A Transformer-based Model for Event Recognition and Characterization in Passive Optical Networks

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Abstract A transformer-based model for identifying and characterizing various events in passive optical networks with nearly equidistant branches is proposed and experimentally validated. It achieves 98.4% accuracy for event identification, 1.4m localization error, and a loss estimation error of 0.5dB, respectively. ©2023 The Author(s)

Introduction

Passive Optical Networks (PONs) are emerging as a crucial broadband access network technology. With PON transmission capacity continuously rising, it is becoming increasingly important to monitor the PON fiber plant to ensure long-term viability and dependability [1]. Optical time domain reflectometry (OTDR) has been widely used to monitor optical fiber links. However, monitoring PON infrastructure with OTDR can be challenging because the backscattered signals from each branch are superimposed, making it difficult to differentiate between the signals emanating from each branch analysis becomes [2]. Event extremely challenging when branch terminations are almost equidistant as reflected signals from branches of similar length overlap and add up. Therefore, event recognition given noisy OTDR signals, has a bottleneck. alwavs been limitina its performance in in-service live PON monitoring. False alarms can occur due to high loss of the optical splitters at the remote node, which causes a significant decrease in the power of the backscattered signal [1], overlap of nearly equidistant branches, complex environmental interference, among other things. Recently,



Fig. 1: Illustration of the proposed approach for event recognition and characterization in PON system.

machine learning (ML) approaches [3-4] have shown great promise in improving OTDR event diagnosis in PON systems. However, such approaches fail to identify the faulty branch or to differentiate faults that occur in PON systems with branches of equal or similar length. In [5], we proposed an ML-based model for identifying optical network units (ONUs) in PON system with nearly equidistant branches. In this paper, we go one step further and present a novel approach based on a transformer neural network using a self-attention mechanism [6] for identifying, localizing, and characterizing a wide range of events includina connectors. splitters. overlapped peaks due to adjacent ONUs in the case of nearly equidistant branches, bv leveraging insights from OTDR data derived from PON systems with similar branch lengths. The effectiveness of the proposed method is experimentally validated using OTDR data.

Proposed Approach

Fig. 1 illustrates our proposed approach for PON monitoring. A reflector is located at each branch close to each ONU for monitoring the integrity of each fiber strand. OTDR measurements are periodically performed. The recorded traces are stored either locally or at a centralized database

(e.g., in a software defined networking (SDN) controller). Each OTDR trace is first normalized to scale the values of the returned power level between 0 and 1. The rescaled trace is then divided into sequences of length 50. each of which consists of rescaled power level values. The generated sequences are fed successively into the ML model for prediction. For each fed sequence, our method event, C_1 : angled physical contact (APC) connector, C_2 :

reflector, C_3 : open PC connector, C_4 : splitter, C_5 : two reflections due to two reflectors, and : C_6 : two peaks due to a reflector and an open PC connector), its location(s), its reflectance value(s), and loss. The outcomes of the ML model along with the information of the network topology and a reference trace (i.e., an OTDR measurement performed when the PON system is deployed or when the network topology is changed) are considered for performing fault monitoring. For example, to check the integrity of a branch, the reflectance of the reflector (assigned to that branch) predicted by the ML model is compared to its initial reflectance value provided by the reference trace. If the difference exceeds a predefined threshold, the branch is detected as faulty. Location information provided by the ML model, on the other hand, can be used to identify the associated optical network unit (ONU) or branch. The reflectance and loss of an event such as a connector, predicted by the ML model can be used to detect the faults with that connector such as dirty connector etc.

Model Architecture

The architecture of the proposed approach is shown in Fig. 2. The input of the ML model, a sequence of length 50 $[P_1 \dots P_{50}]$, is first fed into an encoder transformer, which is composed of an input layer, a positional encoding layer, and three identical encoder layers. The input layer converts the input sequence to a vector of dimension d_{model} through a fully connected network. By adding the input vector element-by-element to a positional encoding vector, sequential information is encoded using positional encoding with sine and cosine functions. The obtained vector is then fed into three stacked encoder layers, whereby each encoder layer consists of two sub-layers: a self-attention sub-layer and a fully connected feed-forward sub-layer. A normalization layer follows each sub-layer. The output of the encoder transformer (dmodeldimensional vector) is transferred to four task specific layers made of 64, 40, 40, and 40 neurons, respectively, dedicated to solving the tasks of event type identification (T_1), event localization (T_2), reflectance estimation (T_3), and loss estimation (T_4), respectively. The ML model's total loss is calculated as the weighted sum of the four individual task losses.



Fig. 2: Proposed ML model architecture.

Experimental Setup

To validate the proposed approach, the experimental setup shown in Fig. 3 is used to generate OTDR data incorporating different event types from a PON system. At the end of each branch, a reflector, or an open PC connector is installed for generating C_2 and C_3 samples. A fixed attenuator with attenuation settings ranging from 1 to 16 dB is used to vary the height of the induced reflection due to the reflector or open PC connector to generate diverse patterns incorporating faulty branch cases. The length difference between the second and the third branche is varied from 1 to 3 m to generate C_5 and C_6 samples with overlapping reflected pulses. An APC connector is placed at different locations of the network to produce C_1 patterns. The patterns of C_4 are reproduced by



cascaded optical 1:4 and 1:8 splitters. The OTDR configuration parameters, namely the pulse width, and the wavelength are set to 10 ns, and 1650 nm. respectively. The laser power and

Fig. 3: Experimental setup for generating different event patterns in a PON.

the averaging time are varied to influence the SNR of OTDR traces. In total, a dataset composed of 57,414 samples (8,202 examples for each investigated event type) is built, and divided into a training (70%), a validation (10%) and a test dataset (20%).

Results and Discussion

The performance of the ML model is assessed using an unseen test dataset. Fig. 4 shows that our model accurately classifies the different event types with an accuracy higher than 93%. The class C_2 can be rarely misclassified as class C_5 or C_6 , especially when one of the reflections in the class C_5 or C_6 has completely disappeared. The class C4 can be infrequently misclassified as class C_1 or C_0 due to the similarity between the event patterns particularly under low SNR levels. C_6 may be misclassified as C_2 if the peak caused by an open PC connector disappears owing to a failure or looks very small due to the noise. Fig. 5 shows that our approach achieves very small localization prediction errors, with a root mean square error (RMSE) of 1.4 m, demonstrating that the ML model accurately pinpoints the events. The histogram depicted in Fig. 6 demonstrates the accuracy of the estimates of the reflectance value, achieving an RMSE of 5 dB, Fig. 6 proves that our model yields very small loss prediction errors (i.e., RMSE of 0.5 dB). We evaluate then the generalization capability of our model when tested with field data. Fig. 7 illustrates the outputs of our approach applied to an unseen trace derived from a live PON system. Our model can accurately identify and localize the different events.



Fig. 4: Confusion matrix achieved by our model.



Fig. 5: Histogram of the event position prediction errors.



Fig. 6: Histograms of reflectance and loss prediction errors.



Fig. 7: Outputs of ML model for an example of live trace. Conclusions

We proposed and experimentally validated an ML-based approach for automatic event identification and characterization in PON systems with nearly equidistant branches. The experimental results have proven that the proposed model achieves good performance (high diagnostic accuracy of 98.4%). The proposed method could improve fault monitoring in PON networks.

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References

- M.-M. Rad, et al, "Passive optical network monitoring: challenges and requirements," IEEE Comm. Mag., vol. 49, no. 2, pp. S45-S52 (2011).
- [2] M. A. Esmail, et al, "Physical Layer Monitoring Techniques for TDM-Passive Optical Networks: A Survey," IEEE Comm. Surv. & Tut., 2013.
- [3] K. Abdelli, et al, "Machine-learning-based anomaly detection in optical fiber monitoring," J. Opt. Commun. Netw. 14, 365-375 (2022).
- [4] K. Abdelli, et al, "Gated Recurrent Unit based Autoencoder for Optical Link Fault Diagnosis in Passive Optical Networks," ECOC 2021.
- [5] K. Abdelli et al., "Branch Identification in Passive Optical Networks using Machine Learning," OFC 2023.
- [6] A. Vaswani, et al, "Attention is All you Need." ArXiv abs/1706.03762 (2017).