Processing Differential Brillouin Gain Spectrum by Support Vector Machine in DPP-BOTDA

Huan Wu[1], Liang Wang[1,*], Zhiyong Zhao[2], Nan Guo[2], Chester Shu[1], and Chao Lu[2]

[1]*Department of Electronic Engineering, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong*

[2]*Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong*

**Email: lwang@ee.cuhk.edu.hk*

Abstract: SVM has been applied to successfully extract temperature from differential BGSs in DPP-BOTDA of different spatial resolution. Compared with LCF, SVM has better performance under high spatial resolution and low SNR with shorter processing time.

OCIS codes: (060.2370) Fiber optics sensors; (290.5900) Scattering, Stimulated Brillouin.

1. Introduction

Differential pulse-width pair Brillouin optical time domain analyzer (DPP-BOTDA) provides a promising way of distributed sensing with sub-meter spatial resolution [1-4]. In DPP-BOTDA, the sub-meter spatial resolution is achieved by obtaining the differential Brillouin gain spectrum (BGS) through the subtraction between two conventional BOTDA traces measured using two pump pulses with slightly different duration. Like in conventional BOTDA, Lorentzian curve fitting (LCF) is usually used to determine the Brillouin frequency shift (BFS) from the differential BGS [3, 4]. Since differential BGSs are usually collected at high sampling rate to resolve sub-meter scale changes, it would take long processing time by LCF for algorithm iteration to find all the BFSs, which is not satisfactory for real-time monitoring. Recently we have reported direct temperature extraction by using Support Vector Machine (SVM) in conventional BOTDA [5]. In addition to better accuracy, SVM exhibits a data processing speed faster than the common LCF by two orders of magnitude. In this paper, we use SVM for temperature extraction in DPP-BOTDA, which is more attractive in the scenario of high spatial resolution and high sampling rate.

2. SVM training using designed ideal differential BGSs

To train the SVM model, ideal differential BGSs are designed using Lorentzian curve as the gain profile, and 601 temperature classes are formed at a temperature step of 0.1℃ and temperature range from 10℃ to 70℃. The BFSs of the ideal differential BGSs are determined using the calibrated temperature coefficient of 0.9749MHz/℃ for our fiber under test (FUT). We determine the bandwidth of ideal differential BGSs according to experimental data using different pump pulse pairs. For each temperature class, we obtain the ideal differential BGSs with the same BFS but different bandwidth varying from 20MHz to 40MHz at 2MHz step, in order to take the bandwidth variation along FUT into account. Thus we have 601×11 ideal differential gain profiles to train the SVM. After training, the SVM model is applied to process the measured differential BGSs by DPP-BOTDA and directly extract the temperature.

3. Experiment and results

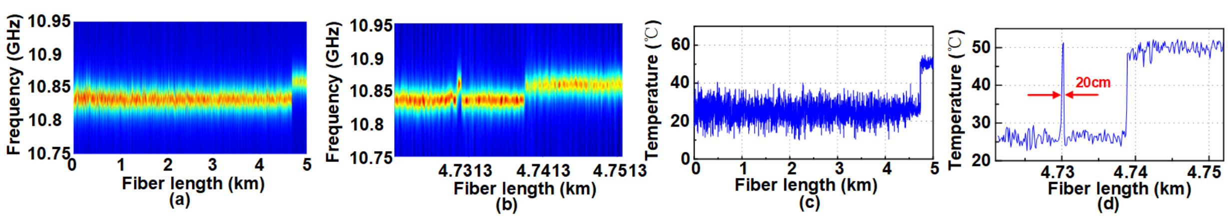

Fig. 1. (a) Differential BGS distribution along FUT measured by using pump pulse pair of 50/48ns; (b) zoom-in view of (a) near the FUT end; (c) temperature distribution extracted by SVM from differential BGSs and (d) the zoom-in view near the FUT end.

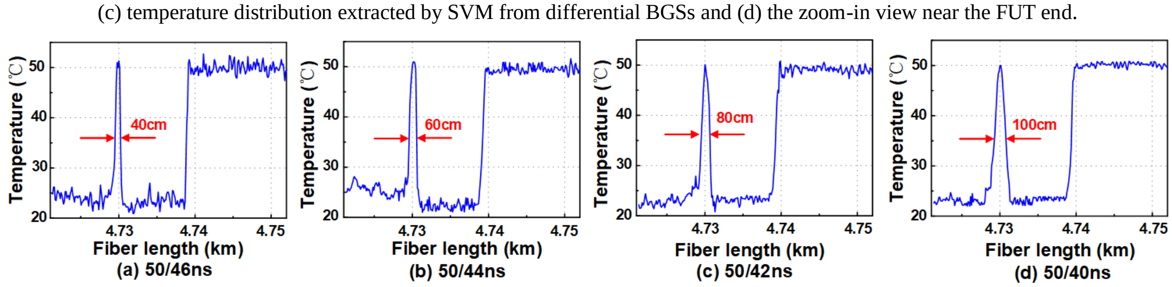

Fig. 2. Temperature distribution near the FUT end extracted by SVM from differential BGSs measured using pump pulse pair of (a) 50/46ns, (b) 50/44ns, (c) 50/42ns, and (d) 50/40ns, respectively.

We adopt the DPP-BOTDA setup in [2] to measure differential BGSs. 1024 times averaging and 1MHz frequency scanning step from 10.75GHz to 10.95GHz are used for the measurement. Our FUT is 5km long with a short section (~cm long) and a long section (200m long) at the FUT end heated to 50℃. The short heated section serves as the sub-meter hot-spot. The data sampling rate is 1GSample/s, thus there are 2000 sensing points along the last 200m heated section, which offers enough data points to evaluate the temperature accuracy by SVM.

Fig. 1(a) shows the differential BGS distribution along FUT measured by using pump pulse pair of 50/48ns. The zoom-in view near the FUT end is given in Fig. 1(b). Here the short heated section is 20cm long and is clearly observed. Fig. 1(c) depicts the temperature distribution along FUT extracted from the measured differential BGSs by SVM and Fig. 1(d) shows the zoom-in view near the FUT end. The temperature distribution has been exactly extracted by SVM, and the temperature uncertainty at the FUT end is calculated to be 2.22℃. We also measure differential BGSs by using other pump pulse pairs in order to analyze the performance of SVM in DPP-BOTDA of different spatial resolution. The results are given in Figs. 2(a)-(d), showing the temperature distribution near the FUT end extracted by the same SVM model for different spatial resolutions, respectively. Note that in the experiment of each pump pulse pair, the length of the short heated section is made equal to 40cm~100cm at a step of 20cm, respectively. Fig. 2 verifies the feasibility of using only one SVM model to extract temperature in DPP-BOTDA of different spatial resolution.

The temperature uncertainty by SVM at the FUT end is found to decrease from 2.22℃ to 0.47℃ as pump pulse width difference increases from 2ns to 10ns, as shown in Fig. 3(a). This is because smaller pump pulse width difference leads to worse signal-to-noise ratio (SNR). The results using LCF to extract temperature are also given in Fig. 3(a) for comparison. It is seen that the uncertainty by SVM is lower than that by LCF, especially when the pulse width difference becomes small. It implies that SVM is more robust to the pulse width difference and thus still has better accuracy at higher spatial resolution. The data processing time of temperature extraction by SVM as a function of temperature step is given in Fig. 3(b). The same 50,000 differential BGSs measured along 5km FUT in Fig. 1 are processed by four SVM models, i.e. SVM-0.1℃, SVM-0.2℃, SVM-0.5℃, and SVM-1℃, respectively. The four models are formed with 601(0.1℃ step), 30 (0.2℃ step), 121 (0.5℃ step) and 61 (1℃ step) temperature classes, respectively, and are separately trained. We can see that the processing time decreases quickly as the temperature step increases, e.g. 133.17s for SVM-0.1℃ and 1.12s for SVM-1℃. This is because there are fewer binary classifiers constructed at larger temperature step using one-against-one strategy for multi-class classification by SVM [6]. The corresponding temperature uncertainty by the four SVM models is also shown in Fig. 3(b), where only small uncertainty degradation is observed at large temperature step. Thus one can use SVM-1℃ to extract temperature at fast speed but without much accuracy degradation. It is worth mentioning that to process the same differential BGSs, LCF consumes 693.55s, which is beyond 5 times and 600 times slower than SVM-0.1℃ and SVM-1℃, respectively.

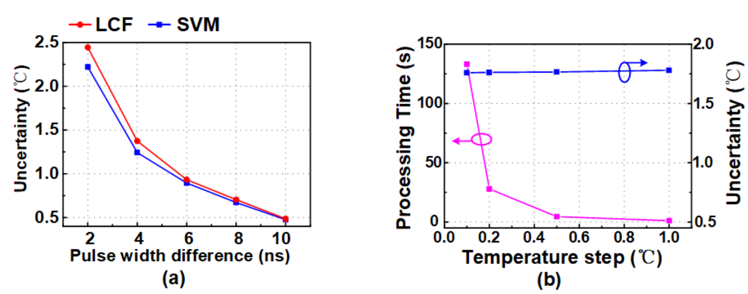

Fig. 3. (a) Temperature uncertainty versus pulse width difference; (b) data processing time and temperature uncertainty by SVM versus temperature step for 50/48ns pump pulse pair.

4. Conclusion

We have experimentally demonstrated SVM for temperature extraction in DPP-BOTDA under different spatial resolution. SVM shows better accuracy than LCF, especially for the measurement of differential BGSs at high spatial resolution. The data processing time of SVM is much shorter than that of LCF. We believe SVM for temperature extraction would be more helpful in the scenario of DPP-BOTDA where the SNR is lower and denser sensing points are collected compared with conventional BOTDA.

This work was supported by CUHK GRF (1406614, 14238816, 14209517), and NSFC (61377093, 61435006).

References

[1] A. Motil, et al., *Opt. Laser Technol.*, 78, 81-103 (2016).
[2] W. Li et al., *Opt. Exp.*, **16**(26), 21616-21625 (2008).
[3] H. Liang et al., *Opt. Lett.*, **35**(10), 1503-1505 (2015).
[4] S. Diakaridia et al., *Opt. Exp.* **25**(15), 17727-17736 (2017).
[5] H. Wu et al., *J. Lightw. Technol.* **35**(19), 4159-4167 (2017).
[6] C. Hsu et al., *IEEE Tans. Neural Netw*., 13(2), 415-425 (2002).