

RNCA Boosts Performance of a 7-Core FBG Sensor Based on the Microwave Photonic Self-Vernier Effect

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Abstract: In this paper, we proposed a 7-core fiber Bragg grating (7-core FBG) curvature sensing system based on the microwave photonic self-Vernier effect, and combined it with a residual network with channel attention (RNCA) to achieve intelligent demodulation. The system achieved the sensitivity amplification through the superposition of the raw response from a single interferometric structure and its delayed replica in the microwave domain. Concurrently, the RNCA model eliminated the cumbersome traditional envelope fitting process by learning the complex nonlinear mapping between the raw microwave spectrum and curvature end-to-end. Experimental results demonstrated that the sensor achieved the sensitivity of up to $-3.693 \text{ MHz/m}^{-1}$ in curvature measurement. Under sparse sampling conditions, the RNCA model maintained $R^2=99.95\%$ and $\text{RMSE}=0.044 \text{ m}^{-1}$ with the single inference time of only 0.2 s, where the RMSE is the root mean square error. This research established a novel technical paradigm for realizing optical fiber curvature sensing systems characterized by structural simplicity, intelligent demodulation, and superior performance.

Keywords: Microwave photonics; 7-core fiber Bragg grating; Vernier effect; RNCA model

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1. Introduction

Optical fiber sensing technologies have been widely applied in fields, such as structural health monitoring [1] and three-dimensional shape sensing [2, 3], due to their advantages, including immunity to electromagnetic interference and capability for remote transmission. Among these, the optical fiber curvature sensors effectively capture complex

deformation information, serving as a crucial approach for multidimensional detection. However, traditional spectral interrogation methods relying on wavelength or power changes are constrained by resolution and detection speed limitations, making it challenging to simultaneously achieve high sensitivity and real-time performance [4]. Microwave photonics (MWP) offers a novel approach to addressing this challenge [5]. This

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technology maps variations in optical signals to easily measurable microwave-domain parameters, thereby significantly enhancing measurement resolution and dynamic response speed [6, 7]. Concurrently, multi-core fibers (MCFs) have attracted considerable attention due to their compact structure and capability for multidimensional curvature sensing [8]. Specifically, the 7-core fiber (7-CF) is considered an ideal platform for constructing vector sensors due to the differential bending responses of its distinct eccentric cores [9, 10]. Integrating the MWP technology with the MCF offers a novel pathway toward advancing optical fiber sensing capabilities.

To further enhance the sensing performance, the Vernier effect has been widely investigated and successfully extended to microwave photonic systems in recent years [11]. By utilizing two interferometers with similar free spectral ranges (FSRs) to generate a Vernier envelope, this mechanism amplifies minute spectral shifts into significant envelope movements, thereby achieving sensitivity multiplication. Conventionally, implementing this effect requires the cascading or parallel arrangement of two independent interference structures, with typical examples including the Sagnac loops or Fabry-Perot interferometers [12–15]. However, such cascaded configurations inevitably introduce high system complexity and poor stability due to the strict requirement for the precise optical path matching between separate interferometers. In contrast, sensors based on a standard single-interferometer architecture offer inherent structural robustness and compactness [16–18], yet they are typically constrained by limited intrinsic sensitivity. Consequently, realizing the Vernier-like amplification within a simplified single-interferometer structure becomes an urgent pursuit to bridge the gap between high sensitivity and structural stability.

This paper proposed a 7-core fiber Bragg grating (7-core FBG) sensor based on the microwave photonic self-Vernier effect. Unlike cascaded schemes, this mechanism was realized solely on a single interferometer structure. By introducing a delay path close to the fiber loop cavity time, the raw signal and its delayed replica underwent superposition in the microwave domain, forming a stable self-Vernier envelope. This achieved a sensitivity amplification (approximately $-3.693 \text{ MHz/m}^{-1}$) without matched dual interferometers, significantly reducing the complexity while maintaining the stability of single-interferometer designs.

Although the self-Vernier effect significantly enhances sensitivity, its signal demodulation process inherits the challenge of accurately extracting the Vernier envelope from complex responses containing dense comb-like spectra [19, 20]. Initially, researchers attempted to address this using digital signal processing (DSP) techniques. For instance, Liao *et al.* [21] and Xie *et al.* [22] employed the Gaussian filtering and frequency-domain bandpass filtering, respectively, to recover the envelope. However, these methods often suffered from waveform distortion or relied heavily on manually set filter parameters, making them computationally intensive and ill-suited for real-time demodulation scenarios.

Fortunately, the prevalence of machine learning (ML) offers a promising avenue to overcome these limitations. Recently, ML has been increasingly integrated into microwave photonic systems to enhance sensing performance. For example, Luo *et al.* [23] utilized the Gaussian process regression (GPR) to upgrade microwave photonic filtering interrogation. Furthermore, Tian *et al.* [24] introduced a deep learning-enhanced time-domain microwave photonic sensor, demonstrating that deep neural networks (DNNs) could significantly improve noise resilience and measurement accuracy. While effective, these approaches either relied on shallow

regression models or focused on different sensing mechanisms, which were not directly applicable to complex spectral demodulation. In parallel, Mei *et al.* [25] successfully applied the convolutional neural network (CNN) and long short-term memory (LSTM) models for the Vernier spectral demodulation, but their approach was confined to the optical domain, constrained by the low scanning speed of optical spectrum analyzers. To bridge these gaps, this paper proposed the residual network with the channel attention (RNCA) intelligent demodulation method. This model achieved end-to-end, high-precision, and high-speed direct mapping from the raw microwave Vernier spectrum to target measurement. By abandoning the traditional envelope extraction process, the network adaptively learnt the characteristics of sparsely sampled spectra, significantly reducing both signal demodulation complexity and system hardware costs.

The significance of this work lies in its synergistic innovation architecture, where the self-Vernier effect provides enhanced sensitivity at the physical level and the RNCA model handles intelligent demodulation at the information level. This work provides a novel technical pathway to address the dual challenges of the structural complexity in the Vernier sensors and cumbersome demodulation, facilitating the development of optical fiber sensors toward greater simplicity, intelligence, and practicality.

2. Principle and modeling of the self-Vernier effect

Figure 1(a) shows the schematic diagram of the proposed scheme. The system uses a broadband optical source (BOS) to generate low-coherence detection light. This light is coupled into the eccentric-core FBG1 of the 7-core FBG sensor via a circulator (Cir1) and a fan-in/out device. The reflected light then makes its way back to the loop via the fan-in/out device and is fed through a

polarization controller (PC) into a Mach-Zehnder modulator (MZM) that is biased at the orthogonality point. Microwave signals output from a vector network analyzer (VNA) intensity-modulate the optical signal. The intensity-modulated light then enters the fiber loop cavity structure formed by a 2×2 optical coupler (OC1), constituting a typical infinite impulse response microwave photonic filter (IIR-MPF) system [26]. To compensate for the loop loss and increase the effective number of taps, an erbium-doped fiber amplifier (EDFA) provides the optical gain within the loop. A chirped fiber Bragg grating (CFBG) simultaneously introduces the dispersion effect, mapping FBG1's reflected wavelength shift to time delay. The signal circulates multiple times within the loop, outputting 50% of the optical signal per round trip. The OC2 and OC3 split this signal into two transmission paths, which are ultimately converted into electrical signals via a high-speed photodetector (PD). When the VNA linearly scans the modulation frequency and measures the S21 parameters at each frequency point, the system's complex transfer function, including magnitude and phase spectral information, is obtained.

The self-Vernier effect is generated by introducing an extra delay path in the microwave photonic 7-core FBG sensing system. As illustrated in Fig. 1(a), the output optical signal from the loop cavity is divided into two paths via a 50:50 optical coupler (OC2), one of which constitutes the raw path and the other constitutes the delay path. The delayed path connects to a segment of the single mode fiber (SMF) that serves as the delay unit and introduces a time delay τ . The length l of the delay path and the length L of the fiber loop cavity are designed to be slightly detuned. This ensures that τ is close to, but not equal to, the round-trip time T . The clever use of two nearly identical time delays causes the raw signal and its delayed counterpart to interfere. This generates the beat frequency effect

that forms a self-Vernier envelope. Then, the system's overall time-domain response $h_{\text{total}}(t)$ and frequency response $H_{\text{total}}(j\omega)$ can be expressed as follows, respectively:

$$h_{\text{total}}(t) = h(t) + h(t - \tau) \quad (1)$$

$$H_{\text{total}}(j\omega) = \sum_{m=0}^k A_m e^{-j\omega m T} + \sum_{m=0}^k A_m e^{-j\omega(mT + \tau)} \quad (2)$$

where t is the time, m is the tap index, and k is the maximum number of effective taps due to the inherent loss of the system. We define $A_m = A_0 \alpha^m$, where A_0 represents the amplitude of the microwave signal after the initial incident light power undergoes the photoelectric conversion, and α represents the

percentage of power remaining after each round trip of the loop. From a time-domain perspective, the system's total impulse response $h_{\text{total}}(t)$ is the linear superposition of the raw path signal $h(t)$ and the delayed path signal $h(t - \tau)$. These two signals have identical envelope shapes and decay characteristics and differ only in a fixed time delay τ . Therefore, the system output exhibits an interleaved pulse sequence. The interleaved structure in the time domain manifests as a pronounced Vernier envelope in the frequency domain. By simplifying the superposition response (2), the magnitude spectrum expression can be derived:

$$|H_{\text{total}}(j\omega)| = \sqrt{2 \sum_{m=0}^k A_m^2 + 4 \sum_{0 \leq m < n \leq k} A_m A_n \cos[\omega(m-n)T] + 2 \sum_{0 \leq m, n \leq k} A_m A_n \cos\{\omega[(m-n)T - \tau]\}}. \quad (3)$$

Equation (3) intuitively reveals the formation mechanism of the self-Vernier spectrum. The $\cos[\omega(m-n)T]$ term in this equation corresponds to the periodic and comb-like spectrum generated by the fiber loop cavity itself. The $\cos\{\omega[(m-n)T - \tau]\}$ term originates from the periodic modulation introduced by the delay path. When $\tau \approx T$, the cosine terms at nearly identical frequencies $[\cos(\omega T)$ and $\cos(\omega \tau)]$ interact to produce a beat effect, forming a slowly varying Vernier envelope. Consequently, the FSR of the self-Vernier envelope can be expressed as follows [27]:

$$\text{FSR}_{\text{Vernier}} = \frac{(1/\tau) \cdot (1/T)}{|(1/\tau) - (1/T)|} = \frac{1}{|T - \tau|} = V \cdot \text{FSR} \quad (4)$$

where V is the sensitivity amplification factor, defined as $V = T/|T - \tau|$. The amplification factor is directly related to the difference between T and τ , and changing the length of the SMF allows flexible adjustment of the amplification level, which is similar to conventional Vernier effect sensors.

When bending is applied to the 7-core FBG in a specific direction, each eccentric-core FBG_{*i*} will experience a varying local tangential strain ε_i . The magnitude of this strain depends on the relative angular position between the bending direction θ_r and the eccentric-core FBG_{*i*}. The strain in any given

FBG can be described as

$$\varepsilon_i = \frac{d}{R} \cos(\theta_r - \theta_i), \quad i = 1, 2, \dots, 6 \quad (5)$$

where d is the distance from the eccentric-core to the fiber center and R is the fiber curvature radius, θ_i is the angular position of the FBG_{*i*} in the position coordinate system shown in Fig. 1(b). The 7-core FBG sensor exhibits the maximum sensing sensitivity, when the fiber core aligns with the bending plane (i.e., when the angular position of the eccentric-core coincides with the bending direction). The delay introduced by curvature into the loop can be expressed:

$$\Delta T = K_e D \lambda_{\text{FBG}_i} \varepsilon_i \quad (6)$$

where K_e represents the axial strain coefficient of the grating, D denotes the dispersion of the CFBG, and λ_{FBG_i} indicates the initial reflection wavelength of the eccentric-core FBG. Curvature sensing is achieved by measuring the frequency shift of the Vernier envelope. Thus, the frequency shift of the self-Vernier envelope can be expressed as

$$\begin{aligned} \Delta f_{\text{Vernier}} &= p \cdot \Delta \text{FSR}_{\text{Vernier}} \\ &= p \cdot \left[\frac{1}{|(T + \Delta T) - \tau|} - \frac{1}{|T - \tau|} \right] \\ &\approx -f_{\text{Vernier}} \cdot V \cdot \text{FSR} \cdot \Delta T \end{aligned} \quad (7)$$

where p denotes the order of the tracked Vernier envelope peak, and f_{Vernier} represents the frequency of the Vernier envelope tracking point. Equation (7) shows that the frequency shift caused by changes in curvature is amplified by the factor V through the self-Vernier effect. Compared to the traditional Vernier effect, requiring two independent interferometers, the self-Vernier effect achieves the same functionality with a single interferometer structure coupled with a delay path. This significantly simplifies the system architecture, while retaining the ability to flexibly adjust the sensitivity amplification factor.

3. Experimental setup and results

3.1 Setup

To validate the self-Vernier concept and investigate the performance of the proposed microwave photonics 7-core FBG sensing system, we constructed the experimental setup shown in Fig. 1(a). The BOS (SLD-D-F-11-S-FA, Fiber-photonics, China) emitted optical signals in the range of 1 250 nm to 1 700 nm with an output power of 11 dBm and a coherence length of approximately 5 μm . The MZM (MX-LN-20, Photline, France) featured a half-wave voltage of 5.5 V and a bandwidth of 20 GHz. The EDFA (AEDFA-IL-18-B-FA, Amonics, China), featuring the saturated output power of 18 dBm, was operated at a current setting of 120 mA to compensate for the loop loss. The CFBG's dispersion value, 3 dB bandwidth, and reflectivity were -555 ps/nm , 1.8 nm, and 99%, respectively. The PD (XPDV2120RA, Finisar, USA) had a bandwidth of 20 GHz. The VNA (3656D, Ceyear, China) was configured with the measurement range of 20 GHz and scanning resolution of 12.5 kHz.

The 7-CF (MC1010-A, YOFC, China) used to manufacture the 7-core FBG sensor had a core diameter of 9 μm and an adjacent core spacing of 42 μm . The interference between adjacent cores was as low as -45 dB , which ensured independent light transmission within each core. The fan-in/out device

(FAN-7-42, YOFC, China) had a single-channel insertion loss of less than 1.5 dB. Seven FBGs were written simultaneously at the same axial position on the 7-CF, and their reflection spectra were measured. As shown in Fig. 1(c), the FBGs exhibit similar

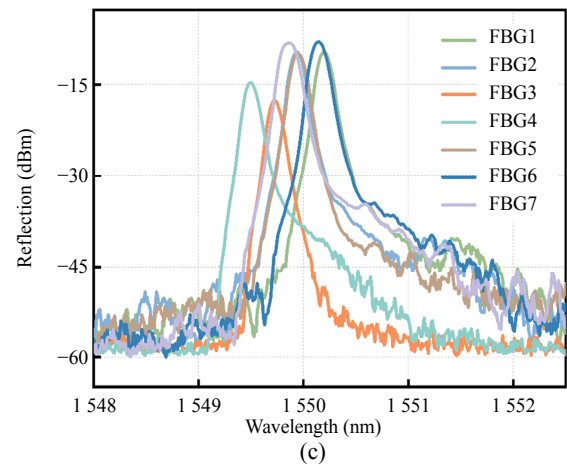
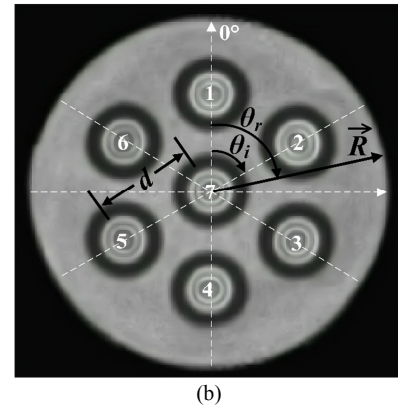
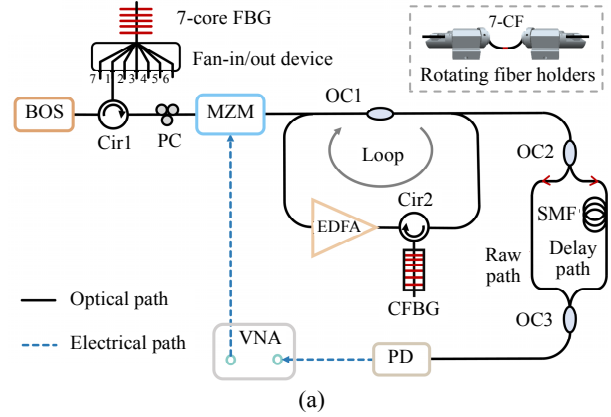


Fig. 1 Configuration of the sensing system: (a) the schematic of the proposed sensing system (inset: the schematic of a bending sensor device), (b) the cross-sectional micrograph and positional coordinate system of 7-CF, and (c) reflection spectra of the FBGs in the 7-CF.

reflection wavelengths and 3 dB bandwidths. The eccentric-core FBG1 had a reflection wavelength of 1 550.2 nm. Detailed information regarding the fabrication of the 7-core FBG sensor can be found in recent work [13].

To optimize the sensitivity of the 7-core FBG sensor, the angular position of the 7-CF must be calibrated. As shown in the inset of Fig. 1(a), two rotating fiber holders with the adjustment precision of the 2° grip both ends of the 7-CF, enabling continuous rotation of the fiber and adjustment of the angular position of core1 within the coordinate system. A downward vertical bend with a specific curvature was then applied to the 7-core FBG. The optimal curvature sensitivity was determined by monitoring the VNA output spectrum in real time when core1 overlapped with the bending plane, relative to the maximum frequency shift observed in the naturally straight state. Next, the right holder was moved axially to apply the varying curvature to the calibrated sensor. The imposed curvature C is defined as the reciprocal of the bending radius ($C=1/R$) and is calculated based on the axial displacement x of the right holder, while the left holder is fixed, using the equation:

$$C = \frac{1}{R} = \sqrt{\frac{24x}{(h-x)^3}} \quad (8)$$

where h is the initial fiber length. In this experiment, h was set to 16 cm. By adjusting x from 0 mm to 10 mm with a step of 0.5 mm, the curvature range of 0 m⁻¹ to 8.433 m⁻¹ was achieved. It is worth noting that due to the nonlinear geometric relationship, the curvature resolution varied from approximately 1.72 m⁻¹ in the low curvature region to 0.30 m⁻¹ in the high curvature region, indicating higher adjustment precision at larger curvatures.

3.2 Results

The measured frequency-domain and time-domain responses of the 7-core FBG sensing system with and without the self-Vernier effect are shown in Fig. 2. The loop length was set to 35.7 m,

significantly exceeding the coherence length of the light source, ensuring the system operated in a non-coherent state. This reliance on optical intensity superposition eliminated the polarization fading

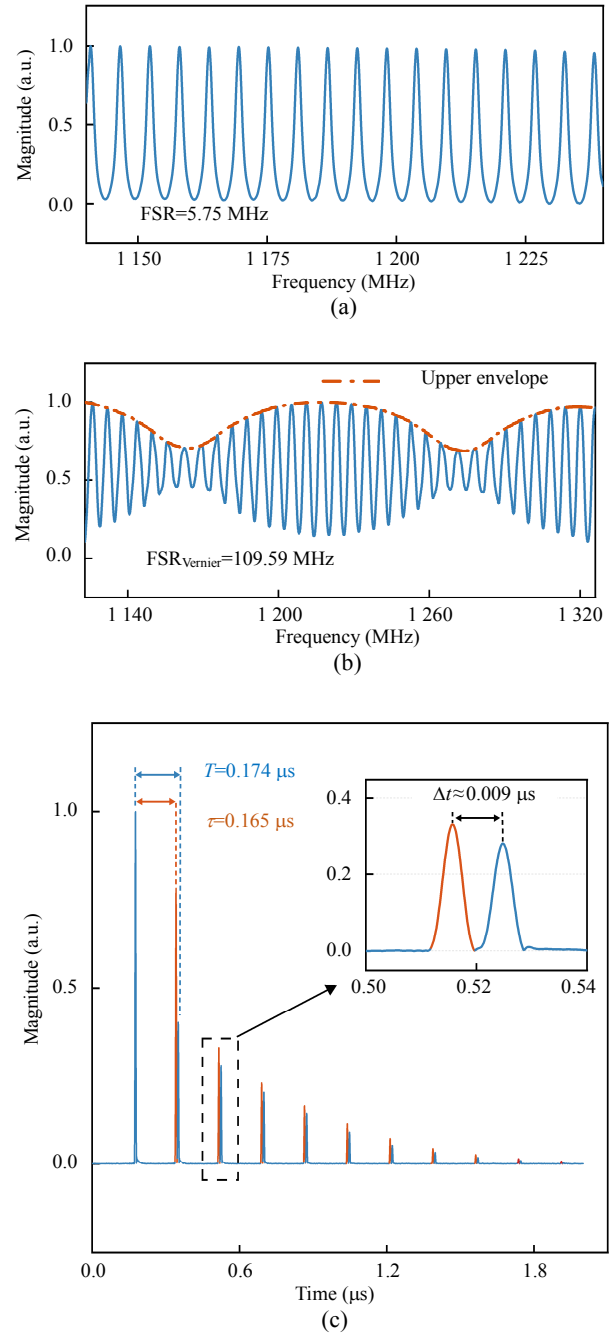


Fig. 2 Response of the sensing system: (a) the frequency domain response without the self-Vernier effect, (b) the frequency domain response with the self-Vernier effect (the orange dashed line: the fitted envelope), and (c) the time domain response with the self-Vernier effect (the blue solid line: the response without time delay; the orange solid line: the response with time delay).

typical of coherent optical systems. When the delay path was disconnected and the self-Vernier effect was disregarded, the raw system output a periodic comb spectrum with a measured FSR of 5.75 MHz, as shown in Fig. 2(a). Subsequently, we investigated the system's response under varying curvatures. The magnitude spectrum of the system was measured and recorded at each curvature step. As observed in Fig. 3(a), the resonance peak shifted toward lower frequencies as curvature increased. By tracking the resonance peak frequency at 1.198 GHz, the curvature sensitivity of $-0.193 \text{ MHz/m}^{-1}$ was obtained.

Subsequently, a delay path was added to the aforementioned system to verify the enhancement of sensing sensitivity via the self-Vernier effect. The SMF length was set to 33.8 m to approximate the loop cavity length, introducing a delay of $\tau=0.165 \text{ }\mu\text{s}$, which was slightly detuned from the loop round-trip

time of $T=0.174 \text{ }\mu\text{s}$. As shown in Fig. 2(c), the raw loop response without the delay path (blue peaks) and the delayed response (orange peaks) appear as an interleaved pulse sequence. Crucially, the beat frequency effect arose from the periodic misalignment caused by the minute time difference $\Delta t=|T-\tau|\approx 0.009 \text{ }\mu\text{s}$ between these pulses. This microscopic time-domain detuning maps to the frequency domain, as shown in Fig. 2(b), where the original dense comb spectrum was modulated by a macroscopic Vernier envelope. By extracting peaks and performing interpolation fitting, the upper envelope's FSR was determined to be 109.59 MHz, which agreed well with the theoretical prediction derived from the time difference ($1/\Delta t \approx 111 \text{ MHz}$). Compared to the raw response in Fig. 2(a), this mechanism yielded a sensitivity amplification factor of 19.1, rendering the frequency shift induced by curvature changes significantly more pronounced.

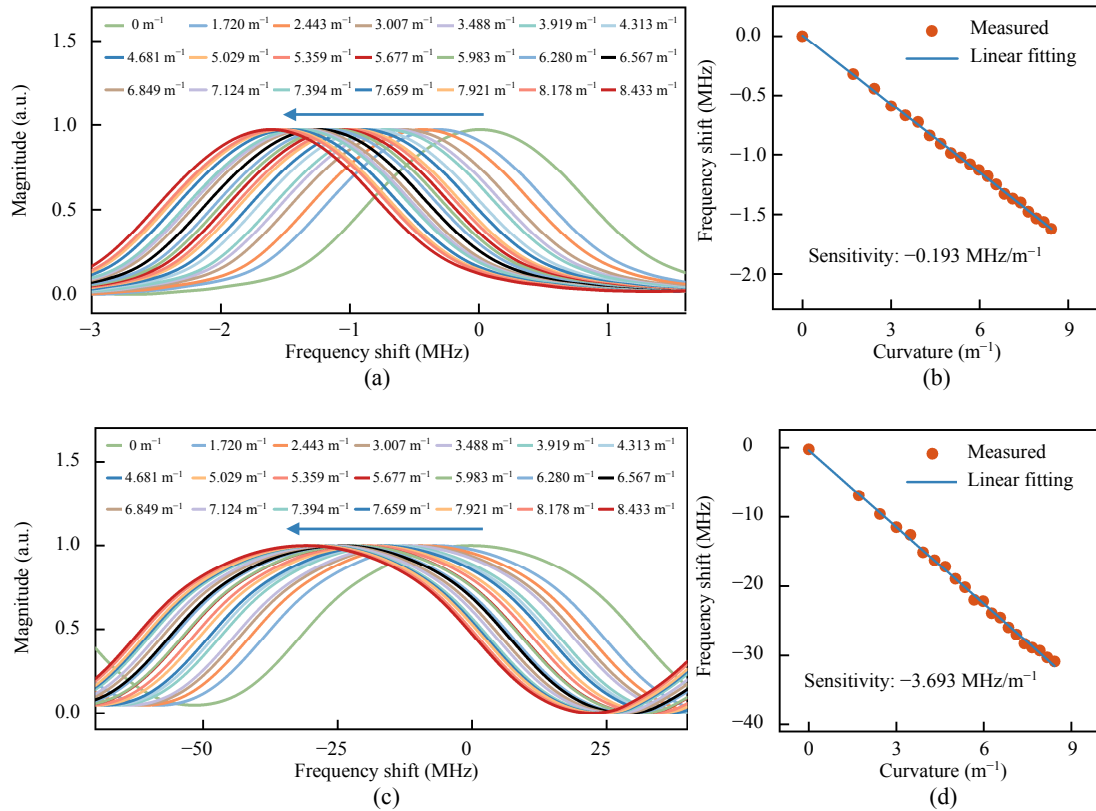


Fig. 3 Curvature sensing performance: (a) the magnitude spectrum without the self-Vernier effect, (b) the frequency shift as a function of curvature [the slope (i.e., measurement sensitivity) is obtained from linear curve fitting], and (c) self-Vernier fitting envelope signals, and (d) the envelope frequency shift as a function of curvature.

We selected the peak point near 1.219 GHz to track frequency shift changes for comparison. Figure 3(c) shows the fitted envelope signals under different curvatures, with the peak point shifting linearly toward lower frequencies as curvature increases. Fitting the frequency shift and curvature revealed a significant enhancement in sensitivity to $-3.693 \text{ MHz/m}^{-1}$, amplifying the raw system's sensing sensitivity by 19.1 times. Notably, the

spectrum shifted toward the lower-frequency region in both cases, indicating a positive amplification factor. Table 1 compares the proposed self-Vernier sensor with the current state-of-the-art Vernier sensor. The results demonstrated that the proposed approach achieved high sensitivity and a large dynamic range at a low cost with a simple structure, based on a single fiber loop configuration.

Table 1 Comparison between the proposed self-Vernier scheme and traditional Vernier methods.

Method	Sensitivity	Magnification factor	Dynamic range	Complexity
Cascaded two FPIs [28]	21.022 nm/m^{-1}	10.4	$<1 \text{ m}^{-1}$	High
Parallel two MIs [29]	38.53 nm/m^{-1}	43.8	$<1 \text{ m}^{-1}$	High
Parallel two FRs [15]	$-33.862 \text{ kHz}/\mu\epsilon$	23	$11\,222 \mu\epsilon$	High
Cascaded two FRs [30]	$-556.856 \text{ kHz}/^\circ\text{C}$	30	54°C	High
This work	$-3.693 \text{ MHz/m}^{-1}$	19.1	29.68 m^{-1}	Low

It should be noted that although the self-Vernier effect could achieve the equivalent amplification to the traditional Vernier effect through a simpler approach, the precise extraction of the Vernier envelope and tracking of its peak required complex and time-consuming signal processing. This process could inadvertently introduce errors that affect sensing performance. Figure 4 illustrates the discrepancy between the actual applied curvature and the inverted curvature. It was evident that the coefficient of determination R^2 was only 99.72%, with a root mean square error (RMSE) as high as 0.118 m^{-1} . These discrepancies were primarily attributed to the signal demodulation process being quite complex and labor-intensive. Furthermore, unlike 7-core FBG sensors based on microwave photonics, which tracked shifts in resonant peaks or valleys within the magnitude spectrum directly, the sensors based on the Vernier effect used shifts in the envelope as the reference variable to enhance sensitivity. The FSR of the envelope was much larger than that of the standard magnitude spectrum, so a high-resolution and wide-bandwidth spectrum analyzer was essential. While the Vernier effect enhanced sensitivity, it also increased the

complexity of signal demodulation and the system's costs. In light of this, the following section proposes a novel signal analysis method to address the demodulation complexity issues inherent in existing Vernier sensors.

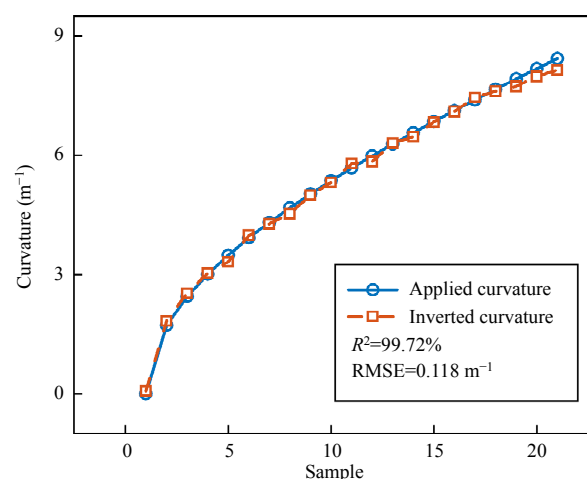


Fig. 4 Applied curvature and inverted curvature by tracking envelope peaks.

4. Spectrum analysis with RNCA

4.1 Model architecture

The aforementioned work primarily focused on the physical implementation of the self-Vernier effect in 7-core FBG sensors, neglecting the signal

demodulation aspect. Figure 5 illustrates the comparison between the traditional method (the envelope fitting method) and the RNCA model proposed in this paper. The traditional method involved a multi-step signal processing workflow, including the peak detection, envelope fitting via nonlinear regression (such as polynomial fitting), and subsequent tracking of envelope peaks or valleys. This process was not only computationally intensive but also lacked robustness, particularly evident under the sparse sampling and low signal-to-noise ratio conditions.

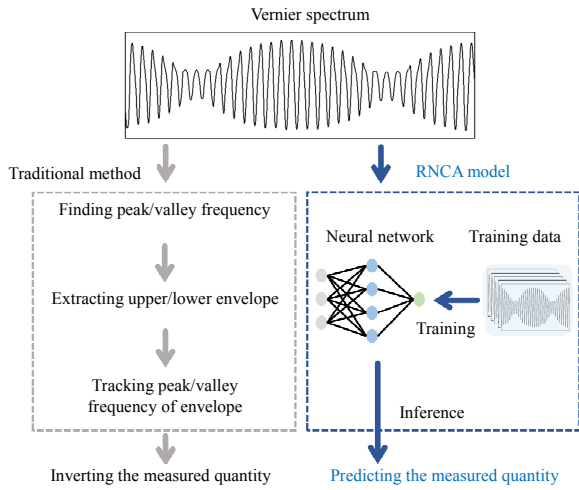


Fig. 5 Side-by-side comparison of traditional methods and the RNCA model for demodulating Vernier sensors.

To establish an intelligent and robust demodulation scheme, we designed the RNCA architecture to learn the end-to-end mapping from the raw microwave spectrum intensity sequence $X \in \mathbb{R}^N$ to the target curvature C . As illustrated in Fig. 6, the model is composed of four functional modules: the initial feature extraction, residual learning backbone, channel attention mechanism, and regression head.

1) Initial feature extraction. The raw spectrum was treated as a one-dimensional (1D) sequential signal. A convolutional layer with a large kernel size ($k=7$) and stride ($s=1$) was employed to extract preliminary spectral features, transforming the single-channel input into a high-dimensional feature map $X_{\text{init}} \in \mathbb{R}^{32 \times N}$. This large receptive field was

essential for capturing the broad morphological trends of the Vernier envelope amidst dense spectral peaks.

2) Residual learning backbone. To capture deep semantic features without suffering from the vanishing gradient problem or performance degradation, we constructed a backbone using stacked residual blocks [31]. Unlike the plain CNNs that learnt the unreferenced mapping, these blocks learnt the residual mapping. Formally, let X_l denote the input to the l th residual block. The output X_{l+1} is defined as

$$X_{l+1} = \sigma \left[X_l + \mathcal{F}(X_l, \{\mathbf{W}_l\}) \right] \quad (9)$$

where $\{\mathbf{W}_l\}$ is the set of weight matrices of the l th residual block, $\sigma(\cdot)$ denotes the rectified linear unit (ReLU) activation function, and $\mathcal{F}(\cdot)$ represents the residual mapping function, implemented by two consecutive 1D convolutional layers (with kernel sizes of 5 and 3) followed by batch normalization (BN). The identity shortcut connection X_l allowed the gradient to flow directly through the network, significantly enhancing the training stability of the deep structure. We employed three such blocks, connected via the max pooling layers, to progressively reduce the temporal dimension while expanding the channel dimension from 32 to 128, resulting in a hierarchical feature representation $X_{\text{feat}} \in \mathbb{R}^{D \times L}$ (where $D=128$ and $L=N/8$).

3) Channel attention mechanism. Not all extracted feature channels contributed equally to curvature demodulation. Some channels might respond to the high-frequency jitter of the comb spectrum (the noise), while others captured the global envelope shift (the signal). To enhance the latter, we introduced a channel attention module [32] to adaptively recalibrate the features. This process involved squeeze and excitation operations. First, global spatial information was squeezed into a channel descriptor $z \in \mathbb{R}^D$ via global average pooling (GAP). Then, an excitation mechanism generated a set of channel-wise weights s . The final re-weighted feature map X_{fin} is obtained by

$$X_{\text{fin}} = s \cdot X_{\text{feat}} = \delta \left\{ \mathbf{W}_2 \sigma \left[\mathbf{W}_1 \cdot \text{GAP} (X_{\text{feat}}) \right] \right\} X_{\text{feat}} \quad (10)$$

where δ and σ refer to the Sigmoid and ReLU functions, respectively; $\mathbf{W}_1$ and $\mathbf{W}_2$ form a bottleneck structure with a reduction ratio $r=4$. Equation (10) mathematically describes how the network selectively emphasizes informative features related to the Vernier envelope while suppressing irrelevant responses.

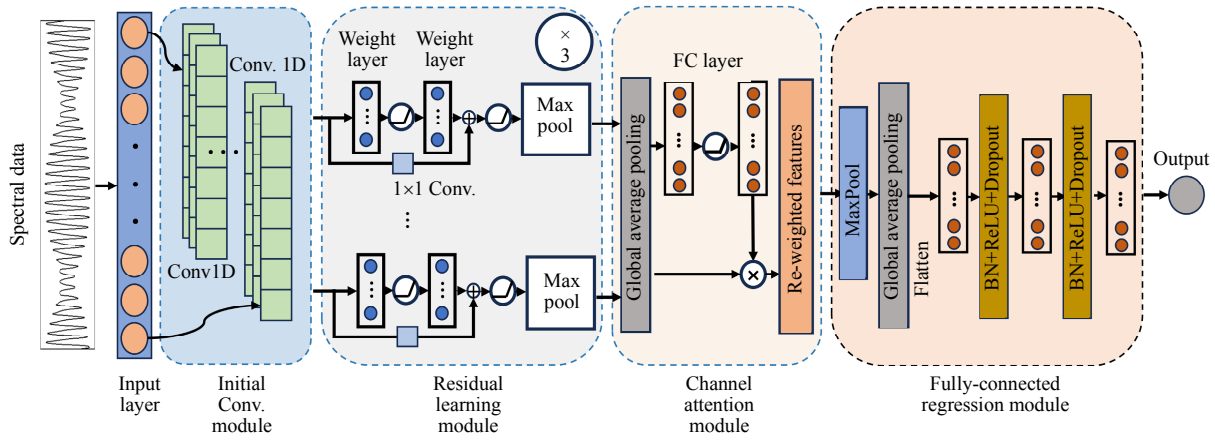


Fig. 6 Schematic of the RNCA structure.

4.2 Setup and data preparation

The experimental dataset was collected from the self-Vernier spectrum generated by a 7-core FBG sensor at 21 different curvature values, with 10 independent repeated measurements performed for each curvature, resulting in 210 raw samples (each containing 16 001 sampling points). To investigate the model's adaptability in sparse sampling environments, we numerically down-sampled these raw spectra to 4 000 points, 2 000 points, and 250 points, thereby constructing four datasets of different resolution and generating a comprehensive dataset of 840 samples in total. To eliminate potential distribution bias, we implemented a stratified random shuffling strategy before data splitting. Specifically, within each resolution-specific dataset (containing 210 samples), the data were independently shuffled and partitioned into training, validation, and test sets using a 6:2:2 ratio. Consequently, the study utilized an aggregate of 504

4) Regression head. The attention-weighted features were flattened into a global vector via a final GAP layer. The curvature regression was then performed by a multi-layer perceptron (MLP) consisting of three fully connected layers (sizes: 128-64-32-1). To prevent overfitting on the limited dataset, the dropout (rate=0.5) was applied before the final prediction.

training samples, 168 validation samples, and 168 test samples. This strategy ensured that the data at each resolution level maintained high statistical consistency between the training and testing phases. It is important to note that for each resolution dataset, a separate RNCA model instance was initialized and trained to adapt to the specific spectral feature scales of that resolution.

During the model training phase, we employed the mean squared error (MSE) as the loss function and the coefficient of determination R^2 (i.e., accuracy) as the evaluation criterion for the model fit quality. They are defined as

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (C_i - \hat{C}_i)^2 \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (C_i - \hat{C}_i)^2}{\sum_{i=1}^N (C_i - \bar{C})^2} \quad (12)$$

where N is the number of test samples, and C_i , $\hat{C}_i$,

and $\bar{C}$ represent the truth value, predicted value, and mean of the truth values, respectively. During the model testing phase, the RMSE is used to quantify the prediction accuracy, defined as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (C_i - \hat{C}_i)^2}. \quad (13)$$

All experiments were implemented by using Python 3.12, PyTorch 2.9.0, and NVIDIA CUDA 13.0, and executed on an Ubuntu 24.04 server platform. A single NVIDIA RTX L20 graphics processing unit (GPU) was utilized for both the training and inference phases.

4.3 Experimental results

The trends of the loss function and the accuracy during the model training process are

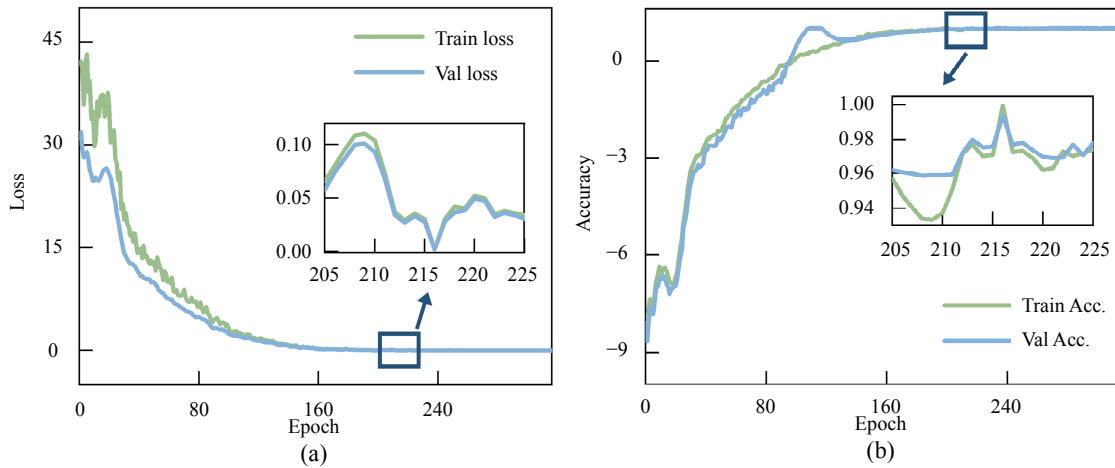


Fig. 7 Loss and accuracy curves during the training process of the RNCA model: (a) loss and (b) accuracy (Acc: accuracy)

To evaluate the model's robustness under varying data qualities, test sets of different resolution were processed. The prediction results are presented in Fig. 8. Under the extremely sparse condition of retaining only 250 sampling points, as shown in Fig. 8(a), the model still maintained excellent demodulation performance (RMSE=0.084 m⁻¹, MAE=0.070 m⁻¹, and R²=99.81%, where MAE denotes the mean absolute error.) This indicates that the RNCA network could extract key morphological features from highly compressed spectra, significantly reducing hardware requirements.

shown in Fig. 7. In the initial training stage (0 epochs–50 epochs), the training loss rapidly decreased while the accuracy rapidly increased, indicating that the model could effectively capture curvature-related features in the Vernier spectrum. After approximately 210 epochs, both the training and validation losses stabilized, eventually converging to a level below 0.01. Concurrently, the accuracy curves for both the training and validation sets approached 1.0 and maintained high congruence. This phenomenon demonstrated that the model had fully learned the stable mapping relationship between the input Vernier spectrum and the target curvature, without exhibiting overfitting. We saved the optimal model parameters for the subsequent test process.

As the sampling density increased to 2 000 points, the demodulation performance reached its optimal state (RMSE=0.044 m⁻¹, MAE=0.035 m⁻¹, and R²=99.95%), as illustrated in Fig. 8(b). The low MAE reflected the minimal average deviation, while its close proximity to RMSE indicated a stable error distribution free from significant outliers. Notably, when the sampling density was further increased to 4 000 points and 16 001 points, as depicted in Figs. 8(c) and 8(d), the performance metrics exhibited a slight decline. This phenomenon arose, because such dense sampling explicitly resolved the

high-frequency comb peaks, which dominated the input distribution and overshadowed the slowly varying envelope signal. Consequently, the model's attention mechanism was distracted by these intense local peak fluctuations rather than focusing on the

target global envelope shifts. Therefore, under the present experimental conditions, 2 000 points represented the optimal trade-off, effectively down-sampling the high-frequency comb spectrum while preserving the envelope integrity.

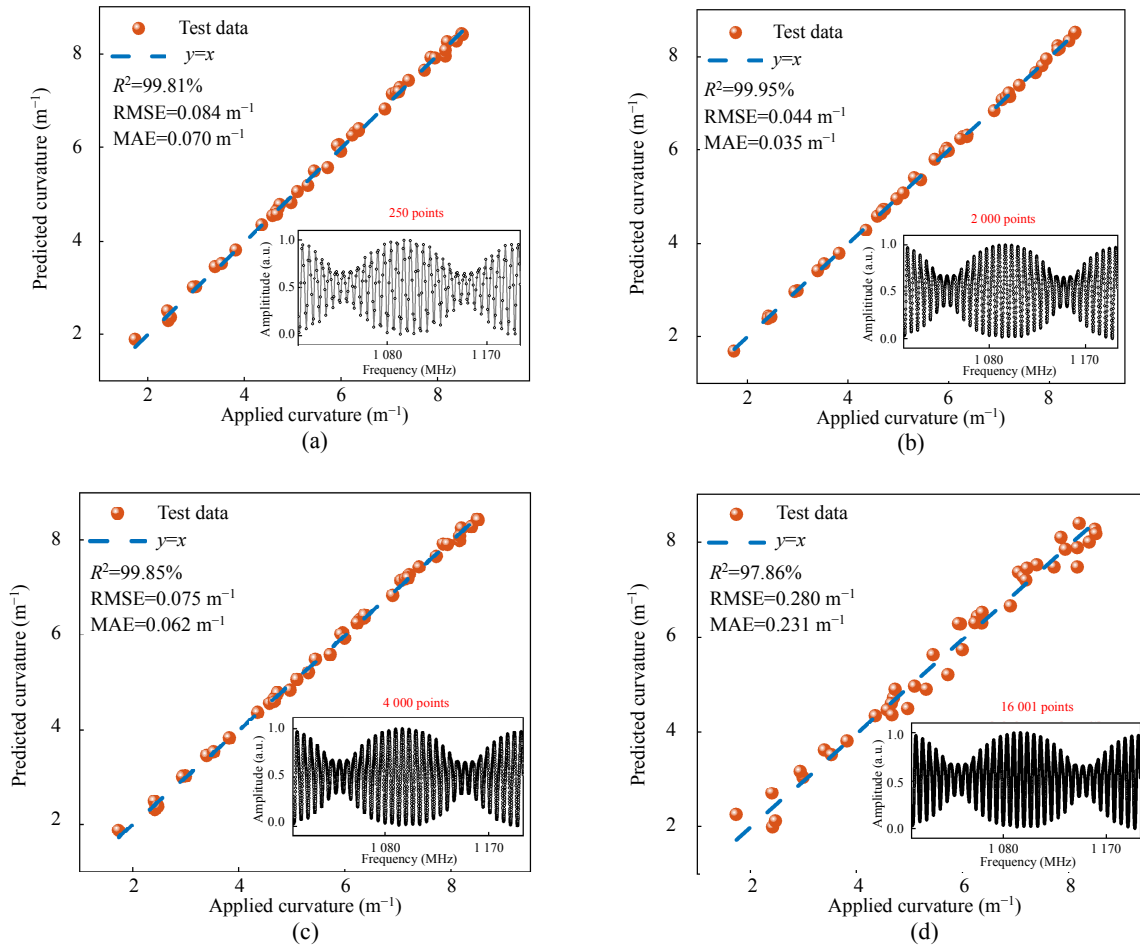


Fig. 8 Predicted curvature relative to the applied curvature after processing the spectra of the model at different resolution: (a) 250 points, (b) 2 000 points, (c) 4 000 points, and (d) 16 001 points (Inset: down-sampled spectrum).

Table 2 compares the performance of the RNCA model (2 000 points) and the traditional envelope fitting method (16 001 points). The RNCA model achieved a 62.7% reduction in the RMSE and a 0.23% increase in R^2 . Unlike the traditional method, which relied on dense spectral information, the RNCA model demonstrated the intrinsic adaptability to sparse sampling, significantly reducing hardware costs. Furthermore, the RNCA model required only 0.2 s for a single inference, whereas the traditional

method exceeded 1 min. This result not only confirmed that the RNCA model broke the inherent trade-off between the hardware cost and sensing accuracy found in the traditional approaches, but its 0.2 s inference speed theoretically could support the dynamic refresh rates as high as 5 Hz. Furthermore, as a static mapping model without internal temporal states, the RNCA exhibited no algorithmic hysteresis, ensuring near-real-time responses to changes in structural curvature.

Table 2 Comparison between the RNCA model and traditional method.

Performance	RNCA model	Envelope fitting method
RMSE (m ⁻¹)	0.044 m ⁻¹	0.118 m ⁻¹
R^2	99.95%	99.72%
Sparse sampling points	Yes	No
Hardware requirement	Low	High
Inference time	0.2 s	>1 min
Complexity	Low	High

Finally, we analyzed the generalization boundary beyond the curvature calibration range. While the model functioned excellently as a high-dimensional interpolator within the current range, the maximum measurable range was physically constrained by the Vernier envelope's $\text{FSR}_{\text{Vernier}}$ [33]. Specifically, to avoid catastrophic prediction errors caused by the phase ambiguity, the maximum curvature must be limited to $\Delta C_{\text{max}} = \text{FSR}_{\text{Vernier}}/S = 29.68 \text{ m}^{-1}$, where S is the curvature sensitivity. Therefore, the operational range in practical applications must be strictly designed within this physical limit.

5. Conclusions

The proposed 7-core FBG sensing scheme based on the microwave photonic self-Vernier effect achieved significant sensitivity amplification without requiring a dual-interferometric structure, greatly simplifying the system architecture and enhancing flexibility. To address the computational intensity and the lack of robustness in the traditional envelope fitting methods, this paper further proposed the neural network model RNCA for intelligent spectrum demodulation. It directly extracted features from the raw microwave spectra and rapidly predicted curvature, achieving high-precision and low-delay end-to-end mapping. Experimental results demonstrated that this method exhibited excellent noise resistance and real-time processing capabilities, maintaining the high-precision prediction even under sparse sampling conditions. Moreover, integrating an optical switch

enabled the sequential interrogation of multiple cores, laying the foundation for future vector sensing and effective temperature crosstalk elimination via the central core, thereby ensuring the model's generalization capability in complex environments without relying on massive training datasets. This study achieved a synergistic architecture combining physical enhancement of the self-Vernier effect with intelligent demodulation via deep learning, offering new insights for advancing the optical fiber sensing technology toward high sensitivity, low costs, and intelligent operations.

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Declarations

Conflict of Interest The authors declare that they have no competing interests.

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Use of AI Statement None.

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