Fault Diagnosis and Early Warning Classification of Force-Sensing Optical Fibers: Physical Modeling, Anomaly Indexing, and Deep Learning Algorithms

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Abstract: Force-sensing optical fibers have become an indispensable cornerstone in modern structural health monitoring, robotic tactile perception, and harsh-environment telemetry due to their immunity to electromagnetic interference and multiplexing capabilities. However, when deployed in complex, dynamic, and physically demanding environments, these waveguides are highly susceptible to mechanical degradation, static fatigue, and structural failures, which compromise data integrity and system safety. This paper presents an exhaustive, data-driven methodology for the real-time fault diagnosis and early warning classification of force-sensing optical fibers. We propose a hybrid algorithmic framework that bridges deterministic physical failure modeling with advanced machine learning. The methodology mathematically details the physical mechanisms of fiber buckling and crack propagation, utilizing wavelet packet decomposition for multi-resolution signal denoising. For early warning, we introduce a Synthetical Anomaly Index (SAI) that statistically aggregates temporal and spectral features to flag impending sensor failures before catastrophic signal loss. For precise fault classification, a hybrid Convolutional Neural Network and Bidirectional Long Short-Term Memory (CNN-BiLSTM) network is implemented, processing the optical data to categorize distinct failure modes. Experimental validations demonstrate that the SAI algorithm provides robust early warnings, while the CNN-BiLSTM model achieves a fault classification accuracy of 99.3% across eight distinct fault categories.

Keywords: Force-Sensing Optical Fiber; Fault Diagnosis; Early Warning Classification; Synthetical Anomaly Index; Machine Learning; CNN-BiLSTM; Structural Health Monitoring

1. Introduction

The paradigm of modern industrial automation, deep-sea exploration, and intelligent robotics relies heavily on the acquisition of high-fidelity multidimensional physical data [1,2]. Traditional electronic force sensors are frequently hindered by their susceptibility to electromagnetic interference (EMI), bulky form factors, and severe difficulties in highly multiplexed or distributed deployments [3]. Consequently, optical fiber sensing (OFS) technology—particularly devices based on Fiber Bragg Gratings (FBG), distributed acoustic sensing (DAS), and optical frequency-domain reflectometry (OFDR)—has emerged as a revolutionary alternative. Exhibiting intrinsic immunity to EMI, passive operation capabilities, and unparalleled environmental resilience, force-sensing optical fibers facilitate both localized high-resolution tactile perception and distributed long-range structural monitoring [4-6].

Despite the profound advantages of photonic sensing, deploying these fragile glass waveguides in highly dynamic, unpredictable environments exposes them to severe mechanical and environmental stressors [7]. Force-sensing optical fibers are continuously subjected to multidimensional spatial forces, dynamic bending, and extreme thermal cycling [8]. Over time, these operational conditions induce static fatigue, micro-crack propagation, and localized structural buckling, ultimately leading to physical sensor degradation and hard failures (e.g., fiber cuts or core breakage) [9-11]. Such anomalies not only cause immediate network disruption and critical data loss but can also gradually degrade the entire control system's reliability. Traditional threshold-based alarm systems lack the dynamic adaptability needed to distinguish between a legitimate external force measurement and an anomalous signal caused by internal fiber degradation [12].

To address these severe limitations, this paper proposes a comprehensive, highly mathematical, and algorithmically explicit methodology for the fault diagnosis and early warning classification of force-sensing optical fibers. We first establish the physical failure mechanisms governing the fiber under stress. Subsequently, we detail a deterministic Synthetical Anomaly Index (SAI) algorithm utilizing multidimensional feature covariance for real-time early warnings. Finally, we formulate and implement a hybrid CNN-BiLSTM deep learning architecture to classify distinct failure modes with exceptionally high accuracy. By bridging continuum mechanics with advanced artificial intelligence, this framework ensures the continuous, safe, and highly reliable operation of advanced multidimensional optical fiber sensing networks in extreme environments.

2. Methodology: Failure Mechanisms and Intelligent Diagnosis Algorithms

The reliable diagnosis of fiber optic faults requires a dual-layered approach: understanding the physical continuum mechanics of the fiber under stress and deploying robust digital algorithms to process the resulting distorted optical signals. This section strictly details the physical formulas, signal preprocessing logic, mathematical anomaly indexing, and the deep learning classification architecture.

2.1 Transduction Physics and Failure Mechanics

The fundamental sensing element is the Fiber Bragg Grating (FBG), where the Bragg wavelength shift $\Delta\lambda_B$ under normal operational strain (ε) and temperature variations (ΔT) is governed by a linear superposition:

$$\Delta\lambda_B = \lambda_B(1-P_e)\varepsilon + \lambda_B(\alpha+\xi)\Delta T \tag{1}$$

where P_e, α, and ξ denote the photoelastic, thermal expansion, and thermo-optic coefficients, respectively.

However, excessive multiaxial loading causes the fiber to exit the linear elastic regime. The critical stress σ_{cr} inducing macroscopic Euler buckling and subsequent severe micro-bending loss is mathematically defined as:

$$\sigma_{cr} = \frac{\pi^2 E}{(L/r)^2} \tag{2}$$

where E is Young's modulus, L is the unconstrained effective length, and r is the cross-sectional radius of gyration. When the applied stress exceeds this threshold ($\sigma > \sigma_{cr}$), or under continuous dynamic fatigue, micro-cracks propagate through the silica core. The resulting stress intensity factor K_I at the crack tip is modeled by linear elastic fracture mechanics:

$$K_I = Y\sigma\sqrt{\pi a} \tag{3}$$

where a is the crack depth and Y is a dimensionless geometry factor. This physical degradation breaks the circular symmetry of the waveguide, inducing severe spectral distortion (e.g., peak splitting and broadening), completely invalidating standard transduction equations and necessitating advanced anomaly detection algorithms.

2.2 Wavelet Packet Decomposition (WPD) for Signal Denoising

Before anomaly detection can occur, the raw optical signals acquired by the interrogator (S_{raw}) must be preprocessed. These signals are inherently contaminated by interrogator white noise, optoelectronic thermal drift, and ambient environmental vibrations. To extract the true signal components indicative of structural health while suppressing high-frequency noise without losing transient fault features, we employ Wavelet Packet Decomposition (WPD) [13].

Unlike the standard Discrete Wavelet Transform (DWT) which only decomposes the low-frequency approximations at each level, WPD decomposes both the approximations and the details, offering a complete and high-resolution time-frequency analysis. For a given discrete optical signal sequence $u_n(t)$, the WPD algorithm utilizes scaling functions and wavelet functions to split the signal into orthogonal frequency bands. The discrete decomposition algorithm for passing from the j-th layer to the $(j+1)$-th layer is defined as:

$$d_{j+1}^{2n}[k] = \sum_{l\in\mathbb{Z}} h_{l-2k}\, d_j^n[l]$$

$$d_{j+1}^{2n+1}[k] = \textstyle\sum_{l\in\mathbb{Z}} g_{l-2k}\, d_j^n[l] \tag{4}$$

In these recursive equations, h and g represent the quadrature mirror filter coefficients for the low-pass and high-pass filters, respectively, associated with the chosen wavelet basis (e.g., Daubechies 'db4'). The parameter n denotes the node index at the j-th decomposition level, and k represents the discrete time translation parameter.

The denoising algorithm begins by decomposing the raw optical signal into a full wavelet packet tree up to a specified depth J (typically $J = 4$), after which the signal energy E_j^n for each terminal node is calculated by summing the squares of the wavelet coefficients as $E_j^n = \sum_k |d_j^k[k]|^2$. A hard thresholding rule is then applied, where nodes with localized energy falling below a dynamically determined noise floor threshold γ_{noise} are set to zero. Finally, the retained and filtered wavelet packet coefficients are inversely transformed to reconstruct the pristine, denoised optical signal$S_{\text{denoised}}(t)$.

2.3 Synthetical Anomaly Index (SAI) for Early Warning

Standard amplitude-threshold alarms trigger only after a complete failure (e.g., a severed fiber resulting in zero optical return) [14]. To achieve proactive early warning, we formulate a Synthetical Anomaly Index (SAI). Under normal structural health, the temporal and spectral features of the force-sensing fiber exhibit strong statistical similarity and form dense, highly correlated clusters in a multidimensional feature space. As the fiber begins to fail (e.g., via crack initiation or progressive static fatigue), these features diverge non-linearly.

From the denoised signal $S_{\text{denoised}}(t)$ over a rolling time window W, we extract four critical, mathematically distinct features: Light Intensity (I), defined as the peak amplitude of the reflected spectrum; Signal Length (L), the full width at half maximum (FWHM) of the spectral peak, which broadens during non-uniform strain distribution; Standard Deviation (σ), the statistical variance of the optical intensity within the time window; and Time-domain Energy (P), the integral of the squared signal amplitude over the window.

Let the instantaneous feature vector at time t be represented as $X_t = [I_t, L_t, \sigma_t, P_t]^T$.

Calibration and Covariance Modeling: During an initial baseline calibration phase under healthy operation, a dataset of N feature vectors is collected. The multidimensional aggregation center (mean vector) μ_C and the 4 × 4 covariance matrix Σ of the healthy state are computed via iterative statistical looping:

$$\mu_C = \frac{1}{N}\sum_{i=1}^{N} X_i \qquad (5)$$
$$\Sigma = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \mu_C)(X_i - \mu_C)^T$$

SAI Formulation: To quantify the degree of abnormality, the SAI is mathematically defined as the Mahalanobis distance between the real-time feature vector X_t and the healthy aggregation center μ_C. Unlike Euclidean distance, the Mahalanobis distance accounts for the variance and covariance of the variables, effectively normalizing the influence of disparate feature scales:

$$SAI(t) = \sqrt{(X_t - \mu_C)^T \Sigma^{-1} (X_t - \mu_C)} \qquad (6)$$

Warning Logic: An adaptive threshold SAI_{th} is established based on the 99.9th percentile of the baseline healthy SAI distribution. If the real-time monitoring system detects that $SAI(t) > SAI_{th}$ for a consecutive number of frames m (to prevent false alarms from transient spikes), a pre-failure early warning alert is explicitly generated, triggering diagnostic classification.

2.4 Deep Learning for Fault Classification (CNN-BiLSTM)

Once an incipient anomaly is flagged by the SAI algorithm, the precise physical nature of the fault must be classified to facilitate automated robotic maintenance or structural repair. Classical mathematical regressions struggle with the complex, non-stationary time-series nature of degraded optical spectra. Therefore, we deploy a hybrid deep learning architecture: a 1D Convolutional Neural Network coupled with a Bidirectional Long Short-Term Memory network (CNN-BiLSTM).Mathematical Formulation of the Network Architecture:

(1)Spatial Feature Extraction (1D-CNN):

The raw time-series optical spectra and the extracted feature vectors are fed into sequential 1D convolutional layers. The convolution operation extracts localized spatial anomalies (e.g., asymmetric spectral peak splitting indicative of transverse crushing). The output feature map $C_i^{(l)}$ at layer l is calculated as:

$$C_i^{(l)} = ReLU\left(\sum_k W_k^{(l)} * X_{t+k}^{(l-1)} + b_i^{(l)}\right) \qquad (7)$$

where W_k represents the convolutional kernel weights, $*$ denotes the convolution operator, b_i is the bias term, and $ReLU(z) = \max(0, z)$ provides nonlinear activation. A subsequent Max-Pooling layer downsamples the feature map, reducing dimensionality while retaining the most salient features.

(2)Temporal Sequence Modeling (BiLSTM):

The spatially extracted feature maps from the CNN are flattened and passed into the BiLSTM layers. Because physical fiber degradation is a progressive temporal event (e.g., a propagating crack), analyzing the sequence from both past-to-future and future-to-past is critical.

For each LSTM cell at time step t, the information flow is governed by three specific gates (Forget f_t, Input i_t, Output o_t) and a cell state update $\widetilde{C}_t$:

$$\begin{aligned} f_t &= \sigma_g(W_f[h_{t-1}, x_t] + b_f) \\ i_t &= \sigma_g(W_i[h_{t-1}, x_t] + b_i) \\ \widetilde{C}_t &= tanh\,(W_c[h_{t-1}, x_t] + b_c) \\ C_t &= f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t \\ o_t &= \sigma_g(W_o[h_{t-1}, x_t] + b_o) \\ h_t &= o_t \odot tanh\,(C_t) \end{aligned} \tag{8}$$

where σ_g is the sigmoid activation function, and $\odot$ denotes element-wise multiplication. The BiLSTM computes the forward hidden sequence $\overrightarrow{h}_t$ and the backward hidden sequence $\overleftarrow{h}_t$. The ultimate hidden state representation is the concatenation of both directions:

$$H_t = [\overrightarrow{h}_t \oplus \overleftarrow{h}_t] \tag{9}$$

(3)Fault Classification (Softmax Layer):

The final aggregated hidden state vectors are mapped through fully connected dense layers to generate raw logit scores Z_k for each of the K distinct fault classes. The final probability distribution p_k is computed using the Softmax function:

$$p_k = \frac{e^{Z_k}}{\sum_{j=1}^{K} e^{Z_j}} \tag{10}$$

The network weights are optimized via Backpropagation Through Time (BPTT) using the Adam optimizer, minimizing the Categorical Cross-Entropy Loss function $\mathcal{L}$:

$$\mathrm{L} = -\sum_{k=1}^{K} y_k \log(p_k) \tag{11}$$

where y_k represents the binary one-hot encoded ground truth label for the k-th fault class

3. Experiments and Validation

3.1 Experimental Setup and Data Sources

To rigorously validate the proposed SAI early warning algorithm and the CNN-BiLSTM fault classification architecture, a highly controlled multiaxial force-sensing and fault-induction testbed was constructed. The experimental configuration was explicitly designed to simultaneously capture standard healthy operation data and to artificially induce specific, quantifiable mechanical failure modes in the optical fiber sensing network [15].

3.1.1 Hardware and optical interrogation setup

The optical data acquisition utilized an ultra-high-resolution Optical Frequency-Domain Reflectometer (LUNA OBR 4600) with a 2 mm spatial and 0.01 pm spectral resolution. The sensing network comprised a 5-kilometer single-mode fiber with 25 WDM-multiplexed FBGs. These nodes were integrated into a compliant 3-UPU multi-axis platform to transform spatial forces into axial strains, with ground-truth reference vectors actively captured by a co-mounted ATI Mini45 six-axis load cell.

3.1.2 Data acquisition and fault induction

Using a precision motorized translation stage and a programmable environmental climate chamber (-20 °C to 80 °C), the optical fibers were subjected to complex thermo-mechanical stresses. Eight distinct operational and failure states were systematically induced: (1) Normal Operation, (2) Excessive Bending (radius < 5 mm), (3) Transverse Crushing (point loads up to 200 N), (4) Static Fatigue/Micro-crack (48-hour high-tension hold), (5) Splice Degradation, (6) Dynamic Impact (high-G shock), (7) Interrogator Signal Drift, and (8) Fiber Cut/Breakage. Data was sampled at 1 kHz over a continuous 120-hour testing period, generating over 850,000 distinct samples. This comprehensive dataset was partitioned into 70% training, 15% validation, and 15% blind testing subsets for algorithm evaluation.

3.2 Early Warning (SAI) Performance

During the static fatigue and progressive micro-crack induction tests, traditional amplitude-threshold alarms completely failed to detect the impending structural failure until the optical fiber physically snapped, resulting in abrupt data loss. Conversely, the proposed Synthetical Anomaly Index (SAI) algorithm actively monitored the multidimensional covariance of the extracted features.

Table 1 summarizes the baseline feature statistics and the resulting SAI values observed at specific intervals leading up to a localized fiber failure.

As demonstrated in Table 1, approximately 47 minutes prior to physical breakage, the calculated $SAI(t)$ value surged from a nominal baseline of 2.15 to 16.55, vastly exceeding the statistically defined adaptive threshold ($SAI_{th} = 5.2$). While the individual absolute values of intensity or signal length had not yet reached traditional hard-alarm levels, the Mahalanobis distance effectively captured the subtle spectral deformations and divergence in their covariance, confirming that the SAI method successfully identifies micro-crack initiation and provides a crucial temporal buffer for preventative maintenance before catastrophic system blindness occurs.

Table 1. Evolution of Optical Features and the Synthetical Anomaly Index (SAI) Preceding A Static Fatigue Fiber Breakage

Time to Failure (T_f)	Intensity (I) [a.u.]	Signal Length (L) [pm]	Variance (σ)	Time Energy (P)	Calculated SAI	Status
Tf-120 min	1.85	150.2	0.012	0.88	2.15	Healthy
Tf-90 min	1.84	151.0	0.015	0.86	3.82	Healthy
Tf-47 min	1.62	168.5	0.058	0.71	16.55	Early Warning
Tf-10 min	0.95	210.4	0.185	0.42	45.20	Critical Alert
Tf-0 min	0.00	N/A	N/A	0.00	∞	Hard Failure

3.3 Fault Classification (CNN-BiLSTM) Results

Following the detection of an anomaly by the SAI algorithm, the raw optical time-series data Following the detection of an anomaly by the SAI algorithm, the raw optical time-series data was passed to the CNN-BiLSTM network to classify the precise nature of the fault among the eight predefined physical categories. The classification performance was evaluated mathematically using standard statistical metrics, notably Precision (Pr), Recall (Rc), and the F1-Score, defined as:

$$Pr = \frac{TP}{TP+FP}; Rc = \frac{TP}{TP+FN}; F1 = 2\times\frac{Pr\times Rc}{Pr+Rc} \tag{12}$$

The classification results on the fully unseen blind test dataset are summarized in Table 2.

Following anomaly detection, the hybrid CNN-BiLSTM network classified the precise physical fault across eight predefined categories. The framework demonstrated exceptional diagnostic capabilities, achieving a macro-average precision of 98.9%, a recall of 98.8%, and an F1-score of 0.988, while maintaining a low overall false negative rate of 1.2%. Crucially, the network effectively differentiated overlapping physical anomalies, resolving "Transverse Crushing" and "Excessive Bending" with F1-scores of 0.989 and 0.979 respectively—a complex challenge where traditional linear matrix decoupling invariably fails. Additionally, it perfectly identified "Fiber Cut/Breakage" events with a 1.000 F1-score and a 0.0% false negative rate. Compared to standalone Autoencoders limited to a 96.8% accuracy limit, this architecture provides vastly superior diagnostic granularity for mapping specific physical repairs

Table 2. Fault Classification Performance Metrics of the Hybrid CNN-Bilstm Network across Eight Distinct Operational and Failure States

Failure Mode Category	Precision (%)	Recall (%)	F1-Score	False Negative Rate (%)
1. Normal Operation	99.8	99.9	0.998	0.1
2. Excessive Bending	98.5	97.4	0.979	2.6
3. Transverse Crushing	99.1	98.8	0.989	1.2
4. Static Fatigue / Micro-crack	97.6	98.2	0.979	1.8
5. Splice Degradation	98.9	99.1	0.990	0.9
6. Dynamic Impact	99.5	99.0	0.992	1.0
7. Interrogator Signal Drift	98.2	97.9	0.980	2.1
8. Fiber Cut / Breakage	100.0	100.0	1.000	0.0
Overall Macro-Average	98.9	98.8	0.988	1.2

4. Conclusion

The widespread deployment of force-sensing optical fibers in critical infrastructure and embodied robotic intelligence is persistently threatened by mechanical degradation and complex physical failure modes. This paper established a highly robust, mathematically rigorous, and data-driven methodology for the real-time early warning and precise classification of such faults. By translating the physical mechanics of fiber buckling and crack propagation into multidimensional digital feature spaces using Wavelet Packet Decomposition, we formulated a Synthetical Anomaly Index (SAI). Utilizing Mahalanobis distance covariance, the SAI demonstrated the capability to provide deterministic early warnings up to 47 minutes prior to catastrophic structural failure, vastly outperforming traditional amplitude thresholds.

Furthermore, the implementation of a hybrid CNN-BiLSTM deep learning architecture effectively eliminated the reliance on manual OTDR trace interpretation and vulnerable linear calibration matrices. By synergizing convolutional spatial feature extraction with bidirectional temporal sequence modeling, the network achieved a phenomenal classification accuracy of 99.3% across eight complex fault and operational conditions. This integrated algorithmic framework significantly enhances the resilience and fault tolerance of optical sensing arrays, ensuring the continuous, safe, and highly reliable operation of next-generation multidimensional sensing networks in demanding environments.

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