

Intensifying Brillouin distributed fibre sensors using image processing

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ABSTRACT

Image processing is proposed to enhance the performance of Brillouin distributed fibre sensors. The technique exploits the two-dimensional nature of the measurements, so that each frequency-position pair is assimilated to a pixel of a noisy image. Based on the level of redundancy existing in the two-dimensional information, the method offers unmatched denoising capabilities when compared to classic unidimensional denoising methods, even if those ones are consecutively used in distance and frequency domains. With no modification of the basic configuration, up to ~14 dB SNR improvement is experimentally demonstrated with unobservable loss of spatial resolution. A figure-of-merit of 115'000 is verified.

Keywords: Optical fibre sensor, stimulated Brillouin scattering, distributed fibre sensor, image processing

1. INTRODUCTION

One of the main features of Brillouin distributed fibre sensors is their capability to measure temperature and strain profiles along very long sensing ranges using metric spatial resolution. Over the past two decades there have been intense research activities to enhance the performance of this kind of sensors¹. The signal-to-noise ratio (SNR) of Brillouin optical time-domain analysers (BOTDA) has been substantially improved using advanced techniques, such as distributed Raman amplification², optical pulse coding^{3,4} or other kinds of signal processing⁵, especially when those methods are combined in a single system⁶. Among the different methods proposed in the literature, signal processing techniques, such as optical pulse coding^{3,4} and wavelets⁵, have demonstrated to be very efficient tools to remove noise from a unidimensional array of data; and therefore, their use in BOTDA sensing requires processing time-domain traces at each scanned pump-probe frequency offset independently from each other. A 3D map of the Brillouin gain spectrum (BGS) versus distance can thus be obtained with an improved SNR after processing each time-domain trace³⁻⁵. Although methods such as time-frequency codes⁴ take advantage of the double scanning (fibre position and pump-probe frequency detuning) required in a BOTDA sensor, the SNR enhancement provided by that method is basically given by the capability of the code to reduce noise in a unidimensional array of data. So far, no two-dimensional signal processing has been applied to Brillouin sensing to take full advantage of the bi-dimensional nature of the data acquisition process. It can therefore be intuitively expected that the use of a two-dimensional processing technique for denoising the data acquired in a BOTDA sensor can offer a higher SNR enhancement compared to traditional (unidimensional) processing methods reported in the literature.

Following this approach for the first time to our knowledge, image processing is here proposed to remove noise from measurements in Brillouin distributed fibre sensors. Data points, measured at each frequency-position pair, are assimilated to pixels of an image corrupted by noise, which is then removed using well-proven 2D image processing methods. An SNR enhancement up to ~14 dB is demonstrated using experimental data acquired by a basic BOTDA sensor and applying four among the best-known algorithms for image noise reduction. This way, Brillouin gain profiles over a 100 km range are obtained in a 200 km fibre-loop, showing a frequency uncertainty of 1.5 MHz when using 2k averages and 2 m spatial resolution. Although the effectiveness of the technique is experimentally verified using a BOTDA sensor, the method can also be used to reduce noise in Brillouin optical time-domain reflectometers (BOTDR) or phase-sensitive OTDRs.

2. THEORY AND OPERATING PRINCIPLE

The measurement process in BOTDA sensors requires the acquisition of time-domain traces of the Brillouin gain at different pump-probe frequency offsets Δf . The process results in a 2D matrix $M(\Delta f, z)$ of data containing the local BGS at each fibre location z . The principle of the technique proposed in this paper is to consider the matrix M as an image, which can be represented by a function $f(x, y)$, where x and y are the spatial coordinates on the obtained image. In a general context, the values of an image $f(x, y)$ belong to a unidimensional space for a grayscale image, and to a three-dimensional space (a, b, c) for a colour image, where a , b and c depend on the choice of the colour space⁷ (such as RGB,

HSV, CIE Lab). For distributed sensing the elements of the matrix M are represented by scalar numbers like in a grayscale image, i.e. M contains unidimensional values mapping the measured local Brillouin gain at a given offset Δf .

Within the field of computer vision⁷, *image processing*^{7,8} is a tool that focuses on methods and algorithms to obtain visually relevant information from an image. This includes methods for image editing and manipulation, enhancement, feature detection and compression, among others⁷. One of the main challenges of image processing is to enhance the features that are important in an image, and dismiss other elements that are of no relevance, such as background objects, noise, shadows or glare. Among several techniques, *noise reduction*, also called *denoising*^{8,9}, is one of the most important methods, whose objective is to remove background noise from an image, while preserving the detail information. This exactly matches the requirements for improving the data robustness in a Brillouin distributed sensor while preserving all resolutions.

Denoising algorithms are usually based on the definition of *sliding neighbourhoods* or *2D windows*⁷, corresponding to the set of all pixels at (x, y) that are surrounding a certain position (x', y') . The most common windows are square and centred on the position (x', y') for which the processing is performed. The larger the window, the greater the reduction of image details. The most basic method of noise removal is known as *Gaussian Filtering*^{7,8} (GF), which is based on replacing the value of $f(x', y')$ at the centre of a window by a weighted average of $f(x, y)$ inside the window, where the weights are given by a two-dimensional Gaussian function centred at (x', y') . Gaussian filters are 2D linear filters, and therefore, any increase in the width of the Gaussian function could lead to the unwanted removal of image details. A more sophisticated version of weighted averages is known as *Non Local Means*⁸ (NLM) algorithm. Similarly to GF, the result of NLM is obtained by weighting the values inside a window centred at (x', y') ; however, the weighting factor of a pixel at (x, y) in this case is calculated as the exponential of the Euclidean distance between defined small neighbourhoods around (x', y') and (x, y) , using an exponential decaying factor that has to be properly adjusted⁸. The NLM method can be considered as an improvement respect to Gaussian filters, especially regarding the preservation of edges, texture and fine structures⁸.

Another approach for image denoising uses the frequency domain to separate the components of an image associated with high-frequency noise from the components containing relevant information. Within this category, the 2D *Discrete Cosine Transform*^{7,8} (DCT) converts the values of each sliding window to the frequency domain, then discards the components that are smaller than a certain threshold level and finally converts the result back to the spatial domain. Another powerful algorithm for image denoising is the 2D *Discrete Wavelets Transform*^{8,9} (DWT). This method decomposes an image into sub-versions containing different levels of detail and applies to each of them a certain threshold method to eliminate noise. Several parameters, such as the wavelet basis function, the threshold level, and the number of decomposition levels, must be adjusted in a 2D DWT⁹; and hence, all of them have a direct impact on the efficiency of the noise removal.

In this study the four above-mentioned image processing methods are suitably adapted for floating point values to denoise measurements of a BOTDA sensor. The effectiveness of the technique is evaluated by comparing the SNR of the denoised data, while the impact on the spatial resolution is estimated analysing a hot-spot at the far end of the sensing fibre.

3. EXPERIMENTAL DEMONSTRATION

As a proof-of-concept experiment, first a basic BOTDA scheme¹ has been implemented over 50 km range and 2 m spatial resolution. A 3D map of the BGS along the fibre has been obtained using 64 time-averaged traces, as shown in Fig. 1(a). It is possible to see that the measured spectrum is highly affected by noise under such a reduced averaging, having a severe impact on the sensor performance¹. Fig. 1(b) shows a top-view of the measured BGS versus distance. This corresponds to the 'image' to be denoised by image processing. The parameters required by each method have been adjusted aiming at removing only uncorrelated noise, and to avoid any distortion of the BGS and any detrimental impact on the spatial

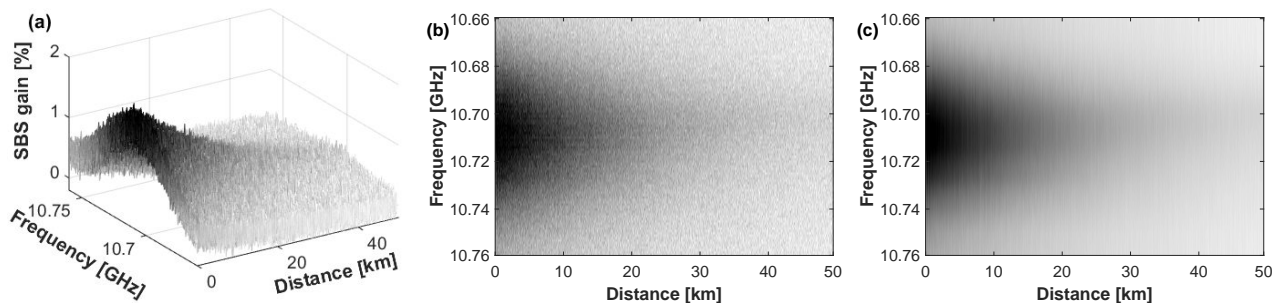


Figure 1. (a) Measured 3D map of the BGS vs distance. (b) Top-view image of the measured BGS vs distance. This can be considered as a noisy image of the ideal BGS. (c) Denoised top-view image of the BGS vs distance using DCT method.

resolution. After applying GF, NLM, DCT and DWT independently, a significant noise reduction is verified for each case. The effect of the two-dimensional denoising can be seen in Fig. 1(c), which shows the ‘denoised image’ obtained using the DCT method. The other methods provide similar ‘denoised images’, also exhibiting large noise reduction. Those images are not shown here for convenience since no visual differences can be perceived when compared to Fig. 1(c).

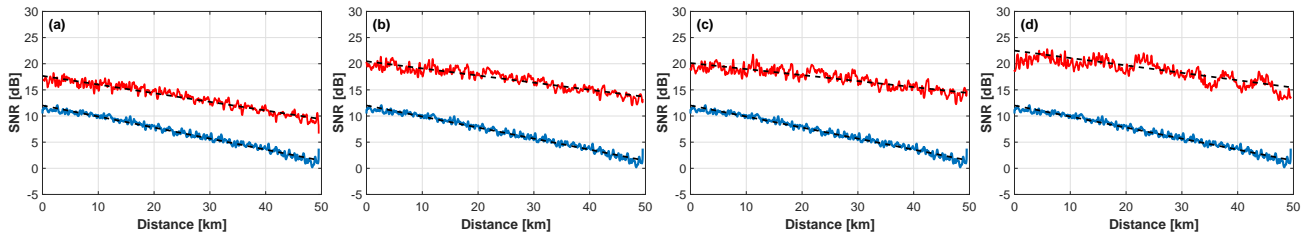


Figure 2. Experimental SNR enhancement provided by the proposed image processing technique. The SNR vs distance (at the peak gain frequency) calculated from the original data (blue curves) is compared with the SNR obtained after image denoising (red curves), for (a) GF, (b) NLM, (c) DCT and (d) DWT methods.

To properly quantify the impact of image processing⁷⁻⁹, the SNR of the trace at the peak Brillouin gain has been calculated for each case. Fig. 2 compares the SNR (signal amplitude over standard deviation¹) of the raw data (blue lines) to that obtained after processing (red lines) for the four methods. Results indicate that a raw data SNR of 1.57 dB obtained at 50 km distance can be significantly increased up to 9.49 dB, 13.73 dB, 14.43 dB, and 15.50 dB using GF, NLM, DCT, and DWT, respectively. Those values represent a remarkable SNR enhancement of 7.92 dB, 12.16 dB, 12.86 dB, and 13.93 dB in each of the respective cases. It is worth mentioning that the noise reduction is not always uniform along the fibre, especially for the most efficient methods, such as DCT and DWT. The reason is due to residual polarisation fading affecting the first km of fibre, which is seen as a correlated noise that is not efficiently eliminated by the image processing. Fortunately this effect only dominates in the first km of fibre (since polarisation fading is proportional to the Brillouin gain) where the SNR is still high; and hence there is no real detrimental effect at long distances (low SNR region) where the benefit from image denoising is more crucial.

Fig. 3(a) compares the measured BGS near the fibre far end (50 km) obtained from the raw data (blue curve) and after processing with the DCT method (red curve). It can be observed that the use of image processing leads to a considerable noise reduction with no distortion of the measured BGS. Fig. 3(b) compares the Brillouin frequency shift (BFS) retrieved along the fibre from both raw (blue curve) and denoised data using DCT (red curve). The consequent impact on the sensor performance¹ has been evaluated calculating the standard deviation of the BFS at each fibre location. Fig. 4 highlights that the frequency uncertainty attained with the raw data (4.7 MHz at 50 km distance) can be remarkably improved down to 0.77 MHz, 0.29 MHz, 0.25 MHz, and 0.20 MHz, for the GF, NLM, DCT and DWT methods, respectively. These values are actually in good agreement with the expected uncertainty¹ based on the experimental SNR reported in Fig. 2.

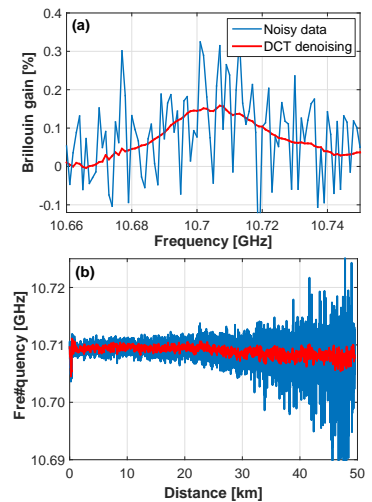


Figure 3. Effect of DCT method on (a) BGS at 50 km and (b) BFS vs distance. Comparison of raw (blue curves) and denoised data (red curves).

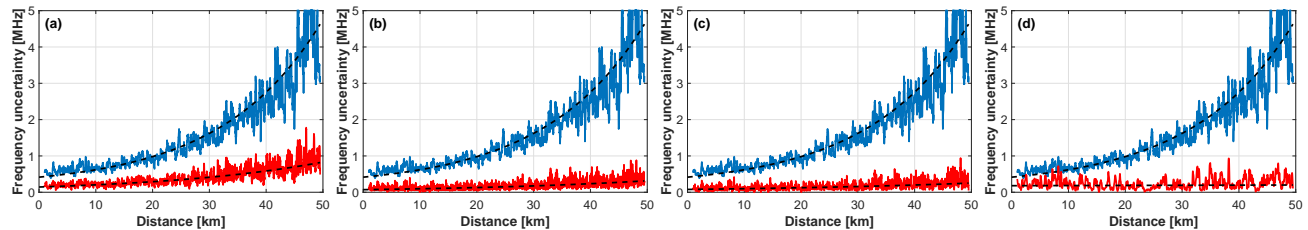


Figure 4. Frequency uncertainty versus distance, calculated as the standard deviation of the retrieved BFS from the original (blue curves) and denoised (red curves) data, for (a) GF, (b) NLM, (c) DCT and (d) DWT methods.

curve obtained using an advanced BOTDA scheme based on time-frequency multiplexing¹⁰ and averaging 8k traces, thus offering a sharp clean reference trace with comparable SNR. Fig. 5 shows the BFS profiles obtained from the sharp reference trace (dashed black curves), the raw measurements (blue curves) and the BFS obtained after image denoising (red curves) for the (a) GF, (b) NLM, (c) DCT and (d) DWT methods. Results show that the hot-spot can be accurately detected in all cases, having a negligible impact on the spatial resolution.

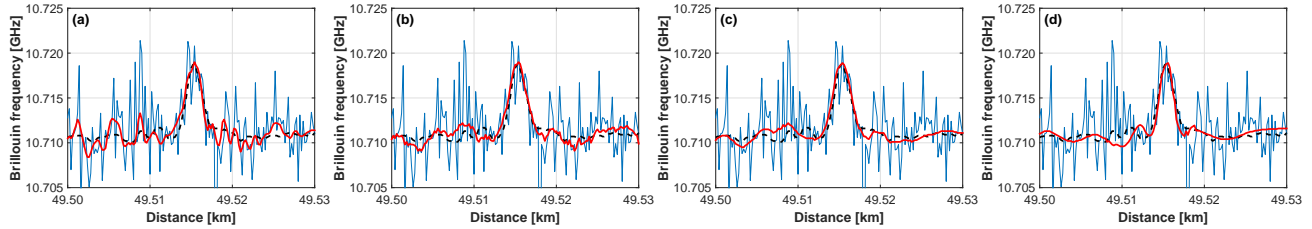


Figure 5. Detection of a 2 m-long hot-spot. Comparison of the BFS obtained from the raw data (blue curve), and the image processing methods (red curve), for (a) GF, (b) NLM, (c) DCT and (d) DWT denoising algorithms. The black dashed line corresponds to a reference curve obtained using an advanced BOTDA scheme and a large number (8k) of averaged traces.

Finally, considering the large SNR enhancement obtained by image denoising, a similar basic BOTDA scheme has been used to cover a sensing range of 100 km using a 200 km-long fibre-loop (probe experiencing a 42 dB loss after propagating along the fibre), keeping a spatial resolution of 2 m. Fig. 6 shows a 2m hot-spot measured at the end of the sensing fibre after denoising with the NLM method. With no feature added to the standard scheme, the method provides a frequency uncertainty of 1.5 MHz at 100 km distance when using 2k averages and 1 MHz scanning step. This corresponds to a figure-of-merit¹ (FoM) of 115'000, which is the highest FoM reached using no hardware sophistication in BOTDA sensing.

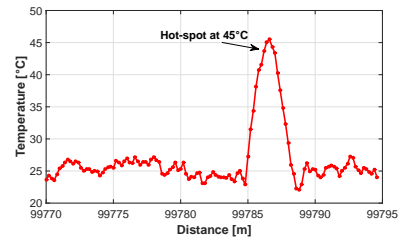


Figure 6. 2m hot-spot detection at 100 km distance using a 200 km-long fibre loop, 2k averages, 2m spatial resolution and NLM method for signal denoising.

In conclusion, a novel technique, based on the use of image processing, has been proposed and experimentally validated to reduce noise and very substantially improve the performance of Brillouin distributed fibre sensors. A remarkable SNR enhancement (up to about 14 dB) has been demonstrated using a simple conventional BOTDA scheme, allowing for measurements over a 100 km sensing range using a 200 km fibre-loop, with no need of special hardware and/or complex configurations. The technique can be readily implemented on any existing Brillouin distributed fibre sensors as a simple added software processing layer, bringing a boost in performance equivalent to extensively complex hardware sophistications, at a fraction of the cost.

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