Comparative performance evaluation of classical methods and a deep learning approach for temperature prediction in fiber optic specklegram sensors

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Abstract

In this study, an algorithm based on convolutional neural networks is employed as an interrogation method for a fiber specklegram sensor. This algorithm is compared with conventional interrogation methods, including correlation between images, measurement of optical power, and radial moments. Fiber specklegram sensors have room for improvement as conventional methods only consider a single characteristic of the specklegram for variable prediction, thus failing to leverage the full spectrum of information within the specklegram. Consequently, the approach put forth here introduces a convolutional neural network for the extraction of specklegram features, accompanied by an artificial neural network for variable regression. The specklegrams used in this investigation are obtained through simulating temperature disturbances in a multimode fiber using the Finite Elements Method. The results reveal prediction RMSE errors ranging from 10.26°C for the first radial moment to 1.42°C for the proposed algorithm. These findings underscore the effectiveness of the proposed strategy in enhancing sensor performance and robustness, all while upholding their cost-efficiency.

Keywords: fiber specklegram sensors; finite element method; interrogation methods; deep learning; convolutional neural network.

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Introduction

Fiber Specklegram Sensors (FSSs) use the optical phenomenon known as modal interference for their operation. Interference or modal noise is a phenomenon that occurs at the output of a multimode optical fiber (MMF) due to the propagation of different light modes that interfere with each other constructively or destructively [1]. In the field of telecommunications, this interference is an undesired effect; however, from the metrological point of view, the speckle pattern generated by the interference contains essential information on the state of the fiber, i.e., on some disturbances that influence it. Thus, the resulting specklegram of a MMF can be used as the main measurement tool in FSS [2]. Measurement with FSS has been evaluated in variables such as mechanical stresses [3, 4], bending [5], pressure [6], temperatures [6 – 9], among others [1, 10 – 13]. This is possible because the change of these variables affects the specklegram distribution. In this context, the challenge has been implementing mathematical tools to establish a relationship between the specklegram and the magnitude of the disturbance incident on the fiber.

Some of the main interrogation methods that have been used to solve this task in FSSs are: correlation between images [2, 6, 7, 14, 15], optical power measurement [2, 8, 16], and radial moments [2, 17]. The correlation between images seeks to compare a reference specklegram with the specklegrams resulting from the application of a disturbance on the MMF. In this type of approach, it has been proven that the correct selection of a part of the specklegram and its size, which is known as region of interest (ROI), has a great influence on the performance of the sensor [6, 14, 18]. In the case of optical power measurement, the aim is to know the total power of an area within the speckle pattern, where this power serves to characterize the sensor in a certain dynamic range, so that each power value corresponds to a disturbance value [16]. On the other hand, the radial moments calculation on the specklegram involves analyzing certain mathematical moments of the speckle pattern, and it is considered an alternative technique that can sometimes yield better results than the correlation-based method [2]. It is recommended to use the latter when the linearity and precision characteristics are more important than the hysteresis characteristic.

In general, the above methods have yielded favorable outcomes. However, due to technological and industrial progress, it is necessary to have systems with enhanced accuracy. In addition, these methods reduce all the information given by the specklegram to a characteristic represented as a single scalar coefficient, which is subsequently employed to predict the perturbing variable. Furthermore, to optimize the sensor performance when employing these techniques, it becomes imperative to meticulously select a ROI wherein the descriptor exhibits a linear behavior within the desired range. In this way, a substantial portion of the valuable information provided by the speckle pattern remains untapped. Taking this into account, deep learning techniques have showcased promising results across various engineering and physics applications [21]. These techniques have found practical application in the realm of fiber sensors [19, 20].

In this work, a deep learning architecture is trained to compare its performance with the conventional methods used for the interrogation of FSSs. The specklegrams used in this proposal are obtained by simulating temperature disturbances in a multimode fiber using the Finite Element Method. The architecture relies on convolutional neural networks (CNNs), which allows us to treat it as a regression problem instead of a classification problem. This is particularly advantageous given the continuous nature of the variable we are measuring, which, in this study, corresponds to temperature values. This approach facilitates its comparison with other continuous metrics, such as Images Correlation, Optical Power Measurement, and Radial Moments.

1. Specklegrams generation

The specklegrams are obtained by computational simulation using the finite element method (FEM), through the COMSOL Multiphysics and MATLAB software, where the vector wave equation (1) is solved numerically for each propagation mode of the MMF under study [7, 16].

$$\nabla \times \nabla \times \vec{\mathrm{E}} - k_0^2 n^2 \vec{\mathrm{E}} = 0, \tag{1}$$

where $\vec{\mathrm{E}}$ is the electric field of each mode, k_0 is the wavenumber in vacuum, and n is the refractive index of the MMF. Furthermore, the refractive index can be recalculated with equation (2) when the MMF is subjected to a thermal change.

$$n \approx n_0 + C_{TO}\left(T - T_0\right). \tag{2}$$

Here, n_0 represents the refractive index at the initial temperature T_0, determined using the Sellmeier equation or included directly from the data in relation to the working wavelength and C_{TO} stands for the thermo-optic coefficient of the fiber material. Then, as described above, the vector field of each of the modes supported by the thermally perturbed MMF is obtained, together with their respective propagation constants. Finally, all the fields of the calculated modes are added vectorially throughout the spatial domain of analysis to find the intensity of the resulting field and obtain the speckle pattern. More details of thermo-optical simulation and specklegram generation can be found in [7, 16].

For the generation of the specklegram dataset used in this work, the optical and FEM parameters considered are presented in Tab. 1. The optical parameters despite inducing a relatively small number of excited modes within the fiber (around 270) are sufficient to evaluate the characteristics of a sensing scheme [7] and to make a comparison with the alternative deep learning prediction. In addition, the dataset is simulated from 0°C to 120°C with steps of 0.2°C, finally obtaining a total of 601 specklegrams with a size of 126 × 126 pixels each. Another critical parameter to consider in the simulations is the length of the part of the MMF that is exposed to the thermal disturbance, which is called the sensing area length [7, 16]. In our simulations this length is set at 2.5 mm, based on previous research conducted by the authors, showing that a length equal to or above this value ensures a practical sensing implementation with adequate sensitivity and a sufficient dynamic range for a similar speckle density [7]. However, it is important to note that this value can be adjusted to optimize specific sensing properties. Simulated specklegrams for the optical fiber under consideration at two different temperatures are presented in Fig. 1.

Tab. 1. Parameters used in the FEM Model to generate the specklegrams

Mesh size	Min. 0.44 µm	Max. 1.88 µm
Boundary condition	Absorbing boundaries	
Material	Fused silica doped with P2O5 (phosphorus pentoxide)	
Refractive index (without temperature disturbances)	Core	1.4447
	Cladding	1.4279
Thermo-optical coefficient	Core	-10×10^{-6}
	Cladding	10.5×10^{-6}
Numerical aperture	0.22	
Diameter	Core	50 µm
	Cladding	125 µm
Wavelength		1490 nm
Length of the sensing zone		2.5 mm

2. Conventional interrogation methods

2.1. Images correlation

Speckle image correlation is carried out through computational image analysis [6, 15, 18], with the goal of characterizing an FSS by computing a correlation coefficient between the specklegrams containing thermal disturbances and a reference specklegram (typically, the initial temperature condition serves as the reference). In this technique, the correlation coefficient is given by:

$$C = \frac{\sum_i \sum_j \left(\left(I_{ref}(i,j) - I_{ref} \right) \cdot \left(I_n(i,j) - I_n \right) \right)}{\sqrt{\left(\sum_i \sum_j \left(I_{ref}(i,j) - I_{ref} \right)^2 \right) \left(\sum_i \sum_j \left(I_n(i,j) - I_n \right)^2 \right)}}. \tag{3}$$

where $I_{ref}(i,j)$ and $I_n(i,j)$ are the point intensity values in the reference state and in the perturbed state, respectively. $\langle I_{ref} \rangle$ and $\langle I_n \rangle$ are the intensity averages in the reference and perturbed specklegrams, respectively.

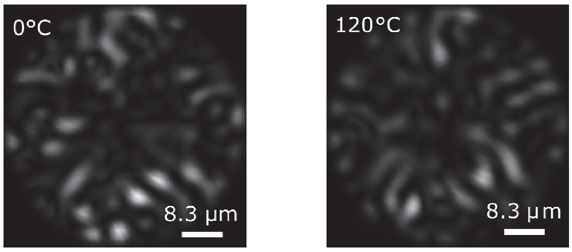

Fig. 1. Simulated fiber optic specklegrams at two different temperatures

2.2. Optical Power Measurement

This method involves capturing optical power at the output of the MMF. Equation (4) expresses this power as a function of the intensity I and of the area A of a selected Region of Interest (ROI) over the speckle pattern. Equation (5) represents the discrete form of equation (4) after applying the fields of the specklegram calculated by FEM from section 2 on the ROI [7, 16].

$$P = \int_A I dA, \tag{4}$$

$$P \approx \sum P_e = \frac{1}{2} c \varepsilon_0 n_{0\text{core}} \Sigma \left| \vec{E}_e \right|^2 A_e, \tag{5}$$

where P is the total power, c the speed of light, ε_0 the vacuum permittivity, $n_{0\text{core}}$ the refractive index of the core, $\vec{E}_e$ the specklegram field in each element, and A_e the area of each element that is integrated in the ROI. These equations are applied to determine the optical power of each simulated specklegram and to characterize the FSS using this approach.

It has been demonstrated that optimizing the size and placement of the Region of Interest (ROI) analyzed within the specklegram can enhance the performance of this technique. This approach enables the quantification of intensity variations without interference from other areas of the image [7, 14, 16, 18].

2.3. Radial Moments

As noted above, this alternative is used in the design of an FSS where the accuracy and linearity characteristics are more important than the hysteresis characteristic [2]. Then, the radial moment of order p is computed with equation (6), where μ_x and μ_y describe the position of the center of mass of the intensity distribution, as defined in equations (7) and (8), respectively.

$$\mu_p = \frac{\sum_{x,y} \left[\left(x - \mu_x \right)^2 + \left(y - \mu_y \right)^2 \right]^{p/2} I\left(x, y\right)}{\sum_{x,y} I\left(x, y\right)}, \tag{6}$$

$$\mu_x = \frac{\sum_{x,y} x I\left(x, y\right)}{\sum_{x,y} I\left(x, y\right)}, \tag{7}$$

$$\mu_y = \frac{\sum_{x,y} y I\left(x, y\right)}{\sum_{x,y} I\left(x, y\right)}, \tag{8}$$

where $I(x, y)$ represents the intensity value at pixel (x, y). Usually, the first and second-order radial moments are used. In this way, the first and second radial moments are found to characterize the FSS with the simulated dataset.

3. Deep learning architecture: CNN-ANN regression

In search of an interrogation method that better represents the temperature-specklegram relationship, a deep learning architecture based on CNNs and ANNs is created, as shown in Fig. 2. This architecture uses the block structure of a VGG (Visual Geometry Group) [20]: conv-RELU → conv-RELU → MaxPooling blocks. Here, the CNN operates as a feature extractor. Each convolution layer had the RELU (Rectified Linear Unit) activation function as output.

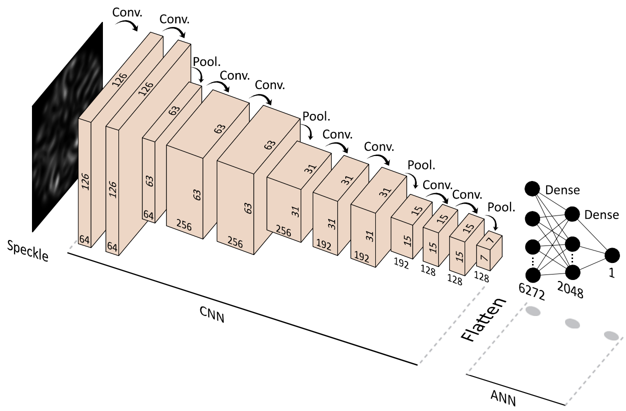

Fig. 2. Proposed CNN-ANN based deep learning architecture for temperature regression in an FSS

In total, 4 conv-RELU → conv-RELU → MaxPooling blocks are used, where the advance in depth reduces the amount of data and separates the most important features. Afterward, an ANN is connected to the CNN, through the flatten operation (converts a matrix into a one-dimensional vector), to perform a regression and predict the temperature values. Note that the variable temperature is continuous in nature, therefore, a regression model is more appropriate than a classification model for the prediction of a scalar value.

On the other hand, to train the model, a dataset of 601 images is labeled according to the corresponding temperature of each image and is divided into two data subsets: training and test, with 481 and 120 specklegrams each subset, respectively. The test data is separated and only used in the final prediction, and never in the training stage. Subsequently, a validation data subset is separated from the training subset, which corresponded to 20 % of the training data (96 specklegrams). The selection of the specklegrams for each subset above is done randomly. The model is trained with a learning rate of 8×10^{-5} and 300 epochs in the Python programming language with the Keras and TensorFlow libraries [21, 22]. Finally, in the hidden layer of the ANN, a dropout of 50 % is added to avoid overfitting.

4. Results

Fig. 3 shows the behavior of the conventional interrogation methods over the entire temperature range of the generated dataset. The linear trend of each method with respect to temperature can be observed in panels (*a*), (*c*), and (*d*), except for the optical power measurement method, panel (*b*). Since this method did not retain monotonic behavior throughout the full range of analysis, it is not included in the final comparison. Generally, in these cases, the dynamic range of the sensor should be limited to oneof the linear behavior zones. On the other hand, Fig. 4 displays the prediction of the regression neural network alongside the actual temperature of the test data.

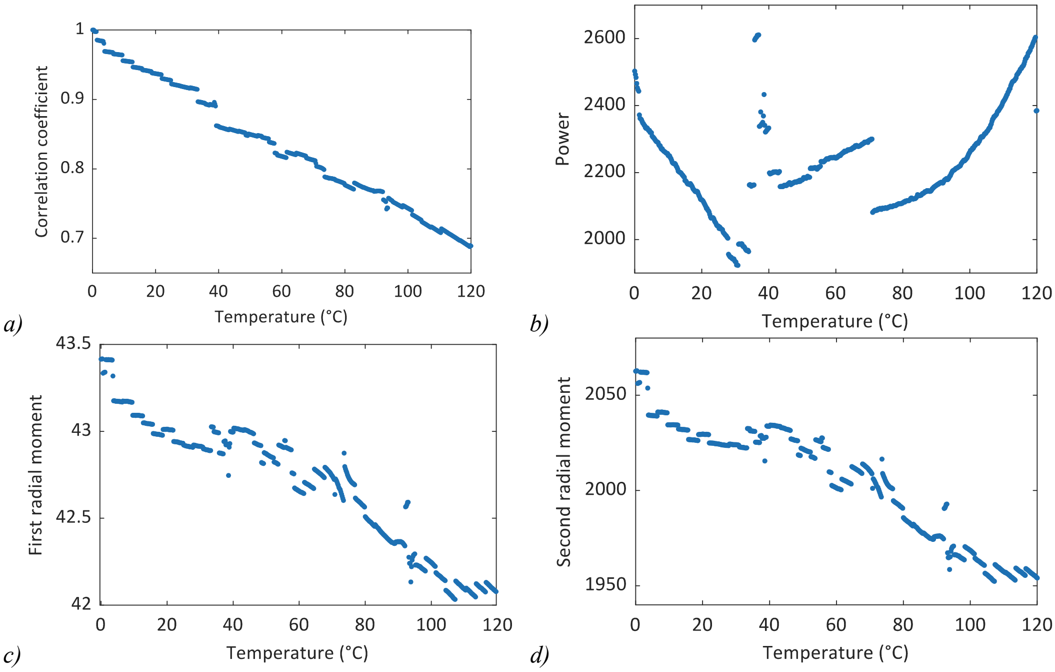

Fig. 3. Characterization of the FSS by the interrogation method: a) correlation between images, b) optical power measurement, c) first radial moment, d) second radial moment

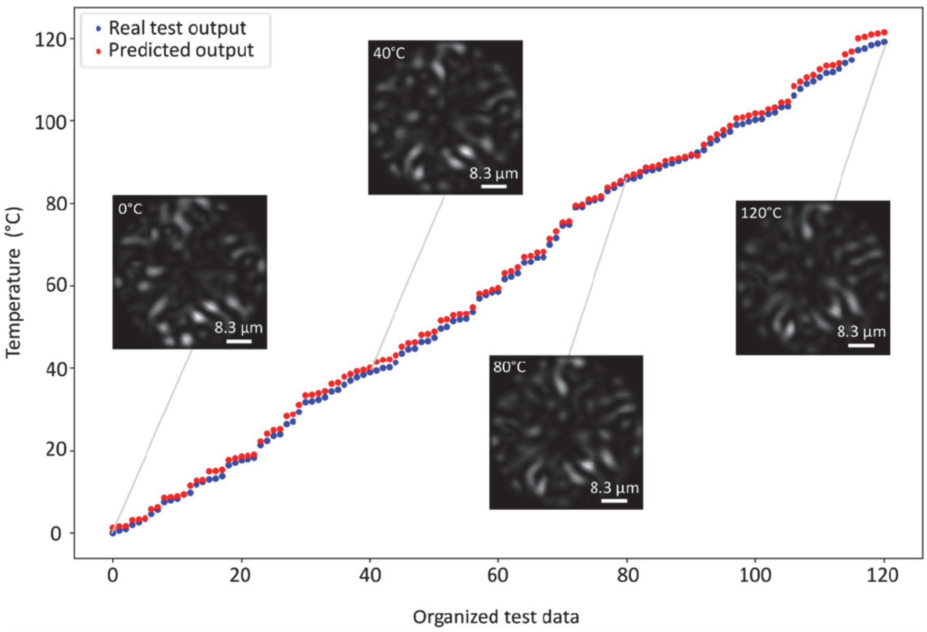

Fig. 4. Prediction of the test data with the regression algorithm with the CNN

To characterize, evaluate and compare the performance of each of the techniques discussed in this work, the root mean square error (RMSE, which penalizes outliers more drastically than the MAE), the mean absolute error (MAE), the maximum error (MAXE) and the R^2 score [23] are found for each of them, and shown in Tab. 2. It can also be observed that the performance of the proposed regression network based on CNN-ANN is better than that of conventional methods in each of the metrics used.

Tab. 2. Performance comparison of the interrogation methods

Method	RMSE (°C)	MAE (°C)	MAXE (°C)	R^2 score
First radial moment	10.26	8.81	31.74	0.920
Second radial moment	10.97	9.62	28.21	0.909
Correlation coefficient	3.21	2.45	9.08	0.992
CNN-ANN regression	1.42	1.31	2.85	0.998

The proposed CNN-based method outperforms conventional approaches in characterizing FSSs due to its ability to consider a broader spectrum of information within the specklegrams. While conventional methods could yield favorable results (3.21°C in RMSE for the correlation coefficient method), they share a common limitation: their inherent processing condenses the complete information embedded in the specklegram into a single scalar coefficient. This approach overlooks a significant portion of the inherent data richness of the speckle pattern, which the proposed method does consider. Although better results could be attained by optimizing these methods, for instance, by carefully selecting the ROI where the descriptor exhibits linear behavior, this task can be challenging and may limit their performance. In contrast, the proposed CNN-based method extracts and processes the full characteristics of the specklegram, offering enhanced accuracy in characterizing the FSS.

Conclusions

In this work, a deep learning architecture based on CNN-ANN for regression is reported, which allows the prediction of temperature values in a simulated FSS. In addition, the performance of this architecture is compared with three of the main conventional interrogation methods, where the performance of this neural network is superior to the conventional methods.

The robustness of the CNN-ANN-based technique is mainly due to how the information is extracted from the specklegram. Although each of the conventional methods extracts relevant information from the specklegram, they only obtain one characteristic of it, and in this way, other characteristics that allow the interpretation and differentiation between specklegrams are not considered. On the other hand, the CNN seeks to extract the features that best describe this pattern, while the ANN is trained to use the combination of features that best fits each temperature. Furthermore, another advantage of this technique over the conventional ones is that an additional reference state (image) is not necessary, which is eliminated by training the model and capturing the multiple features of the specklegrams.

The optical phenomenon resulting from modal interference within the optical fiber is inherently nonlinear, which poses challenges for conventional methods due to their reliance on a single characteristic. This nonlinearity becomes apparent when examining the errors in Tab. 2 and the abrupt discontinuities in the curves presented in Fig. 3. However, it is important to emphasize that the use of the CNN-ANN-based technique has a positive impact on the metrological characteristics of the FSS. Unlike conventional techniques, the CNN-ANN-based approach exhibits significantly lower dispersion in the characterization curve. Furthermore, it effectively addresses the limitations associated with the optical power measurement technique, which is affected by the non-monotonic behavior of the sensor, thereby making it possible to extend its dynamic range.

In conclusion, using CNN and ANN in FSSs is of high methodological contribution because it can make a wide-range interpretation of the specklegram. Moreover, it performs better, giving greater accuracy than conventional methods. Developing techniques based on deep learning is expected to allow a new class of low-cost and more robust optical fiber sensors. These advancements are poised to revolutionize various applications, ranging from industrial quality control to environmental monitoring, healthcare, and beyond. As such, the integration of CNN and ANN in FSSs enhances their accuracy and paves the way for innovative and versatile solutions in various fields, with the potential for far-reaching impact.

As future work, it is considered to conduct a subsequent experimental stage in which the proposed strategy will be implemented on real speckle patterns. This stage aims to further validate and refine the approach introduced in this study.

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