

A Comparative Sensitivity Analysis of SOP-, Phase-, and Intensity-Based Sensing for ML-Driven Threat Classification

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Abstract: We present the first ML-driven comparison of SOP, phase, and intensity sensing on bare fiber and patch cable. All exceed 99 percent on bare fiber; on patch cable a hierarchy emerges: SOP robust, phase weaker, intensity degraded.

Keywords: Optical sensing, machine learning for photonics, AI for optical networks, network security in optical systems, performance monitoring.

I. INTRODUCTION

Optical fiber networks serve an increasingly important function as distributed physical sensors, detecting environmental perturbations without necessarily requiring dedicated sensing hardware [1], [2]. External mechanical events, such as vibrations or malicious fiber tapping, can modify the optical signal through three physically distinct mechanisms: State of Polarization (SOP) rotation caused by stress-induced birefringence [3], phase shifts arising from strain-induced variations in optical path length [4], and intensity fluctuations from bending-induced light leakage and loss [5]. These three sensing modalities underpin a growing field of fiber-based environmental monitoring as a cost-effective complement to dedicated Distributed Acoustic Sensing (DAS) systems [6], [7].

Optical fiber security is a pressing concern, jeopardized by various threats. For example, eavesdropping based on fiber-bending enables covert signal interception with power drops invisible to a conventional Optical Time Domain Reflectometer (OTDR) [8]. Moreover, deliberate or accidental fiber cuts are often preceded by harmful vibrations (e.g., at 80 Hz) from nearby excavations [9]. Machine Learning (ML)-based classification of SOP signatures has proven effective over diverse disturbances, fiber types, and environments [9]–[13].

Despite these advances, two critical gaps remain. Firstly, no study has compared all three sensing modalities under identical experimental conditions using ML analysis. SOP and phase sensing were compared for Intensity-Modulation Direct-Detection (IM-DD) links in [14], demonstrating complementarity via feature-level fusion but considering neither intensity nor cable construction, while phase and polarization sensing over deployed metro fiber were compared in [15] without multi-class ML classification. Secondly, the effect of cable construction on ML classification has received limited attention. Bare and jacketed cables impose fundamentally different mechanical damping on vibration-induced signatures [16]: jacket materials attenuate strain transfer and suppress higher-frequency components, collapsing distinct spectral envelopes into overlapping features. Bare fiber, typical of laboratory and intra-equipment sections, and patch cable, used for indoor interconnects in data centers and central offices, are the focus of this work as two contrasting mechanical coupling regimes.

This paper addresses these gaps through the first experimental comparison of SOP, phase, and intensity sensing for ML-driven classification of harmful events over bare fiber and jacketed patch cable. We develop a unified ML pipeline that processes the three signatures through a common representation and benchmarks 20 supervised classifiers over the six modality-cable configurations, revealing SOP as the most viable modality for both fiber types.

II. EXPERIMENTAL SETUP AND COLLECTED SIGNATURES

The experimental setup, shown in Fig. 1, acquires unique signatures of SOP, phase, and intensity variations from the two cable types under identical conditions. A stabilized C-band Polarization-Maintaining (PM) Continuous Wave Distributed Feedback (CW-DFB) laser injects light through a 1 km Single-Mode (SM) fiber into the 20 m sensing section of the Cable Under Test (CUT), and a second 1 km SM fiber carries the perturbed signal to the detection stage. A 1×3 switch selects the sensing front-end: (i) for SOP sensing, the signal is routed to an optical analyzer that tracks the SOP on the Poincaré sphere; (ii) for phase (PHS) sensing, a 3 dB coupler splits the light into reference and sensing arms, with the CUT as the sensing arm of an unbalanced Mach-Zehnder interferometer recombined at a second coupler, mapping path-length modulation into intensity modulation at the photodiode; (iii) for intensity (INT) sensing, the signal is directly Alternating Current (AC)-coupled and amplified to resolve sub-decibel intensity fluctuations.

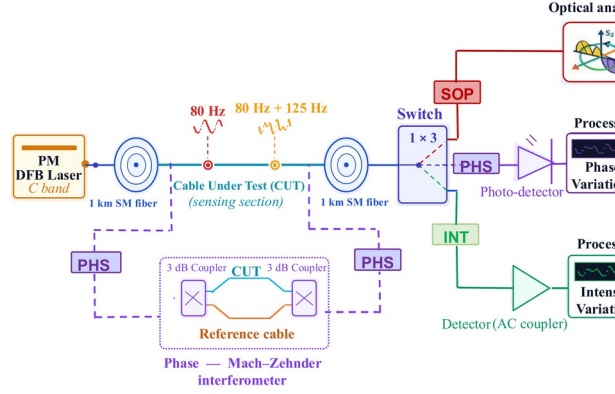


Fig. 1. Experimental setup for collecting SOP, phase (PHS), and intensity (INT) signatures on bare fibers and patch cables.

The two fiber types considered for the CUT are a bare (br) G.657 fiber and a jacketed patch (pc) cable, representing two contrasting levels of mechanical coupling. The CUT is subject to different mechanical vibrations, modeled by a loudspeaker placed 2 cm from the CUT and emitting sinusoidal tones at 70 dBA. We consider three event types: relaxed (rlx) fiber as the baseline; an 80 Hz single-tone vibration (80v), emulating excavator harmonics (4800 RPM) as a predecessor of fiber cuts; and a dual-tone 80/125 Hz vibration (Dual), superimposing a 125 Hz component (in-building fans/elevators) on the harmful 80 Hz precursor.

For each modality, the detected signal is processed through the pipeline validated for SOP analysis [12]: 1 ms sampling over 20 minutes yields ~ 1.2 million Numerical Polarization State Variation (NPSV) samples per event. For SOP, the NPSV encodes the vectorial distance between consecutive samples on the Poincaré sphere; for phase and intensity, it encodes the scalar fluctuations of the interferometric and photodetected signals. Segments of 1 s (1000 samples) are then transformed by a Fast Fourier Transform (FFT) with a Hamming window [17] into 512 frequency bins, producing a time-frequency signature. Each of the 18 signatures, summarized in Table I, yields a $1,200 \times 512$ data matrix, split 80/20 into 960 training and 240 testing samples.

III. ML CLASSIFICATION AND RESULTS

We evaluate 20 supervised ML classifiers over all six configurations, drawn from the Scikit-Learn and LightGBM libraries and spanning five algorithmic families: gradient-boosting ensembles (e.g., LightGBM, Extreme GB, AdaBoost), tree-based ensembles (Random Forest, Extra Trees (ET), Decision Tree), probabilistic models (Gaussian Naïve Bayes (GNB), Quadratic Discriminant Analysis), kernel and distance-based methods (Support Vector Machine, K-Nearest Neighbors), and linear classifiers (Logistic Regression, LDA, Ridge, SGD, Perceptron). Each classifier is evaluated with 5-fold Cross-Validation (CV) on the training set and assessed on a held-out test set. For each configuration, we report the best-performing classifier and the 20-classifier average (Avg.) in Table II, reflecting an upper bound and a consensus view of classification difficulty. Per-class performance is analyzed via the averaged confusion matrices in Fig. 2.

TABLE II
Best-Performing Classifier (with Test Accuracy) and 20-Classifier Average Accuracy per Configuration

Cable	Modality	Best Classifier	Best Acc. (%)	Avg. Acc. (%)
Bare	SOP	GNB	100.00	99.88
	Phase	GNB	100.00	99.88
	Intensity	GNB	100.00	99.97
Patch	SOP	GNB	100.00	99.50
	Phase	ET	100.00	98.42
	Intensity	LightGBM	92.08	85.29

A. Bare Fiber

For bare fiber, any modality yields near-perfect classification (Table II). GNB is the top classifier for all modalities with 100% test accuracy, confirming that the rlx, 80v, and Dual signatures are well separated when the fiber is mechanically unshielded. The 20-classifier average (Table II) reinforces this: intensity attains the marginally highest accuracy of 99.97%, followed by SOP and phase tied at 99.88%. The confusion matrices in Fig. 2(a)–(c) show residual errors in different class pairs per modality. SOP confuses rlx with 80v (0.17%) and Dual with rlx (0.12%), as low-amplitude single-tone perturbations are occasionally indistinguishable from ambient birefringence drift. Phase instead misclassifies 80v as Dual (0.31%), as the 80 Hz tone leaks into neighboring bins near 125 Hz. Intensity gives the cleanest separation ($\leq 0.06\%$ off-diagonal), consistent with the direct power-coupling sensitivity of bare fiber.

B. Patch Cable

TABLE I
Collected Signatures per Cable and Sensing Modality

Cable	Modality	rlx	80v	Dual
Bare	SOP	SOP _{rlx,br}	SOP _{80v,b}	SOP _{Dual,br}
	Phase	PHS _{rlx,br}	PHS _{80v,b}	PHS _{Dual,br}
	Intensity	INT _{rlx,br}	INT _{80v,br}	INT _{Dual,br}
Patch	SOP	SOP _{rlx,pc}	SOP _{80v,p}	SOP _{Dual,pc}
	Phase	PHS _{rlx,pc}	PHS _{80v,p}	PHS _{Dual,pc}
	Intensity	INT _{rlx,pc}	INT _{80v,pc}	INT _{Dual,pc}

As anticipated, jacket-induced damping degrades vibration sensing on the patch cable, but the extent differs sharply across modalities. SOP and phase retain strong performance: their best classifiers reach 100% accuracy and their 20-classifier averages remain above 98%. On average, SOP (99.50%) slightly outperforms phase (98.42%), consistent with polarisation rotation accumulating along the fiber length and being less sensitive to localised damping than the point-like phase perturbation. Fig. 2(d),(e) confirm this: SOP keeps the 80v $\leftrightarrow$ Dual confusion below 0.88%, whereas phase spreads errors over the same pair up to 2.83%. Intensity, however, substantially degrades the classification: the best classifier (LightGBM) reaches only 92.08% accuracy and the average drops to 85.29%. There is severe confusion between 80v and Dual (Fig. 2(f)), where 19.44% of dual events are misclassified as 80 Hz and 10.40% of 80 Hz as dual, indicating that the jacket attenuates the 125 Hz component below the intensity detection threshold, merging two distinct events into nearly identical spectral shapes. This is a critical limitation of intensity-based dual-threat disambiguation in jacketed infrastructures.

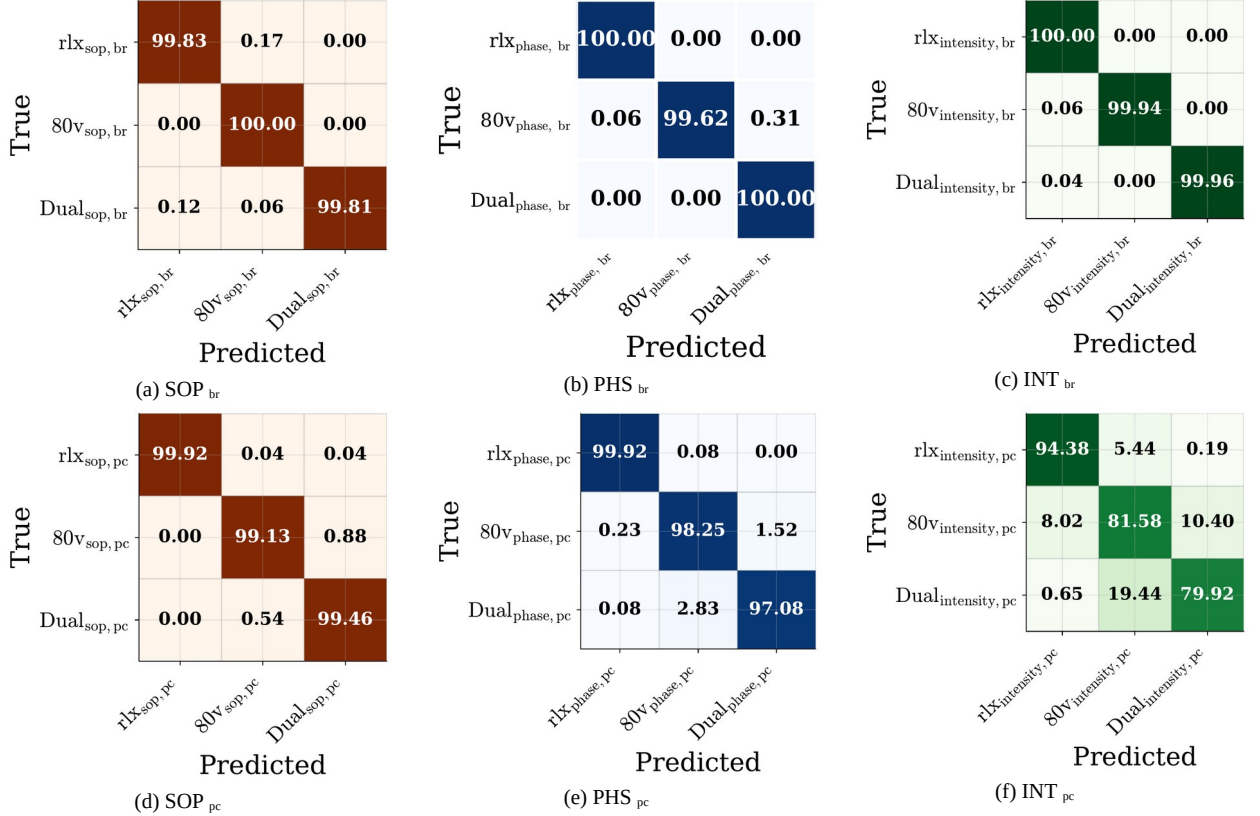


Fig. 2. Averaged confusion matrices (20 classifiers) for bare fiber (a)–(c) and patch cable (d)–(f) over SOP, phase, and intensity modalities.

C. Cross-Modality and Cross-Cable Synthesis

Two key findings emerge. First, the cable type is a decisive factor in modality selection: on bare fiber all three modalities are effectively equivalent ($\geq 99.88\%$ avg. accuracy), while on patch cable a clear hierarchy emerges, SOP $>$ Phase $\gg$ Intensity. This reflects the underlying physics: SOP variations arise from distributed birefringence modulation along the fiber, making them resilient to localized damping; phase requires interferometric detection between reference and sensing paths; and intensity relies on direct power changes, requiring stronger perturbations and thus being the least sensitive. Second, the per-class confusion on patch cable translates into a practical security concern: for intensity sensing, 18.42% of 80 Hz and 20.08% of dual-tone events are misclassified, versus $\leq 0.88\%$ for SOP and $\leq 2.92\%$ for phase. For critical infrastructure protection, this gap establishes SOP- and phase-based sensing as the most viable options for jacketed deployments. This study is limited to indoor patch cables; more robust cables such as underground or submarine fibers may behave differently.

IV. CONCLUSIONS

We presented the first ML-driven sensitivity comparison of SOP, phase, and intensity fiber sensing over bare fiber and jacketed patch cable. While all modalities are equivalent on bare fiber ($\geq 99.88\%$), patch cable exposes a clear hierarchy, SOP (99.50%) $>$ Phase (98.42%) $\gg$ Intensity (85.29%), establishing SOP as the most robust modality for real-world jacketed deployments.

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