

# Real-time 3D shape sensing based on GPU-accelerated OFDR with dynamic sweep-range compensation

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**Abstract:** In this paper, we proposed and demonstrated a dynamic sweep-range compensation method, namely fixed-range k-domain resampling (FR-KDR), for a real-time 3D shape sensing system based on multicore fiber (MCF) and optical frequency domain reflectometry (OFDR). The compensation performance under zero-strain condition was investigated, and the strain root mean square error (RMSE) was reduced from 13.98  $\mu\epsilon$  to 1.27  $\mu\epsilon$ . Moreover, both 2D and 3D shapes were successfully reconstructed, and the position error along the sensing MCF was further analyzed. The maximum position deviations of the reconstructed 2D and 3D shapes with an MCF length of 700 mm were 13.49 mm and 16.95 mm, respectively. Ultimately, the FR-KDR method and the wavelength shift demodulation algorithm were deployed on the graphics processing unit (GPU) to perform parallel computation, and the dynamic stability of the real-time OFDR system was evaluated. The time consumption under different zero-padding sizes and sweep ranges was analyzed, and an update rate of 23.8 Hz was achieved at a spatial resolution of 5 mm with a sweep range of 20 nm and a zero-padding size of 8192. Moreover, the comparison between CPU serial computation and GPU parallel computation confirmed that GPU acceleration significantly improved the data-processing efficiency.

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## 1. Introduction

Optical fiber shape sensing based on multicore fiber (MCF) in optical frequency domain reflectometry (OFDR) has potential applications in soft continuum robotics [1,2], minimally invasive surgery [3–5], and structural health monitoring [6,7] due to its high spatial-resolution and high accuracy [8–10]. In recent years, researchers have devoted considerable efforts to improve the accuracy and reliability of fiber-optic shape sensing, particularly in terms of strain demodulation and shape reconstruction. Several approaches have further improved shape sensing accuracy. For example, Bai *et al.* proposed a post-processing method based on first-order differential local filtering to suppress fake strain peaks, reducing the reconstruction error to 0.20% [11]. Zhang *et al.* proposed a fast strain demodulation method combining deviation calculation and DDSSnet denoising for OFDR-based shape sensing, achieving an average relative reconstruction error of 0.204% [12]. In addition, Zhi *et al.* constructed a deep learning-based mapping model that directly transforms wavelength data into corresponding shape-space coordinates, achieving a median relative terminal point error of 0.76% [13]. Wang and Qi developed a novel deep learning-based shape reconstruction framework without cumulative error, improving the best 2D and 3D reconstruction accuracies by 55.78% and 66.54%, respectively [14].

While these approaches have successfully improved reconstruction accuracy, achieving high-accuracy and real-time shape sensing in dynamic OFDR systems remains challenging. In practical dynamic applications, random sweep-range variations between the reference and measurement scans can introduce spatial misalignment and severely degrade the sensing accuracy. To address this issue, several compensation strategies for random sweep-range variations have been reported. Guo *et al.* introduced a sweep-range calibration strategy to align the measurement-stage sweep range with that of the reference stage, thereby compensating for random sweep-range deviations and ensuring spatial consistency between the reference and measurement signals [15]. In addition, Chen *et al.* proposed a synchronous equal-frequency resampling method to simultaneously compensate for random sweep-range variations and tuning nonlinearity, significantly extending the sensing distance and improving measurement accuracy [16]. However, these compensation approaches require post-processing of both the reference and measurement signals, which limits their applicability in dynamic OFDR systems. Therefore, a dynamic compensation method that can be directly applied in real-time sensing is highly desirable.

Furthermore, achieving real-time OFDR shape sensing requires not only accurate compensation of sweep-range variations but also high-throughput signal processing. As the spatial resolution increases, the data volume involved in cross-correlation grows substantially, leading to a markedly higher computational burden. Therefore, several studies have proposed and demonstrated efficient demodulation algorithms to improve the processing efficiency of OFDR systems. Bai *et al.* developed a joint algorithm combining wavelength-domain differential accumulation and local cross-correlation to reduce the computational complexity for fast strain measurement, achieving a 6.4-time increase in processing speed for a 113.3-m-long sensing fiber [17]. Zhang *et al.* proposed an enhanced Buneman frequency estimation algorithm to extract strain-induced spectral shifts directly from coarse Rayleigh backscattering cross-correlation spectra, which improved demodulation efficiency by more than 17 times [18]. Moreover, Chang *et al.* reported an efficient cross-correlation algorithm based on the Chirp-Z transform, reducing the computational complexity by more than 4400 times under high-spatial-resolution conditions [19].

In addition to algorithmic acceleration, researchers have widely investigated various hardware-acceleration approaches based on field-programmable gate array (FPGA) and graphics processing unit (GPU) to enhance the real-time sensing capability of OFDR systems. Liang *et al.* fully implemented data acquisition and wavelength-shift demodulation in FPGA-based OFDR systems for dynamic strain sensing, improving computational efficiency by 20 times [20]. Similarly, Lee *et al.* developed a dual-edge-triggered dynamic OFDR system with dual-channel FPGA-based high-speed signal processing for real-time structural health monitoring, achieving an effective measurement rate of 100 Hz [21]. Furthermore, Shan *et al.* demonstrated a fast shape-reconstruction OFDR system, in which GPU-based parallel processing for cross-correlation wavelength-shift demodulation of the MCF resulted in a 21-time reduction in overall processing time [22]. Additionally, Harb *et al.* reported a real-time OFDR temperature sensing system based on GPU acceleration, in which the GPU performed the resampling and frequency-shift computation, reducing the processing latency to below 30 ms and improving the computational efficiency by a factor of 45 compared with serial computation [23]. These studies demonstrated that real-time OFDR sensing can be achieved using hardware-acceleration methods.

In this paper, a novel random tuning-range compensation method, namely fixed-range k-domain resampling (FR-KDR) method, was proposed and experimentally demonstrated in a real-time OFDR system for 2D and 3D shape sensing based on MCF. The working principle and implementation procedure of the method were explained, and its compensation performance was investigated. The shape was reconstructed using the middle core and two outer cores of the MCF, i.e., Core1, Core3 and Core4, and the position error of the reconstructed shape was further analyzed. Furthermore, the FR-KDR method and the wavelength-shift demodulation processing were implemented on a GPU and the stability of the dynamic system was evaluated. Finally, the

computation time of parallel processing during the dynamic sensing process was analyzed under different zero-padding sizes and sweep ranges, and the GPU parallel acceleration performance further evaluated.

## 2. Theory and experimental principle

In real-time coherent OFDR systems, accurate distance and wavelength demodulation rely on a linear and repeatable frequency sweep of the tunable laser source (TLS). However, the sweep characteristics of the TLS cannot be perfectly reproduced over successive scans. As a result, fluctuations in the instantaneous sweep speed are introduced, leading to variations in the effective sweep range, and consequently to wavelength-shift demodulation errors. To address the aforementioned issue, a novel dynamic compensation method, i.e., the fixed-range k-domain resampling (FR-KDR) method was proposed and demonstrated, as shown in Fig. 1. Ideally, the wavelength sweep of the TLS could be expressed as:

$$\lambda(t) = \lambda_0 + \gamma \cdot t, \quad (1)$$

where  $\lambda_0$  is the starting wavelength,  $\gamma$  and  $t$  denote the sweep speed and sweep time of the TLS, respectively. In practice, the instantaneous sweep speeds during the reference (Ref.) and measurement (Mea.) states in real-time sensing were generally not identical, i.e.,  $\gamma_{ref} \neq \gamma_{mea}$ , resulting in variations in the effective sweep range. Accordingly, the auxiliary interferometer (AI) signals in both the Ref. and Mea. states were acquired using a data oversampling scheme. The AI signal can be expressed as:

$$I_{AI}(t) = 2E_0^2 \cos \left[ 2\pi \left( f_0 \tau + \gamma \tau t - \frac{1}{2} \gamma \tau^2 \right) + \xi \right], \quad (2)$$

where  $E_0$  is the amplitude of the optical field,  $\tau$  is the delay time of the delay fiber,  $f_0$  is the starting sweep frequency, and  $\xi$  represents random phase noise. The instantaneous phase of the tuning laser was then obtained as:

$$\varphi(t) = \arctan \left\{ \frac{H[I_{AI}(t)]}{I_{AI}(t)} \right\}, \quad (3)$$

where  $\arctan\{\}$  and  $H[\cdot]$  are the arctangent function and Hilbert transform, respectively. After performing phase unwrapping, the instantaneous wavenumber could be reconstructed as:

$$k(t) = \frac{\varphi(t) - \varphi_0}{d}, \quad (4)$$

where  $\varphi_0$  is a constant phase offset and  $d$  is the optical path difference of the AI. It should be noted that, in the experiment, the data acquisition time was slightly longer than the theoretical sweep time of the TLS due to the data oversampling scheme. Therefore, the collected Ref. and Mea. signals may cover physical sweep ranges that are marginally larger than the preset theoretical range. This condition can be expressed as:

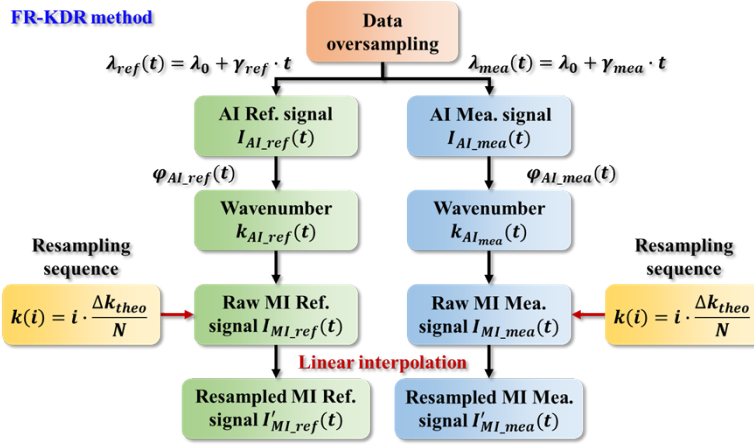
$$\Delta\lambda_{theo} < \min(\Delta\lambda_{ref}, \Delta\lambda_{mea}), \quad (5)$$

indicating that the entire theoretical sweep range was fully contained within the effective wavelength ranges of both the Ref. and Mea. signals. Based on Eq. (5), in the FR-KDR method, a fixed and uniform wavenumber sequence was constructed based on the theoretical sweep range of the TLS, was constructed as:

$$k(i) = i \cdot \frac{\Delta k_{theo}}{N}, \quad i = 0, 1, \dots, N-1, \quad (6)$$

where  $\Delta k_{theo}$  is the theoretical wavenumber range which corresponding to  $\Delta\lambda_{theo}$ , and  $N$  is the number of resampling points. The raw Ref. and Mea. main-interferometer (MI) signals,

i.e.,  $I_{MI\_ref}(t)$  and  $I_{MI\_mea}(t)$ , were then resampled onto the fixed k-domain range using linear interpolation, which provides sufficient spectral accuracy with low computational complexity and is well suited for parallel implementation, to obtain the resampled signals  $I'_{MI\_ref}(t)$  and  $I'_{MI\_mea}(t)$ . Consequently, a fixed theoretical wavenumber range was enforced during k-domain resampling to compensate for sweep-range fluctuations and maintain consistent distance mapping across repeated scans. In the proposed FR-KDR method, the reference scan and each newly acquired measurement scan are independently resampled onto the same predefined theoretical k-domain range without additional frame-by-frame sweep-range calibration or matching. This fixed-range resampling maintains sweep-range consistency with a reduced computational burden, enabling dynamic compensation of random TLS sweep-range fluctuations in the real-time measurement loop.

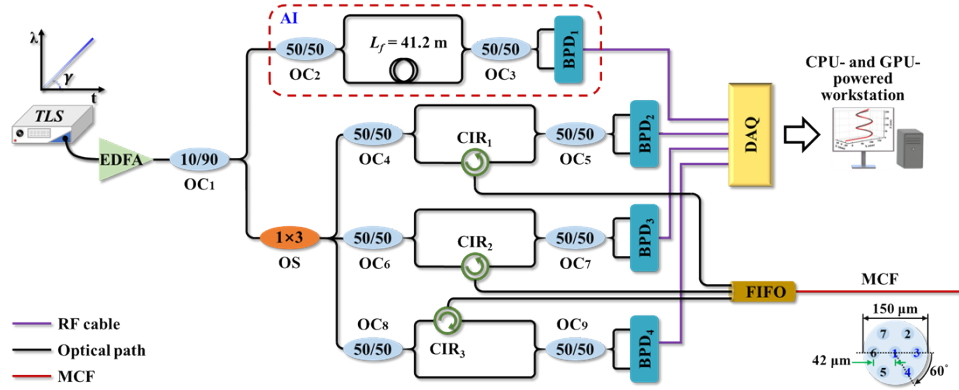


**Fig. 1.** Flowchart of the proposed fixed-range k-domain resampling (FR-KDR) method for compensating sweep range fluctuation based on real-time OFDR system. Ref. signal: reference signal; Mea. signal: measurement signal.

### 3. Experimental setup and results

The experimental setup for real-time 3D shape sensing based on a simplified three-channel OFDR system with MCF was shown in Fig. 2. A TLS (TLB-8800-HSH-CL, Newport Inc.) was employed, sweeping from 1540 to 1560 nm. The theoretical sweep speed was set to 5000 nm/s, while the effective speed was measured at approximately 4995 nm/s, which satisfied the data oversampling requirement of the proposed FR-KDR method. The output light from the TLS was amplified through an erbium-doped fiber amplifier (EDFA) and divided into two paths using a 10/90 optical coupler (OC1). 10% of light was sent to the AI configured as a Mach–Zehnder interferometer, which consisted of a 41.2-metre-long delay fiber. The AI beat frequency signal was detected by a balanced photodetector (BPD1) with a bandwidth of 200 MHz, and converted into electrical signal, which was acquired by the data acquisition card (DAQ) at a sampling rate of 500 MS/s. The AI signal was subsequently used to compensate for laser sweep nonlinearity and random sweep range fluctuations. The remaining 90% of the light was split into three parallel paths via a 1 × 3 optical splitter (OS) and injected into three Mach–Zehnder MIs. In each MI, the input laser was separated into a reference arm and a test arm by a 50:50 OC. The test arm consisted of a multicore fiber (MCF, YOEC Inc.) with a cladding diameter of 150 μm and the core spacing of 42 μm between the central core and the outer cores, and the angle between each adjacent cores was 60°, as shown in the inset of Fig. 2. Three cores of the MCF, i.e., Core1,

Core3, and Core4, were independently connected to the MIs through a fan-in/fan-out (FIFO) and employed in the experiment. Then, the optical signals from the reference and test arms were recombined by the 50/50 OCs and detected by BPDs, i.e., BPD2, BPD3 and BPD4. Finally, the beat signals were acquired by the DAQ and transferred to the workstation for device control and real-time data processing. The workstation was equipped with a CPU (i7-12700KF, Intel Inc.), 32 GB of system RAM, and a GPU (GeForce RTX 3070 Ti, NVIDIA Inc.) with 8 GB of video RAM. The CUDA version is NVIDIA CUDA 12.9.



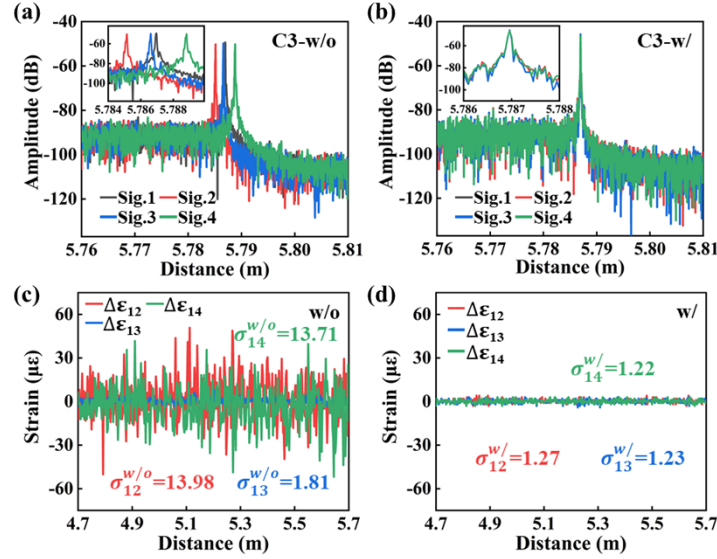
**Fig. 2.** Experimental configuration for real-time 3D shape sensing based on a simplified three-channel GPU-based OFDR system with a multicore fiber (MCF). TLS: tunable laser source; EDFA: erbium-doped fiber amplifier; OC: optical coupler; OS: optical splitter; CIR: circulator; BPD: balanced photodetector; DAQ: data acquisition card; FIFO: fan-in/fan-out. Inset: schematic diagram of MCF end face. The workstation integrates a CPU and a GPU for device control and data processing.

To evaluate the performance of the proposed compensation method, the distance-domain signals and the demodulated strain distributions of Core3 (C3) under zero-strain conditions were analyzed. In OFDR systems, the spatial resolution of a single data point, i.e.,  $\Delta z$ , can be expressed as:

$$\Delta z = \frac{c}{2n \cdot \Delta \lambda_{eff}}, \quad (7)$$

where  $c$  and  $n$  are the velocity of light in vacuum and the refractive index of the fiber,  $\Delta \lambda_{eff}$  is the effective tuning range of TLS. This indicated that variations in the sweep range result in inconsistencies in the distance domain, leading to apparent position deviations along the sensing fiber. As depicted in Fig. 3(a), without compensating the random tuning range, noticeable fluctuations in the end position of C3 were observed across four repeated measurements. Then, Signal 1 (Sig.1) was selected as the reference signal, and the strain distributions under zero-strain conditions were demodulated over a 1-m length at a spatial resolution of 5 mm using the conventional method for three signal combinations, i.e., Sig.1–Sig.2, Sig.1–Sig.3, and Sig.1–Sig.4, as illustrated in Fig. 3(c). The zero-strain conditions were obtained by keeping the MCF in a straight configuration without external bending under stable temperature conditions. The root-mean-square errors (RMSEs) of the demodulated strain for these three signal combinations were then calculated to be 13.98, 1.81, and 13.71  $\mu\epsilon$ , respectively. In contrast, as shown in Fig. 3(b) and 3(d), the end positions of C3 were well aligned at 5.787 m across the repeated measurements using the proposed compensation method, and the corresponding strain RMSEs were reduced to 1.27, 1.23, and 1.22  $\mu\epsilon$ , respectively. These results indicated that both the sensing

position and strain distribution of the MCF could be accurately demodulated using the FR-KDR method.



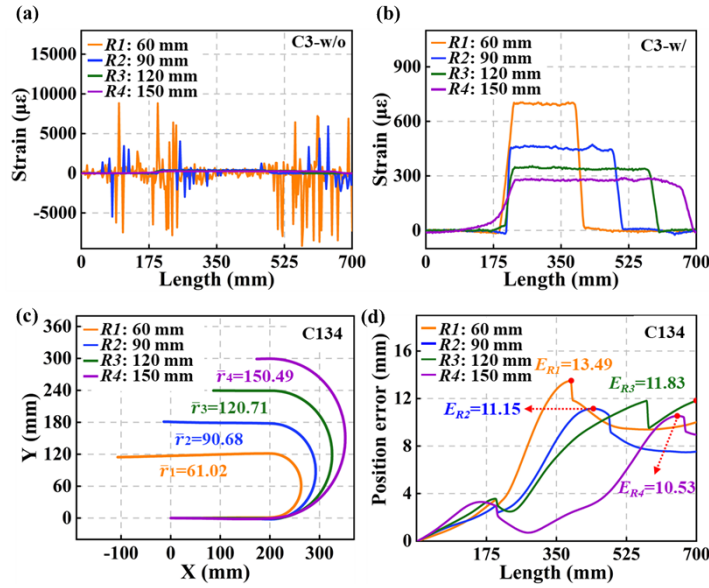
**Fig. 3.** Comparison of the distance-domain signal and demodulated strain distributions of core3 (C3) under zero-strain conditions for four repeated measurements: (a) and (c) without compensation (w/o), (b) and (d) with compensation (w/). Sig. denotes signal;  $\Delta\epsilon_{12}$ ,  $\Delta\epsilon_{13}$ ,  $\Delta\epsilon_{14}$  represent the demodulated strain results obtained from signal pairs 1-2, 1-3, and 1-4, respectively. Note that the sensing spatial resolution was 5 mm.

Additionally, to evaluate the performance of the proposed method under applied strain, the 2-D and 3-D shape sensing characteristics were further investigated. Using C3 as an example, the demodulated strain distributions without compensation exhibited severe fluctuations and abnormal strain peaks under different bending radii, as shown in Fig. 4(a), indicating that random sweep-range fluctuations introduced noticeable strain errors under applied strain. In contrast, after applying the proposed FR-KDR method, smoother and more stable strain distributions were obtained, as shown in Fig. 4(b). The strain distributions increased with decreasing bending radius, which was consistent with the applied curvature. These results confirm that the FR-KDR method effectively improves strain demodulation accuracy under non-zero strain conditions.

Then, with a spatial resolution of 5 mm, the 2-D shapes of a 700-mm-long MCF were successfully reconstructed using the Bishop framework [24] based on the core combination of Core1, Core3 and Core4, i.e., C134, as shown in Fig. 4(c). The central core is mainly sensitive to axial strain and temperature variations, whereas the outer cores are affected by both bending-induced strain and common effects of axial strain and temperature variations. Therefore, the central core was used as a reference to compensate for the effects of axial strain and temperature variations. For the designed curvature radii of 60, 90, 120, and 150 mm, the corresponding average reconstructed curvature radii were calculated using the vector projection method as 61.02, 90.68, 120.71, and 150.49 mm, respectively. The Euclidean distance between the theoretical and the reconstructed shape along the MCF was used to evaluate the position error, which is calculated as follows:

$$E(i) = ||P_{rec}(i) - P_{theo}(i)||, \quad (8)$$

where  $P_{rec}(i)$  and  $P_{theo}(i)$  denote the coordinates of the reconstructed shape and the theoretical shape, respectively. The position errors along the sensing section were analyzed in Fig. 4(d),



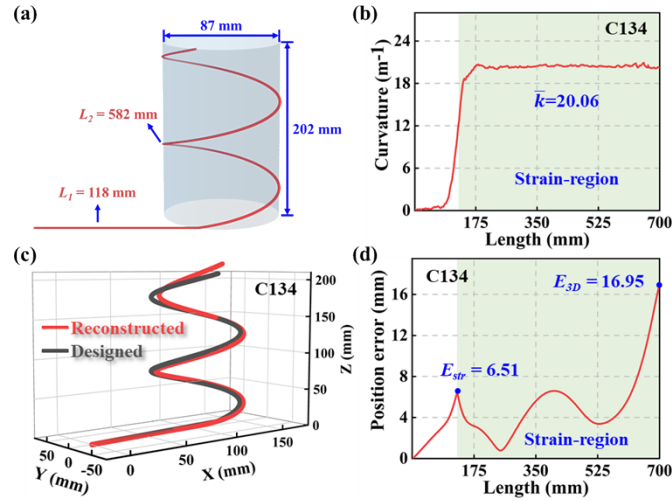
**Fig. 4.** Comparison of strain distributions and 2-D shape reconstruction results under designed curvature radii of 60, 90, 120, and 150 mm. Strain distributions of C3 (a) without compensation and (b) with compensation; (c) the reconstructed 2-D shapes and (d) corresponding position errors along the sensing section based on C134. Note that C134 is the combination of core1, core3, and core4.

it could be observed that the reconstruction error gradually accumulated along the length, and the maximum position errors for the aforementioned curvature radii were measured to be 13.49, 11.15, 11.83, and 10.53 mm, respectively.

Meanwhile, to further investigate the proposed method for 3-D shape sensing, the MCF was placed in a spiral groove on the cylinder with a diameter of 87 mm and a height of 202 mm, as shown in Fig. 5(a). The length of the designed spiral curve was 582 mm, i.e.,  $L_2$ , whereas the total sensing length of the MCF was 700 mm. Consequently, an additional 118-mm-long fiber segment was reserved as a zero-strain section, i.e.,  $L_1$ . As illustrated in Fig. 5(b), the average curvature within the strain-region was calculated to be  $20.06 \text{ m}^{-1}$  based on C134, approaching the theoretical spiral curvature of  $20.24 \text{ m}^{-1}$ . The reconstructed 3D shape closely matches the designed curve in the front section of strain-region, whereas progressively increasing deviations were observed toward the end of the sensing fiber, as shown in Fig. 5(c). The position error along the sensing fiber was illustrated in Fig. 5(d). At the end of zero-strain section, the error reached 6.51 mm, primarily due to placement errors between the fiber and the cylindrical groove at the junction between the zero-strain and strain regions. In the strain-region, the error increased gradually with length due to slight torsion of the MCF, with a maximum deviation of 16.95 mm observed at the end position.

#### 4. Real-time OFDR shape sensing architecture and performance

Furthermore, the real-time sensing performance of the GPU-based OFDR shape sensing system was evaluated, and the data processing workflow was depicted in Fig. 6. The overall real-time data processing operation was divided into two stages, i.e., the reference (Ref.) signal processing stage and the measurement (Mea.) signal processing stage. In the Ref. stage, firstly, an initialization operation was executed to set the experimental parameters of TLS and DAQ, as well as to allocate

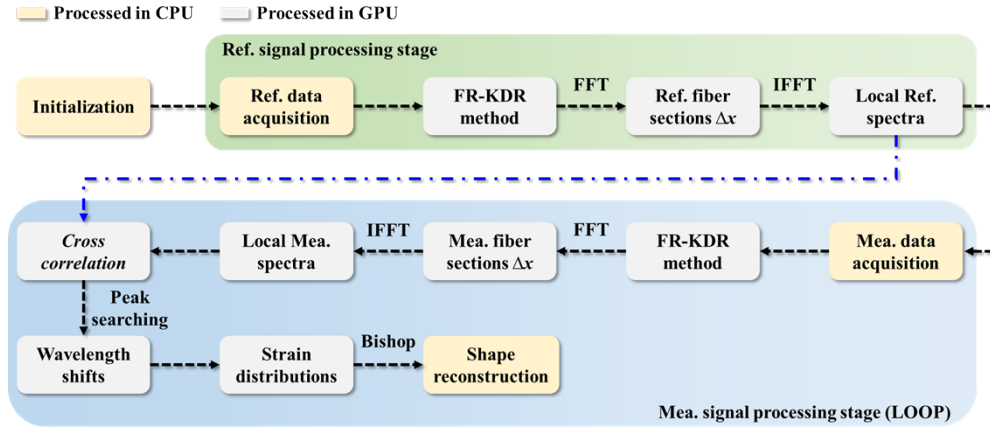


**Fig. 5.** (a) Schematic of using MCF for 3-D shape sensing; (b) calculated curvature distribution; (c) reconstructed 3D shape of a helical cylinder; and (d) the corresponding position errors along the sensing fiber, based on the sensing core combination C134.

the GPU's memory. Then, the raw collected Ref. data was resampled using the proposed FR-KDR method and transformed from the frequency-domain to distance-domain through fast Fourier transform (FFT). Subsequently, the obtained signal was segmented into multiple sensing sections with a sensing spatial resolution of  $\Delta x$ , and the inverse fast Fourier transform (IFFT) operation was performed on each section with a zero-padded size of  $M$  to obtain the local Ref. spectra. These local reference spectra along the sensing fiber were temporarily stored in the workstation memory and subsequently used as reference signals for the Mea. stage. Therefore, during the repeated measurement stage, only the newly acquired measurement signal needs to be resampled onto the predefined fixed theoretical k-domain range and compared with the stored reference spectra. This avoids repeated paired sweep-range matching between the reference and measurement signals in each frame, thereby reducing the computational burden and enabling real-time dynamic compensation.

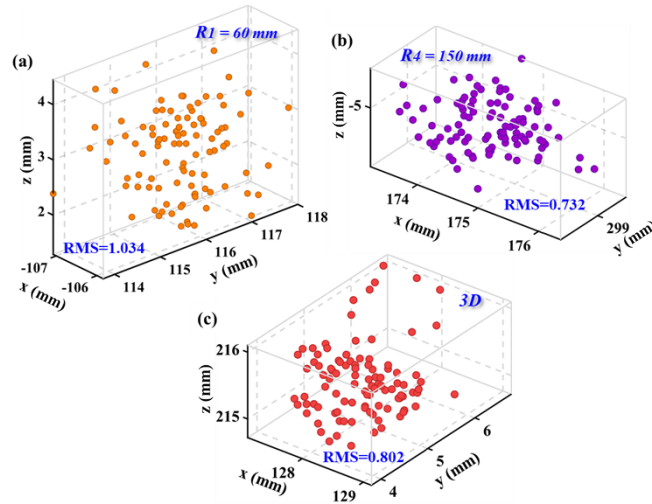
Similarly, in the Mea. stage, the local measurement spectra were obtained following the same data processing procedure as that used for the reference spectra. Subsequently, the cross-correlation operation was applied to each local measurement spectrum and its corresponding local reference spectrum, followed by a peak-search procedure to determine the wavelength shift. The obtained spectral shifts were then converted into the strain profiles, which were further utilized for shape reconstruction based on the Bishop frame. Note that only the initialization, data acquisition, and shape reconstruction operation were performed on the CPU using serial calculation, whereas all other data processing operations were performed on the GPU using parallel computation, and the Mea. signal processing stage was repeatedly executed to achieve dynamic shape sensing.

To further verify the stability of the GPU-accelerated OFDR shape sensing system, the distributions of the reconstructed end-position coordinates for the 2D and 3D shapes were investigated over 100 repeated measurements. As shown in Fig. 7(a) and 7(b), the root mean square (RMS) deviations of the end position for curvature radii of 60 mm and 150 mm were 1.034 mm and 0.732 mm, respectively. In addition, the end-position distribution obtained for the 3D shape was presented in Fig. 7(c), with an RMS deviation of 0.802 mm. As depicted in the figures, the reconstructed coordinates fluctuated randomly without significant directional bias,



**Fig. 6.** Data processing flowchart of a real-time shape sensing based on OFDR using the FR-KDR method, with processing implemented on the CPU and GPU. FFT: fast Fourier transform; IFFT: inverse fast Fourier transform.

indicating the absence of major systematic errors. Notably, the smallest RMS value was observed for the 150 mm curvature radius, which may be attributed to the lower applied strain. Furthermore, the comparable RMS value of the 3D shape indicated that increased spatial complexity did not compromise sensing accuracy. Ultimately, these results demonstrated that the dynamic system maintained robust stability in both 2D and 3D shape sensing.



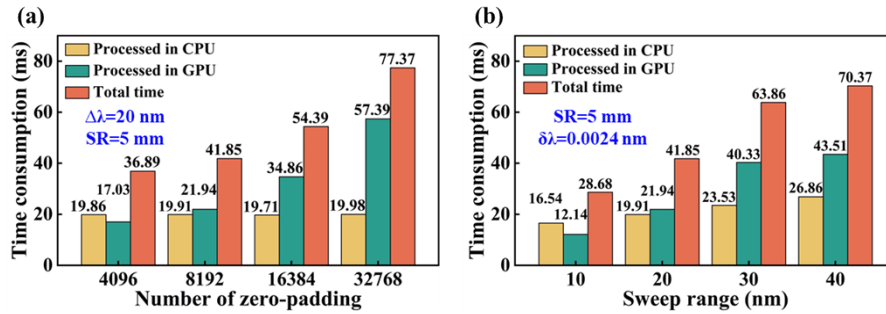
**Fig. 7.** The distributions of the end-position coordinates of the MCF obtained from 100 repeated measurements for curvature radii of (a) 60 mm and (b) 150 mm, and for (c) the 3D shape.

Then, to evaluate the real-time sensing capability of the GPU-accelerated OFDR system, the processing time during the Mea. stage was analyzed under different demodulation parameters. The time consumed by DAQ data acquisition, data transmission and display updating was included in the CPU processing time, while the CPU-GPU data transfer time was included in the GPU runtime. As shown in Fig. 8(a), with a fixed sweep range of 20 nm and a sensing spatial resolution

of 5 mm, the processing time of the CPU and GPU was evaluated for different zero-padding sizes of 4096, 8192, 16384, and 32768, corresponding to the demodulated spectral resolutions were 0.0048, 0.0024, 0.0012, and 0.0006 nm, respectively. As the zero-padding size expanded, the processing time on the GPU increased significantly from 17.03 ms to 57.39 ms. In contrast, the processing time of CPU remained nearly constant at approximately 20 ms, primarily because the number of collected raw data points remained identical across these cases, and the additional time required for shape reconstruction was only several milliseconds. Thus, the system update rate can be expressed as:

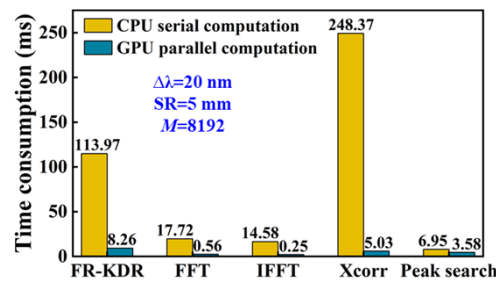
$$f_{update} = \min \left( f_{TLS}, \frac{1}{T_{frame}} \right), \quad (9)$$

where  $f_{TLS}$  is the maximum scan repetition rate of the TLS and  $T_{frame}$  is the total time required to complete one measurement signal processing frame. Note that the maximum scan repetition rate of the TLS was limited to 30 Hz [25], which constrained the maximum achievable update rate of the system. Consequently, the update rate dropped from 27.1 Hz to 12.9 Hz with the zero-padding size increased.



**Fig. 8.** Time consumption of CPU and GPU operations during the measurement signal processing stage. (a) Processing time under different numbers of zero-padding points. (b) Processing time under different sweep ranges.  $\Delta\lambda$ : sweep range; SR: spatial resolution;  $\delta\lambda$ : spectral resolution.

Meanwhile, the processing time under sweep ranges of 10, 20, 30 and 40 nm was presented in Fig. 8(b), with the sensing spatial resolution fixed at 5 mm. To maintain a constant spectral resolution of 0.0024 nm, the corresponding zero-padding sizes were set to 4096, 8192, 12288 and 16384, respectively. As the sweep range increases, the processing times of both the CPU and GPU increased due to the enlarged data size, resulting in an increase in the total processing time from 20.68 ms to 70.37 ms. Under the experimental configuration with a sweep range of 20 nm, a spatial resolution of 5 mm, and a zero-padding size of 8192, a real-time shape sensing update rate of 23.8 Hz was achieved based on Eq. (9), as shown in Visualization 1. To further evaluate the acceleration effect of GPU parallel computation, the processing times of key demodulation operations were compared with CPU serial implementations, as shown in Fig. 9. The compared key operations included FR-KDR resampling, FFT, IFFT, cross-correlation, and peak search. Specifically, the processing time of FR-KDR resampling was reduced from 113.97 ms to 8.26 ms, while that of cross-correlation was reduced from 248.37 ms to 5.03 ms. The FFT, IFFT and peak-search operations were also accelerated from 17.72 ms, 14.58 ms, and 6.95 ms to 0.56 ms, 0.25 ms, and 3.58 ms, respectively. These results indicate that GPU parallel computation significantly enhances the data-processing efficiency of the main demodulation operations, thereby facilitating real-time OFDR shape sensing.



**Fig. 9.** Time consumption comparison of FR-KDR resampling, FFT, IFFT, cross-correlation, and peak-search operations implemented by CPU serial computation and GPU parallel computation under a sweep range of 20 nm, a spatial resolution of 5 mm, and a zero-padding size of 8192.

## 5. Conclusion

In conclusion, what we believe to be a dynamic sweep-range compensation method, i.e., FR-KDR method, was proposed and demonstrated for real-time 3D shape sensing in OFDR system. Using the proposed method, the strain RMSE under zero-strain conditions was reduced to  $1.27\ \mu\epsilon$ , and the 2D and 3D shapes were well reconstructed with the spatial resolution of 5 mm and MCF length of 700 mm, and the maximum position deviations of reconstructed 2D and 3D shapes were 13.49 mm and 16.95 mm, respectively. Furthermore, the parallel computation capability of GPU was utilized to perform the FR-KDR method and wavelength-shift demodulation processing for real-time shape sensing, and the stability RMS of 2D shapes with curvature radii of 60 mm and 150 mm were 1.034 mm and 0.732 mm, respectively, while the RMS for the complex 3D shape was 0.802 mm. Finally, a real-time shape sensing update rate of 23.8 Hz for the dynamic OFDR system was achieved with a spatial resolution of 5 mm, a sweep range of 20 nm, and a zero-padding size of 8192. The comparison between CPU serial computation and GPU parallel computation for the main demodulation steps further confirmed that GPU acceleration significantly enhanced the data-processing efficiency of the real-time OFDR system.

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**Disclosures.** The authors declare no conflicts of interest.

**Data Availability.** Data underlying the results explained in this paper are not publicly available at this time but may be obtained from the authors upon reasonable request.

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