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# Asynchronous amplitude histogram-based multi-parameter monitoring for $M$-PAM optical communication channels

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Short-reach optical communication systems represented by data center interconnections (DCI) have gradually adopted intensity-modulation direct-detection (IM/DD) and multi-level pulse amplitude modulation ($M$-PAM) to achieve low-cost, high-speed transmission [1]. With the continuous increase in transmission rate and link complexity, optical performance monitoring (OPM) has become an indispensable part of network management, which is used to realize real-time state perception, fault diagnosis, and adaptive adjustment of optical channels, as shown in Figure 1(a).

In recent years, machine learning-driven OPM methods have received extensive attention [2]. Among them, asynchronous amplitude histogram (AAH) has become a high-efficiency signal characterization method because it does not require clock recovery and has low requirements for sampling equipment [3]. However, the original AAH is easily affected by oscilloscope bandwidth limitations, sampling noise, and optical power fluctuations, resulting in distorted feature distribution and poor monitoring stability.

To solve the above problems, this study proposes a multi-parameter OPM scheme for $M$-PAM optical channels based on AAH preprocessing and a light gradient boosting machine (LightGBM) [4]. By designing a combined preprocessing method including sliding window smoothing and averaged-cross-correlation alignment, the robustness of AAH features is significantly enhanced. The scheme realizes high-precision joint monitoring of six key parameters under a low sampling rate, and has strong engineering application value compared with existing deep learning-based OPM schemes [5].

*Methods.* The original AAH obtained by asynchronous sampling contains obvious burrs and amplitude offsets, which reduce the classification accuracy of the model. This study uses two preprocessing algorithms to optimize the features.

Sliding window (SW) smoothing adopts a simple moving average (SMA) with a window length of 6 and a step size of 2. This method can effectively suppress high-frequency noise and distortion caused by insufficient hardware bandwidth, and retain the effective amplitude distribution structure of the histogram at the same time. Compared with other filtering methods, it has lower computational complexity and is more suitable for real-time processing.

Averaged-cross-correlation (Axcorr) alignment is used to eliminate feature shift caused by optical power fluctuation. By calculating the cross-correlation between the sample histogram and the reference histogram, the amplitude distribution is calibrated to a unified dimension, which greatly improves the consistency of features under different optical signal-to-noise ratio (OSNR) and chromatic dispersion (CD) conditions.

The preprocessed AAH features are sent into the LightGBM classifier for multi-parameter joint identification. The model is optimized for efficiency and accuracy, and can simultaneously identify six parameters: modulation format (MF), baud rate (BR), CD, OSNR, roll-off factor (ROF), and probabilistic shaping (PS).

LightGBM is selected over deep learning models (e.g., CNN, LSTM) for several reasons: (1) the AAH input is a compact 1-D vector of 200 bins, for which gradient boosting decision trees are inherently well-suited, whereas CNN and LSTM architectures are primarily designed for 2-D spatial or sequential data; (2) LightGBM enables fast training and inference without GPU acceleration, aligning with the low-cost hardware philosophy; (3) the relatively small dataset (100 samples per class) favors ensemble tree methods that generalize well with limited training data; (4) LightGBM achieves 93.99% accuracy in the six-parameter joint monitoring task, confirming sufficient classification capability.

The experimental system is built on a 1550 nm IM/DD platform. The transmitter generates PAM3/4/6/8 signals with different configurations. The signals pass through a tunable dispersion module and a noise loading module. A low-speed oscilloscope samples the signals at 12.5 MSa/s to generate AAH sequences. The

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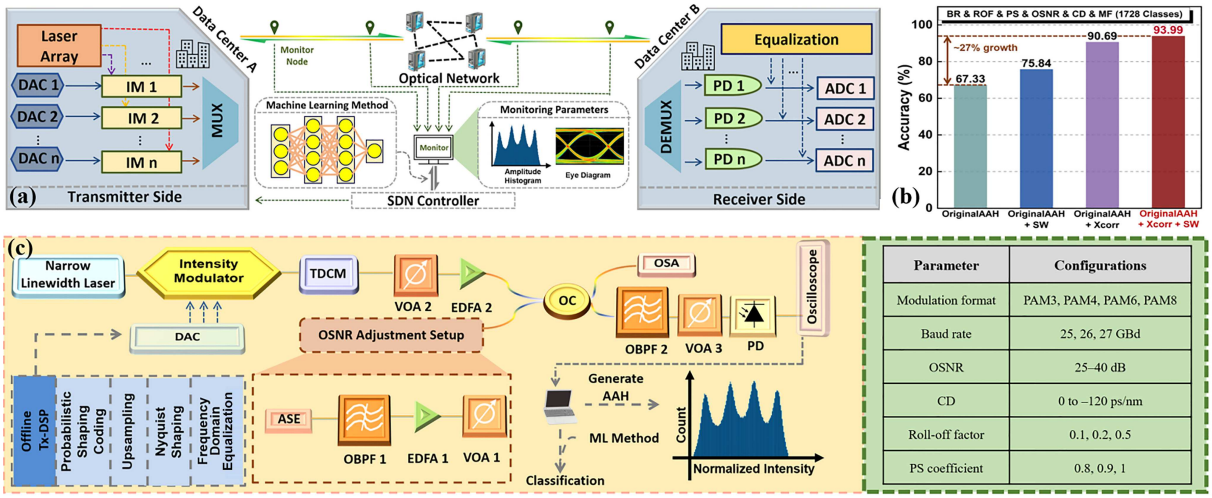


| Parameter | Configurations |
|---|---|
| Modulation format | PAM3, PAM4, PAM6, PAM8 |
| Baud rate | 25, 26, 27 GBd |
| OSNR | 25–40 dB |
| CD | 0 to –120 ps/nm |
| Roll-off factor | 0.1, 0.2, 0.5 |
| PS coefficient | 0.8, 0.9, 1 |

**Figure 1** (Color online) Multi-parameter PAM monitoring in inter-DC systems. (a) Conceptual diagram; (b) six-parameter classification accuracy distribution; (c) the experimental transmission link.

specific parameter configurations are shown in Figure 1(c).

*Results.* After Axcorr+SW combined preprocessing, the accuracy of single-parameter monitoring is close to 100%. For parameters with high monitoring difficulty such as CD and baud rate, the proposed method effectively suppresses the accuracy degradation caused by high-order modulation. In the PAM8 scenario, the monitoring error is reduced by 90%, showing strong anti-interference ability.

In multi-parameter joint monitoring tasks, the proposed scheme shows excellent performance. For 4-parameter combined monitoring, the accuracy exceeds 97%, and the fluctuation is controlled below 0.25%. For 5-parameter monitoring, the accuracy is increased from less than 80% for the original AAH to more than 93.5%.

As shown in Figure 1(b), in the full-parameter (6-parameter) monitoring task, the total number of classes reaches 1728. The Axcorr+SW+LightGBM scheme achieves 93.99% monitoring accuracy, which is 26.66% higher than that of the original AAH. At the same time, the accuracy variance is reduced from 0.28 to 0.12, and the monitoring stability is significantly improved.

The influence of sampling points on monitoring accuracy is greater than that of the sampling rate. With the help of preprocessing, low-cost oscilloscopes with a sampling rate of 12.5 MSa/s and sampling points greater than 62.5k can achieve more than 95% monitoring accuracy. The scheme does not depend on high-performance sampling equipment or a clock recovery module, which greatly reduces the cost of OPM.

It is worth noting that the bandwidth limitation effect does not undermine the proposed monitoring scheme. Since AAH captures the statistical distribution of signal amplitudes rather than the time-domain waveform, bandwidth-induced distortions are encoded as distinguishable features in the AAH, which can actually aid parameter classification. The experimental results across 108 oscilloscope configurations confirm the scheme's robustness under bandwidth-constrained conditions.

Although the 12.5 MSa/s sampling rate is far below the Nyquist rate relative to the signal baud rate (up to 27 GBd), valid features can still be extracted because the AAH relies on amplitude statistics rather than waveform reconstruction. Asynchronous sampling at sub-Nyquist rates can be viewed as an i.i.d. random sampling process of the signal amplitude; with 500k sampling points, the resulting histogram converges to a stable statistical distribution regardless of the sampling rate.

*Conclusion.* This study proposes a low-cost and robust multi-parameter OPM scheme for $M$-PAM optical communication channels. By combining SW smoothing and Axcorr alignment preprocessing with a LightGBM classifier, the scheme realizes high-precision joint monitoring of six parameters under a low sampling rate.

Experimental results show that the 6-parameter monitoring accuracy reaches 93.99%, and it still maintains stable performance under high-order modulation and large dispersion. The scheme has the advantages of low hardware deployment complexity (requiring only a low-sampling-rate oscilloscope without clock recovery or GPU), low cost, and strong real-time performance, and provides a feasible solution for multi-parameter perception in short-reach optical networks.

Since the AAH-based feature extraction is inherently independent of the specific modulation format, the proposed framework can in principle be extended to other modulation formats such as QAM, where different signal configurations produce distinguishable amplitude distributions after direct detection. In practical deployment, the proposed monitoring method can be reliably placed at either the transmitter side or the receiver side, and both positions offer valid and accurate monitoring performance. The low-cost hardware footprint and clock-free operation are most advantageous for source-level quality assurance and SDN-enabled adaptive feedback. The method is also deployable at other tap points along the link.

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