Investigation of Peak Detection Algorithms for Fiber Bragg Grating Interrogation based Sensing Systems for Temperature, Depth and Salinity Measurements

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Abstract. Fiber Bragg Grating (FBG) sensors are now one of the prominent and emerging technologies in in the field of optical sensing technology and are used for measurement of strain, depth, temperature and many other applications. This paper reviews the accuracy and stability parameters of four conventional peak seeking algorithms. These algorithms are used in for calculating the peak Bragg wavelength for three different scenarios in which the reflection spectrum of FBG sensors are calculated in our case we consider temperature at 25°C, depth at 6 cm and salinity at 25 PSU. The performance of each of the algorithms i.e., centroid method, Gaussian fitting, polynomial fitting and spline fitting are compared for the above parameters for the actual spectrum and the noisy spectrum on the basis of accuracy and stability and the results are reviewed.

Keywords: Centroid method, polynomial fitting, spline fitting, Gaussian fitting, accuracy, stability, noisy spectrum.

1. Introduction
Fibre Bragg gratings (FBG) have become a hotspot in the field of optical sensing technology. FBG sensors are commonly employed in assessment of several physical parameters for instance strain, vibration, pressure, temperature and concentration. FBG being passive sensors are highly immune to electrical interference also they are corrosion resistant. A key advantage of FBG sensors is that depending on our requirements it can be constructed as an array of sensors along the length of the fiber enabling multiplexed and distributed measurements. FBG sensors have various advantages such as they are light weight, high sensitivity and have stable chemical characteristics, compact size, and high accuracy.

The incident light propagating through the FBG sensor undergoes Fresnel reflections which results in the Bragg wavelength being reflected back while the remaining spectrum is transmitted through the sensor unaffected [1], [2], [3]. The Bragg wavelength is calculated using Bragg law and is given as

\[ \lambda_B = 2n_{eff}\Lambda \]  

where \( \lambda_B \) is the Bragg wavelength, the fibre core has the refractive index is given by \( n_{eff} \) and \( \Lambda \) is the Bragg grating wavelength.
Strain Sensing

FBG sensors when undergoes axial strain, results in a proportional shift of the Bragg wavelength [2], [4], [5],[6]. This shift is given by

\[ \frac{\delta \lambda_B}{\lambda_B} = [1 - p_e] \epsilon \]  

(2)

where \( \epsilon \) homogenous and the strain is isotropic and the effective constant of photoelasticity which is described as \( p_e \).

\[ p_e = \frac{n^2}{2} [p_{12} - \mu (p_{11} + p_{12})] \]  

(3)

where \( p_{ij} \) are parts of the strain optic tensor, \( n \) is the refractive index and \( \mu \) the Poisson ratio.

Temperature Sensing

FBG sensor experiences a shift in the Bragg wavelength whenever there is the change in temperature [2], [7], [8]. The fractional shift in the Bragg wavelength for the change in temperature \( T \) is given by

\[ \frac{\delta \lambda_B}{\lambda_B} = \alpha + \frac{1}{n} \frac{dn}{dT} \]  

(4)

where \( \alpha \) is the thermal expansion coefficient of the fiber and the refractive index of the core is given by \( n \).

The sensitivity of the system of FBG sensor is defined by the ratio of the reflected wavelength that is shifted to the amount of change in the measuring parameter being detected. In FBG sensing applications, the shift in wavelength \( \Delta \lambda_B \) helps in estimating either \( \Delta \epsilon \) or \( \Delta T \) from equations (2) and (4) respectively.

The characteristics mentioned in this section have led to the inception of sensors that find applications in electrical measurements, aeronautic engineering, health monitoring as well as in civil engineering where the mechanical loading be measured for maintaining bridges, buildings etc by calibrating the distributed strain of the building. FBG sensors also find use as notch filters and the field of optical fibre communication networks because of their characteristic of reflecting wavelengths in the narrow band range.

2. Review of Peak Detection Methods

For practical sensing applications, the small shift in Bragg wavelength which is caused by the change in the various parameters has to be traced. The convectional ways for peak detection in FBG sensors can be categorised into the following:

- Direct methods where peak tracing is performed on spectrum without processing the shape of the spectrum [3], [9], [10].
- Curve Fitting methods detect the peak of the spectrum by interposing on the spectrum with an analytical function [3], [9], [10].
- Correlation-based methods use several correlation based methods such as mutual correlation, cross correlation etc between the a reference FBG spectrum and measured spectrum [3], [9], [10].
- Transform-based methods are used to move the analysis to an alternative domain from the domain in which the spectrum is measured [10], [12].
- Optimization-based method, in this a model is optimized to the measured data [10], [13].

In this section the algorithms that are reviewed and examined with experimental data are described. The algorithms are implemented to measured data for temperature, depth [14] and salinity.

Centroid Method

The centroid algorithm described in [9], [10], [15] gives a point which relates to the geometric centroid of the reflection spectrum. The centroid of the spectrum is computed algorithmically with two summations which is given by

\[ \lambda_B = \frac{\sum_{i=1}^{N} \lambda_i A_i}{\sum_{i=1}^{N} A_i} \]  

(5)

where the size of the spectrum points vector, the i-th point wavelength and the i-th point amplitude are given by \( N \), \( \lambda_i \), \( A_i \) respectively. The summation can be extended to the entire reflection spectrum or only a part of the spectrum can be examined.

Polynomial Fitting Algorithm

Polynomial fitting method [9], [10], [15] utilize a polynomial function to fit the reflection spectrum. In most cases a second order polynomial is availed.

\[ R(\lambda) = a_2 \lambda^2 + a_1 \lambda + a_0 \]  

(6)
where $R(\lambda)$ is the calculated amplitude for the $\lambda_0$ wavelength. The polynomial fitting is executed on the innermost section of the reflection spectrum that approximates to a parabolic function such that $a_2 < 0$.

**Gaussian Fitting Algorithm**

The Gaussian fitting [9], [10], [15] is executed by reducing the squared errors by utilizing the Gauss-Newton algorithm. The expression for Gaussian fitting is expressed as:

$$R(\lambda) = A \exp \left[ -\frac{(\lambda - \lambda_0)^2}{2\sigma^2} \right]$$ (7)

where $A$ is the amplitude, $\lambda$ is the center, $\sigma$ is the deviation, and $R(\lambda)$ is the calculated amplitude for the $\lambda_0$ wavelength. A Gaussian fitting has a symmetrical bell-shape around its center, and the spread of the spectrum decreases smoothly when it moves away from its center on the x-axis.

**Spline Fitting**

In spline fitting the interpolation of the reflection spectrum is with a piece-wise polynomial function [10], [15]. The calculations in spline fitting is described below: $R(\lambda)$ is the given spectrum which is sampled on the wavelength grid $\lambda_1, \lambda_2, \ldots, \lambda_N$ there is one interpolant function in each pair of adjacent knots where the wavelength constitute the knots.

$$R(\lambda) = a_{3,k}\lambda^3 + a_{2,k}\lambda^2 + a_{1,k}\lambda + a_{0,k}$$ (8)

where $k = 1, \ldots, N-1$. Each $k$-th cubic spline function is defined between $\lambda_k$ and $\lambda_{k+1}$.

**3. Experimental Setup**

The simulations are performed in MATLAB 2020 version and Origin Pro. The diagrammatic representation of the setup is exhibited in the Fig 1. A broadband light source in our case a super-luminescent light emitting diode (SLED) which has a produces a spectrum in between 1530 nm to 1570 nm is used. The input power that the SLED produces is about 1.92mW. A 3 port optical circulator is connected to the source and the FBG sensing unit (I-MON 256 USB) where the reflection spectrum is observed. The detector tracks the change in the position of the Bragg wavelength of the spectrum.

![Fig 1. Schematic diagram of the experimental setup](image)

When observing the spectrum for temperature variations the salinity of the water solution as well as the water level in which the FBG is placed is kept constant. The data is taken by increasing the temperature of the system by 1°C for each set of readings. Similarly, for salinity and depth measurements, the corresponding parameters are kept constant. The salinity of the system is increased by 1 PSU and for depth the water level is increased by 1cm for subsequent readings. Since the objective of this paper is to find the peak of the spectrum we consider one set of data from each type of system to carry out the algorithms.
4. Result And Discussion Of Experimental Data

The different algorithms described above are used to track the peak wavelength for three different conditions i.e., for temperature at 25°C, salinity at 25 PSU [16] and depth at 6 cm [14]. The algorithms are iterated and a definite central peak wavelength is obtained for each of the spectrum. To measure the performance parameters explained in [17], [18] the error is calculated by using the expression given by

\[ \text{Error} = | \text{Peak value of measured spectrum} - \text{Theoretical peak value} | \]

In the above equation, the measured value is the experimentally derived FBG spectrum and the theoretical peak value is derived from the algorithm. The mean and variance determines the performance of algorithms. The mean explains the accuracy while variance describes the stability of the system. Table 1 describes the errors from the four algorithms.

From the tabulations in Table 1 and Table 2 it is seen that the Gaussian fitting has the worst performance in terms of accuracy in all three types of spectrum. The polynomial fitting has the highest accuracy for temperature and salinity reflection spectrum while for depth measurement spline fitting has highest accuracy. Centroid fitting has the best stability in the all the three categories while followed by polynomial and Gaussian fitting whereas spline has the worst stability in all the three types of spectrum.

Figure (2), (3), (4) and (5) shows the implementation of four the algorithms for three set of data where in the x-axis we plot the wavelength and in the y-axis the amplitude is plotted.

Table 1: Fitting errors for the experimental data for the different peak tracking techniques

|                | Centroid Fitting | Spline Fitting | Polynomial Fitting | Gaussian Fitting |
|----------------|------------------|----------------|--------------------|------------------|
| Actual Wavelength (nm) | Fitting Wavelength (nm) | Fitting Error (nm) | Fitting Wavelength (nm) | Fitting Error (nm) |
| Temp at 25°C   | 1549.08          | 1548.994       | 0.086              | 1549             | 0.08              | 1549.02          | 0.06             | 1548.99          | 0.09              |
| Salinity at 25 PSU | 1549.08          | 1549.095       | 0.015              | 1549.14          | 0.06              | 1549.11          | 0.03             | 1549.14          | 0.06              |
| Depth at 6 cm  | 1549.08          | 1548.963       | 0.117              | 1549.04          | 0.04              | 1548.99          | 0.09             | 1548.97          | 0.10              |

Table 2: Mean and variance of the different algorithms’ error

|                | Centroid | Spline Fitting | Polynomial Fitting | Gaussian Fitting |
|----------------|----------|----------------|--------------------|------------------|
| Mean (nm)      | 59.9     | 57             | 30.4               | 185.3            |
| Variance (nm)  | 0.00049  | 0.081          | 0.00014            | 0.0412           |
| Temp at 25°C   | 47.44    | 63.33          | 26.5               | 67.22            |
| Variance (nm)  | 0.00024  | 0.044          | 0.00158            | 0.0106           |
| Salinity at 25 PSU | 99.4     | 57             | 125                | 115.3            |
| Variance (nm)  | 0.00024  | 0.081          | 2.025              | 0.0198           |

(a) Temperature at 25 o C    (b) Salinity at 25 PSU    (c) Depth at 6cm

Fig 2. Centroid fitting for three FBG reflection spectrum
Fig. 2 depicts the centroid of spectrum given by equation (5) and from the plot it is evident that algorithm is not meant for curve fitting rather it is used for directly calculating the geometric centroid. Fig. 3 shows the polynomial curve fitting. The polynomial fitting algorithm has high accuracy but while plotting only a few samples of data are used for calibration for proper fitting instead of the whole spectrum i.e., innermost section that resembles a parabola is considered. That is why other curve fitting methods such as Gaussian and spline fitting methods are considered. Spline fitting, shown in Fig. 4 completely traces the spectrum and hence finding an exact equation for mathematical calculation becomes difficult. Fig. 5 shows the plot for Gaussian fitting which has traces the spectrum in accordance to equation (7).

To further investigate the application of the algorithm we use MATLAB 2020 to add noise of various SNR levels, the Fig. 6 shows the noisy spectrums. We consider 10dB and 5dB SNR to check the performance of the algorithms. In the above table 3, 4 and 5 we use spline, polynomial and Gaussian fitting. The fitting on the corrupted spectrum is performed in the same manner as it is done for the actual spectrum shown in figures 3, 4 and 5. Centroid fitting becomes more complicated to analyze for noisy spectrum as well as the result obtained is inaccurate, hence is not used in this case.
Table 3: Mean, Variance And Standard Deviation For Temperature At 25ºC For 10 dB And 5 dB SNR

|                  | 10 dB SNR       |               | 5 dB SNR       |               |
|------------------|-----------------|---------------|----------------|---------------|
|                  | Gaussian Fitting| Polynomial Fitting | Spline Fitting | Gaussian Fitting | Polynomial Fitting | Spline Fitting |
| Variance (nm)    | 0.0031          | 0.000096      | 0.000214       | 0.0038        | 0.0164             | 0.00054       |
| Mean (nm)        | 0.044           | 0.098         | 0.016          | 0.056         | 0.144             | 0.02          |
| Standard Deviation (nm) | 0.0361        | 0.00979       | 0.00419        | 0.0411        | 0.0546             | 0.021         |

Table 4: Mean, Variance And Standard Deviation For Salinity At 25 PSU For 10 dB And 5 dB SNR

|                  | 10 dB SNR       |               | 5 dB SNR       |               |
|------------------|-----------------|---------------|----------------|---------------|
|                  | Gaussian Fitting| Polynomial Fitting | Spline Fitting | Gaussian Fitting | Polynomial Fitting | Spline Fitting |
| Variance (nm)    | 0.000056        | 0.04924       | 0.00033        | 0.00038       | 0.0164             | 0.00054       |
| Mean (nm)        | 0.088           | 0.22          | 0.082          | 0.096         | 0.174             | 0.074         |
| Standard Deviation (nm) | 0.0074        | 0.2219        | 0.0183         | 0.0195        | 0.128             | 0.0233        |
TABLE 5: Mean, Variance And Standard Deviation For Depth Of 6cm For 10 Db And 5db Snr

|               | 10 dB SNR | 5 dB SNR |
|---------------|-----------|----------|
|               | Gaussian Fitting | Polynomial Fitting | Spline Fitting | Gaussian Fitting | Polynomial Fitting | Spline Fitting |
| Variance (nm) | 0.00202   | 0.0014   | 0.00088   | 0.0001   | 0.0009   | 0.0007 |
| Mean (nm)     | 0.596     | 0.122    | 0.06      | 0.112    | 0.288    | 0.054  |
| Standard Deviation (nm) | 0.049     | 0.0861   | 0.0260    | 0.026    | 0.095    | 0.028  |

5. Conclusion
The four peak-detection methods for FBG interrogation have been analyzed. It is seen that the performance of each of the algorithm depends on the what type of environment it is placed. From the experimental data it is inferred that spline fitting gives the highest accuracy for depth measurements but it has the worst stability for all three environments. Centroid fitting on the other hand has the best performance in terms of stability for all three categories while Gaussian fitting has the worst accuracy in all three categories. The polynomial fitting algorithm has moderate accuracy but the overall fitting of the algorithm is not applicable to the entire spectrum.

The algorithms that have been used in this paper are works when the system has very low noise. But in case of noisy spectrums these algorithms do not provide the best results. Hence for our further research we will into different denoising methods that can be employed along with traditional methods to get a more precise peak.

This paper gives a brief a comparison of the different algorithm's performance when applied to spectrum obtained from different environmental conditions such as temperature, salinity etc. So depending on application one can choose the proper algorithm that fits their performance criterion.

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