BRILLOUIN OPTICAL TIME DOMAIN ANALYZER ENHANCED BY ARTIFICIAL/DEEP NEURAL NETWORKS

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ABSTRACT

We report our recent studies on the use of Neural Networks to process the measured Brillouin gain spectrum (BGS) from Brillouin Optical Time Domain Analyzer (BOTDA) and extract temperature information along fiber under test (FUT). Artificial Neural Network (ANN) is trained with ideal Lorentizian BGS before it is used for temperature extraction. Its performance is evaluated by comparison to conventional curve fitting techniques, showing better accuracy especially at large frequency scanning step during the acquisition of BGSs. We have also applied advanced hierarchical Deep Neural Network (DNN) in BOTDA for temperature extraction to improve the training and testing efficiency. We believe that ANN/DNN can be attractive tools for direct temperature or strain extraction in BOTDA system with high accuracy.

Keywords: *Distributed fiber sensor, Stimulated Brillouin scattering, BOTDA, neural networks*

1. INTRODUCTION

Intensive research efforts have been made in distributed Brillouin fiber sensors during the past two decades. Among them, Brillouin Optical Time-Domain Analyzer (BOTDA) has attracted much research interest due to its promising properties for temperature and strain monitoring [1]. In BOTDA the local Brillouin Gain Spectrum (BGS) is reconstructed by scanning the frequency offset of a continuous wave and a pump pulse around Brillouin frequency shift (BFS) when they are counter-propagating inside fiber under test (FUT), and the local BFS and hence the temperature and/ or strain information are determined accordingly. However, due to the noise on the measured BGSs, the determination of BFS is not such easy. Curve fitting methods, e.g. Lorentzian curve fitting (LCF) and quadratic curve fitting, are usually adopted to estimate the BFS [2, 3]. However, the BFS accuracy by curve fitting techniques depends on the proper setting of initial parameters and it could lead to poor estimation if the initializations are far away from the expected values [2, 4]. Moreover, the data points collected on the BGS should be as many as possible to ensure the fitting accuracy.

Recently we have applied the Artificial Neural Network (ANN) in a BOTDA system and has successfully extracted temperature distribution from the measured BGSs [5]. Neither curve fitting process nor the BFS determination are needed. The training makes ANN learn the knowledge of the BGS patterns under different temperatures, thus it allows better accuracy even if the data points collected on BGS become fewer. To improve the training and testing efficiency, we further replace ANN by more advanced hierarchical Deep Neural Network (DNN) in BOTDA to extract temperature [6]. In this paper, we will review our work on using ANN/DNN for temperature extraction in a BOTDA system.

2. TEMPERATURE EXTRACTION BY ARTIFICIAL NEURAL NETWORK

Fig. 1 (a) plots a typical ANN structure with input, hidden, and output layers, which are interconnected by neurons with different weights. O_i, O_j and O_k are the outputs of ith, jth and kth neurons in the input, hidden and output layers, respectively. w_{ij} and w_{jk} are connecting weights among different layers. Fig. 1(b) shows the two independent training and testing phases required for ANN to extract temperature from the BGSs measured by BOTDA. In the training phase, a number of known BGS-Temperature (BGS-T) pairs are used as the input-output patterns to optimize the connecting weights in ANN before temperature extraction. The optimization is realized by back-propagation (BP) algorithm [5]. The training of ANN by BP algorithm starts with random initial weights and is repeated until the pre-defined target error is satisfied for all the known BGS-T pairs. After the training is finished, the local BGSs measured by BOTDA are fed to the ANN input layer and the temperature distribution along FUT is directly obtained at the ANN output layer.

We construct ideal Lorentzian BGSs as the known BGS-T pairs for ANN training in the following way: the BFS at each T is determined using the calibrated BFS temperature coefficient of ~0.92924 MHz/ºC for

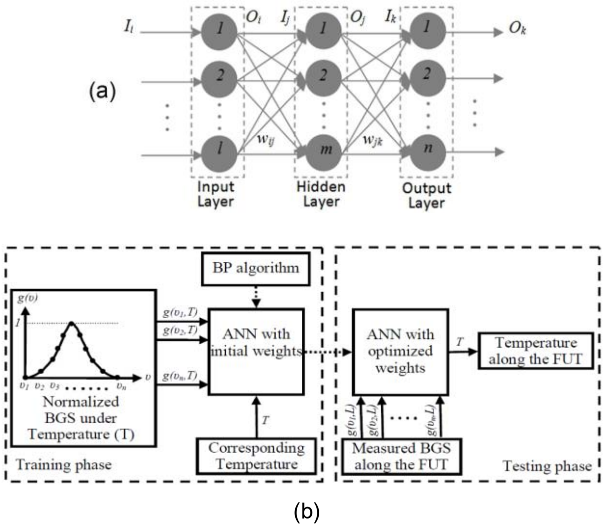

Fig. 1. (a) Structure of typical feed-forward ANN with one hidden layer; (b) training and testing phases of ANN to extract temperature information from BGS.

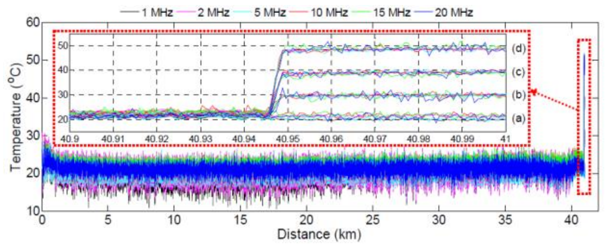

Fig. 2. Temperature distribution along FUT by ANN when the oven is set at (a) room temperature ~21 ºC, (b) 29.90ºC, (c) 39.14ºC and (d) 48.63 ºC; inset: zoom-in view from 40.9 km to 41 km [5].

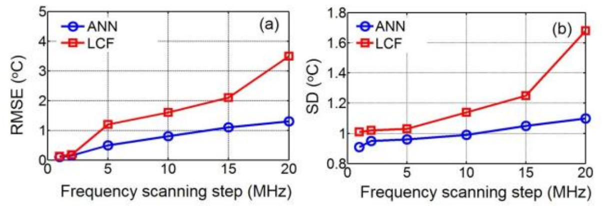

Fig. 3. (a) RMSE of the temperature calculated within the last 50 m fiber heated to 29.90 ºC; (b) SD of the temperature calculated near the end of FUT [5].

our FUT; the temperature range is from 10 ºC to 70 ºC with 1 ºC step and under each temperature the linewidth of the ideal BGSs with the same BFS transverses values from 25 to 70 MHz with 1 MHz step in order to minimize the linewidth variation effect along FUT; the frequency range and step for the ideal BGSs are the same as the frequency scanning range and step in the experiment. In the testing phase, we use a conventional BOTDA setup for BGSs acquisition, where 40 ns pump pulse, 2000 times averaging and frequency scanning steps of 1, 2, 5, 10, 15 and 20 MHz are adopted, respectively. The collected BGSs are processed by ANNs with optimal weights for those frequency steps to directly extract temperature information. A 41 km long FUT is used in our demonstration and the last 50 m section is put into the oven.

Fig. 2 shows the temperature distribution along the FUT extracted by ANN when the oven is set at different temperatures. We can see that the extracted temperatures for large scanning steps are almost the same as those for 1 MHz scanning step, indicating the performance of ANN does not degrade much at large frequency scanning steps, unlike the case using LCF. Quantitative comparison of the ANN and LCF performance is given by calculating the Root Mean Square Error (RMSE) and Standard Deviation (SD) of the temperature extracted by ANN and LCF, respectively. The RMSE is calculated along the last 50 m fiber heated to 29.90ºC, while the SD is obtained near the end of the FUT. The results are depicted in Fig. 3. As the RMSE and SD have similar trend, we use RMSE as an example in the following description. At each frequency scanning step the ANN provides smaller RMSE than LCF does, which means the extracted temperature using ANN is more closer to the value displayed on the thermometer. As the frequency scanning step increases, the RMSE using LCF degrade much more quickly than that using ANN, e.g. the RMSE using ANN at 15 MHz scanning step is even smaller than that using LCF at 5 MHz scanning step. It implies that using ANN to extract temperature under large scanning step for BGS collection is even more accurate than that using LCF under small scanning step for BGS collection. In other words, BOTDA using ANN for temperature extraction can employ large frequency scanning step to reduce the data acquisition time but still maintain better accuracy compared to those adopting small frequency scanning step with LCF for temperature extraction. Therefore, by adopting large scanning step, BOTDA systems using ANN for temperature extraction can significantly reduce the measurement time but without much sacrifice of the sensing accuracy.

3. TEMPERATURE EXTRACTION BY DEEP NEURAL NETWORK

In order to improve the training and testing efficiency, we further apply more advanced hierarchical Deep Neural Network (DNN) in BOTDA to replace ANN for temperature extraction. As DNN can learn the features

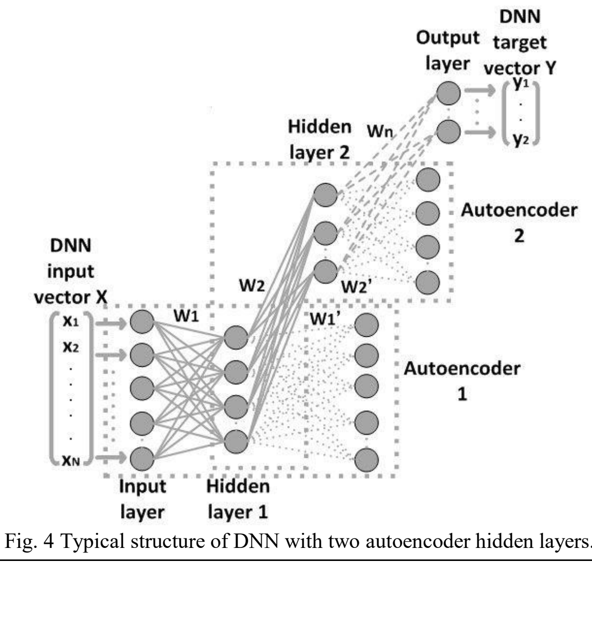

Fig. 4 Typical structure of DNN with two autoencoder hidden layers.

of the input data automatically through a feature learning process, it is more easier to design and train than ANN, especially when the relationship between input and output is complicated. Fig. 4 shows a typical DNN structure with two autoencoder hidden layers. The function of autoencoder hidden layers is to extract features from the input of the previous layer to represent the input and hence compress the data size for processing. Each hidden layer is trained individually with given activation functions and initial values of weight vectors, where the input features are extracted by autoencoders and serve as the input to the next hidden layer. The output layer is trained in a supervised way using the features from the last hidden layer and the target output vector. After the individual training of hidden layers and output layer, the fine tuning of the whole DNN structure is performed by using the known input-output pairs in BP algorithm. We use the following parameters to obtain ideal Lorentzian BGS-T pairs for DNN training: the BFS temperature coefficient of 0.974968 MHz/ºC for the FUT, the temperature range from 0 ºC to 100 ºC with 0.1 ºC step, the linewidth range of the ideal BGSs from 40 to 70 MHz with 1 MHz step, and the frequency range from 10.760 to 11.010 GHz with frequency step of 1 MHz. In the testing phase, the BGSs are collected by BOTDA where 20 ns pump pulse, 1000 times averaging and 38.46 km FUT with last 607 m section put into the oven are used. The collected BGSs are processed by DNN to directly extract temperature information. Fig. 5 shows the temperature distributions extracted by DNN along the whole FUT and near the heated section when the last 607m section is heated to 30, 40, 50, 60 and 70 ºC, respectively. As an example, when the last section is heated to 40 ºC, the RMSE and SD of the temperature

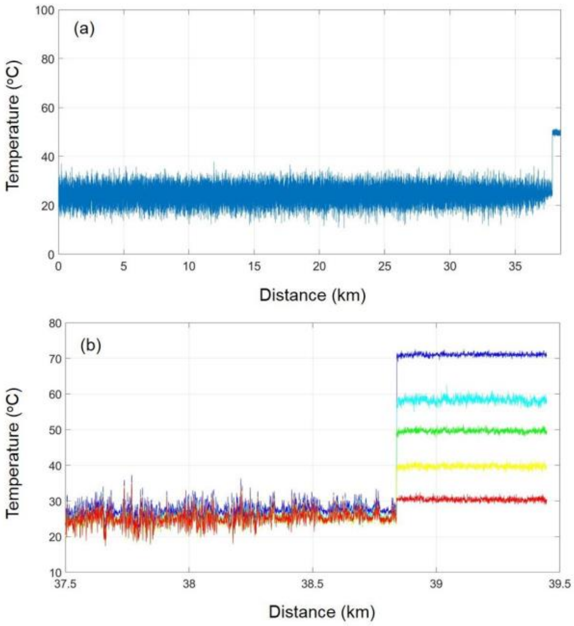

Fig. 5 (a) Temperature distribution along FUT by DNN when the last 607m section is heated to 50ºC; (b) zoom-in view of temperature distribution around last 2km section by DNN when the last 607m section is heated to 30, 40, 50, 60 and 70 ºC, respectively [6].

extracted by DNN are calculated to be 0.6733 ºC and 0.6094 ºC. For comparison, the two values by LCF are 0.7015 ºC and 0.6172 ºC, respectively. We can see that the accuracy of temperature extraction using DNN is comparable to that of LCF when the frequency scanning step is 1 MHz, which agrees well with the case of ANN. Like ANN when the frequency scanning step is increased, the DNN will outperform LCF as DNN is an advanced type of ANN.

4. CONCLUSION

We have reviewed our recent work on the use of ANN/DNN to extract distributed temperature information from the BGSs measured along FUT by BOTDA. The ANN/DNN are trained using ideal Lorentzian BGS-T pairs before used for temperature extraction. At large frequency scanning step, temperature extraction using ANN/DNN has better accuracy than that using LCF. The BOTDA using ANN/DNN for temperature extraction can adopt large frequency scanning step to reduce the measurement time without much sacrifice of accuracy. Therefore ANN/DNN are potential for direct temperature or strain extraction in BOTDA system with high accuracy and fast speed.

5. ACKNOWLEDGMENTS

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6. REFERENCES

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