LPG Spectrum Estimation Using Neural Networks and Temperature Modulated FBG

Felipe Oliveira Barino, Alexandre Bessa dos Santos
Departamento de Engenharia Elétrica, Universidade Federal de Juiz de Fora.
Rua José Lourenço Kelmer, s/n, São Pedro, 36036-900, Juiz de Fora, Minas Gerais, Brazil.
felipe.barino@engenharia.ufjf.br, alexandre.bessa@engenharia.ufjf.br

Abstract: This work proposes a novel approach to Long Period Fiber Grating (LPFG) interrogation involving power measurements to estimate the transmission spectra. The aim of this work is to develop a cheap alternative to the Optical Spectrum Analyzer. To accomplish this task a temperature modulated Fiber Bragg Gratings array was used. Accuracy close to half input spectrum resolution was obtained.

1. Introduction

Advances in instrumentation field have helped develop optical sensors technology due to optical components offer increase at a good cost benefit and a vast option of suppliers [1]. The so called Bragg Gratings (FBGs) and Long Period Fiber Gratings (LPFGs) are two important structures in optical sensing. Both are in fiber devices based on periodic modulation of fiber's refractive index.

The LPFGs are easier to build structures in comparison to FBGs, once its modulation period is considerably bigger. This devices can be treated as sensor once they are notch filters whose central wavelength, denoted by $\lambda_{\mathrm{res}}^{\mathrm{m}}$, varies accordingly to the environment, such as effective refractive index of the core $n_{\mathrm{eff,co}}$, cladding $n_{\mathrm{eff,cl}}$ and grating period Λ [2,3]. The relationship between those parameters is:

$$\lambda_{res}^{m} = \left(n_{eff,co} - n_{eff,cl}^{m}\right)\Lambda \tag{1}$$

This way one is able to correlate the actual measurement to LPFG's transmission spectra. This process is called interrogation and there is a great amount of techniques reported in literature, some require big and expensive equipment. One approach is to apply a broadband light source to the optical sensor and trace the spectrum variation using an Optical Spectrum Analyzer (OSA), another technique uses Tunable-lasers [4,5]. A cheap and compact solution is to use band-pass filters and photodetectors and track power variation [6-8].

Here we propose a mixed technique, in which, based on power measurements provided by an FBG array, LPFG's transmission spectra is estimated. To accomplish this task 5 temperature modulated FBGs and 5 photo-detectors are used to send their readings to a computer.

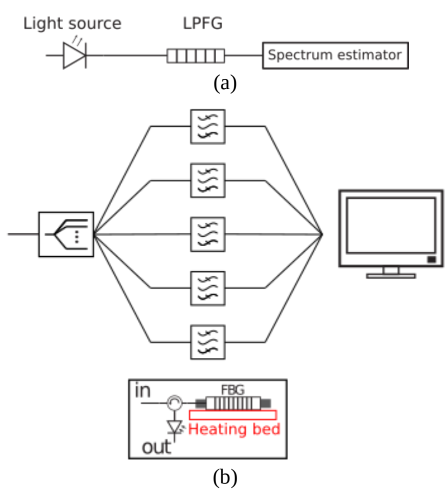


Fig. 1. (a) Experimental setup. (b) Spectrum estimator scheme.

2. Methods

The experimental setup proposed in this work consists of a broadband light source, the LPFG sensor and the spectrum estimator, as illustrated in Fig. 1a. The spectrum estimator itself is shown in Fig. 1b and it's made by a set of five filters and a PC. Each filter block has a FBG, a controlled heating bed to perform the temperature modulation, an optical circulator and a photodetector.

Simulation of the proposed interrogation method was made to validate the quality of spectrum estimation, all of those five FBGs were simulated on OptiGrating at the central wavelengths: 1500nm, 1520nm, 1535nm, 1550nm and 1570nm. Each FBG were characterized by varying temperature in grating from 15°C to 125°C. A linear regression between temperature variation (where reference temperature considered was $T_{ref} = 25°C$) and central wavelength displacement on each FBG was performed to obtain the gratings sensitivities. Those regression plots can be seen in Fig. 2.

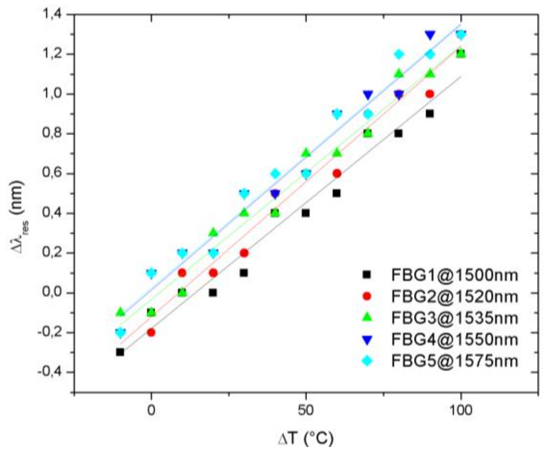


Fig. 2. Linear regression between temperature variation and central wavelength displacement on each FBG.

Optical power at measured by the photodetector is calculated by numerical integration on the reflected spectrum of FBG. Let $R(\lambda)$ be the FBG refraction spectrum (after filtering the LPFG's spectrum) and $\Delta\lambda_{OSA}$ the OSA resolution:

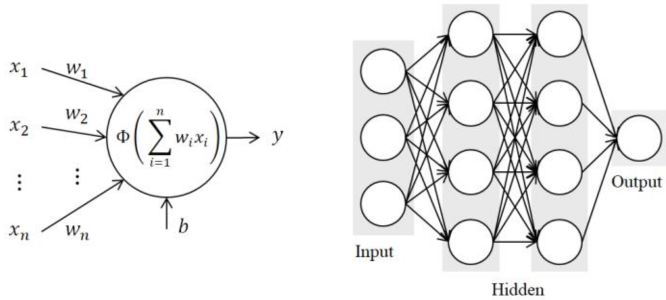
$$P_{photodetector} \approx \frac{1}{\Delta\lambda_{\{OSA\}}} \int R(\lambda) d\lambda \quad (2)$$

This calculation is performed for each filter that composes the array 11 times, since the FBG array is modulated with temperatures from 25°C to 100°C in eleven evenly spaced rounds. Therefore, a total of 55 power measurements are made, and those values are used as input to a Neural Network. The output of this network is the LPFG transmission spectra, and the reference data used to train and test the estimator is given by 24 transmission spectra of four different LPFGs, obtained previously by an OSA Anritsu MS9740A.

Those reference data were filtered using mean-average filter to smooth the curve and to simplify the neural network architecture all of the 24 filtered spectra were down-sampled to 133 points at the same wavelength, so that the spectrum can be treated as a vector. Those 133 points corresponds to 1500nm to 1580nm evenly spaced samples, therefore, resulting resolution is 600pm. Finally, the dataset were split into groups: train (70%), test (15%) and validation (15%).

The Artificial Neural Network (ANN) used in this work has a single hidden layer and sigmoid activation function. An ANN is a computation model inspired by animal's nervous system. This model is made by a set of units called artificial neurons, connected between each other, and it is capable of mapping input-output based on a set of examples learned at training phase [9].

An artificial neuron makes a linear combination of its input (x_i) by weights tuned during training (w_i), summed with a given bias (b) and passes this value to an activation function (Φ), as illustrated in Fig. 3a. Those neurons are layered in a net structure, the first layer is called input layer, the last output layer and all layers between those are called hidden layers, Fig. 3b shows a three input network with two hidden layers (four neurons each) and single output.



(a) (b)

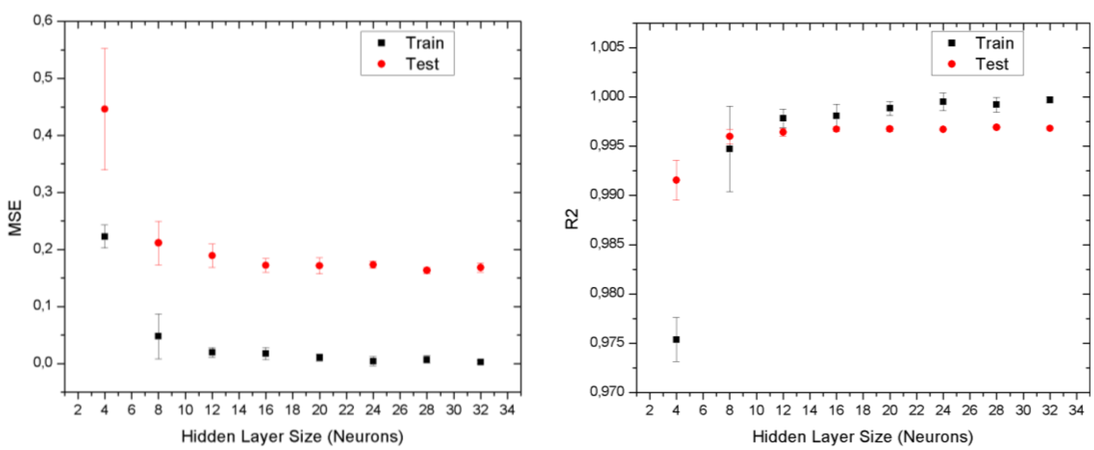
Fig. 3. (a) Artificial neuron. (b) 3x4x4x1 neural network (bias were omitted).

To train the network used in this work, Bayesian Regularization Backpropagation algorithm was used. This method was chosen because regularization algorithms aims not only to minimize the neural network error, but also the weights, so that the network is smoother and has a better generalization [10], being great for small datasets.

3. Results

In order to find the best hidden layer size, several ANNs were developed, trained and the resulting data analyzed. Ten tests were made for each topology, to minimize random initial weights impact. Those ANNs had from 4 to 32 neurons in its hidden layer. To determine the most efficient hidden layer size, comparison based on Mean Squared Error (MSE) and Coefficient of Determination (R^2) on both train and test dataset was made.

The chosen number of neurons is the least one that has acceptable error at train and test stage, to avoid overfitting. In order to improve the ANN generalization, similar performance in both train and test are desirable. Fig. 4 shows the results obtained from this model selection study, note that for a hidden layer size greater than 16 neurons there is no significant improvement in MSE and R^2 from the test set data, indicating that there is no improvement in model's generalization for bigger hidden layers. Therefore the 55x16x133 topology was adopted to perform the spectrum regression.



(a) (b)

Fig. 4. (a) Relationship between Hidden Layer Size and MSE. (b) Relationship between Hidden Layer Size and R^2.

The resulting MSE for the final Neural Network chosen is 0.0194 at the train set, close to the mean of tests for 16 neurons on hidden layer obtained at the model selection (0.0174). During training, weights optimization is made to reduce the error (MSE), this error gives an idea of how well the predicted spectrum curve represents the actual LPFG's transmission spectra, since outputs are given by optical power at a fixed set of wavelengths, so MSE has units of dBm². But to evaluate the spectrum approximation, resonant wavelength displacement ($\delta\lambda_{res}$) was also taken into account. Once MSE evaluates the whole spectrum approximation, $\delta\lambda_{res}$ evaluates the measure error, since it changes with environment properties variation. Table 1 shows both errors on each subset of the actual dataset.

Table 1. Spectrum estimation errors.

	MSE (dBm²)	$\delta\lambda_{res}$ (nm)
Train	0.0194	0.1889
Test	0.8609	0.9114
Validation	1.0444	0.4557

Note that obtained mean resonant wavelength error in train and validation subsets are smaller than input spectrum resolution, while test resonant wavelength is smaller than twice this value. And especially, the whole dataset errors: MSE and $\delta\lambda_{res}$ are, respectively, 0.3305dB and 354.4pm, being that resonant wavelength error close to half the target spectrum resolution.

4. Conclusion

Although a practical implementation of the proposed method is required to measure the time needed to perform the FBG modulation and its stability, this work shows that one can estimate a long period fiber grating transmission spectra using only five temperature modulated FBGs. This method decrease overall cost in interrogation methods that need whole spectrum evaluation. Future studies on other FBG modulation techniques and the use of fixed FBGs can lead to more practical applications of the proposed interrogation system.

The proposed method also gives the opportunity to not only trace resonant wavelength displacement, but other spectrum based variables like attenuation and rejection band, for example. And accuracy can be improved by increasing reference spectrum resolution and training examples.

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