ROBUST POST-STACK AND PRESTACK SIGNAL-TO-NOISE RATIO ESTIMATION ON LAND SEISMIC DATA

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Summary

This study applies a stacking-based data-driven signal-to-noise ratio (SNR) estimation approach to 3D synthetic and field data from the desert environment. This method delivers a volume of absolute SNR estimates, with each estimate requiring a local 3D window. Analysis of SNR volumes and slices provides valuable insight into acquisition geometries and processing steps. We suggest simple SNR bounds for reliable event tracking and amplitude interpretation on migrated volumes. We discover extremely low SNR in prestack field data down to -40 dB, significantly complicating processing effort. While acquisition density can significantly raise SNR of imaged post-stack data, it remains to be seen if time processing can robustly handle such a low SNR and lead to reliable prestack migrated data suitable for acoustic impedance inversion. We advocate the use of SNR volumes for quantitative assessment of prestack and post-stack data from in-field QC to processing. The stacking-based method is entirely data-driven and only requires approximate NMO velocities to generate SNR volumes. Avoiding human bias typical during qualitative data assessment by various experts and establishing data-driven metrics can be helpful for industry decisions and automatic evaluations.

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Introduction

The signal-to-noise ratio (SNR) is an essential metric for seismic acquisition and processing. While SNR is easily computed in theory as the ratio of signal power to the noise power, its estimation in practice remains extremely difficult. Several data-driven methods exist to estimate SNR using an ensemble of traces with a flat signal. Most popular ones are stacking-based method, SVD-based approach, and correlation-based method. Bakulin et al. (2021) analyzed and contrasted these three algorithms for realistic low SNR typical for desert environments (-10 to -60 dB). They have revealed important limits of each approach and suggested that the stacking-based method is the most robust provided an appropriate number of traces is used in the ensemble. This study applies the stacking-based method to compute SNR on post-stack complex synthetic data and challenging field data both from the desert environment.

Method

Suppose that seismic data is the superposition of signal and noise:

$$d_{ij} = s_{ij} + n_{ij}, \quad i = 1, \dots, N, \quad j = 1, \dots, M, \tag{1}$$

where $d_{ij} = d(t_i, x_j)$ is seismic recordings, $s_{ij} = s(t_i, x_j)$ is signal, and $n_{ij} = n(t_i, x_j)$ is noise. By definition of SNR is the ratio of signal power to noise power. SNR can be formulated in the decibel scale as follows:

$$SNR = 10\, log_{10}\, (\sum_{i=1}^{N} \sum_{j=1}^{M} s_{ij}^2 / \sum_{i=1}^{N} \sum_{j=1}^{M} n_{ij}^2). \tag{2}$$

The formula for SNR computation based on signal estimate via stacking coherent events also assumes that the windowed seismic records' signals are linearly correlated. Therefore, it can be represented as follows (Liu and Li, 1997):

$$SNR_{stack} = 10\, log_{10}\, (\frac{1}{M} \sum_{i=1}^{N} (\sum_{j=1}^{M} d_{ij})^2 / (\sum_{i=1}^{N} \sum_{j=1}^{M} d_{ij}^2 - \frac{1}{M} \sum_{i=1}^{N} (\sum_{j=1}^{M} d_{ij})^2). \tag{3}$$

Taking into account the definition of the semblance (Neidell and Taner, 1971), we arrive at SNR representation via semblance:

$$SNR_{stack} = 10\, log_{10}\, (Semblance/(1 - Semblance)). \tag{4}$$

Post-stack SNR estimates on 3D synthetic SEAM Arid data

We simulated a synthetic 3D land survey with typical orthogonal geometry using the SEAM Arid model (Oristaglio, 2012) with sources 50x100m, receivers 25x150m, and 9-geophone receiver arrays. Two versions of the data are of interest: raw and processed data subject to the typical time processing sequence. Both versions were depth migrated with the PSPI algorithm. In addition, true bandpassed reflectivity volume was generated as an ideal reference. SNR was computed on all three volumes using the stacking-based method. Single estimate of SNR results from a 3D window x-y-z and assigned to the window center of gravity. Then the window is run along the entire 3D volume to deliver a 3D SNR volume of the same size as the data volume. The local window 400x400x20 m in x,y, and z consists of 561 traces. Theoretically, this allows reliable SNR estimation down to -25 dB. Figure 1 shows vertical sections of the SNR volume for the three scenarios at hand. One can observe that typical SNR values for images of raw data are between -20 dB to 20 dB. Images from processed data have better SNR, especially in a middle depth part of the model. SNR values for true reflectivity vary within a range of 10 dB to 20 dB except when we hit faults and karsted zones where coherency measures drop. Visual inspection of the sections suggests that negative SNR outlines areas where reflected events are not trackable by eye (Figure 1a above 2km or Figure 1b above 1 km). In contrast, some visible reflectors may become observable for SNR> 0 (Figure 2b, between 1 and 2 km). Areas with SNR > 10 dB correspond to strong and conitinous reflectors (all images below 2.2 km). The same conclusions are reached when analyzing horizon slices at a shallow depth around 1.1 km (Figure 2). True model contains meandering channels well observed in depth slice through a reflectivity volume (Figure 2c). However, channels are not seen on slices from migrated raw and processed data (Figures 2a,b). Inspecting corresponding SNR slices, we conclude that mean values of -3.3 dB or 1.4 dB do not appear sufficient to convey amplitude information reliably to the interpreter. Slice from reflectivity volume with SNR=11.7dB has no problem delineating both the channels and faults, suggesting that an SNR level of around 10 dB represents a desired level for amplitude map interpretation.

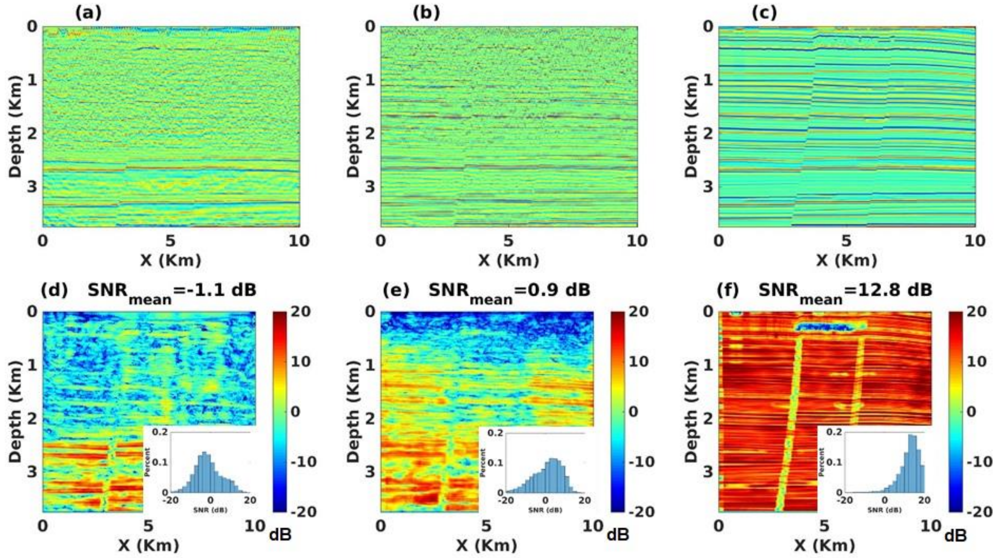

Figure 1 *Depth-migrated images and corresponding SNR attributes computed using raw data (a,d), pre-processed data (b,e), and bandpassed reflectivity volume used as an ideal reference (c,f). Images were extracted from 3D depth-migrated volumes at y=5 km. Synthetic data from the SEAM Arid model with orthogonal geometry (S50x100 m, R25x150m, 9-geophone array) is used.*

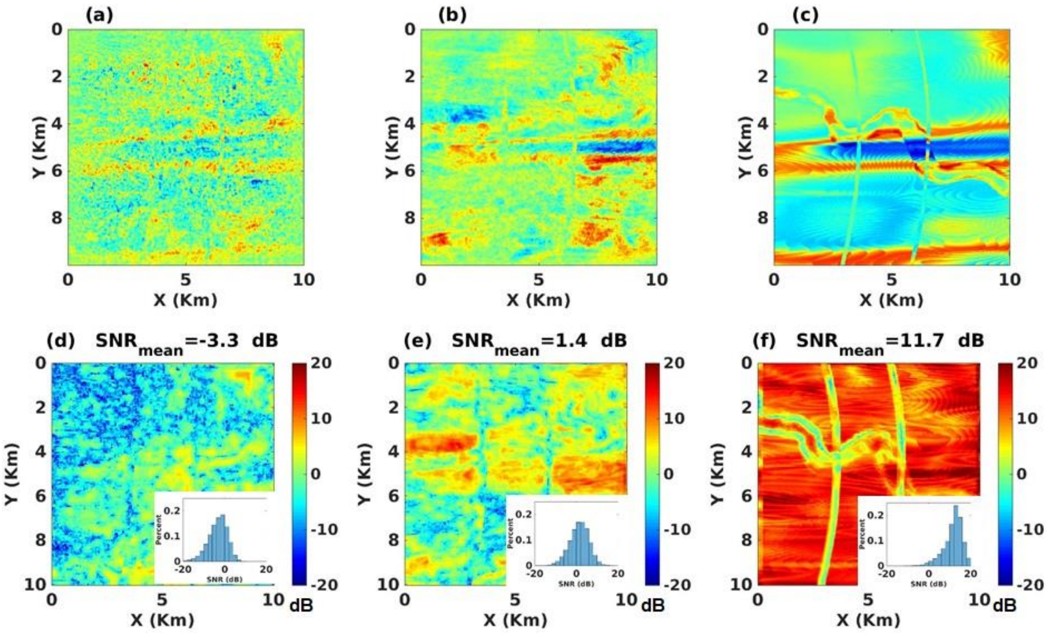

Figure 2 *Horizon slices at the shallow horizon (~ 1.1 km) and corresponding SNR attributes computed using raw data (a,d), pre-processed data (b,e), and bandpassed reflectivity volume used as an ideal reference (c,f). Horizon slices are extracted from 3D depth-migrated volumes. Synthetic data from the SEAM Arid model with orthogonal geometry (S50x150 m, R25x100m, 9-geophone array) is used.*

Now let us examine the deeper horizon at ~ 3 km that contains geobodies (Figure 3). SNR level is higher mainly because this is a stronger reflector (similar noise but stronger signal). Even without any processing, slice through the migrated volume of raw data reveals around 60% of the geobodies (compare Figures 3a and 3b). Therefore, SNR slices suggest a mean value of ~ 5 dB could become sufficient to start identifying geobodies with variable reflectivity. Furthermore, of course, SNR of the reflectivity volume of around 12 dB allows perfect identification of all geobodies. Why may such conclusions be of practical relevance? It is hard to judge whether what we see in seismic data reflects subsurface geology in real life. If the slice or image is geologically implausible, it can be dismissed as “too noisy”. Armed with the SNR metric and volumes, we may have a more quantitative assessment telling us if an obtained image or slice could be deemed reliable.

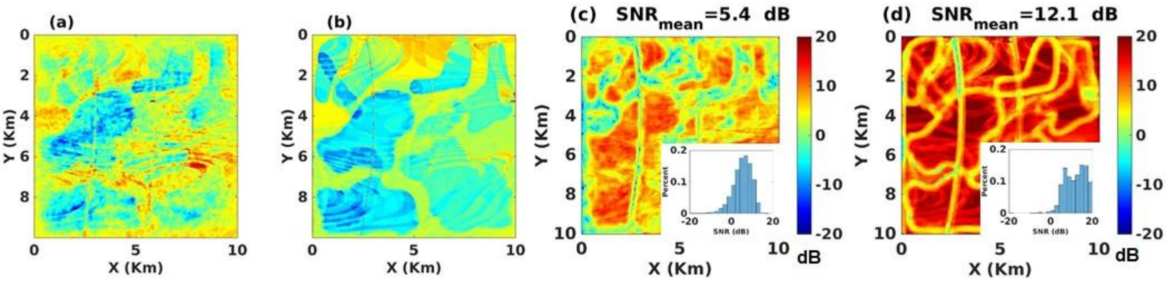

Figure 3 *Horizon slices at the deep horizon (~3 km) and corresponding SNR attributes computed using raw data (a,c), and bandpassed reflectivity volume used as an ideal reference (b,d). Horizon slices are extracted from 3D depth-migrated volumes. Synthetic data from the SEAM Arid model with orthogonal geometry (S50x100 m, R25x150m, 9-geophone array) is used.*

Prestack SNR of real single-sensor land data

The same SNR estimation technique can be applied to 3D prestack gathers instead of post-stack cubes. Let us analyze SNR of field single-sensor data from a challenging desert environment. Figure 4a shows a 2D slice through a 3D cross-spread gather formed by fixing one receiver line and one source line orthogonal to each other. With a maximum inline offset of 6,250 m, a cross-line offset of 4,200 m, and a sampling of 12.5 m in both directions, the total number of traces in this 3D gather is 672,000. A conventional global moveout correction is applied to the data to make the reflection events flat, as required by equation (1) for SNR estimation. SNR computed from a single ensemble is output to the geometric center of the ensemble. Figures 4 and 5 show the SNR estimates of raw field gathers and gathers after typical preprocessing. For the acquisition geometry at hand and selected cross-spread domain, the estimation ensemble of 10,000 traces translates into a local window of 1,200 m by 1,200 m, formed by 97 adjacent sources and 97 receivers in lateral directions and 0.1 s in the time direction. Such large ensembles are required to estimate reliable absolute SNR down to -40 dB (Bakulin et al., 2022). One can observe that typical SNR values for raw data are between -40 dB to -20 dB. The ground-roll noise cone at near offsets (Figure 4a) is robustly identified as a triangle with the lowest SNR. Indeed, visual inspection suggests higher energy of the groundroll (noise) and, therefore, lower values of SNR are seen. Reflections are less overwhelmed outside the noise cone, and SNR values are higher. After a typical data processing, the SNR consistently increases across the gathers, falling into a range of -20 dB to -5 dB. We note that according to the theoretical curve from the controlled experiment (Bakulin et al., 2021), all these absolute SNR values can be trusted and used to assess data quality during acquisition and processing. Identifying absolute SNR for prestack land data is important for field QC and better understanding prospects of the professing. We feel it is important to start evaluating the performance of various processing solutions in terms of SNR. Currently, in the industry, there is no good understanding of what are the SNR limits for conventional time processing steps (statics, surface-consistent scaling and decon etc) to perform robustly. Some may fail at -10dB, some at -30 dB. Considering single-sensor can be in the range of -30 dB or less, this is not a well-explored territory by anyone. Every method would likely fail at certain SNR, and a more systematic study of algorithms dependence on SNR is required.

Conclusions

We apply stacking-based SNR estimation to challenging seismic data from the synthetic SEAM Arid model and field data from the desert environment. The method allows robust estimation of absolute signal-to-noise ratio for extremely challenging land seismic data down to -40 dB and lower. On imaged data synthetic data, we gained valuable insights into what values of SNR may be required to interpret kinematic events (SNR> 0 dB) and what values are needed for reliable interpretation of amplitude maps (SNR>5-10 dB). On real prestack data from the desert environment, we observed low SNR from -40 to -20 dB. While SNR is greatly improved after typical time processing, it remains below 0 dB suggesting that such data may either not be suitable for prestack amplitude inversion or require more advanced processing. Such low signal levels are not unusual for single-sensor data from a desert environment. Although better SNR can be achieved on imaged data through denser acquisition geometries, we must find more robust approaches to evaluate statics, velocities, amplitude scalars, and decon operators from data with intrinsically low SNR during time processing. Therefore, revisiting the performance of various algorithms from deblending to statics estimation to surface-consistent processing at low SNR requires more effort in order to succeed with “dense” and “light” blended acquisition with small arrays or single sensors.

References

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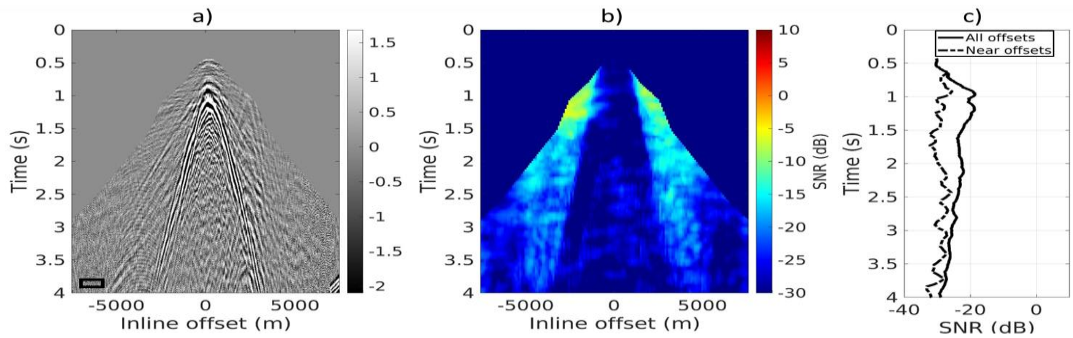

Figure 4 *An example of SNR computation using the stacking-based method on a 3D cross-spread gather extracted from raw field single-sensor land dataset: (a) 2D slice (corresponding to a fixed source) from a 3D cross-spread gather after normal moveout corrections; (b) corresponding 2D slice of prestack SNR calculated with equation (7); (c) vertical profiles of an average SNR computed for the whole offset range as well as near offsets only (0 to 1 km). The black rectangle shows the 2D cross-section of the time-space window (1250 m x 1250 m x 0.1 s) used in SNR computation.*

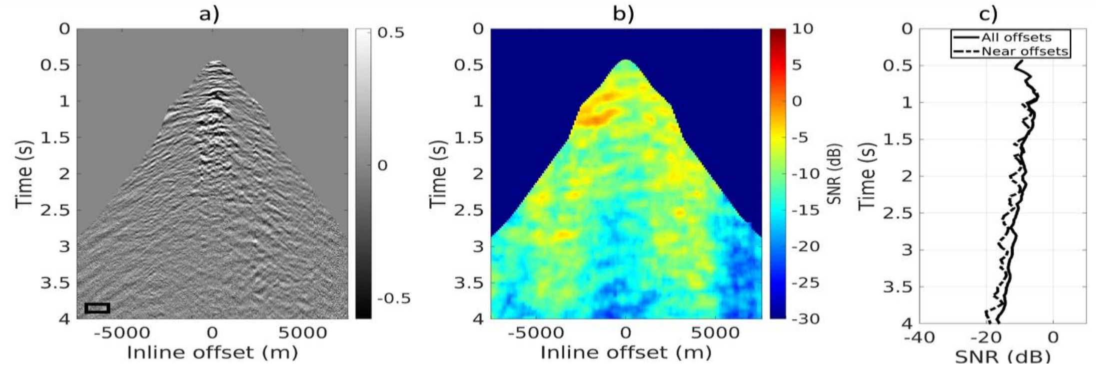

Figure 5 *Same as Figure 4 but for a gather after typical pre-processing. Compared to Figure 4, observe consistently higher SNR values with the average uplift of ~15 dB.*