Training-free feature extraction of BOTDA based on sparse representation

Hongxiu Tan, Yating Xiang, Hao Wu, Li Shen, Kangjie Li, Maoqi Zhang, Can Zhao, Lin Gan, Songnian Fu, Ming Tang*

Wuhan National Lab for Optoelectronics (WNLO) & National Engineering Laboratory for Next Generation Internet Access System, School of Optical and Electronic Information, Huazhong University of Science and Technology, 430074, Wuhan, China

**tangming@mail.hust.edu.cn*

Abstract: We propose a method based on sparse representation to extract amplitude, linewidth, and Brillouin frequency shift (BFS) in BOTDA using dictionary-learning algorithm without feedback and off-line training, which enables more accurate BFS measurements in real-time. © 2020 The Author(s)

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1. Introduction

Brillouin optical time-domain analyzer (BOTDA) systems have attracted a great interest owing to their capability to distributed monitoring of strain and temperature, which is widely used in the detection of oil and gas pipeline leakage, monitoring of bridge safety and fire alarms [1]. In the fiber under test, a pulsed pump light interacts with a counter-propagating continuous probe light through stimulated Brillouin scattering (SBS). The energy of the high-frequency pump light will transfer to the low-frequency signal when the frequency offset between them is within the local Brillouin gain spectrum (BGS). The peak gain frequency of the BGS is called the Brillouin frequency shift (BFS). Since the BFS depends linearly on the temperature and strain, BOTDA can perform distributed measurements of temperature and strain in km-long fibers at meter or less resolutions.

To extract the distributed BFS, Lorentz curve fitting (LCF) is generally used to determine the BFS of the BGS [2]. However, this method takes significant time to process the data and is accessible to over-fitting. The improved cross-correlation method (XCM) calculates the frequency difference to obtain BFS by convolving the ideal Lorentz BGS with the noisy BGS [3]. On the other hand, many studies have been done to extract BFS directly from measured BGS without any curve fitting process. Machine learning algorithms such as deep neural networks (DNN) [4], artificial neural networks (ANN) [5], and pattern recognition methods based on principal component analysis (PCA) [6] have been proven effective. However, machine learning algorithms need a lot of training in advance, which is relatively time-consuming. Besides, retraining or fine-tuning is required to accommodate different actual data, which significantly affects its application potential.

In this paper, we propose a novel real-time and no-feedback feature extraction method for BOTDA systems. We use dictionary-learning algorithm K-means singular value decomposition (K-SVD) to learn the best sparse dictionary of the BGS. Considering that the BGS can be described by only three parameters in the Lorentz curve, the signal can be represented as 3-sparse under the dictionary. After two dictionary learnings, the amplitude, BFS, and linewidth along the fiber can be extracted without curve fitting. It is worth mentioning that, unlike other machine learning methods, our method uses prior information, which is summarized as the Lorentz curve distributed BGS. Besides, K-SVD algorithm can obtain sparse feature parameters directly without training set in different scenarios.

2. Principle of dictionary learning algorithm K-SVD

Sparse representation is a crucial feature extraction method, which represents the raw signal with as few prototype signal-atoms as possible by using an over-complete dictionary. Therefore, designing suitable dictionaries to fit a model better can be achieved in two ways: either selecting one from a prespecified set of linear transforms or adapting the dictionary to a set of training signals [7]. The goal of dictionary learning is to learn an ideal over complete dictionary matrix D: $Y \approx D \times X$, where Y denotes the signal matrix to be trained, and X is the coefficient matrix to represent Y as sparsely as possible. Each column of the dictionary D refers to an atom, and each column of the signal matrix Y represents a sample.

Here, we choose the K-SVD algorithm as the way to obtain the dictionary and sparse representation. K-SVD is a dictionary learning algorithm that combines two processes of sparse coding of signal and dictionary updating for better adaptation [8]. The procedures of the K-SVD algorithm are as follows:

1. Initialize dictionary D randomly. We choose k samples randomly from signal matrix Y. These samples are used as the initial atoms of dictionary D. Meanwhile, initialize coefficient matrix X as an all-zero matrix.

2. Fix dictionary D, then calculate sparse coding of all samples. The objective function is shown in Equation (1).
3. Update dictionary D. The process is to update only one column of the dictionary D each time, while fixing X. Suppose that we are going to update the *k-th* atom a_k. And x_k is the corresponding *k-th* column of coefficient matrix X. The objective function is rewritten as Equation (2). And it can be solved by directly using SVD. The final solution D is the dictionary of sparse representations, and X is the sparse coefficient to be addressed.

$$D, X = \arg\min_{D,X}\{\| X \|_0\} \mathrm{st.} \| Y - DX \|^2 \le \varepsilon \qquad (1)$$

$$\|Y - DX\|_F^2 == \left\|(Y - \sum_{j\neq k}\alpha_j \cdot x_j) - \alpha_k \cdot x_k\right\|_F^2 = \|E_k - \alpha_k \cdot x_k\|_F^2 \qquad (2)$$

where ε is the maximum of reconstruction error.

3. Experimental setup and signal processing

The setup of our BOTDA system is shown in Fig. 1. We use a narrow-bandwidth laser as the light source whose center wavelength is about 1550 nm. The laser light is split into two branches by a 3dB optical coupler. One branch is modulated with an electro-optic modulator (EOM) to produce the probe light. The microwave synthesizer (MS) is the driver to sweep the probe frequency from 10.6 GHz to 10.9 GHz at a 2 MHz step. A polarization switch (PS) is used to eliminate the effects of polarization. Then the probe light is launched into the test fiber. Along the 2km-fiber at room temperature of 25 ℃, a 100 m section is put in a temperature-controlled chamber (TCC) which is set to 35 ℃, 42 ℃, 52 ℃, 57 ℃ and 62 ℃. The other branch passes through a semiconductor optical amplifier (SOA) driven by an arbitrary function generator (AFG) to produce pump pulses. Then the optical pulses pass through the erbium-doped fiber amplifier (EDFA) and a band-pass filter (BPF) and are launched into the fiber by a circulator. Finally, the probe light passes through a bandwidth-variable tunable filter (BVTF) and is converted into digital signals by the 125 MHz photodiode (PD).

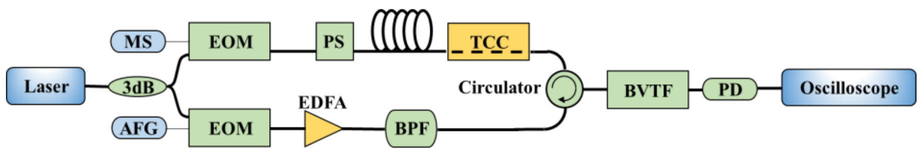

Fig. 1. Experiment setup of BOTDA.

The signals obtained from the BOTDA system are processed, as shown in Fig. 2. The three-dimensional BGS can be split into two-dimensional Lorentz distribution curves at each distance, each of which can be described by amplitude, BFS and linewidth. Therefore, our goal is to solve three characteristic parameters corresponding to each amplitude, BFS, and linewidth. The transformation from a curve to three characteristic parameters can be seen as a limit sparseness of signal based on a priori information. Since K-SVD is more effective for linear and dependent data, here we need to go through a two-step dictionary learning. According to Equation (3), BGS has a linear relationship with the amplitude. In the first step, sparsity is set to 3, then the amplitude and two cross-terms between BFS and linewidth are obtained. In the second step, set the sparsity to 2, and use the amplitude in step 1 to put the BFS into the dependent relationship as in Equation (4) to obtain BFS and linewidth. The smoothed data is processed by a dictionary learning algorithm, and sparsely represents three parameters.

$$g(\upsilon) = \frac{g_B}{1 + 4\left[(\upsilon - \upsilon_B)/(\Delta\upsilon_B)\right]^2} \qquad (3) \qquad\qquad \frac{g_B}{g(\upsilon)} - 1 = \frac{4(\upsilon - \upsilon_B)^2}{(\Delta\upsilon_B)^2} \qquad (4)$$

where g_B is the peak amplitude, υ_B is the BFS and $\Delta\upsilon_B$ is the full-width half maximum (FWHM), which is the spectral linewidth here.

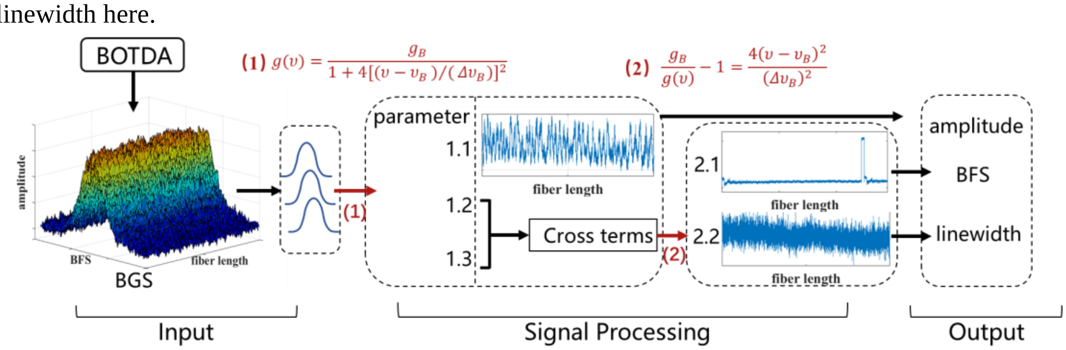

Fig. 2. Schematic diagram of signal processing (1) first dictionary learning (2) second dictionary learning

4. Results and discussion

The results obtained by the first dictionary learning of the BGS are shown in Fig. 3. It shows that the trend of obtained amplitude is extremely similar to amplitude variation through LCF along the fiber. However, the other two parameters are interacting, that is, the jitter of the linewidth and the BFS changes affect both parameters, which require further separation. Fig. 4 shows a comparison of the amplitude obtained by LCF and K-SVD at different temperatures, which proves that the first step has excellent performance in separating the amplitude.

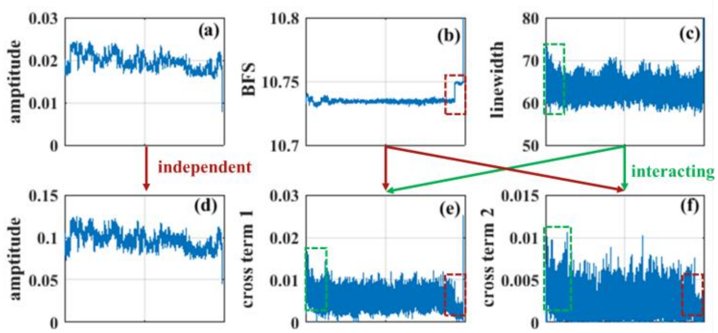

Fig. 3. Amplitude(a), BFS(b) and linewidth(c) obtained by LCF, and amplitude(d), two cross terms (e-f) obtained by the first dictionary learning.

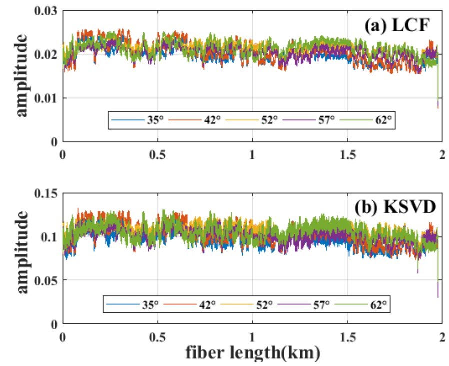

Fig. 4. Comparison of amplitude by LCF (a) and K-SVD (b) along the fiber

Based on the above experience, we know that the independence of parameters is crucial. To separate the BFS and the linewidth in the second dictionary learning, we perform the processing of Equation (4) on the data based on a priori information of the curve's Lorentz distribution. Fig. 5(b) shows BFS obtained by the second signal processing, which is compared to the LCF's result of Fig. 5(a) under the same signal-to-noise ratio (SNR) conditions. Fig. 6 shows the linear relationship between BFS and temperature. It can be seen that the BFS obtained by sparse representation has a better linear relationship with temperature than that of the LCF's BFS. Moreover, the two step K-SVD converges within one iteration with a total time of 59 s, which is much faster than the 180 s using LCF in the same computing platform. All in all, in our sensing systems, BFS can be obtained by observing three sparse parameters without Lorentz fitting methods. It is worth mentioning that the method we use is different from other machine learning methods. Due to the existence of prior information, our algorithm does not need to adjust parameters manually and traditional tedious off-line training stage.

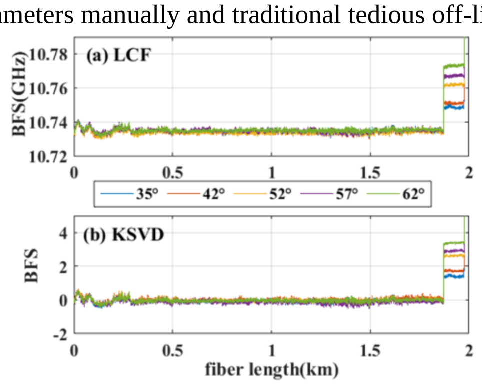

Fig. 5. Comparison of BFS obtained by LCF (a) and K-SVD (b) along the fiber under the same SNR conditions

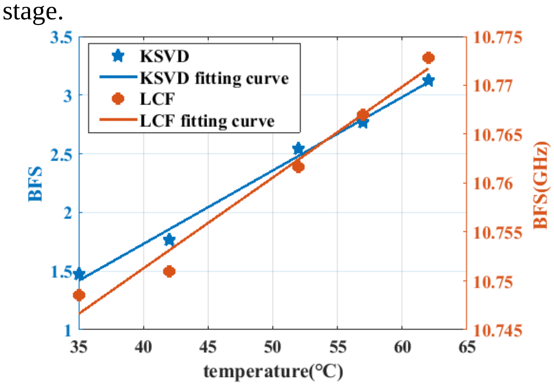

Fig. 6. Linear relationship between temperature and BFS obtained by LCF and KSVD.

5. Conclusions

We propose a method based on sparse representation to extract BFS in BOTDA without curve fitting. The proposed technique utilizes the prior information of the BGS's Lorentz distribution, and can obtain three sparse parameters through the dictionary learning algorithm without feedback and off-line training. We believe that it will be a more flexible feature extraction method for multiple sensing scenarios.

6. References

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