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Deep learning classification and regression models for temperature values on a simulated fibre specklegram sensor

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Abstract. Fiber optic specklegram sensors use the modal interference pattern (or specklegram) to determine the magnitude of a disturbance. The most used interrogation methods for these sensors have focused on point measurements of intensity or correlations between specklegrams, with limitations in sensitivity and useful measurement range. To investigate alternative methods of specklegram interrogation that improve the performance of the fiber specklegram sensors, we implemented and compared two deep learning models: a classification model and a regression model. To test and train the models, we use physical-optical models and simulations by the finite element method to create a database of specklegram images, covering the temperature range between 0 °C and 100 °C. With the prediction tests, we showed that both models can cover the entire proposed temperature range and achieve an accuracy of 99.5%, for the classification model, and a mean absolute error of 2.3 °C, in the regression model. We believe that these results show that the strategies implemented can improve the metrological capabilities of this type of sensor.

1. Introduction

Fiber optic specklegram sensor (FSS) uses the modal interference pattern at the end of a multimode optical fiber as a metrological tool [1]. This speckle pattern is the result of the propagation and interference of modes along the fiber, so the pattern may have changes due to some disturbances external to the fiber. Therefore, the FSS can be used to know the magnitude of an external disturbance according to the change produced in that specklegram, hence different parameters are considered in these measurements including temperature [2], mechanical deformations like strain [3] or bending [4], etc.

Compared to other technologies that also use waveguides as a measurement method, the FSS, which base their operation on the speckle interpretation, have advantageous features such as easy implementation and cost reduction. In general terms, these sensors have been of interest because of their high measurement sensitivity, low cost, and metrological versatility [5,6]. Because of this, researchers have proposed some measurement methods on the speckle pattern, among which are point measurements of intensity and correlation indexes between images [7].

To evaluate the response of the FSS sensor, various investigations are supported by digital image analysis, whose algorithms allow the analysis of multiple records and estimate the variations induced in



the speckle patterns in the face of external disturbances. Therefore, when alterations are presented in variables such as temperature, changes will be induced that can be estimated through correlation analysis carried out on the interference patterns from the sensing system. In this line, studies are reported that analyze the patterns captured by digital cameras at the output of the multimode fiber, which perform digital image processing and correlation analysis in selected regions [8,9].

Much of the information provided by the speckle pattern is not exploited by these methods, which affects the metrological characteristics of the sensor. Therefore, in this work we propose the use of convolutional neural networks (CNN) to generate models that represent the relationship between the specklegrams and the temperatures to which a fiber is subjected. to which a fiber is subjected [4,10,11].

In this way, we seek to obtain an improvement in the metrological characteristics of the FSS and the approach of this technology to industrial implementation. For this purpose, this work aims to train and compare 2 CNN models: a classification model and a regression model. The speckle images used to train the models are obtained by means of physical-optical simulation using the finite element method (FEM) [12].

2. Methodology and materials

First, to calculate the electric field intensity distributions for a multimode fiber under the application of a given temperature, the vector wave Equation (1) is solved numerically by FEM for a monochromatic wave and each propagation mode [12,13].

$$\nabla \times \nabla \times \vec{E} - k_0^2 n^2 \vec{E} = 0, \quad (1)$$

where \vec{E} is the electric field of each mode, $k_0 = 2\pi/\lambda_0$ is the free-space wavenumber, λ_0 is the wavelength, n is the refractive index of the multimode fiber. This index can be calculated, for a given temperature T , using Equation (2) [2,14].

$$n_x \approx n_y \approx n_z \approx n_0 + C_{TO}(T - T_0). \quad (2)$$

Being $C_{TO} = 11.9 \times 10^{-6}/^\circ\text{C}$ the thermo-optic coefficient (TOC) [14], and n_0 is the refractive index at an initial temperature T_0 (room temperature). n_0 for the core is calculated by using Sellmeier's equation (Equation 3) for fused silica [12].

$$n_{0co}^2(\lambda) = 1 + \frac{0.6961663\lambda_0^2}{\lambda_0^2 - 0.0684043^2} + \frac{0.4079426\lambda_0^2}{\lambda_0^2 - 0.1162414^2} + \frac{0.8974794\lambda_0^2}{\lambda_0^2 - 9.896161^2}, \quad (3)$$

n_0 for the cladding was computed from Equation (3) and the numerical aperture (NA) of the fiber under study with Equation (4).

$$n_{0cla} = \sqrt{n_{0co}^2 - NA^2}. \quad (4)$$

In this way, the vector field of the modes and their propagation constants are obtained for the thermally disturbed system. Then, all the calculated modes are added vectorially to find the intensity of the resulting field, finally obtaining the speckle pattern (specklegram) for a given temperature T [12,14]. Figure 1(a) shows the result of the simulation for the temperature of 25 °C and Figure 1(b) for the temperature of 50 °C.

With this methodology a database that covers a range of temperatures from 0 °C to 100 °C in steps of 0.1 °C was generated, in total 1001 specklegrams. It was also simulated with a wavelength of 632.8 nm, a numerical aperture of 0.13, and a length of sensing zone [14] of 0.3 mm. This database is the one used to train both the classification and the regression algorithms.

To generate the classification model, we built a deep learning architecture consisting of a CNN connected (with the flatten operation) to an artificial neural network (ANN). The CNN was built on the basis of a visual geometry group network (VGG), which adopts a conv-RELU \rightarrow conv-RELU \rightarrow MaxPooling block structure [4]. It should be noted that the CNN, compared to other methods, allows us to acquire more information from the specklegrams, *i.e.*, the spatial information typical of these images. On the other hand, the ANN output layer contains 20 output neurons corresponding to the 20 temperature classes we are defining as being predicted (Figure 2).

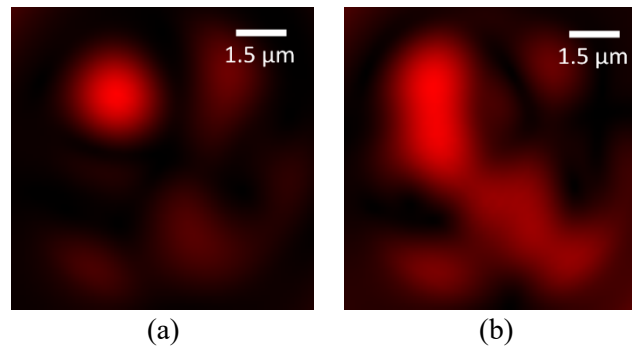


Figure 1. Specklegrams simulated using FEM; (a) at a temperature of 25 °C, (b) at a temperature of 50 °C.

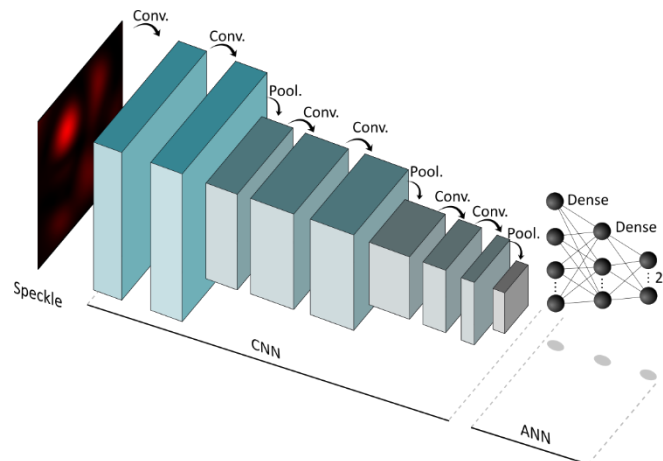


Figure 2. Proposed architecture for classification model.

To train this model, we divided the database of 1001 specklegrams into 20 classes. This means that each class covers a range of 5 °C within the complete range of 100 °C and contains around 50 unique specklegrams. Subsequently, all the data are divided into two groups: training and test, with 801 and 200 images, respectively. These images are taken randomly from each of the 20 classes. Similarly, the data of the training group were also divided into training and validation sets, 80% and 20%, respectively. In this way, 160 of the 801 training specklegrams are used for validation. This was done to avoid overfitting the model.

The network architecture implemented for this regression model is also based on the VGG block structure used in the classification model. In this case, we modified the CNN adding another conv-RELU \rightarrow conv-RELU \rightarrow MaxPooling block. We also modified the ANN increasing the number of neurons in the hidden layer and changing the final number of neurons to just one neuron.

For the training of this regression model, we used the same database of 1001 speckle pattern images with their respective temperature labels. Like the conditioning of the classification model, the database was randomly divided into training and test, containing 801 and 200 images, respectively. The training set was then randomly divided into 641 specklegrams for training and 160 specklegrams for validation.

3. Results and discussions

The results of this work are based on the possibility of modelling the optical phenomena given in the transmission of electromagnetic waves in an optical fiber through finite element simulations. With these simulations we have been able to overcome one of the most limiting requirements in the use of deep learning techniques, which is the collection of data and its correct labelling. Figure 3(a) shows the confusion matrix resulting from the classification model. It can be observed that there is a good performance in classification, with a global precision of 99.5% when predicting the 20 classes of temperature within the test data.

This classification model has a discrete predictive nature from its conception as a classifier; this causes its results to have an intrinsic uncertainty associated with the width in temperatures covered by each class. This indicates that this model is susceptible to improvement by reducing the width of temperatures covered by each class, *i.e.*, by defining a larger number of classes for the same temperature range, so that the discretization is smaller and approaches a continuous variable. However, with a larger number of classes, the model may have a lower classification accuracy. This is a factor to be considered for optimization, *i.e.*, to find a compromise between class width and class prediction accuracy for this model.

On the other hand, Figure 3(b) shows the result in predicting the test temperatures produced by the regression model. This graph shows a good fit between the test and the predicted values, with some variation around certain specific regions. These regions of greater variation generally correspond to abrupt changes in the sequence of specklegrams, which is precisely where the models obtained with interrogation strategies based on correlation have the greatest problem. These abrupt changes between some of the specklegrams make this type of model only valid in a limited range of temperatures [2,7,14]. Otherwise, the two proposed models based on machine learning can obtain a representation that covers the entire proposed range of temperatures, which means that they may be better able to handle those abrupt changes between specklegrams.

From a quantitative point of view, for the regression model, there was a mean absolute error (MAE) of 2.34 °C, a root means square error (RMSE) of 2.97 °C and a maximum error of 9.49 °C. These values mean that there is some variation in the magnitudes of the prediction errors, but the fact that the difference between the MAE and RMSE values is not high shows that very high errors are unlikely. Comparing the proposed models with each other, it is possible to say that both models achieve reasonable predictions over the entire proposed temperature range; that the regression model more closely represents the continuous-type variable to be predicted; and that the results of the regression model show an average error that, for our tests, is better than the uncertainty given by the class width of the classification model.

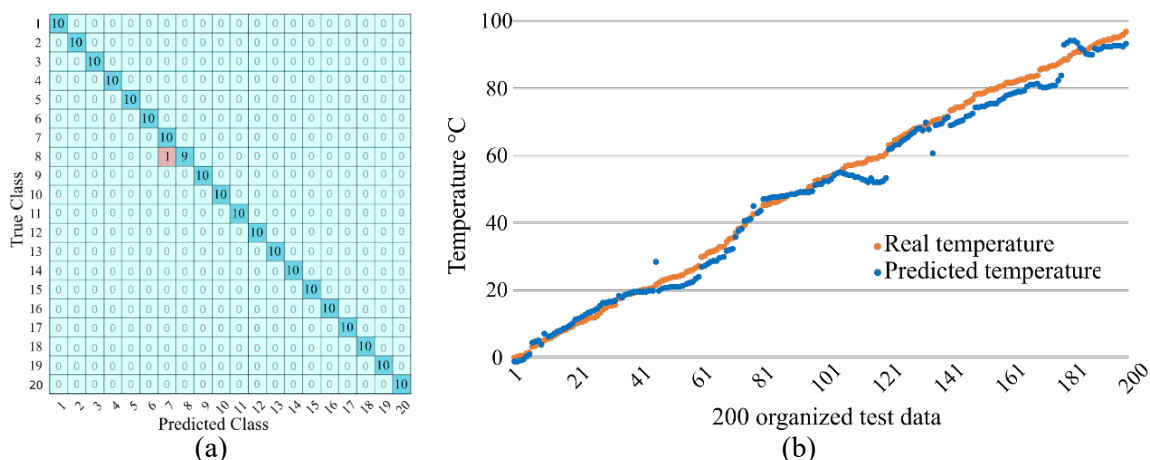


Figure 3. Prediction results: (a) confusion matrix of the classification model when predicting the 20 classes, (b) regression model prediction for the 200-test data arranged in ascending order.

4. Conclusions

The results of the two proposed models showed that these machine learning-based strategies can be suitable as a method of interrogating fiber optic specklegram sensors, since both the regression and classification models are able to interpret the specklegrams. Additionally, we showed that they can be useful to extend the measurement range, and furthermore, improve the sensitivity of this type of sensors. Our comparison also showed that the regression model is a more promising alternative. Thus, it is sensible to think that this model can reach a reasonable uncertainty, which would allow to implement this system as the interrogation scheme in a specific application.

It should be noted that the implemented strategy of using physical-optical simulations allows a faster evaluation while changing different parameters, but that these results need to be validated with experimental measurements. Future work will continue to improve the proposed models and evaluate their performance using experimental data.

Acknowledgements

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References

- [1] Fujiwara E, dos Santos M F M, Suzuki C K 2017 Optical fiber specklegram sensor analysis by speckle pattern division *Applied Optics* **56**(6) 1585
- [2] Castaño L F, *et al.* 2018 Temperature measurement by means of fiber specklegram sensors (FSS) *Optica Pura y Aplicada* **51**(3) 50306
- [3] Hoyos A, Gómez N D, Gómez J A 2013 Fiber specklegram sensors (FSS) for measuring high frequency mechanical perturbations *8th Ibero American Optics Meeting/11th Latin American Meeting on Optics, Lasers, and Applications* (Porto: Society of Photo-Optical Instrumentation Engineers)
- [4] Liu Y, Li G, Qin Q, Tan Z, Wang M, Yan F 2020 Bending recognition based on the analysis of fiber specklegrams using deep learning *Optics & Laser Technology* **131** 106424
- [5] Krohn D A, MacDougall T W, Mendez A 2015 *Fiber Optic Sensors: Fundamentals and Applications* (Bellingham: SPIE press)
- [6] Efendioglu H 2017 A Review of fiber-optic modal modulated sensors: specklegram and modal power distribution sensing *IEEE Sensors Journal* **17**(7) 2055
- [7] Fujiwara E, Ri Y, Wu Y T, Fujimoto H, Suzuki C K 2018 Evaluation of image matching techniques for optical fiber specklegram sensor analysis *Applied Optics* **57**(33) 9845
- [8] Gubarev F, Li L, Klenovskii M, Glotov A 2016 Speckle pattern processing by digital image correlation *MATEC Web of Conferences* **48** 04003
- [9] Crammond G, Boyd S W, Dulieu-Barton J M 2013 Speckle pattern quality assessment for digital image correlation *Optics and Lasers in Engineering* **51**(12) 1368
- [10] Wei M, Tang G, Liu J, Zhu L, Liu J, Huang C, Zhang J, Shen L, Yu S 2021 Neural network based perturbation-location fiber specklegram sensing system towards applications with limited number of training samples *Journal of Lightwave Technology* **39**(19) 6315
- [11] Razmyar S, Mostafavi M T 2020 Deep learning for estimating deflection direction of a multimode fiber from specklegram *Journal of Lightwave Technology* **39**(6) 1850
- [12] Aristizabal V H, *et al.* 2016 Numerical modeling of fiber specklegram sensors by using finite element method (FEM) *Optics Express* **24** 27225
- [13] Torres P, Aristizabal V H, Andrés M V. 2011 Modeling of photonic crystal fibers from the scalar wave equation with a purely transverse linearly polarized vector potential *Journal of the Optical Society of America B* **28**(4) 787
- [14] Arango J D, *et al.* 2021 Numerical study using finite element method for the thermal response of fiber specklegram sensors with changes in the length of the sensing zone *Computer Optics* **45**(4) 534