Knowledge Representation and Engineering for Smart Diagnosis of Cyber Physical Systems

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1. Motivation

Machine breakdowns pose a substantial expenses for equipment manufactures, such as Canon and Philips, and their customers. A considerable portion of the expenses comprises salaries for service engineers, costs for providing spare parts, and training service engineers for fault diagnosis. Furthermore, breakdowns and subsequent downtime have extensive implications on the plant capacity as customers are unable to utilize the machine during these periods. Therefore, manufacturers must prioritize effective fault diagnosis to minimize costs and mitigate the adverse impacts on the operation of their customers. The current maintenance approach of the manufacturers involved in this project includes training their own service engineers to diagnose the fault, by providing them with valuable documentation and sometimes videos. However, this documentation cannot encompass all the necessary support for service engineers because of the complexities involved in navigating intricate documentation and the ever-increasing complexity and size of machinery, particularly with Cyber–Physical Systems (CPS) like Canon printers and Philips magnetic resonance imaging scanners. Additionally, providing training video to support service engineer is costly in terms of time and resources.

2. Proposal

To overcome this challenge and enhance support for service engineers, several methods for fault diagnosis of CPS have been introduced including model-based [9], signal-based [10], and quantitative-knowledge-based [2]. However, these methods have limitations, such as the need for precise physical models and reliance on extensive historical (sensor) data, both of which can be prohibitively expensive to develop. To mitigate these limitations, a promising approach

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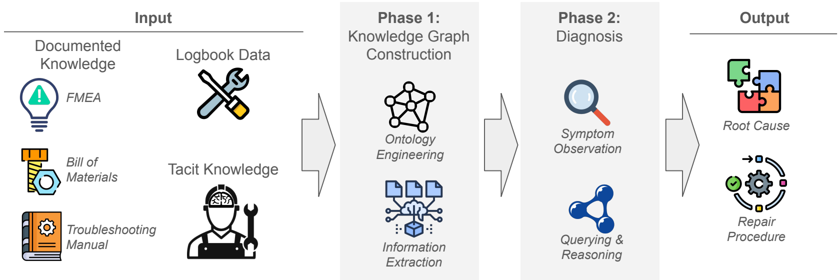

Figure 1: Construction and application framework of the domain fault knowledge graph

is qualitative-knowledge-based fault diagnosis [3] [1]. One key aspect of this method is the need for a reasonable model that accurately describes knowledge related to faults. Classical models like fault trees [6], petri nets [8], and rule systems [7], have been used in the past, but they typically require prior analysis of potential equipment fault modes and involve manual editing, which makes them inflexible and challenging to update dynamically. Therefore, we proposes to use knowledge graph (KG) technology to mine fault knowledge from vast and diverse documents and then construct a structured and interconnected fault knowledge base.

3. Framework

Figure 1, presents our framework for the construction and application of a fault knowledge graph, which we have created in close collaboration with our industrial partners. Two main phases including knowledge graph construction and diagnosis are depicted along with input sources and output results. The input sources are knowledge and data that have been used in diagnosing faults. We identified and categorized them by regularly interviewing authorities in the two aforementioned manufacturers. It is worth mentioning that these various sources are complementary, we utilize all of them to leverage their strengths while compensating for their limitations. For example, the Bill of Materials provides the physical structure and location of each part but lacks information on potential issues. In contrast, sources like Failure Mode Effects Analysis, troubleshooting manuals, and logbook data offer insights into these problems. Integrating these sources enables more accurate and effective fault diagnosis.

In the first phase, we manually developed an upper-level ontology that serves as the foundation for structuring the schema of the knowledge graph. This involved a comprehensive analysis of various input sources to identify valuable knowledge, relevant entities, and relationships for fault diagnosis. We also formulated competency questions to highlight key queries for the knowledge graph and conducted interviews with industrial partners to align their expectations with the ontology. Our fault diagnosis ontology is further inspired by the Industrial Domain Ontology [5] and the Industrial Ontology Foundry-Maintenance Reference Ontology [4] by considering and comparing the entities and relations. Currently, we are using this ontology to create a cohesive KG that allows for the analysis of fault frequencies, locations, interactions, and solutions. To this end, we apply different information extraction techniques such as Regular Expressions, Named Entity Recognition and Large language Models to populate data based on the ontology. Ongoing development indicate that the upper-level ontology allows us to model a diverse set of qualitative features related to the functioning and repair of complex cyber-physical systems.

4. Future Work

The next phase, diagnosis, shows the application of our proposed method in which service engineers observe symptoms of the failure, which should be converted to a query for KG-based reasoning. As a result, the root cause of the issue along with a procedure should be suggested to solve the issue. To this end, we are planning develop querying and reasoning systems for diagnosis, with the aim of supporting different fault diagnosis reasoning techniques.

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References

[1] Jianfeng Deng et al. "Research on event logic knowledge graph construction method of robot transmission system fault diagnosis". In: *IEEE Access* 10 (2022), pp. 17656–17673.

[2] Jingchuan Dong et al. "Fine-grained transfer learning based on deep feature decomposition for rotating equipment fault diagnosis". In: *Measurement Science and Technology* 34.6 (2023), p. 065902.

[3] Huihui Han et al. "Construction and evolution of fault diagnosis knowledge graph in industrial process". In: *IEEE Transactions on Instrumentation and Measurement* 71 (2022).

[4] Melinda Hodkiewicz et al. *Industrial Ontology Foundry (IOF) Maintenance Reference Ontology*. English. 2024. DOI: 10.26182/chzp-vs60.

[5] ISO. *ISO 15926-14:2020(E), ISO 15926 Part 14: Industrial top-level ontology*. Tech. rep. ISO, Geneva, CH, 2020.

[6] Kai Pan et al. "Towards a systematic description of fault tree analysis studies using informetric mapping". In: *Sustainability* 14.18 (2022), p. 11430.

[7] Ziyi Wang et al. "A new topology-switching strategy for fault diagnosis of multi-agent systems based on belief rule base". In: *Entropy* 24.11 (2022), p. 1591.

[8] Chuannuo Xu, Jiming Li, and Xuezhen Cheng. "Comprehensive Learning Particle Swarm Optimized Fuzzy Petri Net for Motor-Bearing Fault Diagnosis". In: *Machines* 10.11 (2022).

[9] Seung-Han You, Young Man Cho, and Jin-Oh Hahn. "Model-based fault detection and isolation in automotive yaw moment control system". In: *International Journal of Automotive Technology* 18 (2017), pp. 405–416.

[10] Kun Zhang et al. "A novel Fast Entrogram and its applications in rolling bearing fault diagnosis". In: *Mechanical Systems and Signal Processing* 154 (2021), p. 107582.