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Wavelength detection in FBG sensor network using least squares support vector regression

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Abstract. A wavelength detection method for a wavelength division multiplexing (WDM) FBG sensor network is proposed based on least squares support vector regression (LS-SVR). As a kind of promising machine learning technique, LS-SVR is employed to approximate the inverse function of the reflection spectrum. The LS-SVR detection model is established from the training samples, and then the Bragg wavelength of each FBG can be directly identified by inputting the measured spectrum into the well-trained model. We also discuss the impact of the sample size and the pre-process of the input spectrum on the performance of the training effectiveness. The results demonstrate that our approach is effective in improving the accuracy for sensor networks with a large number of FBGs.

Keywords: Least squares support vector regression, fiber Bragg grating, fiber-optic sensor, wavelength division multiplexing.

1. Introduction

A key issue in wavelength division multiplexing (WDM) fiber Bragg grating (FBG) sensor network is the accurate detection of the Bragg wavelength of each FBG within the sensor network[1]. A common scheme to detect the Bragg wavelength is the conventional peak detection (CPD) technique, including interferometric detection [2], optical filter [3] and tunable laser technique [4]. In the CPD technique, the system is relatively complex and the overlapping spectrum would cause crosstalk and introduce error in detecting the Bragg wavelength. Recently, much attention has been paid to improving the peak wavelength detection accuracy by using the evolutionary algorithms (EAs), such as genetic algorithm (GA) [5], particle swarm optimizer (DMS-PSO [6], TS-DMS-PSO [7]) and differential evolution algorithm (DE) [8]. These techniques are capable of accurately determining the Bragg wavelengths when the spectra of FBGs in the network are partially or completely overlapped. However, as the sensor number increases, evolutionary algorithms require longer processing time to achieve high accuracy.

In this paper, we describe a novel approach for interrogating arrays of FBG sensors based on a promising machine learning technique called least squares support vector regression(LS-SVR). The basic principle of the proposed method is transforming the wavelength detection problem into a nonlinear regression problem. LS-SVR introduced by Suykens et al. [9-11], which is originated from support vector machines regression (SVR) [12], has the outstanding advantages including the superior generalization and accurate prediction to deal with nonlinearity problems. The LS-SVR detection model is established from the training samples of the spectra of the FBG sensor network, and then the Bragg wavelength of each FBG is directly determined by inputting the measured spectrum into the well-trained LS-SVR model. Meanwhile, the proposed method permits the wavelength operating ranges of any two FBGs be overlapped, which can improve the multiplexing capability of the WDM network.

2. Principles

2.1. Regression model

The schematic diagram of applying the least squares support vector regression technique to FBG sensor network may be explained as shown in Figure.1. Assume that the measured spectrum from an optical spectrum analyzer (OSA) is $R(\lambda)$, and the Bragg wavelength of the i th FBG is λ_{Bi} . The expression of the measured spectrum is given by:

$$R(\lambda) = G(\lambda, \lambda_B) + Noise(\lambda) \quad (1)$$

where $\lambda_B = [\lambda_{B1}, \lambda_{B2}, \dots, \lambda_{Bn}]$ is the Bragg wavelength vector of the FBGs within the network. $G(\lambda, \lambda_B)$ is the theoretical reflection spectrum, which can be derived through the coupled-mode theory or the transfer matrix method. $Noise(\lambda)$ is the spectral noise in the system. From (1), λ_B can be calculated by the inverse function of the reflection spectrum containing spectral noise, denoted as $\tilde{G}^{-1}(\cdot)$. Hence, the wavelength detection

Figure 1. Schematic diagram of (a) the experimental setup. OSA: optical spectrum analyzer; FBG: fiber Bragg grating; PC: personal computer. (b) the segmented LS-SVR based wavelength detection model.

problem is transformed to the estimation of the nonlinear function $\tilde{G}^{-1}(\cdot)$.

Here, least squares support vector regression (LS-SVR) is applied to perform this multi-input multi-output regression. The diagram of the proposed LS-SVR model is shown in Figure.1(b). LS-SVR is a supervised learning scheme and needs to provide a training set

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

where the inputs $x_k = R(\lambda) \in R^m$, which are the sampling points from the reflection spectrum generated by (1). $y_k = \lambda_B \in R^n$ are the corresponding target outputs. In order to multiplex more FBG sensors without sacrificing the accuracy, the input spectrum is split into l segments according to the given wavelength operating ranges of the FBGs in the preprocessing step. This idea is inspired by the technique of stacked generalization [13-14]. The segments here should be viewed as different pieces of information that can be integrated [13]. Each segment may contain multiple FBGs, whose spectral shape and the wavelength operating range can be different. By means of learning from the training sample data for every segment separately, a proper LS-SVR model is established after the integration of all segments. Then input the measured spectrum into the well-trained LS-SVR model, the Bragg wavelength vector is the output. Moreover, for the case that the spectra of the any two FBGs are overlapped, the corresponding operating spectral

ranges are identified as an individual segment to eliminate the crosstalk. Thereby, it can enhance the detection efficiency. The details of the implementation procedure of LS-SVR are described in the following.

2.2. LS-SVR

The basic idea of LS-SVR is to map the data into a so-called higher-dimensional feature space. Here, we consider a multi-input multi-output LS-SVR model [15,16]. Linear regression is done in a high dimensional space and corresponds to nonlinear regression in the low dimensional input space. In LS-SVR, one works with equality instead of inequality constraints and a sum squared error (SSE) cost function, which simultaneously minimizes model complexity and estimation error [10, 17,18].

Considering a training sample set $D = \{(x_k, y_k)\}_{k=1}^N, (x_k, y_k) \in R^m \times R^n$, we construct a regression function of the following form:

$$y(x) = \begin{bmatrix} \omega_1^T \phi_1(x) + b_1 \\ \vdots \\ \omega_i^T \phi_i(x) + b_i \\ \vdots \\ \omega_n^T \phi_n(x) + b_n \end{bmatrix} \quad (3)$$

where $\omega_i \in R^n$ is weight vector, $b_i \in R$ is bias term and $\phi_i(\cdot) : R^m \rightarrow R^{h_i}$ maps the input data into a higher dimensional feature space and h_i is the dimension of the i^{th} feature space. The regression problem could be equivalent to an optimization problem:

$$\begin{aligned} \min_{\omega_i, b_i, e_{ik}} J(\omega_i, e_{ik}) &= \frac{1}{2} \sum_{i=1}^n \omega_i^T \omega_i + \frac{1}{2} \sum_{i=1}^n \gamma_i \sum_{k=1}^N e_{ik}^2 \\ \text{s.t. } y_{ik} &= \omega_i^T \phi_i(x_k) + b_i + e_{ik}, i = 1, \dots, n, k = 1, \dots, N \end{aligned} \quad (4)$$

where $\frac{1}{2} \sum_{i=1}^n \omega_i^T \omega_i$ related to the interval of classification influences generalization performances of regression function. e_{ik} is the error between the target output and estimated value of the sample k . γ_i is a positive constant parameter called regularization parameter, which determines a compromise between the training error and the model complexity. Using Lagrange multiplier method for (4) yields an unconstrained optimization problem. After constructing the Lagrangian equation, setting equality constraints, and simplifying, the optimization problem can be transformed into solving a linear Karush-Kuhn-Tucker (KKT) system. For a more in depth description, see [15].

In LS-SVR model, the suitable kernel function and parameters should be pre-specified. There are several kinds of kernel functions, such as polynomial, hyperbolic tangent, and radial basis function (RBF). This study focus on the RBF kernels, defined as follows:

$$K_i(x_k, x_l) = \exp \left\{ -\|x_k - x_l\|_2^2 / \sigma_i^2 \right\}, i = 1, \dots, n \quad (5)$$

The selection of two major parameters, regularization parameter γ_i in (4) and the RBF kernel function parameter σ_i^2 in (9), plays a crucial role in the performance of LS-SVR.

γ_i balances the models complexity and the training errors and is important to improve the generalization performance of LS-SVR model. σ_i^2 controls the value of function regression error and also reflects the sensitivity of LS-SVR model to the noises from input variables [19]. Here, we use leave-one-out (LOO) cross-validation method [20] to tune the optimal values for these two parameters.

3. Results

The experimental setup of a WDM n-FBGs sensor network is shown in Figure. 1(a). A broadband source with FWHM of 50 nm and power of 100mW was used to illuminate the FBG sensors array via a 50/50 fiber coupler. An OSA was used to measure the reflection spectrum of the sensor array with a sample resolution of 2pm. The OSA spectra were transferred to a PC (Xeon 2.13G, 16GB) for further signal processing. The PC also performed the training process of LS-SVR. 60 FBGs used here are of approximately the same spectrum with a FWHM $\Delta\lambda_{Bi} = 0.2$ nm. The peak reflectivities and/or the shapes of the FBGs in the WDM network should be different, so the peak reflectivity of the i th FBG in the WDM FBG sensor network is set to $I_{peak} = i/n$. Assume that the spectra of the FBGs are of Gaussian shape [21-22]

$$R(\lambda, \lambda_{Bi}) = I_{peak} \exp \left[-4 \ln 2 * \left(\frac{\lambda - \lambda_{Bi}}{\Delta\lambda_{Bi}} \right)^2 \right] \quad (6)$$

The root-mean-square (RMS) Bragg wavelength measurement error was used to evaluate performance of the proposed method.

The LS-SVR was trained with the spectrum samples of a 60-FBG sensor network generated by the theoretical value (1) based on the given wavelength operating range of each FBG. During the training process, the sample size and the number of segments would result in different computation cost and generalization characteristics. The tests were conducted on 200-2000 sample size and the number of FBGs in one segment was set to 2-30. The results are shown in Figure.2 and Figure.3. It can be observed that the training time increases with the increase of sample size, but high accuracy is achieved. There is a trade-off between the training time and the measurement accuracy. If we divided the input region into fewer segments, that is, if the number of FBGs per segment is more, the model would spend less training time but result in a higher RMS value. In fact, the number of FBGs in different segments usually is different. Therefore, the proper sample size and segment number should be selected regarding the practical demand to train the model.

After training, an unknown spectrum not within the training samples was used as the input to test the performance of the well-trained LS-SVR model (2000 sample size, 10 FBG spectra per segment). The white noise was added to the spectra with a signal to noise ratio (SNR), which ranged from 20dB to 100 dB. Figure.4 shows RMS measurement error and the corresponding detection time for different SNR values. Figure.5 provides the input and output spectra of the entire sensor network and the partial detailed spectrum at a SNR of 20dB. The RMS Bragg wavelength measurement

Figure 2. RMS measurement errors for different sample size and different number of FBGs per segment.

Figure 3. Training time for different sample size and different number of FBGs per segment.

error is 3.955 pm with the detection time of 0.0736s when SNR is 20dB. It can be seen that the trained model has strong detection ability to quickly identify the Bragg wavelength of FBG even in a noisy environment.

To test the model for the overlap case, the model was used to detect the Bragg wavelengths when any two FBGs were partially or completely overlapped. The SNR was set to be 20dB. As shown in Figure.6, it can be seen that the spectra of FBGa and FBGb are completely overlapped. Each Bragg wavelength was determined from the combined input spectra, respectively. The LS-SVR model still achieved acceptable RMS error of 2.695 pm for these two FBGs. But the measurement accuracy would be reduced with the increase of the overlapping FBG number.

Figure 4. RMS measurement errors and detection time for different SNR.

Figure 5. FBG spectrum before and after the LS-SVR model when SNR=20dB.

In order to further give the efficiency of the proposed method, the comparison of results between the LS-SVR and other wavelength detection methods reported in previous works [3-8] are present in Table 1. Compared with the results of EAs and CPD methods, a significant improvement in measurement accuracy is achieved by our method. It should be also noted that the CPD methods are unsuitable to detect Bragg wavelengths when overlap spectra exist.

Figure 6. The overlapping part of the input spectrum before and after the LS-SVR model.

Table 1. Comparison of results

Method		FBG number	RMS(pm)	Data source
LS-SVR		10	3.955	This paper
EAs	GA	10	301.82	Ref.[5]
	DMS-PSO	10	78.69	Ref.[6]
	TS-DMS-PSO	10	8.01	Ref.[7]
	DE	2	<1 (non-noise)	Ref.[8]
CPD	MEMS-based	3	7.2 (non-overlap)	Ref.[3]
	fiber laser based	4	~20(non-overlap)	Ref.[4]

4. Conclusion

In this letter, the least squares support vector regression (LS-SVR) has been applied to handle the Bragg wavelength detection for a WDM FBG sensor network. Considering this problem as a nonlinear regression, the LS-SVR model shows the powerful learning ability and superior generalization. The results indicate that the well-trained LS-SVR is capable of accurately determining the Bragg wavelength even in a noisy environment and when the spectra of any two FBGs within the network overlap. Compared with the previously reported results, the measurement accuracy is enhanced. This technique has the potential to increase the number of FBG sensors in the sensor network.

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