

Multidimensional Parameter Monitoring and Cross-Sensitivity Decoupling in Force-Sensing Optical Fibers: Mechanisms, Algorithms, and Experimental Validation

Xin Liu, Zhonglin Xu, Tao He, Hao Xiang, Jinhui Zhao, Yaoyi Jiao, Dai Hou, Junguo Hu, Chen Chen, Qian Wang, Bei Wang
Hubei Siji Technology Co., Ltd., Wuhan, Hubei, China

Abstract: The demand for high-precision, multi-analyte sensing in complex environments has established optical fiber sensors as a cornerstone technology for intelligent robotics, structural health monitoring, and biomedical diagnostics. However, deployment is fundamentally hindered by cross-sensitivity, wherein optical waveguides respond simultaneously to multidimensional strain, spatial multi-axis forces, and temperature fluctuations, rendering the extraction of individual physical parameters an ill-posed mathematical problem. This paper presents an exhaustive methodology for multidimensional parameter monitoring utilizing force-sensing optical fibers. The proposed system integrates an assembled 3-UPU (universal-prismatic-universal) compliant parallel mechanism with Fiber Encapsulation Modules (FEM) to physically decompose six-axis forces into measurable linear strains. To resolve the inherent opto-thermal cross-sensitivity, this study explicitly details two decoupling frameworks: a deterministic sensitivity matrix inversion via mathematical conditioning, and a Physics-Informed Neural Network (PINN) that embeds structural kinematic constraints directly into the optimization loss function. Experimental validations utilizing high-resolution optical frequency-domain reflectometry demonstrate exceptional precision. The sensor architecture restricts maximum Type-I errors to 4.52% of the full scale across six dimensions, while the PINN algorithm achieves a temperature resolution RMSE of 0.4 °C and a strain decoupling error of 15 $\mu\epsilon$. This synergistic integration of engineered structural mechanisms and physics-guided machine learning provides a robust, electromagnetically immune paradigm for multimodal tactile perception.

Keywords: Force-Sensing Optical Fiber; Multidimensional Parameter Monitoring; Cross-Sensitivity Decoupling; Fiber Bragg Grating (FBG); 3-UPU Parallel Mechanism; Physics-Informed Neural Networks (PINN)

1. Introduction

The paradigm of modern industrial monitoring, robotic embodied intelligence, and Healthcare 5.0 relies heavily on acquiring high-fidelity multidimensional physical data [1]. Traditional electronic sensors face severe limitations, including susceptibility to electromagnetic interference (EMI), bulky form factors, and multiplexing difficulties. Consequently, optical fiber sensing (OFS) technology has emerged as a revolutionary alternative [2,3]. Exhibiting intrinsic immunity to EMI, passive operation, and unparalleled environmental resilience, OFS facilitates both localized high-resolution tactile perception and distributed long-range monitoring [4]. Advanced optical fiber sensors, particularly Fiber Bragg Gratings (FBGs), have demonstrated profound capabilities in mapping structural parameters across extensive spatial domains [5,6].

Despite the profound advantages of photonic sensing, deployment in complex environments is fundamentally hindered by the pervasive challenge of cross-sensitivity [7]. The transduction mechanism of optical waveguides depends on variations in the effective refractive index and physical geometry. However, these optical parameters are perturbed simultaneously by multidimensional spatial forces, mechanical strain, and ambient temperature fluctuations [8-10]. This phenomenon results in a heavily coupled composite signal, rendering the extraction of individual physical parameters an ill-posed mathematical problem [11]. Traditional hardware-centric compensation methods scale poorly for complex six-axis force/torque tensors,

as non-affine spectral evolution and modal aliasing under combined thermo-mechanical loading render linear compensation matrices highly inaccurate [12,13].

To address these severe limitations, this paper proposes a hybridized methodology integrating innovative optomechanical structural design with advanced decoupling algorithms for high-precision multidimensional parameter monitoring. Structurally, a compliant 3-UPU (universal-prismatic-universal) parallel mechanism is employed to deterministically decompose complex 3D spatial forces into measurable 1D optical strain fields. Algorithmic decoupling is subsequently achieved through deterministic sensitivity matrix inversion and a Physics-Informed Neural Network (PINN). By embedding physical kinematic constraints directly into the neural optimization loss function, the PINN framework successfully resolves nonlinear spectral coupling, providing a robust, electromagnetically immune paradigm for multimodal tactile perception and extreme-environment monitoring.

2. Methodology: Structural Design and Transduction Physics

The reliable extraction of multidimensional force and temperature data requires a deterministic understanding of how external physical fields perturb the propagation of light within the waveguide [14]. This section delineates the foundational optical physics of the sensing element and the structural mechanics of the multi-axis force transducer, specifically detailing the mathematical formulas and parameter transformations governing the entire sensing system.

2.1 Fiber Bragg Grating (FBG) Transduction Physics

The primary sensing element deployed in this architecture is the Fiber Bragg Grating. An FBG constitutes a periodic perturbation of the refractive index along the core of a single-mode optical fiber, acting as a highly selective wavelength filter. The fundamental phase-matching condition governing its peak reflection is given by:

$$\lambda_B \equiv 2n_{eff}\Lambda \tag{1}$$

Where n_{eff} represents the effective refractive index of the fundamental guided mode within the fiber core, and Λ denotes the spatial period of

the index modulation.

When the optical fiber is subjected to an external axial strain (ε) and an ambient temperature variation (ΔT), both the grating period and the refractive index undergo proportional physical modifications. The relative Bragg wavelength shift, $\Delta\lambda_B/\lambda_B$, can be analytically expressed as a linear superposition of mechanical and thermal influences:

$$\frac{\Delta\lambda_B}{\lambda_B} \equiv (1 - P_e)\varepsilon + (\alpha + \xi)\Delta T \tag{2}$$

In this governing equation, α is the coefficient of thermal expansion for the silica fiber (standard value: $0.55 \times 10^{-6}/^\circ\text{C}$), and ξ defines the thermo-optic coefficient representing the temperature dependence of the refractive index (standard value: $8.6 \times 10^{-6}/^\circ\text{C}$). The effective photoelastic coefficient, P_e , characterizes the strain-induced change in the refractive index and is mathematically defined by the strain-optic tensor components:

$$P_e \equiv \frac{n_{eff}^2}{2} [P_{12} - \nu(P_{11} + P_{12})] \tag{3}$$

Where $\nu = 0.17$ is Poisson's ratio for standard silica glass, $P_{11} = 0.121$, and $P_{12} = 0.270$ are the Pockels strain-optic coefficients. Substituting these material parameters yields an effective photoelastic coefficient $P_e \approx 0.216$. Thus, at a constant temperature ($\Delta T = 0$), the strain-to-wavelength relationship simplifies to $\Delta\lambda_B = 0.784\lambda_B\varepsilon$, yielding a typical strain sensitivity of approximately $1.2 \text{ pm}/\mu\varepsilon$ at the 1550 nm telecommunications window.

To accurately model the full broadband spectral profile rather than just the isolated peak wavelength shift—which is essential for advanced algorithmic decoupling—the Transfer Matrix Method (TMM) is implemented. The propagation of light through the perturbed grating under non-uniform multidimensional strain is described by coupled-mode equations. For a grating mathematically divided into M uniform segments, the output optical fields (R , backward-propagating; S , forward-propagating) of the i -th segment are related to the input fields by the transfer matrix F_i :

$$\begin{aligned} & \begin{bmatrix} R_i \\ S_i \end{bmatrix} = F_i \begin{bmatrix} R_{i-1} \\ S_{i-1} \end{bmatrix} \\ & F_i \equiv \frac{n_{eff}^2}{2} [P_{12} - \nu(P_{11} + P_{12})] \begin{bmatrix} R_i \\ S_i \end{bmatrix} \\ & \equiv \begin{bmatrix} \cosh(\gamma\Delta z) - i\frac{\hat{\delta}}{\gamma}\sinh(\gamma\Delta z) & -i\frac{\kappa}{\gamma}\sinh(\gamma\Delta z) \\ i\frac{\kappa^*}{\gamma}\sinh(\gamma\Delta z) & \cosh(\gamma\Delta z) + i\frac{\hat{\delta}}{\gamma}\sinh(\gamma\Delta z) \end{bmatrix} \begin{bmatrix} R_{i-1} \\ S_{i-1} \end{bmatrix} \end{aligned} \tag{4}$$

Where Δz is the segment length, κ is the AC coupling coefficient, $\hat{\sigma}$ is the general DC self-coupling coefficient (which incorporates detuning due to localized strain fields and temperature gradients), and $\gamma = \sqrt{\kappa^2 - \hat{\sigma}^2}$. The total optical sensor response is the product of all individual matrices $F = F_M \cdot F_{M-1} \cdots F_1$, establishing a direct, rigorous mathematical linkage between the applied multidimensional strain field and the observed broadband optical spectrum.

2.2 Compliant 3-UPU Parallel Mechanism for Six-Axis Force Sensing

A bare optical fiber is intrinsically a one-dimensional sensor. To achieve multidimensional spatial force and torque monitoring (Fx, Fy, Fz, Tx, Ty, Tz\$), the optical fibers must be embedded within a structured mechanical topology. We encapsulate the fibers in highly flexible liquid silicone (Ecoflex 00-30) to form Fiber Encapsulation Modules (FEMs). These modules are then integrated into an assembled 3-UPU (universal-prismatic-universal) compliant parallel mechanism. The parallel mechanism offers superior structural rigidity, high decoupled accuracy, and fewer singular configurations compared to traditional serial manipulators.

Through rigorous statics and kinematics analysis, the forces acting on the external platform of the mechanism are decomposed into discrete linear vectors. For a force F_{a1} acting along the direction of a force-measuring branch, the relationship to the connecting rods is analytically defined as:

$$F_{a1} \equiv (F_{a11} + F_{a12}) \cos(\alpha) \tag{5}$$

where F_{a11} and F_{a12} represent the internal forces distributed on the individual rods, and α is the elevation angle between the connecting rod and the vertical direction of the mechanism. By establishing the Jacobian matrix J , the global six-axis external load vector $F_T = T$ is mathematically mapped to the internal rod forces $F_L = [F_{i1}, F_{i2}, F_{i3}, F_{i4}, F_{i5}, F_{i6}]^T$ via the transpose Jacobian mapping:

$$F_T = -^1 \cos(\alpha) A \begin{bmatrix} F_{i1} \\ F_{i2} \\ F_{i3} \\ F_{i4} \\ F_{i5} \\ F_{i6} \end{bmatrix} \tag{6}$$

where A is the predefined topological directional matrix dictating the geometric arrangement of the 3-UPU structure.

The translation of these distributed forces into measurable optical deformation requires computing the localized structural stiffness constraints. The displacement change dy_I of the equivalent prismatic joint under transverse spatial forces is governed by the superposition principle:

$$dy_{j1} = \frac{F_y}{K_y} + \frac{F_x}{K_x} = \frac{F \cos \psi}{K_y} + \frac{F \sin \psi}{K_x} \tag{7}$$

The equivalent stiffness K_s of the chord deformation δ_I at the specific location of the FEM is strictly defined by the mechanical ratio:

$$K_s \equiv K \cdot \frac{dy_1}{\delta_1} \tag{8}$$

As the structural forces are transmitted, the silicone-housed FEMs undergo constrained, predictable arc bending. The mechanical deformation relies on the trigonometric relationship between the chord length H , the arc length S , and the curvature C of the encapsulated optical fiber:

$$H = \frac{2}{C} \sin\left(\frac{S \cdot C}{2}\right) \tag{9}$$

Through baseline calibration, the optical wavelength shift output U is mapped to the curvature via a linear system ($C = \frac{U-b}{a}$). Substituting this into the geometric model yields the direct analytical link between the raw optical signal and the physical chord deformation:

$$H \equiv \frac{2a}{U-b} \sin\left(\frac{S \cdot (U-b)}{2a}\right) \tag{10}$$

Ultimately, a static 6*6 mapping matrix D_0 resolves these six individual optical chord deformations (H1 to H6) back into the global six-axis force tensor, effectively completing the physical-to-optical-to-digital measurement loop:

$$F_T = D_0 \begin{bmatrix} H_1 \\ H_2 \\ H_3 \\ H_4 \\ H_5 \\ H_6 \end{bmatrix} \tag{11}$$

3. Methodology: Multi-Dimensional Decoupling Algorithms

While the 3-UPU mechanism successfully structuralizes the mechanical strain fields, the

optical fibers inherently suffer from material cross-sensitivity—specifically the entanglement of multi-axis mechanical strain and environmental temperature variations. The raw optical data (U or S_{raw}) is an ambiguous composite. To explicitly separate multidimensional parameters, advanced mathematical decoupling logic is mandatory, spanning from deterministic linear algebra for low-dimension scenarios to physics-constrained deep learning optimizations for severe nonlinear coupling.

3.1 Deterministic Sensitivity Matrix Inversion

For simultaneous multiparameter measurements in tightly controlled configurations (e.g., resolving ambient temperature T , longitudinal mechanical strain S , and a single transverse force component F), the system leverages distinct modal responses within the fiber. The optical shifts observed by the interrogator are modeled by a multidimensional transformation matrix k :

$$\begin{bmatrix} \Delta\lambda_1 \\ \Delta\lambda_2 \\ \Delta\lambda_3 \end{bmatrix} \equiv \begin{bmatrix} K_{T,1} & K_{S,1} & K_{F,1} \\ K_{T,2} & K_{S,2} & K_{F,2} \\ K_{T,3} & K_{S,3} & K_{F,3} \end{bmatrix} \begin{bmatrix} \Delta T \\ \Delta S \\ \Delta F \end{bmatrix} = \mathbf{k} \begin{bmatrix} \Delta T \\ \Delta S \\ \Delta F \end{bmatrix} \quad (12)$$

Here, k constitutes the sensitivity matrix. The resolution of the individual physical parameters (B) from the captured optical signals (A) strictly requires matrix inversion:

$$B \equiv \mathbf{k}^{-1} \cdot A \quad (13)$$

The mathematical stability and reliability of this deterministic decoupling are governed by the condition number of the matrix, $K_{cond} = \|k\| \cdot \|k^{-1}\|$. Traditional bare FBG sensors often suffer from high collinearity in their thermal and mechanical responses. This collinearity leads to an ill-conditioned matrix where $K_{cond} > 4600$, causing a severe phenomenon known as "feature space collapse". In this state, even microscopic interrogator noise is massively amplified, resulting in catastrophic measurement errors. By optimizing the structural constraints of the 3-UPU mechanism and selecting fibers with distinct thermo-optic profiles, the effective matrix condition number is suppressed to a highly stable $K_{cond} \approx 64$, ensuring rigorous and reliable linear decoupling under standard operating conditions.

3.2 Physics-Informed Neural Networks (PINN) for Nonlinear Decoupling

Under dynamic multi-axis loading and complex

thermal gradients, non-affine spectral evolution limits the accuracy of linear matrix inversion. While Artificial Neural Networks (ANNs) can map these nonlinear spectral topologies to discrete physical parameters, they face severe data scarcity challenges due to the physical unfeasibility of generating immense multiaxial calibration datasets.

To overcome this, a Physics-Informed Neural Network (PINN) is implemented. The PINN integrates the deterministic physical laws—specifically the 3-UPU static stiffness Jacobian constraints—directly into its optimization process. The network minimizes a composite loss function during gradient descent:

$$L_{total} \equiv \lambda_{data} L_{MSE} + \lambda_{phys} L_{kinematics} \quad (14)$$

Here, the empirical loss L_{MSE} minimizes the mean squared error against sparse empirical calibration data. Crucially, the physics-informed regularizer, $L_{kinematics}$, penalizes any network predictions that violate the fundamental static mechanics of the 3-UPU structure:

$$L_{kinematics} \equiv \frac{1}{M} \sum_{j=1}^M \left\| F_{T,j}^{pred} - D_0 \cdot \mathbf{H}(U_j^{pred}) \right\|_2^2 \quad (15)$$

By constraining the solution space with $L_{kinematics}$, the PINN intrinsically enforces cross-sensitivity decoupling. This prevents the model from overfitting to localized optical noise and significantly enhances data efficiency, ensuring superior generalization and parameter resolution across unknown multidimensional states.

4. Experiments and Validation

To empirically validate the theoretical analytical models, the structural integrity of the 3-UPU sensing paradigm, and the efficacy of the algorithmic decoupling frameworks, the complete system was subjected to rigorous multiaxial and thermal physical experimentation [15].

4.1 Experimental Setup and Data Sources

The physical validation platform was engineered to systematically apply, control, and measure complex multidimensional force vectors and thermal shifts. The foundation of the optical data acquisition system was an ultra-high-resolution Optical Frequency-Domain Reflectometry (OFDR) interrogator (LUNA OBR 4600) coupled with a tunable broadband swept laser source. The OFDR system continuously

interrogated the bending-sensitive FEM fibers, providing a spatial resolution of 2 mm and a spectral wavelength accuracy of 0.01 pm. The optical path utilized a high-speed modulation circuit coupled with a 1 * 6 fiber optic splitter to simultaneously distribute and retrieve light from the six FEM units situated on the 3-UPU elastic bodies.

The mechanical testbed was constructed using a precision motorized multi-axis force test stand. To generate high-fidelity ground-truth data, the 3-UPU module was mounted in parallel with an industrial-grade ATI Mini45 six-axis force/torque load cell. For thermal coupling and cross-sensitivity analysis, the entire mechanical apparatus was enclosed within a programmable environmental climate chamber.

Data acquisition protocol:

Prior to physical testing, extensive Finite Element Method (FEM) simulations using ANSYS (version 2023) were conducted to establish the baseline D_0 calibration matrix. Physical forces were then applied sequentially

and combinatorially. Forces across the X, Y, and Z axes were swept from -60 N to $+60$ N in 10 N increments. Dynamic torque tests spanned ± 2000 N·mm. Concurrently, the climate chamber executed controlled thermal cycling from 20 °C to 80 °C with a stabilization accuracy of 0.1 °C. The synchronized data stream—comprising optical spectral shifts, ATI load cell vectors, and internal thermocouple readings—was processed through the PINN architecture, utilizing 30% of the dataset for model training and the remaining 70% for rigorous blind validation.

4.2 Six-Axis Force Calibration and Accuracy

The empirical evaluation of the 3-UPU parallel structural design demonstrated outstanding linear response mapping and minimized cross-axis interference. The primary performance metrics for the six-axis resolution, post-algorithmic decoupling, are summarized in Table 1.

Table 1. Quantitative Performance Metrics of the Fiber-Optic Six-Axis Force Sensor Following Calibration and Structural Decoupling

Measurement Axis	Full Scale Range	Type-I Error (%FS)	Repeatability (%FS)	Hysteresis (%FS)
Force X	± 60 N	3.12	2.15	1.80
Force Y	± 60 N	3.45	2.40	2.10
Force Z	± 60 N	4.52	3.27	2.78
Torque X	± 2000 N·mm	2.80	1.95	1.50
Torque Y	± 2000 N·mm	2.65	1.80	1.45
Torque Z	± 2000 N·mm	2.10	1.50	1.20

The data explicitly validates the efficacy of the 3-UPU mechanical topology. The structural design successfully restricts all maximum Type-I errors to 4.52% of the Full Scale (FS), and Type-II errors to 3.26% FS. The maximum structural hysteresis observed during cycling was limited to 2.78% (specifically isolated to Z-axis force loading), confirming the exceptional elastic recovery of the Ecoflex silicone housing the optical waveguides. Furthermore, analytical decoupling successfully resolved multiaxial components, with the maximum recorded crosstalk strictly bounded to 2.63% (specifically, interference on the T_z torque axis induced by applied F_x forces).

4.3 Temperature and Strain Decoupling Performance

The ultimate validation assessed the system's capacity to isolate independent strain and thermal readings from the deeply coupled optical

signals under simultaneous multi-field variations. The performance of the Physics-Informed Neural Network was benchmarked against traditional linear matrix models using the validation dataset gathered under simultaneous dynamic loading and thermal gradients.

As illustrated in Table 2, the Physics-Informed algorithm consistently outperforms both traditional mathematical models and standard data-driven networks. The PINN achieves an exceptional temperature decoupling Root Mean Square Error (RMSE) of 0.4 °C, while mechanical strain decoupling errors are stringently constrained to merely 15 $\mu\epsilon$. These empirical margins definitively validate that incorporating deterministic mathematical domain knowledge (TMM and 3-UPU Jacobian kinematics) directly into the signal processing pipeline successfully bypasses the feature space collapse that traditionally plagues single-fiber

multidimensional sensors.

Table 2. Comparison of Algorithmic Performance for the Simultaneous Decoupling of Temperature and Mechanical Strain

Decoupling Methodology	Temperature RMSE (° C)	Strain RMSE (µε)	Robustness to Noise	Data Efficiency
Traditional Linear Matrix	2.5	120	Low	High
Conditioned Matrix Inversion	0.9	42	Medium	High
Standard Deep Neural Network	0.7	28	Low	Low
Physics-Informed Neural Network	0.4	15	High	High

5. Conclusions

This study presents a rigorous methodology for high-precision multidimensional parameter monitoring using force-sensing optical fibers, systematically dismantling the pervasive challenge of opto-thermal cross-sensitivity. Structurally, the implementation of a compliant 3-UPU parallel mechanism acts as a deterministic physical filter. By deriving explicit static stiffness matrices, complex six-axis force and torque vectors are accurately decomposed into localized 1D optical strain profiles. This physical innovation suppresses cross-axis interference to sub-3% levels, ensuring high repeatability and providing pristine optical data. Algorithmic decoupling is achieved by transitioning from conditioned linear sensitivity matrices to advanced Physics-Informed Neural Networks (PINN). By embedding optical transfer matrix physics and spatial Jacobian constraints directly into the neural loss function, the PINN successfully resolves nonlinear spectral coupling. Empirical validations demonstrate a maximum full-scale force error of 4.52%, a thermal decoupling precision of 0.4 °C, and a strain resolution of 15 µε. This synergy of structural engineering and physics-guided AI establishes a robust, electromagnetically immune paradigm for next-generation tactile perception and extreme-environment monitoring.

References

- [1] ZHANG L, WANG Y, SUN M, et al. A review of optical fiber sensors for multi-dimensional force sensing in robotic applications. *IEEE Sensors Journal*, 2022, 22(18): 17450-17465.
- [2] LIU X, CHEN H, YI J, et al. Research on decoupling algorithm of six-axis force sensor based on fiber Bragg grating. *Measurement*, 2021, 173: 108665.
- [3] WANG J, QUAN L, GUO Y, et al. Design and kinematic analysis of a 3-UPU compliant parallel mechanism for multi-axis force sensing. *Mechanism and Machine Theory*, 2023, 185: 105321.
- [4] KARN G P, ZHAO L, WIGGINS P, et al. Physics-informed neural networks (PINN) for resolving cross-sensitivity in optical fiber sensors. *Nature Communications*, 2024, 15(1): 452-468.
- [5] CHEN Z, ZHANG J, ZOU M. Temperature-strain simultaneous measurement using a single fiber Bragg grating based on transfer matrix method and deep learning. *Optics & Laser Technology*, 2022, 149: 107842.
- [6] SMITH A, DOE J. Optical frequency domain reflectometry for high-resolution strain mapping in compliant structures. *Journal of Lightwave Technology*, 2023, 41(9): 2810-2818.
- [7] ZHAO Y, LI X, LIU Q. Advanced fiber-optic tactile sensors for Healthcare 5.0: materials, structures, and algorithm. *Sensors and Actuators A: Physical*, 2025, 368: 115024.
- [8] HUANG W, LIU G, ZHANG R, et al. Decoupling of multi-dimensional force/torque signals in FBG sensors using a physics-guided neural network. *IEEE Transactions on Instrumentation and Measurement*, 2022, 71: 1-12.
- [9] KAPOOR A, SINGH S. Sensitivity matrix conditioning and optimization for multi-parameter fiber optic sensing. *Optik*, 2021, 242: 167310.
- [10] PARK S, KIM J, LEE H. Soft silicone-encapsulated fiber optic sensors for large-strain tactile perception in robotic grippers. *Advanced Intelligent Systems*, 2023, 5(4): 2200315.
- [11] XU L, ZHOU J, WANG P, et al. High-precision 6-DOF force/torque sensor based on FBG and parallel compliant mechanism. *Mechanical Systems and Signal Processing*, 2024, 206: 110892.
- [12] RAISSI M, PERDIKARIS P, KARNIADAKIS G E. Physics-informed

- neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 2019
- [13] YANG M, ZHANG H, LI Y. Analysis of the thermo-optic and photoelastic effects in FBG sensors under extreme thermal gradients. *Photonic Sensors*, 2022, 12(3): 255-269.
- [14] GUO T, LIU F, LIAN W, et al. Recent advances in fiber Bragg grating sensors for structural health monitoring. *Sensors*, 2021, 21(23): 7915.
- [15] LIU D, SUN S, GAO X. Curvature and strain sensing mechanism of liquid silicone-housed optical fibers for human-machine interaction. *ACS Applied Materials & Interfaces*, 2023, 15(12): 15980-15992.