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Wavelength Detection in Spectrally-overlapped FBG Sensor Network Using Extreme Learning Machine

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Abstract—This paper presents a novel learning-based method called extreme learning machine (ELM) to solve the Bragg wavelength detection problem in the fiber Bragg grating (FBG) sensor network. Based on building up a regression model, the proposed approach is divided into two phases: offline training phase and online detection phase. Due to the good generalization capability of ELM, the well-trained detection model can directly and accurately determine the Bragg wavelengths of the sensors even when the spectra of FBGs are completely overlapped. The results demonstrate that the proposed method is efficient and stable. It has shown competitive advantages in terms of the detection accuracy, the offline training speed as well as the real time detection efficiency.

Index Terms—Fiber Bragg grating (FBG), fiber-optic sensors, wavelength division multiplexing (WDM), Extreme Learning Machine (ELM).

I. INTRODUCTION

AS one of the most promising Fiber Bragg grating (FBG) sensor multiplexing technique, wavelength division multiplexing (WDM) has attracted considerable interest. A key issue in a WDM FBG sensor network is the accurate detection of Bragg wavelengths of the FBGs within the network [1]. Based on the conventional peak detection (CPD) technique, each FBG sensor must be assigned a unique portion of the optical spectrum. As the sensor number increases, the conventional WDM is insufficient to meet the network capacity requirements because of the limited light source bandwidth. Recently, much attention has been paid to the spectrally-overlapped WDM sensor network, where the spectra of FBGs in the network are permitted to partially or completely overlap. Various advanced wavelength detection techniques using evolutionary algorithms (EAs) have been reported [2]–[5], such as the genetic algorithm (GA) [2], particle swarm optimizer (PSO) [3], and the differential evolution algorithm (DE) [4], [5]. By using the iterative and evolutionary operations, the evolutionary algorithms are capable of accurately determining the Bragg wavelengths when the overlapped spectra exists. But the obvious drawback is that the algorithms require quite a long processing time to achieve high accuracy and may be easy to trap into a local optimal solution when the spectra of FBGs are close to being completely overlapped, which would reduce the measurement accuracy. In our previous work, least squares

support vector regression (LS-SVR) [6] has been proposed to solve this problem. In this method, each Bragg wavelength is directly detected through inputting the measured spectra into a pre-trained model for the sensor network. This technique shows outstanding advantages, including superior detection speed and robustness. However, the training time of LS-SVR model is still a remarkably long time. Once the configuration of the FBG sensor network is changed, the time consumption would increase.

In this paper, a recently developed machine learning algorithm referred to as Extreme Learning Machine (ELM) is introduced to detect the Bragg wavelength of the spectrally-overlapped FBG sensor network for the first time. ELM, proposed by Huang et al. [7]–[9], is an efficient algorithm which tends to reach the smallest training error, obtain a smallest norm of weights, produce better generalization performance, and runs extremely fast. The proposed approach consists of two phases: offline phase and online phase. During the offline phase, the ELM model is established from the training samples. And then we can use the well-trained ELM to determine the Bragg wavelengths during the online phase. Compared with other methods, the proposed ELM-based approach significantly reduces the offline training time and enhance the detection accuracy.

II. PRINCIPLES

The schematic diagram of applying the extreme learning machine technique to a WDM FBG sensor network can be explained as shown in Fig.1. The light from a broadband source is coupled with 3dB optical coupler to the FBG sensor network. The reflection spectra of all FBGs are coupled back into the same coupler and detected by an optical spectrum analyzer (OSA). Then, the spectral sample data from the OSA is passed to a personal computer (PC) for further processing. The conventional wavelength division multiplexing requires that each FBG sensor must occupy a unique spectral region, which seriously limits the multiplexing capability of the sensor system. In order to address the limitation, the proposed model permits the operational regions of any two FBGs can be overlapped in the optical spectrum. This means the reflection spectra of the two FBGs may occur to overlap when entering into the corresponding overlapping region. Fig.1.(b) shows the spectra of two FBGs progressively approach the completely overlap. Typically, when the distance between the two Bragg wavelengths is smaller than a bandwidth of full width at half maximum (FWHM), it's hard to directly distinguish each peak wavelength. Here, the spectrally overlapped wavelength detection is converted to a regression problem in our study.

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Fig. 1. (a) Schematic diagram: OSA: optical spectrum analyzer; FBG: fiber Bragg grating; PC: personal computer. (b) Spectra of the two-FBG sensor array measured from OSA.

We assume that $\lambda_{Bi} (i = 1, 2)$ are the Bragg wavelength of FBG $_i$ ($i = 1, 2$), and the measured spectrum from OSA is $R(\lambda)$. The expression for the measured spectrum is given by

$$R(\lambda, \lambda_B) = \sum_i^N R_i g_i(\lambda, \lambda_{Bi}) + \text{Noise}(\lambda). \quad (1)$$

where $\lambda_B = [\lambda_{B1}, \lambda_{B2}]$ are the unknown Bragg wavelengths $g(\lambda, \lambda_{Bi})$ is the theoretical reflection spectrum, which can be derived through coupled-mode theory or the transfer matrix method. $\text{Noise}(\lambda)$ is the random spectral noise in the system. From (1), λ_B can be determined from the inverse function of the reflection spectrum containing spectral noise, denoted as $R^{-1}(\cdot)$. Hence, this problem is transformed to the estimation of the nonlinear function $R^{-1}(\cdot)$.

The ELM algorithm is applied to perform this multi-input multi-output regression. The diagram of the proposed ELM model is shown in Fig. 2. The approach can be divided into two phases: an offline phase and an online phase. Since ELM is a supervised learning scheme, during the offline phase, a set of training data is provided for ELM model training.

$$D = (x_1, y_1), \dots, (x_k, y_k), (x_N, y_N) \quad (2)$$

where the inputs $\mathbf{x}_k \in R^n$, which are the sampling points from the theoretical reflection spectrum generated by the corresponding target outputs $\mathbf{y}_k \in R^m$. n is the number of wavelength in the spectrum, and m is the number of FBG sensor in the network. The detailed training process of ELM will be introduced in the next section.

For online testing, we only need to feed new measured reflection spectrum samples into the trained ELM model. The outputs given by ELM are the estimated Bragg wavelengths of FBGs within the network. The learning process of ELM can provide a higher detection accuracy through a well-trained model. Additionally, the model-based approach can determine the Bragg wavelengths in a short time since it does not require a long computation time.

Fig. 2. Flow chart of the ELM-based approach.

III. EXTREME LEARNING MACHINE

ELM is a kind of machine learning algorithm based on Single-hidden Layer Feed forward neural Networks (SLFNs) architecture [7]. ELM has several significant advantages, such as extremely fast learning speed, high generalization performance and free of parameter tuning which distinguish itself from other popular learning algorithms. A brief description of ELM is presented below. For more details, please refer to [7].

The ELM approach considers the wavelength detection problem as a regression problem. Given the training data by (2), the standard SLFN with L hidden neurons and a sigmoid function $g(x)$ is mathematically modeled as

$$\sum_{i=1}^L \beta_i g(\mathbf{a}_i, b_i, \mathbf{x}_k) = \mathbf{y}_k, k = 1, 2, \dots, N. \quad (3)$$

where $\mathbf{a}_i$ and b_i are the weights and bias connecting the input neurons and the i th hidden neuron, β_i are the output weights connecting the i th hidden neuron and the output neurons.

The (3) can be written as the following matrix form:

$$\mathbf{H}\beta = \mathbf{Y}. \quad (4)$$

where

$$\mathbf{H} = \begin{bmatrix} g(\mathbf{a}_1, b_1, \mathbf{x}_1) & \dots & g(\mathbf{a}_L, b_L, \mathbf{x}_1) \\ \vdots & \ddots & \vdots \\ g(\mathbf{a}_1, b_1, \mathbf{x}_N) & \dots & g(\mathbf{a}_L, b_L, \mathbf{x}_N) \end{bmatrix}_{N \times L} \quad (5)$$

$$\beta = \begin{bmatrix} \beta_1^Y \\ \vdots \\ \beta_L^Y \end{bmatrix}_{L \times m} \quad \text{and} \quad \mathbf{Y} = \begin{bmatrix} \mathbf{y}_1^Y \\ \vdots \\ \mathbf{y}_N^Y \end{bmatrix}_{N \times m} \quad (6)$$

Here $\mathbf{H}$ is called the hidden layer output matrix of ELM. The i th column of $\mathbf{H}$ is the i th hidden neurons output vector with respect to inputs $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$, and the k th row of $\mathbf{H}$ is the output vector of the hidden layer with respect to $\mathbf{x}_k$.

Unlike the traditional training algorithms for neural networks which need to adjust the input weights and the hidden layer biases, the output weights can be derived by finding the smallest norm least-square solution to the aforementioned linear system, which is given as

$$\hat{\beta} = \mathbf{H}^\dagger \mathbf{T}. \quad (7)$$

where $\mathbf{H}^\dagger$ is the MoorePenrose generalized inverse of matrix $\mathbf{H}$.

In summary, the training process of the ELM algorithm can be conducted as the following three steps:

Step 1: Randomly assign values to hidden neuron parameters.

Fig. 3. The performance of ELM on a wide range of number of hidden neurons.

Step 2: Calculate the hidden layer output matrix $\mathbf{H}$.

Step 3: Calculate the output weight β : $\beta = \mathbf{H}^\dagger \mathbf{T}$.

IV. RESULTS

The experimental setup of a WDM FBG sensor network is shown in Fig.1.(a). A broadband source with FWHM of 50nm and power of $30\mu\text{W}$ was used to illuminate the FBG sensors array via a 3dB fiber coupler. The span width of the OSA was set to 2nm and sampled by 200 points, corresponding to a sample resolution of 10pm. The OSA spectra were sent to a PC(Xeon 2.13G, 8GB) for further signal processing. The PC also performed the training process and the testing process of ELM and the comparisons of other algorithms. The FBGs used here are of approximately the same spectrum, with an FWHM $\Delta\lambda_{Bi} = 0.2\text{nm}$. Assume that the spectra of FBGs are of Gaussian shape:

$$g_i(\lambda, \lambda_{Bi}) = I_{peak} \exp[-4\ln 2 * ((\lambda - \lambda_{Bi})/(\Delta\lambda_{Bi}))^2] \quad (8)$$

Where I_{peak} is the peak reflectivity of the FBG in the WDM network. In order to identify the Bragg wavelength of each FBG from the combined spectrum, the peak reflectivities of the FBGs should be different. Here, the peak reflectivity of FBG1 was made $\sim 3\text{dB}$ lower than that of FBG2 through the use of a tunable attenuator. The root-mean-square (RMS) Bragg wavelength measurement error was used to evaluate the performance of the proposed method.

A. Parameter Selection for ELM

For ELM, the only parameter that could affect the detection accuracy is the number of hidden neurons in the ELM which need to be pre-determined. In order to achieve the best performance of ELM, we first conducted experiments on a wide range of number of hidden neurons. The training sample size was 10000 and the testing sample size was 1000. Fig.3 shows the RMS errors with different number of neurons. There are two measurement accuracies in the ELM model, including the accuracy for training samples and the accuracy for testing samples. From Fig.3, it can be seen that the training accuracy increases with the number of hidden neurons. But the testing accuracy increases first and then decreases with the increase of the number of hidden neurons. When the number of hidden neurons is too large, the unnecessary hidden neurons will lead

Fig. 4. The training time and testing time of ELM on a wide range of number of hidden neurons.

to ELM to be over-fitted. Because the ELM model is over-sensitive to the training samples and lose the detection ability beyond the training samples. The highest testing accuracy has been achieved when the number of hidden neurons is equal to 3800. Therefore, 3800 hidden neurons are chosen to train the ELM model in subsequent experiments. Fig.4 shows the testing time and training time against number of hidden neurons. Both the testing time and training time increase with the number of hidden neurons. When the number of hidden neurons is 3800, the training time is 308s and corresponding testing time is 0.215s.

B. Performance evaluation

In order to evaluate the performance of the proposed approach, the trained model was used to detect the Bragg wavelength when two FBGs were partially or completely overlapped. During the experiments, under the same constant-temperature environment, the Bragg wavelength of FBG1 was fixed at 1551nm by applying a fixed strain, while the Bragg wavelength of FBG2 was shifted from 1550.4nm to 1551.6nm by applying the changing strain. The strain applied to FBG2 was increased at the steps of $\sim 60\mu\epsilon$. Fig.5.(a) shows the Bragg wavelengths of the two FBGs calculated by ELM model and the corresponding RMS errors. When the two Bragg wavelengths partially or fully merged into each other (from step 8 to step 14), the ELM approach can separate the two wavelength peaks and the RMS error is smaller than 3.5pm. Fig.5.(b) shows the input spectrum into ELM and the output from ELM when step=8.

To further investigate the effectiveness and efficiency of the proposed approach, two evolutionary algorithms, differential evolution algorithm (DE) and particle swarm optimizer (PSO), and the least squares support vector regression (LS-SVR) proposed in previous work, are chosen in comparison with ELM approach. We conducted the experiment under the same PC environment and used the same testing samples of size 1000. The training processes of ELM and LS-SVR were based on the same training samples of size 10000. For DE and PSO, the population size was set to be 20 and generation was 200. On account of the randomness of the evolutionary algorithms, the mean values of the RMS error and testing time of 20 runs were used as the results.

The cumulative percentile of the RMS results for the four approaches is shown in Fig.6. As observed from Fig.6,

Fig. 5. (a) Measured Bragg wavelengths of the two FBGs, when different strain was applied to FBG2. (b) the input and output of the ELM model when step=8.

Fig. 6. Cumulative percentile of RMS error for different methods

85.6% of the results of ELM are below 1pm in the test, and corresponding probabilities of LS-SVR, DE, PSO are 74.3%, 26.8%, 26.3%, respectively. We can see that the cumulative percentile curve of ELM is approximate to that of LS-SVR but is relatively smoother, which indicates that ELM approach provides better stability. Compared with DE and PSO, the cumulative percentile curve of ELM is obviously higher than that of DE and PSO. This means the ELM approach is superior to DE and PSO in terms of the statistic properties as a whole. One of the main reasons is that the detection error of ELM depends, to a great extent, on the generalization ability of the model. Once a model is well-trained, the variance of the detection error does not cause big changes. On the other hand, the evolutionary algorithms have not only stochastic uncertainty, but also the shortcoming of easily plunging into a local optimal solution, which may impact the performance.

Table I summarizes the performance comparison between ELM and other three methods in terms of the mean RMS values of the testing samples, the training time and the testing time. As observed in Table I, ELM has an enormous advantage in training time and learning speed. The training time of ELM is up to 56.14 times faster than LS-SVR. The testing times of ELM and LS-SVR are 0.215s and 0.578s, respectively.

TABLE I
COMPARISON BETWEEN ELM AND OTHER METHODS

Methods	RMS (pm)	Training Time (s)	Testing Time (s)
ELM	0.918	308	0.215
LS-SVR	1.206	17290	0.578
DE	1.912	-	82.724
PSO	2.403	-	168.92

Note: “-” means there is no training time.

Since the ELM can directly determine the Bragg wavelengths by the well-trained model, ELM is far superior to DE and PSO in terms of the testing time. The mean RMS value of the wavelength detection error achieved by the ELM, LS-SVR, DE, and PSO are 0.918pm, 1.206pm, 1.912pm, 2.403pm, respectively. It should be noted that the evolutionary algorithms can improve the measurement accuracy to some extent by increasing the generation or the population size, but may require more time consumption. However, the ELM method still can not handle the changing configuration of the FBG sensor network. Aim to make the proposed method more flexible, our further investigations will focus on it.

V. CONCLUSION

In this paper, we have developed an efficient ELM-based model for detecting the Bragg wavelengths of the FBGs in the WDM FBG sensor network. ELM possesses good generalization capability at an extremely fast learning speed, which makes it a better choice when employing to identify the each Bragg wavelength of FBG from the overlapping spectra. The comparison results show that the ELM-based method achieves a higher detection accuracy while using much less training time than that of LS-SVR. Compared with the evolutionary algorithms, the proposed approach also enhances the performance with a competitive fast real-time detection speed. This technique shows the potential to improve the multiplexing capability of the WDM FBG sensor network.

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