

High-Resolution Raman-OTDR Distributed Temperature Sensors Based on Fast-Non Local Means Denoising Algorithm

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Abstract—Raman-optical time domain reflectometry (R-OTDR)-based distributed temperature sensing (DTS) with high temperature resolution is of great significance in extremely harsh environment of deep wellbore. In this work, we experimentally demonstrate a Fast-non local means (Fast-NLM) algorithm for performance improvement without modifying the hardware architecture of a conventional R-OTDR system. In the proposed method, the first-in-first-out (FIFO) data transmission protocol is used to reconstruct the two-dimensional (2D) temperature image in real time. An integral image is employed to simplify the calculation of Euclidean distance between similarities in the 2D space-time domain. The overall response time by using the method decreases from 27.9 s to 1.7 s, marking a 16-fold enhancement over traditional NLM denoising methodologies. An average temperature resolution is below 0.01 °C at the end of fiber. The evolution of the measured temperature at the hot spot position does not produce delay or distortion. Moreover, two segments fiber at 300 m and 9.68 km are rigorously tested with the temperature range from 50 °C to 300 °C and time span of 4 hours, compared with conventional wavelet denoising algorithm, the root means square error decrease from 1.02 °C to 0.42 °C. In all, the Fast-NLM denoising based R-OTDR illustrates great improvement in temperature resolution while maintaining fast response time. This achievement holds immense potential for

diverse applications, including dynamic monitoring in the realms of energy development, oil and gas exploration, and allied fields.

Index Terms—Distributed optical fiber sensing, Raman OTDR, Fast-NLM, high temperature resolution.

I. INTRODUCTION

DISTRIBUTED optical fiber sensors (DOFS) [1], [2], known for their compact structure, corrosion resistance, and immunity to electromagnetic interference [3], are ideal for measuring physical quantities in various environments [4], [5], [6]. These advantages have sparked significant interest across multiple domains [7], [8]. Among these sensing technologies, Raman scattering-based optical fiber distributed temperature sensing (DTS), standing as the most mature and stable long-distance distributed temperature sensing technique, is receiving extensive attention in oil and gas exploration sensing [9], real-time power line monitoring [10], [11], and other distributed temperature monitoring fields [12], [13]. The performance metrics of the Raman DTS system typically encompass temperature accuracy and precision, spatial resolution, as well as sensing distance. Significantly, improving the accuracy and resolution of temperature measurement constitutes a substantial challenge. This is attributed to the fact that the backscattered light signal in the Raman system is approximately 60-70 dB inferior in strength compared to the incident pulse power [1], [9]. Moreover, the Anti-Stokes signal, which exhibits better temperature sensitivity, is around 4 dB lower than the Stokes signal and thus more susceptible to noise contamination from auxiliary equipment. Consequently, the typical signal of the Raman DTS exhibits a relatively lower signal-to-noise ratio (SNR), thereby leading to lower accuracy and precision.

SNR improvement or noise suppression could improve the temperature accuracy and resolution of the Raman system. Over recent decades, various methods for SNR improvement and noise suppression such as the Anti-Stokes demodulation approach, optical pulse coding [14], wavelet denoising [15], and Fourier transform [16], have been demonstrated for performance improvements [17]. In 2012, Soto M. et al. [18] employed the Anti-Stokes demodulation method within the dual-terminal Raman-DTS system. The demodulation temperature accuracy improved from 1.5 °C to 1.1 °C. Nevertheless, this method is

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susceptible to environmental fluctuations, and its improvement effect is limited. In 2017, Vazquez G. et al. [19] demonstrated a pseudo-random pulse sequence optical pulse coding and deconvolution algorithms, with temperature resolution of 1.5 °C at a spatial resolution of 2 m. In 2019, Li et al. [20] demonstrated a cumulative average, differential temperature compensation, and wavelet transform modulus maxima method for the Raman signal and temperature signal denoising. The accuracy improves from 15 °C to 0.56 °C along the 10.8 km. These methods increase the complexity of the system, while improving the SNR, thereby raising the hardware cost of the sensor. Besides, the combination of these signal denoising techniques can further improve the SNR and spatial resolution [21], [22], [23] although the configuration cost would increase due to the complexity of demodulation.

Image denoising technology, such as non-mean [24] and bilateral filter method [25], illustrates an effective method for performance improvement in DOFS. The non-mean filter method effectively preserves image details during noise reduction but it may generate artifact in homogeneous regions. And the bilateral filter, integrating spatial and intensity information, is highly sensitive to parameter selection and incurs high computational costs. One significant advancement is the successful application of the Non-Local Means (NLM) algorithm from image processing techniques to DOFS [26]. This approach fully leverages the high similarity and redundancy contained in the one-dimensional information obtained from distributed Raman sensors, resulting in a significant enhancement of the temperature resolution. Despite these advancements, the computational time of the NLM algorithm is still a formidable task [27], [28], [29]. It remains a big challenge to realize a reliable distributed high-temperature sensing system that offers long-distance sensing, high temperature, high speed, and temperature resolution simultaneously. The computational demands of the NLM algorithm can hinder its practical application in real-time or near-real-time monitoring scenarios.

In this article, we demonstrate a Fast-NLM-based real-time denoising algorithm specifically tailored to Raman DTS signals without modifying the hardware architecture of a conventional R-OTDR system. In proposed algorithms, the 2D temperature image is real-timely reconstructed by utilizing a FIFO data transmission protocol and using integral image technique to accelerate calculation. Compared to the traditional algorithm, the system's time consumption, the temperature resolution, the delay characteristics, and the long-term stability are analyzed by using the oil bath furnace. The experimental results show an average temperature resolution of 0.01 °C at the end of the fiber. Compared with the wavelet denoising (WD) algorithm, the temperature accuracy is improved from 1.59 °C to 0.39 °C. Furthermore, the long-term stability over 4 hours measurement shows the root mean square error (RMSE) of the Fast-NLM decrease from 1.02 °C to 0.42 °C, and the maximum deviation decrease from 3.36 °C to 0.88 °C, at 300 °C, respectively. As a result, the remarkable denoising performance makes it highly suitable utilization for DTS in oil and gas, power, smelting, and aviation industries.

II. PRINCIPLES OF OPERATION

A. The Principle of Raman Temperature Demodulation

In the R-OTDR system, spatial positioning is carried out by the time-of-flight of the spontaneous Raman scattering light, while the temperature is determined by analyzing their intensity variations. The temperature sensitivity of Raman scattering originates from the thermally modulated vibrational energy states of silica molecules. In addition the interaction between photons and thermally moving chemical bonds produces Raman scattering Anti-Stokes and Stokes photons. The strength of the signal as function of temperature T (in Kelvin) was expressed as:

$$\frac{P_{as}(T)}{P_s(T)} = \frac{K_{as}}{K_s} \left(\frac{v_{as}}{v_s} \right)^4 \exp \left(\frac{h\Delta v}{k_B T} \right) \exp [(\alpha_s - \alpha_{as}) L], \quad (1)$$

where $P_{as}(T)$ ($P_s(T)$) is the power of Anti-Stokes (Stokes) light in temperature (T), K_{as} (K_s) is the scattering coefficient of the Anti-Stokes (Stokes) light, which is related to the scattering cross section. The v_{as} (v_s) is the optical frequency of Anti-Stokes (Stokes) light, α_{as} (α_s) is the transmission loss of Anti-Stokes (Stokes) light in the fiber, h is the Planck constant, k_B is the Boltzmann constant, and Δv is the frequency difference between the upper and lower energy levels of the Raman scattering spectrum.

As given the reference temperature T_0 in Raman DTS, the demodulated temperature using the Anti-Stokes light and Stokes light generated by the spontaneous Raman backscattering effect, could generally be expressed as:

$$\begin{aligned} T &= \left\{ \frac{1}{T_0} - \frac{k_B}{h\Delta v} \left[\ln \frac{P_{as}(T) \cdot P_s(T_0)}{P_{as}(T_0) \cdot P_s(T)} \right] \right\}^{-1} \\ &= \left\{ \frac{1}{T_0} - \frac{k_B}{h\Delta v} \left[\ln \frac{R(T)}{R(T_0)} \right] \right\}^{-1}. \end{aligned} \quad (2)$$

Compared with the single-way demodulation methods (i.e., demodulated by Anti-Stokes signal) in [14], the two-way method (i.e., (2)) with two-way light ratio could enhance the stability of the DTS system and other factors.

B. The Principle of Fast-NLM Method

The Fast-NLM method achieves fast 2D image reconstruction using FIFO data queues, integral image technology and achieves noise reduction using the high degree of similarity and redundancy within the image. In the DTS, the temperature change trend among adjacent sensing points is highly correlated (spatial similarity). The temperature fluctuation patterns at the same location at different times may repeat (time similarity). Abnormal events (such as fires) exhibit similar local hotspot diffusion patterns in the space-time map (Structural similarity). The unique advantages of this algorithm in processing temperature data are as follows: anti-local mutation interference and single-point noise are effectively suppressed through non-local similar block weighting. Similar thermal diffusion patterns in different time slices can be identified due to cross-temporal correlation enhancement. And the algorithm pre-calculates the cumulative sum of storage (the original image is calculated as

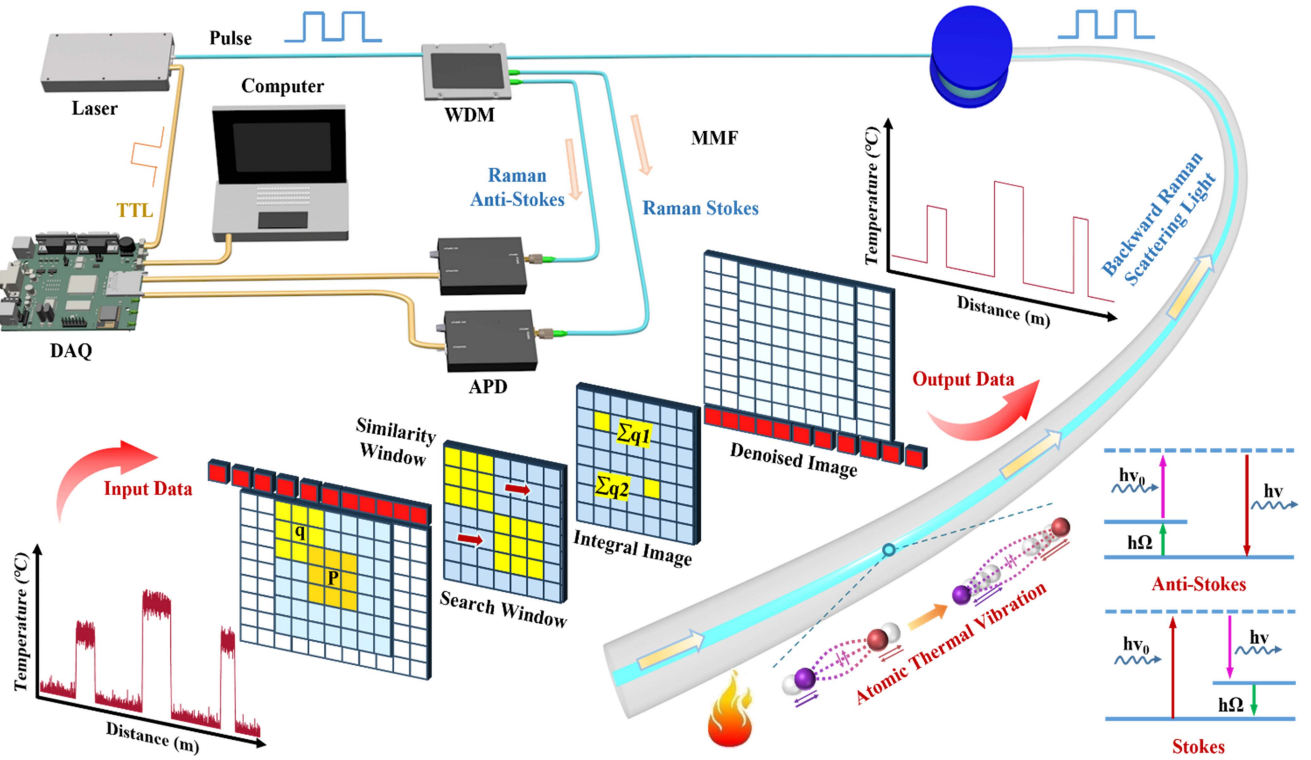


Fig. 1. Schematic diagram of Raman distributed temperature sensing system and denoising algorithm.

an integral image) by the integral image technology to avoid point-by-point calculations. This ensures a fast response time while effectively achieving denoising.

The whole algorithm denoising process is shown in Fig. 2(a). In step 1, the 2D imagination data reconstructed by the FIFO data queues. An optical fiber temperature data graph at ambient temperature is simulated in advance. The one-dimensional original signal is embedded at the top of the two-dimensional temperature data image. In step 2, slide the similarity window in the search window and calculate the Euclidean distance between the two similarity windows. Firstly, a search window $R \times R$ ($R = 2R_s + 1$, R_s is the radius of search window) centered on the target pixel p , and a similarity window $r \times r$ ($r = 2r_s + 1$, r_s is the radius of similarity window) sliding within the search window are applied to the 2D signal. The Euclidean distance $\|V(p) - V(q1)\|^2$, between the two similarity windows centered on p and $q1$, is calculated as follows:

$$\|V(p) - V(q1)\|^2 = \frac{1}{r^2} \sum \|b(p+s) - b(q1+s)\|^2. \quad (3)$$

Where s is the sampling interval. In this work, when repeatedly calculating the Euclidean distance for temperature pixel values, we employ integral image technology to significantly reduce the computational burden and enhance the calculation speed.

In step 3, weights are calculated based on the similarity derived from the Euclidean distance. First, the similarity $W(p, q1)$ is determined by the distance between the rectangular similarity windows centered on p and $q1$:

$$W(p, q1) = \frac{1}{Z(p)} \exp\left(-\frac{\|V(p) - V(q1)\|^2}{g^2}\right). \quad (4)$$

Here, parameter g is the smoothing parameter, which plays a crucial role in regulating the attenuation of the function. As g increases, the transformation of the Gaussian function becomes smoother. Conversely, when g decreases, a larger proportion of edge-detail components are retained. However, this reduction may lead to an excessive number of noise points remaining.

In step 4, the noisy image n is calculated from the denoised image b :

$$n(p) = \sum W(p, q1) \cdot b(q1). \quad (5)$$

In step 5, the integral image technique is used to simplify the calculation. A two-dimensional integral image is constructed and pre-store the cumulative square sum for each position, as shown in Fig. 2(b4). $I(i, j)$ represent a pixel point in the original image, while x and y denote the dimensions of the original region. $Q(x, y)$ is used to calculate the sum of pixels within a specific rectangular region of the temperature map

$$Q(x, y) = \sum_{i \leq x, j \leq y} I(i, j)^2. \quad (6)$$

In step 6, the processed data are normalized through weighted averaging of pixel values for all temperature data points within the search window. Additionally, edge areas of the image are filled to prevent boundary crossing in the integral image,

$$\hat{I}(p) = \frac{\sum W(p, q1) \cdot I(q1)}{\sum W(p, q1)}. \quad (7)$$

Through this procedure, the denoised image is generated.

Finally, in step 7, one-dimensional temperature data are extracted from the denoised image in order. As shown in Fig. 2(b5)

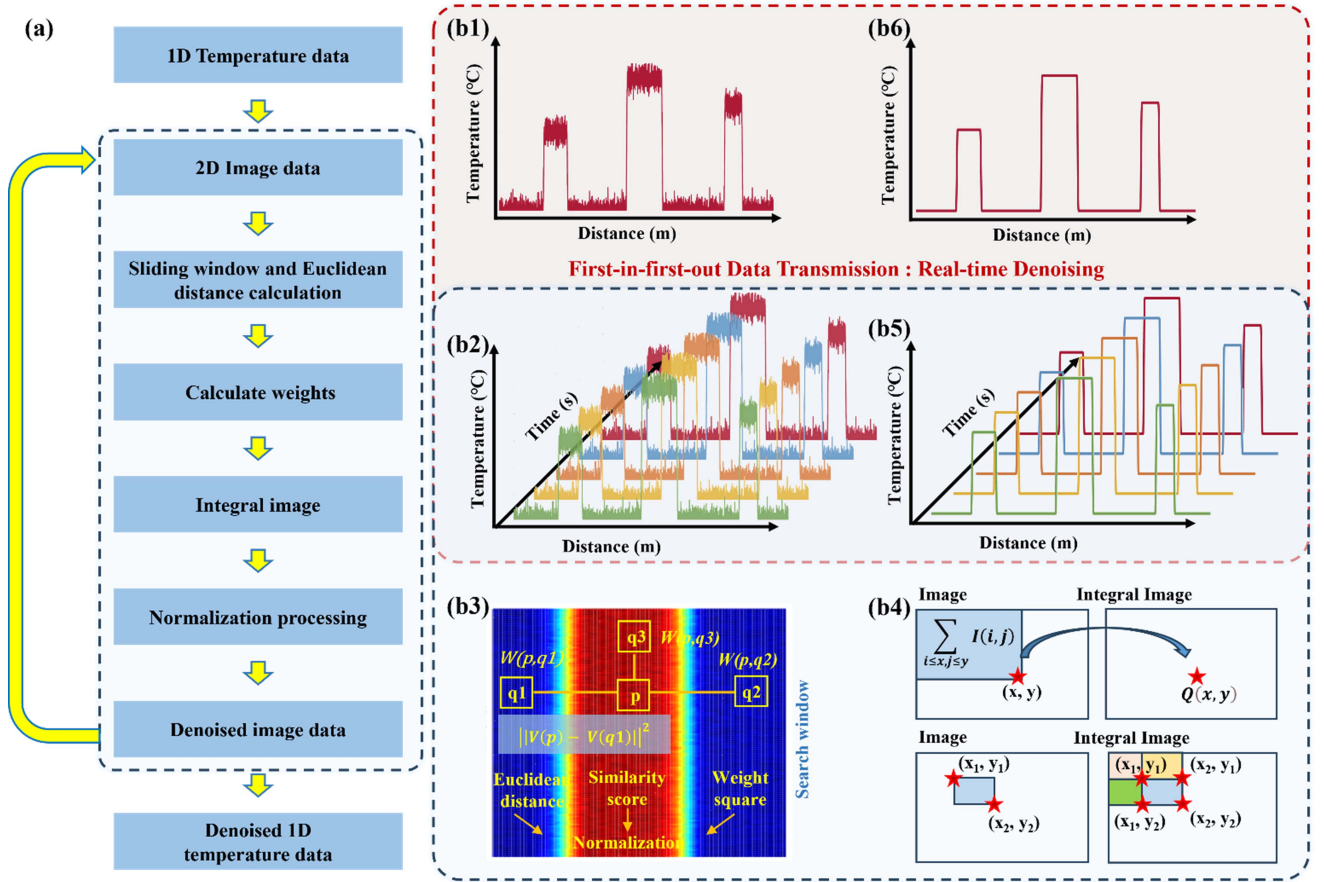


Fig. 2. Schematic of the Fast-NLM-based denoising method for DTS. (a) The denoising process; (b1) noisy 1D temperature data; (b2) image data composed of noisy 1D temperature data; (b3) definition of the similarity window, the search window, the filter parameter, the weight, and similarity calculated using Euclidean distance; (b4) the integral image used for calculating the pixel spacing of the original image; (b5) the denoised image data; (b6) the denoised 1D temperature data.

and (b6), continuity is maintained across both temporal and spatial dimensions.

III. EXPERIMENTS AND RESULTS

The configuration of the Raman-DTS system is depicted in Fig. 1. The system comprises a distributed feedback laser (1550 nm, 8 ns), a wavelength division multiplexer (WDM), a high-speed data acquisition card (DAQ), two avalanche photodiodes (APDs), and a personal computer. The fiber under test (FUT) in the experiments is a graded-index multimode fiber (50/125, MMF). The laser pulses, with a peak optical power of 13.5 W and a repetition rate of 10 kHz, launch into the FUT via the WDM. As the light pulse propagates through the FUT, spontaneous Raman backscattering light produced while the probe light interacts with the fiber core. These optical signals are filtered by the WDM and subsequently converted into electrical signals by the APD. The electrical signals are then collected by DAQ and transmitted to the computer, configured with a 2.3-GHz processor and 8 GB of RAM. Within this computational environment, demodulation and image-based denoising procedures are implemented to reconstruct the temperature curve. Besides, a high-precision second-class platinum resistance thermometer and an oil bath furnace are used to conduct the high-temperature experiments.

At first, the Fast-NLM algorithm for DTS was optimized. A fiber segment with length of 10 m at 9.68 km are heated from ambient to 60 °C. Fig. 3 illustrates the optimization results of the signal from this segment. As shown in Fig. 3(a1), the spatial-temporal temperature curve varies as the similarity window widths increase from 5 to 21. It should be noted that the spatial resolution is quantified by the positions corresponding to 10% to 90% response in the temperature profile. As shown in Fig. 3(a2) and (a3), the spatial resolution and temperature resolution both degrade as the increasing window width smooths the rising edge, confirming a more optimal spatial and temperature scale fidelity with a smaller window width. As shown in Fig. 3(a4), the response time gradually increases from 1.8 s to 3.0 s with expanding similarity window width, indicating that larger window widths may result in slower responses. As a result, to obtain better performance, the similarity window widths are better to be the minimum. Under this condition, the spatial resolution, the temperature resolution, and the response time are optimized to 2.5 m, 0.06 °C, and 1.8 s, respectively.

The magnitude of the search window plays a pivotal role in system-related processing time. As shown in Fig. 3(b1), the spatial-temporal temperature curve varies as the search window widths increase from 9 to 33. The variation of spatial-temporal resolution versus search window widths is illustrated in

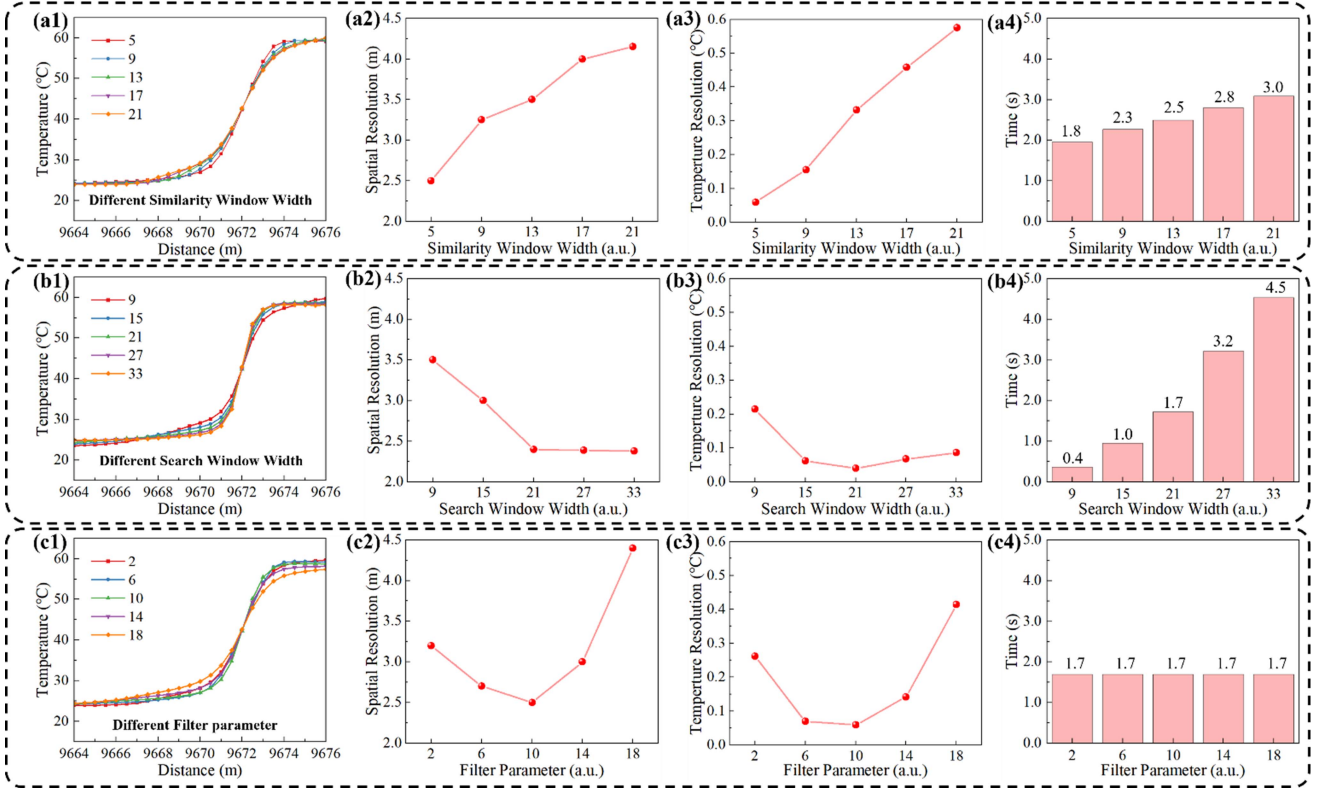


Fig. 3. Measured results of R-DTS using Fast-NLM algorithm for temperature denoising. (a1), (b1), and (c1) The denoised temperature curves using three varying parameters (similarity window width, search window width, and filter parameter, respectively). (a2), (b2), and (c2) The influences on spatial resolution. (a3), (b3), and (c3) The influences on temperature resolution. (a4), (b4), and (c4) The influences on response time.

Fig. 3(b2). As the search window width incrementally increases, the spatial resolution illustrates a decline-stabilization pattern trend. As the search window width incrementally expands to 21, the spatial resolution reaches a minimum of 2.5 m. As shown in Fig. 3(b3), the temperature resolution illustrates a falling-then-rising trend as search window width increases. When the search window width incrementally expands to 21, the temperature resolution reaches minimal of 0.06 °C. As shown in Fig. 3(b4), the response time (in seconds) increased from 0.4 to 4.5 seconds. To obtain the better performance, the search window widths is better to be set as 21, while the spatial resolution, the temperature resolution, and the response time are optimized to 2.5 m, 0.06 °C, and 1.7 seconds, respectively.

The selection of an appropriate filter coefficient is particularly significant in the algorithmic processing. Suboptimal filter coefficients lead to insufficient noise reduction, whereas supra-threshold coefficients induce twofold degradation: spatial resolution deterioration and temperature measurement distortion due to over-smoothing. The systematic evaluation of filter parameters from 2 to 18 is shown in Fig. 3(c1)–(c4). As predictably shown in Fig. 3(c2) and (c3), both the temperature resolution and spatial resolution display a falling-then-rising trend. When the filter is 10, optimal spatial resolution and temperature resolution are optimized to be 2.5 m and 0.06 °C, respectively. Besides, filter parameter variations exert negligible impact on the response time (1.7 seconds). Taking all into account, the optimal similarity window width, search window width, and filter parameter are 5, 21, 10, respectively.

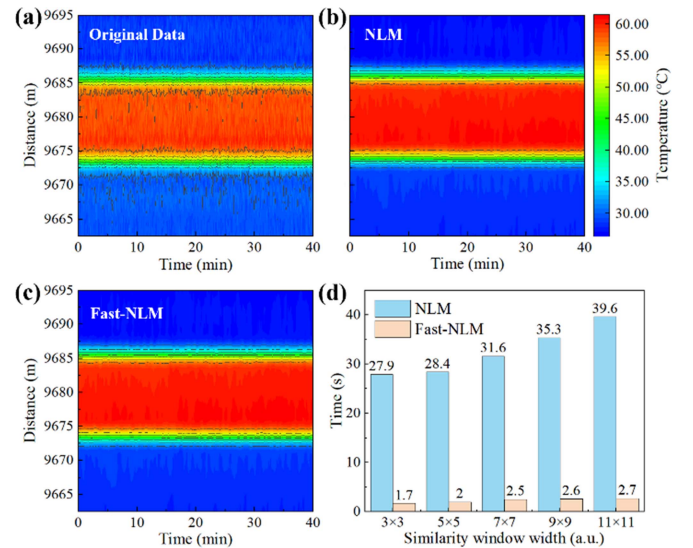


Fig. 4. The 2D spatiotemporal images using different denoising methods. (a) The original data; (b) 2D image data processed by NLM algorithm; (c) 2D image data processed by Fast-NLM algorithm. (d) The processing time of the conventional NLM algorithm and optimized Fast-NLM algorithm.

The computational time of the proposed method and the traditional NLM method are compared. Fig. 4(a)–(c) illustrate the consecutive 2D temperature image of the sensing fiber at heating temperature of 60 °C with a time span of 40 minutes. The temperature image data are processed by the 2D NLM and Fast-NLM

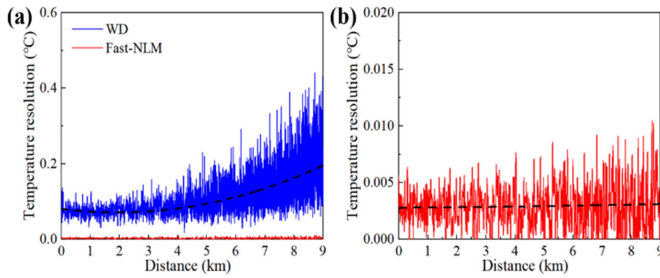


Fig. 5. (a) The temperature resolution as functions of distance by using the WD and Fast-NLM algorithms. (b) The variation in temperature resolution versus distance by using the Fast-NLM algorithm.

algorithm shown in Fig. 4(b) and (c). Compared with the original data in Fig. 4(a), the data processed by these two algorithms curtail the temperature fluctuation from 1.59 °C to 0.39 °C. As depicted in Fig. 4(d), a comparison of the computation times (in seconds) is made under disparate similarity window sizes. Thanks to integral image technology, the processing time is substantially curtailed without appreciably compromising the denoising capabilities of the algorithm. For all window sizes, the Fast-NLM algorithm demands significantly less computation time (1.7 s ~ 2.7 s) than the NLM algorithm (27.9 s ~ 39.6 s). This empirical finding indubitably demonstrates that the proposed Fast-NLM algorithm is more efficient in terms of computational resources. Under the precondition of noise reduction and data quality assurance, this efficiency is a highly pivotal factor for large-scale temperature data processing or real-time applications engendered by long-distance optical fiber.

The improvement in temperature resolution of the proposed method verifies the traditional WD method. Taking temperature resolution and temperature fluctuations into account, the optimal wavelet function, decomposition level and threshold are *coif5*, 4, *Heursure*, respectively. Fig. 5 illustrates the performance of the newly proposed Fast-NLM algorithm in comparison to the WD algorithm. As shown Fig. 5(a), a total distance spans a measured distance of 9 km. As the distance increases, the signal-to-noise ratio gradually deteriorates due to the continuous attenuation of the pump light and the scattering signal. As a result, the measured temperature resolution shows an upward and fluctuating trend. Compared with the WD algorithm (depicted by the blue curve), the Fast-NLM algorithm (represented by the red curve) indicates stable and significantly lower the temperature resolution. As shown in Fig. 5(b), compared with the WD method, the Fast-NLM algorithm improves the temperature resolution from 0.42 °C to 0.01 °C, indicating a remarkable improvement.

To validate the temperature sensing performance of the algorithm, the optical fiber is positioned in a normal temperature environment. A segment fiber of 15 m at 9602 m is put into a high temperature oil bath. The temperature of the bath is set to be 60 °C. Fig. 6(a) illustrates the temperature distribution of the whole fiber using three specific algorithms: WD algorithm (blue curve), NLM algorithm (green curve), and Fast-NLM algorithm (orange curve). The illustrations enlarge the local section spanning 8.5 km to 9 km. Compare with the WD algorithm, the data processed by the NLM and Fast-NLM algorithm curtails the

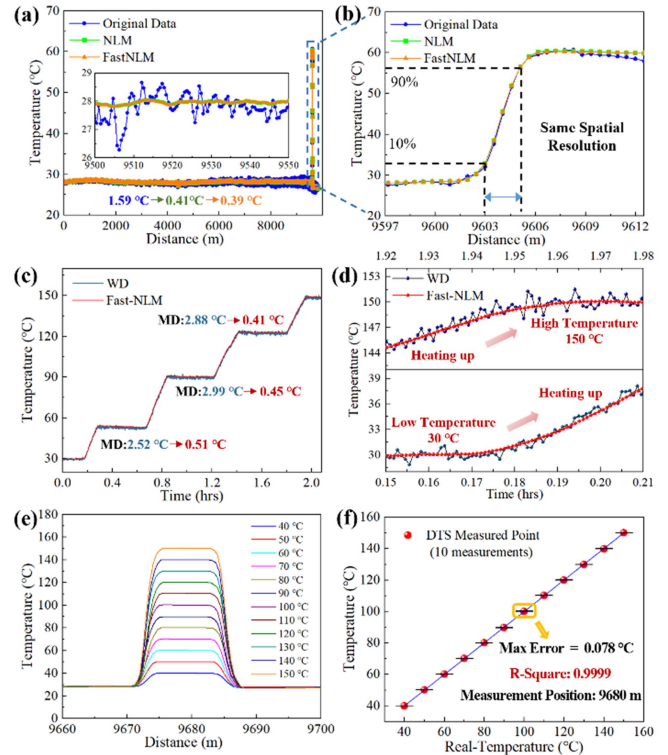


Fig. 6. The sensing performance of R-DTS using Fast-NLM method. (a) Denoising temperature curves using WD, NLM, and Fast-NLM methods, respectively. (b) Zoom-in of (a) at a specific region of 9597-9612 m. (c) The evolution of measured temperature from 30 °C to 150 °C with a time span of two hours. (d) Zoom-in of (c) at 0.15 - 0.21 h and 1.92 - 1.98 h. (e) The measured temperature distribution in the heated region, from 40 °C to 150 °C with an interval of 10 °C. (f) The R-DTS measured temperatures as a function of referenced temperatures at 9680 m and the max error is 0.078 °C (standard deviation of 10 measurements).

temperature fluctuation from 1.59 °C to 0.41 °C and 0.39 °C. As shown Fig. 6(b), the spatial resolution remains 2 m without any deterioration. The results demonstrate that the denoising process produces no perceptible loss of spatial resolution.

The proposed method's real-time response was evaluated. Temperature in the bath is heating up from 30 °C to 150 °C with a timespan of two hours. At each constant temperature setpoint, the holding time is 0.4 hours. Fig. 6(c) displays the uninterrupted temperature evolution using the WD and Fast-NLM algorithms method. Across multiple constant temperature setpoints (50 °C, 90 °C, and 130 °C), the proposed WD method displays the maximum deviation (MD) values of 2.52 °C, 2.99 °C, and 2.88 °C, respectively. In stark contrast, the Fast-NLM algorithm demonstrated significantly reduced MDs of 0.51 °C, 0.45 °C, and 0.41 °C, respectively, representing a 6.5-fold improvement over WD. Additionally, the details of the turning point at 30 °C and 150 °C is illustrated in Fig. 6(d). The simultaneous turning of the red (Fast-NLM) and blue (WD) curves indicates that the algorithm has excellent real-time response characteristics. The temperature was then incrementally elevated from 40 °C to 150 °C in steps of 10 °C at 9.68 km. As shown in Fig. 6(e), 10 measurements were taken at each temperature point under various heating conditions to minimize the impact of the device's inherent fluctuations. The average temperature distribution

TABLE I
TYPICAL ALGORITHM DENOISING SCHEMES AND EXPERIMENTAL RESULTS OF R-OTDR BASED DISTRIBUTED TEMPERATURE SENSORS

Scheme	Distance (km)	Temperature accuracy (°C)	Temperature range (°C)	Reference
Dynamic sampling correction scheme	20.0	1.00	-25.0–45.0	[34]
D-SVD algorithms	0.60	0.87	45.2–60.0	[21]
Deep one-dimensional denoising CNN	10.0	0.70		[35]
Wavelet transform modulus maxima method	10.8	0.56	42.6–90.6	[20]
Short term Fourier transform	0.23	0.50		[16]
Principal component analysis	0.65	0.30	20.0–100.0	[36]
Fast-NLM (This work)	9.68	0.39	30.0–300	

reveals a flat curve in the heating region. As shown in Fig. 6(f), at the 9680 m position of the optical fiber, the measurement error is less than 0.078°C (maximum value) after calculating data 10 times across multi-temperature points ranging from 40°C to 150°C . The linear fitting curve of the measured temperatures and reference temperature show an R^2 value of 0.9999, which proves a high level of consistency and accuracy prevailing between the measured temperature and the actual temperature.

The long-term stability of the sensors using Fast-NLM algorithm versus WD algorithm is tested. Two segments of optical fiber located at 300 m and 9.68 km positions were placed in a constant temperature oil bath. The constant temperature set-points are set at 50°C , 100°C , 200°C , and 300°C , respectively. Each temperature setpoint was maintained for 4 hours. The measured temperatures are illustrated in Fig. 7. As shown in Fig. 7(a) and (b), the red curves, representing the measured temperature using the Fast-NLM algorithm at both near-end (300 m) and far-end (9.68 km), exhibit significantly reduced fluctuations compared to the blue curves corresponding to the WD method. At the near-end position (300 m), the Mean Square Error (MSE) values for the blue curves are 0.48°C , 0.51°C , 0.76°C , and 1.02°C , respectively while those for the red curves are 0.18°C , 0.24°C , 0.22°C , and 0.42°C , respectively. At the far-end position (9.68 km), the corresponding MSE values for blue curves are 0.76°C , 0.78°C , 0.76°C , and 1.08°C , respectively, with the red curve exhibiting values of 0.21°C , 0.28°C , 0.16°C , and 0.46°C , respectively. The corresponding long-term accuracy of temperature measurements is improved by a factor of over 2.5. As shown in Fig. 7(b) and (d), the temperature data processed by the Fast-NLM algorithm exhibit lower MSE and MD values at each test temperature point. These results demonstrate that under varying thermal conditions, the fast-NLM method outperforms the traditional approach in maintaining precision. Furthermore, the near-end (300 m) and far-end (9.68 km) results confirm that temperature measurement performance remains consistent across the entire fiber span—from short to long distances—even under low SNR conditions. And we have compared the temperature sensing measurement results obtained after algorithm processing with the Raman-DTS results reported in the existing literature, as shown in Table I. Compared to other algorithms, the integral image technology proposed in this paper enhances the real-time denoising Fast-NLM algorithm combined with the FIFO protocol. At long distances along the optical fiber, it demonstrates higher temperature accuracy and resolution while maintaining a fast response time. Additionally, the system's long-term stability is verified under both high and low temperature conditions.

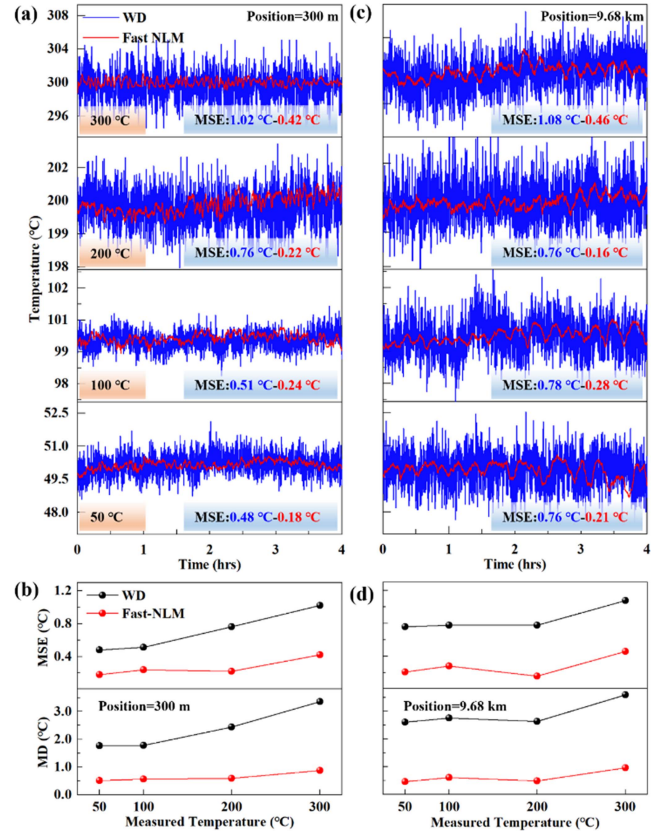


Fig. 7. The sensing performance before and after Fast-NLM denoising. (a), and (c) The measured temperatures at 300°C , 200°C , 100°C , and 50°C , respectively. With time span of 4 hours, at 300 m and 9.68 km of sensing fiber. (b), and (d) The MSE and MD variation versus the temperature ranging from 50°C to 300°C . WD: wavelet denoising; MD: Maximum Deviation; MSE: mean squared error.

IV. CONCLUSION

We have successfully demonstrated a novel Fast-NLM real-time denoising algorithm for Raman DTS without hardware modification to conventional R-OTDR systems. The proposed method achieves a 16-fold improvement in response rate over traditional NLM methodologies while maintaining an average temperature resolution below 0.01°C over 9.68 km. Compared with the WD algorithm, the temperature accuracy is improved from 1.59°C to 0.39°C at room temperature. Moreover, the temperature sensor demonstrates excellent linearity (with an R^2 value of 0.9999) against reference temperature and exhibits superior real-time performance during continuous temperature variations. Furthermore, the long-term accuracy of temperature

measurements is improved by a factor of over 2.5-fold versus MD method. In summary, the algorithm achieves both high temperature resolution and high-speed response under the condition of long distances and high temperatures, thus could be applied to various types of DOFS, including Raman, Rayleigh, and Brillouin scattering-based configurations, for dynamic monitoring in the realms of energy development, oil and gas exploration, and allied fields.

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