Temperature sensor based on modal distribution in LPFGs: A Deep Learning Approach

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1. Introduction

Fiber optic sensors have revolutionized temperature measurement with advantages like electromagnetic immunity, small size, and multiplexing. Among various sensor designs, Long Period Fiber Gratings (LPFGs) stand out for their simplicity, cost-effectiveness, and ability to monitor multiple parameters. LPFGs couple core and cladding modes at specific wavelengths, creating resonances sensitive to changes in temperature or strain.

Traditional LPFG sensor analysis relies on shifts in resonance wavelength or power, but these methods can lack sensitivity and require complex setups. Recent advancements in imaging and deep learning offer new approaches for sensor interrogation. By capturing the modal distribution in LPFGs and applying convolutional neural networks (CNNs), it's possible to accurately predict temperature changes.

This study introduces a novel LPFG-based temperature sensor using deep learning for precise real-time monitoring. A CNN trained on near-field images of the LP_{11} mode, which is highly temperature-sensitive, achieves accurate predictions. This method provides a fast and reliable solution for applications in industrial, biomedical, and environmental monitoring.

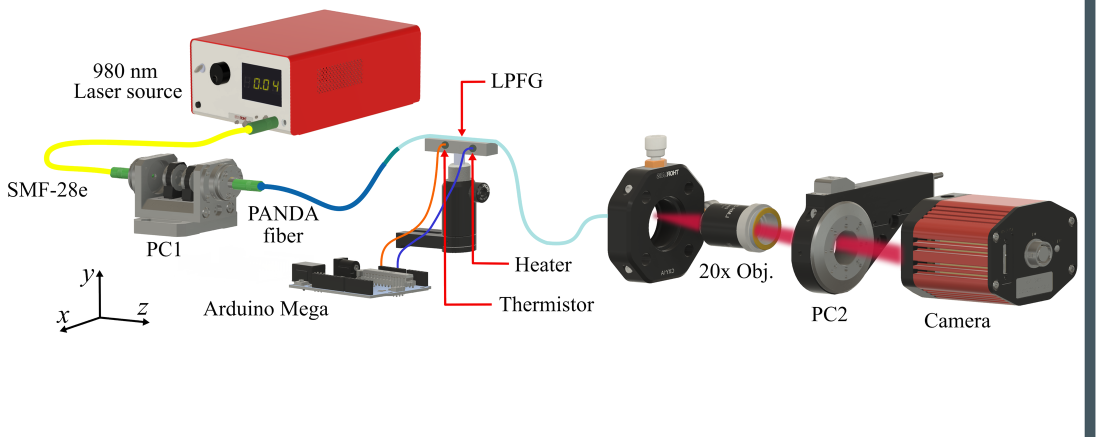

Fig 1. Schematic of the experimental setup

2. Operating Principle

The design of LPFGs relies on periodic refractive index perturbations to enable energy transfer between modes. The Coupled Mode Theory (CMT) is used to model this interaction, describing how optical power transfers between the LP_{01} and LP_{11} modes. The electric field amplitudes for these modes are **[1]**:

$$\mathbf{E}_{01}(x,y,z) = a_{01}(z)\tilde{\mathbf{E}}_{01}(x,y)e^{-i\beta_{01}z}$$
$$\mathbf{E}_{11}(x,y,z) = a_{11}(z)\tilde{\mathbf{E}}_{11}(x,y)e^{-i\beta_{11}z}$$

Where β_{01} and β_{11} are the propagation constants. Energy transfer occurs when the phase matching condition is met: $\beta_{01} - \beta_{11} + \frac{2\pi}{\Lambda} = 0$. This can be rewritten as:

$$\Lambda = \frac{\lambda_{\text{res}}}{n_{\text{eff},01} - n_{\text{eff},11}},$$

where λ_{res} is the resonance wavelength. Temperature changes affect the refractive index, altering the coupling coefficients and shifting the resonance wavelength.

3. Experimental Setup

The LPFG was inscribed using a CO_2 laser system (Iradion, model 155), with a grating period (Λ) of approximately 450 µm for LP_{01} and LP_{11} modes at 980 nm, inscribing fifty periods per cycle via a PC interface. *Fig. 1* shows the experimental setup for capturing modal images at different temperatures. A 980 nm laser (FP-B-980-150, Optilab) was paired with a linear polarizer (PC1) to ensure 0° polarization. The light traveled through a 0.2 m PANDA fiber and was spliced to the LPFG in a single-mode optical fiber (SMF-28, Corning). A 20x objective lens collected the transmitted light, while an adjustable analyzer (PC2) assessed polarization effects. Modal intensity distributions were recorded with a WiDy SWIR 640v camera. Temperature changes were induced using a ceramic heater in a controlled environment (24 °C, 65 % humidity), monitored by an Arduino-based system to ensure thermal uniformity along the LPFG.

5. Results and Discussion

Fig. 2 shows LP_{11} mode images captured at various temperatures, illustrating intensity distribution changes due to temperature variations. The MobileNet model's performance for temperature regression was assessed using Mean Squared Error (MSE).*Fig. 3* presents the optimization history via Optuna, highlighting optimal hyperparameters: initial learning rate of 0.00228, decay rate of 0.8559, and decay steps of 6480.

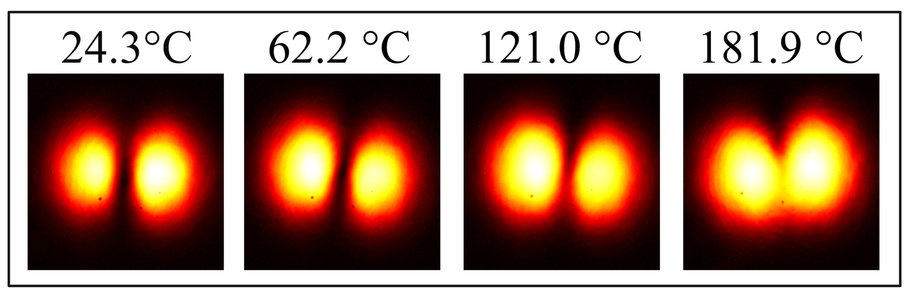

Fig 3. Intensity patterns of the LP_{11} mode captured at different temperature conditions.

Fig. 4 compares actual (x-axis) and predicted (y-axis) temperature values, with most points near the line $y = x$, indicating accurate predictions and strong generalization. Training and validation losses converge with minimal overfitting.

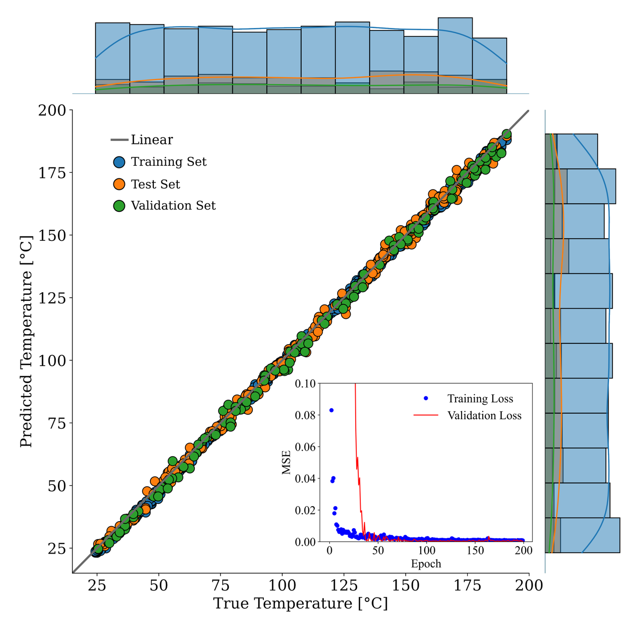

Fig 4. Scatter plot of actual vs. predicted temperatures, showing model accuracy.

- Prediction accuracy: 98.5 % - Maximum error: 3.77 °C - RMSE: 0.94 °C (24 to 190 °C range) - Inference time: 0.055 seconds for 32 images

These findings confirm the effectiveness of the machine learning approach for precise and efficient temperature predictions.

4. Model Training

The CNN model used is based on the MobileNet architecture for image classification. Our dataset consists of 16-bit grayscale images (640×512 pixels), which were converted to RGB by replicating grayscale values and cropped to 224×224 pixels.

Data augmentation techniques, such as contrast adjustment and Gaussian noise, increased dataset diversity. The final dataset contained 1200 images, split into 70 % for training, 20 % for validation, and 10 % for testing.

The MobileNet architecture was adapted from classification to regression for temperature prediction. We used transfer learning with pre-trained weights from ImageNet, replacing the classification layer with three fully connected layers (1024 neurons, ReLU activations) and a dropout layer (0.1 rate). The model, implemented in Python with Keras and TensorFlow, also featured hyperparameter optimization using the Optuna library and a learning rate scheduler with exponential decay for efficient convergence.

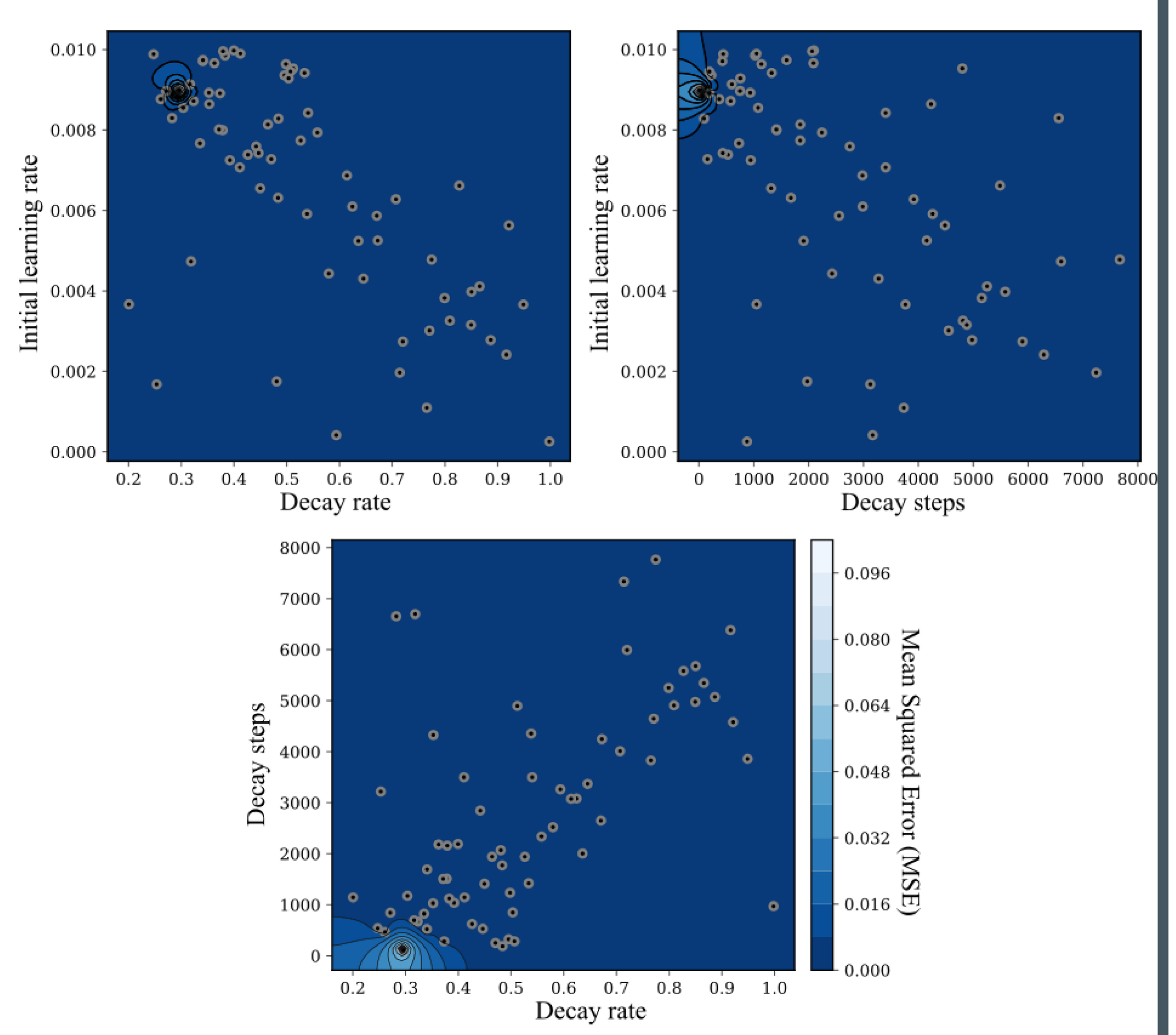

Fig 2.Scatter plots of the optimization history showing the variations in MSE across 100 trials using different hyperparameter configurations.

6. Conclusions

This study developed a temperature sensor using Long Period Fiber Gratings (LPFG) and deep learning. By training a MobileNet-based CNN on LP_{11} mode images, we achieved a prediction accuracy of 98.5 % and an RMSE of 0.94°C.Results indicate strong predictive capabilities, with data clustering along the diagonal and low histogram dispersion. The model's fast inference time of 0.055 seconds for 32 images makes it suitable for real-time applications. This work demonstrates the effectiveness of integrating LPFG sensors with machine learning for

References

[1] Soto-Perdomo, J.; Reyes-Vera, E.; Montoya-Cardona, J.; Torres, P. Experimental Dataset of Tunable Mode Converter Based on Long-Period Fiber Gratings Written in Few-Mode Fiber: Impacts of Thermal, Wavelength, and Polarization Variations. Data 2024, 9, 10.