

# Impact of Fitting and Digital Filtering on Signal-to-Noise Ratio and Brillouin Frequency Shift Uncertainty of BOTDA Measurements

Simon Zaslowski, Zhisheng Yang, Marcelo A. Soto<sup>†</sup> and Luc Thévenaz

EPFL Swiss Federal Institute of Technology, Institute of Electrical Engineering, SCI-STI-LT Station 11, CH-1015 Lausanne, Switzerland

<sup>†</sup>Current address: Department of Electronic Engineering, Universidad Técnica Federico Santa María, 2390123 Valparaíso, Chile

Corresponding author email: simon.zaslowski@epfl.ch

**Abstract:** The intricate relationships linking signal-to-noise ratio and Brillouin frequency shift uncertainty after post-processing of Brillouin optical time-domain analysis measurements are investigated, highlighting the crucial impact of fitting. © 2018 The Author(s)

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## 1. Introduction

Brillouin optical time-domain analysis (BOTDA) relies on the local activation of stimulated Brillouin scattering (SBS) in optical fibres in order to perform distributed strain and temperature measurements. SBS is locally enabled by the interaction between a pulsed optical signal, called pump, with a counter-propagating continuous-wave (CW) probe. Properly adjusting the frequency detuning between pump and probe enables scanning the Brillouin gain spectrum (BGS) of the sensing fibre, ultimately leading to the determination of its peak resonance frequency called Brillouin frequency shift (BFS), at each fibre position. The optical aspects related to this technique have benefited from more than two decades of dedicated research, thus qualifying BOTDA as a mature technology. Due to the tremendous accumulated amount of work that has been placed in its development, conventional BOTDA is now reaching its peak performance, facing ultimately fundamental limits.

A BOTDA sensor aims at measuring the BFS profile of a given optical fibre with minimum uncertainty  $\sigma_B$ . A recent study [1] showed that the performance of any BOTDA system is ultimately determined by the signal-to-noise ratio (SNR). Thus, the uncertainty on the BFS estimation of BOTDA system (dominated by additive white Gaussian noise) can be written as:

$$\sigma_B = \frac{1}{\text{SNR}} \sqrt{\frac{3}{4} \delta \Delta\nu} \quad (1)$$

where  $\delta$  is the frequency detuning scanning step and  $\Delta\nu$  is the full-width at half maximum (FWHM) of the BGS. The numerical factor  $\frac{3}{4}$  is strictly valid for a quadratic fitting on the upper half of the curve and other techniques may result in a modified factor, but the essential information is in the functional dependence on SNR,  $\delta$  and  $\Delta\nu$  which remains the same. Recently, the scientific community started to pay a close attention to post-processing of the acquired data in order to boost the performance of standard BOTDA systems by increasing the SNR of the measurements without further modifying the optical setup. Using first one-dimensional noise removal techniques [2] followed later by sophisticated two-dimensional image processing algorithms [3], SNR improvements as large as 13 dB have been reported. To the best of our knowledge, the exact behavior of these techniques and the way they impact BOTDA measurements remain unclear such that no universal guideline on how to adjust them for given experimental conditions has been proposed yet. In this paper, we thoroughly analyze how a 2D digital filter impacts SNR and BFS uncertainty, under the strict requirement that the sensor spatial resolution (SR) must not suffer from the filtering operation. BOTDA measurements at different SNR levels (3 dB, 6 dB and 9 dB) and SR (1 m, 2 m, 5 m), using a frequency scanning step  $\delta = 1$  MHz and a sampling interval of 0.5 m have been acquired. The sensing fibre employed in this case has been specifically selected to present a non-uniform BFS profile in order to identify any impact of the filter on the SR. The sensor SR is further validated using a reference measurement for each spatial resolution at 12 dB SNR (achieved by a large number of averaged traces).

## 2. BGS Fitting and Filtering

Generally speaking, the BFS of a given fibre is retrieved at any longitudinal position by fitting the measured data points over a function well approximating the shape of the BGS. In this paper, the uppermost part of the gain spectrum is fitted over a quadratic function, as illustrated in Figure 1.a). In order to minimize  $\sigma_B$ , we demonstrate here the importance of carefully selecting the window size  $W_{\text{fit}}$  containing the samples employed for fitting.

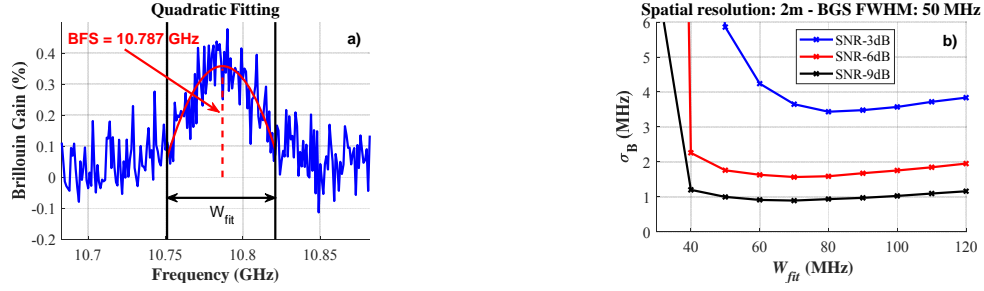


Figure 1. a) Fitting procedure for BFS retrieval from a noisy BGS. b) Measured BFS uncertainty  $\sigma_B$  when varying the window used in the fitting procedure, under different SNR conditions.

The BFS uncertainty  $\sigma_B$  at the fibre end is evaluated for a window size  $W_{fit}$  varying between 30 and 120 MHz, as shown in Figure 1.b). Results clearly point out that a sufficiently large fitting window must be employed in order to minimize  $\sigma_B$ . At low SNR (e.g. 3 dB), the proper selection of the window size becomes extremely critical and its optimal value turns out to be larger than the BGS FWHM. Indeed, it can be observed in Figure 1.b) that changing the window size from 50 MHz to 80 MHz (with 3 dB SNR) results in nearly halving the measurement uncertainty (i.e.  $\sigma_B$  reduces from 5.9 MHz at 50 MHz down to a minimum value of 3.4 MHz using a 80 MHz window). As a matter of fact, fitting should always be exploited to its maximum capability, as it might otherwise provide misleading results. Consider for instance the use of a noise removal algorithm that would bring the SNR level from 3 dB up to 6 dB when measuring with the same spatial resolution of 2 m: a window size equal to 50 MHz would exhibit an apparent uncertainty reduction of about 4 MHz (i.e. from 5.9 MHz at 3 dB SNR down to 1.8 MHz at 6 dB SNR), whereas an optimal width of 80 MHz would reduce  $\sigma_B$  only by a bit less than 2 MHz (from 3.4 MHz down to 1.6 MHz). Finally, notice that when the SNR further increases (e.g. up to 9 dB), the ideal window width moves closer to the Brillouin FWHM without perfectly reaching it yet. This behavior illustrates that the fitting window is to some extent dependent on the original SNR.

In order to reduce the frequency uncertainty on the BFS estimation, the use of a 1D digital filter applied on each acquired BGS has been here considered for efficient noise removal. We compute the Fourier transform of the BGS in order to analyze its spectral composition. Since we are not interested in the underlying physical mechanisms producing such a spectral distribution, the BGS is treated here as a digital signal, corresponding to a series of numerical values stored in a vector. Its Fourier transform is therefore given in terms of normalized frequency, a unitless quantity corresponding to a fraction of the signal sampling frequency. The BGS is essentially a low-frequency signal as illustrated by its Fourier transform given in Figure 2.a) for three different SNR levels (values at the end of the sensing fiber) corresponding to the measurements depicted in Figure 2.b). This spectral response motivates the use of low-pass filters for noise reduction. The results presented here are obtained using Gaussian filters, although similar conclusions may be drawn using any kind of low-pass digital filter. Gaussian filters present several interesting properties, including a simple frequency response as well as a single set parameter corresponding to the standard deviation of the Gaussian curve  $\sigma_{BGS}$ . The latter was adapted to the normalized FWHM of the considered BGS using  $\sigma_{BGS} = \text{FWHM}/(\Delta f k_{BGS})$  where  $k_{BGS}$  is a correction factor enabling to finely adjust the filter. Intuitively,  $k_{BGS} = 1$  corresponds to a Gaussian filter which standard deviation matches the BGS FWHM. In this case, the filtering operation was found to oversmooth the BGS, thus biasing the BFS estimation. Increasing  $k_{BGS}$  from 1 to 3 relaxed the filter strength and provided optimal results. Figure 2.c) illustrates an overall SNR increase of about 8 dB with respect to Figure 2.b). The filtering performances were challenged by comparing the SNR increase with the reduction in BFS uncertainty which, according to (1), should be identical. BFS uncertainty versus distance for raw data and filtered data are given in Figures 3.a) and 3.b), respectively.

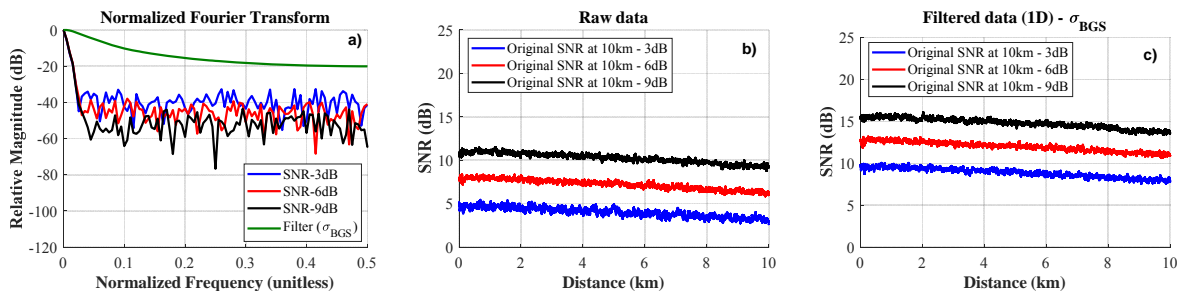


Figure 2. a) Normalized Fourier transform of the BGS at different SNR together with the spectral response of Gaussian filter over frequency detuning. b) SNR versus distance for raw (unprocessed) data acquired at 2 m spatial resolution. c) SNR versus distance for data filtered in 1D by sweeping the Gaussian kernel  $\sigma_{BGS}$  over each acquired local BGS.

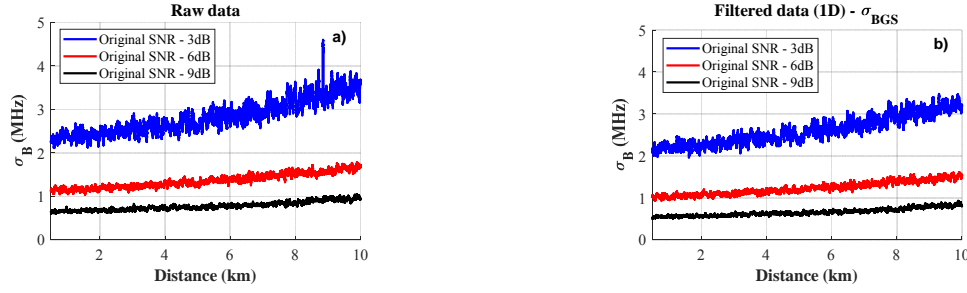


Figure 3.  $\sigma_B$  versus distance for raw (unprocessed) data (a) and data data filtered in 1D (b) by sweeping the Gaussian kernel  $\sigma_{BGS}$  over each acquired local BGS acquired at 2 m spatial resolution over 10 km.

Quite counterintuitively, the results show only a marginal BFS uncertainty reduction, strongly questioning the relevance of filtering the acquired BGS before fitting. Quadratic fitting in BOTDA consists in finding the parabolic curve that will best match the uppermost part of the BGS. Intuitively, one seeks at extracting the low-frequency information that has been corrupted by high frequency noise, and therefore fitting performs a mathematical operation similar to the application of a low-pass filter. Polynomial fitting is actually fundamentally equivalent to filtering using a special class of filters called Savitzky-Golay filters [4], making the prior use of a low-pass filter redundant. To our understanding, the various existing techniques aiming at retrieving the fibre BFS with lowest uncertainty are all comparable to an optimized fitting procedure. For instance, BFS retrieval by cross-correlation of the noisy BGS with an ideal Lorentzian as described in [5] is equivalent with low-pass filtering as cross-correlation and convolution are virtually the same operation. Finally, the major discrepancies observed between SNR and  $\sigma_B$  can be explained by the fact that (1) was derived assuming the statistical independence of each point within the considered gain spectrum. The use of a filter will however correlate all spectral points within the kernel size, thus making the filtered data on BGS no longer compliant with the assumptions underlying (1).

### 3. 2D Filtering

BOTDA measurements are corrupted by noise, dominated either by detector noise or in some cases by optical noise. Noise typically takes the form of an additive white Gaussian noise, resulting in a uniform contribution over the whole detection bandwidth. Since it proves practically challenging to perfectly match the detection bandwidth to the signal bandwidth, BOTDA measurements generally end up occupying only a restricted portion of the measurement spectrum. BOTDA measurements are 2D matrices holding the value of the fibre Brillouin gain at every location for each frequency detuning step. Note that 2D Gaussian filters are separable filters, and therefore noise removal based 2D Gaussian filtering can be achieved by applying two successive 1D Gaussian filters with standard deviations denoted as  $\sigma_{BGS}$  and  $\sigma_{dis}$  along the rows (frequency detuning) and columns (distance) of the matrix. We assume here that the first case corresponds to the sweeping of a Gaussian kernel across each of the measured BGS (i.e. Brillouin gain versus frequency detuning) as described in Section 2, whereas the second case consists in filtering each of the acquired BOTDA temporal traces (i.e. Brillouin gain versus distance). It must be pointed out that the latter should depend on the sensor spatial resolution (SR), since the corresponding pump pulse width defines the measurement bandwidth. The standard deviation of the normalized distance Gaussian filter  $\sigma_{dis}$  is set to  $\sigma_{dis} = SR/(\Delta d k_{dis})$  where  $\Delta d$  is the sampling interval and  $k_{dis}$  is a correction factor enabling to finely match the filter bandwidth to the signal bandwidth. We found here that using  $k_{dis} = 3$  enables for the highest attained noise removal while preserving the initial sensor SR. Note that the BGS Gaussian filter employed here  $\sigma_{BGS}$  is rigorously the same as the one described in Section 2.

Figure 4.a) shows the normalized Fourier transform of a Brillouin gain temporal trace under different SNR conditions together with 1D Gaussian filtering over distance ( $\sigma_{dis}$ ) employed for noise removal. Figures 4.b) and 4.c) contain the resulting SNR measured after 2D and 1D filtering along distance only, respectively. Compared to the raw data shown in Figure 2.b), 2D filtering provides a massive SNR increase of about 11 dB, being consistent

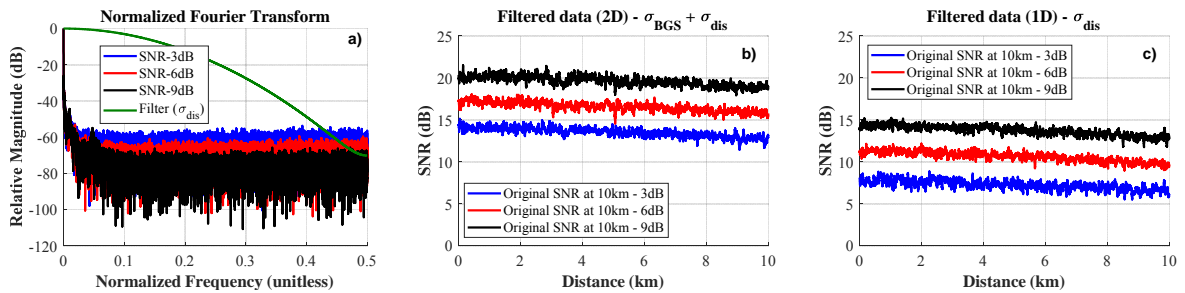


Figure 4. a) Normalized Fourier transform of BOTDA traces at different SNR together with the spectral response of the Gaussian filter over distance. SNR versus distance for data processed by 2D (b) and 1D (c) Gaussian filtering over distance ( $\sigma_{dis}$ ) at 2 m spatial resolution.

with the results reported in [3], while the 1D distance filter results in a moderate 3 dB increase (compare Figure 4.c) with Figure 2.b)). Note that individual contributions of the two 1D filters employed (Figures 2.c) and 4.c)) sum up to correspond to the improvement brought by the 2D filter (Figure 4.b)). The observed SNR enhancements are also challenged with the resulting BFS uncertainties given in Figures 5.a) and 5.b), respectively.

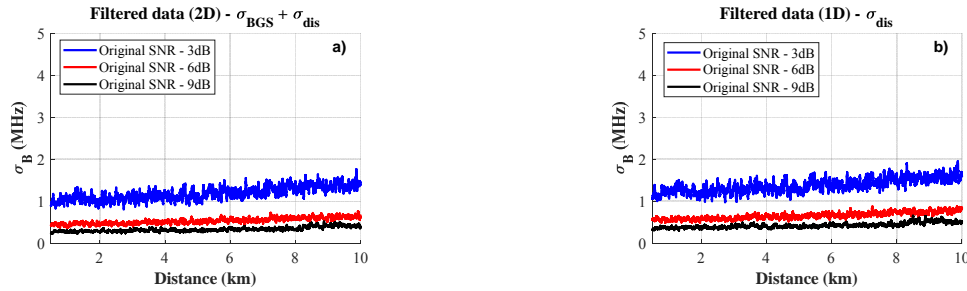


Figure 5.  $\sigma_B$  versus distance for data filtered using a 2D (a) and 1D (b) Gaussian filter over distance ( $\sigma_{dis}$ ).

The results show no major difference, emphasizing that the uncertainty reduction provided by filtering with a 2D Gaussian filter comes almost exclusively from the 1D filtering applied over distance, while the filtering along the second dimension (frequency detuning) is intrinsically redundant to the BGS fitting process. The SNR increase, provided by the filtering over distance (3 dB), is this time consistent with the corresponding uncertainty reduction (approximately a factor 2) according to (1). Finally, it is checked that the Gaussian filter over distance  $\sigma_{dis}$  does not affect the initial spatial resolution. This is experimentally verified by comparing the BFS profile retrieved from the filtered data with a reference (not filtered) profile obtained with a 12 dB SNR (achieved by a large increase of the number of averages). The impact on the spatial resolution could be visually inspected at BFS transitions. The results, shown in Figure 6 for every original SNR level and at each spatial resolution (1 m, 2 m and 5 m), illustrate clearly that the applied filter preserves the sensor original spatial resolution.

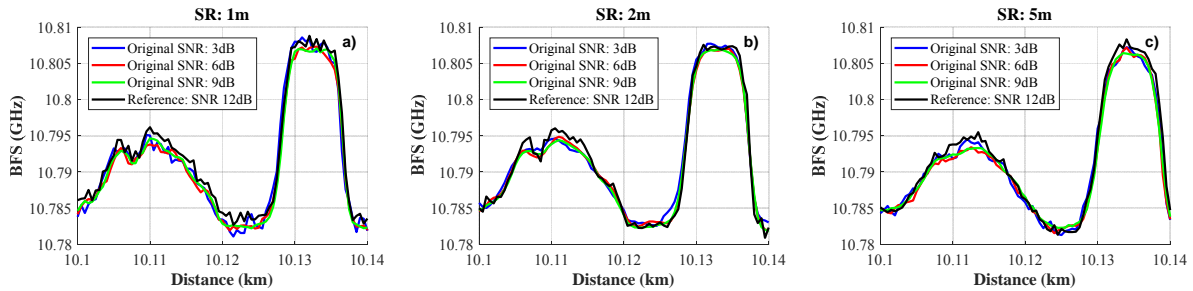


Figure 6. BFS versus distance for 1m (a), 2m (b) and 5m (c) SR after data filtering using a 1D Gaussian filter over distance ( $\sigma_{dis}$ ).

#### 4. Conclusion

We presented here two crucial aspects of post-processing on BOTDA measurements. First, the various consequences of using a non-optimized fitting procedure were investigated. The fitting parameters have to be matched to the measurement spatial resolution, as well as to the signal-to-noise ratio, in order to obtain the lowest BFS uncertainty. The evolution of SNR, BFS uncertainty and SR with 2D filtering was then thoroughly studied. It turns out that the filtering of the BGS is highly redundant with the fitting procedure, thus having no real impact on the reduction of the measurement uncertainty. This suggests that a good fitting procedure is essentially more beneficial than a complex filtering post-processing using sophisticated algorithms. Filtering and post-processing makes essentially sense on the temporal traces (gain vs distance) and guidelines are provided to design optimized noise removal filters based solely on the signal bandwidth, the latter being dictated by the sensor spatial resolution.

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#### 5. References

- [1] M. A. Soto and L. Thévenaz, "Modeling and evaluating the performance of Brillouin distributed optical fiber sensors," *Opt. Express* **21**, 31347-31366 (2013)
- [2] M. A. Farahani, M. T. V. Wylie, E. Castillo-Guerra and B. G. Colpitts, "Reduction in the Number of Averages Required in BOTDA Sensors Using Wavelet Denoising Techniques," in *Journal of Lightwave Technology*, vol. **30**, no. 8, pp. 1134-1142, April 15, 2012.
- [3] M. A. Soto, J. A. Ramírez and L. Thévenaz, "Intensifying the response of distributed optical fibre sensors using 2D and 3D image restoration," in *Nature Communications*, vol. **7**, no 10870, 2016
- [4] R. W. Schafer, "What Is a Savitzky-Golay Filter? [Lecture Notes]," in *IEEE Signal Processing Magazine*, vol. 28, no. 4, pp. 111-117, July 2011.
- [5] M. A. Farahani, E. Castillo-Guerra and B. G. Colpitts, "A Detailed Evaluation of the Correlation-Based Method Used for Estimation of the Brillouin Frequency Shift in BOTDA Sensors," in *IEEE Sensors Journal*, vol. 13, no. 12, pp. 4589-4598, Dec. 2013.