Event Detection in Optical Signals via Domain Adaptation

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***Abstract*—Data-driven models trained in an end-to-end manner can reliably detect events within optical signals. Unfortunately, event detection models poorly generalize when monitoring signals collected from devices with different acquisition procedures. We overcome this limitation by presenting a novel domain adaptation solution for event detection networks that enables inference across multiple types of devices. Rather than training a black-box detection network, we decouple event localization and classification tasks. Localization is performed by the Interval Proposal Algorithm (IPA), which leverages signal processing techniques to localize candidate events and derive *context* features. These events are then standardized and fed to a feature extractor to obtain *morphological* features. By combining domain-specific context features with domain-invariant morphological features, the classifier achieves good generalization capabilities through different domains. Our method can successfully detect events in OTDR traces achieving a mAP@0.5 of 75.33% on traces from the source domain and generalizing well (mAP@0.5 of 69.27%) on traces from the target domain, despite being trained solely from the source domain.**

***Index Terms*—otdr, domain adaptation, event-detection.**

I. Introduction

The success of machine learning models is closely tied to the availability of large amounts of data. Unfortunately, in some applications, acquiring new data is costly, and data scarcity undermines the application of such techniques.

A notable example comes from the monitoring of fiber optics, where optical signals are analyzed to guarantee the quality of transmissions. In particular, Optical Time Domain Reflectometer (OTDR) devices [11] are used to monitor the status of fiber links. These devices inject a short laser pulse at one end of a fiber link and measure the backscattered and reflected light. This process results in an *OTDR trace*, i.e., a graphical representation of the optical power as a function of the distance along the fiber.

Automatic event-detection networks simultaneously localize and classify *event signatures* in OTDR traces to identify the presence of specific impairments along the fiber, such as a bad connector or a broken fiber, which require triggering corrective actions. Specifically, [12] solves the event-detection problem by leveraging a 1D Faster R-CNN. Despite its accuracy, this approach is limited to operating on OTDR traces acquired with the very same type of device used for collecting the training set, and falls short when applied to traces acquired by other types of devices. In fact, the acquisition technology heavily influences the event shapes.

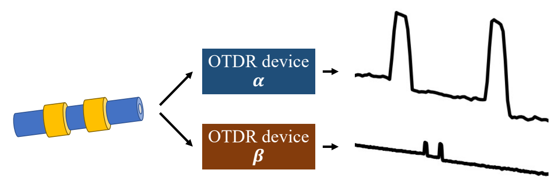

Fig. 1: On the left-hand side, a fiber link with two connectors. The PASS-THROUGH event signatures on the right-hand side generated by devices of type α and β show substantial differences both in terms of the number of samples and power intensity.

An example of this issue is depicted in Fig. 1 representing two types of OTDR devices, α and β, connected to the same fiber link. The resulting traces present two bumps corresponding to two physical connectors along the fiber link (depicted in yellow). Despite representing the same fiber span, the two OTDR traces are extremely different in magnitude and scaling. In particular, the events (two bumps) from β appear smaller and much shrank, as a result of the lower sampling frequency of device β in that region. These differences are caused by the physical configuration of the OTDR devices acquiring the signal. Therefore, an event detection network trained in an end-to-end manner on OTDR traces acquired by device α (source domain) could not extract relevant features to detect events acquired by device β (target domain).

The lack of feature invariance across devices hinders the portability of the event detection network from α to β. As a matter of fact, these models must be trained using data specific for each type of device, limiting their applicability and requiring time-consuming data preparation.

We address this limitation as a Domain Adaptation (DA) problem. First, we show that event-detection networks relying on end-to-end training have little flexibility for adaptation without training data from the target domain. Therefore, we design a novel event-detection network that is easier to adapt when the device changes.

Inspired by the R-CNN architecture [7], we rely on expert-driven algorithms to localize the events leveraging their morphology. In particular, our *Interval Proposal Algorithm* (IPA) exploits signal processing techniques and robust fitting methods to obtain a sequence of candidate events with their *context*