Anomaly Detection in Optical Fiber: A Change-Point Detection Perspective

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Abstract: We present a change-point detection algorithm for optical fibers. Utilizing SNR, our approach swiftly identifies soft anomalies, aiding early failure detection. This proactive identification can mitigate connectivity disruptions, an important step toward enhancing network reliability.

1. Introduction

Change-point detection (CPD), pivotal for identifying soft failures in systems, has been a key focus in statistics and machine learning. Its significance is rooted in the challenges posed by detecting when a system deviates from its expected behavior, applicable across various fields. For instance, optical fiber communication networks depend on CPD to manage disruptions [1]. Studies such as [2] emphasize the importance of early detection, but often focus only on classifying data abnormalities and failure types. The early detection of soft failures, potentially leading to significant connectivity issues [3], is still underexplored. We suggest combining quickest CPD with classification methods for more effective abnormality management and strengthened fiber network resilience.

To illustrate the use of CPD for anomaly detection in optical fiber communication, we present a generic model to represent the generation of observation data over time used as input to the change-point detector. This is in light of the fact that current research, as noted in [2, 3], lacks physics-based models for simulating gradual changes in optical fiber systems. We introduce a test statistic that is stable before a change point and then spikes, aiding prompt anomaly detection. We explore its operation in a malfunctioning erbium-doped fiber amplifier (EDFA) scenario [3], accounting for the effect of an automatic gain control (AGC) unit at the receiver, with the sliding window (SW) signal-to-noise ratio (SNR) as the input feature for the change-point detector.

2. Proposed Change Evolution Model

For concreteness, we consider the case of a single-parameter anomaly, such as the gain of an EDFA in an optical fiber channel. Fig. 1 (solid lines) presents several options to describe the evolution of the gain experiencing a reduction by ψ dB. The abnormal state starts at T_{start} and evolves differently based on the change type: instantly for abrupt changes or progressively until T_{end} for linear and nonlinear patterns. Despite the common use of abrupt models in anomaly detection research (e.g., [2, 3]), a gradual model better reflects reality and aids in early failure detection. For numerical studies in Sec. 4, we adopt a piecewise linear model with M segments (dashed line) to simulate an EDFA's gradual gain reduction.

A simulation model should also account for the presence of receiver components that obfuscate the effects of gradual changes. For the EDFA case, we incorporate an AGC, whose function offsets a change in amplifier gain, into the simulation.

3. Problem Formulation and Test Statistic

We now briefly outline the basic operation of CPD and its application to the EDFA malfunction scenario. Consider a sequence of observations denoted as $\{X_n\}_{n\geq 1}$. An unknown change point, $T_{\text{start}} \in \mathbb{N}$, signifies when an abnormality occurs. Observations before this point, $\{X_1, X_2, \ldots, X_{T_{\text{start}}-1}\}$, follow a distribution with density p. Observations after the change, $\{X_{T_{\text{start}}}, X_{T_{\text{start}}+1}, \ldots\}$, follow a distinct density q, different from p. The goal is to identify if a change has occurred at any point $1 < t < n$ within the input sequence $\{X_n\}_{n\geq 1}$. This involves comparing a function of the observed sequence, termed test statistics, to a predetermined threshold. While various types of observations can be fed into the test statistic, we found that the SW SNR is an informative input feature for the EDFA malfunction problem, as will be demonstrated in Section 4.

The cumulative sum (CUSUM) is a well-known test statistic that balances detection delay, $\mathbb{E}\left[(t - T_{\text{start}})^+\right]$, and false alarm probability, $\mathbb{P}(t < T_{\text{start}})$ [4]. It is given by

$$Y_n = \max_{k=1,\ldots,n} |X_k^n|, \text{ and } X_k^n = \frac{(n-k)\sum_{i=1}^k X_i - k\sum_{i=k+1}^n X_i}{\sqrt{nk(n-k)}}. \tag{1}$$

Under specific conditions [4], CUSUM equates to the generalized likelihood ratio (GLR) test for hypothesizing change at sample $1 < t < n$. CUSUM's drawback is its complexity. In particular, the number of terms in (1)

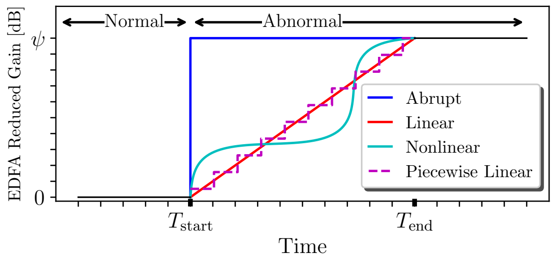


Fig. 1: Examples of transitions for gradual change.

increases linearly with the observation interval n. To improve scalability, we propose using the window-limited GLR (WL-GLR) [5], a CUSUM variant that limits maximization to the latest L samples:

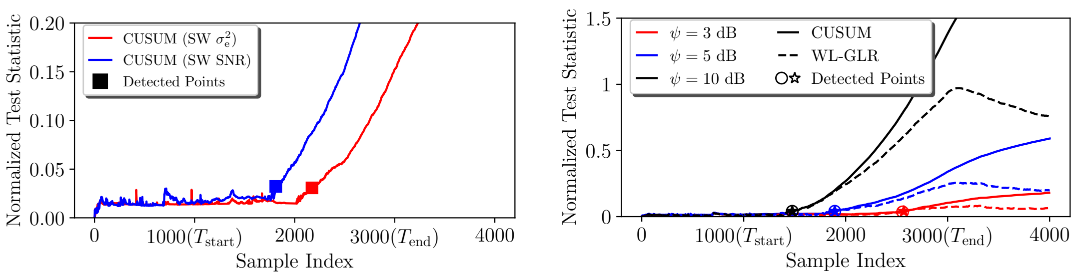
$$Z_n = \max_{k=n-L+1,\ldots,n} |X_k^n|. \tag{2}$$

Though WL-GLR differs from GLR, our findings indicate that it performs similarly to CUSUM in the pre-change and early post-change phases. To conclude the process, Z_n is compared to a predetermined threshold; exceeding it reports a change. The adjustable threshold balances the expected detection delay and the false alarm probability.

4. Numerical Results

We analyze a dual-polarized 64-QAM transmission at 32 GBaud with three WDM channels. The fiber link has eight 80 km spans, featuring fiber loss of 0.21 dB/km, CD of 16.8 ps/nm/km, nonlinearity of 1.14 $\mathrm{W}^{-1}\mathrm{km}^{-1}$, and DGD of 0.1 ps/$\sqrt{\mathrm{km}}$ at 1552.93 nm. Each span is followed by a 6 dB noise figure EDFA. Anomalies are modeled as $3,5$, or 10 dB gain losses in the 6-th EDFA, evolving from $T_{\text{start}} = 1000$ to $T_{\text{end}} = 3000$ in samples, using a piecewise linear model with $M = 40$ segments. Post-reception, signals undergo coherent detection, double-rate sampling, matched filtering, CD compensation, AGC, and 2×2 MIMO equalization for PMD compensation.

In Fig. 2a, we compare CUSUM's performance using normalized SW equalizer error variance (σ_e^2) and SW SNR as inputs, normalized pre-change. A 0.03 threshold balances false alarms and detection delay. SW SNR emerges as a superior feature for early CPD in gradual shifts. Fig. 2b evaluates CUSUM and WL-GLR (L=200) across EDFA-gain reductions. CUSUM consistently increases post-T_{start}, while WL-GLR initially rises, then declines near T_{end}. However, both methods reliably detect early changes, with WL-GLR's performance, despite its complexity reduction, mirroring CUSUM's. As failure severity decreases, detection delay increases for both, yet WL-GLR maintains comparable early detection efficiency to CUSUM, confirming its suitability for CPD.



(a) (b)

Fig. 2: Performance comparisons with pre-FEC BER of 0.01 and threshold of 0.03 between (a) different features for CUSUM algorithm with $\psi = 5$ dB and (b) CUSUM and WL-GLR for $\psi \in \{3,5,10\}$ dB with SW SNR as input.

5. Conclusion

In this paper, we introduced a framework for detecting anomalies in optical fibers, including a change-point detection algorithm effective for EDFA malfunction, enhancing current change-type classification methods.

References

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