Seismic speckle as multiplicative noise explaining land reflections distorted by near-surface scattering

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Summary

Land seismic challenges are usually attributed to superimposed near-surface noise. We suggest that small-scale near-surface scattering distorts the reflections themselves via a mechanism we refer to as "seismic speckle," similar to speckle noise in optics and acoustics. We describe a simple mathematical model of multiplicative seismic noise that captures the main features of such distortions seen on the field data. The first type of multiplicative noise with random phase perturbations explains the severe coherency loss and a substantial amplitude reduction after stacking. Residual statics is another type of multiplicative noise leading to progressive loss of higher frequencies. Both mechanisms combined quantitatively explain amplitude transformation observed while locally stacking field data. We present field observations confirming seismic speckle and also numerically demonstrate how local stacking can recover the accurate phase of the undistorted signal on synthetic data.

Introduction

In the presence of complex near surface, seismic data often exhibit highly obscured and chaotic prestack reflections even after processing. Such behavior severely disrupts processing and impedes single-sensor acquisition (Bakulin et al., 2020a, 2020b). At the same time, data with field receiver arrays appear significantly simpler. Similarly, local stacking in the processing can retrieve robust reflected events. However, after such stacking, the absolute amplitude level experiences a substantial reduction across the entire frequency band, reaching -10-20 dB or more. Also, a significant and escalating loss of higher frequencies is observed. Field observations are blamed on "complex near surface", yet no simple models explain such behavior. This study suggests that the underlying mechanism of "seismic speckle" can quantitatively describe field data distortions. The proposed mathematical model also opens ways to mitigate them in processing.

Field data example from a desert environment

An example of processed CMP gather from a complex 3D land dataset is shown in Figure 1a. The prestack signal is feeble, as there are only hints of underlying reflections observed. Figure 1b shows the same CMP gather after nonlinear beamforming (Bakulin et al., 2020a), which performs local stacking of ~ 200 neighboring traces. Reflections become easily recognizable in the entire offset range. However, the high-frequency content of the signal is suppressed. In addition, enhanced reflections are overly smoothed. Such a behavior is typical for many desert environment datasets. We attempt to answer: 1) why even after hard processing, we do not see clear, coherent reflections in prestack data; 2) why, after local stacking signals become significantly more coherent; 3) how observed distortions transform during stacking.

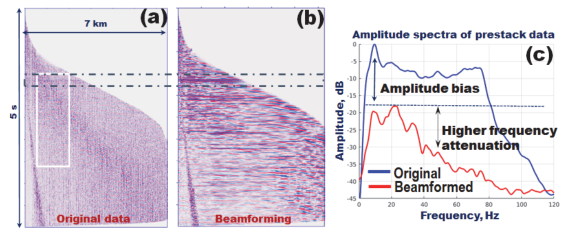

Figure 1. CMP gather after moveout corrections extracted from the land seismic dataset: (a) after standard processing; (b) after local stacking using nonlinear beamforming; (c) comparison of amplitude spectra computed on data from (a) and (b) (calculated inside the white box).

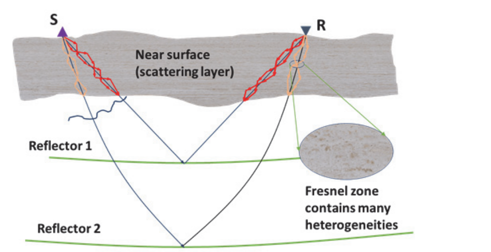

Figure 2. Seismic speckle involves complex interference of forward-scattered arrivals leading to severe signal distortions.

Seismic speckle and multiplicative noise model

Near-surface scattering is usually invoked as a qualitative explanation of described data complexity. However, without identifying a specific mechanism, such an explanation is uncertain and not practically useful. Inspired by studies of optical and ultrasonic speckle noise (Goodman, 2007), we hypothesize that seismic data experiences similar distortions caused by near-ballistic forward scattering of multiple arrivals (Figure 2). Therefore, it could be referred to as "seismic speckle". We emphasize that it is not an interference with near-surface arrivals or diffractions. It is the distortion of the signal itself bouncing on small heterogeneities. The superposition of multiply forward-scattered waves creates a complex interference pattern near ballistic arrival. Such patterns are unique for each wavepath

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and do not conform to surface-consistent assumptions commonly used in time processing. Speckle is typically modeled as multiplicative noise. Let us describe the seismic trace model with a general multiplicative noise. Let the registered signal in *k*-th channel be represented as

$$x_k(t) = r_k(t) * s(t) + n_k(t), \quad (1)$$

where $s(t)$ is the desired signal, $r_k(t)$ is multiplicative noise defined as a linear system described with some random parameters, $n_k(t)$ is additive random noise, "*" means convolution, $k=1,...,K$ (K is a number of the channels). In the Fourier domain (1) is written as:

$$X_k(\omega) = R_k(\omega)S(\omega) + N_k(\omega), \quad (2)$$

where X_k, R_k, S, N_k are Fourier transforms of the corresponding time-domain functions in (1). Additive noise $N_k(\omega)$ is uncorrelated between channels and has zero mean ($E[N_k(\omega)] = 0$); E denotes the math expectation operator. Signal and noise are assumed uncorrelated.

Signal transformation while stacking in the presence of multiplicative noise

Speckle studies suggest that phase fluctuations play an outsize role. Therefore let us further specify a more explicit form of multiplicative noise as a random frequency-dependent phase fluctuations occurring in each channel:

$$R_k(\omega) = e^{i\varphi_k(\omega)}. \quad (3)$$

At a given frequency ω, random variables $\varphi_k(\omega)$ are assumed independent for all channels. The result of local stacking (averaging) of the K traces in the frequency domain is given by

$$\hat{S}(\omega) = \frac{1}{K}\sum_{k=1}^{K}\{S(\omega)e^{i\varphi_k(\omega)} + N_k(\omega)\}. \quad (4)$$

Since the number of traces used in the stacking process is limited, $\hat{S}(\omega)$ would be a random variable for different trace ensembles. Its math expectation is expressed as:

$$E[\hat{S}(\omega)] = S(\omega)\frac{1}{K}\left[\sum_{k=1}^{K} E[e^{i\varphi_k(\omega)}]\right]. \quad (5)$$

Let us denote

$$\Phi_k(\omega) = E[e^{i\varphi_k(\omega)}]. \quad (6)$$

Using the notation $x = \varphi_k(\omega)$:

$$\Phi_k(\omega) = \int_{-\infty}^{\infty} P_k(x)e^{ix}\,dx, \quad (7)$$

where P_k is a probability density function of a random variable φ_k at a given frequency ω in a k-channel. From eq. (7) one can deduce that if the probability density function of the phase fluctuations of the multiplicative noise is even, i.e., $P(x) = P(-x)$ (i.e. expected value is zero), then $\Phi_k(\omega)$ would be real-valued. Using notation (6), we may rewrite (5) as

$$E[\hat{S}(\omega)] = |S(\omega)|e^{i\varphi_s(\omega)}\frac{1}{K}\left[\sum_{k=1}^{K}\Phi_k(\omega)\right], \quad (8)$$

where $|S(\omega)|$, φ_S are amplitude and phase spectra of the clean signal. If random variables $\varphi_k(\omega)$ describing phase perturbations have the same distributions in each channel, $\Phi(\omega)$ then:

$$E[\hat{S}(\omega)] = |S(\omega)|e^{i\varphi_s(\omega)}\Phi(\omega), \quad (9)$$

where $|S(\omega)|$, φ_S are amplitude and phase spectra of the clean signal. Without specifying any further details of the near surface, we can draw important conclusions. First, stacking performs phase "cleanup" or averaging and leads either to a signal phase (if $\Phi(\omega) > 0$), or flipped signal phase rotated by π (if $\Phi(\omega) < 0$). Second, real-valued $\Phi(\omega)$ denotes filtering coefficient for the signal amplitude spectra during stacking. To obtain quantitative results, let us derive a specific form of $\Phi(\omega)$ for two practically significant types of noise: (1) random phase perturbations and (2) random time-shifts (residual statics).

Type 1 multiplicative noise – Phase perturbation with normal distribution. If phase perturbations $\varphi_k(\omega)$ have the same normal (Gaussian) distribution with zero mean and standard deviation $\sigma(\omega)$, then mathematical expectation can be expressed as

$$E[\hat{S}(\omega)] = |S(\omega)|e^{i\varphi_S(\omega)}e^{-\frac{\sigma^2(\omega)}{2}}. \quad (10)$$

The resulting phase spectrum after stacking in expression (10) is the same as the phase of the clean signal, whereas a real-valued factor reduces amplitude compared to a clean signal. Furthermore, amplitude reduction is the same across the entire band if standard deviations remain independent on frequency. In contrast, the loss of signal amplitude after stacking would progressively increase with frequency if we assume that standard deviation increases with frequency.

Type 2 multiplicative noise – Residual statics with normal distribution. Let the multiplicative noise be caused by random time shifts τ_k between channels (residual static). In this case, multiplicative noise has a form:

$$R_k(\omega) = e^{-i\omega\tau_k}. \quad (12)$$

If statics is normally distributed with zero mean and standard deviation σ_T, then

$$E[\hat{S}(\omega)] = |S(\omega)|e^{i\varphi_s(\omega)}e^{-\frac{\omega^2\sigma_T^2}{2}}. \quad (13)$$

Again, the phase spectrum of the stack (13) is the same as that of the clean signal, whereas amplitude experiences exponential loss with frequency. Berni and Roever (1989) derived exponential amplitude loss analyzing intra-array residual statics without employing a multiplicative model.

Combination of Type 1 and Type 2: Let us consider a combination of both types of multiplicative noise (3) and (12) acting together. Assume that τ_k and $\varphi_k(\omega)$ are independent of each other and both random normally distributed with standard deviations σ_φ and σ_τ, then the mathematical expectation is given by:

$$E[\hat{S}(\omega)] = |S(\omega)|e^{i\varphi_s(\omega)}e^{-\frac{\omega^2\sigma_\tau^2}{2}}e^{-\frac{\sigma_\varphi^2}{2}}. \quad (14)$$

The phase of mathematical expectation is equal to the clean signal phase. In contrast, the amplitude loss factor is a product of two terms – one caused by phase perturbations and another by residual statics.

Figure 3 visualizes amplitude loss in dB induced by both types of multiplicative noise during local stacking. Residual

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statics with a standard deviation σ_τ creates amplitude loss escalating as a square of frequency f

$$A_\tau = -171.45 \cdot (f\sigma_\tau)^2\ dB. \qquad (15)$$

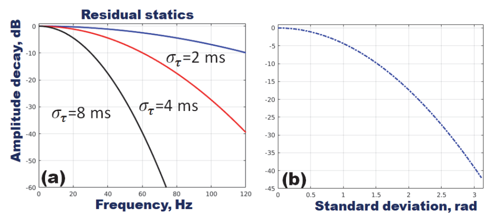

Figure 3. (a) Frequency-dependent amplitude attenuation during stacking caused by time delays with normal distribution possessing different standard deviations ($\boldsymbol{\sigma_\tau}$ =2,4,8); (b) Frequency-independent amplitude attenuation during stacking caused by phase perturbations with normal distribution. Amplitude decay in dB vs. standard deviation $\boldsymbol{\sigma_\varphi}$ (in radians) is shown.

This relationship is consistent with the one presented by Baeten and van der Heijden (2008). Amplitude reduction is proportional to a square of standard deviation (Figure 3a). On the other hand, phase perturbations with normal distribution lead to a constant amplitude loss

$$\mathbf{A}_{\boldsymbol{\varphi}} = -\mathbf{4.343} \cdot (\boldsymbol{\sigma}_{\boldsymbol{\varphi}}^{\mathbf{2}}), \qquad (16)$$

provided that $\boldsymbol{\sigma_\varphi}$ is independent of frequency.

Residual phase distribution in real data

Let us now evaluate whether the proposed model assumptions reflect the behavior of phase of real data. Figure 4a shows a selected time window taken from gather in Figure 1a. An obscured reflector is recognizable in Figure 4a, whereas beamforming (Figure 4b) makes it coherent albeit lower frequency. Original data reveals chaotic phase angles oscillating in the interval $[-\pi, \pi]$ as shown in Figure 4c. In contrast, beamformed data has smooth phase variation (Figure 4d). As demonstrated above, local stacking leads to an unbiased estimation of the true phase. Let us denote $\varphi_{orig}(\omega)$ and $\varphi_s(\omega)$ to be a phase of original and beamformed data. Their difference $\varphi_k(\omega) = \varphi_{orig}(\omega) - \varphi_s(\omega)$ can be construed as a residual phase describing the original random phase perturbation observed on each channel. Figure 5 shows resulting histograms of residual phase distributions computed using an ensemble of 500 traces. First, phase perturbations appear symmetric with expected values close to zero. Second, estimated standard deviations are significant (~50-112 deg). Finally, we observe dependence on the frequency with the smallest deviation at mid frequencies characterized by the highest signal-to-noise ratio. We conclude that field data phase distribution suggests it can be well approximated as multiplicative noise described by random phase perturbations with normal distribution.

Numerical example

Let us now validate the accuracy and usefulness of presented equations for math expectation of phase and amplitude for

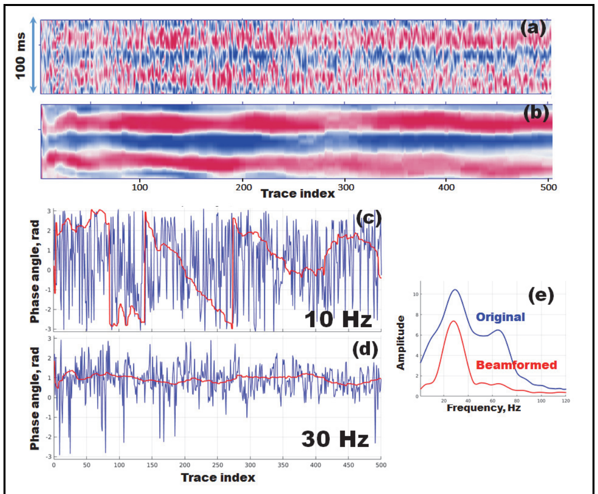

Figure 4: Time-windowed data around the target reflector (100 ms) along with phase and amplitude spectra: (a) original data; (b) data after beamforming; (c) phase angles (in radian) at 10 Hz as a function of trace index; (d) phase angles at 30 Hz as a function of trace index; (e) averaged amplitude spectra of time windowed data shown in (a) and (b).

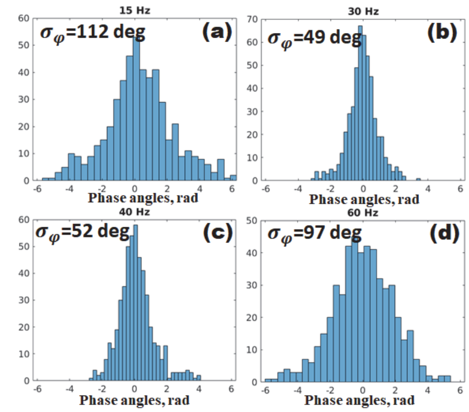

Figure 5: Histograms of residual phase (random phase perturbations) estimated on real data from Figure 4a for different frequencies: (a) 15 Hz, (b) 30Hz; (cd) 40 Hz, (d) 60 Hz. Estimated standard deviation is posted assuming normal distribution.

realistically limited ensembles of data from local stacking. Right away, we consider the joint effect of random time delays and frequency-dependent phase variations. A single trace from a processed CMP gather (Figure 1a) is shown in Figure 6, along with its amplitude spectrum. "Clean" gather is obtained by simply replicating this trace 200 times (Figure 7a). To simulate realistic non-surface consistent seismic speckle noise, each 100-ms window of each channel was subject to a combination of multiplicative noises of Type 1 and 2 (Figure 7b). We stress that adjacent channels experience different noises. Likewise, different time windows of the same channel also experience various realizations of multiplicative noise. Only statistical parameters, e.g., standard deviations $\sigma_{Ph} = \boldsymbol{\pi}/2$ and $\sigma_T = 4\ ms$, remain constant.

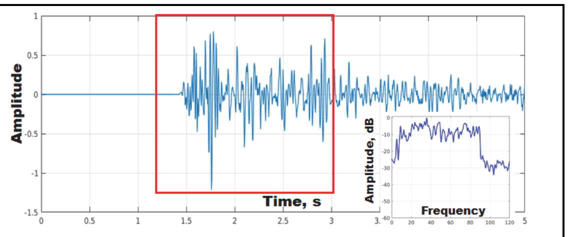

Figure 6. Real trace taken from processed real CMP gather in Figure 1a. The amplitude spectrum is shown as an insert.

The theoretical prediction is computed using equation (14) for math expectation. The synthetic numerical result is calculated by stacking 200 noisy traces. Figure 7c compares theoretical and numerical results. While spectra of "clean" (blue) and perturbed (green) data are similar, stacked amplitude (red) is severely curtailed, exposing the joint effect of two types of multiplicative noise. Stacked amplitude experiences a drop in overall level caused by phase perturbations and progressive attenuation of higher frequencies induced by residual statics. We observe good agreement between numerical results and the theory ("red" and "black" lines), suggesting the usefulness of derived equations for limited ensembles. Figure 7d shows a normalized plot where each spectrum is normalized by its maximum. After normalization stacked (red) spectrum tracks the "clean" (blue) spectrum in low and mid-frequency intervals, whereas two curves diverge at higher frequencies as expected (effect of time delays). Figure 7e validates that stacking performs phase "cleanup" with the stacked phase approaching the true signal phase (without multiplicative distortions) as predicted by theory. Finally, Figure 7f presents a time-domain verification that the stacking process reconstructs the accurate phase in the presence of multiplicative noise.

Conclusions

We describe a new type of multiplicative seismic noise called "seismic speckle." In contrast to other kinds of noise, multiplicative noise is a signal distortion caused by the scattering of ballistic arrivals on small-scale near-surface heterogeneities. We propose a simple mathematical model describing seismic speckle as random phase perturbations. We also show that residual statics can be recast as another type of multiplicative noise. We demonstrate that the combined action of phase perturbations and residual statics can replicate complex signal distortions observed in land seismic data that severely reduce the coherency of specular reflections. While extremely damaging, seismic speckle has remarkable properties that may help address it using multi-channel processing. Specifically, we demonstrate that local stacking leads to an estimate of a clean signal phase free from harmful effects of scattering. Such unbiased phase estimation is a key towards unraveling the damaging effects of scattering from prestack data using phase substitution, seismic time-frequency masking, and other methods.

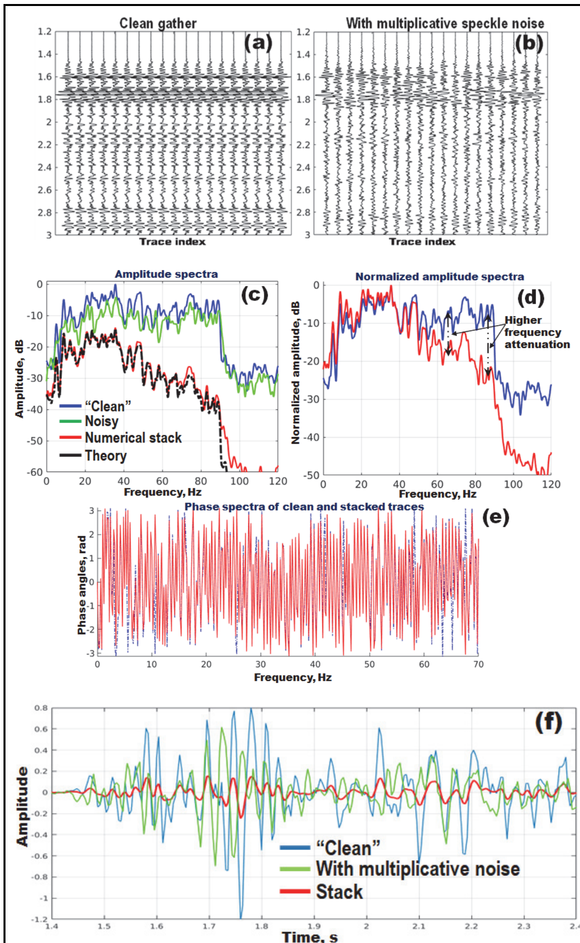

Figure 7: Numerical validation of equations describing stacked amplitude and phase: (a) "Signal-only" gather obtained by repeating real data trace from the red box of Figure 6; (b) Perturbed gather after introducing spatially changing and time-variant multiplicative noises with fixed statistical distributions ($\boldsymbol{\sigma_\tau} = 4$ ms, $\boldsymbol{\sigma_\varphi = \pi/2}$); (c) non-normalized amplitude spectra showing amplitude bias and progressive attenuation of higher frequencies after stacking similar to real data from Figure 1c; observe good match between numerical red curve and predicted curve in black from equation (14); (d) normalized amplitude spectra showing progressive loss of higher frequencies after stacking; (e) phase spectra of the stacked trace (red) closely tracks "clean" phase (blue) validating unbiased estimation of undistorted signal phase by stacking; (f) stacked trace (red) with accurate phase accurately tracks arrival times of the "clean" signal (blue) but also exhibit pronounced broadening of the waveforms due to combined actions of residual statics and phase perturbations.

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