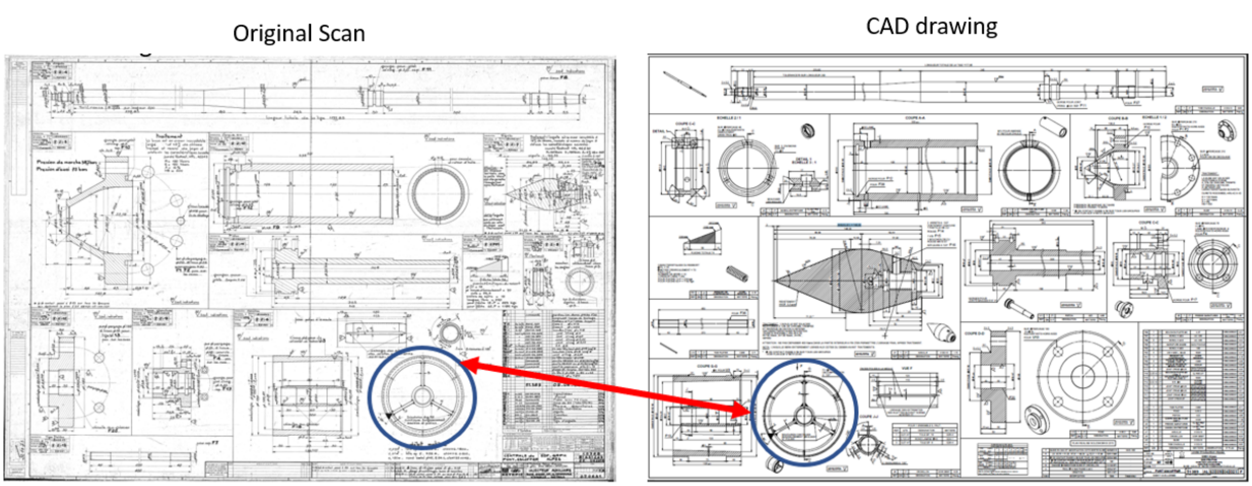

Figure 2: Example of an original scanned paper plan (on the left) and the CAD version (on the right).

works cannot explicitly pinpoint the location of the differences between the two images.

Compared to NN-based solutions, symbolic AI techniques are well suited to produce explainable outcomes to a software problem. Automated deterministic planning [7] has been used to perform activity recognition in the context of a system managed by human operators whose currently pursued operational goal has yet to be determined [10]. Several goal recognition [11] fields of application have surfaced, including "operator modeling" to improve the efficiency of man-machine systems.

An automated planning task can be represented as a directed graph model, where the nodes correspond to the different *situations* (or *states*) in which a system can be, and the edges represent *actions* that drive the system from one situation to a new one. Solving a planning problem consists in finding a sequence of actions $\langle a_1, ..., a_n \rangle$, also called *plan* π, that drive the system from an initial state to a desired goal, or a final situation. The length $|\pi|$ corresponds to the number of actions in the plan π: the length of a plan is commonly considered as a preference criterion to evaluate it.

Automated planning techniques such as goal and plan recognition have been used to aid systems engineers to design models in a freehand way using large multi-touch screens. They have proved to be a viable alternative process to NN-based solutions for online recognition of systems engineering models [4] while providing explainable outcomes without compromising the performance. Adapting the approach to detecting similarities (or non-similarities) in two technical drawings is a viable process as: i) offline recognition of existing technical drawings brings fewer constraints than online, real-time recognition in terms of performance (recognition speed), ii) recognizing technical drawings that conform to standard guidelines is simpler than recognizing freehand drawings as the input is cleaner and less noisy – automated planing approaches being less tolerant to drawing imperfections than the NN-based counterparts –, and iii) under the assumption that AI planning provides engineers with two symbolic (explainable) representations of the two drawings to compare, the problem comes to finding similarity patterns in large graphs.

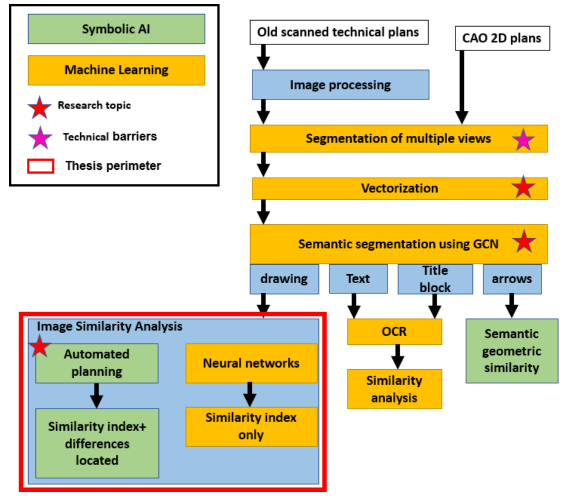

Figure 3: The proposed methodology addresses the various challenges by providing effective solutions tailored to each aspect of the project. Please note that the scope of the PhD primarily focuses on the last component, which is the image similarity analysis.

3 Project Sherlock

This Ph.D. proposal is part of a larger project known as Sherlock. The objective of Sherlock is to develop a software solution that aims to accelerate the plan verification phase conducted by experts and to reduce the number of undetected non-conformities. To this end, a methodology consisting of five components, illustrated in Fig. 3, has been proposed. Since February 2023, a dedicated Kaizen research team has been diligently working on the four initial stages: image processing, component segmentation, vectorization, and GNN-based segmentation. Within this context, the Ph.D. candidate will specifically focus on the Image Similarity Analysis component, which is a crucial aspect of the overall project.

4 Main scientific challenges

The primary focus of this research is to develop an AI-based approach for ensuring consistency between two technical drawings. Two exploration avenues have been identified to achieve this goal. The first avenue leverages Graph Neural Networks, known for their effectiveness in providing similarity scores between technical drawings. By utilizing this approach, the similarity between the diagrams can be assessed, and potential inconsistencies can be identified.

The second avenue focuses on adapting symbolic AI techniques, specifically *plan and goal recognition*, to assist architects in detecting consistency errors. This approach enhances the verification process by enabling explainable model recognition, providing insights into the underlying logic, and facilitating more accurate error detection. Both avenues will be compared to determine their respective strengths and limitations in achieving the desired level of consistency in technical drawings.

These two avenues collectively aim to enhance the verification process by combining the expertise of the verification engineer, the power of AI techniques, and the convenience of automation. By integrating these elements, the research aims to ensure accurate and efficient error detection, ultimately improving the overall quality and reliability of technical diagrams.

5 Scientific Contribution

The main objective of the Ph.D. is to formalize a semi-automatic approach to pinpoint consistency errors between the technical diagrams. By applying algorithms and machine learning models, the system analyzes the diagrams and highlights potential inconsistencies, providing valuable support to architects in the process of error detection and verification.

The second objective of the Ph.D. is to develop a demonstrator to instrument the approach and to assist architects in detecting non-similarities between two technical drawings. The approach and the tool will be assessed through a set of technical drawings that are available at the Kaizen research group.

The combined use of GNN- and symbolic AI-based solutions opens new avenues in terms of similarity detection and correction. Taking error identification a step further by offering automated quick fixes for correcting the identified inconsistencies is theoretically achievable using plan recognition by defining corrective actions. Such techniques have been explored in [4]. However, the application to the Sherlock project has to be assessed since it has to modify the 3D CAD model of the mechanical component to verify and not only the 2D technical drawing that results from it. Exploring the technical limitations of such a fully-automatic approach could constitute a possible objective of the Ph.D.

It is expected that the different scientific contributions obtained during the Ph.D. timeline are presented in terms in the form of scientific publications to international conferences and journals.

6 Contact

The Ph.D. is expected to start in October 2023 for a 3-year duration. We welcome any application. Should you be interested, please send a resume to:

KZS `<grenoble.recrutement@kaizen-solutions.net>`

LIG `<nicolas.hili@univ-grenoble-alpes.fr>`

References

[1] Anagha R Bhople and Surya Prakash. Learning similarity and dissimilarity in 3d faces with triplet network. *Multimedia Tools and Applications*, 80(28-29):35973–35991, 2021.

[2] Jane Bromley, Isabelle Guyon, Yann LeCun, Eduard Säckinger, and Roopak Shah. Signature verification using a" siamese" time delay neural network. *Advances in neural information processing systems*, 6, 1993.

[3] Chen Cai, Dingkang Wang, and Yusu Wang. Graph coarsening with neural networks. *CoRR*, abs/2102.01350, 2021.

[4] Sandra Castellanos-Paez, Nicolas Hili, Alexandre Albore, and Mar Pérez-Sanagustin. Board-ai: A goal-aware modeling interface for systems engineering, combining machine learning and plan recognition. *Frontiers in Physics*, 10, 2022.

[5] Ushasi Chaudhuri, Biplab Banerjee, and Avik Bhattacharya. Siamese graph convolutional network for content based remote sensing image retrieval. *Computer Vision and Image Understanding*, 184:22–30, 2019.

[6] Matthias Fey, Jan E Lenssen, Christopher Morris, Jonathan Masci, and Nils M Kriege. Deep graph matching consensus. *arXiv preprint arXiv:2001.09621*, 2020.

[7] Malik Ghallab, Dana Nau, and Paolo Traverso. *Automated Planning: theory and practice*. Elsevier, 2004.

[8] Xufeng Han, Thomas Leung, Yangqing Jia, Rahul Sukthankar, and Alexander C Berg. Matchnet: Unifying feature and metric learning for patch-based matching. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3279–3286, 2015.

[9] Muhammad Shehzad Hanif. Patch match networks: Improved two-channel and siamese networks for image patch matching. *Pattern Recognition Letters*, 120:54–61, 2019.

[10] Erik Hollnagel. Plan recognition in modelling of users. *Reliability Engineering & System Safety*, 22(1-4):129–136, 1988.

[11] Henry A Kautz and James F Allen. Generalized plan recognition. In *Proceedings of the Fifth AAAI National Conference on Artificial Intelligence*, volume 86, pages 32–37, 1986.

[12] Vijay Kumar BG, Gustavo Carneiro, and Ian Reid. Learning local image descriptors with deep siamese and triplet convolutional networks by minimising global loss functions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5385–5394, 2016.

[13] Jonathan Masci, Davide Migliore, Michael M Bronstein, and Jürgen Schmidhuber. Descriptor learning for omnidirectional image matching. *Registration and recognition in images and videos*, pages 49–62, 2014.

[14] Khanh Nguyen, Hoang Huy Nguyen, and Aleksei Tiulpin. Adaptive gradient triplet loss with automatic margin learning for forensic medical image matching. In *Medical Imaging with Deep Learning*, 2022.

[15] Akshay Gadi Patil, Manyi Li, Matthew Fisher, Manolis Savva, and Hao Zhang. Layoutgmn: Neural graph matching for structural layout similarity. *CoRR*, abs/2012.06547, 2020.

[16] Benjamin Sanchez-Lengeling, Jennifer Wei, Brian Lee, Emily Reif, Peter Wang, Wesley Qian, Kevin McCloskey, Lucy Colwell, and Alexander Wiltschko. Evaluating attribution for graph neural networks. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 5898–5910. Curran Associates, Inc., 2020.

[17] Yantao Shen, Hongsheng Li, Shuai Yi, Dapeng Chen, and Xiaogang Wang. Person reidentification with deep similarity-guided graph neural network. *CoRR*, abs/1807.09975, 2018.

[18] Dries Van Daele, Nicholas Decleyre, Herman Dubois, and Wannes Meert. An automated engineering assistant: Learning parsers for technical drawings. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 15195–15203, 2021.

[19] Lingfei Wu, Peng Cui, Jian Pei, Liang Zhao, and Le Song. *Graph Neural Networks*, pages 27–37. Springer Nature Singapore, Singapore, 2022.

[20] Hao Yuan, Haiyang Yu, Shurui Gui, and Shuiwang Ji. Explainability in graph neural networks: A taxonomic survey. *CoRR*, abs/2012.15445, 2020.

[21] Sergey Zagoruyko and Nikos Komodakis. Learning to compare image patches via convolutional neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4353–4361, 2015.