DAS VSP Flow Noise Attenuation Based on Matching Pursuit

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Summary

Production-related noise on DAS VSP data generally not only obscures the underneath seismic signal but also results in a distorted VSP image. This paper presents an effective flow noise attenuation workflow for DAS VSP data based on Matching Pursuit. It decomposes DAS VSP traces into Gabor atoms followed by a reconstruction of the flow noise model using a linear combination of selected components. Flow noise attenuation is achieved by subtracting the reconstructed flow noise from the input data. We demonstrate performance on field DAS VSP data recorded in a producing well. Examples on field data with strong flow noise illustrate the effectiveness of the method.

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Introduction

Distributed acoustic sensing (DAS) technology has enabled seismic acquisition utilizing a fiber-optic cable either deployed downhole or laid on the ground/seabed as sensors to record seismic data. For the acquisition of vertical seismic profiling (VSP) data using DAS, most fiber-optic cables that provide sensing capabilities along fiber lengths are clamped on tubing in production and injection wells. Compared to conventional VSP geophones with deployable arms that push the point sensors against the wall of the well, the fiber is usually in loose contact with the wellbore and thus the coupling of the seismic waves from the formation to the sensing fiber is suboptimal. As a result, DAS VSP data often exhibits more noise than conventional geophone VSP data. When acquiring DAS VSP data in flowing wells, the noise issue is further exaggerated by fluid flow inside the wellbore which induces flow noise (unwanted acoustic signal) that contaminates the seismic signal (Zhan et al., 2022).

Flow noise is generally the strongest noise in DAS VSP data acquired on active production and injection wells. And it is also challenging to remove in processing using standard noise suppression tools. Currently, simple low-cut filtering of DAS channels affected by fluid-flow is mostly adopted since the flow noise appears mainly at low frequencies (Kiyashchenko et al., 2020). Although a low-cut filter can effectively suppress most high-amplitude flow noise, the low-frequency seismic signal that has an overlapping frequency band with flow noise is also destroyed. Therefore, we seek a denoising method which suppresses the unwanted flow noise whilst preserving the low-frequency components of the useful seismic signal.

In the area of acoustic event classification, spectrograms are commonly used to examine frequencies of sound waves produced by humans for distinguishing and characterizing different types of human activities. Figures 1a and 1c show the spectrograms of two non-speech human sounds. Notice that in the depicted time interval, the ‘laughter’ sound is almost periodic while the ‘yawn’ sound is relatively stationary except a decreasing pitch in the first half second. To look at frequency behaviour of DAS data continuously recorded in a production well, we compared the spectrograms of two different DAS recordings in Figures 1b and 1d. In the displayed time interval of Figure 1b, 6 airgun shots were fired on the surface and seismic waves were detected by a downhole fiber when the well was shut in. Interestingly, the ‘seismic’ signal exhibits a periodic behaviour as similar as ‘laughter’. Conversely, the pure ‘fluid-flow’ signal recorded in the same well but under flowing condition demonstrates a rather stationary behaviour in time which is comparable to ‘yawn’.

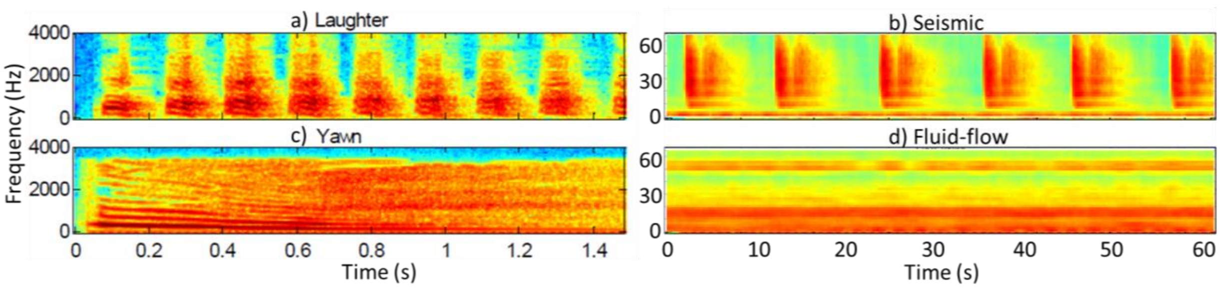

Figure 1 *Similarity between spectrograms of human sounds (left column, modified from Temko et al., 2008) and spectrograms of DAS data (right column).*

Since both ‘seismic’ and ‘fluid-flow’ events have shown distinct acoustic fingerprints, these might be utilized to distinguish between seismic signal and flow noise through techniques similar to those used for audio and acoustic signal processing. Matching Pursuit (MP) (Mallat and Zhang, 1993) is such a technique that has been widely used in acoustic event classification for robust sound recognition. It has also been used in seismic signal analysis (Wang, 2007). Most recently, it was adopted by Martuganova et al. (2021) for the elimination of DAS ringing noise. Motivated by its usefulness and effectiveness in both acoustic signal representation and seismic signal representation, we explore the use of MP to identify repeated patterns that characterize and eliminate flow noise from DAS VSP data.

Matching Pursuit signal decomposition and reconstruction

Matching Pursuit (MP) is an iterative algorithm (Mallat and Zhang, 1993) that decomposes a signal such as a seismic trace into a sparse linear combination of waveforms (called atoms) that belong to a redundant set (dictionary) of functions. Commonly used with dictionaries of Gabor atoms (Gabor, 1946), it offers several advantages in signal analysis and classification. Figure 2 exhibits a decomposition of a field DAS trace of 8 s into 50 Gabor atoms followed by a reconstruction of it which is a linear combination of all the atoms. Time-frequency amplitude maps of the DAS signal before and after reconstruction are also displayed at the bottom of Figures 2a and 2c. It is observed that most of the signal energy can be accounted for with only a small number of Gabor atoms.

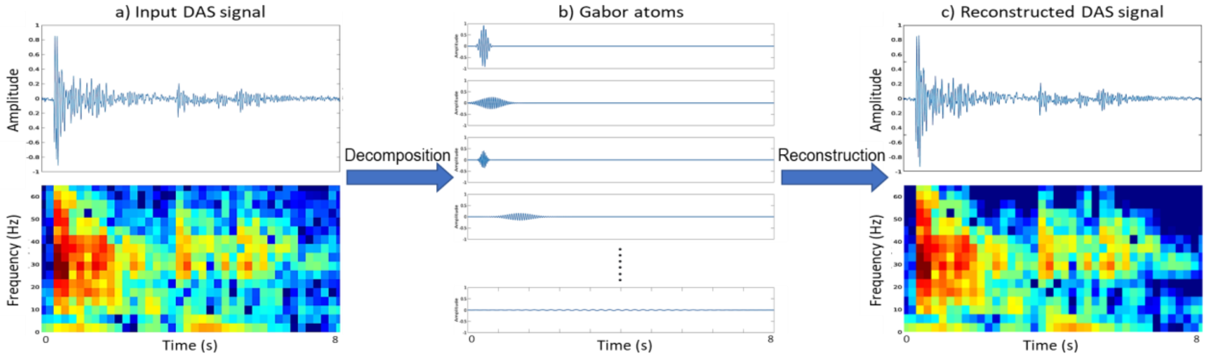

Figure 2 *The decomposition and reconstruction of a field DAS signal obtained by Matching Pursuit.*

Flow noise attenuation workflow based on MP

Figure 3 represents the workflow of flow noise removal from a noisy DAS trace. Both time series and its associated time-frequency amplitude map are displayed for the purpose of comparison. The experimental data shown in Figure 3a was obtained by adding field recorded flow noise to the clean DAS signal displayed in Figure 2a. The resulting noisy trace contains both low-frequency and high-frequency noise which overlap with the frequency of the signal. 5 over 80 Gabor atoms derived from this noisy trace using MP are displayed in Figure 3b. Compared to the Gabor atoms derived from the clean DAS signal (Figure 2b), additional sine waves at various frequencies were computed to approximate the flow noise. Kernel density estimation for frequency values of decomposed Gabor atoms is plotted in Figure 3c where the identified density peaks at 11 Hz and 50 Hz are mainly contributed by flow noise. Gabor atoms with a frequency that falls into these two highlighted frequency columns (±3 Hz from the peaks) are selected to reconstruct the flow noise and the resulting flow noise model is presented in Figure 3d. Through subtraction of the estimated flow noise (Figure 3d) from the input trace (Figure 3a), the underlying DAS signal is restored in Figure 3e. To validate the performance of noise attenuation, we compared the denoised DAS trace (Figure 3e) with the noise-free DAS trace (Figure 3f) in both time domain (top) and time-frequency domain (bottom). Although there is a little residual noise remaining in the output, the similarity between Figures 3e and 3f denotes that the MP based flow noise attenuation approach achieved an impressive recovery of seismic signal from the flow noise contaminated DAS data.

Field results

Figure 4 shows an example of the proposed flow noise attenuation workflow applied to a field DAS VSP shot acquired from a producing well. The raw shot record (Figure 4a) demonstrates a significant detrimental impact from the production flow. MP was used to reconstruct the flow noise between 5.2 km and 7.1 km measured depth followed by a subtraction of the noise model from the raw shot. The denoised shot (Figure 4b) is much cleaner, and the weak seismic signal underneath the strong flow noise has been successfully recovered. The conventional flow noise attenuation approach using a low-cut filter was also applied and compared in Figure 4c. This conventional approach has not been as effective as the MP approach. It is also worth noting that the application of the MP denoising method has removed more flow noise while preserving the low frequency seismic signal.

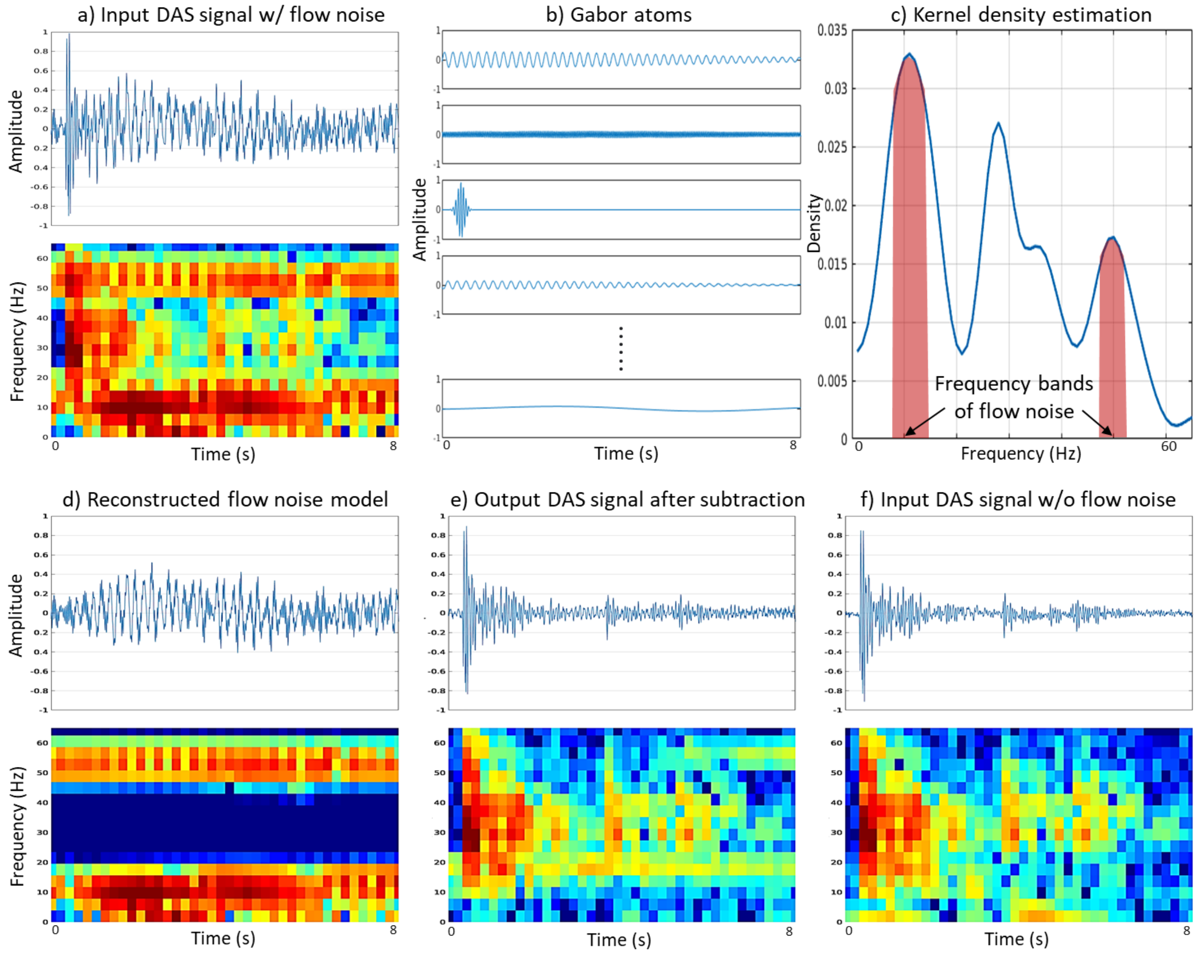

Figure 3 *Illustrations of flow noise attenuation workflow based on Matching Pursuit.*

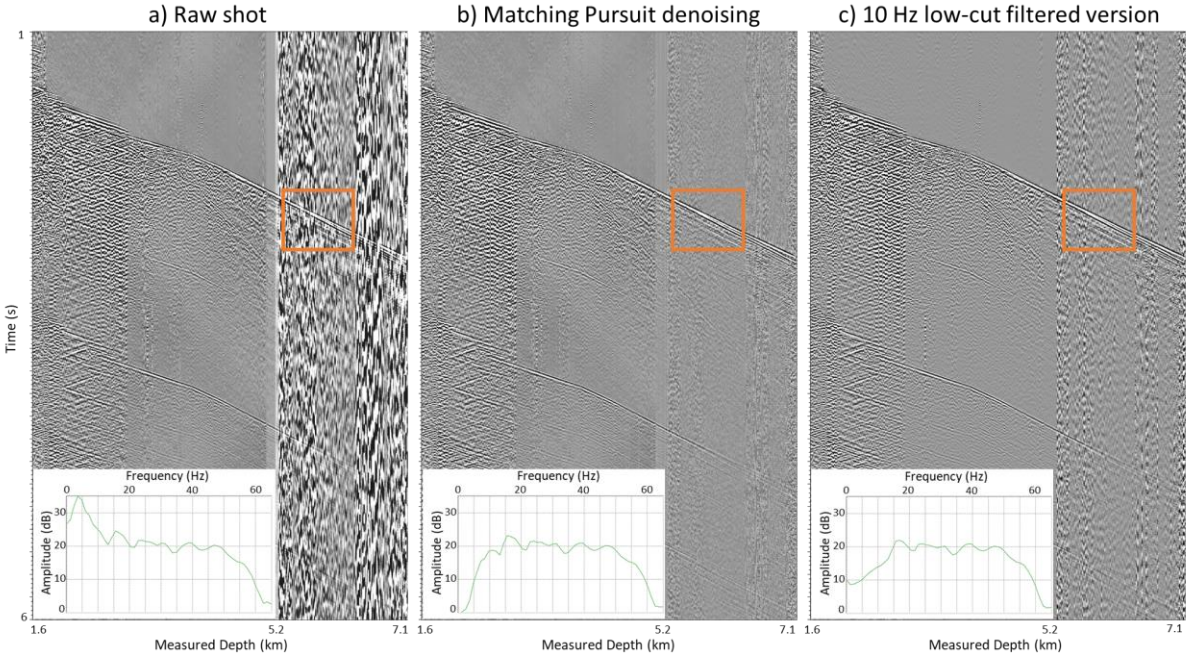

Figure 4 *A sample raw shot a) before and b) after Matching Pursuit flow noise attenuation. c) The application of a conventional denoising process. Amplitude spectra of the selected area (orange) are also compared at the bottom of each figure.*

Conclusions

We have demonstrated a Matching Pursuit based noise attenuation workflow for attenuating flow noise from DAS VSP data. Results show that it is a robust and effective workflow that can remove flow noise while preserving low-frequency seismic signal. Therefore, it is suitable for routine processing of DAS VSP data contaminated by flow noise.

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