Imaging near-surface sharp lateral variations with surface-wave methods — Part 1: Detection and location

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Imaging near-surface sharp lateral variations with surface-wave methods — Part 1: Detection and location

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ABSTRACT

Near-surface sharp lateral variations can be either a target of investigation or an issue for the reconstruction of reliable subsurface models in surface-wave (SW) prospecting. Effective and computationally fast methods are consequently required for detection and location of these shallow heterogeneities. Four SW-based techniques, chosen between available literature methods, are tested for detection and location purposes. All of the techniques are updated for multifold data and then systematically applied on new synthetic and field data. The selected methods are based on computation of the energy, energy decay exponent, attenuation coefficient, and autospectrum. The multifold upgrade is based on the stacking of the computed parameters for single-shot or single-offset records and improves readability and interpretation of the final results. Detection and location capabilities are extensively evaluated on a variety of 2D synthetic models, simulating different target geometries, embedment conditions, and impedance contrasts with respect to the background. The methods are then validated on two field cases: a shallow low-velocity body in a sedimentary sequence and a hard-rock site with two embedded subvertical open fractures. For a quantitative comparison, the horizontal gradients of the four parameters are analyzed to establish uniform criteria for location estimation. All of the methods indicate ability in detecting and locating lateral variations having lower acoustic impedance than the surrounding material, with errors generally comparable or lower than the geophone spacing. More difficulties are encountered in locating targets with higher acoustic impedance than the background, especially in the presence of weak lateral contrasts, high embedment depths, and small dimensions of the object.

INTRODUCTION

Near-surface seismic surveys may involve subsurface lateral heterogeneities with strong lateral contrasts in physical and mechanical properties. Typical heterogeneities are objects having lower acoustic impedance than the background. These include cavities, fractures and faults, buried slopes, and embedded low-velocity bodies. In other investigations, lateral variations having higher acoustic impedance than the enclosing medium may also be of interest, as in the case of steeply dipping mineralized veins and seams or buried ore bodies.

The presence of these heterogeneities can affect the results of a wide variety of studies, ranging from regional and local geology (Carpentier et al., 2012; Hyslop and Stewart, 2015; Ikeda and Tsuji, 2016) to geotechnical engineering investigations (Hévin et al., 1998; Gischig et al., 2015) or potential hydrogeologic and mineral explorations (Bièvre et al., 2012). Ray-based P- and S-wave tomography may be inadequate for effectively delineating the location and depth of these sharp variations with desirable detail due to limitations in ray coverage and behavior of refracted rays, particularly when dealing with low-velocity heterogeneities (Colombero et al., 2016; Ikeda and Tsuji, 2016). In contrast, surface waves (SWs) that propagate parallel to the ground surface and with lower attenuation with respect to body waves, may be potentially valuable for detecting and imaging local heterogeneities.

The recognition of sharp lateral changes is also of primary importance for SW data processing itself. Common techniques are indeed aimed at the reconstruction of local 1D subsurface models, neglecting the presence of lateral variations. However, this assumption leads to erroneous velocity models in the presence of lateral variations. Different strategies have been proposed in the literature to overcome this

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limitation. In the case of smooth lateral variations, spatial windowing of the seismic records for dispersion curve estimation was found to offer a good compromise to reconstruct local properties and gradual changes (Bohlen et al., 2004; Boiero and Socco, 2011). Nevertheless, a different approach is needed in the presence of sharp lateral contrasts. In this context, the separate processing of traces belonging to local homogeneous subsurface portions is preferable (Strobbia and Foti, 2006; Bergamo et al., 2012). As a consequence, detection and location of sharp lateral variations are necessary before processing. In previous decades, several SW-based methods have been developed for this purpose.

Park et al. (1998) first propose the use of SWs to image near-surface sharp heterogeneities, which are expected to cause phase-velocity and attenuation changes and generate higher modes and reflected or diffracted waves. The method involves a dynamic linear moveout correction in the frequency domain followed by stacking of the corrected shot gather. The anomalous low-velocity zone shows attenuated amplitudes in the results. Hévin et al. (1998) develop a spectral analysis method to estimate the depth of open cracks in concrete beams when the location of the crack is a priori known.

Nasseri-Moghaddam et al. (2005) propose the attenuation analysis of Rayleigh waves to detect shallow underground cavities, later extended to multifold data by Bergamo and Socco (2014). In this last work, the single-fold autospectrum method of Zerwer et al. (2005) was also applied on a seismic data set acquired on a fault system. Adapted versions of the multioffset phase analysis of Strobbia and Foti (2006) were used by Vignoli and Cassiani (2010) and Vignoli et al. (2011) to identify abrupt lateral heterogeneities in the seismic records.

Xia et al. (2007) use diffracted SWs for imaging shallow buried objects and lateral variations, whereas several authors propose the use of scattered SWs for the same purpose. These techniques are mainly devoted to the separation of the scattered and incident wavefields, to image attributes of the scattered wavefield or for interferometry and inversion purposes (Herman et al., 2000; Leparoux et al., 2000; Kaslilar, 2007; Schwenk et al., 2016; Liu et al., 2017). Hyslop and Stewart (2015) focus on SW reflections and produce reflectivity maps for imaging faults in synthetic and field data.

Reviewing the existing techniques, three tasks can be identified. The first, which is common to almost all methods, is the detection of the heterogeneity and its spatial location. A second task is the estimation of the depth of persistence or embedment of the object. Finally, future perspectives are methods to quantify the contrast in physical and mechanical properties between the object and the background. This paper focuses on the first task, whereas the other two steps are intentionally left for future work. In particular, the effectiveness of the detection and location of sharp lateral variations of four methods (i.e., computation of energy, energy decay exponent, attenuation coefficient, and autospectrum) is here compared and discussed using synthetic and real data. These methods were originally introduced in the works of Nasseri-Moghaddam et al. (2005), Zerwer et al. (2005), and Bergamo and Socco (2014). These methods are directly applicable to raw data, without requiring any preprocessing (e.g., filtering, muting, wavefield, or SW mode separation) or a priori knowledge of the investigated subsurface. This enables users to carry out systematic analyses with fast, effective, and site-independent computations. All of the used methods are here updated for multifold data by introducing stacking to improve readability and interpretation of the results. The four

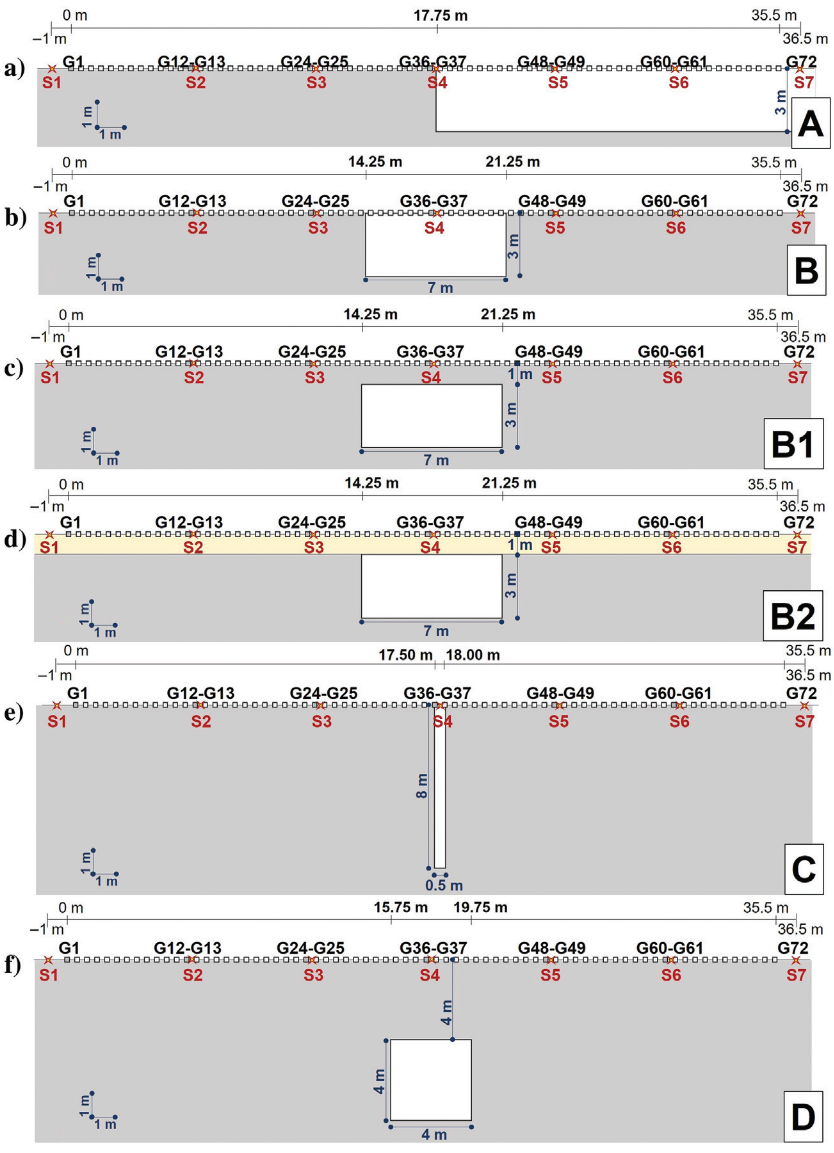

Figure 1. Geometries adopted for the synthetic models, reproducing different shapes of the heterogeneities and embedment conditions. The model parameters are summarized in Table 1 (the model name and subscript refer to geometry and material parameters, respectively). (a) A_1, (b) B_1, B_2, and B_{2R}, (c) $B1_2$ and $B1_{2R}$, (d) $B2_2$ and $B2_{2R}$, (e) C_3 and C_{3R}, and (f) D_3 and D_{3R}. G1–G72: geophone locations; S1–S7: shot locations.

methods are first applied to 2D synthetic models simulating different shapes, embedment conditions, and impedance contrasts with respect to the background. Finally, the methods are validated on two field cases in which a priori knowledge about targets is available.

METHODS

The complete workflow adopted in this study for the different methods is summarized in Appendix A. Hereafter, a detailed description of the theoretical basis of each method is provided.

Energy

One of the most straightforward methods for detection and location of sharp lateral variations is the computation of the energy of the seismic traces acquired along a profile. Energy E_i is computed for each receiver i as the sum of the squared amplitudes $A_{f,i}$ at each frequency f as follows (Nasseri-Moghaddam et al., 2005):

$$E_i = \sum_f |A_{f,i}|^2 r_i. \quad (1)$$

Table 1. Physical, mechanical, and geometric parameters (P-wave, S-wave, Rayleigh-wave velocity, Poisson's ratio, density, P-wave quality factor, depth, and length of the heterogeneity) for the materials outside (Mat 1) and inside (Mat 2) the subsurface heterogeneity.

Model name	Geometry	Material parameters	Material	V_P (m/s)	V_S (m/s)	V_R (m/s)	ν (-)	ρ (kg/m^3)	Q (-)	Z (m)	L (m)
A_1	A (Figure 1a)	1	Mat 1	330	175	163	0.3	2200	30	\	\
			Mat 2	200	110	102	0.3	1900	15	3	\
B_1	B (Figure 1b)	1	Mat 1	330	175	163	0.3	2200	30	\	\
			Mat 2	200	110	102	0.3	1900	15	3	7
B_2	B (Figure 1b)	2	Mat 1	1040	600	558	0.25	2200	30	\	\
			Mat 2	400	231	215	0.25	2000	20	3	7
B_{2R}	B (Figure 1b)	2R	Mat 1	400	231	215	0.25	2000	20	3	7
			Mat 2	1040	600	558	0.25	2200	30	\	\
$B1_2$	B1 (Figure 1c)	2	Mat 1	1040	600	558	0.25	2200	30	\	\
			Mat 2	400	231	215	0.25	2000	20	3	7
			Mat 3 (=Mat 1)	*1040*	*600*	*558*	*0.25*	*2200*	*30*	*1*	\
$B1_{2R}$	B1 (Figure 1c)	2R	Mat 1	400	231	215	0.25	2000	20	\	7
			Mat 2	1040	600	558	0.25	2200	30	3	\
			Mat 3 (=Mat 1)	*400*	*231*	*215*	*0.25*	*2000*	*20*	*1*	*7*
$B2_2$	B2 (Figure 1d)	2	Mat 1	1040	600	558	0.25	2200	30	\	\
			Mat 2	400	231	215	0.25	2000	20	3	7
			Mat 3	*260*	*150*	*140*	*0.25*	*1600*	*15*	*1*	\
$B2_{2R}$	B2 (Figure 1d)	2R	Mat 1	400	231	215	0.25	2000	20	\	\
			Mat 2	1040	600	558	0.25	2200	30	3	7
			Mat 3	*260*	*150*	*140*	*0.25*	*1600*	*15*	*1*	\
C_3	C (Figure 1e)	3	Mat 1	2675	1500	1380	0.27	2570	75	\	\
			Mat 2	340*	\	\	\	1200*	\	8	0.5
C_{3R}	C (Figure 1e)	3R	Mat 1	2675	1500	1380	0.27	2570	75	\	\
			Mat 2	4795	2935	2700	0.2	2900	75	8	0.5
D_3	D (Figure 1f)	3	Mat 1	2675	1500	1380	0.27	2570	75	\	\
			Mat 2	340*	\	\	\	1200*	\	4	4
			Mat 3 (=Mat 1)	*2675*	*1500*	*1380*	*0.27*	*2570*	*75*	*4*	\
D_{3R}	D (Figure 1f)	3R	Mat 1	2675	1500	1380	0.27	2570	75	\	\
			Mat 2	4795	2935	2700	0.2	2900	75	4	4
			Mat 3 (=Mat 1)	*2675*	*1500*	*1380*	*0.27*	*2570*	*75*	*4*	\

Note: For embedded targets, Mat 3 is the material of the overburden.

*Air velocity and density (at a temperature of approximately 20°C).

To compensate for geometric spreading, the results are multiplied by a gain function accounting for the distance r_i between the source and receiver. For each common-shot gather (CSG), the resulting E_i values are finally normalized to the maximum E_i recorded along the seismic line and visualized in E-r (energy-distance) plots. Marked energy concentrations or decays are expected at a subvertical discontinuity, as a result of back reflections or energy trapping and amplification within the target. Nasseri-Moghaddam et al. (2005) apply this method to single-fold data to determine the location of underground cavities, observing energy fluctuations in the proximity of the voids. The same method was applied by Bergamo and Socco (2014) to synthetic and real data of a fault zone, noting sharp energy decays at the discontinuity location. Colombero et al. (2017) adopt the same method for locating open fractures within a granitic rock mass. Marked energy concentrations at fracture locations were interpreted as the result of back reflections at the discontinuity interfaces. All of these previous applications were based on single-fold data. Here, we improve the method by developing its application to multifold data. For each CSG, the energy of each trace is computed following equation 1. The results are normalized to the maximum for each shot position. The computation is repeated for all of the shots along the seismic line, and the results are finally stacked and renormalized to the global maximum. The resulting normalized E-r plot is used to identify energy concentrations or decays that can be potentially diagnostic of subsurface lateral changes.

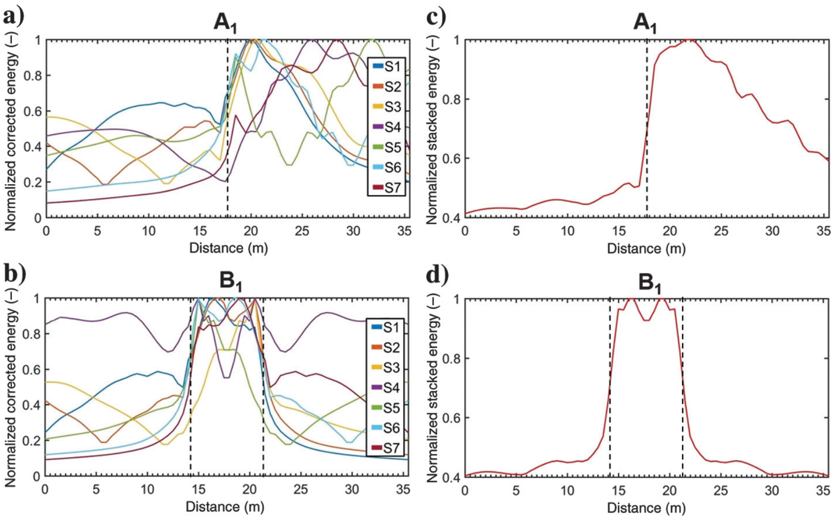

Figure 2. Energy results on (a and c) A_1 and (b and d) B_1. Left column: single-fold results; right column: multifold stacked results. In each section, the vertical dashed lines highlight the real position of the lateral variations.

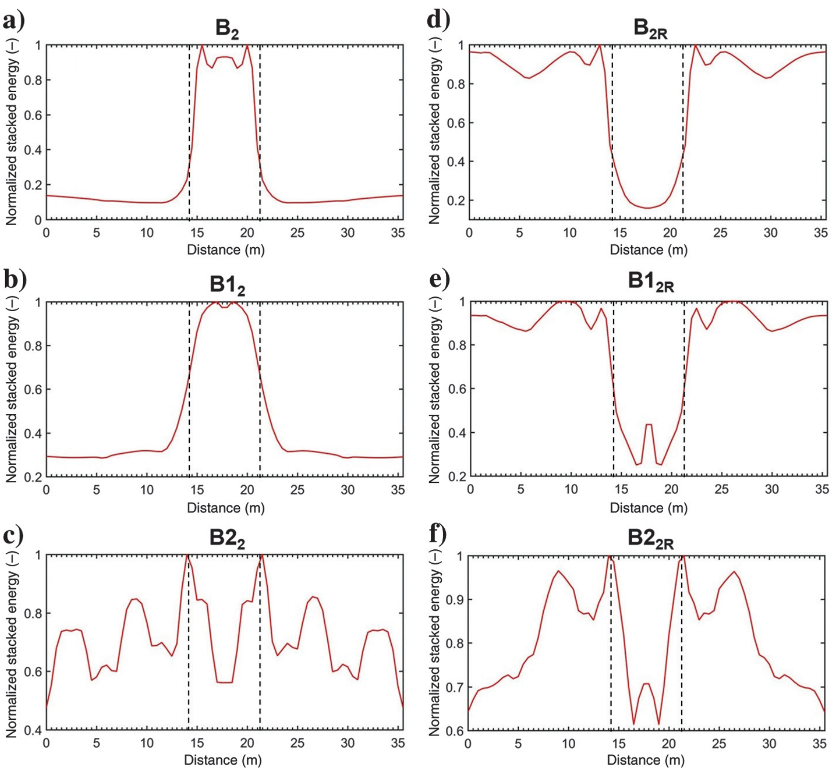

Figure 3. Multifold stacked energy results. (a) B_2, (b) $B1_2$, (c) $B2_2$, (d) B_{2R}, (e) $B1_{2R}$, and (f) $B2_{2R}$. In each section, the vertical dashed lines highlight the real position of the lateral variations.

Energy decay exponent

The energy decay exponent γ can be defined by (Bergamo and Socco, 2014):

$$\frac{E_{i+1}}{E_i} = \left(\frac{r_{i+1}}{r_i}\right)^{-\gamma}, \tag{2}$$

where E_{i+1} and E_i are the energy values computed at two subsequent receivers i and $i+1$ having offsets r_i and r_{i+1} from the source position. If intrinsic attenuation is disregarded, after recovering geometric spreading, γ is expected to be zero in a laterally homogeneous medium. If strong deviations from zero are found, these can be interpreted as the result of energy decays (if $\gamma > 0$) or concentrations (if $\gamma < 0$) induced by back reflections and/or energy trapping within the heterogeneity, coherently to what is described for the previous method.

This technique was originally developed and implemented for multifold data by Bergamo and Socco (2014). Taking advantage of data redundancy, the authors obtained a stable estimation of γ values along the seismic profiles. However, the method was tested on a single field case, and there are no other applications in the literature to evaluate its effectiveness in detecting and locating lateral variations. As a consequence, further tests of the method on real and synthetic data are performed in this study. In summary, for each CSG, a moving window is shifted along the traces to calculate γ as the slope of the E-r plot, in bilogarithmic scale, following (Bergamo and Socco, 2014):

$$\log\left(\frac{E_{i+1}}{E_i}\right) = -\gamma \log\left(\frac{r_{i+1}}{r_i}\right). \tag{3}$$

For each window, γ values obtained from the different shots are averaged and the related standard deviation is computed, for the positive and negative offsets. Plotting together the averaged results, the presence of sharp lateral variations in the subsurface is expected to generate marked γ oscillations, with opposite trends for positive and negative offsets, caused by the constructive or destructive interaction of the incident and reflected waves at the discontinuity position.

Attenuation coefficient

The evaluation of marked and localized changes of seismic wave attenuation in the subsurface can help to confirm and locate the presence of sharp lateral variations. After compensating for geometric spreading, the attenuation coefficient α_f can be retrieved from (Bergamo and Socco, 2014):

$$E_{f,i+1} = E_{f,i}e^{-2\alpha_f(r_{i+1}-r_i)}, \tag{4}$$

where $E_{f,i+1}$ and $E_{f,i}$ are the energy values computed at two subsequent receivers i and $i+1$ (having offsets r_i and r_{i+1} from the source) for each frequency contribution f.

The value of α_f is a measure of the local attenuation of different frequency components of the propagating wavefield. When a sharp lateral variation is found, the attenuation is strongly influenced by energy reflection at the interface (Xia et al., 2002; Foti, 2004). As for the energy decay exponent, the computation procedure was developed by Bergamo and Socco (2014) on multifold data. For each CSG, a moving window is shifted along the traces to calculate α_f as the slope of the E-r plot (with E in natural logarithmic scale), following:

$$\ln\left(\frac{E_{f,i+1}}{E_{f,i}}\right) = -2\alpha_j(r_{f+1} - r_i). \tag{5}$$

Given that for location purposes, the variations of the parameter along the profile are more interesting than the value itself, to emphasize sudden variations and to enable frequency comparison, the obtained α_f is normalized as follows:

$$\overline{\Delta\alpha_{f,w}} = \frac{\overline{\alpha_{f,w}} - \langle\overline{\alpha_f}\rangle}{\mathrm{stdev}(\overline{\alpha_f})}, \tag{6}$$

where $\overline{\alpha_{f,w}}$ is the average attenuation coefficient computed for the window w and frequency f, $\overline{\alpha_f}$ is the average attenuation coefficient computed for the frequency f along the whole line, and $\mathrm{stdev}(\overline{\alpha_\mathrm{f}})$ is the related standard deviation value. This procedure is repeated for all of the shot gathers along the line and considers the positive and negative offsets. Eventually, these results are averaged over corresponding windows w and frequency ranges f to obtain a single $\overline{\boldsymbol{\Delta\alpha}}$ plot for the positive and negative offsets.

Ikeda and Tsuji (2016) apply a similar method on numerical and field data including lithologic contrast and fracture presence. The attenuation coefficient was computed considering amplitude instead of energy values (in equation 4), using data sorted into common-midpoint gathers instead of CSGs. Abrupt changes in the attenuation coefficients were clearly observed around fault locations.

In this work, the computation procedure of Bergamo and Socco (2014) is applied to several synthetic and real data to test its applicability on a wide range of cases. Also for this method, to increase the quality of data interpretation, an improvement in the visualization of the results is introduced by stacking the absolute value of the positive ($\overline{\boldsymbol{\Delta\alpha}_{\mathbf{POS}}}$) and negative ($\overline{\boldsymbol{\Delta\alpha}_{\mathbf{NEG}}}$) plots, following:

$$\overline{\boldsymbol{\Delta\alpha}_{\mathbf{STACK}}} = |\overline{\boldsymbol{\Delta\alpha}_{\mathbf{POS}}}| + |\overline{\boldsymbol{\Delta\alpha}_{\mathbf{NEG}}}|. \tag{7}$$

Autospectrum

The autospectrum method was originally developed by Zerwer et al. (2005) for the detection of cracks in concrete beams. The

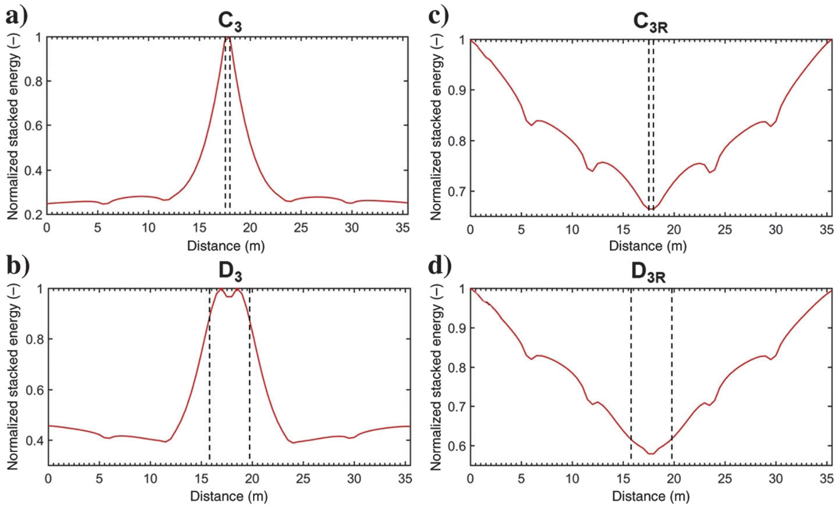

Figure 4. Multifold stacked energy results. (a) C_3, (b) D_3, (c) C_{3R}, and (d) D_{3R}. In each section, the vertical dashed lines highlight the real position of the lateral variations.

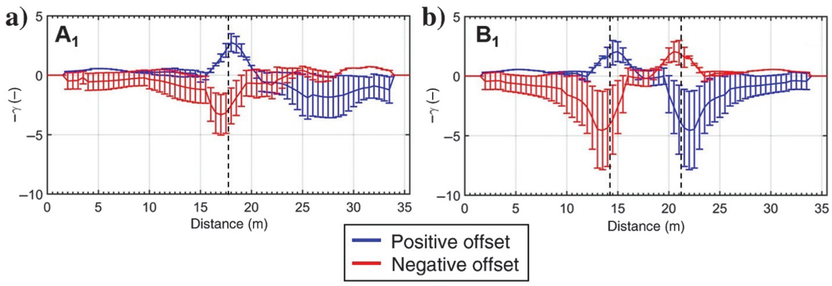

Figure 5. Energy decay exponent results on (a) A_1 and (b) B_1. In each section, the vertical dashed lines highlight the real position of the lateral variations.

autospectral density G_i of a seismic trace $y_i(t)$ can be defined as the sum of the squared real and imaginary parts of the discrete Fourier transform $Y_i(f)$ of the signal, following (Zerwer et al., 2005):

$$G_i(f) = \{\mathrm{Re}[Y_i(f)]\}^2 + \{\mathrm{Im}[Y_i(f)]\}^2. \tag{8}$$

As a consequence, computing G_i for a CSG is an alternative way to display the energy content of a seismogram as a function of the frequency and offset. In the presence of sharp lateral variations, the same considerations about energy concentration and decay of the previous methods are valid. This technique was applied to the field case study reported by Bergamo and Socco (2014). Seismic energy was found to clearly undergo a decay due to the fault presence, back-reflecting a significant portion of the energy of the incoming wavetrain. Nevertheless, only a qualitative indication of the presence of a lateral change was retrieved from the autospectrum plots, whereas clear location boundaries and information on the discontinuity shape were not successfully obtained. These limitations are potentially due to the application of the method to single-fold data. To strengthen the effects of the heterogeneity presence, in this work the procedure is adapted to multifold data. Coherently to the procedures of the other three methods, for each shot location the autospectral density of the traces is computed and geometric spreading is recovered to remove the effect of the source position on the final plot. The results of different shots are then stacked to improve data readability. Eventually, the normalized plot of the stacked autospectra is used to identify anomalies related to the discontinuity presence.

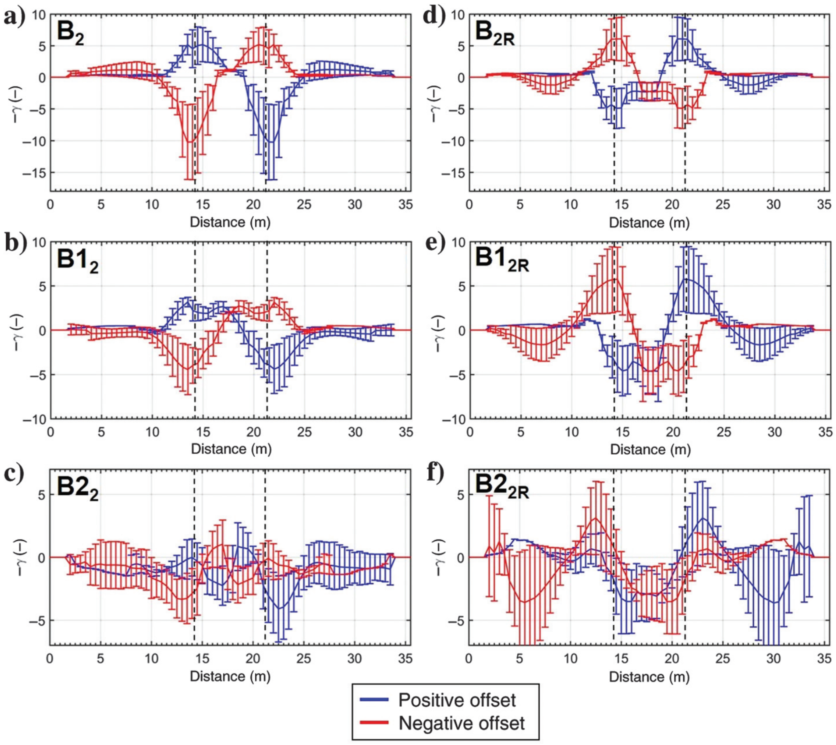

Figure 6. Energy decay exponent results on (a) B_2, (b) $B1_2$, (c) $B2_2$, (d) B_{2R}, (e) $B1_{2R}$, and (f) $B2_{2R}$. In each section, the vertical dashed lines highlight the real position of the lateral variations.

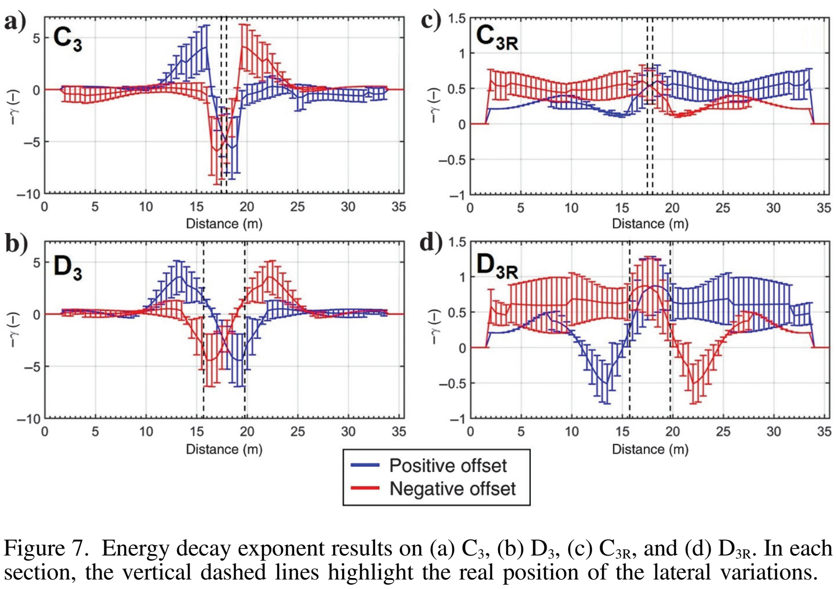

Figure 7. Energy decay exponent results on (a) C_3, (b) D_3, (c) C_{3R}, and (d) D_{3R}. In each section, the vertical dashed lines highlight the real position of the lateral variations.

SYNTHETIC MODELS

To test the effectiveness of the four methods, finite-element model simulations (2D FEM) were implemented in the structural mechanics module of COMSOL Multiphysics over different models including a localized heterogeneity representing the detection target. The wave-propagation problem is faced in the software using an implicit generalized alpha time-dependent solver. For all models, a half-space configuration (height $= 1000$ m, width $= 2000$ m) with low-reflecting boundaries at the bottom and lateral sides of the domain was chosen to avoid reflections. In addition, the bottom corner points were fixed to zero displacement. The upper boundary was a free surface. In its central part, a synthetic array of 72 geophones (spacing $= 0.5$ m) was simulated, for a total length of 35.5 m (G1–G72 in Figure 1). Seven sources were located along the seismic line, at the ends (S1 and S7) and within the array (S2–S6), with a moveup of 12 geophones (Figure 1). A Ricker wavelet centered at 45 Hz was chosen as the seismic input for all of the simulations. This central frequency was chosen coherently with the highest spectral peak depicted in the field recordings closest to the sledgehammer sources, to simulate comparable frequency content.

For all materials, Rayleigh damping was introduced in the models, according to the Q values listed in Table 1. Free triangular meshes (i.e., variable element size) were built for all of the models, a mesh refinement window of 200×50 m was applied around and below the synthetic array to respect a maximum element size lower than one-tenth of the minimum wavelength propagating in each model domain, following Mullen and Belytschko (1982). Synthetic CSGs were generated for each model and source location with a time-dependent study in the range of 0–0.4 s (coherent with field data recordings) and a sampling frequency of 5 kHz. The peak of the source was centered at 0.1 s, to reproduce the trigger delay in field acquisitions.

The four methods were then directly applied to the synthetic CSGs, without any preprocessing stage. A wide set of geometries and model parameters were used in the simulations with the attempt of testing and comparing the performance of the methods in different and meaningful geologic settings. In Figure 1, we show the model geometries used in the simulations. They mimic a sharp lateral discontinuity (e.g., emerging fault or steep slope, A, Figure 1a), a local heterogeneity emerging to the surface (B, Figure 1b) or embedded at 1 m depth in different background conditions (B1 and B2, Figure 1c and 1d), a thin outcropping vertical object (C, Figure 1e), and an embedded equidimensional target (D, Figure 1f). Different model configurations were tested on these geometries; the name of each model corresponds to the adopted geometry, with subscripts indicating the material properties summarized in Table 1. Models with different geometry but the same material properties were compared (e.g., A_1 and B_1), as well as models having the same geometry but different parameters (e.g., B_1 and B_2). Different embedment conditions were tested for the low-velocity rectangular box of model B_2: homogeneous surrounding material ($B1_2$) and a low-velocity layer at the top ($B2_2$). For these three models (B_2, $B1_2$, and $B2_2$), material properties outside and inside the box were also reversed (subscript "R") to additionally account for high-velocity targets (B_{2R}, $B1_{2R}$, and $B2_{2R}$). Analogously, the acoustic impedance contrast between object and background was reversed for models with geometry C, to simulate a fracture (C_3) and a vein/mineralization (C_{3R}), and D, to reproduce a cavity (D_3) and a massive ore body ($D3_R$). In these cases, the parameters of the enclosing material were kept constant, whereas the object was alternatively filled with air (C_3 and D_3) or high-density, high-velocity material (C_{3R} and D_{3R}).

SYNTHETIC RESULTS

In the following, we present the results of applying the four methods to synthetic data. We use models A_1 and B_1 to show the improvement ob-

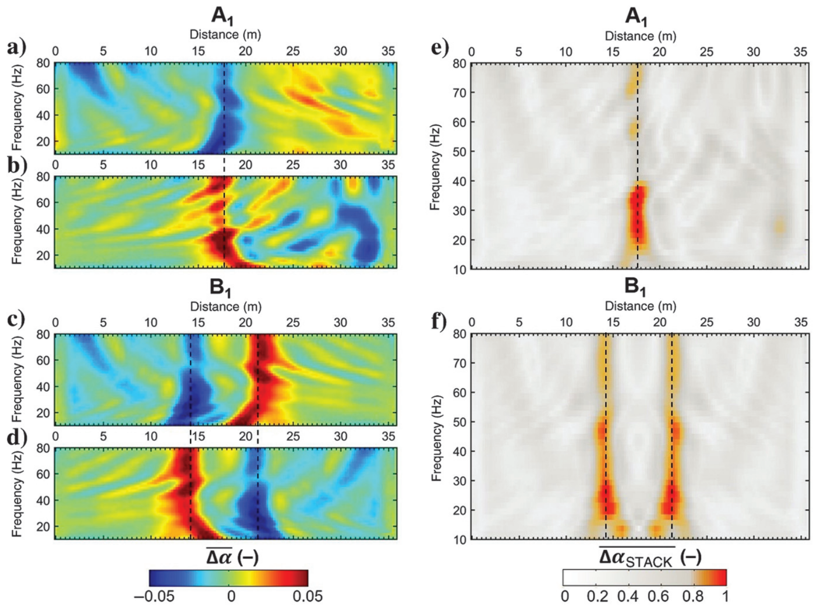

Figure 8. Attenuation coefficient results on (a, b, and e) A_1 and (c, d, and f) B_1. Left column: separate plots for positive (top) and negative (bottom) offsets. Right column: stacked plot of the single-offset plots (absolute value) on the left. In each section, the vertical dashed lines highlight the real position of the lateral variations.

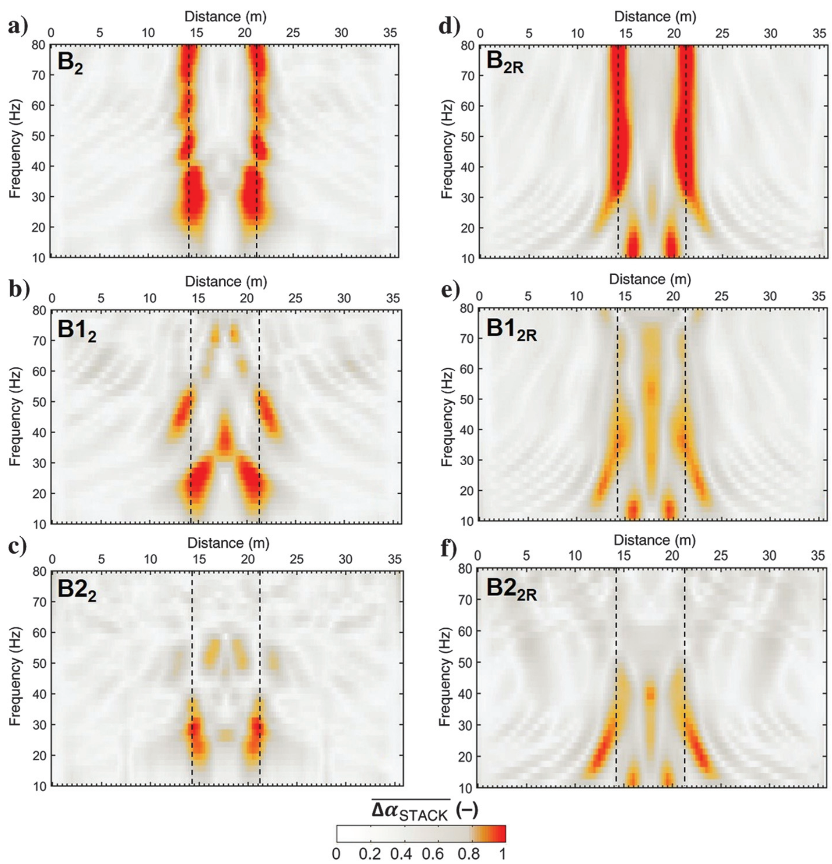

Figure 9. Stacked attenuation coefficient results on (a) B_2, (b) $B1_2$, (c) $B2_2$, (d) B_{2R}, (e) $B1_{2R}$, and (f) $B2_{2R}$. In each section, the vertical dashed lines highlight the real position of the lateral variations.

tained by stacking the information from different shots with respect to single-fold results. For all of the other models, only the stacked results are shown (single-shot and single-offset results for all of the models are available as supplementary information that can be accessed through the following links: Figures S1, S2, S3, S4, S5, S6, S7, and S8). An example test on the stability of the location results in relation to the quality of raw data is discussed in Appendix B, in which exemplificative synthetic CSGs are also shown.

For the parameters computed as a function of frequency (attenuation coefficient and autospectrum), the results are plotted with frequency axes from high to low frequencies downward. This reflects the SW propagation (i.e., high frequencies propagating closer to the surface and low frequencies having a higher penetration depth).

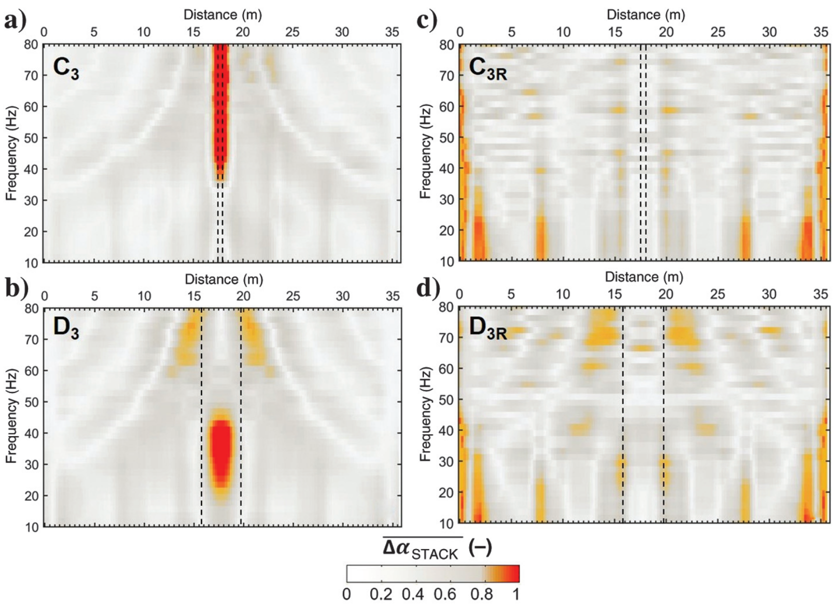

Figure 10. Stacked attenuation coefficient results on (a) C_3, (b) D_3, (c) C_{3R}, and (d) D_{3R}. In each section, the vertical dashed lines highlight the real position of the lateral variations.

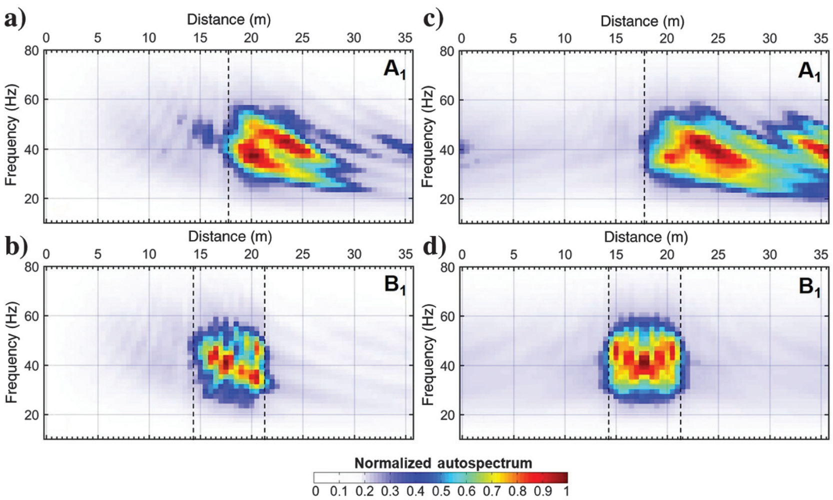

Figure 11. Autospectrum results on (a and c) A_1 and (b and d) B_1. Left column: single-fold autospectrum of shot S1. Right column: multifold stacked autospectrum. In each section, the vertical dashed lines highlight the real position of the lateral variations.

Energy

The results of the energy-based method applied to single-shot and multifold data are given for models A_1 and B_1 in Figure 2. Single-shot normalized energy-distance plots are reported in Figure 2a and 2b, whereas normalized stacked plots of energy are shown in Figure 2c and 2d. In the stacked plots, the position of the target results in a clear anomaly that depicts the geometry of object. The stacking significantly reduces the influence of the shot positions, which are indeed clearly visible on the single-shot data.

For all of the other models, we show the stacked energy plots only (Figures 3 and 4). A clear energy concentration within the low-velocity material is shown for the outcropping bodies (B_1 and B_2, Figures 2d and 3a) and box embedded in the homogeneous surrounding material ($B1_2$, Figure 3b). In all of these models, the position of the target is marked by a clear energy increase and energy peaks are always observed within the low-velocity material. The box with a 1 m low-velocity layer at the top ($B2_2$, Figure 3c) exhibits a different pattern, with energy peaks highlighting the true positions of the box edges. For models having the same geometry but reverse material parameters, we observe an opposite trend with localized energy drops within the high-velocity heterogeneities. For models B_{2R} and $B1_{2R}$ (Figure 3d and 3e), the normalized energy values outside the bodies are close to one, and the box edges are located on the descending energy trends. In contrast, $B2_{2R}$ (Figure 3f) is still located on the two peak positions, as observed in the reverse configuration (Figure 3c). Similar results are also observed over the models with extreme subsurface contrasts and geometries: The fracture (C_3, Figure 4a) and cavity (D_3, Figure 4b) models returned plots coherent to Figure 3a and 3b (B_2 and $B1_2$), with clear energy concentrations in correspondence of the heterogeneity; the high-velocity bodies (C_{3R} and D_{3R}, Figure 4c and 4d) gave opposite results, with a minimum of energy localized over the objects, coherently to Figure 3d and 3e (B_{2R} and $B1_{2R}$), even if the location of these discontinuities is not sharply defined in the plots.

Energy decay exponent

Energy decay exponent plots are reported in Figures 5, 6, and 7. We plot the values of $-\gamma$ in the results such that the maxima correspond to energy concentrations and the minima correspond to energy decays. Positive and negative offset results correspond to spatial windows that are located at the right and left sides with respect to the shot positions.

In all models, the energy concentrations can be observed passing from the high-velocity to the low-velocity material, whereas energy decays are noted going through the opposite material contrast. Targets in models A_1 and B_1 (Figure 5) are correctly localized by negative and positive $-\gamma$ peaks created by the vertical interfaces between media with different velocities. The optimum location estimation is obtained as the average of the positions of negative and positive offset peaks. The amplitude of the peak depends on the contrast between the velocity of target and background. This can be seen by comparing Figure 6a (higher contrast, see Table 1) with Figure 5b (lower contrast, Table 1). We obtained similar trends for the models with embedded target ($B1_2$ and $B2_2$, Figure 6b and 6c). Even where the location of the boundaries is less sharp, the body edges can be still tentatively localized between the positive and negative offset peaks. The $-\gamma$ anomalies on models $B1_{2R}$ and $B2_{2R}$ (Figure 6e and 6f) appear more marked than in the reverse configurations (Figure 6b and 6c). The results of Figure 7 are coherent with the above observations. Clear energy concentrations are observed before the fracture edges (C_3, Figure 7a) for the positive and negative offsets, whereas negative peaks are located after them. Model D_3 (embedded cavity) shows a similar trend (Figure 7c). Conversely, only negative γ values are obtained for the vein model (C_{3R}, Figure 7c), even if a slight increase in the curve of positive offsets is found at the vein location. Symmetric behavior is observed in negative offsets. However, without a priori knowledge of the target, these results may be insufficient to quantitatively interpret and locate the thin object. Clearer results are obtained on the buried high-impedance body (D_{3R}, Figure 7d).

Attenuation coefficient

Attenuation coefficient plots for models A_1 and B_1 are shown in Figure 8. In the left column, positive and negative offset results are separately reported, whereas, in the right column, the stacking of the absolute values of the plots on the left is presented. In the single-offset results, a reduction in attenuation ($\overline{\Delta\alpha} < 0$), reflecting the energy concentration, can be observed passing from the high- to the low-velocity material, whereas an increase in attenuation ($\overline{\Delta\alpha} > 0$), reflecting energy decay, is noted going through the opposite material contrast. The stacked plots offer better imaging potentials, with clearer target location with respect to single-offset plots and the overall indication of the target shape. Stacked results are reported in Figures 9 and 10 for the other models. The highest stacked value of attenuation coefficient variations occurs at the lateral heterogeneity, with the exception of models C_{3R} and D_{3R} in which the stiff inclusions are not clearly detected (Figure 10c and 10d). In addition, for this parameter, the results on the embedded targets are less clear than those on outcropping targets.

Autospectrum

We show the autospectrum plots in Figure 11 for models A_1 and B_1, Figure 12 for the remaining bodies, and Figure 13 for the fracture and cavity models. Single-fold results are shown only for models A_1 and B_1 (Figure 11a and 11b) and the first shot location (S1,

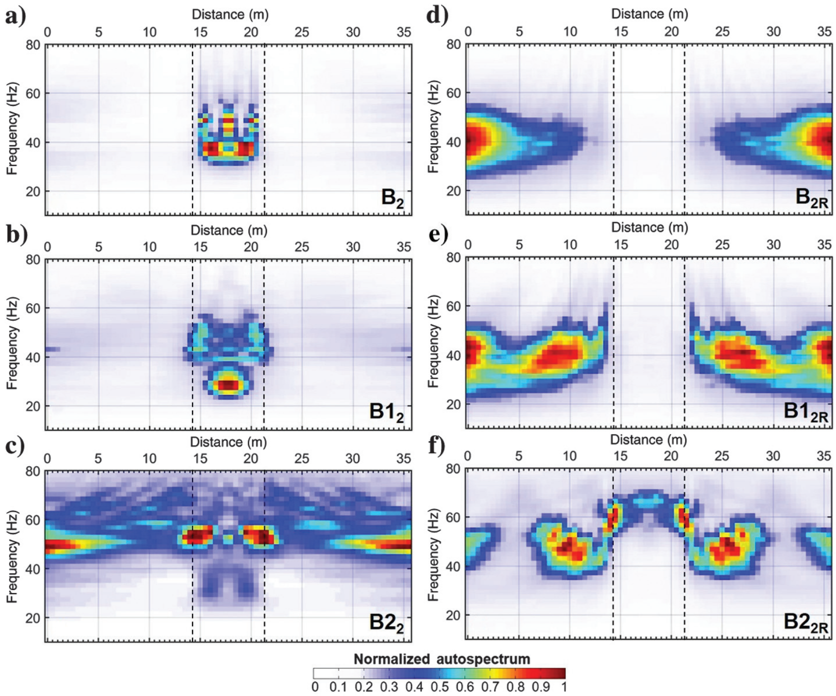

Figure 12. Multifold stacked autospectrum results on (a) B_2, (b) $B1_2$, (c) $B2_2$, (d) B_{2R}, (e) $B1_{2R}$, and (f) $B2_{2R}$. In each section, the vertical dashed lines highlight the real position of the lateral variations.

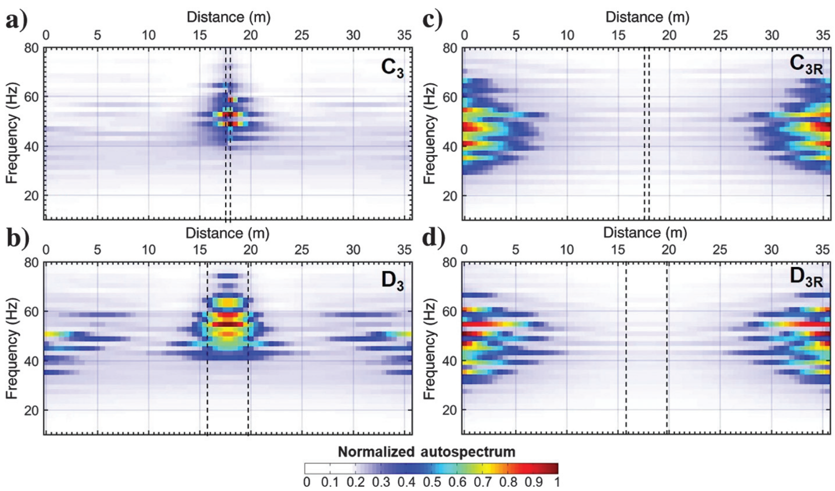

Figure 13. Multifold stacked autospectrum results on (a) C_3, (b) D_3, (c) C_{3R}, and (d) D_{3R}. In each section, the vertical dashed lines highlight the real position of the lateral variations.

Figure 1). High autospectral values are observed inside the targets when its velocity is lower than the one of the surrounding medium. For all models, multifold results are observed to offer a clearer interpretation of the autospectrum plots, confirming the benefits of data redundancy in sharpening the target aspect. Even if the improvement is only slight for the targets intersecting the ground surface (Figure 11), stacking significantly strengthens the effects of the embedded objects. Unlike previous methods, the box having a lower contrast with the enclosing material (B_1 in Figure 11d with respect to B_2 in Figure 12a) seems to produce clearer evidence. The highest autospectral values are located outside the bodies when the acoustic impedance inside the target is higher than the background (the right column of Figure 12). This makes the detection of the high-velocity objects a nonstraightforward task, especially considering the thin geometry of the vein and the relevant embedment depth of the massive body reported in Figure 13c and 13d. In these configurations, the autospectrum plot can help in target detection, but the location and shape are not identified. Conversely, the fracture and the embedded cavity are correctly located and imagined (Figure 13a and 13b).

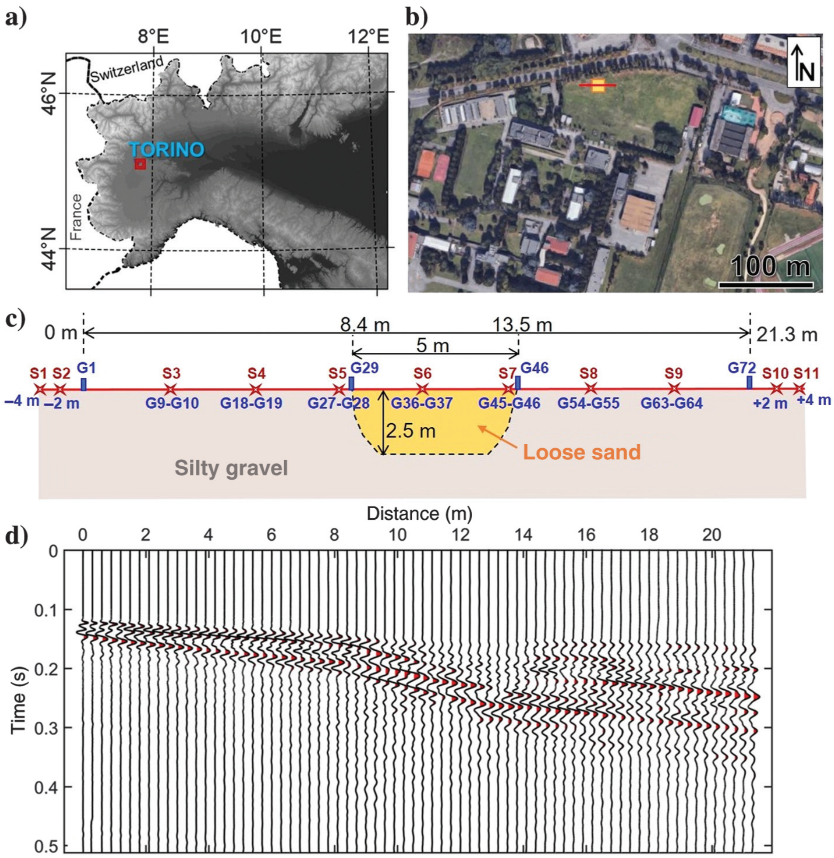

Figure 14. The CNR test site. (a) Geographic location. (b) Aerial view of the site with location of the sand box (the yellow square) and the seismic array (the red line). (c) Geometry of the target and seismic layout. G1–G72: geophone locations; S1–S11: shot locations. (d) CSG for S1.

REAL CASE STUDIES

In the following, we apply the four methods to field data sets acquired at two test sites. The first case study is a shallow low-velocity body in a sedimentary sequence, similar to model A_1 for target geometry and material parameters. The second case study is a hard rock site with two large open fractures, similar to model C_3 for the material parameters, but with the presence of a shallow overburden and different fracture depths.

CNR test site

Site description

An artificial target was built in an area of the CNR (National Research Council) headquarters in Torino, northwest Italy (Figure 14a and 14b). The area is flat and characterized by a shallow soil layer overlapping a thick sequence of alluvial deposits of the river plain, mainly composed of gravels with a silty matrix. Within these materials, a square area (length = 5 m, width = 5 m) was dug down to approximately 2.5 m depth. The void was then filled with loose sand (Figure 14c). A seismic line of 72 vertical geophones (4.5 Hz) at 0.3 m spacing was deployed on site (total length = 21.3 m) with the sand box in the center of the acquisition line (Figure 14c). Eleven shots (8 kg

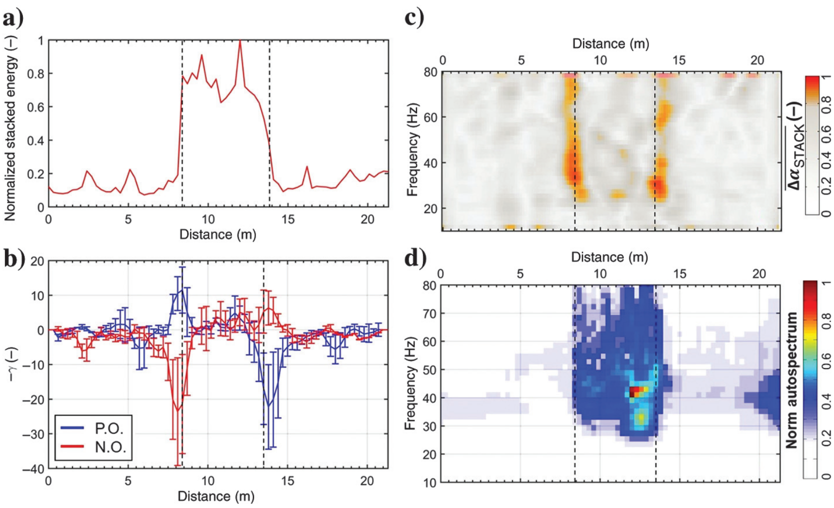

Figure 15. The CNR results. (a) Multifold stacked energy-distance plot. (b) Energy decay exponent results. (c) Stacked attenuation coefficient results. (d) Multifold stacked autospectrum plot. In each section, the vertical dashed lines highlight the approximate real position of the box edges.

sledgehammer) were struck at the line ends and along the array. The first and the last two shots were located at 4 and 2 m, respectively, from the first and last receiver, whereas the remaining were evenly spaced along the seismic line. Traces were recorded at a 0.125 ms sampling rate, with a trigger delay of 0.1 s, for a total acquisition time of 0.512 s. An exemplificative shot gather (S1) is shown in Figure 14d.

Results

The results of the four methods are summarized in Figure 15. The normalized stacked energy plot, obtained from the 11 shots along the line, is shown in Figure 15a. A clear energy concentration is found inside the sand body, in agreement with the synthetic results (e.g., B_1, Figure 2d). In both plots, the target edges are located at the steep increase and decrease of the normalized energy values. The energy decay exponent results are reported in Figure 15b. As observed for the synthetic models (e.g., B_1, Figure 6a), the peaks in the $-\gamma$ values correctly detect and localize the position of the sand body. For the positive and negative offsets, the energy concentration is found entering the low-velocity body, whereas energy decay is recorded exiting from it. The attenuation coefficient and autospectrum results succeed as well in the location of the target, with a clear and sharp imaging in the stacked plot (Figure 15c and 15d). Comparable results are obtained for synthetic model B_1 (Figures 8f and 11d).

Madonna del Sasso

Site description

The unstable cliff of Madonna del Sasso (northwest Italy, Figure 16a) is a granitic rock mass with five main fractures (F1 to $F4_1$ and $F4_2$, in Figure 16b and 16c) potentially isolating two unstable rock prisms at the top of the cliff. Several geophysical surveys were carried out on site. P- and S-wave crosshole tomography was used to image fractures $F4_1$ and $F4_2$ (Colombero et al., 2016). Despite identifying two low-velocity zones in the tomographic results, the low ray coverage and the resulting smooth tomograms did not allow fracture locations and boundaries to be shapely delineated. The single-fold energy method was applied on a surface seismic line in Colombero et al. (2017).

In this work, we apply all four methods to the same data set. Data were acquired with 48 vertical (4.5 Hz) geophones at a spacing of 0.75 m, covering the longest available line on the top of the cliff (G1–G48, Figure 16c and 16d). A total of 13 shot positions (8 kg sledgehammer) were struck at the line ends and along the array. The first and last source positions were located at a 1 m distance from the first and last geophones (S1 and S13, Figure 16d). S1 CSG is shown in Figure 16e. According to the previous studies, the two

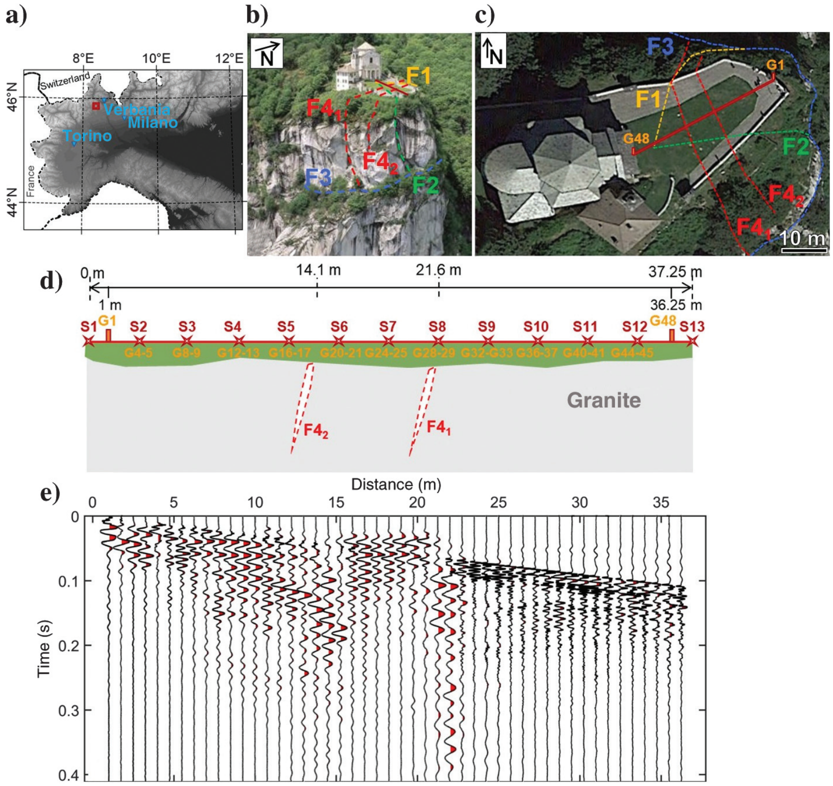

Figure 16. Madonna del Sasso test site. (a) Geographic location. (b and c) Aerial views of the site with location of the main fractures (F1 to F4, dashed lines) and seismic array (the red continuous line). (d) Geometry of the seismic layout and fracture locations. G1–G48: geophone locations; S1–S13: shot locations. (e) CSG for S1.

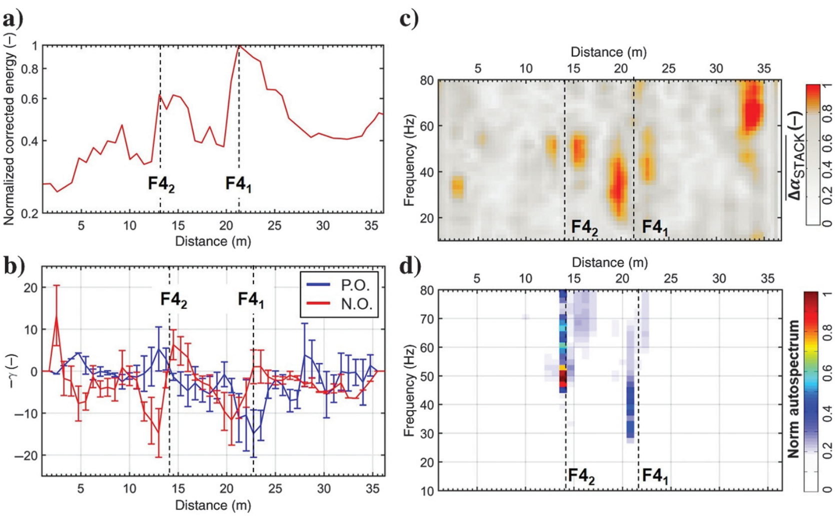

Figure 17. Madonna del Sasso results. (a) Multifold stacked energy-distance plot. (b) Energy decay exponent results. (c) Stacked attenuation coefficient results. (d) Multifold stacked autospectrum plot. In each section, the vertical dashed lines highlight the approximate real position of the fractures.

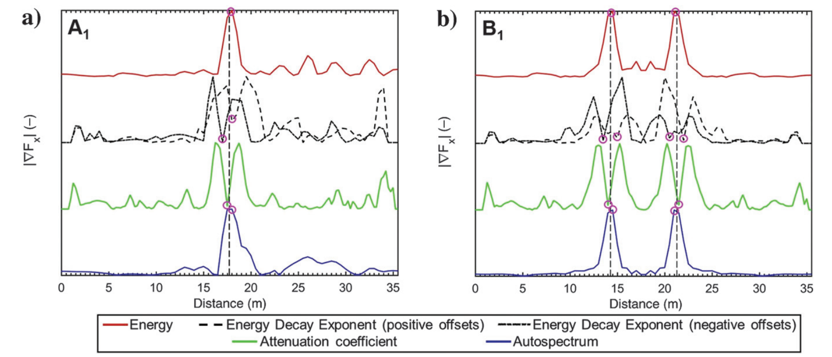

Figure 18. Normalized absolute value of the horizontal gradients of the four parameters on the (a) A_1 and (b) B_1 synthetic models: energy (in red), energy decay exponent (in black; dashed line: positive offsets; dashed-dotted line: negative offsets), attenuation coefficient (in green), and autospectrum (in blue). In each section, the vertical dashed lines mark the real position of the lateral variations, whereas the magenta circles highlight the locations of the lateral variations, according to the criteria described in the text.

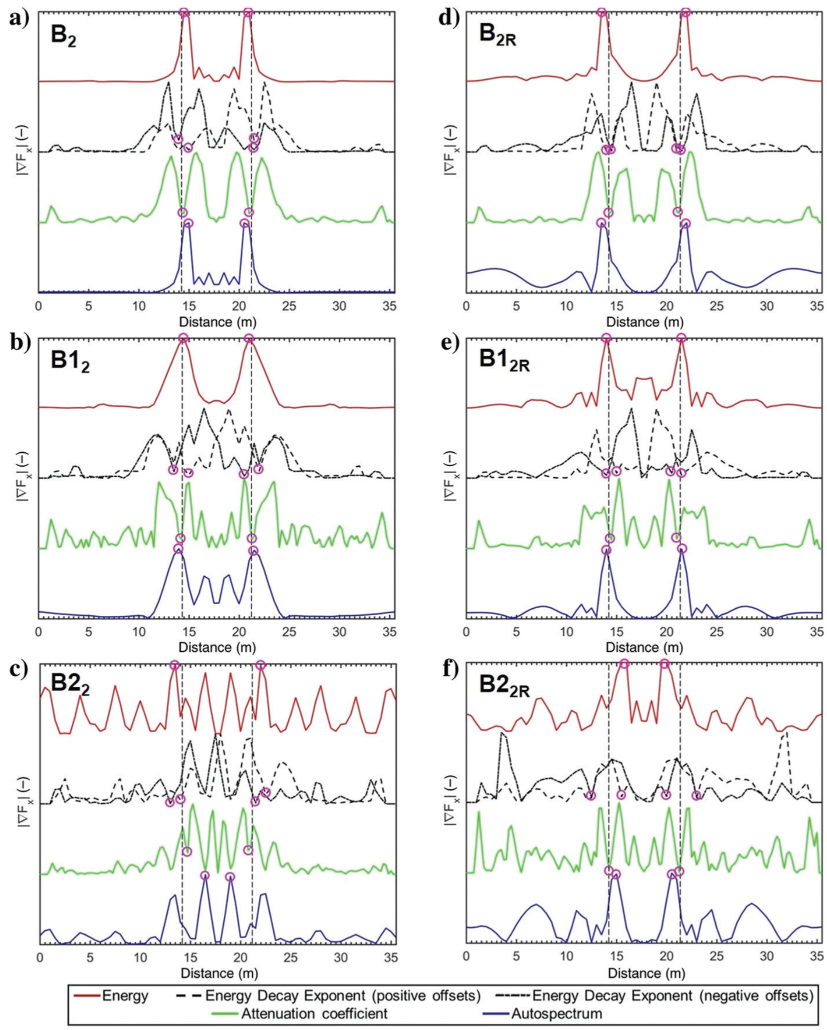

Figure 19. Normalized absolute value of the horizontal gradients of the four parameters on (a) B_2, (b) $B1_2$, (c) $B2_2$, (d) B_{2R}, (e) $B1_{2R}$, and (f) $B2_{2R}$ synthetic models: energy (in red), energy decay exponent (in black; dashed line: positive offsets; dashed-dotted line: negative offsets), attenuation coefficient (in green), and autospectrum (in blue). In each section, the vertical dashed lines mark the real position of the lateral variations, whereas the magenta circles highlight the locations of the lateral variations, according to the criteria described in the text.

fractures are supposed to cross the seismic line almost perpendicularly at a distance of approximately 14.1 m ($F4_2$) and 21.6 m ($F4_1$) with a subvertical dip. Below a thin soil cover, they are expected to be open, as demonstrated by past episodes of collapse of the cover. Their width is estimated in approximately 0.5 m, with a depth of several meters from the ground surface (16 ± 2 m for $F4_1$ and 8 ± 2 m for $F4_2$, according to the results of Colombero et al., 2017).

Results

The results of the four methods are summarized in Figure 17. The stacked normalized energy-distance plot is reported in Figure 17a. Also in this case, clear energy concentrations are noticed at the fracture locations, in agreement with the synthetic results on the single fracture C_3 (Figure 4a). The cross points between the positive and negative peaks of the energy decay exponent (Figure 17b) are located in proximity of the fractures, as in the synthetic results obtained on model C_3 (Figure 7a). Nevertheless, the real results are not as clear. Marked peaks are found on the two sides of the fractures in the attenuation coefficient results (Figure 17c), different than the synthetic results on the single open fracture highlighting a maximum inside the target (Figure 10a). An additional maximum is found between 33 and 35 m at high frequencies. This anomaly can also be noticed in the energy results (Figure 17a), but it does not appear in the energy decay exponent (Figure 17b) and stacked autospectrum plot (Figure 17d). The autospectrum produces a sharp image of the investigated fractures in agreement with synthetic data (Figure 13a).

DISCUSSION

To compare the effectiveness of the four methods in detecting and locating sharp lateral variations, clear criteria for the quantitative interpretation of the results were needed. We chose the horizontal gradient of the four computed parameters to highlight the strongest lateral variations and consequently provide clear common location criteria. The gradient computation along the seismic line was straightforward for energy and energy decay exponent curves. To provide comparable results for the 2D plots of the other two methods, the attenuation coefficient and autospectral values at different frequencies were summed along the frequency axis to obtain a single value for each receiver location. The horizontal gradient was then computed on the resulting vectors.

Interpretation of synthetic and field results

We show the plots of the horizontal gradients (normalized absolute values) in Figure 18 for models A_1 and B_1, Figure 19 for all the other box configurations (B2, $B1_2$, $B2_2$, $B2_R$, $B1_{2R}$, and $B2_{2R}$), and Figure 20 for the remaining synthetic models (C3, D3, $C3_R$, and $D3_R$). The results on the two real case studies are reported in Figure 21.

In the synthetic results, the sharp lateral variations were generally located on the steep energy increases and decreases. We consequently chose the maxima in the absolute value of energy gradients as representative locations of the lateral variations for this method. The same criterion was adopted for the absolute value of the autospectrum gradients. For the energy decay exponent, considering that the sharp lateral variations were observed to be approximately located between the location of the minima and maxima of the positive and negative offsets, the absolute value of the horizontal gradient was computed for both offsets. The local minimum between two gradient peaks was then selected as representative of the lateral variation location for each offset curve. These minima are located on either side of the discontinuity for opposite offsets, consistently with the $-\gamma$ results. The average value of the positive and negative offset gradient minima was consequently chosen as the representative point for the discontinuity location. A similar criterion was followed for the attenuation coefficient results. Given that maxima in the stacked attenuation plots were generally observed at the edges of the heterogeneities, the local minimum between two gradient peaks was selected as the location of the lateral variation.

Errors in the location obtained following these criteria for all of the simulated and real heterogeneities are summarized in Table 2. In general, the energy gradient maxima were found to perform well in locating the outcropping anomalies having lower velocity than the surrounding material (A_1, B_1, B_2, and C_3 in Figures 18, 19a, and 20a), with errors less than the geophone spacing (0.5 m). Comparing results are recorded on the embedded box $B1_2$ and $B1_{2R}$ (Figure 19b and 19e), with maximum errors of ± 0.25 m from the real locations. Higher errors were found for the embedded boxes with a low-velocity layer at the top, i.e., $B2_2$ (± 0.75 m; Figure 19c) and $B2_{2R}$ (± 1.50 m; Figure 19f). For these models, it was already observed in the energy results of Figure 3c and 3f that the exact location of the targets corresponds to the energy peaks, and not the increasing and decreasing energy ramps. The vein and the massive ore body in models C_{3R} and D_{3R} could not be located following the same criterion (Figure 20c and 20d). Even if local maxima in the energy gradient are present close to these discontinuities, higher peaks are observed toward the line ends. These complex patterns make the location almost impossible on energy gradient curves, whereas the original energy plots (Figure 4c and 4d) gave at least an indication of the presence of a body with high acoustic impedance in the center of the profiles.

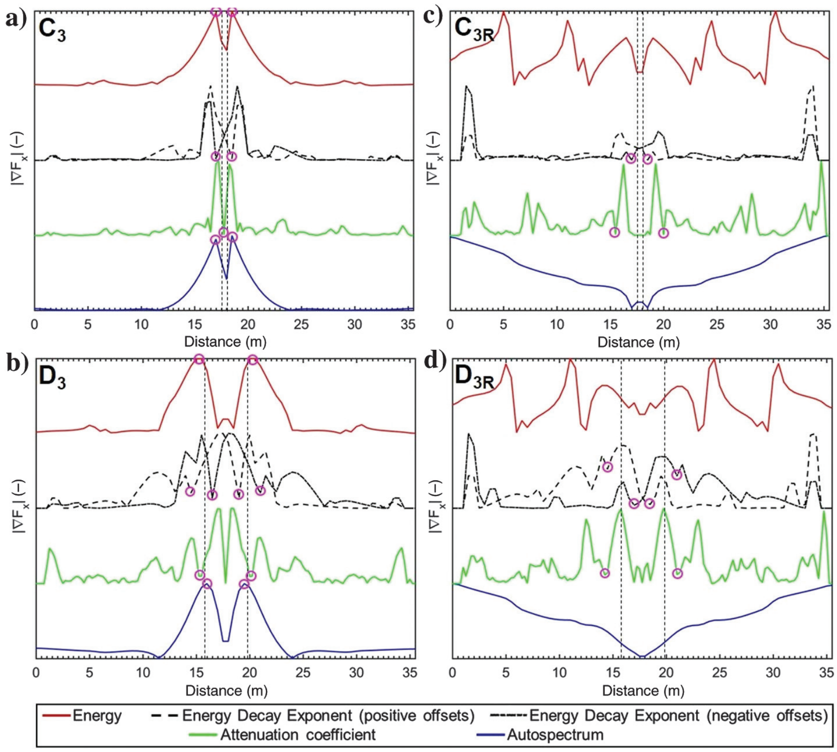

Figure 20. Normalized absolute value of the horizontal gradients of the four parameters on (a) C_3, (b) D_3, (c) C_{3R}, and (d) D_{3R}: energy (in red), energy decay exponent (in black; dashed line: positive offsets; dashed-dotted line: negative offsets), attenuation coefficient (in green), and autospectrum (in blue). In each section, the vertical dashed lines mark the real position of the lateral variations, whereas the magenta circles highlight the locations of the lateral variations, according to the criteria described in the text.

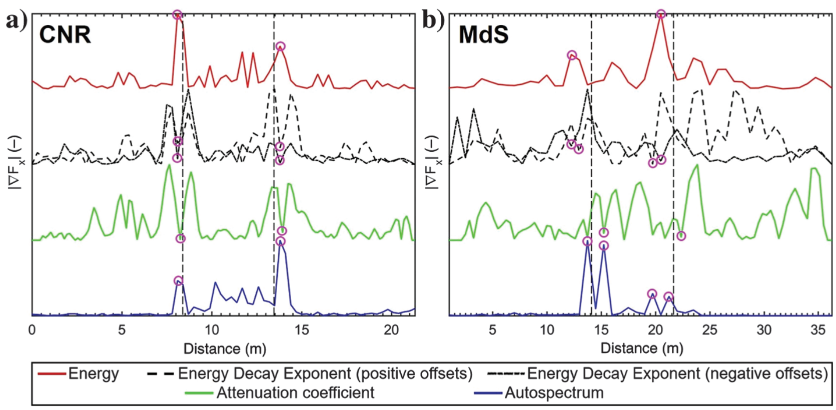

Figure 21. Normalized absolute value of the horizontal gradients of the four parameters on (a) CNR test site and (b) Madonna del Sasso cliff: energy (in red), energy decay exponent (in black; dashed line: positive offsets; dashed-dotted line: negative offsets), attenuation coefficient (in green), and autospectrum (in blue). In each section, the vertical dashed lines mark the real position of the lateral variations, whereas the magenta circles highlight the locations of the lateral variations, according to the criteria described in the text.

The peaks in the energy gradient are also found to locate the edges of the sandbox for the CNR test site (Figure 21a), with errors comparable to the geophone spacing adopted on site (0.3 m). The fractures of Madonna del Sasso are located with errors generally double the adopted 0.75 m geophone spacing (Figure 21b). Similar considerations apply to the autospectrum gradients of synthetic and real data. The highest errors are recorded for model $B2_2$ (±0.75 m; Figure 19c). For this model, local maxima closer to the real edge locations are present in the gradient results.

Picking of the lateral variation locations on the energy decay exponent gradient plots is clear and in agreement with the real locations for the outcropping targets A_1, B_1, B_2, and B_{2R} (Figures 18, 19a, and 19d), independently from the material contrast. Boxes embedded in the homogeneous background ($B1_2$ and $B1_{2R}$) also showed clear gradient curves and location errors lower than the adopted geophone spacing (Figure 19b and 19e). However, the results on the box with low-velocity overburden (Figure 19c and 19f) are more complex, gradient curves on $B2_{2R}$ exhibit maxima close to the line ends, which could lead to erroneous picking without a comparison with the other methods. Despite energy and autospectrum results, an estimation of the vein and massive body locations in models C_{3R} and D_{3R} is possible with the energy decay exponent

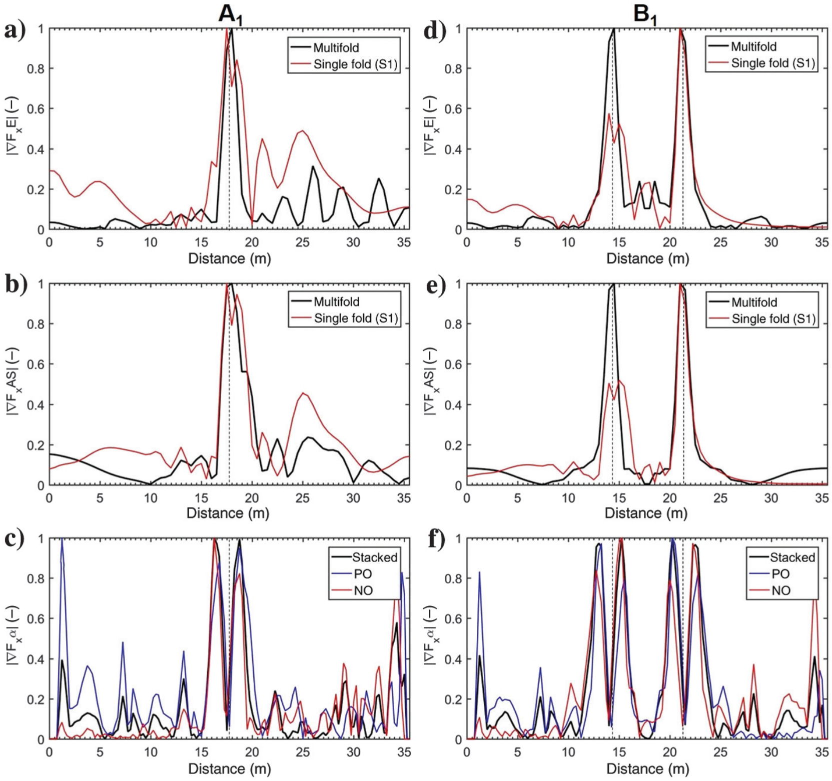

Figure 22. Comparison of single-fold/offset and stacked results for the synthetic model (a-c) A_1 and (d-f) B_1. (a and d) S1 and multifold stacked normalized energy gradients. (b and e) S1 and multifold stacked normalized autospectrum gradients. (c and f) Attenuation coefficient normalized gradients for the positive offset, negative offset, and stacked results.

Table 2. Location errors, reported as the distance between the real position (estimated from previous works for the real case studies) and the location retrieved from the gradient of the four parameters.

Model/case study	*E*		*γ*		*α*		Autospectrum	
	LE (m)	RE (m)	LE (m)	RE (m)	LE (m)	RE (m)	LE (m)	RE (m)
A_1	−0.25		0.25		0.25		0.00	
B_1	−0.25	0.25	0.00	0.00	0.25	−0.25	−0.25	0.25
B_2	−0.25	0.25	−0.25	−0.25	−0.25	0.25	−0.75	0.75
B_{2R}	0.75	−0.75	0.00	0.00	0.00	0.00	0.75	−0.75
$B1_2$	−0.25	0.25	0.00	0.00	0.00	0.00	0.25	−0.25
$B1_{2R}$	0.25	−0.25	−0.25	0.25	−0.25	0.25	0.25	−0.25
$B2_2$	0.75	−0.75	0.75	−0.75	−0.50	0.50	−2.25	2.25
$B2_{2R}$	−1.50	1.50	0.25	−0.25	0.00	0.00	−0.75	0.75
C_3	0.50	−0.50	0.50	−0.50	−0.25	0.25	0.50	−0.50
C_{3R}	n.d.	n.d.	0.50	−0.50	2.00	−2.00	n.d.	n.d.
D_3	0.25	−0.25	0.25	−0.25	0.25	−0.25	−0.25	0.25
D_{3R}	n.d.	n.d.	0.00	0.00	1.25	−1.25	n.d.	n.d.
CNR	0.30	−0.30	0.30	−0.30	0.15	−0.45	0.30	−0.30
MdS	1.60	1.10	1.48	1.48	−1.15	−0.78	−0.40	1.10

Note: n.d., not determined; LE, left edge; RE, right edge of the box models. For the Madonna del Sasso (MdS) site, LE and RE refer to the average locations of fractures F42 and F41, respectively.

(Figure 20c and 20d). However, gradient spikes are observed at the line ends. Comparable results are obtained with the attenuation coefficient gradients for synthetic and real data. Also for this method, it is possible to retrieve an estimation of the vein and massive body locations, even if errors are higher than 1 m.

Despite these limitations, evaluating the horizontal gradients can help to quantitatively compare the results of the four methods and in the coherent selection of the discontinuity locations. However, when the obtained gradient curves become unclear and noisy due to the complexity of the subsurface conditions, an approximate location estimation based on the plots shown in the results of each method should be preferred. It must be additionally noticed that the errors in the location (Table 2) strictly depend on the receiver spacing adopted in the synthetic and real case studies. With higher receiver spacing, the uncertainty in the location would proportionally increase.

We observed poor location results for anomalies having a higher acoustic impedance than the surrounding material. This weakness probably depends on the strength of the acoustic impedance contrast between the two media (e.g., higher on B_{2R} than on C_{3R}), on the geometry of the anomaly (e.g., C_{3R} is extremely thin if compared with B_{2R}), and on the embedment depth (e.g., D_{3R} versus $B1_{2R}$). In these cases, the joint computation of all four methods can, however, help to detect the anomaly presence.

Results of CNR field data were found in good agreement with similar synthetic data (i.e., model B_1), whereas major differences were observed between Madonna del Sasso field data and model C_3 (single fracture). For the field case, the presence of two discontinuities interfering in a short space and of a shallow overburden, the unknown geometry and filling of fractures at depth and the possible heterogeneity in the background material (due to additional fracturing and weathering) are all factors that probably contributed to the observed discrepancies with synthetic data.

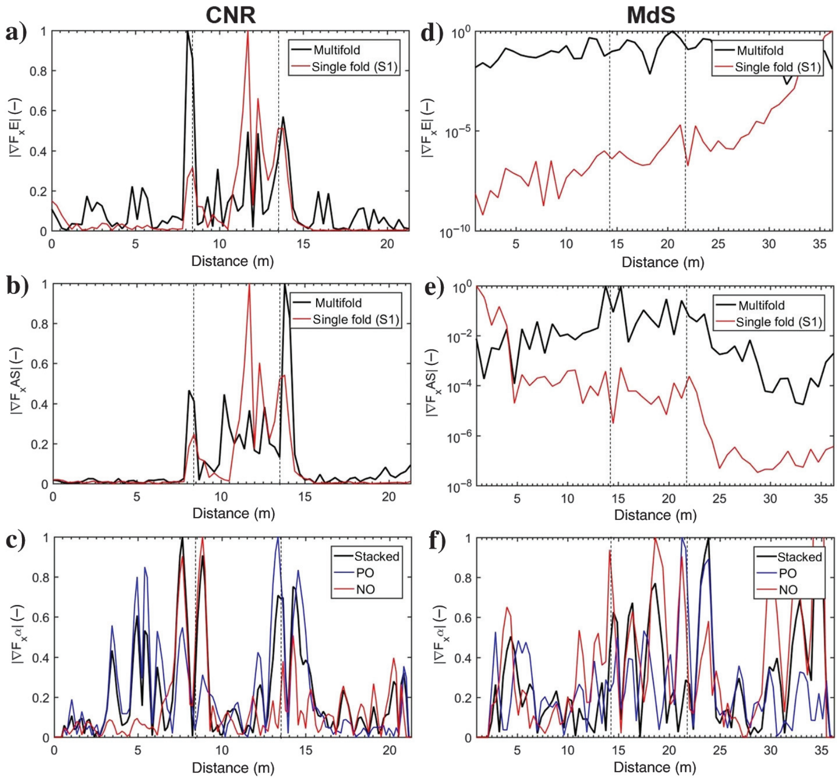

Figure 23. Comparison of single-fold/offset and stacked results for the field data (a-c) CNR and (d-f) Madonna del Sasso. (a and d) S1 and multifold stacked normalized energy gradients. (b and e) S1 and multifold stacked normalized autospectrum gradients. (c and f) Attenuation coefficient normalized gradients for positive offset (PO), negative offset (NO), and stacked results. In (d and e), the *y*-axis is in logarithmic scale to intensify the small fluctuations of single-fold gradients.

Comparison with single-fold and single-offset results

The advantage of introducing stacking of CSG results in energy and autospectrum computations and of positive and negative offset plots for attenuation coefficient is already clear by visual comparison of single-fold/offset plots and multifold results (e.g., Figures 2, 8, and 11 and supplementary information that can be accessed through the following links: Figures S1–S8). However, it was quantitatively analyzed with the same gradient criteria. As a synthetic example, the gradient of energy and autospectrum for a single shot gather (S1) are shown in comparison with the gradients of multifold results for models A_1 (Figure 22a and 22b) and B_1 (Figure 22d and 22e). For the same models, the gradients of positive and negative offset results for the attenuation coefficient are reported in comparison with the gradient of the stacked plots in Figure 22c and 22f. Even if the errors in target locations are similar for single and stacked results, stacking strengthens and sharpens the effect of the anomaly in all plots. The peaks linked to the target are sharpened, and their amplitude is increased, whereas the amplitude of secondary peaks (not related to the target) is decreased in the stacked results (e.g., secondary peaks in Figure 22a or high positive and negative offset peaks at the ends of the profile in Figure 22c and 22f). This may reduce the uncertainty in the interpretation of field data with unknown target number and features.

In Figure 23, we show similar comparisons for the field data of CNR and Madonna del Sasso. In both cases, data interpretation based on the peak positions in the single-fold results of energy and autospectrum would lead to erroneous detection and location estimations.

CONCLUSION

Sharp lateral variations in the shallow subsurface can be either a target of investigation for near-surface seismic surveys or an issue for local 1D model reconstructions of the subsurface in SW processing. Reliable, effective, and computationally fast methods are consequently required to recognize their presence. These methods can use SW propagation, given their strong interaction with local subvertical discontinuities and lower attenuation with respect to body waves. The tasks explored in this work were the detection and location of the sharp lateral variations. Four SW-based methods were chosen, for their fast and effective workflows, not requiring any preprocessing of raw data, wavefield, or mode separations. The proposed methods were adapted to multifold data to strengthen the effects of the discontinuity and improve reliability in the interpretation of the results. The horizontal gradient of the four parameters was analyzed to establish objective and quantitative criteria for target location.

All of the tested methods showed a good ability to detect and locate lateral variations having acoustic impedance lower than the surrounding material on synthetic data with errors lower than 1–2 m, for the adopted receiver spacing. These results were confirmed on two real case studies having the same configuration (low acoustic impedance targets). More difficulties were encountered in locating targets with higher acoustic impedance than the surrounding material. In this configuration, weak contrasts in acoustic impedance, high embedment depths, and small dimensions of the discontinuity can prevent from a precise location of the targets. The strength of the proposed methods lies in (1) the absence of any preprocessing and (2) robustness of the results, also in the case of noisy data. The complete workflow, from the upload of the seismic records to the final results, over a commercial laptop requires less than 5 min (for 10–15 CSGs of 48–72 receivers), making this approach a potential method for fast object identification directly in the field.

In all of the simulated conditions, sharp lateral variations were considered as vertical interfaces, but additional simulations on dipping interfaces showed analogous detection potentialities. However, the evaluation of location errors due to the presence of dipping interfaces is left for future work. In addition, the sensitivity of the four techniques to variable depths of the target and the potentiality in indirect depth estimation from the frequency-dependent methods (attenuation coefficient and autospectrum plot) represent the natural continuation of this work. Further analyses will also clarify the dependence of the investigated parameters from the contrast in physical and mechanical properties between the heterogeneity and the background.

DATA AND MATERIALS AVAILABILITY

Data associated with this research are available and can be obtained by contacting the corresponding author.

APPENDIX A

PROCESSING WORKFLOW

The complete workflow for the four methods is shown in Figure A-1.

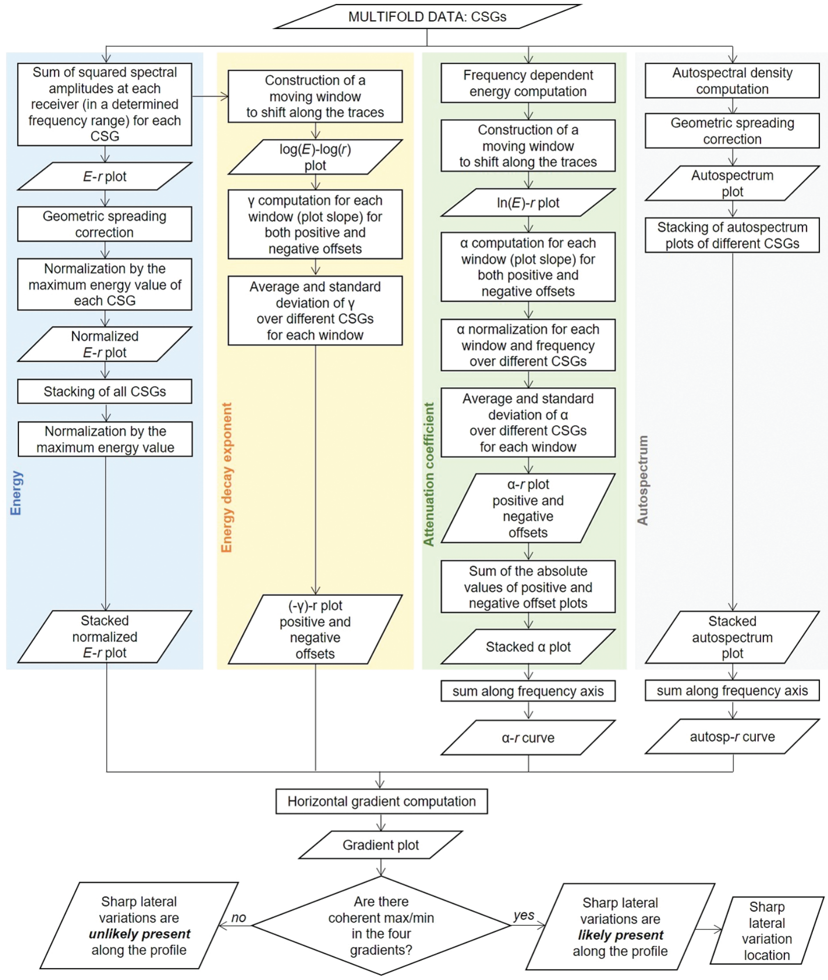

Figure A-1. Complete processing workflow including computation for energy, energy decay exponent, attenuation coefficient, and autospectrum for detection and location of sharp lateral variations.

APPENDIX B

EFFECT OF SIGNAL-TO-NOISE RATIO ON THE SYNTHETIC RESULTS

In this appendix, the effect of noise on the results obtained with the four methods is analyzed on the synthetic CSGs of model B_2 (geometry and model parameters in Figure 1b and Table 1).

Two unperturbed CSGs for the model are shown in Figure B-1a (S1, Figure 1b) and B-1e (S4, Figure 1b). We considered the signal-to-noise ratio (S/N) as the ratio between the mean power of the signal and the mean power of the noise. For all of the CSGs, each trace was perturbed with additive Gaussian noise, considering S/Ns equal to 2 (+3 dB, e.g., Figure B-1b and B-1f), 0.5 (−3 dB, e.g., Figure B-1c and B-1g), and 0.1 (−10 dB, e.g., Figure B-1d and B-1h). The energy, energy decay exponent, attenuation coefficient, and autospectrum results are shown in Figure B-2, whereas gradient computations are summarized in Figure B-3.

The target is detected in all of the test configurations, even with very low S/Ns. Location errors (Table B-1) are stable in the range of the unperturbed model and independent from S/N decreases. Similar results can be obtained for all of the other synthetic models, with

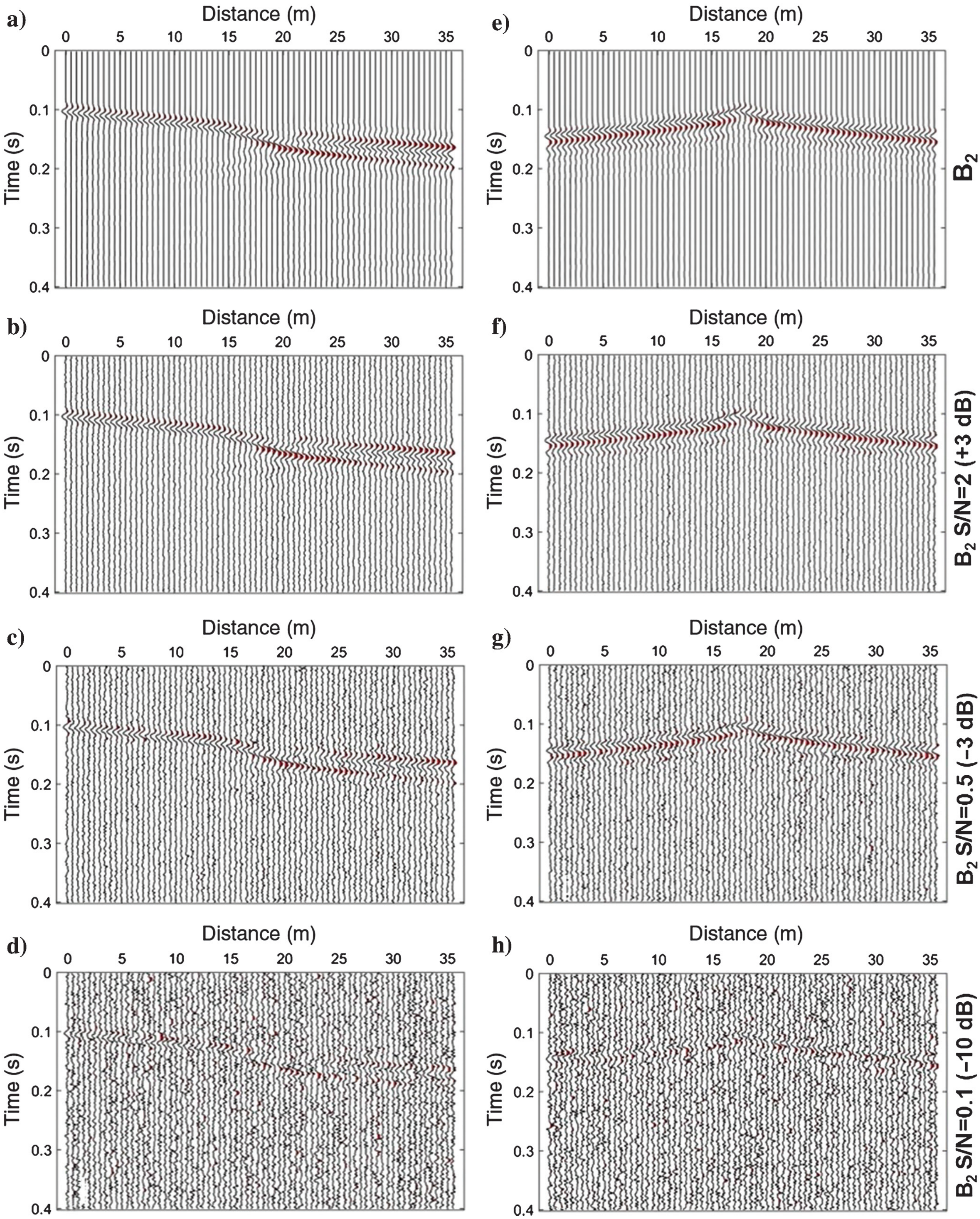

Figure B-1. Synthetic CSGs for model B_2. (a-d) S1 and (e-h) S4. (a and e) Unperturbed traces, (b and f) S/N = 2, (c and g) S/N = 0.5, and (d and h) S/N = 0.1.

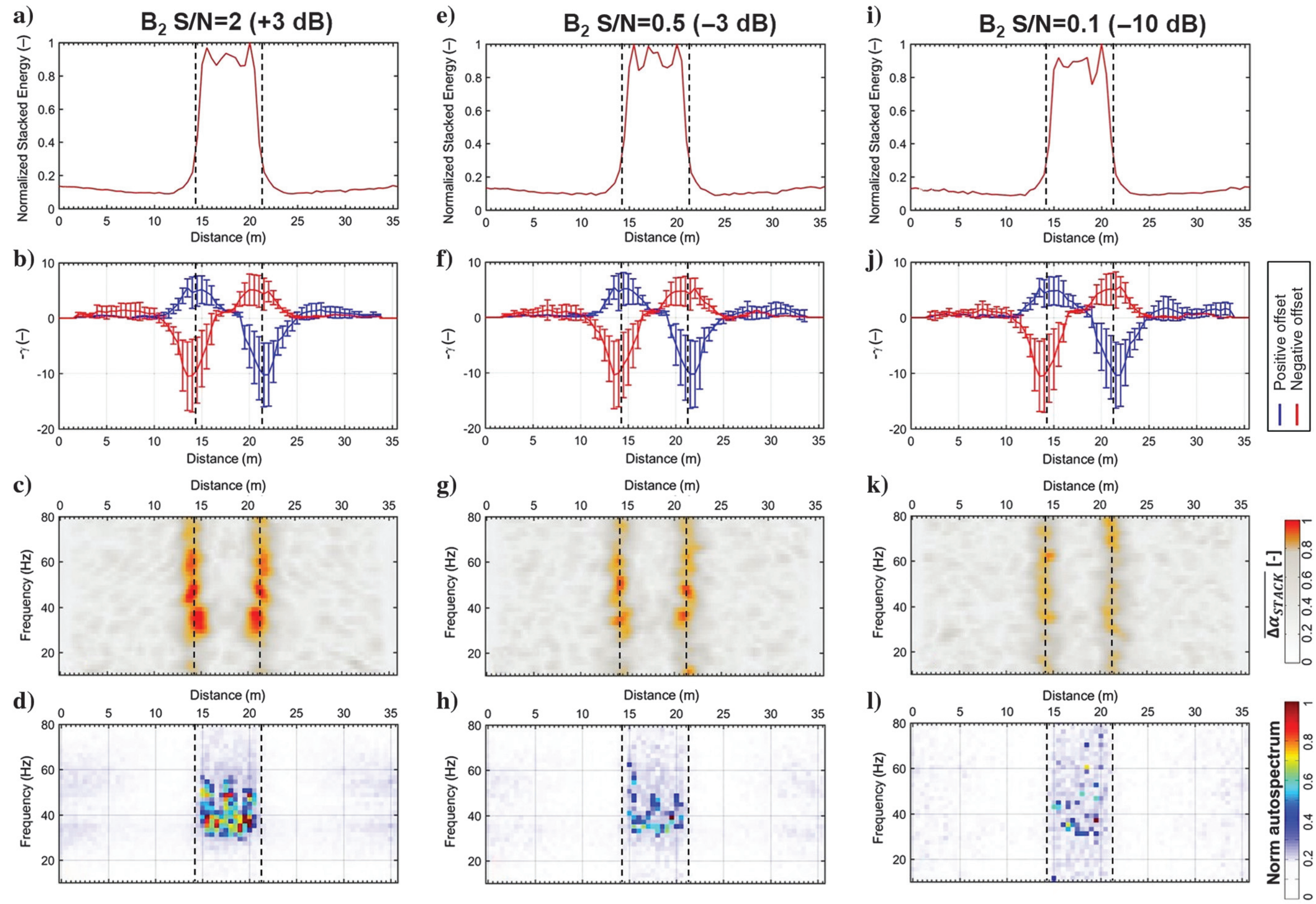

Figure B-2. Results on the perturbed model B_2 (a-d) S/N = 2, (e-h) S/N = 0.5, and (i-l) S/N = 0.1. (a, e, and i) Multifold stacked energy plots. (b, f, and j) Energy decay exponent results. (c, g, and k) Stacked attenuation coefficient plots. (d, h, and l) Multifold stacked autospectrum plots.

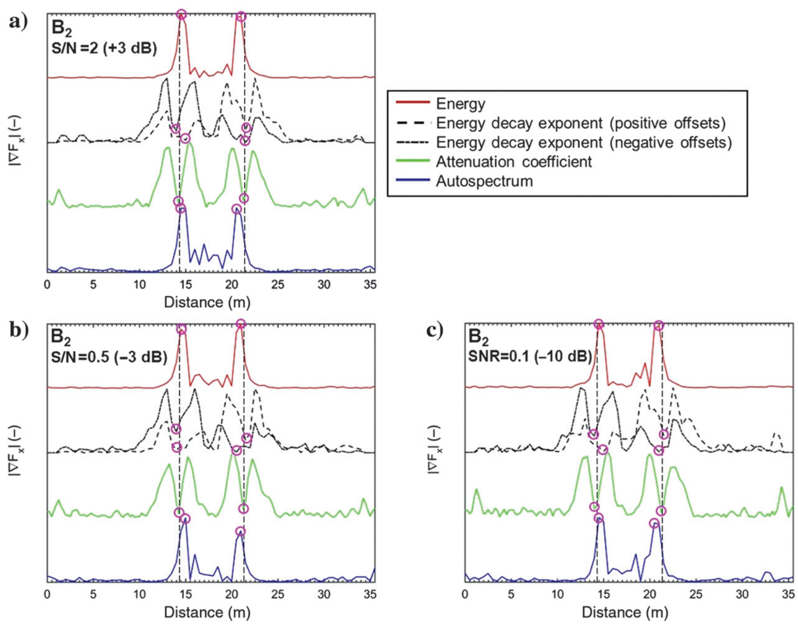

Figure B-3. Normalized absolute value of the horizontal gradients of the four parameters on the perturbed model B_2 (a) S/N = 2, (b) S/N = 0.5, and (c) S/N = 0.1: energy (in red), energy decay exponent (in black; dashed line: positive offsets; dashed-dotted line: negative offsets), attenuation coefficient (in green), and autospectrum (in blue). In each section, the vertical dashed lines mark the real position of the lateral variations, whereas the magenta circles highlight the locations of the lateral variations, according to the adopted criteria.

Table B-1. Location errors for unperturbed (in bold) and perturbed CSGs of model B_2 (with S/Ns of 2, 0.5, and 0.1).

Model	E		γ		α		Autospectrum	
	LE (m)	RE (m)	LE (m)	RE (m)	LE (m)	RE (m)	LE (m)	RE (m)
B_2	**−0.25**	**0.25**	**−0.25**	**−0.25**	**−0.25**	**0.25**	**−0.75**	**0.75**
B_2 S/N = 2	−0.25	0.25	−0.25	−0.25	0.00	0.00	−0.25	0.75
B_2 S/N = 0.5	−0.25	0.25	0.25	0.25	0.00	0.00	−0.75	0.25
B_2 S/N = 0.1	−0.25	0.25	−0.25	0.00	0.25	0.00	−0.25	0.75

Note: LE, left edge; RE, right edge of the box.

location errors diverging from the unperturbed values (Table B-1) of less than the receiver spacing (0.5 m).

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