ADAPTIVE FILTER FOR SEISMIC SIGNALS OF VARIABLE SLOWNESS

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1 Introduction

Recently, wide-angle seismic techniques are getting popular for ocean subsoil research. For these studies, an array of sensors is deployed at the bottom of the sea to record the reaction of the subsoil to a set of airguns that shoot nearby the surface. These shots are regular enough to detect reflected signals through their coherent appearance. In order to take advantage of these similarities, the response of each shot is aligned side by side according to their shot time, making a time-distance image called record section (RS).

On these plots, high energy waves usually mask in the time-distance domain weak signals that carry valuable information on the fine structure of the Earth. To analyze these signals in detail, we need to use other attributes that allow us to distinguish them.

The frequency-wavenumber (f–k) filter, τ–p filter and hyperbolic Radon are common tools to distinguish seismic phases through their apparent velocity [1]. f–k provides an extremely good selectivity but, because of being based on the 2-D Fourier transform, it completely loses any time-space resolution. The others use a Radon transform, which cannot adapt to variable trajectories.

To solve the limitations of the Radon and f–k approaches, we introduce a new tool that allows to filter a RS according to the slowness (inverse of velocity), while adapts to the specific signal trajectories and maintains the other signals with minimal distortion [2].

2 Slowness filter

In a RS, the slowness of a seismic phase is the gradient along the travel-time trajectory of this phase. Because of its slow variation, it is possible to approximate locally the trajectory of any phase by a straight line or beam, and to identify its gradient with its slope. Moreover, as lateral coherency is high along a wave front and low in other directions, we can distinguish which phases contribute to each sample.

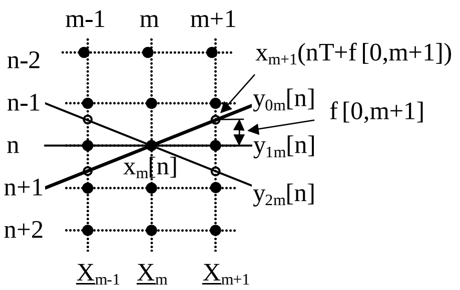

Figure 1: Decomposition of one sample into three slowness components.

For continuous functions, the projection along one beam is done through a line integral, solid lines in Figure 1. For discrete functions, this integral turns into a sum. But as the samples along beams are usually not available, we have to interpolate them. For simplicity, we only estimate the samples at the intersection points between beams and traces, circles on Figure 1.

Our filter is divided in 2 steps: first, the RS is decomposed into a set of different RSs, one for each slowness step (see 2.1), and then, we apply a 3-D filter and a back transform to build the filtered RS. For the second step, two opposite strategies can be followed: either we can build the filtered RS from the desired components, or we can keep the undesired components to estimate the signals to be removed and substract them from the original RS. Both strategies require an inversion of a linear system of equations. This kind of operations can be expensive and very unstable if performed directly. But, as locally the energy of a seismic phase is mainly confined into a narrow slowness range, the undesired phase can be approximated by the sum of a small set of slownesses. Hence, this operation becomes trivial.

2.1 Instantaneous slowness estimation

The aim is to estimate all possible projections along a set of parallel beams with slope s that crosses every sample at trace m. For any element of this projection , a sum of the values at points where beams and traces intersect must be determined. For the example on Figure 1, the estimation at trace of the element n of a projection with slope s is:

$$y_{sm}[n] = \sum_{m'=m-1}^{m+1} x_{m'}(nT + f[s,m']) \qquad (1)$$

where is the distance between the interpolated point and the nearest previous sample, and is an interpolated version of . It is sufficiently accurate to use a polynomial interpolation [3] of degree with the nearest samples of the same trace. The decomposition of into three slope components using three trace long windows can be summarized in vectorial notation as:

$$\begin{bmatrix} \underline{Y}_{01} \\ \underline{Y}_{11} \\ \underline{Y}_{21} \end{bmatrix} = \begin{bmatrix} \underline{IP}_{00} & I & \underline{IP}_{02} \\ I & I & I \\ \underline{IP}_{20} & I & \underline{IP}_{22} \end{bmatrix} \begin{bmatrix} \underline{X}_0 \\ \underline{X}_1 \\ \underline{X}_2 \end{bmatrix} \qquad (2)$$

In (2), is an M square Toeplitz matrix with no more than P+1 non-zero diagonals. When no interpolation is required, these matrices have only a single diagonal equal to one, so at trace and at slope , is an identity matrix I. This system can be generalized for SL projections and windows of M traces as:

$$\underline{Y}_{sm} = \sum_{\tau=m-\Delta M}^{m+\Delta M} \underline{IP}_{s\tau}\underline{X}_{\tau} \qquad (3)$$

where $\Delta M = (M-1)/2$ and M is odd.

3 Results

In the following we apply the slowness filter to attenuate one well-defined interferent seismic phase. For sake of simplicity, a rough trajectory and domain of the interference signal has been specified to estimate its slowness and its time-space region of influence.
The RS shown in Figure 2 is composed of two waves with a hyperbolic trajectory and a random noise with the same amplitude spectrum. It should be noted that at the beginning, both traces have the same slope.

In this test, we want to remove the second hyperbola having the minimal distortion on the rest of the RS, and particularly on the first hyperbola. We can notice in Figure 2 that the slowness filter has removed successfully the undesired phase preserving the desired one. These results could never been achieved using a f–k filter because of the slope variation of this wave and, the lack of time-space resolution that forces to choose between removing or preserving all equal-slope signals.

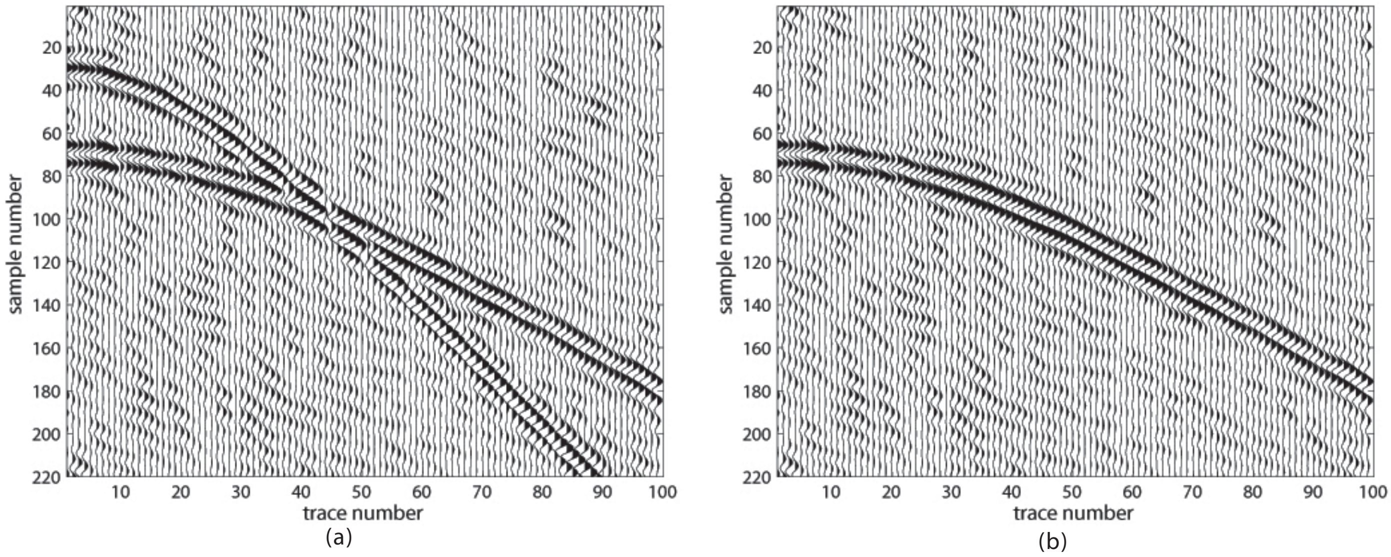

Figure 2: Two synthetic seismic phases. (a) Original RS. (b) Filtered RS with M = 9

4 Conclusion
We have presented a new method for adaptively filtering RS depending on the instantaneous slowness of seismic phases. The proposed method works efficiently even in a non-stationary context, being completely adapted to any specific signal trajectory and preserving the other signals with minimal distortion. This makes possible to analyze weaker signals and to extract much more information from seismic RS.

5 Acknowledge
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COMPARATIVE RESPONSE OF TWO DIFFERENT HYPERSPECTRAL SENSORS. APPLICATION TO DERIVATIVE ANALYSIS OF ABSORPTION SPECTRA

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1. Introduction
A broad range of in situ and remote hyperspectral sensors, covering from several hundreds to thousands spectral bands, have been developed recently for different environmental monitoring applications. Several studies using hyperspectral data and derivative spectroscopy have been done so as to assess qualitative and quantitative information about water components [1]. One of the key aspects to take into account is the processing techniques applied to raw spectral data to get comparable results between different measurements.

The commonly derivative spectroscopy used to explore subtle features in spectral data is notoriously sensitive to noise [2]. Noise level in hyperspectral data is high as their narrow bandwidth can only capture very little energy that may be overcome by the self-generated noise inside the sensors. To remove the noise from hyperspectral data smoothing techniques are commonly used [3]. However, for preserving the properties of the original data, smoothing and derivative techniques should be carefully applied to minimize possible numerical artifacts. There is a trade-off between noise removal and the ability to resolve fine spectral details. The main factor controlling the extent of smoothing is the size of the filter window used for averaging or convolution. The greater the size of the filter window, the smoother the result. The spectral details revealed in the derivative spectra are a function of the band separation (BS=$\Delta\lambda$). Features smaller than $\Delta\lambda$ will be lost and features at the scale of $\Delta\lambda$ will be enhanced.

In the present study, a comparison between the spectral data obtained using two hyperspectral sensors with different spectral resolution is exposed. Smoothing and derivative algorithms have been applied to both types of spectral data in order to assess qualitative information from their spectral features.

2. Results and Discussion
Two different hyperspectral sensors have been employed: the Ocean Optics USB4000 Spectrometer, that uses the Toshiba TCD1304AP 3648-element linear CCD-array detector and the MicroParts GmbH UV/VIS Microspectrometer, a lower cost and lower energy-consuming device more suitable for being part of a node in a monitoring sensor network [4], that uses the Hamamatsu S8378 256-element linear CMOS-array detector.