Denoising and Robust Temperature Extraction for BOTDA Systems based on Denoising Autoencoder and DNN

Biwei Wang[1], Nan Guo[1], Liang Wang[2,*], Changyuan Yu[1], and Chao Lu[1]
[1] Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong.
[2] Department of Electronic Engineering, The Chinese University of Hong Kong, NT, Hong Kong.
** e-mail address: lwang@ee.cuhk.edu.hk*

Abstract: Denoising autoencoder is used for denoising of the data obtained by the Brillouin optical time-domain analyzer (BOTDA) sensing system and is also used to form the deep neural networks (DNN) for robust temperature information extraction.
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1. Introduction

Since it was first proposed and demonstrated [1, 2], distributed optical fiber sensors based on stimulated Brillouin scattering (SBS) have been developed with significant achievements. Among them, Brillouin optical time-domain analysis (BOTDA) systems utilize the SBS interaction of the pulsed pump and probe lightwaves to obtain the distributed Brillouin frequency shift (BFS) and thus realize distributed temperature and/or strain sensing. The signal-to-noise ratio (SNR) of the Brillouin response determines the limitation of the performance of a BOTDA system in terms of spatial resolution, sensing range, and frequency uncertainty. [3] However, high SNR usually requires high input powers of the pump or probe lightwave which could be detrimental to the system, since simply increasing the input powers may introduce fiber nonlinearities [4, 5] and the non-local effects [6].

To conquer the limitation mentioned above, many efforts have been made in recent years, including pulse coding [7], distributed fiber amplification [8, 9], coherent detection [10]. In addition, some signal processing methods have been used to remove the noise of experimental data, including Fourier transform, wavelet transform, non-local means and even some image denoising methods. The denoising autoencoder (DAE) from the machine learning field is usually used to reconstruct images or stacked to form a DNN model for some classification tasks. In this work, a DAE is introduced for denoising of the experimental data from the BOTDA system. In addition, a DAE is easily stacked with a linear output layer to form a simple DNN model, which is then used to extract the temperature information for the BOTDA sensing system.

2. Denoising autoencoder (DAE) and deep neural networks (DNN)

2.1. Data reconstruction using DAE

The autoencoder is usually used in the pre-training process for the DNN. The simplest autoencoder includes three layers including an input layer, an interlayer and an output layer, which is shown as the figure 1. The number of neurons in the input layer and the output layer is the same, which means that the output has the same dimension with the input. And the interlayer usually has less neurons than the input layer and output layer, so it can be used to compress the input information. In the training process of autoencoder, first, the interlayer is used to extract some features of the data from the input layer, which is so-called encoder. Then, the reconstructed data will be given by the output layer, which is the decoder part. Next, the selected loss function such as the mean square error (MSE) is used to train the autoencoder, while the input data is also used as the target. Thus, the training process of the autoencoder is to make the reconstructed data from the output layer to be as similar as possible with the input, which also means that the interlayer has extracted useful features of the input data. However, one of the problems of the autoencoder is that it has little resistance to the noise in the input data, which means is not robust when the input data is noisy. Under this background, one variation of the autoencoder, the denoising autoencoder (DAE) has been proposed to extract robust features of the input data, which could also be used to reconstruct clear data from noisy data. Therefore, we have proposed to use the DAE to denoise the input data from the BOTDA sensing system.

The structure of the DAE is the same as that of the common autoencoder. The only difference is that the noisy data is used as input while the corresponding clear data is used as the target instead of the noisy data itself in the training process. In this work, the simulated BGS of 200/251 sampling points of the Lorentzian lineshape with additive Gaussian white noise (AWGN) are used as the input data and the corresponding ideal BGS without AWGN are used as the targets in the training processes of the DAE. Then the experimental noisy data from the BOTDA sensing system can be given to the DAE model after training and the reconstructed data with less noisy will be output by the DAE.

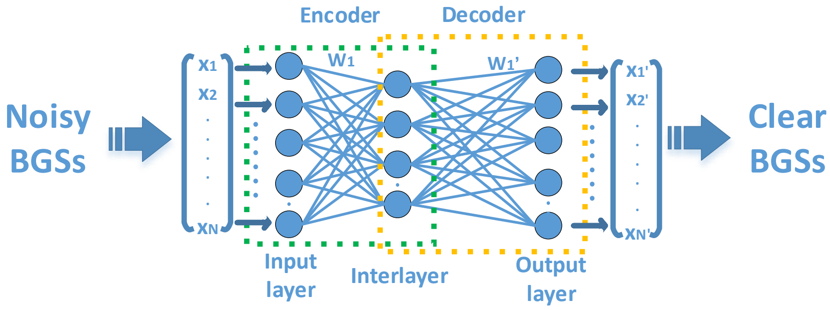

Fig. 1 The structure of autoencoder or DAE.

2.2. DNN based on DAE for temperature information extraction

The encoder part of a DAE can be stacked with a linear output layer easily to form a simple DNN model, which is shown as the figure 2 below. The input layer and the interlayer of the DAE is also used in the DNN, while the output layer is using the linear function as the activation function instead of the sigmoid function used in the DAE. The number of neurons in the input layer is also equal to the number of frequency sampling points in the BOTDA experimental system. And the number of neurons in the interlayer is adjusted based on the performance of the results, while the output layer has only one neuron which means the temperature we want to obtain. After the pre-training processes of the DAE, the DNN is trained using the scaled conjugate gradient (SCG) algorithm. The simulated BGS with AWGN and the corresponding temperature value are used as the input and the target in the process. Then the DNN can be used to produce the temperature information from the input experimental BGS data of the BOTDA system.

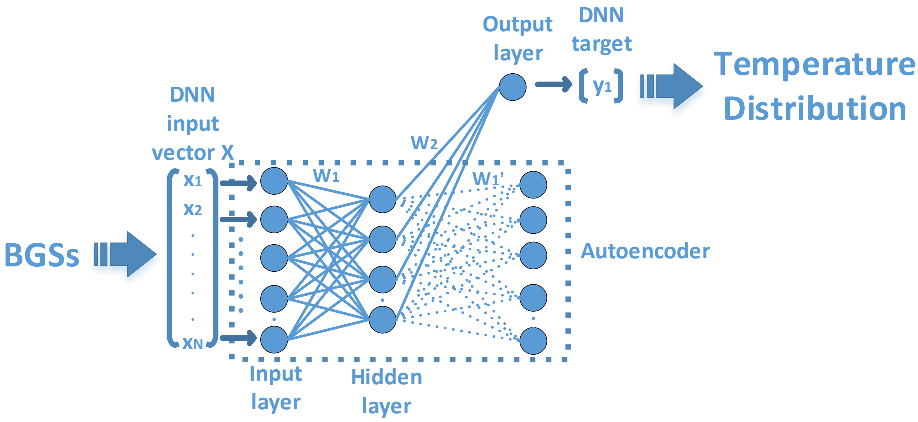

Fig. 2. The structure of DNN with one autoencoder.

3. BOTDA experiment setups

The experimental data used in this work are obtained using the system setup which has been introduced before. The output continuous wave (CW) light of around 1550nm wavelength from the tunable laser is amplified by an Erbium-doped fiber amplifier (EDFA) and filtered by an optical filter. Then it is divided into two branches by an 80/20 coupler. The light at the upper branch is modulated by electro-optic modulator (EOM) biased at null point to suppress the optical carrier and driven by a radio frequency (RF) source around the Brillouin frequency shift (BFS). A variable optical attenuator (VOA) is used to control the probe light power before entering the about 20km fiber under test (FUT) and an isolator is used to block the light entering in reverse direction. At the lower branch, the CW light is modulated by one other EOM with a pattern generator to generate 20 ns pump pulse which corresponds to 2 m spatial resolution of this system. One other EDFA is used to amplify the peak power of the pump pulse and the other filter is used to remove the amplified spontaneous emission (ASE) noise brought by EDFA. In addition, a polarization scrambler (PS) is used to suppress the polarization dependent noise since the stimulated Brillouin scattering (SBS) effect is sensitive to polarization. The CW probe and pump pulse are counter propagating and interacting under SBS in the FUT. Then the CW probe signal is filtered using a fiber Bragg grating (FBG) and detected by a 125 MHz photodetector. The local BGS along the FUT for processing is obtained by sweeping the frequency of probe light around the BFS.

4. Results

The linear relationship between the BFS and temperature measured using the BOTDA experiment system is used to simulate the needed BGS for the training of the DAE and the DNN models. After the training of DAE, a group of experimental noisy BGS data along about 20.3kmUT is given to the DAE, the obtained trace is shown in the figure 3 and the BGS data are shown in figure 4. From the figures we can see that the SNR of the experimental data has been improved largely.

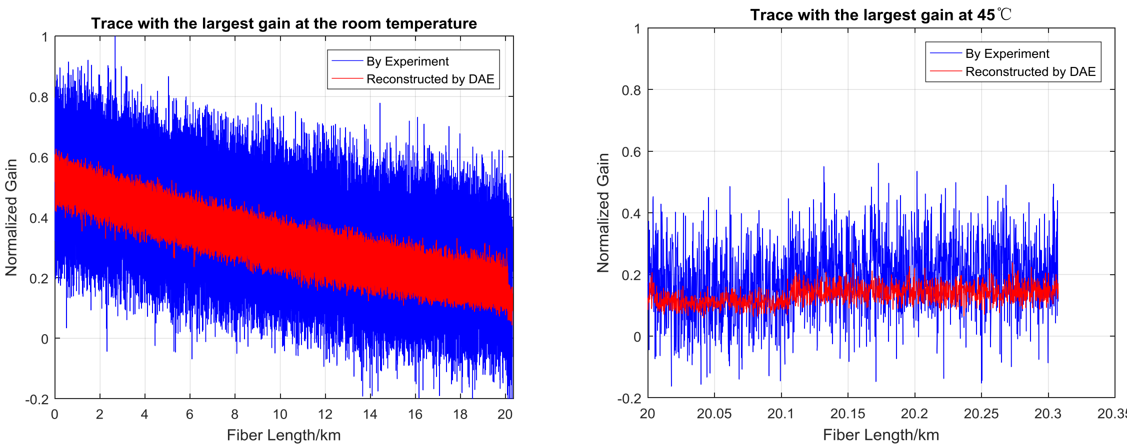

Fig.3. Trace of the whole FUT obtained by experiment and DAE (Left: the whole FUT; Right: the last 300m FUT;)

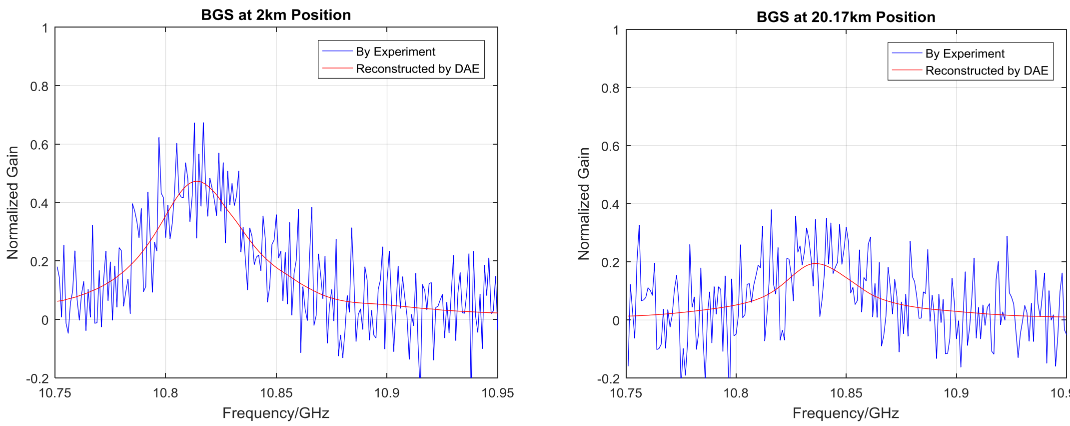

Fig.4 Trace of the BGS at two positions obtained by experiment and DAE (Left: the whole FUT; Right: the last 300m FUT;)

In addition, the experimental data is given to the DNN to measure the temperature. The temperature distribution is shown in the figure 5. The root-mean-square error (RMSE) and the standard deviation (SD) of the last 200m FUT heated to 45ºC re found to be 3.56 ºC and 3.55 ºC obtained by the Lorentzian curve fitting method, respectively. And the RMSE and SD of the last 200m FUT measured using the DNN is found to be 3.18 ºC and 3.08 ºC, which are both less than the error obtained by conventional LCF method.

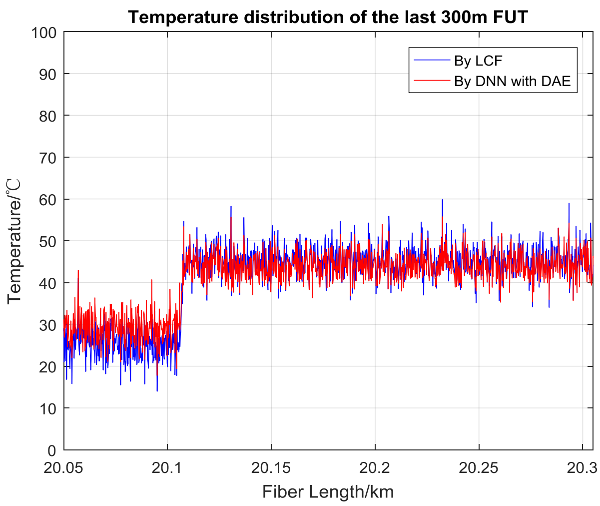

Fig.5. Temperature distribution obtained by LCF and DNN.

5. Conclusions

Denoising autoencoder used for denoising of the data obtained by the Brillouin optical time-domain analyzer (BOTDA) sensing system has successfully improved the SNR of the experimentally obtained data and the DNN based on the DAE also shows its ability of robust temperature information extraction.

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