Optik - International Journal for Light and Electron Optics 172 (2018) 753–759

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.com/locate/ijleo

Original research article

Fiber Bragg grating temperature calibration based on BP neural network

Yang An[a], Xiaocen Wang[a], Zhigang Qu[a,*], Tao Liao[b], Zhongliang Nan[a]

[a] Tianjin University of Science & Technology, College of Electronic Information and Automation, No. 1038, DaGu South Street, Tianjin, 300222, China
[b] Beijing Institute of Spacecraft Environment Engineering, No. 5, National Park Street, Beijing, 100094, China

ARTICLE INFO

Keywords:
Fiber optic sensors
Fiber Bragg gratings
Temperature metrology
Fitting
BP neural network

ABSTRACT

A novel method which applies BP neural network (BPNN) to temperature calibration of fiber Bragg grating (FBG) sensors is proposed and discussed. Processing and analysis of experimental data showed that this method fitted very well the complex relationship between the center wavelength of FBG and temperature which is approximately linear in room temperature whereas nonlinear in low temperature. The maximum absolute error and root mean squared error were respectively 0.9434 °C, 0.2102 °C in fitting and 0.8943 °C, 0.2081 °C in testing which verified the advantage of BPNN fitting compared with the previous polynomial fitting. The forecasting performance of BPNN was also satisfactory. The novel FBG temperature calibration method based on BPNN has considerable application prospect in FBG temperature measurement.

1. Introduction

Since Morey used fiber grating for sensing in 1989, fiber Bragg grating (FBG) has become one of the most promising and representative optical fiber passive components and has become a research hotspot of sensing technology [1–4]. With the advantages of immunity to electromagnetic interference, corrosion resistance, high sensitivity, FBG sensors are widely used in various fields even in harsh environments such as aerospace and structural health monitoring. The temperature sensing ability of an FBG is based on the fact that the center wavelength of the FBG changes with temperature due to thermal expansion effects and thermo-optic effects. A lot of methods and techniques have been proposed to improve the temperature measurement performance such as temperature sensitivity and measurement resolution [5–7]. However, the study of temperature calibration methods which can influence the temperature measurement accuracy is usually overlooked and limited to linear fitting or polynomial fitting. Xueguang Qiao et al. analyzed the temperature sensing characteristics of fiber gratings and obtained the second order polynomial [8]. Guiwen Jia introduced sixth order polynomial and BIC criterion into the FBG temperature sensing system [9]. Tiegen Liu et al. utilized linear fitting to obtain a demodulation matrix which based on the measured sensitivity coefficients of FBG so that the changes of temperature can be acquired [10]. However, since experiment results showed that the relationship between the FBG center wavelength and temperature is approximately linear in room temperature whereas non-linear in low temperature, the methods mentioned above are either unsatisfactory or complicated in temperature calibration of FBG.

Some previous research have introduced artificial neural network to FBG [11–13]. Lucas Negri et al. utilized neural network which was trained by the Neuron by Neuron algorithm to solve spectrum distortion problems caused by noise and non-uniform disturbance in fiber Bragg grating sensors [11]. Taymour A. Hamdalla et al. introduced an artificial neural network modeling which

* Corresponding author.
E-mail address: qzgwin@gmail.com (Z. Qu).

https://doi.org/10.1016/j.ijleo.2018.07.064
Received 7 May 2018; Received in revised form 12 July 2018; Accepted 16 July 2018
0030-4026/ © 2018 Elsevier GmbH. All rights reserved.

was used for modeling the relationship between ocean depth and temperature measured by FBG [12]. Antonio Carlos Zimmermann et al. applied an artificial neural network to extend the measurement range of FBG interrogators based on fixed narrowband filter demodulation which can reduce the ambiguities created in both edges of each FBG filter and obtain a continuous linear output [13]. However, none of them focused on the temperature calibration of FBG to our knowledge. In this paper, BP neural network (BPNN) is applied to fit simultaneously and accurately the complex wavelength-temperature relationship in room temperature as well as in low temperature ambient.

2. Principle

2.1. Principle of fiber Bragg grating temperature sensing

According to the coupled mode theory [14], the wavelength λ_B of an FBG accords with the following equation:

$$\lambda_B = 2n_{eff}\Lambda \tag{1}$$

where, n_{eff} is the effective refractive index, Λ is the modulation cycle. The center wavelength of the FBG can be affected by temperature and strain. According to thermal-optic effects and thermo-expansion effects, temperature changes give rise to the change of modulation cycle as well as the effective refractive index. Taking only temperature into account, the change of the center wavelength can be obtained as [15]:

$$\Delta\lambda_B = 2n_{eff}\Delta\Lambda + 2\Delta n_{eff}\Lambda = 2n_{eff}(\alpha\Lambda\Delta T) + 2(\varepsilon n_{eff}\Delta T)\Lambda = (\alpha + \varepsilon)\lambda_B\Delta T \tag{2}$$

where ε is the thermal light coefficient of optical fiber, α is the thermal expansion coefficient of optical fiber, K_T is called the temperature sensitivity coefficient and $K_T = (\alpha + \varepsilon)\lambda_B$.

2.2. Principle of BP neural network

With the ability of processing nonlinear and complex system problems, BPNN has been widely used in regression, prediction and pattern recognition at present. The main idea of BPNN is to modify weights between nodes in an iteration through error back propagation so as to reduce in the next iteration the error between output of neural network and the expected output until error goal is met or iteration number is reached [16]. Fig. 1 shows the structure of a three layer neural network.

Neural network gives a way of defining a complex, non-linear form of hypotheses $h_{W,b}(x)$, with parameters W,b that can be fitted to the data. The computation of neural network is given by:

$$z_j^{(l+1)} = \sum_{i=0}^{s_l-1} w_{ij}^{(l)}a_i^{(l)} + b_j^{(l)} \tag{3}$$

$$a_i^{(l)} = f(z_i^{(l)}) \tag{4}$$

where, $z_i^{(l)}$ denotes the total weighted sum of inputs to node i in layer l, $w_{ij}^{(l)}$ is the weight associated with the connection between node j in layer l and node i in layer $l+1$, $b_j^{(l)}$ is the bias associated with unit i in layer $l+1$, $a_i^{(l)}$ denotes the activation (meaning output value) of node i in layer l, for $l = 1$, $a_i^{(1)}$ is also used to denote the i-th input x_i, s_l denotes the number of nodes in layer l, $f(\cdot)$ is called the activation function.

Specifically, if the activation function $f(\cdot)$ is extended to apply to vectors in an element-wise fashion (i.e. $f([z_1, z_2, z_3]) = [f(z_1), f(z_2), f(z_3)]$), then the equations above can be written more compactly as:

$$\boldsymbol{z}^{(l+1)} = \boldsymbol{w}^{(l)}\boldsymbol{a}^{(l)} + \boldsymbol{b}^{(l)} \tag{5}$$

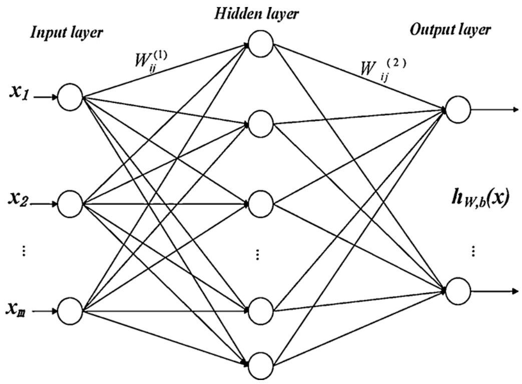

Fig. 1. Structure of a three layer BP neural network.

Download English Version:

https://daneshyari.com/en/article/7223010

Download Persian Version:

https://daneshyari.com/article/7223010

Daneshyari.com