Robust Convolutional Neural Network Model for Wavelength Detection in Overlapping Fiber Bragg Grating Sensor Network

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Abstract: We have designed a CNN model to detect Bragg wavelengths in overlapping spectra. The mean RMS error of 0.123pm and mean testing time of 12.4ms are achieved, which outperforms most of the existing techniques.

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1. Introduction

In recent years, fiber Bragg grating (FBG) sensors have been studied intensively and used widely in various fields such as structural health monitoring, military defense and aerospace industry [1] due to its unique advantages like small size, lightweight, good linearity, etc. Besides, FBG sensors have extremely high multiplexing capability, which allows hundreds of FBG to be written in a single network. The quasi-distributed FBG sensing network monitors parameters such as temperature, strain and vibration in real-time. Wavelength division multiplexing (WDM) is used to multiplex FBG sensors for quasi-distributed FBG sensing network, conventional peak detection (CPD) is normally deployed to detect the Bragg wavelength. However, CPD is limiting the overall performance of the network as overlapping spectra would cause crosstalk between each FBG. Recently, various wavelength demodulation techniques and algorithms such as particle swarm optimizer (PSO) [2] and differential evolution (DE) algorithm [3] are proposed to improve the wavelength detection accuracy in the overlapping spectra. However, those proposed techniques require long computational time, which fails the real-time parameters monitoring. Besides, machine learning techniques such as extreme learning machine (ELM) [4] and least squares support vector regression (LS-SVR) [5] were proposed to handle the overlapping problem as well. The accuracy of these machine learning techniques was promising but the testing time was about 0.5 seconds, which is not ideal for real-time parameters monitoring. Therefore, a technique with fast and accurate detection and demodulation abilities is needed to realize the real-time parameters monitoring.

There are two main types of neural network namely convolutional neural network (CNN) and recurrent network (RNN), both of them can be used to construct the sequence model. Neural network consists of multiple layers that have excellent capabilities to deal with complex and nonlinear data. In most of sequence modeling tasks, simple convolutional architecture is more effective than recurrent architecture [6]. CNN has achieved state-of-the-art performance in various fields such as image processing and speech recognition because of its ability to extract features efficiently from raw data [7].

In this work, we demonstrate a novel technique to demodulate Bragg wavelengths in overlapping spectra using a promising deep learning technique CNN. The wavelength demodulation of the FBG network is regarded as a nonlinear regression problem and the proposed CNN model is a sequence model that can deal with nonlinear regression problems. In the proposed CNN model, feature extraction of the long sequence spectra data input would be done automatically by the convolutional layers. Instead of using wavelength as the x-axis data, the model uses matrix indices. Therefore, the input data is modified into one-dimensional (1D) data which shortens the demodulation time and made real-time parameters monitoring for quasi-distributed FBG sensing network possible.

2. Principles

The schematic diagram of the quasi-distributed FBG sensing network is shown in Fig.1. The overall sensing network is split into four individual networks through a 1x4 optical splitter and each individual consists of m number of FBGs. For simplicity, we will address the four individual networks as four rows and every m^{th} FBG of the rows as m^{th} column. Overlapping spectra in the same row will introduce crosstalk, which reduces overall network performance significantly. However, FBGs from each column can share the same wavelengths without affecting overall network performance. The four FBGs in the same column have identical Bragg wavelength and spectrum band. The proposed model is built based on a single column and it is usable for all other columns as the data is modified into 1D data using matrix indices.

Assume λ_{Bi} is the Bragg wavelength for FBGi and the overall measured spectrum from OSA for the proposed network can be expressed as:

$$R(\lambda) = \sum_{i=1}^{n} r_i g_i(\lambda, \lambda_{Bi}) + N(\lambda)\,. \qquad (1)$$

Where r_i and g_i (λ,λ_{Bi}) is the peak reflectivity and the reflection spectrum of FBGi respectively. $N(\lambda)$ is the random white noise in the system. The ultimate goal is to find out λ_{Bi} (where i =1, 2, ⋯ n) in the proposed model. λ_{Bi} can be computed by finding the inverse function of the overall reflection spectrum R^{-1} [4]. It is extremely hard to solve the inverse function by traditional numerical methods and neural network has excellent capability in dealing with complex nonlinear data. Hence, we proposed a CNN model that is a nonlinear regression model to estimate the best R^{-1} for the network.

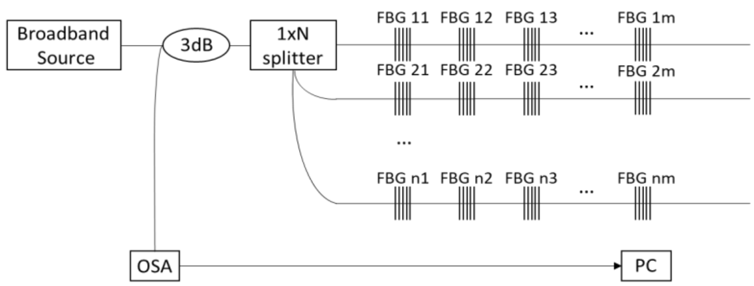

Fig.1. Schematic diagram of FBG network. OSA: optical spectrum analyzer; PC: personal computer.

3. Convolutional neural network

A convolutional neural network is a deep learning algorithm that typically consists of convolutional, pooling and fully connected layers. A deep model is formed by stacking different layers. In the proposed CNN model, convolutional layers with leaky rectified linear unit (ReLU) and a fully connected layer were used.

In this work, we employed 1D spectra data, where the wavelengths range are mapped to indices of the array. Since indices were used instead of wavelengths, the wavelength range will not affect the accuracy of the proposed model.

3.1 CNN model training

For deep learning, a powerful GPU is required to do the complex training, here we used a computer with the following specifications (Eight-Core Intel Xeon E5-1680v4 CPU and NVIDIA GTX1080 Ti, 11GB GDDR5X GPU) to train the proposed CNN model. The individual FBG reflectivity is assumed to be a Gaussian shape which can be expressed as:

$$R(\lambda, \lambda_{Bi}) = I_{peak} \exp\left[-4\ln 2\left(\frac{\lambda - \lambda_{Bi}}{\Delta\lambda_{Bi}}\right)^2\right]. \qquad (2)$$

Where I_{peak} and $\Delta\lambda_{Bi}$ are the peak reflectivity and linewidth of the i^{th} FBG in the quasi-distributed FBG sensing network. In CNN, unique local patterns increase model detection accuracy significantly. Therefore, we set the I_{peak} to be 0.8 and 0.7 for FBGs in row one and two respectively. Besides, we modified the linewidth to 0.2nm for the first row of FBGs and 0.3nm for the second row. The model was trained using 24000 of samples that are calculated using (2). The batch size and learning rate used were 32 and 0.00025 respectively. The combined spectrum is fed to the model as input and two FBG spectra are the outputs of the model. The two Bragg wavelengths are extracted from the two FBG spectra. The proposed model has 70 layers, each layer consisting of convolution, batch normalization and leaky ReLu Residual connections [8] are added between each layers to reduce vanishing gradient problem in models with large number of layers. The Adam stochastic optimization algorithm was used in the training to reduce the loss between the outputs of the model and the actual individual FBG spectrum. The proposed CNN model was constructed using PyTorch 1.2.

4. Results and discussion

There are three typical situations for the quasi-distributed FBG sensing network namely partially, fully and non-overlapped as shown in Fig.2. The best-validated model was tested with 3000 sets of data and a mean root-mean-square (RMS) error of 0.123pm is achieved. The average testing time is 12.4ms. The initial wavelength of the test data will be detected and recorded by the test algorithm. For example, the initial wavelength is 1553nm and the detected index is 213, then the detected Bragg wavelength will be 1553.213nm. To further justify the robustness of the proposed model, test data with different wavelength ranges (1549nm to 1551nm, 1551nm to 1553nm and 1553nm to 1555nm) are used to test the model and the mean RMS error remained around 0.123pm.

To evaluate the performance of the proposed CNN model, we have set up a comparison table with the existing works [2-5, 9] as shown in Table1. The metrics used were RMS error and testing time. The model has similar RMS compared to DE but significantly outperforms DE in testing time. The model also outperformed a long short-term memory (LSTM) neural network [9], with almost 5 times RMS error reduction. Other methods such as ELM, least squares support vector regression (LS-SVR) and particle swarm optimization based simulated annealing (PSO-SA) have generally high RMS error or long testing time, which is unsuitable for real-time parameters monitoring.

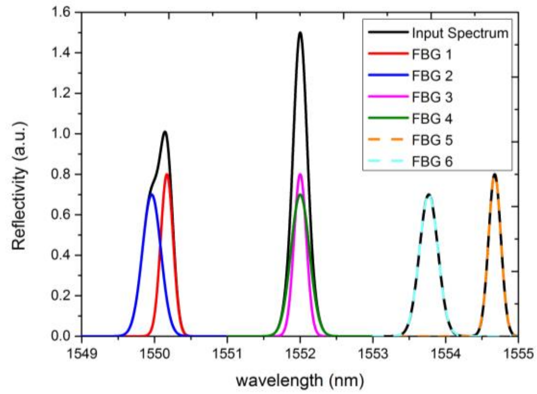

Fig.2. Testing of overlapping spectra under three typical situations

Table 1. Comparison of different algorithms

Method	RMS (pm)	Testing Time (ms)	Data Source
CNN	0.123	12.4	This work
DE	<0.2	2500	Reference [3]
LSTM	0.674	1.625	Reference [9]
ELM	0.918	215	Reference [4]
LS-SVR	1.206	578	Reference [5]
PSO-SA	<5	Not Available	Reference [2]

5. Conclusions

This paper proposed a robust CNN model that detects Bragg wavelength for overlapping FBG sensing network with extreme low RMS errors and fast detection time. The model is built based on sequence modeling which includes 70 convolutional layers with leaky ReLU. The performance of the proposed model is promising for different wavelength ranges even when the spectra are fully overlapped. The model allows increasing in numbers of FBGs in the rows without any degradations in detection accuracy. The accuracy and detection time outperform most of the existing techniques.

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