

Use of a convolutional neural network to predict temperature values in a simulated fiber specklegram sensor and comparison with conventional methods of analysis

Abstract: In this work, an algorithm based on convolutional neural networks as an interrogation method for a fiber specklegram sensor was implemented. This algorithm is compared with conventional interrogation methods such as correlation between images, measurement of optical power and radial moments. These sensors can still be improved since the conventional methods only take one characteristic of the specklegram for the variable prediction, and so, they fail to take advantage of the whole information in the specklegram. Thus, we propose a convolutional neural network for extracting the specklegram characteristics and an artificial neural network for the regression of the variable. The specklegrams used in this work were obtained by simulating temperature disturbances in a multimode fiber using the finite element method. In the results, the prediction RMSE errors ranged from 10.26 °C, for the first radial moment, to 1.42 °C, for the proposed algorithm. These results show that the use of the proposed strategy improves the performance of these sensors and makes them more robust while maintaining their low-cost profile.

Keywords: Optical fiber sensor; fiber specklegram sensor; machine learning; convolution neural network; regression.

1. 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 important information on the state of the fiber, i.e., on some disturbances that have an influence on 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 descriptors that have been used to solve this task in FSS 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 specklegram is an alternative technique that can sometimes have better results than the

correlation-based one [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 had good results. However, due to technological and industrial progress, it is necessary to have systems with greater accuracy. In addition, these methods reduce all the information given by the specklegram to a characteristic represented as a scalar coefficient, with which the perturbing variable is subsequently predicted. Moreover, to improve the performance of the sensor when using these techniques, it is necessary to ensure a proper selection of a ROI where the descriptor presents a linear behavior for the range of interest. In this way, much information provided by the speckle pattern is not used. Taking this into account, in addition to the promising results that the use of machine learning techniques has had in different engineering and physics applications [19], in this work a deep learning architecture is trained to compare its performance with the conventional methods used for the interrogation of FSSs. This architecture is based on convolutional neural networks (CNNs), and artificial neural networks (ANNs). It should be noted that the proposed architecture approaches this problem as if it were a regression problem rather than a classification problem, due to the continuous nature of the variable to be measured, which in this work corresponds to temperature values [20].

2. Specklegrams Generation

The specklegrams were 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].

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

where \vec{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.

$$n \approx n_0 + C_{TO}(T - T_0) \quad (2)$$

where n_0 is the refractive index at an initial temperature T_0 , which is calculated with the Sellmeier equation, and C_{TO} is the thermo-optic coefficient of the fiber material [7], [16]. 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 then find the intensity of the resulting field, finally obtaining the speckle pattern. More details of thermo-optical simulation, and specklegram generation can be found in [7], [16].

On the other hand, for the generation of the specklegram dataset used in this work, the following commercial fiber and light source parameters were used: numerical aperture of 0.22, core diameter of 50 μm , cladding diameter of 125 μm , and wavelength of 1490 nm. In addition, the dataset was simulated in a range from 0 $^{\circ}\text{C}$ to 120 $^{\circ}\text{C}$ with steps of 0.2 $^{\circ}\text{C}$, finally obtaining a total of 601

specklegrams with a size of 126 x 126 pixels each. Another key parameter to take into account 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 and has been shown to play an important role in sensor sensitivity [7], [16]. In our simulations the sensing zone length was 2.5 mm.

3. Conventional interrogation methods

3.a. Images Correlation

Speckle image correlation is performed using digital image processing [6], [15], [18], where the objective is to characterize an FSS by means of a correlation coefficient between the specklegrams with thermal disturbances and a reference specklegram (the initial temperature condition is usually used as reference). In this technique, the correlation coefficient is given by:

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

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.

It has been shown that the size and location of the ROI that is analyzed in the specklegram can improve the performance of this technique [7], [14], [16], [18]. In this work, this method was implemented using a well-performing ROI on the dataset of specklegrams produced by the FSS simulated by FEM.

3.b. Optical Power Measurement

This method can be implemented analogically with a photosensor and a single-multi-single mode fiber scheme, in which a single mode fiber (SMF) is used as a filtering fiber that captures the power at the output of the MMF transducer. Equation (4) represents the power as a function of the intensity and of the sensing area A of the SMF that captures the power from the specklegram generated in the MMF. Equation (5) represents the discrete form of equation (4) after applying the fields of the specklegram calculated by FEM from section 2 on the sensing area of the SMF [16].

$$P = \int_A I dA \quad (4)$$

$$P \approx \sum P_e = \frac{1}{2} c \varepsilon_0 n_{0core} \sum |\vec{E}_e|^2 A_e \quad (5)$$

where P is the total power, c the speed of light, ε_0 the vacuum permittivity, n_{0core} the refractive index of the nucleus, \vec{E}_e the specklegram field in each element, and A_e the area of each element that integrates the sensing area of the SMF. These equations were implemented to find the optical power of each simulated specklegram and characterize the FSS by this method.

3.c. Radial Moments

This alternative, as noted above, 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), being μ_x and μ_y the intensity averages on the x-axis and y-axis, and that are defined in equations (7) and (8), respectively.

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

$$\mu_x = \frac{\sum_{x,y} x I(x,y)}{\sum_{x,y} I(x,y)} \quad (7)$$

$$\mu_y = \frac{\sum_{x,y} y I(x,y)}{\sum_{x,y} I(x,y)} \quad (8)$$

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 were found to characterize the FSS with the simulated dataset.

4. Deep learning Architecture: CNN-ANN regression

In search of an interrogation method that would better represent the temperature-specklegram relationship, a deep learning architecture based on CNNs and ANNs was created, as shown in Figure 1. This architecture used the block structure of a VGG (Visual Geometry Group) [21]: conv-RELU \rightarrow conv-RELU \rightarrow MaxPooling blocks. Here, the CNN functioned as a feature extractor. Each convolution layer had the RELU (Rectified Linear Unit) activation function as output. In total, 4 conv-RELU \rightarrow conv-RELU \rightarrow MaxPooling blocks were used, where the advance in depth reduces the amount of data and separates the most important features. Afterward, an ANN was 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 was labeled according to the corresponding temperature of each image and was divided into two data subsets: training and test, with 481 and 120 specklegrams each subset, respectively. The test data was separated and only used in the final prediction, and never in the training stage. Subsequently, a validation data subset was separated from the training subset, which corresponded to 20% of the training data (96 specklegrams). The selection of the specklegrams for each subset above was done randomly. The model was trained with a learning rate of 8×10^{-5} and 300 epochs in the Python programming language with the Keras and TensorFlow libraries [22]. Finally, in the hidden layer of the ANN, a dropout of 50% was added to avoid overfitting.

5. Results

Figure 2 shows the behavior of the conventional interrogation methods over the entire temperature range of the generated dataset. The linear trend of each of the methods with respect to temperature can be observed, except for the method of measurement of optical power. This method did not retain monotonic behavior throughout the full range of analysis, and for this reason it is not included in the final comparison. Generally, in these cases, the dynamic range of the sensor should be limited to one of the linear behavior zones. On the other hand, Figure 3 shows the prediction of the regression neural network and the actual temperature of the test data.

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 Table 1. 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.

Table 1. Caption 8 points size

| 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 |

6. Conclusions

In this work, a deep learning architecture based on CNN-ANN for regression was developed, 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, as can be seen in Table 1.

The robustness of the CNN-ANN-based technique is mainly due to the way in which 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.

It should also be noted that the use of the CNN-ANN-based technique has a positive effect on the metrological characteristics of the FSS, such as the dynamic range and sensitivity. This is observed in contrast to the case of the optical power measurement technique, which would have a more limited dynamic range because the sensor does not behave monotonically in the study range. Furthermore,

the optical phenomenon resulting from the modal interference with the disturbance of the optical fiber is not linear in nature, which causes conventional methods to not generalize correctly since they only use one characteristic. This can be seen from the errors in Table 1, and from the abrupt discontinuities in the curves presented in Figure 2.

In conclusion, the use of CNN and ANN in FSSs is of high methodological contribution because it can make a wide-range interpretation of the specklegram. Moreover, it presents a better performance giving greater fidelity than conventional methods. Finally, the development of techniques based on deep learning applied to these sensors is expected to allow a new class of low-cost and more robust detection systems.

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Lists of figures

Fig.1. Deep learning architecture based on CNN-ANN proposed for temperature regression in an FSS.

Fig.2. Characterization of the FSS by the interrogation method: a) correlation between images, b) optical power measurement, c) first radial moment, and d) second radial moment.

Fig.3. Prediction of the test data with the CNN-ANN regression algorithm.