Demonstration of Alarm Knowledge Graph Construction for Fault Localization on ONOS-based SDON Platform

Zhuotong Li[1], Yongli Zhao[1], Yajie Li[1], Sabidur Rahman[2], Ying Wang[3], Xiaosong Yu[1], Lizhong Zhang[4], Guoli Feng[4], and Jie Zhang[1]
[1]State Key Laboratory of Information Photonics and Optical Communications, Beijing University of Posts and Telecommunications, Beijing, 100876, China; [2]University of California, Davis, CA, 95616, USA; [3]State Grid Information & Telecommunication Company, Beijing, 100761, China;[4]State Grid Ningxia Electric Power Co., Ltd. Information and Communication Company, Ningxia, 750001, China
Author e-mail address: {lizhuotong, yonglizhao}@bupt.edu.cn

Abstract: We demonstrate construction of alarm knowledge graphs, which is helpful for fault localization in software defined optical networks (SDON). The demonstration shows the method of constructing alarm knowledge graphs on ONOS-based platform using knowledge extraction.

1. Introduction

Optical network carrying gigabytes of data per second, has high requirements of network reliability. A single network fault (e.g., node or link failure) may cause Quality of Service (QoS) degradation or even service interruption leading to significant revenue loss. Thus, once network faults occur, network operators need to accurately locate the source of faults. However, due to the scale of the optical networks, identifying the fault location is very difficult. When a fault occurs, the Network Management System (NMS) receives multiple alarms reported by multiple devices. Even if these alarms include location information, it is difficult to identify the root alarm in the alarm storm.

Recently, knowledge graphs (KGs) have been an active research topic as a core driving force for the development of artificial intelligence (AI) [1]. KGs represent knowledge bases (KBs) as a graph whose nodes and edges represent entities and relations between entities, respectively [2]. Introducing the concept of KGs as a universal semantic description framework into the analysis of alarms in optical networks can reflect the derivative relationship between alarms. This KG based representation of knowledge is helpful for AI to enhance cognitive ability and identify the root alarms in alarm storms and identify the cause of faults.

Due to the complexity of alarm knowledge in optical networks, 'how to construct an alarm KG automatically' is the key to use it for fault localization. This demonstration is based on the ONOS platform and demonstrates how to extract the relationship between alarms and faults from existing data to construct alarm KGs. This work is the basis for the subsequent practical application of the fault localization function in optical networks using alarm KGs.

2. Overview

In recent years, software defined optical networks (SDON) is introducing the advantages of software defined networks (SDN) into optical networks [3]. In such a software-controlled optical network, AI can help to control and optimize network resources intelligently. In our prior study [4], we proposed a novel optical network architecture integrating AI technology into SDON to improve the intelligence of optical networks (namely, self-optimizing optical networks (SOON)). Fig. 1(a) shows the SOON framework based on the ONOS platform. The network database is the source of all the data in the model layer, including the traffic engineering database (TED), data plane status database (DPSD), and the constructed alarm KGs. There are two kernel modules which are network control core (NCC) and machine learning engine (MLE). NCC is the basic network control module. MLE implements the optimization and control functions based on machine learning (including the construction and reasoning of alarm KGs). The policy layer constructs service applications (e.g., fault localization) based on the underlying abstract network functions.

Fig. 1(b) shows the process of fault localization based on alarm KGs. When the link between NE5 and NE7 breaks, it will generate five types of alarms. Although there are alarm sources and location information in each alarm data, it is difficult to identify the root alarm(s). Alarm KGs can help to identify the root alarm(a). The subgraph of alarm KGs contains two types of entities (*cause of fault* and *alarm*) and two types of relations (*reason_of* and *derive*) as shown in Fig. 1(b). The root alarms can be selected using the reasoning technique of KGs such as the reasoning model based on graph neural network (GNN) [5]. For this example, the root alarms are *R_LOS* and *NE_COMMU_BREAK*, and the cause of the fault is *Physical Link Interruption*. From here, the fault can be accurately located using the location information of the root alarms.

However, constructing alarm KGs automatically is not trivial. Most of the alarm knowledge exists in two forms: i) structured data such as collected alarm data stored in the database, and ii) semi-structured data such as commercial equipment manuals and alarm knowledge bases constructed by operators. The structured data mainly includes attribute information such as ID, types, and levels of alarms. Commercial equipment manuals and alarm KBs include more complete information about the relationship between alarms and the cause of the alarm in *infoboxes*.

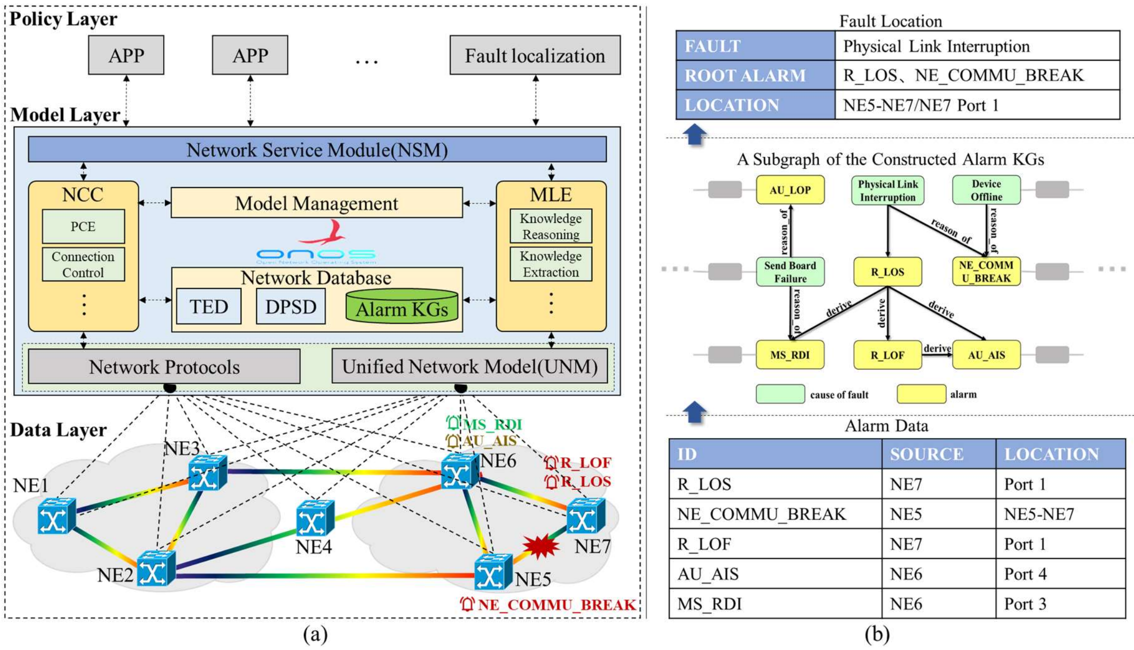

Fig. 1 (a) Network architecture based on SOON and KGs; (b) the process of fault localization using alarm KGs.

Fig. 2 shows the process of constructing alarm KGs based on knowledge extraction. The triples (entity-relation-entity) represent events in KGs. Since the semi-structured data exists in the form of HTML, wrappers need to be generated to extract useful information from documents. The method of generating wrappers can be selected from the manual method, wrapper induction or automatic extraction according to the specific page layout. Then, the entities, relations, and attributes can be extracted using the wrappers. For structured data, the information of alarm data can be mapped into the resource description framework (RDF) directly to represent KGs. The alarm KG constructed by extracting knowledge directly from two types of data is sparse, and the relationship between alarms is not complete. The quality of the alarm KG needs to be evaluated, and the alarm KG can be updated and completed through the knowledge reasoning and alarm correlation analysis.

Figure 3 shows the sample of constructed alarm KGs on the experimental platform using knowledge extraction. The alarm KG consists of two levels: the schema level and the data level. The schema level mainly reflects the abstract relationship and category of network alarms and faults, and the entities in the data level are instances of network alarms and faults. Each instance has a corresponding category in the schema level, and each alarm entity has attributes such as the explanation, level, type, and impact of the alarm. Thus, an alarm KG can not only visualize the network alarm knowledge, but also can be used to locate the network faults through knowledge reasoning.

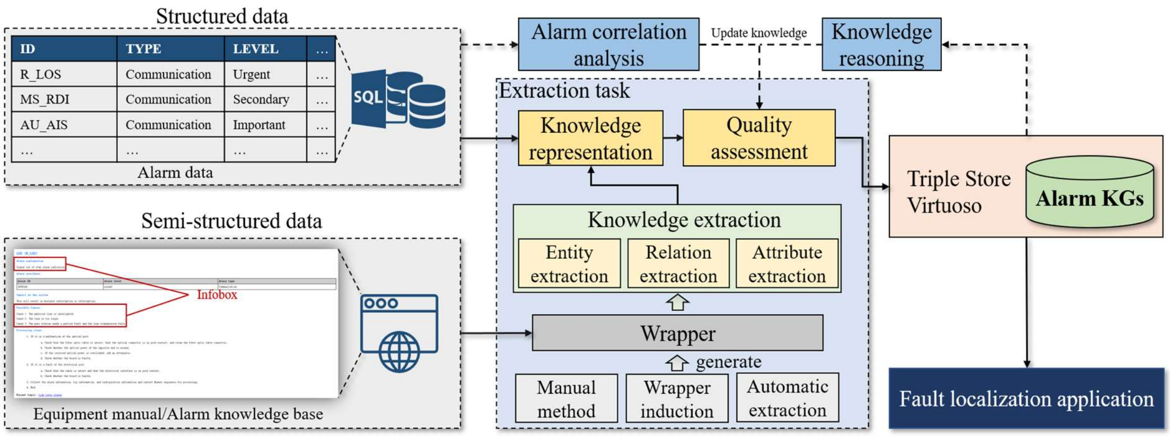

Fig. 2 The process of constructing alarm KGs based on knowledge extraction.

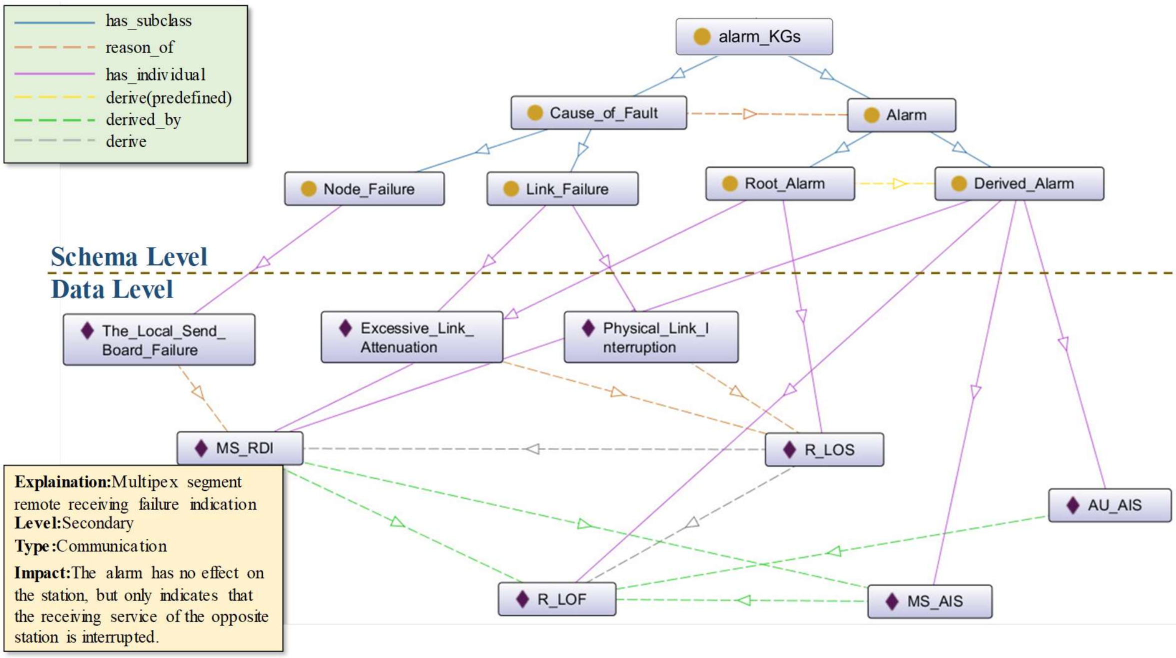

Fig. 3 The sample of constructed alarm KGs on the experimental platform.

3. Innovation

This demonstration combines alarm KGs with the ONOS controller, which can be used in practical industries, and automatically constructs the alarm KG using the existing alarm data and alarm KBs. Introducing KGs into the field of optical network alarm analysis is a very promising research direction. By taking advantage of the link relationships of KGs and mature knowledge reasoning technology, it can effectively solve the problem that the alarm relationship in the network is complex and the root cause fault is difficult. KGs can help the AI algorithm to learn the relationship between alarms for reasoning.

4. OFC relevance

AI has become an increasingly popular topic at the OFC conference in recent years. More researchers are paying attention to the application of AI in optical networks. However, the application of AI to network alarm analysis is not trivial. KGs help us to represent human knowledge into graphs and help AI to learn automatically. By participating in this demo, participants can learn the construction mechanism of alarm KGs, and how these KGs can establish a complete knowledge system for root alarm localization. Participants can also join discussions on how to use the knowledge reasoning technology can be used in other important problems of optical networks.

Acknowledgments

This work has been supported in part by National Natural Science Foundation of China (NSFC) (61822105, 61971068), the Fundamental Research Funds for the Central Universities (2019XD-A05), State Key Laboratory of Information Photonics and Optical Communications of China (IPOC2019ZR01).

References

[1] C. Xiong, et al., "Explicit semantic ranking for academic search via knowledge graph embedding," Procs., of the 26th intl. conf. on world wide web, pp. 1858-1861, 2005.
[2] D. Nathani, et al., "Learning Attention-based Embeddings for Relation Prediction in Knowledge Graphs, " arXiv preprint:1906.01195, 2019.
[3] Y. Zhao, et al., "Coordination Between Control Layer AI and On-Board AI in Optical Transport Networks [invited]," IEEE/OSA Journal of Optical Communications and Networking, vol. 12, no. 1, pp. A49-A57, 2019.
[4] B. Yan, et al., "First Demonstration of Machine-Learning-based Self-Optimizing Optical Networks (SOON) Running on Commercial Equipment," 2018 European Conference on Optical Communication (ECOC), IEEE, pp. 1-3, 2018.
[5] Z. Wang, et al., "Deep Reasoning with Knowledge Graph for Social Relationship Understanding," arXiv preprint:1807.00504, 2018.