

Robust Brillouin Frequency Shift Extraction in BOTDR under Noisy Condition Using AdaBoost Regression

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Abstract

Accurate extraction of the Brillouin Frequency Shift (BFS) is vital for high-performance distributed fiber sensing, particularly under noisy or low-resolution conditions. This study presents a robust machine learning approach using the AdaBoost regression algorithm to extract BFS from Brillouin Gain Spectra (BGS) under challenging spectral scenarios, including low signal-to-noise ratio (SNR), limited frequency range, and coarse resolution. Experimental BGS data were obtained from a Differential-Cross Spectrum (DCS) BOTDR setup based on the correlation of two optical pulses, measured over a temperature range of 25 degree to 70 degree. To enhance model generalization, synthetic noisy datasets were generated through data augmentation, and Savitzky-Golay filtering was applied to preserve spectral peak structure. The results demonstrate the model's robustness and highlight the importance of maintaining high SNR, sufficient frequency coverage, and fine resolution for reliable BFS extraction in practical sensing environments.

1. Introduction

Distributed fiber optic sensing has emerged as a pivotal technology for real-time monitoring of temperature and strain across long distances with high spatial resolution. Among the various techniques, Brillouin Optical Time-Domain Reflectometry (BOTDR) stands out due to its one-end accessibility and its ability to derive critical parameters from the Brillouin Frequency Shift (BFS), which is inherently sensitive to environmental variations.

To improve the extraction of Brillouin Frequency Shift (BFS) from Brillouin Gain Spectra, a number of machine learning techniques have been investigated. Although commonly used, traditional techniques like Lorentzian Curve Fitting (LCF) frequently become unreliable and inefficient under low signal-to-noise ratio (SNR) conditions, resulting in slower and less precise temperature or strain estimations. Machine learning methods have been presented as a more reliable and effective way to overcome these restrictions. These data-driven algorithms immediately learn the underlying spectral patterns, allowing for quicker and more precise BFS extraction. In this regard, a variety of techniques have been presented, such as support vector machines (SVMs) [1], k-nearest neighbors (KNNs) [2], convolutional neural networks (CNNs) [3], [4], and artificial neural networks (ANNs) [5], each of which has special benefits for managing complex and noisy spectrum data.

Recent developments have investigated the incorporation of machine learning for spectrum analysis in response. Among these, AdaBoost regression has demonstrated potential for noise resistance and nonlinear mapping learning. By integrating several weak classifiers into a robust model, AdaBoost enhances BGS classification, particularly in noisy environments where the method can adjust to varying BFS values [6]. However, the majority of earlier research lack validation using actual experimental settings or other BOTDR configurations and mostly rely on simulated data.

To address these gaps, this study proposes a robust BFS extraction framework using AdaBoost regression trained on experimentally acquired BGS data from a Differential-Cross Spectrum (DCS) BOTDR system. By



leveraging pulse correlation, noise augmentation, and Savitzky-Golay smoothing, the approach aims to improve extraction accuracy under real-world spectral limitations.

2. Methodology

Figure 1 illustrates the AdaBoost regression framework model developed for Brillouin Frequency Shift (BFS) extra. The AdaBoost model was applied at the regression stage, where normalized and optionally smoothed BGS inputs were mapped to their corresponding BFS values. The input data consisted of experimental and augmented BGS traces across temperature conditions, while the target outputs were labeled BFS values. The model was trained and evaluated using MATLAB's ensemble learning framework with decision tree regressors.

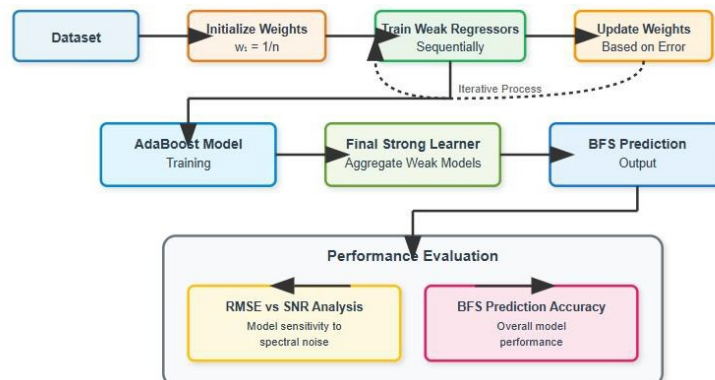


Figure 1. AdaBoost Regression Framework for BFS Extraction

3. Result & Discussion

Under more challenging conditions specifically at 0 dB signal-to-noise ratio (SNR), the model maintained a reasonable level of accuracy, with an RMSE of 24.52 MHz. Figure 2 shows the error was substantially reduced to 12.51 MHz when Savitzky-Golay filtering was applied, indicating the benefit of preprocessing in suppressing noise while preserving peak features.

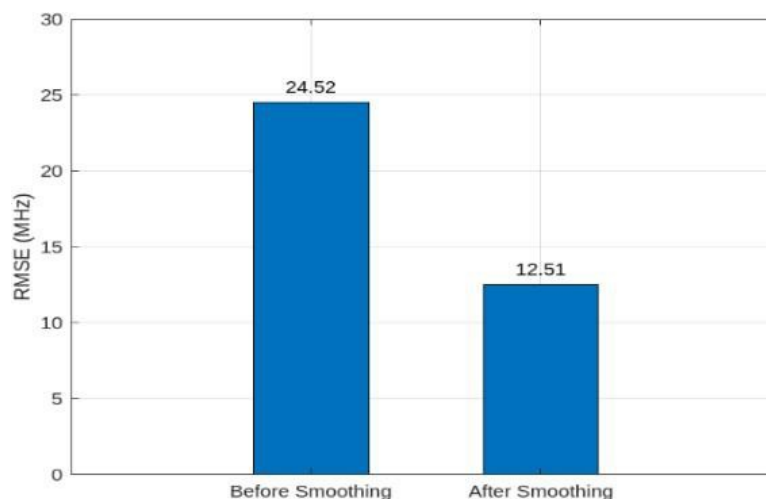


Figure 2. Effect of Savitzky-Golay Smoothing on AdaBoost Prediction (0 dB SNR)

A detailed analysis revealed that BFS prediction accuracy is significantly influenced by spectral conditions. As shown in Figure 3, as the SNR decreased from 30 dB to 0 dB, the RMSE increased from 1.23 MHz to 24.52 MHz. Next, to further analyze model behavior across noise levels, BFS prediction accuracy was calculated versus SNR using both a 100 MHz standard reference window and a 45.56 MHz measurement range. Figure 4 shows that while accuracy exceeds 97% at 30 dB SNR in both cases, it declines more steeply under the tighter range, dropping to 46.2% at 0 dB SNR. This emphasizes the sensitivity of fine-resolution sensing to noise and underscores the benefit of using robust regression techniques like AdaBoost.

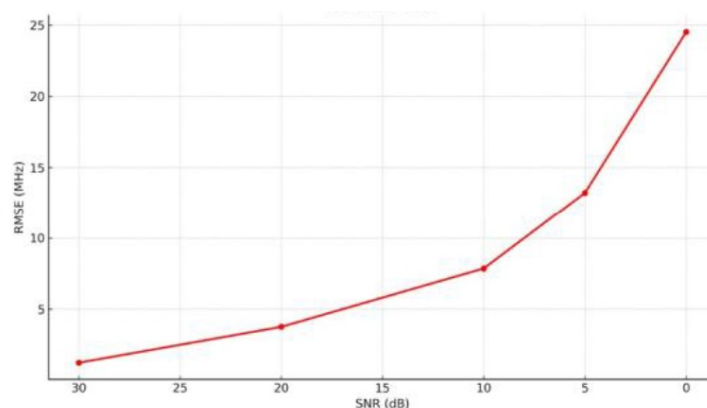


Figure 3. RMSE of BFS prediction as a function of SNR highlighting model sensitivity to spectral noise.

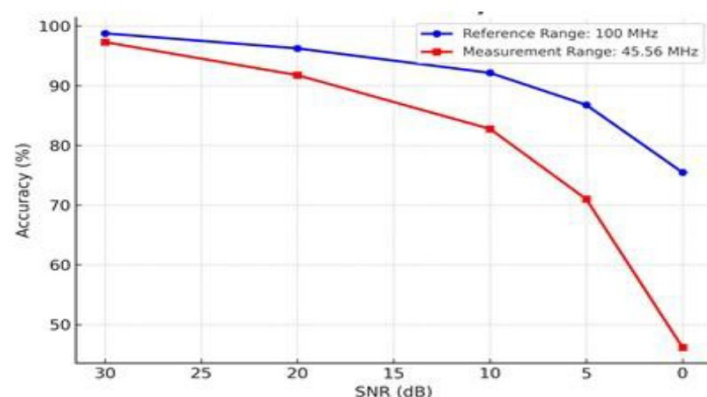


Figure 4. BFS Extraction Accuracy vs SNR

4. Conclusion

These findings underscore the importance of high-quality spectral input in enabling accurate BFS extraction. Compared to conventional curve-fitting methods, AdaBoost when combined with noise-augmented training and effective smoothing offers superior robustness across varying spectral constraints.

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