Temperature sensing in BOTDA system by using artificial neural network

Abul Kalam Azad, Liang Wang, Nan Guo, H. Y.Tam, C. Lu

We propose and demonstrate the use of Artificial Neural Network (ANN) for extraction of temperature profile from local Brillouin gain spectrum in a Brillouin Optical Time Domain Analysis (BOTDA) fiber sensor system. ANN is applied to process the Brillouin time-domain trace in order to extract the temperature information along the fiber after data acquisition process. Our results show that ANN provides higher accuracy and larger tolerance to measurement error than Lorentzian curve fitting does, especially at large frequency scanning step. Hence the measurement time can be greatly reduced by adopting larger frequency scanning step without sacrificing accuracy.

Introduction: Brillouin Optical Time Domain Analysis (BOTDA) distributed fiber-optic sensor systems have attracted a great deal of attention over the past few decades due to their ability of monitoring temperature and strain over a long sensing range with superior accuracy and resolution [1-3]. In such systems, the pump signal transfers part of its energy to the counter-propagating probe signal through the interaction with acoustic phonons. This energy transfer takes place as long as the frequency difference of the two signals is within the local Brillouin Gain Spectrum (BGS) and maximum amplification occurs when the frequency difference is exactly equal to the Brillouin frequency shift. The local BGS is obtained by subsequently scanning one of the signal frequencies over the Brillouin gain bandwidth and the Brillouin Frequency Shift (BFS) is determined by finding the frequency with peak gain in the BGS. Usually, Lorentzian Curve Fitting (LCF) method is adopted to find BFS [4]. However, the accuracy of this method is limited in practical situation for noisy Brillouin gain spectrum. Moreover, when using short pulses to improve spatial resolution and when the measurement range is long, the shape of the BGS may diverge completely from Lorentzian shape [4,5] and thus, LCF provides poor estimation of the BFS and affects the measurement accuracy.

In recent years, ANN has been widely employed for different applications of estimation in science and engineering [6-8] to achieve complex input-output relationship as well as nonlinear mapping ability. As a nonlinear model, it outperforms other conventional methods since it does not require entire and accurate knowledge on the system model. Therefore, it is inherently much more flexible when implemented in practice. As the estimation of BFS, and hence temperature, from the BGS is actually a non-linear process, ANN can be employed to estimate the temperature/strain along the fiber. In this paper, we propose the use of ANN to directly retrieve temperature information along the fiber from a BOTDA system without the process of determination of BFS, and hence conversion from BFS to temperature. By comparison of the performance between ANN and LCF, we show that ANN provides higher accuracy and hence greater tolerance to the measurement error, especially at large frequency scanning step. Therefore, BOTDA systems with ANN to extract temperature/strain information can adopt larger frequency step which greatly reduces the measurement time and makes it practical in real-time monitoring of temperature/strain.

Principle and Experiment Setup: An ANN is a computational model of interconnected elements, also known as neurons or nodes. A typical artificial neural network with two hidden layers is shown in Fig. 1. It is usually trained with backpropagation (BP) learning algorithm [9]. The training of ANN with this algorithm consists of two passes. In the forward pass, the input signals propagate forward through the network and the output signals of each nodes are determined. In the reverse pass, the error signals propagate backwards through the network and the weights are updated. The two passes are executed at each iteration until algorithm converges to satisfy a pre-defined mean square error value. After the adjustment of weights between nodes of different layers, ANN produce output of each nodes by Eq. (1)

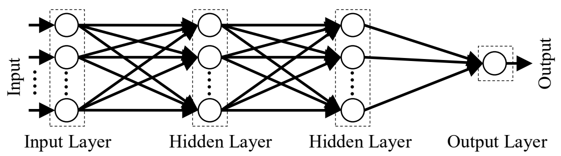

Fig. 1 *Typical ANN with two hidden layers.*

$$y_j = f_j\left(\sum_i w_{ij}x_i - \theta_j\right) \qquad (1)$$

where, 'y_j' is the output of the node 'j', 'x_i' is the i^{th} input to the node, 'w_{ij}' is the adjusted weights between nodes 'i' and 'j', 'θ_j' is the threshold of the j^{th} node and 'f_j' is a nonlinear activation function.

In order to train the ANN used in temperature extraction of BOTDA system, the BGSs at different temperatures are collected using our BOTDA experiment setup in Fig. 2. The output of a CW tunable laser operating at 1550 nm is split into two branches using a 20/80 coupler to generate the pump and probe signals, respectively. The CW signal at the upper branch is modulated by an electro-optic modulator (EOM1) to generate 40 ns pump pulse which indicates a spatial resolution of 4 m. An erbium-doped fiber amplifier (EDFA) is used to increase the peak pump power at one end of the fiber under test (FUT). Then the pump pulse passes through a polarization scrambler (PS) to suppress the polarization dependent noise. The signal at the lower branch is modulated by another electro-optic modulator (EOM2) biased at Null point to suppress the optical carrier and driven at a frequency around BFS. A variable optical attenuator is used to control the probe power. The probe signal is amplified by the counter-propagating pump pulse when passing through the FUT and it is detected by a photodetector after the unwanted sideband is filtered out by a fiber Bragg grating (FBG). For the training of ANN, a whole short fiber of tens of meters is put into the oven and the BGSs along the fiber are collected with a frequency scanning range of 10.75 GHz to 10.95 GHz. Since the whole fiber is set at one temperature, we average all the BGSs along the fiber to obtain one BGS representing that particular temperature. The BGS together with the particular temperature constitutes one input-output pair. The experiment is repeated with the fiber heated from room temperature to 65ºC and the input-output pairs obtained in this way are used to train the ANN with BP learning algorithm. Once the training is completed, the weights between different layers of ANN are optimized and the ANN is ready to be used in calculation of the temperature distribution along the FUT. Moreover, in order to examine the performance of ANN at large frequency scanning step, the above procedures are repeated for different frequency scanning steps used in our experiment. For each scanning step, we obtain one trained ANN suitable for temperature extraction at that scanning step.

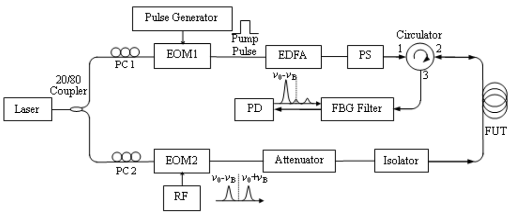

Fig. 2 *BOTDA experiment setup.*

Results and Discussion: In our demonstration, a FUT of 92 m is put into the oven for detection of temperature using the setup in Fig. 2. The 3-D distribution of the BGS collected at 1MHz frequency scanning step for the oven temperature of 29.35ºC is shown in Fig. 3(a), indicating an average BFS and linewidth of ~10.833 GHz and ~34 MHz, respectively. Fig. 3(b) depicts the measured BFS versus temperature with a slope of 0.93 MHz/ºC.

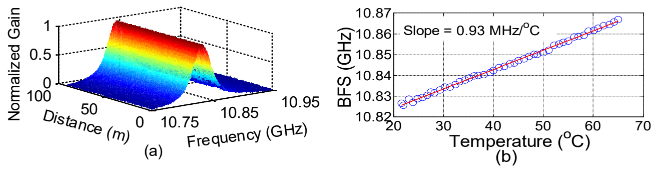

Fig. 3(a) *BGS along FUT at 29.35 °C and (b) BFS vs temperature.*

Using the data in Fig. 3, the temperature distribution along the FUT obtained by conventional LCF method is plotted in Fig. 4(a). Except for 1 MHz scanning step, the results for five other scanning steps are also given. Similar to Fig. 4 (a), Fig. 4 (b) and (c) show the temperature distribution when the oven temperature is set at 44.60ºC and 60.40ºC, respectively. On the other hand, after completing the training session, the ANNs with optimized weights for different scanning steps are used to directly retrieve the temperature along the FUT from the Brillouin time-domain traces. The results are given in Fig. 5. For both LCF and ANN, as the scanning step increases, the fluctuations of the temperature distribution along the FUT become larger. The performance degradation at large scanning step is due to the fact that fewer frequency components can be used to reconstruct the local BGS since the Brillouin linewidth is only ~34 MHz. However, for each scanning step the temperature distribution by ANN in Fig. 5 have much less variation than that by LCF in Fig. 4, and even at large scanning step the performance of ANN approach does not degrades seriously while that of LCF shows obvious errors (e.g. 16 MHz). It implies that ANN has larger tolerance to measurement noise and error than LCF does.

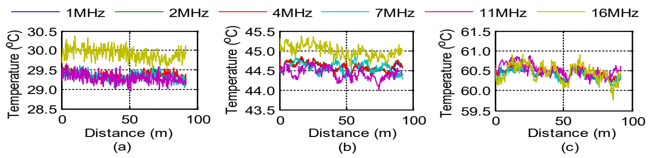

Fig.4 *Temperature distribution using LCF at different scanning steps when the oven is set at (a) 29.35 °C (b) 44.6 °C and (c) 60.4 °C.*

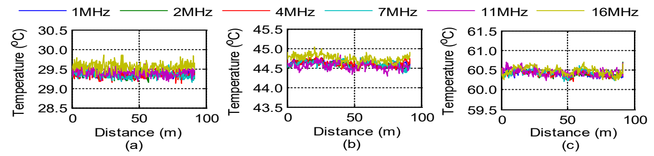

Fig. 5 *Temperature distribution using ANN at different scanning steps when the oven is set at (a) 29.35 °C (b) 44.6 °C and (c) 60.4 °C.*

To give a quantitative comparison between the performance of ANN and LCF, Root Mean Square Error (RMSE) and Standard Deviation (SD) are calculated using Eq. (2),

$$RMSE = \sqrt{\sum (T_m - T_c)^2 / N} \ and, SD = \sqrt{\sum \left(T_c - \overline{T}_c\right)^2 / N} \qquad (2)$$

where, T_m is the temperature measured by thermometer, T_c is the one calculated by LCF or ANN, $\overline{T}_c$ is the mean value of T_c, and N is the total number of local BGS processed along the FUT. The results are given in Fig. 6 and Fig. 7 respectively. From Fig. 6 and Fig. 7, we can

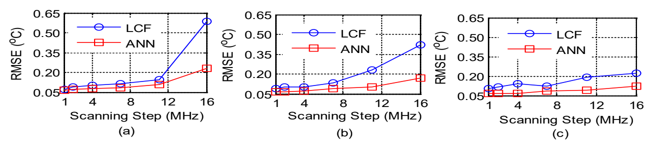

Fig. 6 *Performance comparison of ANN and LCF at different frequency scanning steps in terms of Root Mean Square Error (RMSE) for three temperatures (a) 29.35 °C (b) 44.6 °C and (c) 60.4 °C.*

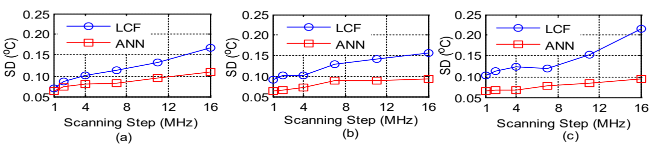

Fig. 7 *Performance comparison of ANN and LCF at different frequency scanning steps in terms of Standard Deviation (SD) for three temperatures (a) 29.35 °C (b) 44.6 °C and (c) 60.4 °C.*

see that for each scanning step the ANN approach has both smaller RMSE and SD than LCF approach, and both RMSE and SD in LCF approach degrades much more quickly than that in ANN when the scanning step increases. By taking the temperature of 44.6 ºC as an example, the RMSE using ANN for 7 MHz and 11 MHz scanning steps are 0.088 and 0.102 respectively, which are very close to the RMSE (0.093) using LCF at 1 MHz scanning step. Similar results are also obtained for other two temperatures. Moreover, the comparison of SD in Fig. 7 confirms the superiority of ANN over LCF as well. This implies that one can adopt 11 MHz scanning step instead of 1 MHz when using ANN for temperature extraction with almost the same performance as that in the case of 1 MHz scanning step using LCF. As a result, the measurement time can be greatly reduced by ten times or even more if the performance for larger scanning step is acceptable in real situation. Fig. 6 and Fig. 7 again show the ANN approach has higher accuracy and larger tolerance to measurement noise and error compared to the LCF approach.

Conclusion: ANN has been successfully employed to retrieve the temperature distribution along the fiber. Compared with conventional LCF method, ANN provides better temperature accuracy and tolerance to measurement noise and error. Under a given temperature accuracy, BOTDA systems with ANN approach can effectively adopt larger scanning step than those with LCF approach, significantly reducing the measurement time of temperature once the ANN is trained. Therefore, ANN can be a good alternative for the fast monitoring of temperature/strain along the fiber in BOTDA sensor system.

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