Seismic Data Enhancement and Targeted Noise Removal Using Time-frequency Masking Guided by Beamformed Data

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Summary

Land seismic data are often quite challenging for reliable seismic imaging. The mechanism responsible for difficulties in data processing may be identified as severe frequency-dependent phase and amplitude perturbations making events incomprehensible in multi-channel records. We present a new approach by combining nonlinear beamforming and time-frequency masking to compensate for such effects in two steps. First, we construct a crude signal "guide" using data-driven nonlinear beamforming. Second, we employ trace-by-trace time-frequency masking to repair damaged phase and amplitude. Phase masks are of paramount importance to heal the wavefield and make desired events coherent and trackable. Amplitude masks aim to suppress noise from the amplitude spectra. Introduced methods avoid smearing of amplitude information across channels and preserve frequency bandwidth of desired signals.

Introduction

Modern land seismic acquired with single sensors or small arrays requires significant prestack enhancement. Separating signal and noise appears to be an insurmountable challenge when reflections become broken up and invisible while scattered noise dominates. Local multidimensional stacking can successfully identify and enhance weak signals on prestack seismic data (Buzlukov and Landa, 2013; Bakulin et al. 2018). While massive multidimensional stacking methods summing hundreds and thousands of traces are efficient at finding events in the noisy original data, they are infrequently used in mainstream seismic processing because of undesired side effects: 1) Original amplitudes at each receiver point are biased (heavily averaged); 2) Data is overly smoothed and important local traveltimes or amplitudes features characterizing near surface or subsurface are distorted; 3) higher frequencies are suppressed during beamforming/local stacking. Beamforming is often used to condition the data for deriving time processing parameters (Bakulin and Erickson, 2017), but distortions introduced by local stacking are typically considered as too severe for reliable quantitative analysis. Here we propose an alternative approach that uses massively beamformed data as a "signal guide" that "corrects" corrupted data but only to the extent required for conventional methods to work.

Time-frequency masking guided by beamformed data

The propagation of seismic signals is a nonstationary process. As a consequence, desired signal estimation procedure is designed in the time-frequency (TF) domain using the short-time Fourier transform (STFT). It is useful to relate the "healing" procedure to time-frequency masking (TFM) from speech processing (Yilmaz and Rickard, 2004). While in the speech processing, there is usually "noisy speech" and approximately estimated "clean speech," we replace them with the analogs of "noisy data" $x(t)$ and "enhanced (beamformed) data" $s(t)$. The enhanced dataset from beamforming or local stacking represents our best estimate of the signal with a much higher signal-to-noise ratio but suffering from limitations above. We assume that the enhanced dataset retains identical structure and number of traces.

As in speech processing, our goal is to extract the best estimate of desired signals contained in $x(t)$ using corresponding enhanced trace $s(t)$ as a guide. Applying STFT to $x(t)$ and $s(t)$, we obtain complex-valued time-frequency (TF) spectra of the traces $X(k,l)$, $S(k,l)$ with k, l representing the discrete frequency bin and time frame indices, respectively. The input signal in TF domain $X(k,l)$ contains superposition of actual signal and noise. TFM

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provides an estimate of desired signal TF spectrum $\hat{S}(k,l)$ as a multiplication

$$\hat{S}(k,l) = M(k,l) \cdot X(k,l). \quad (1)$$

In speech processing $M(k,l)$ is typically a real-valued function, $0 \leq M(k,l) \leq 1$ (Wang, 2008); however, a complex-valued TFM has also been recently introduced (Williamson and Wang, 2017). Clean speech (i.e., "signal") and noise properties are required to design TFM. In contrast to seismic, in speech processing, a reliable estimate of the desired signal spectral distribution is usually available. We propose to utilize an enhanced dataset from local stacking as an analog of clean speech. Having a "guide" dataset from beamforming identical in the number of channels, we can perform single-channel TFM filtering where each "noisy trace" is subject to specialized TFM derived solely based on corresponding "enhanced trace" from beamforming, thus simplifying the processing sequence to trace-by-trace transformations.

Phase corrections (phase-only TFM)

Bakulin et al. (2019) has demonstrated that phase plays an outsized role in restoring coherency of broken up reflections. Specifically, two phase methods were introduced. *Phase substitution: We take the TF phase of the enhanced trace as our best estimate of the signal phase, whereas the amplitude spectrum remains untouched.* TF spectrum of the desired signal trace is given as:

$$\hat{S}(k,l) = |X(k,l)| \exp[i\varphi_S(k,l)], \quad (2)$$

where $|X(k,l)|$ is amplitude TF spectrum of original trace, and φ_S is the phase spectrum of the enhanced trace after beamforming. Phase substitution method can be considered as a special case of complex-valued phase-only TFM with

$$M(k,l) = \exp[i\{\varphi_S(k,l) - \varphi_x(k,l)\}], \quad (3)$$

as can be easily observed by substituting (3) into (1). Here φ_x and φ_S are phase spectra of original ("noisy") and enhanced traces, respectively.

Phase sign corrections: We correct the phase of original data using phase sign-correction mask (PSM)

$$\hat{S}(k,l) = X(k,l) \cdot PSM(k,l),$$
$$PSM(k,l) = sign[\cos\{\varphi_S(k,l) - \varphi_x(k,l)\}]. \quad (4)$$

If original and enhanced data are in phase (phase difference is less than $\pm\pi/2$) at a specific frequency – then no correction is made ($PSM = 1$). If they are out of phase (difference more than $\pm\pi/2$), then phase at this frequency is flipped by $\pm\pi/2$($PSM = -1$).

Both methods represent specialized phase-only TFMs maintaining original amplitude information as well as higher frequencies without smearing across multiple channels. In this study, we introduce the next step of targeted noise removal by additional application of amplitude TFMs also guided by the same beamformed data.

Targeted noise suppression with amplitude TFM

TFM are widely used for single-channel enhancement of noisy speech signals. Amplitude TFM applies a simple real-valued function, which is close to 1 in a "signal dominance" region of the TF spectrum and close to 0 in a "noise dominance" area. One of the most popular "soft amplitude" based TFM is the so-called Ideal Rationale Mask (IRM). One possible realization of IRM is defined as:

$$IRM(k,l) = \sqrt{\frac{|S_{est}(k,l)|^2}{|S_{est}(k,l)|^2 + |N_{est}(k,l)|^2}}, \quad (5)$$

where $|S_{est}(k,l)|^2$ and $|N_{est}(k,l)|^2$ are estimates of desired signal and noise power spectra, respectively. In speech processing the noise power TF spectrum is estimated using established methods such as minimal statistic (MS) approach (Martin, 2001). After that, the clean speech power spectrum is estimated by spectral subtraction. In seismic exploration, we have little a priori information about the real behavior of the noise power spectrum. Noise and desired signals in seismic data do not necessarily satisfy the assumptions of the MS approach or other methods widely used in speech processing. Also, one usually deals with broadband sources, i.e., with signals which have useful components within the entire frequency band (2-100 Hz), so models of "colored" uncorrelated noise are not very useful. Instead, we can rely on some rough signal estimation obtained as a result of a data enhancement based on local stacking (beamforming) procedure. This information

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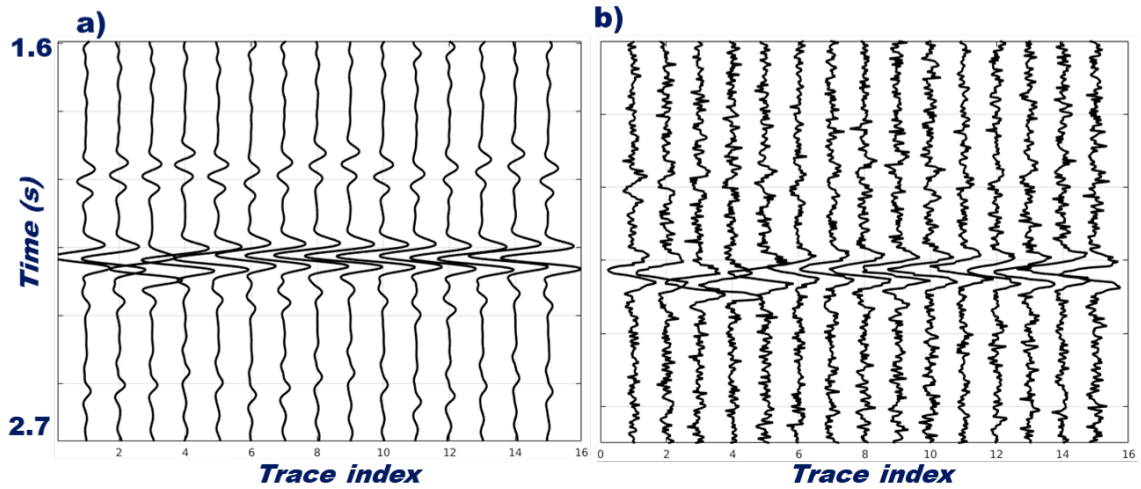

Figure 1: (a) Ensemble of original 15 traces. Reference trace has index 1. (b) The same ensemble contaminated by white gaussian noise (SNR=-2dB)

may be used to construct "Seismic IRM" utilizing the following scheme.

1. Original trace $x(t)$ and a "guide" trace $s(t)$ are normalized by their energy $Q_1 = \sum x^2(t)$, $Q_2 = \sum x^2(t)$, so we further deal with the traces $x_n(t) = x(t)/Q_1$ and $s_n(t) = s(t)/Q_2$.
2. STFT is applied to $x_n(t)$, $s_n(t)$.
3. Phase correction mask, PSM is calculated using expressions (3) or (4).
4. "Signal intersection" power spectrum is calculated as $|SI(k,l)|^2 = \min\{|X(k,l)|^2, |S(k,l)|^2\}$ at each point k, l.
5. Noise power spectrum is estimated by spectral subtraction $|N_{est}(k,l)|^2 = |X(k,l)|^2 - |SI(k,l)|^2$.
6. Normalized "enhanced" trace power spectrum is used as an estimation of the "signal," $|S_{est}(k,l)|^2 = |S(k,l)|^2$.
7. Estimated IRM is applied together with the phase correction masks (3) or (4) $\hat{S}(k,l) = X(k,l) \cdot PSM(k,l) \cdot IRM(k,l)$.
8. After inverse STFT, the obtained trace is renormalized by the energy of the original trace Q_1, i.e. $\hat{S}(t) = Q_1 * ISTFT[\hat{S}(k,l)]$.

We emphasize that the most essential and nontrivial item in the whole procedure is how noise and signal power spectra are estimated. We described here only one of the many possibilities.

Synthetic example: noisy ensemble from elastic model

We demonstrate the performance of phase and amplitude TFM's on synthetic elastic data calculated for the 3D SEG/EAGE Overthrust model using land acquisition geometry. *Figure 1* shows an ensemble of 15 traces formed in the receiver domain before and after adding moderate white Gaussian noise (WGN) with SNR ~ -2dB. Our objective is to compare and contrast three different methods of estimating the original (noise-free) reference trace (first in the ensemble) from the noisy ensemble: conventional local stacking (with intra-array statics), phase correction method, and combined phase and amplitude TFM. We refer to the stacked trace as a "pilot" trace, and this "pilot" will be used for TFM constructions. *Figures 2 and 3* demonstrate that the pilot trace is deviating from the original trace due to time shifts and uncompensated phase variations of waveforms in the original ensemble. The pilot trace has SNR~5.1 dB in comparison with the reference noise-free trace. Here we treat the direct difference of output traces and known reference trace as "noise" in SNR calculation. Corrected trace after phase corrections is shown in *Figure 2b* (SNR~2.2dB). It has better restoration of amplitudes

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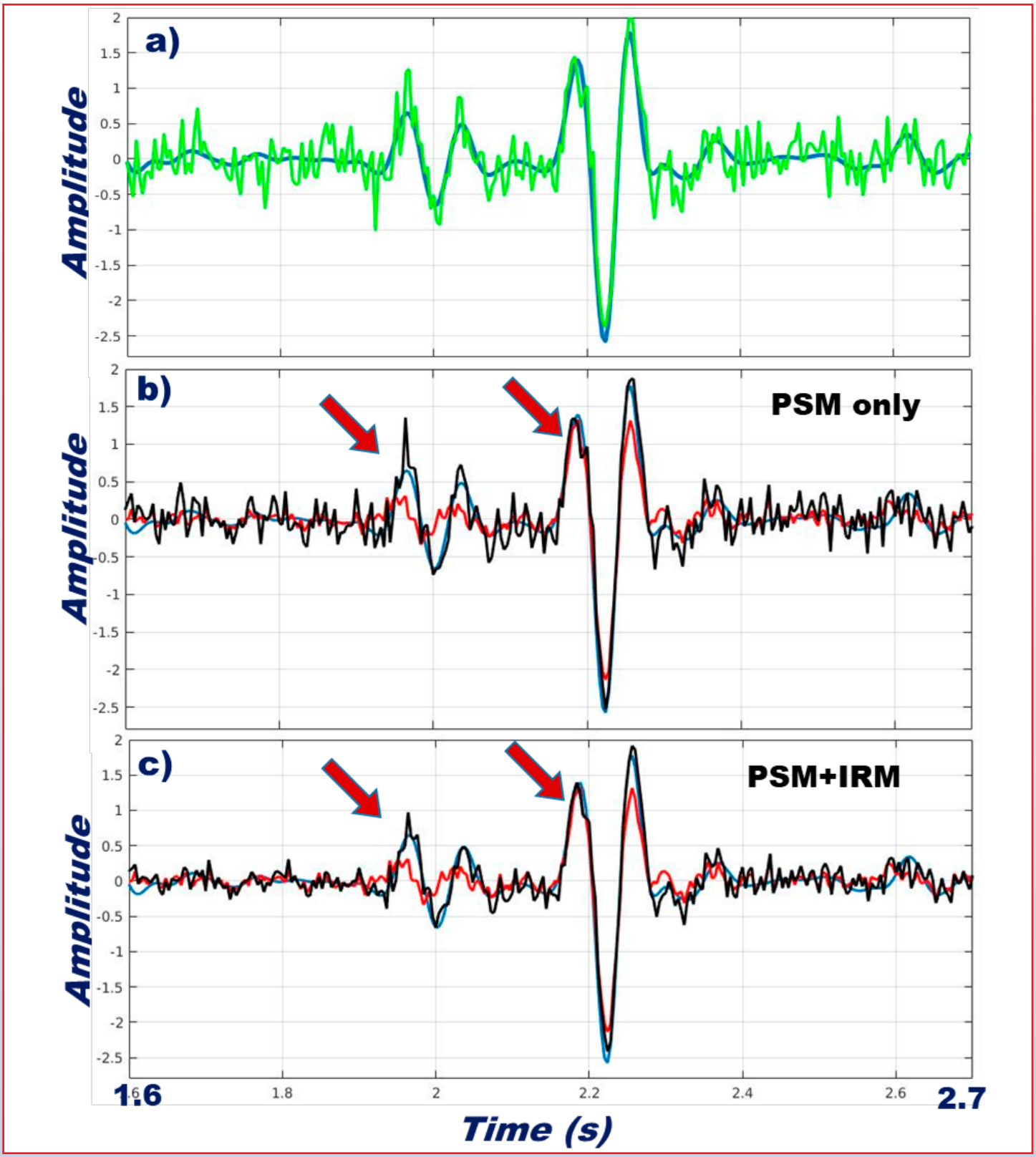

Figure 2: (a) Comparison of reference trace (blue) and its noisy counterpart (green, SNR is -2dB); (b) Comparison of reference noise-free trace (blue) with a trace after stacking (red, SNR=5.1 dB) and the output trace after phase correction (black, SNR = 2.2 dB); (c) Comparison of the reference trace (blue) with a trace after stacking and the output trace after phase corrections + IRM (black, SNR=6.4dB).

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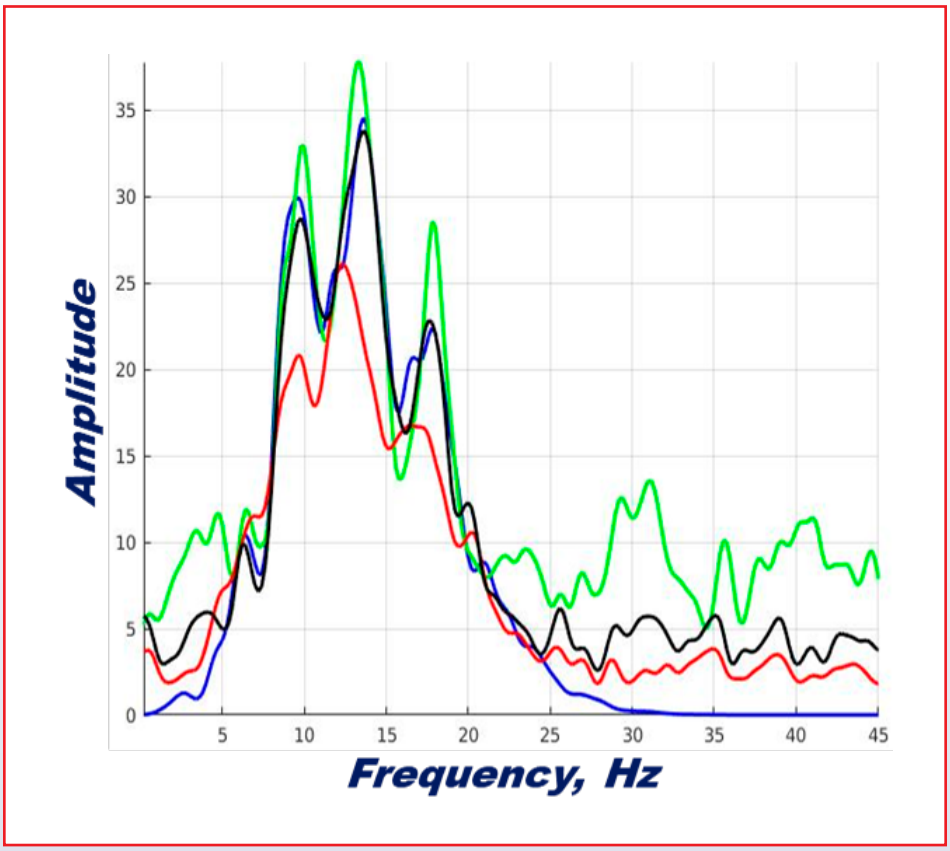

Figure 3: Comparison of amplitude spectra of input and output traces: reference trace (blue); reference trace with noise (green); trace obtained by (red); trace after phase corrections + IRM (black).

of weak reflections (marked by arrows), but the random amplitude noise remains unsuppressed. The trace produced by a combination of phase corrections with amplitude TFM has visible reduction in noise level (SNR = 6.4dB), more accurate peak signal amplitudes, whereas coherent arrivals remain properly positioned. *Figure 3* confirms that conventional stacking reduced amplitude spectra too much (hitting both noise and signal), whereas the combination of phase and amplitude TFM provides a most accurate estimate of noise-free spectra, efficiently harvesting information from the entire ensemble.

Single-sensor data example from a desert environment

An example of common-midpoint (CMP) gather from a challenging 2D land single sensor dataset acquired in a desert environment is shown in *Figure 4a*. Original data was partially stacked within offset bins 100 m. This dataset has already been passed through a standard processing flow of noise suppression and is ready for imaging. Nevertheless, data remains noisy with target reflections being barely visible, especially at the near offsets and later times. *Figure 4b* shows the same CMP gather after enhancement using nonlinear beamforming or NLBF (Bakulin et al., 2018) with summation apertures of 100 m x 100 m. Approximately 150 neighboring traces are used in the local summation to enhance each original trace. After the enhancement, the reflections are easily recognizable in the whole offset range. The high-frequency content of the signals is suppressed due to suboptimal stacking (averaged amplitude spectra of the gathers are overlaid on the figures). Using beamformed data as a "guide" and applying phase substitution method *(Figure 4c)*, reflections remain visible in the entire offset range without oversmoothing and with higher frequencies preserved. Application of amplitude TFM reveals better low frequencies (10 Hz) and also suppresses higher-frequency noise (60-100 Hz), leading to a more natural roll-off *(Figure 4d)*. Computed amplitude spectra validate that introduced corrections led to the preservation of higher frequencies in the data. A comparison of stacks reveals that while the NLBF image *(Figure 5b)* has better event correlation at the middle frequencies, both TFM images possess finer spatial and temporal details *(Figure 5c, d)*. Besides, amplitude TFM shows a visible reduction of non-geologic high-frequency noise *(Figure 5d)*. The fact that higher frequencies are surviving after stacking suggests that we gained additional signals on prestack records that coherently added up during the imaging step. We conclude that the combination of phase and amplitude TFM provides clear uplift in prestack and post-stack images obtained with challenging single-sensor data.

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Conclusions

We present a new approach that can perform delicate seismic data enhancement. We utilize massive beamforming with large apertures to uncover hidden reflectors. Such enhanced data forms a "guide" multi-channel dataset with the same number of traces serving as an approximate "signal model". We exploit this "guide" to correct original data using specially designed time-frequency masking analogous to speech processing. We demonstrate that frequency-dependent phase corrections are crucial to restoring the coherency of broken up reflectors. Amplitude TFM masks are designed to attack noise. As before, "guide" dataset traces are used to design targeted amplitude masks surgically knocking noise in places of domination while not touching areas with signals. Examples from synthetic and real seismic data validate the effectiveness of new methods. Corrected multi-channel gathers become acceptable for conventional processing by existing methods. Described TFM masking with the "guide" can also be considered an alternative to existing signal processing techniques that are often rather brute-force and limited in guidance and precision. Time-frequency masking guided by beamformed data opens a new avenue for multi-channel signal processing. We presented some initial designs for phase and amplitude masks, whereas the new methods pave the way for new possibilities in data enhancement and targeted noise removal. □

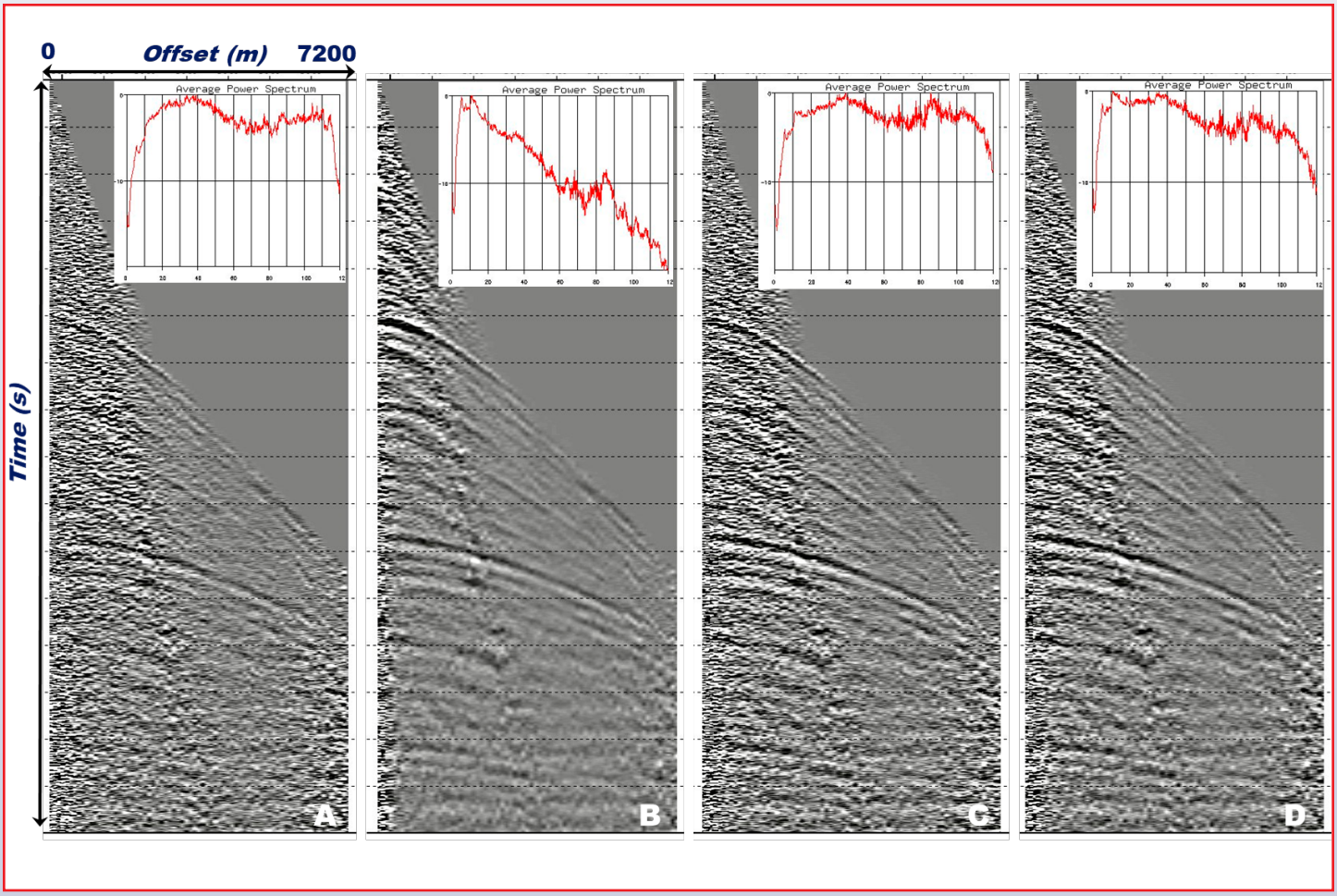

Figure 4: Real data example showing prestack CMP gathers obtained with different approaches: (a) Original data after conventional processing; (b) data after nonlinear beamforming; (c) data after phase substitution; (d) data after phase correction. While nonlinear beamforming (b) greatly improves coherence and continuity, observe loss of higher frequencies and oversmoothed character. In contrast, new methods (c) and (d) deliver significant improvement avoiding oversmoothing, preserving higher frequencies.

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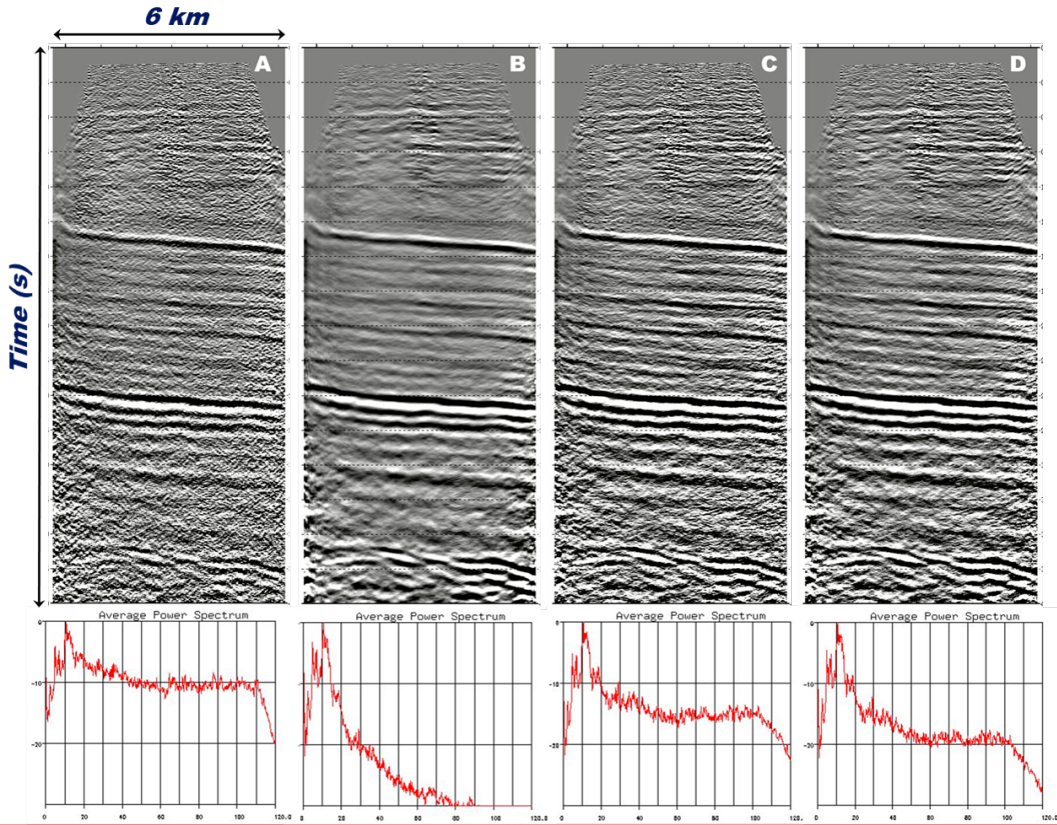

Figure 5: Real data example showing stack sections (bottom)corresponding to the gather presented in Figure 4: (a) Stack obtained with original data; (b) stack obtained with the data after nonlinear beamforming; (c) stack of the data after phase substitution; (d) data after phase correction + IRM. Corresponding averaged amplitude spectra are shown below stacks.

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Permalink: https://doi.org/10.1190/segam2020-3420095.1