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Data Descriptor

Experimental Dataset for Fiber Optic Specklegram Sensing Under Thermal Conditions and Use in a Deep Learning Interrogation Scheme

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Abstract: This dataset comprises specklegram images acquired from a multimode optical fiber subjected to varying thermal conditions. Designed for training neural networks focused on developing Fiber Optic Specklegram Sensors (FSSs), these experimental data enable the detection of changes in speckle patterns corresponding to applied temperature variations. The dataset includes 24,528 images captured over a temperature range from 25 °C to 200 °C, with incremental steps of approximately 0.175 °C. Key acquisition parameters include a wavelength of 633 nm, a sensing zone length of 20 mm, and a multimode fiber with a core diameter of 62.5 µm. This dataset supports developing and validating temperature-sensing models using fiber optic technology and can facilitate benchmarking against other experimental or synthetic datasets. Finally, an implementation is presented for utilizing the dataset in a deep learning interrogation scheme.

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Dataset License: CC-BY-SA

Keywords: optical sensors; specklegram; fiber optic sensing; deep learning; temperature measurement

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1. Summary

The speckle pattern, or specklegram, observed at the output of a multimode optical fiber arises from the interference between multiple modes propagating through the fiber. The spatial characteristics of this specklegram are highly sensitive to external perturbations applied to the fiber, making them a rich source of information for sensing applications [1–5]. This sensitivity forms the basis of Fiber Specklegram Sensors (FSSs), where the relationship between external disturbances and specklegram changes is exploited for detection and measurement [6–8]. Over the years, various analytical techniques have been employed to interpret specklegram data in optical fiber sensing systems. Traditional approaches, such as cross-correlation, have been used for spatial analysis of speckle patterns [9,10]. More recently, the integration of machine learning techniques has enabled advanced feature extraction, leading to more precise interpretation of disturbances [3,11–14]. These advancements have significantly broadened the scope and capabilities of FSS technology.

Research in FSS has involved both simulated and experimental datasets. Simulated data enable researchers to explore a wide range of parameters in a controlled environment, though the computational cost can be a limiting factor for complex scenarios [15,16]. Conversely, experimental data provide real-world validation but require considerable time, resources, and manual effort for acquisition, particularly when performed without automation [12–14,17,18]. Given the importance of large datasets for training machine learning models, recent efforts have focused on automating the data collection process. Automated systems reduce workload and facilitate the generation of high-quality datasets, which are critical for advancing the performance of machine learning algorithms in FSS applications [19,20].

However, there is still a lack of systematic, publicly available and sufficiently large datasets for temperature sensing applications using FSSs, which hinders further advancements in machine learning-based sensor development. To address this gap, we present a Specklegram Temperature Dataset to support the development of Fiber Optic Specklegram Sensors (FSSs), specifically for temperature applications using optical fiber technology. Although widely studied, temperature sensing is crucial in industrial, biomedical, or environmental contexts where traditional electrical sensors cannot be used (e.g., harsh environments, EMI-sensitive areas, etc.). This dataset includes experimental specklegram images acquired using a custom-built automated acquisition system. The dataset serves as a benchmark for developing deep learning models that predict temperature values based on speckle patterns. Applications of this dataset extend to enhancing the metrological characteristics of fiber optic sensors and validating experimental data against synthetic datasets [15].

The images were captured during controlled heating and cooling cycles, ensuring comprehensive thermal characterization. Heating was applied along the length of the sensing zone, which is the part of the MMF directly affected by the thermal disturbance and has been shown to influence the sensitivity of the sensor [21]. The availability of the dataset in .tiff format and its detailed labeling make it accessible for researchers in optics and data science.

The remainder of this paper is organized as follows: Section 2 describes the dataset structure, acquisition parameters and image details. Section 3 presents the method for image generation. Finally, Section 4 discusses the use of the reported dataset in a deep learning interrogation scheme.

2. Data Description

2.1. Dataset Overview

- Total Datasets: 14
- Images per Dataset: 1752
- Total Images: 24,528
- Image Format: .tiff

2.2. Acquisition Parameters

- Wavelength: 633 nm
- Temperature Range: 25 °C to 200 °C
- Incremental Temperature Step: ~0.175 °C
- Length of Sensing Zone: 2 cm
- Fiber Refractive-Index Profile: Step-index
- Fiber Core Diameter: 62.5 µm
- Fiber Cladding Diameter: 125 µm
- Fiber Numerical Aperture (NA): 0.14

2.3. Image Details

The specklegram images exhibit distinct patterns influenced by the temperature changes within the sensing zone. Some dataset images are presented in Figure 1.

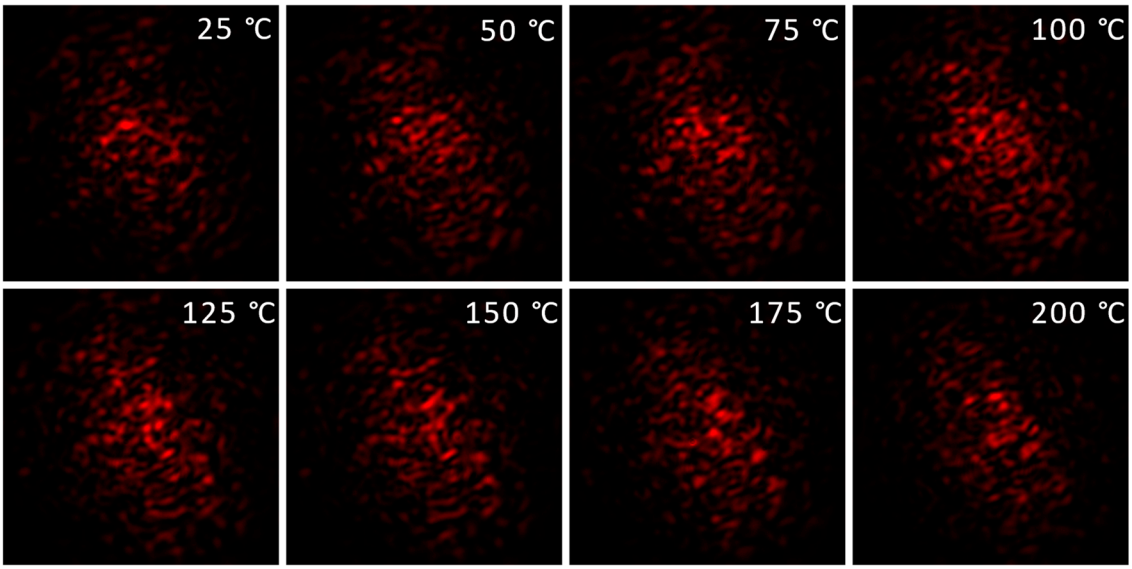


Figure 1. Examples of specklegram images from the dataset.

Each image is labeled according to its acquisition conditions, with filenames encoding details such as the temperature and whether the data were collected during heating ("up") or cooling ("dw"). The convention used is presented in Figure 2.

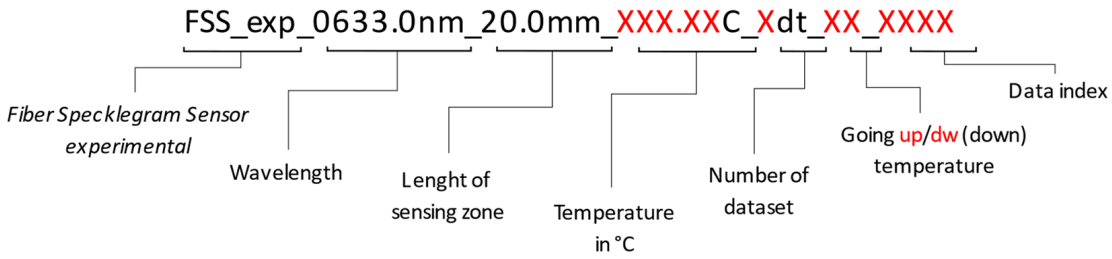


Figure 2. Dataset image file naming convention. The letters in red (Temperature, Going up/dw and Data index) represent the only variable elements in the filename structure.

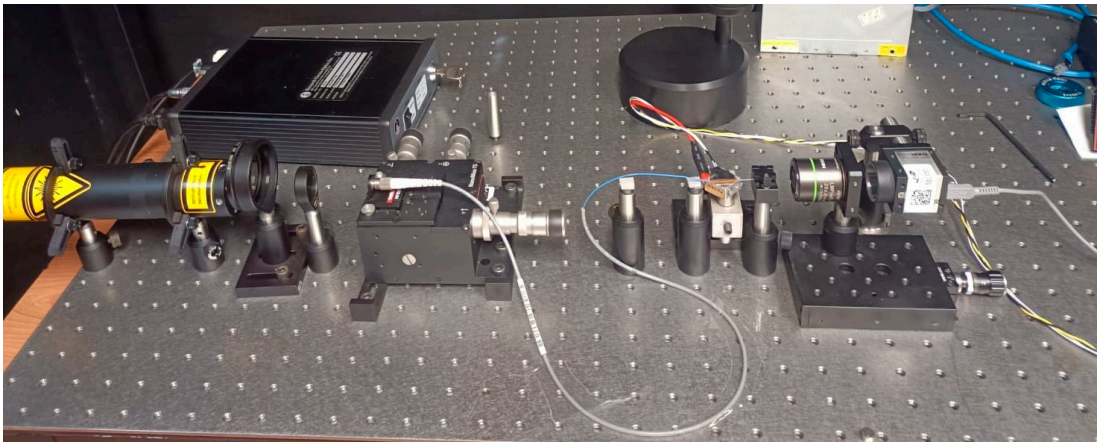
3. Methods

The dataset was generated using an automated system that consists of a multimode optical fiber and a temperature-controlled heating system with PID (Proportional–Integral–Derivative) control. This system regulates the temperature along a section of the optical fiber, ranging from 25 °C to 200 °C. The total length of the multimode optical fiber used in our experimental setup is 70 cm. It is essential for automating the acquisition of experimental specklegrams and allows for perturbation over the length of the sensing zone, which in this case is 2 cm, positioned 5 cm from the distal end of the fiber. A helium–neon (HeNe) laser at 633 nm with a power of less than 2.5 mW and a spectral bandwidth of 2 pm was used as the light source for the setup.

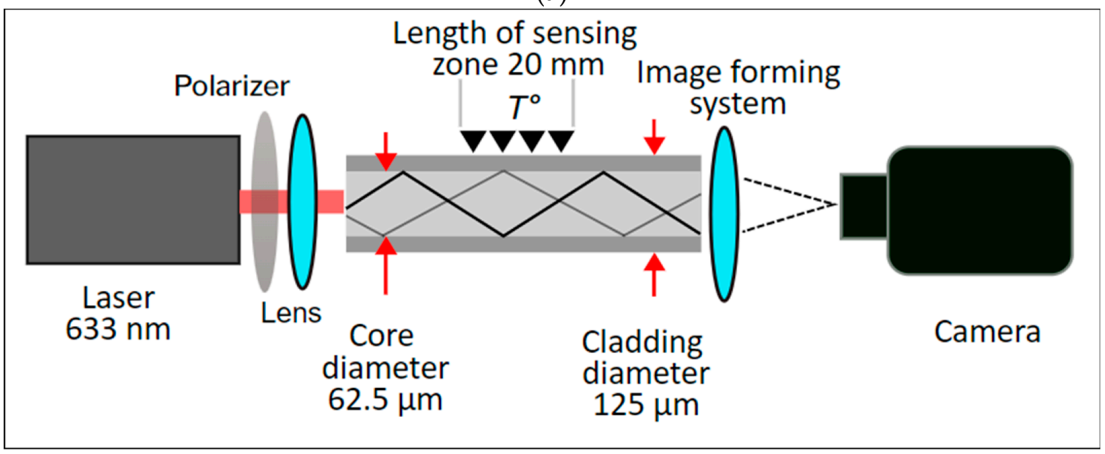
The system includes the following: (1) an aluminum block for different perturbation lengths; (2) an NTC 100 K thermistor for temperature sensing; (3) a 12 V 40 W heating tube; (4) an Arduino Mega 2560; (5) a 12 V power supply; (6) a RAMPS 1.4 power control board; and (7) structural components for assembly and a high-resolution camera (CCD

camera with 1280 × 1024 pixel resolution). The RGB camera used in this study features an 8-bit depth per channel. The exposure time was set to approximately 50 ms, optimized to maximize the dynamic range of around 48 dB while avoiding pixel saturation. Noise levels in the acquired images were found to be non-significant, and ongoing computational validation, including data augmentation with random noise addition, confirms the robustness of the results.

The aluminum block serves as the primary interface for heating the MMF, with copper tape securing the fiber in direct contact. This ensures efficient thermal transfer and uniform perturbation of the speckle-generating region. The optical fiber was exposed to incremental temperature changes, and specklegram images were captured at each step. After each heating cycle, images were also captured during the cooling phase by deactivating the heat source [20]. An image of the complete lab arrangement is shown in Figure 3a, while a simplified schematic of the fiber illumination and detection principle is provided in Figure 3b.



(**a**)



(**b**)

Figure 3. (**a**) Photograph of the experimental setup, including the laser source (**left**), the heating zone (**center**), and the camera module (**right**). (**b**) Schematic of the Fiber Specklegram Sensor (FSS). Black arrows indicate the thermal perturbation region, red arrows delimit core and cladding diameters.

In Figure 3a, the optical components used to condition the laser light include a 633 nm helium–neon laser, a polarizer to ensure linear polarization, and a lens for focusing or collimating the light into the optical fiber during free-space propagation. The optical connector used is an FC/PC connector, and the optical fiber is a multimode fiber with a 62.5 µm core diameter, 125 µm cladding diameter, and a 2 cm sensing zone length. In Figure 3b, the lens used in the image-forming system is a 20× Olympus microscope

objective, which typically has a focal length of approximately 9–10 mm. This objective lens is responsible for forming the speckle pattern image captured by the camera.

The optical fiber was exposed to incremental temperature changes, and specklegram images were captured at each step. The experimental setup ensures repeatability and minimizes noise, providing high-quality images for deep learning training. Key steps include the following:

1. Preparation
   - The MMF is fed by a 633 nm laser source and mounted so that the sensing zone is in good thermal contact with the heating block.
   - The fiber output is imaged through an Olympus 20× objective onto the CCD camera, which is aligned using XYZ translation stages to capture the speckle pattern consistently.
2. Temperature Control
   - A PID loop running on the Arduino Mega 2560 drives the 12 V/40 W heater.
   - The NTC thermistor provides real-time temperature feedback, ensuring stable and precise increments from 25 °C up to 200 °C.
   - After reaching each setpoint, the system holds the temperature to allow the fiber to equilibrate before an image is taken.
3. Image Acquisition
   - For each temperature setpoint, specklegram images are recorded using the high-resolution camera at 1280 × 1024 pixels.
   - This process is repeated stepwise from the lowest to the highest temperature.
   - Once the heating cycle is complete, the heat source is turned off, and cooling-phase specklegrams are also captured as the fiber returns to ambient temperature [20].

Data curation involved validating image quality; valid images were labeled with metadata (e.g., temperature setpoint, heating or cooling phase) and systematically stored in .tiff format for ease of use in computer vision pipelines. This structure labeling ensures repeatability and maximizes usability for subsequent deep learning experiments or comparative studies.

4. Use of Dataset in a Deep Learning Interrogation Scheme

The curated dataset was utilized in a deep learning workflow aimed at temperature estimation from Fiber Speckle Sensor (FSS) images. A Convolutional Neural Network architecture was employed to extract robust features from the speckle patterns and then map those features directly to temperature values via regression. A customized MobileNet architecture, referred to here as MNet-reg, was adapted for regression tasks. MobileNet is a lightweight and efficient architecture recognized in computer vision that uses depthwise separable convolutions to reduce computational requirements, making it ideal for mobile device implementation without compromising performance in tasks such as classification or detection [22]. To tailor this network for temperature regression, some modifications were incorporated:

1. A GlobalAveragePooling2D layer to reduce overfitting and dimensionality.
2. Three Dense layers with 1024 neurons each for high-capacity feature learning.
3. A dropout layer (50% rate) for regularization and improved generalization.
4. A final single-neuron output layer to produce the scalar temperature estimate.

The model evaluation with the dataset was performed by comparing the actual temperature curves against the estimated temperature in the experimental range from 25 °C to 200 °C used during training.

The neural network was trained using Dataset 1, which comprised 1752 specklegram pattern images captured across a temperature range of 25 °C to 200 °C, with temperature increments of approximately 0.175 °C. The data were partitioned following standard machine learning practices, with 80% allocated for training and the remaining 20% equally split between validation and testing sets to ensure comprehensive model evaluation. The implementation was carried out in Python 3.9.16, leveraging the Keras 2.11.0 framework with TensorFlow 2.11.0 backend. Training parameters were optimized through experimentation, utilizing a learning rate of 8×10^{-5} over 300 epochs, while implementing a 50% dropout rate to prevent overfitting and enhance model generalization.

After training, temperature predictions were compared against ground-truth measurements in the 25 °C to 200 °C range. As shown in Figure 4, the estimated temperature values align closely with the actual temperature. Additionally, the Root Mean Square Error (RMSE) was found to be 0.94 °C. These results demonstrate robust model behavior across the entire temperature spectrum, thus indicating the potential of CNN-based architectures for high-accuracy temperature interrogation in FSS applications.

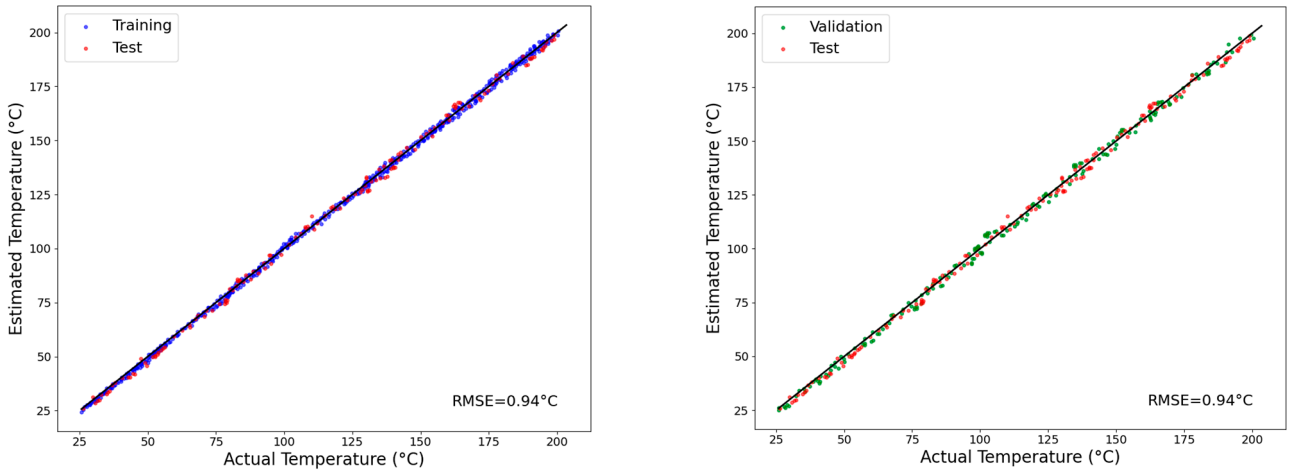


Figure 4. Actual vs. estimated temperature across the 25–200 °C range for (**a**) test and training, and (**b**) test and validation. The RMSE is 0.94 °C.

5. User Notes

Dataset Access: the dataset is publicly available under a CC-BY license, allowing use and modification with proper attribution.

Potential Applications: The dataset supports a range of applications, including the development and validation of deep learning models for temperature sensing, comparative analysis between experimental and synthetic specklegram data, optimization of fiber optic sensing systems, and advancement of intelligent sensing technologies. It serves as a benchmark resource for evaluating novel machine learning approaches and validating computational models in optical fiber sensing. Additionally, it can aid in the study of multimode fiber behavior under thermal variations, improving the understanding of mode interference dynamics and enhancing the design of new sensing architectures.

Limitations: This dataset is tailored to the specified acquisition parameters, which may limit its direct applicability to different experimental configurations. Adaptations may be required to ensure compatibility with alternative sensing applications or optical

setups. Users should consider variations in fiber type, laser wavelength, and environmental conditions when applying the dataset to different experimental scenarios.

Future Work: Future research will focus on hybrid modeling approaches that integrate both synthetic and experimental datasets. This methodology aims to enhance model generalization by leveraging the controlled conditions of synthetic data while incorporating the complexity of real-world experimental measurements. Additionally, expanding the dataset to include new sensing parameters, such as fiber deformation and curvature, will further extend the applicability of Fiber Optic Specklegram Sensors (FSSs) beyond temperature monitoring. These advancements will contribute to the development of more robust and versatile deep learning models for fiber optic sensing applications.

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Conflicts of Interest: The authors declare no conflicts of interest related to this work.

Abbreviations

The following abbreviations are used in this manuscript:

FSSs	Fiber Optic Specklegram Sensors
PID	Proportional–Integral–Derivative
CCD	Charge Coupled Device
MMF	Multi-Mode Fiber
CNNs	Convolutional Neural Networks

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