Demonstration of Fault Localization in Optical Networks Based on Knowledge Graph and Graph Neural Network

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Abstract: A fault localization method for optical networks using knowledge graph and graph neural network is proposed. Experimental demonstration shows that the proposed method is effective in automating the localizing of optical network faults.

1. Introduction

As the underlying infrastructure bearing network traffic, the optical network has high requirements for 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 loss of gigabytes of data. Thus, once network faults occur, network operators need to accurately locate the source of fault and then fix it as soon as possible. However, due to the scale of the optical networks, identifying the fault location is very difficult. When a single node or link fails, the Network Management System (NMS) receives a series of alarms reported by multiple devices. Even if these alarms include location information, it is difficult to identify the root alarm in the alarm storm.

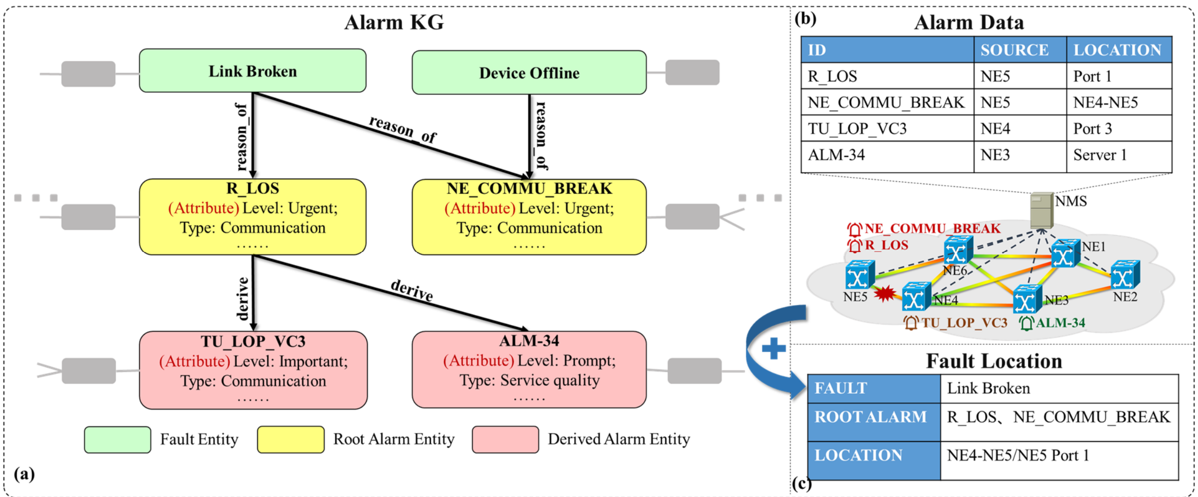
Prior studies have been explored methods to identify fault location. Failure localization method based on the case database can accelerate failure location identification by simplifying the process of failure localization [1]. However, the proposed method relies on alarm data. The accuracy of fault localization will vary on how comprehensive the collected data is. Machine learning (ML) is introduced into optical networks gradually due to the better fitting performance [2]. Ref. [3] proposed a deep learning-based method for soft-failure detection. Nevertheless, the model is neither systematic nor generalized, meanwhile it is time-consuming to retrain models in different scenarios.

This work introduces the concept of knowledge graphs (KGs) for optical network alarm relation reasoning. KGs help to form an easy-to-understand alarm knowledge system. We also report verification experiments showing the alarm relation in the KGs through real network data. A graph neural network (GNN) is trained to find the root alarm. The experimental results show that the combination of alarm KGs and GNN can locate faults with promising accuracy.

2. Optical Network Fault Localization Method

2.1. Knowledge Graph for Alarms

Recently, KGs have been an active research topic in the field of Natural Language Processing (NLP). KGs represent knowledge bases (KBs) as a graph whose nodes represent entities, and edges represent relations between entities. A triple (entity-relation-entity) can reflect the relationship between events. In optical networks, there is a strong



ID	SOURCE	LOCATION
R_LOS	NE5	Port 1
NE_COMMU_BREAK	NE5	NE4-NE5
TU_LOP_VC3	NE4	Port 3
ALM-34	NE3	Server 1

FAULT	Link Broken
ROOT ALARM	R_LOS、NE_COMMU_BREAK
LOCATION	NE4-NE5/NE5 Port 1

Fig. 1 (a) A subgraph of the alarm KG; (b) alarm data in optical networks, (c) fault location based on alarm KGs.

relationship between alarms and faults i.e., which means that most alarms are generated due to link or node faults. It's helpful for administrators to visually locate faults by introducing KGs into optical networks. The alarm KGs can also help machine learning models to perform appropriate alarm relationship learning and reasoning.

Figure. 1(a) shows a subgraph of the alarm KG which we designed based on commercial equipment alarm information manuals. There are three main types of entities (fault entities, root alarm entities, and derived alarm entities) and two types of relation edges (*reason_of* and *derive*) in the graph. Each alarm entity contains its inherent attributes, such as the level and the type of alarm. Such KG can be used to reason the relationship between the alarms and faults in optical networks. Thus, when multiple alarm signals are generated in optical networks, the root cause can be found through the relationship between entities in the graph. Fig. 1(b) and Fig. 1(c) show the fault localization process based on the alarm KG. When the link between NE4 and NE5 is broken, the NMS will receive 4 types of alarm (*ALM-34, TU_LOP_VC3, R_LOS, and NE_COMMU_BREAK*). Through reasoning in the KG, we identify that the fault is link broken, and the root alarms are R_LOS and NE_COMMU_BREAK. Thus, the proposed method can compress the number of alarms and locate the fault according to the location information of root alarms.

2.2. Reasoning Model based on Gated Graph Neural Network

It is simple to reason the above results (in Fig. 1) by human brain. However, it is necessary to reason the root alarms and faults automatically using artificial intelligence (AI) in large scales of alarm KGs. Recent research has shown that GNN can perform relational reasoning well on KGs [4]. Our reasoning model is based on gated graph neural network (GGNN) which is a variant of GNN [5]. GGNN propagates and aggregates node information in graphs by using neural networks.

Figure. 2(a) shows the principle of our reasoning model based on GGNN. The input of the model is the alarm KG represented as $\mathcal{G}=\{\mathbf{V},\mathbf{A}\}$, where $\mathbf{V}$ is the entity node set and $\mathbf{A}$ is the adjacency matrix representing the graph structure. For each node $v \in \mathbf{V}$, it has a hidden state h_v^t at timestep t to represent the node information. When $t=0$, the hidden state is initialized by the input feature vectors x_v. As shown in Fig. 2(a), the hidden state h_v^t of each node receives the information $h_{v'}^t$ propagated from the neighbor nodes, where v' is the neighbor node of v. The matrix $\mathbf{A}$ determines the connection between the entities, and the parameters of each sub-matrix are represented by the type and direction of the edges. The specific propagation model similar to GGNN, is formulated as:

$$a_v^t = \mathbf{A}_v^\top \left[h_1^{(t-1)\top} \ldots h_{|\mathbf{V}|}^{(t-1)\top} \right]^\top + b \quad (1)$$

$$z_v^t = \sigma\left(W^z a_v^t + U^z h_v^{t-1}\right) \quad (2)$$

$$r_v^t = \sigma\left(W^r a_v^t + U^r h_v^{t-1}\right) \quad (3)$$

$$\widetilde{h_v^t} = \tanh\left(W a_v^t + U\left(r_v^t \odot h_v^{t-1}\right)\right) \quad (4)$$

$$h_v^t = \left(1 - z_v^t\right) \odot h_v^{t-1} + z_v^t \odot \widetilde{h_v^t} \quad (5)$$

$$\mathrm{o}_v = \boldsymbol{o}\left([h_v^T, x_v]\right) \quad (6)$$

where $\mathbf{A}_v$ is the two columns of blocks in $\mathbf{A}^{(out)}$ and $\mathbf{A}^{(in)}$ corresponding to the node v. σ is the logistic sigmoid function and $\odot$ is element-wise multiplication. z_v^t and r_v^t are the update gate and the reset gate, respectively. Eq. (6) is the output of the final state of the node v, where $\boldsymbol{o}$ is the output function.

Figure. 2(b) shows the fault reasoning process. First, the alarm message needs to be clean to remove redundant and duplicate data. The alarm message is encoded into a d-dimensional vector to initialize the input feature x_v of the entity node v. The input feature vector of the entity node corresponding to the alarm that does not occur is initialized by a d-dimensional zero vector 0_d. Second, the reasoning model based on GGNN is deployed to propagate node message to update the node embedding. After the update of T time step, the method delivers the final state o_f of the fault entity node $f \in F$, where F is the total number of fault entities. At the final step, a simple fully connected neural network (FCNN) is deployed as a classifier to identify the fault. After finding the fault cause, the root alarms can be selected according to the KG structure and the alarm data.

3. Demonstration Experiment Setup and Results

In order to verify the effectiveness of the fault localization method based on the alarm KG, the alarm data of a single fault is used in the experimental demonstration. The alarm data is obtained from the real optical transport network (OTN) as shown in Fig. 3(a). The performance data and other attribute information of the alarms are not considered. One-hot coding is used as the 'Encoder'. We consider the training iteration time step T=3. The output function $\boldsymbol{o}$ is implemented by a layer of neural network with the activation function as *tanh*. The dimension of the output feature is

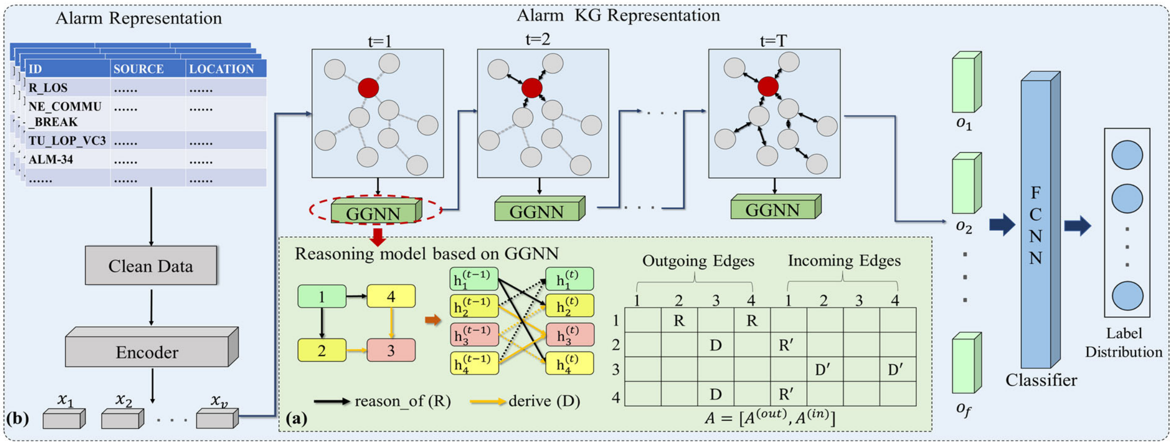


Fig. 2 The pipeline of the fault localization model based on GGNN: (a) the principle of reasoning model, (b) the fault reasoning process.

set as 10. Cross-entropy loss is used as the objective function and the GGNN is trained with Adam optimizer. The experimental results (in Fig. 3(b)) are achieved by an NVIDIA GTX TITAN XP GPU core.

Figure. 3 shows the results of the experimental demonstration. As shown in Fig. 3(b), 1000 sets of alarm data are trained for the proposed model. These alarm data are mainly caused by four types of faults. After 500 iterations, the loss value converges and stabilizes at around 0.165. We report the accuracy of fault localization model on the test set every 10 iterations. As Fig. 3(b) shows, the accuracy of the model can reach ~99%. Moreover, we are more concerned about the impact of the scale of the KG on the fault localization model. Three different small scales of alarm KGs are built for testing the performance of the model, where the number of entity nodes is 15, 20, and 25. The result shows that as the scale of the alarm KG increases, the time consumption increases slightly. In the meantime, the accuracy is significantly high for all three cases.

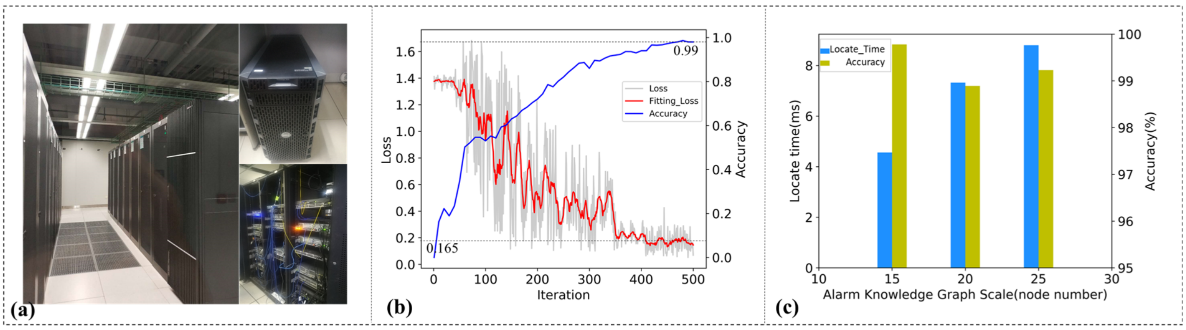


Fig. 3 Demonstration Experiments: (a) experiment environment (OTN for acquiring the alarm data), (b) the performance of fault localization model, (c) the performance of different-scale alarm KG.

4. Conclusion

In this work, we first design an alarm KG that can help network administrators to analyze and visualize the relationship between alarms. Then, we propose a GGNN based method to reason the relationship between alarms to identify the root alarm. The experimental demonstration results show a strong case for the proposed model. Our future work will focus on how to automatically extract knowledge from alarm data to complete the alarm KGs.

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