Quantitative assessment tools for objective-based optimization of seismic acquisition geometry selection

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SUMMARY

Through our research, we help optimize seismic survey design selection by developing quantitative tools to evaluate seismic amplitude fidelity and establish signal-to-noise ratio (SNR) thresholds for robust quantitative analysis in complex near-surface environments. Utilizing the SEAM Arid model to simulate desert near-surface features, we develop various tools, including amplitude standard deviation and quality factor metrics, to aid in the optimal selection from six acquisition geometries. We correlate these metrics with stack-based SNR volumes from Bakulin et al. (2022a) to assess seismic data suitability for certain quantitative interpretation objectives. Finally, we successfully apply these tools to Non-Uniform Optimal Sampling (NUOS) field data from the Powder River Basin, investigating compressive sensing seismic amplitude fidelity.

INTRODUCTION

One way to assure the suitability of seismic data for quantitative analysis is to optimize the acquisition survey design to ensure the resulting data has a sufficient signal-to-noise ratio (SNR) for its interpretation objective. Land seismic data acquisition comes with numerous challenges, but perhaps the greatest of all is near surface complexity that in many cases causes significant seismic amplitude information loss due to its effect on seismic wave propagation. The small- to large-scale heterogeneities in complex near-surface environments cause significant scattering of the seismic wavefields (Sato et al., 2012; Xie et al., 2020). In such situations, all aspects of seismic analysis are affected, from acquisition, to processing, to data interpretation, and a good measure of the seismic data quality is its SNR.

Acquisition geophysicists have an established way of estimating SNR during the design of seismic acquisition surveys using the Signal-Strength Estimate (SSE) as a function of frequency (f) from Meunier and Gillot (2000), and Meunier (2011),

$$SSE(f) = SS(f) \cdot \sqrt{SD \cdot NR \cdot RA}, \qquad (1)$$

where SS is the source strength, SD is the source density, i.e., the number of shot points per surface unit, NR is the number of receivers per shot point, and RA is the number of receivers per shot point. SSE is then converted to theoretical signal-to-noise ratio, $\mathrm{SNR}^{\mathrm{t}}$, in decibels using,

$$SNR^t_{dB} = 20\log_{10}(SSE). \qquad (2)$$

But for long, acquisition relied heavily on this theoretical SSE estimation without a quantitative validation of its accuracy from the processing side.

To close this loop between acquisition and processing, and to provide a quantitative validation to the SSE equation, Bakulin et al. (2022a) proposed a data-driven experimental SNR estimation method ($\mathrm{SNR}^{\mathrm{e}}$), which computes stack-based SNR using semblance (S). The formula for $\mathrm{SNR}^{\mathrm{e}}$ estimation is,

$$SNR^e = \frac{S}{1-S}, \qquad (3)$$

$$S = \frac{\sum_{i=1}^{N}\left(\sum_{j=1}^{M} d_{ij}\right)^2}{M\left(\sum_{i=1}^{N}\sum_{j=1}^{M} d_{ij}^2\right)}, d_{ij} = s_i + n_{ij}, \qquad (4)$$

where, $s_i = s(t_i)$ is signal, $n_{ij} = n(t_i, x_j)$ is noise, i is time sample index, N is the total number of time samples, j is trace index, and M is the total number of traces.

This experimental $\mathrm{SNR}^{\mathrm{e}}$ estimation has successfully validated the theoretical $\mathrm{SNR}^{\mathrm{t}}$ from the SSE equation (Bakulin et al., 2022b), and provided a quantitative and objective feedback from processing that addresses whether the acquisition design achieved its SNR objectives.

However, the feedback loop can be fully closed when interpretation geophysicists provide specific quantitative seismic data requirements that suits their objectives. Therefore, the objective of this study is to investigate different acquisition geometries for their ability to preserve the amplitude information needed for robust quantitative interpretation, and correlate our findings to the stack-based SNR estimations. As a result, designing optimal acquisition surveys can be tailored to the interpreters' goals by setting a target SNR value that is sufficient for interpretation, and an acquisition geometry that is suitable for complex near-surface environments, leading to a more streamlined process between acquisition, processing, and interpretation.

METHODOLOGY

For the first part of the study, we were provided with six seismic stacks of the SEAM Arid model simulating six different acquisition geometries. We first examined equalizing the amplitude ranges of the different seismic volumes to facilitate a one-to-one comparison. We then performed conventional seismic interpretation and attribute analysis to identify and map the structural and amplitude-dependent features, mainly targeting two shallow channel systems and two deep shale geobody accumulations. Subsequent qualitative and quantitative analyses were performed to assess amplitude information preservation and identify potential signal compromise areas.

Amplitude Standard Deviation

As part of our quantitative analysis of the data, we used the seismic interpretation and attribute analysis to develop the first

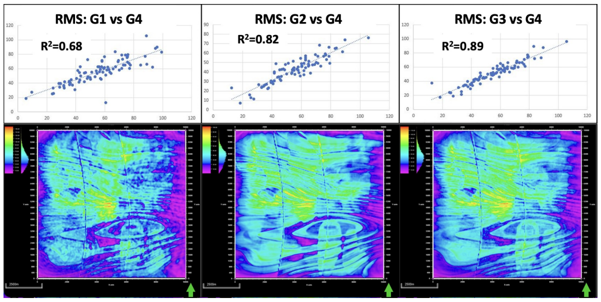

Figure 1: Extracted values of RMS attributes at 2700m deep geobodies level in geometries G1 to G3, cross plotted against the reference. The R^2 values correlate well with how successful the attribute mapped the geobodies.

quantitative assessment tool by calculating the standard deviation of the amplitudes relative to the reference seismic volume with the best overall SNR. The standard deviation measures the dispersion of amplitudes for each seismic stack in relation to the reference, and, thus, the higher the standard deviation, the lower the amplitude information preservation of the data. However, the significance of the standard deviation is not its value, but its fraction of the mean. For example, a standard deviation of 5 when the mean is 10 is much more significant than a standard deviation of 5 when the mean is 50. Therefore, in our analysis we divide the standard deviation by the mean, giving us the percentage of standard deviation in relation to the reference, which is also known as the Coefficient of Variation (CV).

Quality Factor Metric

The quality factor metric provides an objective measure of success of each seismic stack in mapping the subsurface features using seismic attributes. This metric is inspired by Ourabah et al. (2015), who similarly compared prestack seismic attributes of different acquisition geometries to a reference volume with the highest acquisition density. In our case, we used the seismic stack with the highest SNR as the reference, and compared its attributes for each of the subsurface features with the attributes of the other seismic stacks. The comparison is done by cross plotting the extracted values from the seismic attribute surfaces, and the quality factor would be the R^2 value from the cross plots, ranging between 0 and 1, where 1 is the highest correlation factor and 0 is the lowest. The example in figure 1 shows cross plots of extracted values of RMS attributes at the geobodies level (@ 2700m depth) in all seismic stacks against the reference stack. The R^2 values correlate well with how successful the attribute mapped the geobodies.

RESULTS

Throughout the study, we correlate SNR values with seismic analyses across structural interpretation, amplitude dependent features identification, and amplitude fidelity assessments. This correlation across various steps addresses a central question in our study: Can stack-based SNR estimations indicate the seismic volume's suitability for robust quantitative interpretation?

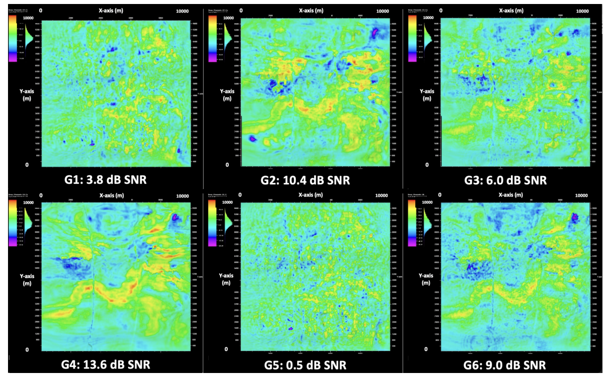

Figure 2: Detection of a channel at 1700m depth using a sum of amplitudes attribute over the six tested geometries. The channel was successfully detected only in G2, G3, G4, and G6, where they all have SNR values higher than 6 dB.

One example is correlating SNR with the channel detection attributes across the six geometries in figure 2. The figure shows a direct correlation between high SNRs of around 6 dB or more with successful detection of the channel. Another example is from the results of the standard deviation calculations in figure 3A, which demonstrate the trend of the standard deviations from the shallowest horizon (Horizon 1) to the deepest horizon (Horizon 6) for all seismic stacks. The trend is the same for all seismic stacks as they start with high standard deviations in the shallow section and drop to low standard deviations in the deep section. Figure 3B shows how SNR has an opposite trend to standard deviation, where high SNR correspond to low standard deviations, and vice versa. Generally, figure 3 shows that with low standard deviations we tend to have high SNR values, suggesting a correlation between the two metrics, and, thus, a correlation between SNR and amplitude information preservation. We tested this observation in figure 4, by taking the average standard deviations per horizon per volume and plotting them against the corresponding SNR values. The figure illustrates a clear correlation between standard deviations and SNR, with an R^2 correlation of 0.89.

For the second quantitative assessment, the results from one of the quality factor metric generation is seen in figure 5, which shows quality factor values for each attribute mapping the deep channels at 1700m depth in the different geometries. Using the results in the figure, we can objectively measure how well each attribute mapped the desired feature. For example, we observe that G6 and G2 have the highest quality factors for their attribute mapping with varying degrees of success, while G3 has a relatively high quality factor in two attributes only. The quality factor can also help analyze the performance of certain attributes in mapping features, and the risk of any drilling decision made based on these attributes. We've generated similar plots for each subsurface target and correlated the results with the SNR values along the target level and found a high direct correlation between the quality factor metric and SNR.

We implemented these metrics on field data from the Powder River Basin, where we estimated a cross-correlation-based

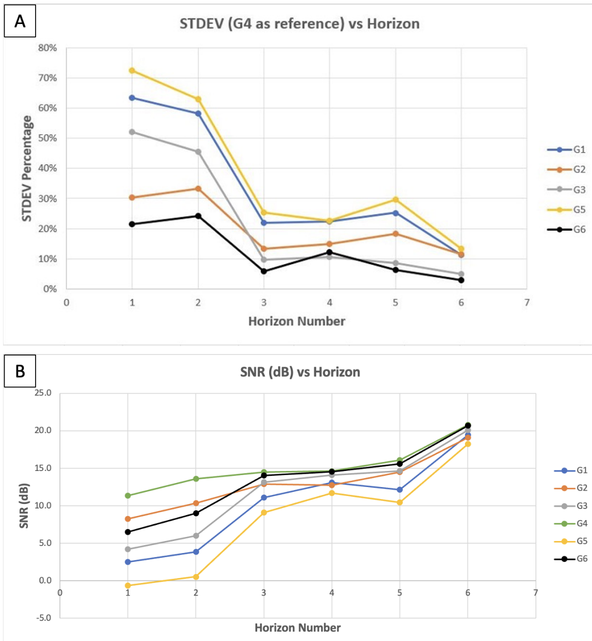

Figure 3: (A) The trend of the standard deviations from the shallowest horizon (Horizon 1) to the deepest horizon (Horizon 6) for all seismic stacks. (B) The trend of SNR from the shallowest horizon to the deepest horizon for all seismic stacks. SNR values are high where standard deviations are low, and vice versa.

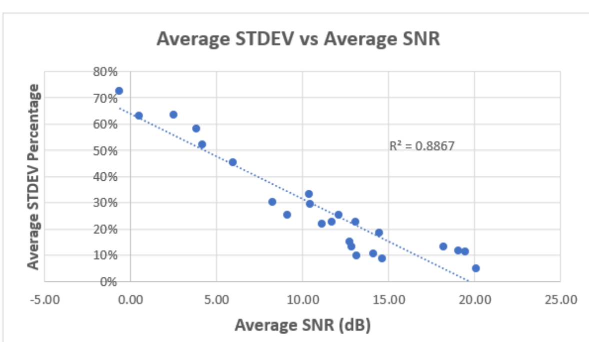

Figure 4: Cross plot of average standard deviations against average SNR for each horizon in each seismic stack, showing a good R^2 correlation of 0.89. This suggests a correlation between SNR and amplitude information preservation does exist.

SNR to mimic the stack-based SNR we had in the SEAM Arid study. The results from the SNR estimations show higher SNR in the west compared to the east of the survey, which also corresponded to better acoustic impedance inversion results in the west compared to the east. As for the calculation of standard deviation, we correlated the dispersion of the seismic trace amplitudes at the well locations in relation to the reference, which in this case is the synthetic seismogram. As a result, we found that the high SNR wells had the lowest standard deviations with an average of 34%, while the low SNR wells had high standard deviations of around 80%. We see similar trends between the standard deviation and SNR values in field data compared to the trends from the SEAM Arid model shown in figure 3, which boosts our confidence in those SNR estimations being good indicators to amplitude information preservation.

CONCLUSIONS

The implications of our findings are significant for determining the optimal survey designs for quantitative seismic analysis in complex near-surface environments. Our study confirms the value of data-driven volumetric estimations of SNR in predicting the suitability of a seismic survey for robust seismic interpretation. This could facilitate more automated feasibility studies of different acquisition geometries, leading to a more streamlined collaboration between acquisition, processing, and interpretation. We provided quantitative metrics for optimizing seismic survey designs tailored to interpreter goals by setting a target SNR value that is sufficient for interpretation, and an acquisition geometry that is suitable for complex near-surface environments. As can be seen in figure 6, we determined that effective mapping of structural and amplitude-dependent features requires a minimum SNR of 6 dB, as SNR values below this threshold tend to obscure amplitude information. We also found that areas with low standard deviation of amplitudes relative to the reference volume are associated with successful mapping of subsurface features and high SNR values. we also observed that the quality factor metric suggests the significance of dense acquisition designs for accurate mapping of amplitude-dependent features in shallow targets, whereas all tested acquisition geometries were proficient in mapping deeper targets due to high reflectivity. Finally, we observed a correlation between the stack-based SNR estimations and the quantitative metrics, demonstrating that stack-based SNR provides valuable insights into the suitability of seismic data for robust quantitative seismic interpretation.

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Quality Factor								
Deep Channels Mapping								
Attribute		Average Instantaneous Frequency	Minimum Amplitude	RMS	Standard Deviation of Amplitude	Sum of Amplitudes	Sum of Positive Amplitudes	Average Quality Factor
Geometry	G4 (Ref)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	G6	0.58	0.67	0.66	0.61	0.64	0.64	0.64
	G5	0.02	0.11	0.07	0.02	0.04	0.00	0.04
	G3	0.28	0.11	0.21	0.11	0.41	0.52	0.27
	G2	0.53	0.43	0.37	0.37	0.43	0.48	0.43
	G1	0.04	0.13	0.14	0.13	0.17	0.06	0.11

Figure 5: Quality factor values for each attribute mapping the deep channels at 1700m depth in the six seismic stacks. G6 and G2 have the highest quality factors for their attribute mapping, while G3 has a relatively high quality factor in two attributes only.

Survey	Acquisition Geometry	Source/Receiver Spacing (meters)		Shallow Channels (~1100m depth)			Deep Channels (~1700m depth)			Shallow Geobodies (~2700m depth)			Deep Geobodies (~3300m depth)		
		Source	Receiver	Structure	SNR (dB)	Amplitude	Structure	SNR (dB)	Amplitude	Structure	SNR (dB)	Amplitude	Structure	SNR (dB)	Amplitude
G1	Semi-HCC 3x3 Array	100x50	25x150		2.5			3.8		✓	12.1	✓**	✓	15.8	✓**
G2	HCC 3x3 Array	50x50	25x100	✓	8.3	✓	✓	10.4	✓	✓	12.8	✓	✓	16.8	✓
G3	Nodal HCC 3x3 Array	100x100	25x25	✓*	4.2		✓*	6.0	✓**	✓	13.6	✓	✓	17.4	✓
G4 Reference	NAZ Nodal HCC 3x3 Array	50x50	25x25	✓	11.4	✓	✓	13.6	✓	✓	14.6	✓	✓	18.5	✓
G5	Nodal Single Sensor	50x50	25x25		-0.6			0.5		✓	10.4	✓**	✓	14.3	✓**
G6	Nodal Single Sensor	50x50	12.5x12.5	✓	6.5	✓	✓	9.0	✓	✓	14.3	✓	✓	18.1	✓

* Reflector is clear, but faults are not clear
** Amplitude-dependent features are detectible, but noisy

Figure 6: Performance of each geometry in detecting the major subsurface targets, along with their corresponding SNR values.