Joint ray + Born least-squares migration and simulated annealing optimization for target-oriented quantitative seismic imaging

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ABSTRACT

A seismic processing workflow based on iterative ray + Born migration/inversion and target-oriented postprocessing of the migrated image is developed for fine-scale quantitative characterization of reflectors. The first step of the workflow involves linear iterations of the ray + Born migration/inversion. The output of the first step is a true-amplitude migrated image parameterized by velocity perturbations. In a second step, postprocessing of the migrated image is performed through a random search with a very-fast simulated annealing (VFSA) algorithm. The forward problem of the global optimization is a simple convolutional model that linearly relates a vertical profile of the band-limited migrated image after depth-to-time conversion to a 1D velocity model composed of a stack of homogeneous layers of arbitrary velocity and thickness. The aim of the postprocessing is to eliminate the limited bandwidth effects of the source from the migrated image for resolution improvement and enhanced geological interpretation of selected targets. The global optimization approach allows for uncertainty analysis required by the intrinsic nonuniqueness of the velocity model output by the postprocessing. The relevance of the convolutional model when applied to the output of the ray + Born migrated inversion is first illustrated with a one-layer model. The accuracy and the robustness of the workflow to image geologically complicated models are then illustrated with an application to the synthetic Marmousi model. Some practical issues (e.g., the source wavelet estimate and the scaling of the migrated image required by the VFSA optimization) are discussed with an application to a 2D real seismic multichannel reflection data set collected in the Gulf of Guayaquil (Ecuador). The postprocessing is applied to derive the fine-scale velocity structure of a décollement zone on top of the subduction channel. The postprocessing allows for mapping structural variations along different segments of the décollement, which can be associated with changes in fluid content and porosity.

INTRODUCTION

There is a strong need for high-resolution quantitative inferences about the seismic properties of rocks (P- and S-wave velocities, density, attenuation, anisotropy) for geological interpretation in various geodynamical contexts and in reservoir characterization.

The most complete approach for true-amplitude seismic imaging is the so-called full-waveform inversion (FWI). This is based on complete resolution of the two-way wave equation for the forward problem and iterative minimization of the misfit between the recorded and the modeled data with local optimization approaches (e.g., Tarantola, 1987; Pratt et al., 1998). In FWI, the starting model is updated at each iteration with the final model from the previous iteration. This nonlinear iterative approach allows one to continuously fill up the wavenumber spectrum of the subsurface model as the inversion proceeds over increasing temporal frequencies (Sigure and Pratt, 2004). As such, FWI should be the most suitable framework to close the gap between velocity model building and migration (Sigure et al., 2010), provided that the starting velocity model has a sufficiently broad low-wavenumber content for the available source bandwidth and acquisition geometry. However, FWI still suffers from several limitations. One obvious limitation is the computational cost of the forward problem, which requires local optimization approaches for the inverse problem and prevents

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extensive uncertainty analysis and model appraisal. The computational cost of FWI also prevents 3D applications at high frequencies. Other limitations concern the sensitivity of the local optimization to the inaccuracies of the starting model and to the lack of low frequencies. Accurate velocity model building is a difficult task when limited azimuth and aperture acquisition geometries are considered because of the limited sensitivity of short-offset data to the intermediate wavelengths (Jannane et al., 1989; Sirgue and Pratt, 2004). Although long-offset data are theoretically suitable for building the long and intermediate wavelengths, the inversion of long-offset data is more nonlinear because of the wavefield complexity integrated over many propagated wavelengths (Sirgue, 2006; Pratt, 2008). A last difficulty is the sensitivity of the FWI to the amplitude errors resulting from the incomplete modeling of the wave-propagation physics. This sensitivity results from the fact that the data residuals are back propagated at each nonlinear iteration of the inversion. Although robust minimization criteria (e.g., the L1-norm) may help to mitigate the footprint of the amplitude errors (Brossier et al., 2010), FWI has mainly shown promising results at low frequencies (e.g., Ravaut et al., 2004; Plessix, 2009; Plessix and Perkins, 2010; Sirgue et al., 2010). However, recent applications of 3D FWI have shown that information carried out by low frequencies is quite rich and that high-resolution velocity models useful for geological interpretation can be inferred from these low frequencies. This highlights the benefit of the low-frequency information for geologic interpretation (Oldenburg et al., 1983).

Alternative quantitative seismic imaging relies on least-squares prestack-depth migration (Lambaré et al., 1992; Nemeth et al., 1999; Symes, 2008; Valenciano et al., 2009). Unlike in FWI, the processed data set is limited to the reflected wavefield to reconstruct the short-wavelength components of the subsurface. A linear relationship between the reflected wavefield and the reflectivity can be found by means of the Born approximation, and the adjoint of the linear forward problem operator provides the migration operator. In least-squares migration, the reflected wavefield is back propagated instead of the data residual, which makes migration less sensitive to amplitude errors than FWI. In the framework of least-squares inverse theory, the migrated section is formed by the product of the inverse of the Hessian operator with the unscaled migrated image, which corresponds to the gradient of the cost function. Only one iteration of least-squares migration is generally performed, which might be justified by the fact that the cost function is made quadratic after linearization of the forward problem. However, the single-scattering approximation underlying the linearization of the inverse problem would justify iterating the inversion (Lambaré et al., 1992). In iterative migration, the background model is kept constant over iterations. This implies that the background model and the migrated image are left uncoupled because of the wavenumber gap between the long-wavelength background velocity model and the short-wavelength migrated section.

One limiting factor of least-squares migration is the limited bandwidth of the migrated images. The wavenumber bandwidth is controlled by the frequency bandwidth of the source and the reflection angle coverage provided by multichannel seismic reflection geometries (Miller et al., 1987; Lambaré et al., 2003; Lecomte et al., 2005). The smallest wavenumber of the migrated image is controlled by the smallest frequency of the source and the largest reflection angle, whereas the highest wavenumber is controlled by the highest frequency of the source and corresponds to the inverse of half of the smallest wavelength. The limited wavenumber bandwidth, in particular toward the lower part of the spectrum, affects the resolution power of the imaging.

The motivation of this study is to present a seismic reflection workflow that consistently combines ray-based least-squares migration and a postprocessing of the migrated section. The main aim of the postprocessing is to deconvolve the migrated section from limited bandwidth effects and build target-oriented broadband velocity models with a vertical resolution and a parameterization suitable for geological interpretation. The least-squares migration is performed by iterative ray + Born migration/inversion, which has been recast rigorously in the theoretical framework of least-squares inverse problem theory (Jin et al., 1992; Lambaré et al., 1992; Thierry et al., 1999). The ray + Born migrated section can be parameterized by P-wave velocity or impedance perturbations (Thierry et al. 1999; their equations 17 and 18). In this study, the migration/inversion is iterated linearly until convergence is achieved for velocity-perturbation amplitudes that are as accurate as possible. The postprocessing is based on the convolutional model for the forward problem (e.g., Oldenburg et al., 1983), which linearly relates a vertical profile of the migrated section after depth-to-time conversion to the velocity (or impedance) profile that is sought through time-domain convolution with the seismic wavelet (Ribodetti et al., 2000). The inverse problem aims to reconstruct the broadband velocity model from the band-limited migrated section. The velocity models reconstructed by the postprocessing models are parameterized by a stack of homogeneous layers of arbitrary thickness. The layered-earth parameterization is suitable to reconstruct the low and high wavenumbers of the subsurface that lie outside of the source bandwidth after depth-to-time conversion. The ability to reconstruct the missing low and high wavenumbers of the subsurface from a limited bandwidth source was shown by Oldenburg et al. (1983) and Walker and Ulrych (1983), who recast the recovery of the acoustic impedance as an autoregressive process. The postprocessing is applied trace by trace to each vertical profile of the migrated section covering the target, and the assemblage of all of the profiles builds the final structural model. The postprocessing is an ill-posed problem because of the nonuniqueness of the velocity model estimation (an infinity of broadband velocity models can fit one band-limited migrated profile). To sample as much as possible the range of velocity models allowing for the data fit, the postprocessing is recast as a global optimization that is performed with the very-fast simulated annealing (VFSA) algorithm (Sen and Stoffa, 1991). Uncertainty analysis of the population of the best-fitting models is performed using several runs of VFSA (Sen and Stoffa, 1995; Jackson et al., 2004).

The seismic workflow presented in this study shares some similarities with that used in reservoir characterization. However, most of the techniques for reservoir characterization are based on stratigraphic inversion, in which amplitude variation with offset (AVO) and amplitude variation with angle (AVA) behaviors of waves are inverted for estimation of the subsurface attributes (Demirbag et al., 1993; Yilmaz, 2001; Veeken and Rauch-Davies, 2006). Stratigraphic inversions have recently...
be recast as geostatistical stochastic AVA inversions to evolve toward automation of the processing and more rigorous model appraisal (Ma, 2002; Hicks and Williamson, 2003; Veeken and Silva, 2004; Walia et al., 2004; Escobar et al., 2006). Unlike stratigraphic inversion used in reservoir characterization, the AVA analysis is directly embedded in the depth migration process in our approach and the stochastic inversion is applied to the depth-migrated image in the poststack domain. This assumes that a simple convolutional model is sufficiently accurate to account for the band-limited effects on the migrated image. One advantage is that the forward modeling associated with the global optimization is very fast, and it is applied to a reduced volume of data in the poststack domain, allowing for an extensive exploration of the model space.

In the first part of the study presented here, we review the two main steps of the processing workflow (iterative ray + Born migration followed by the stochastic postprocessing of the migrated section). In the second part, we discuss the validity of the assumptions underlying the convolutional model used in the postprocessing with a simple one-layer model. In the third part, we apply the processing workflow to the Marmousi model to assess the potential of the method for imaging structurally complex media. Both examples allow us to discuss the resolution of migration followed by the stochastic postprocessing of the migrated section. In the second part, we discuss the validity of the assumptions underlying the convolutional model used in the framework of linear inverse theory, in which the misfit between the observed and the modeled scattered wavefields is minimized in a least-squares sense (Jin et al., 1992; Lambaré et al., 1992).

The weighted misfit function is given by

$$C(\delta m) = \frac{1}{2} \sum_x \sum_r \sum_s \| \delta G_{\text{obs}} - \delta G_{\text{cal}} \|^2,$$

(3)

where $\delta G_{\text{obs}}$ and $\delta G_{\text{cal}}$ are the recorded and modeled scattered wavefields, respectively.

The solution of the weighted least-squares inverse problem at iteration $k$ is

$$\delta m^{(k)} = \left( B_0^{\dagger} Q B_0 \right)^{-1} B_0^{\dagger} Q \left( \delta G_{\text{obs}} - \delta G_{\text{cal}} \left( \Delta m^{(k-1)} \right) \right),$$

(4)

where $\delta G_{\text{cal}}(\Delta m^{(k-1)}) = B_0 \Delta m^{(k-1)}$ and $\Delta m^{(k-1)} = \sum_{l=1}^{k-1} \delta m^{(l)}$. $\Delta m^{(l)}$ represents the model perturbation that is built at iteration $l$ from the data residuals, whereas $\Delta m^{(k)}$ is the model perturbations integrated over the iterations and represents the migrated image.

Of note, at iteration one, $\delta G_{\text{cal}} = 0$ because the background model is smooth (i.e., $\Delta m^{(0)} = 0$). The operator $Q$ is a local weighting operator that varies from one diffractor point to the next (Jin et al., 1992). This is chosen such that a diagonalization of the Hessian operator can be performed in the framework of the high-frequency approximation (Thierry et al., 1999; their equation 9).

![Figure 1. Parameters involved in ray + Born migration/inversion.](image)

The lines connecting the source $s$ and the receiver $r$ to the diffractor point $x$ are rays, along which travel-times, amplitudes, and slowness vectors are computed. Nomenclature: $p_s$ and $p_r$ are source and receiver slowness vectors, respectively; $q = p_s + p_r$; $x$ is the diffractor point; $\theta$ is the diffraction or aperture angle; $\phi_s$ and $\phi_r$ are the takeoff angles of the source and receiver rays at the diffractor point $x$.
After diagonalization of the Hessian operator, the ray + Born migration/inversion reduces to a weighted stack of the wavefield perturbation residuals

\[
\delta m(x) = \frac{1}{[\theta(x)]_{\min}} \sum_s \sum_r e(r, x, s) \left( \delta \mathcal{Q}_{\text{obs}} - \delta \mathcal{Q}_{\text{cal}}(\Delta m^{(k-1)}) \right)
\times (T_0(r, x, s)),
\]

where \( \mathcal{Q}(t) = \mathcal{H}[\delta(t)] \) and \( e(r, x, s) = \left| q \right|^2 \delta(|q| - \omega \rho_{0}|q|). \) Time convolution is denoted by \( * \), \( \mathcal{H} \) denotes the Hilbert transform, and \( \delta(t) \) denotes the Dirac function. \( s \) and \( r \) denote the source and receiver, respectively; \( \Delta s \) and \( \Delta r \) are the source and receiver spacings, and \( \omega \) is the angular frequency. The vector \( q \) is the slowness vector, which is obtained by summing the source and receiver slowness vectors at the diffractor point \( x \) (Figure 1). The modulus of the vector \( q \) depends on the local velocity and the diffraction or aperture angle \( \theta \). The angles \( \phi_s \) and \( \phi_r \) are the angles made by the source and the receiver slowness vectors with the vertical, respectively. The complete derivation of equation 5 can be found in Thierry et al. (1999).

Resolution analysis of ray + Born migration/inversion

Substitution of the asymptotic Born operator (equation 2) in the expression of the Hessian operator gives

\[
B_0^+ \mathcal{Q} B_0(x, x_0) = \sum_s \sum_r \mathcal{D}(r, x, x_0, s, \omega) \times e^{-i \omega \Delta T(x-x_0)},
\]

where \( \mathcal{D}(r, x, x_0, s, \omega) = (\Delta x)^2 |K(\omega)|^2 A(r, x_0, s) A(r, x, s) \) and \( \Delta T(x-x_0) = T(r, x, s) - T(r, x_0, s) \) (Thierry et al., 1999). \( K(\omega) \) is the signature of the Born operator.

Jin et al. (1992) recognized the analogy between the expression of the asymptotic Hessian and that of a 2D Dirac function that allows for the diagonalization of the Hessian operator. The diagonalization of the Hessian operator is performed by applying the change of variables \( (S, R, \omega) \rightarrow (|k|, \Psi, \theta) \) in equation 6. Keeping the leading asymptotic terms of the amplitude and phase of the Hessian operator around the diagonal \( x = x_0 \), a judicious choice of the weighting operator \( \mathcal{Q} \), allows the Hessian to be written as a sum over the diffraction angle \( \theta \) of truncated Dirac functions:

\[
\mathcal{H}(x, x_0) = \int_{\theta_{\min}}^{\theta_{\max}} d\theta \int_{\Psi_{\min}^{(\theta)}}^{\Psi_{\max}^{(\theta)}} d\Psi \int |k| e^{-i k \cdot (x-x_0)},
\]

where the truncated Dirac function is written in polar coordinate \( k = \omega q(r, x_0, s) = \omega |p(x_0, s) + p(x_0, r)| \), and \( \Psi \) is the dip.

Assuming an infinite source bandwidth on the line and an infinite acquisition device, the Hessian operator can be approximated by a Dirac function \( \delta \):

\[
\mathcal{H}(x, x_0) \approx \frac{1}{[\theta(x)]_{\min}} \delta(x - x_0).
\]

This approximation is used in equation 5 where the term \( 1/[\theta(x)]_{\min} \) acts as a local scaling factor of the migrated image.

Expression 7 provides clear insights into the expected resolution of the ray + Born migration/inversion. Ray + Born inversion can be viewed as a redundant summation of common-\( \theta \) migrated images in which each individual migrated image has its own local wavenumber and dip resolutions (Lambare´ et al., 2003). According to the relationship \( k = \omega q \), the local wavenumber bandwidth at a diffractor point \( x_0 \) in the stacked migrated image is given by

\[
|k|_{\min} = \frac{2 f_{\min}}{c_0} \cos(\theta_{\max}/2); |k|_{\max} = \frac{2 f_{\max}}{c_0} \cos(\theta_{\min}/2),
\]

where \( f_{\min} \) and \( f_{\max} \) define the frequency bandwidth of the source. The dip coverage depends mainly on the offset coverage provided by the acquisition geometry and on the medium heterogeneities. Of note, the aperture coverage (i.e., the minimum and the maximum aperture angles \( \theta \)) varies from one diffractor point to the next (e.g., the wide aperture coverage decreases with depth). This analysis shows that variations in the local resolution of the ray + Born migrated image depend on the local aperture coverage.

Postprocessing of the migrated image by multiple VFSA

Problem statement

The postprocessing of the migrated section is formulated as a global optimization (Sen and Stoffa, 1995; Sambridge and Mosegaard, 2002) in which the data space is one vertical profile of the migrated image, noted as \( d(z) \). In the framework of the ray + Born migration/inversion, a vertical migrated profile is a band-limited velocity model of the subsurface. The postprocessing seeks to reconstruct broadband velocity models, noted as \( c_i(z) \), from the band-limited migrated section. To reconstruct the low- and high-frequency information that is missing in the migrated section, we use a suitable earth-layered parameterization for \( c_i(z) \) (Oldenburg et al., 1983). We assume that the migrated profile can be linearly related to the broadband velocity model, after depth-to-time conversion, by a convolution with the source wavelet \( s(t) \) that is assumed to be known, as \( d(t) = s(t) * \tilde{c}(t) \), where \( d(t) \) and \( \tilde{c}(t) \) denote the migration profile and the broadband velocity model, respectively, after depth-to-time conversion. This time convolution defines the forward problem of the global optimization. The depth-to-time conversion is performed using the migration background velocity model. The misfit function of the optimization is the least-squares norm of the misfit between the migrated profile and the convolved velocity model in the time domain \( E = \| \tilde{d}(t) - s(t) * \tilde{c}(t) \|^2 \).
The inversion is solved by a random exploration of the model space using the VFSA algorithm to deal with the nonuniqueness of the solution (Sen and Stoffa, 1995). The inversion is applied independently to each profile of the migrated section, and a final 2D velocity model is built by the assembly of each 1D model in the distance-depth domain.

During the VFSA inversion, the models are parameterized by a stack of \( n \) homogeneous layers of arbitrary thickness \( \Delta z_i \) and velocity \( \Delta c_i \), where \( i = 1, n \). One benefit of this parameterization is to limit the model space to be explored during VFSA optimization. More importantly, such layered parameterization of the velocity model implies that the reflectivity associated with the layered model can be written as the sum of \( n \) delayed Dirac delta functions, \( r(t) = \sum_{k=1}^{n} r_k \delta(t - \tau_k) \), where \( r_k \) is the reflection coefficient at the bottom of layer \( k \) and \( \tau_k \) is the two-way traveltime to the \( k \)th layer (Oldenburg et al., 1983). This layered parameterization forces the velocity model built during the postprocessing to have a broad wavenumber bandwidth.

The minimum thickness of the layer is set to \( \lambda_j/4 \), where \( \lambda \) denotes the dominant wavelength of the source according to the Rayleigh criterion of resolution (Jenkins and White, 1957). The maximum allowable thickness is the maximum depth of the model, and the sum of the layer thickness is forced to match the maximum depth of the model. The number of layers \( n \) in the model (namely, the order of the autoregressive process in Oldenburg et al., 1983) can vary from one VFSA iteration to the next. The layered models can be parameterized in terms of (absolute) velocities or velocity perturbations (\( \Delta c \)) with respect to the velocity background model used for migration. One advantage of the velocity-perturbation parameterization is to further narrow the model space by limiting the exploration in the vicinity of the background velocity model. Minimum and maximum allowable velocity bounds are input into the algorithm and can be inferred from a priori constraints provided by well logs or from the values extracted from the migrated section.

### Implementation of VFSA

In our implementation of the VFSA algorithm, the parameters for the layer thickness \( \Delta z_i^{(k+1)} \) and the velocity perturbations \( \Delta c_i^{(k+1)} \) of the \( i \)th layer at iteration \( k + 1 \) (annealing step) are generated from the values at the previous iteration \( k \):

\[
\Delta z_i^{(k+1)} = \Delta z_i^{(k)} + y(T)\Delta z_{\text{max}}; \quad \Delta c_i^{(k+1)} = \Delta c_i^{(k)} + y(T)\Delta c_{\text{max}},
\]

(10)

where \( T \) denotes the temperature of annealing and \( y(T) \) is chosen as a Cauchy distribution of the temperature (Ingber, 1992):

\[
y(T) = \text{sgn}(u - \frac{1}{2})T \left[ \left(1 + \frac{1}{T} \right)^{[2u-1]} - 1 \right],
\]

(11)

where the variable \( u \in [0, 1] \) is generated pseudorandomly

With this probability distribution, Ingber (1992) showed that the global minimum is reached if the temperature satisfies

\[
T(k) = T_0 \exp\left( -\frac{k}{n(k)} \right),
\]

(12)

where \( n(k) \) is the total number of parameters in the model \( m^{(k)} \) at iteration \( k \) and \( z \) is the cooling factor. Suitable values of the scalars \( z \) and \( T_0 \) must be tuned by trial and error for each particular problem. This algorithm is known as the VFSA, and it allows the convergence to be accelerated compared with a conventional simulated annealing algorithm (Sen and Stoffa, 1995).

Our implementation of the VFSA algorithm is outlined in Figure 2. The algorithm contains four nested loops. The outer loop is over the temperature \( T \). As according to Jackson et al. (2004), we explore several models per temperature in the second loop of the algorithm over the “moves per temperature.” A random walk satisfies the conditions of Markov chains if a model generated at the iteration \( k + 1 \) is close to that of the previous iteration. To satisfy this condition, a layer-stripping approach is implemented with the third loop of the algorithm over the layers of the model: The algorithm proceeds hierarchically from the shallow layers to the deep layers. The innermost loop is over the model parameters, which include the thickness and the velocity of the layers located above the deepest level defined by the layer-stripping reconstruction (third loop). Within the innermost loop, the model parameters are randomly perturbed \( np \) times following equation 10. If the misfit function \( E_{k+1} \) computed for the model of iteration \( k + 1 \) is smaller than the misfit function \( E_k \) computed for the model of iteration \( k \), the new model is accepted; otherwise the model is accepted with a probability of \( e^{-(E_k - E_{k+1})/T} \), following the Metropolis criterion (Sen and Stoffa, 1996; Sambridge and Mosegaard, 2002).

### Estimation of parameter uncertainties through multiple VFSA

For quantitative estimates of the nonuniqueness of the parameters, it is necessary to estimate a multidimensional probability distribution that quantifies how likely different model-parameter combinations are given the uncertainties in the observations. During the search for the optimal model, the simulated annealing algorithm samples an area of the model space. Sen and Stoffa (1995) proposed to perform several independent runs of the simulated annealing optimization in which each run is under different initial conditions and the corresponding posterior probability density function (PDF) \( \pi(m) \) is estimated. The PDF is defined as the frequency of the visits weighted by its PDF \( L(m) = \exp(-E(m)) \) (Tarantola, 1987). This estimate will necessarily be skewed, although the error will depend of the true form (distribution) of \( \pi(m) \) and naturally on the number of independent tests carried out. Jackson et al. (2004) proposed to fix the temperature in the simulated annealing algorithm and to count the number of visits of different cells of the model space.
The frequency (normalized by the probability) of the visits will converge toward \( \pi(m) \). In practice, the simulated annealing algorithm can be run at constant temperature over many iterations. The number of accepted models satisfying the Metropolis criterion and having visited a given cell of the model space (i.e., a depth-velocity pair) can be counted. At the end of the iterations, each cell of the velocity-depth matrix represents the frequency of visits to each portion of the model space. The mean model and the standard deviation can be inferred from this matrix.

**SYNTHETIC EXAMPLES**

**Validation in a one-layer model**

We first consider a homogeneous background velocity model with a velocity of \( c_0 = 3500 \text{ m/s} \) containing a 100-m-thick horizontal layer with a velocity of \( c_L = 3700 \text{ m/s} \) that is located at a depth of 1.5 km. The thickness of the layer and the amplitude of the velocity perturbation are sufficiently small to satisfy the criterion of small perturbations that is imposed by the Born approximation. The source wavelet is a zero-phase signal with...
a trapezoidal amplitude spectrum \([0,10,35,55]\) Hz (Thierry et al., 1999). The shots and receivers are on the surface and mimic a multichannel seismic reflection experiment. The shot and receiver spacings are 50 and 25 m, respectively. The minimum offset is 50 m, and there are 60 receivers, which leads to a maximum offset of 1.5 km.

**Iterative migration/inversion**

We first assess the wavenumber content of the migrated section reconstructed by iterative ray-Born migration/inversion. The macromodel for migration is the homogeneous background velocity model with a velocity of 3500 m/s. The vertical profile extracted in the middle of the 2D ray-Born migrated image after the 1st and the 14th iterations of the ray-Born inversion are shown in Figure 3. To assess the vertical wavenumber content of the migrated image, we match the migrated profile with the true profile after band-pass filtering with a trapezoidal filter. The band-pass filtering is applied in the time domain after depth-to-time conversion. At iteration 1, the filter providing the best match has a spectrum given by \([0,10,35,55]\) Hz, which is the same as that of the source wavelet (Figure 3a). According to the resolution analysis of the ray-Born inversion, this suggests that at iteration 1 the inversion mainly exploits the short apertures and the high-frequency content of the data. At iteration 14 (Figure 3b), the best-fitting filter has a broader bandwidth, \([0,3.5,35,55]\) Hz, toward low frequencies, and it shows the ability of the ray-Born migration/inversion to exploit low frequencies and wide-aperture angles over iterations for this simple model.

For completeness, the match between the ray-Born seismograms computed in the true model and the migrated images at iterations 1 and 14 are shown in Figure 4, along with the residuals. Figure 4 allows for a qualitative assessment of the impact of the data amplitude match on the true-amplitude reconstruction of the model perturbations.

**Validity of the convolutional model**

The convolutional model of the postprocessing assumes that the vertical wavenumber content of the migrated image \(|k_{\min} = \frac{2\pi f}{c_0}; |k_{\max} = \frac{2\pi f_{\max}}{c_0}|\) is only controlled by the source...
bandwidth and that the structure is laterally homogeneous (which would justify the postprocessing as a series of independent 1D problems). In contrast, the resolution analysis of the ray + Born migration/inversion showed that the wavenumber content of the migrated image depends on the local aperture coverage provided by the acquisition geometry, in addition to the frequency, equation 9. The vertical wavenumber content of the migrated image would only depend on the source bandwidth in the case of normal-incidence data (i.e., $\theta = 0^\circ$) and laterally homogeneous media (i.e., zero horizontal wavenumbers). The aim of the following experiment is to assess the validity of the convolutional model used in the postprocessing as a function of the aperture coverage provided by the source-receiver offset coverage. For this, we compute ray + Born data sets in the true model for several receiver devices of increasing length (see Table 1) and migrate the resulting data sets. Secondly, we convolve the true model with the source wavelet after depth-to-time conversion and assess the range of maximum source-receiver offsets in the data that lead to an acceptable match between the ray + Born perturbation model and the convolved model (Figure 5a). Of note, for this experiment, we performed only one iteration of the ray + Born inversion such that the spectrum of the migrated profile after depth-to-time conversion is close to that of the source spectrum (Figure 5).

The rms misfit between the migrated and the convolved vertical profiles suggests that for this simple example the convolutional model is a reasonable approximation for a maximum aperture angle of 100° in the data (Figure 5b). The wavenumber content of the migrated profiles obtained close to one iteration of ray + Born migration/inversion as a function of the maximum aperture angle and does not vary significantly in Figure 5a, which justifies why an acceptable fit was obtained for maximum aperture angles as high as 100°.

Results of the VFSA postprocessing

The VFSA optimization was applied to the one-layer model case study. Ray + Born data were computed using 100 receivers per shot gather, leading to a maximum aperture angle of 80° at a depth of 1.5 km. The migration macromodel is homogeneous and has a velocity of 3500 m/s. The maximum depth in the model is 3 km. The minimum and maximum layer thicknesses allowed in the VFSA layered models are 100 and 500 m, respectively. Therefore, the minimum and maximum number of layers in the output models are six and 30, respectively. The maximum velocity perturbation allowed in the output models is 250 m/s. One key tunable parameter of the VFSA optimization is the initial temperature $T_0$. The impact of the initial temperature in the exploration of the model space is illustrated in Figure 6, which shows the first 20 models explored during three independent runs of the VFSA algorithm performed with three different initial temperatures. If too high of a value of the initial temperature is used, most of the sampled models are accepted, allowing extensive exploration of the model space at the expense of the computational cost (Figure 6a). For intermediate temperatures, the number of accepted models is close to that of the rejected models (Figure 6b). For low temperatures, very few models are accepted, hence favoring the speed of the convergence at the expense of the exploration of the model space (Figure 6c). A criterion to select an appropriate starting temperature is seen in the balance between the accepted and rejected models; therefore, the intermediate temperature exploration of Figure 6b can provide a good trade-off between model-space exploration and computational efficiency. Note also that the amplitudes of the perturbations decrease with temperature because of the dependence of the PDF.

We then performed 13 runs of the VFSA optimization using the same starting temperature but with different starting models of the random walks and with different roots of the pseudorandom series.

![Figure 5. Validation of the postprocessing forward problem. The target is the one-layer model considered in Figure 3. (a) Migrated traces (gray lines) computed for the acquisition setups listed in Table 1. The horizontal labels denote the maximum aperture angle illuminated by the acquisition geometry at the target depth (1.5 km). True velocity profiles after convolution with the source wavelet (black lines) are superimposed for comparison. (b) rms misfit function between the two sets of profiles shown in panel a as a function of the maximum aperture angle. The shaded area delineates the range of aperture angles providing a sufficiently good match between the two sets of profiles.](image)

### Table 1. Acquisition geometry used during the numerical tests.

<table>
<thead>
<tr>
<th>$\theta$</th>
<th>10</th>
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<th>30</th>
<th>40</th>
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<td>$nr$</td>
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<td>30</td>
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<td>118</td>
<td>141</td>
<td>169</td>
<td>205</td>
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<td>327</td>
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<tr>
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<td>0.72</td>
<td>1.03</td>
<td>1.35</td>
<td>1.65</td>
<td>2.02</td>
<td>2.45</td>
<td>2.92</td>
<td>3.50</td>
<td>4.20</td>
<td>5.10</td>
<td>6.35</td>
<td>8.15</td>
</tr>
</tbody>
</table>

*Here, $\theta$ represents the diffraction angle at the reflector, $nr$ is the number of receivers, and $L$ is the length of the acquisition device in kilometers.*
The best-fitting models for each run are shown in Figure 7a. The best-fitting models can be subdivided into two categories: one model family reproduces the correct shape of the layer, in contrast to the second one, which is dominated by a strong negative velocity contrast at a depth of 1.6 km at the bottom of the layer. The match between the migrated profiles and the modeled profiles and the corresponding misfit function are shown in Figure 7b and c, respectively. The match obtained with the category of models that reproduces the correct shape of the layer is significantly better than that obtained with the second category of model. This suggests that the inversion remained stuck in a local minimum for several runs of the VFSA. These results show that the inverse problem is sufficiently well posed for this case study to discriminate accurate models from erroneous ones on the basis of the final values of the misfit function. However, the convergence of the VFSA algorithm appears to be sensitive to the starting model, and several independent runs of the VFSA might be necessary to guarantee convergence toward the global minimum of the cost function. Another remark is that the shape of the layer was perfectly reconstructed from the band-limited migrated profile. This illustrates how the layered parameterization allows us to reconstruct the missing low-wavenumber and high-wavenumber information that was lacking in the migrated profile when the model parameterization conforms to the true earth structure.

Uncertainty analysis

Even in this simple case, the estimate of the posterior PDF \( p(m) \) appears computationally expensive. To overcome this computational burden, we have applied the multiple VFSA approach, as proposed by Jackson et al. (2004). We performed 20 independent runs of the simulated annealing algorithm. The temperature of this exploration was fixed, as suggested by Jackson et al. (2004). The number of visits of the accepted models in the velocity-depth domain represents the posterior PDF (Figure 8a). The footprint of the two abovementioned model families is visible in Figure 8a. However, because each explored model \( m \) is weighted by \( \exp(-E(m)) \), the best-fitting models (i.e., those reproducing the correct shape of the layer) have a dominant contribution in Figure 8a. As a result, the stack of the columns of the PDF matrix provides an average \( \mu(m) \) of the matrix and the standard deviation \( \sigma(m) \). The average model is very close to the exact solution, which is inside of the shaded area of Figure 8b.

![Figure 6](image6.png)

Figure 6. Influence of the starting temperature on the VFSA exploration of the model space. The target is the one-layer model considered in Figure 3. The first 20 models explored during three independent runs of the VFSA inversion are shown for three different starting temperatures: (a) \( T_0 = 1.0 \), (b) \( T_0 = 0.5 \), and (c) \( T_0 = 0.1 \). The accepted and rejected models are plotted in gray and black, respectively.

![Figure 7](image7.png)

Figure 7. Influence of the starting model in VFSA inversion. The target is the one-layer model considered in Figure 3. (a) Best-fitting models for 13 independent runs of VFSA inversion. The starting temperature was the same for each of the 13 runs, and only the starting model changes from one run to the next. The arrows indicate the models for which the VFSA inversions converge to the global minimum. (b) Match between the migrated velocity profiles (gray lines) and the convolved VFSA model (black lines) for the 13 runs. (c) Final misfit function for the 13 runs. A smaller misfit function is obtained when the VFSA inversion converges toward accurate models.
Application to the complex Marmousi model

We applied the processing workflow to the complex Marmousi model (Figure 9a), which was created by the Institut Français du Pétrole (IFP). The macromodel for ray + Born migration/inversion was built by smoothing the true velocity model with a 2D Gaussian filter of horizontal and vertical correlation lengths of 76 m (Thierry et al., 1999; Operto et al., 2000) (Figure 9b). The source bandwidth is [0–10–35–55] Hz. We used a velocity macromodel sufficiently accurate to guarantee accurate migration results and therefore reliable assessment of the postprocessing optimization. In this application, the VFSA models returned by the postprocessing will be parameterized in terms of velocity perturbations with respect to the velocity background model to make the VFSA optimization relatively independent to the macromodel used for migration. The background velocity model will be used during the postprocessing for depth-to-time conversion of the perturbation model and as an a priori to bound the exploration of the model perturbations. More extensive discussion on the sensitivity of the ray + Born migration to the accuracy of the starting model is provided in Operto et al. (2000).

Iterative ray + Born migration/inversion

We roughly mimic the true migrated image by band-pass filtering the true velocity model in the time domain within the bandwidth [5–10–35–55] Hz (Figure 10a). The bandwidth used to build the true migrated image was chosen to match as well as possible the computed migrated image. The ray + Born migration was computed for velocity perturbations and the density was considered as constant and equal to 1. We computed nine iterations of ray + Born single-arrival migration/inversion using the strongest arrival in the migration. The migrated images after iterations 3 and 9 are shown in Figure 10b and c without any constant scaling or automatic gain control and with the same amplitude scale as for the true perturbation model (Figure 10a). The successive iterations of the ray + Born migration/inversion allow for reliable reconstruction of the amplitudes of the velocity perturbations. Interestingly, a good image of the target at a depth of 2.5 km and a distance of 6.5 km was obtained after nine iterations, although only one arrival was involved in the migration. Of note, unlike in the single-layer model, the wavenumber spectrum of the migrated image did not significantly change over iterations. Only the amplitudes of the velocity perturbations strongly increase over iterations. The migrated images built from the data residuals at iterations 3 and 9 of the ray + Born inversion are shown in Figure 11. Of note, the last iterations of the ray + Born inversion mainly generated perturbations in the target zone intersected by multivalued ray paths (see Figure 11 in Thierry et al., 1999, for a plot of a multivalued ray paths in the Marmousi model), whereas the perturbations were more uniformly distributed in the model during the earlier iterations. We conclude that iterative single-arrival ray + Born migration/inversion allows multipathing to be managed over iterations and provides an alternative to more elegant, but more complex, inversion algorithms in which the multivalued
raypaths are taken directly into account in the modeling and inversion algorithms (Xu and Lambare, 2004). For completeness, the accuracy of the reconstruction of the velocity perturbations can be assessed more quantitatively by comparison between different profiles extracted from the true migrated section and the computed migrated section at iterations 1 and 9 (Figure 12). The match is similar to that obtained by Xu and Lambare (2004). The match between the data computed in the true migrated section and in the reconstructed ones at iterations 1 and 9 are illustrated in Figure 13 for three shot gathers. The reduction of the misfit function summed over the full data set was 30% between iterations 1 and 9. Of note, the bandwidth of the filter used to build the true migrated section ([5–10–35–55] Hz) is slightly narrower that of the source wavelet ([0–10–35–55] Hz). This suggests that, unlike the case of the one-layer model shown in the previous section, the ray + Born migration/inversion failed to exploit the low-frequency content of the source over iterations in the case of the structurally complex Marmousi model.

**Postprocessing of the migrated images and uncertainty analysis**

We first applied the VFSA inversion to each profile of the true migrated section (Figure 10a) to validate the approximations used in the convolutional model of the postprocessing in the case of complex structures. In the following, the output models of the postprocessing will be referred to as “layered velocity perturbation models” (LPMs). The velocity model obtained by summing the velocity background model with the mean of the accepted LPMs is shown in Figure 14a, and it is very close to the true Marmousi model (Figure 9a), apart from lateral high-frequency artifacts resulting from independent processing of each profile of the migrated image. Then, the VFSA inversion was applied to the final ray + Born migrated image (Figure 10c). The velocity model obtained by summing the velocity background model with the mean of the accepted LPMs is shown in Figure 14b. The match with the true Marmousi model is reasonably good, especially in the shallow structure. The standard deviation for Figure 14a and b are plotted in Figure 14c and d. Figure 14c shows small uncertainties of results (i.e., the standard deviation is less than 100 m/s). Figure 14d shows standard deviations of approximately 300 m/s at 2-km depth, indicating that in this region uncertainties of results are bigger.

![Figure 10](image1.png)

**Figure 10.** Marmousi example. (a) True perturbation model obtained by band-pass filtering the true model in the time domain with a filter of trapezoidal bandwidth [5–10–35–55] Hz. (b and c) Ray + Born migrated images \(d_m(\mathbf{r})\) after iterations 3 (b) and 9 (c) of ray + Born inversion. The three velocity perturbation images are plotted with the same amplitude scale, ranging from \(-500\) to 500 m/s.

![Figure 11](image2.png)

**Figure 11.** Marmousi example. Perturbation models \(d_m(\mathbf{r})\) built at iterations 1 (a) and 9 (b). During the late iterations, the inversion mainly updated deep areas intersected by multivalued raypaths.
Figure 12. Marmousi example. Comparison between vertical profiles extracted from the true perturbation model (black lines) and the ray + Born migrated images (gray lines) at iterations 1 (a) and 9 (b). The profiles are taken at horizontal distances of 3.7, 5.0, 6.2, and 8.0 km. The true perturbation model and the ray + Born migrated image at iteration 9 are shown in Figure 10a and c.
Figure 13. Marmousi example. (a) Three ray + Born shot gathers computed in the true model. (b) Corresponding shot gathers computed in the ray + Born migrated images at iterations 1 (first three panels on the left) and 9 (last three panels on the right). (c) Residuals between seismograms of panels (a and b).
Comparisons between a few velocity profiles extracted from the Marmousi model and the reconstructed ones (background model + LPM) are shown in Figure 15a through d (left). The comparison between the corresponding profiles of the true migrated section and the ray + Born migrated section is shown in Figure 12b. A comparison between Figure 12b and Figure 15 illustrates how the errors in the reconstruction of the velocity perturbations in the ray + Born migrated images translate into errors in the reconstruction of the broadband velocity models returned by the VSFA inversion.

For the uncertainty analysis, we performed three runs of the VFSA for a fixed temperature and one vertical profile located at a horizontal distance of 8 km (Figure 16). We used the true migrated section (Figure 10a) and the final ray + Born migrated section (Figure 10c) as data for this uncertainty analysis. The posterior PDFs and the average model ± standard deviation are shown in Figure 16a through c for the true migrated section (Figure 10a) and in Figure 16b through d for the final ray + Born migrated section (Figure 10c). The pattern of this map closely follows the velocity profiles shown in Figure 15. Comparison between the profiles of the migrated section at a distance of 8 km (Figure 12a and b) with the LPMs (Figure 16c and d) allows one to assess the broader wavenumber content of the perturbation models returned by the postprocessing compared with that of the migrated profiles. However, significant differences are shown between the LPMs inferred from the true migrated section and the computed one (Figure 16c and d) that give some insights into the sensitivity of the stochastic inversion to the accuracy of the migrated images.

REAL DATA CASE STUDY

We applied the processing workflow to a 2D multichannel seismic reflection profile acquired in the Gulf of Guayaquil across the Ecuador subduction margin during the SISTEUR cruise (Collot et al., 2002). The data set consists of 1900 shot gathers with a shot interval of 50 m. The streamer is composed of 348 receivers spaced by 12.5 m. The frequency bandwidth of the source is approximately [8-20] Hz. The line 72, processed in this study, was initially processed with a kinematic prestack-depth migration using the SIRIUS-2.0 software package (Calahorrano et al., 2008). The migrated image revealed major trench and margin wedge structures associated with the Ecuador subduction zone, including a small accretionary wedge, and a well-imaged, 0.8-km-thick subduction channel defined as a layer of poorly consolidated sediment dragged down the subduction with the downgoing plate (Shreve and Cloos, 1986). The subduction channel is roofed and floored by thick, strong, and continuous reflections that Calahorrano et al. (2008) interpreted as the interplate décollement zone (Bates and Jackson, 1987) and the top of the underthrusting oceanic crust. At subduction zones, the plate boundary fault, which accommodates plate convergence through seismic or aseismic slip, has been shown to be a weak décollement or detachment zone located at the top of the subduction.
Figure 15. Marmousi example. Comparison between velocity profiles from the true model (black lines) and from the velocity models shown in Figure 14a and b (gray lines). The profiles are taken at the same horizontal distances as in Figure 12: (a) 3.7 km, (b) 5.0 km, (c) 6.2 km, and (d) 8.0 km. In the left and right panels of (a through d), the gray profiles are taken from the velocity model of Figure 14a and b, respectively.
channel (Taira et al., 1992). Because the mechanical coupling along the décollement zone depends on the fault hydrologic properties, it is important to investigate its velocity-porosity variations. Mapping of these variations is the motivation beyond the application of the VFSA optimization to the migrated section.

These structures just described are labeled in the true-amplitude ray + Born migrated section developed in this study (Figure 17). An initial background velocity model for ray + Born migration/inversion was built from a classic common depth point (CDP) velocity analysis followed by interval velocity conversion using the Dix formula. Ray + Born migration/inversion with iterative refinement of the background model based on the migration-based velocity analysis of Al-Yahya (1989) was subsequently applied to obtain a first migrated image (Agudelo et al., 2006). The preserved-amplitude data preprocessing for ray + Born migration/inversion includes mute, multiple attenuation, spiking deconvolution, and band-pass filtering. The density was not taken into account in the imaging; therefore, the migrated image is described by velocity perturbations. Once the final background model was inferred from the migration-based velocity analysis, five linear iterations of the ray + Born migration/inversion were computed to minimize the data residuals. The absolute values of the velocity perturbations in the migrated image were scaled using the reflection coefficient on the sea bottom, which was inferred from the ratio between the amplitude of the normal-incidence reflection on the sea bottom and that of the free surface multiple (Warner, 1990). We apply the VFSA postprocessing to the migrated image in the area of the décollement zone to attempt documenting the variability of its physical properties. We estimate the source wavelet required by the convolutional model of the postprocessing using three methods. We first consider the source signature inferred from the method of Ziolkowski et al. (1982) based on the near-field measurement of the source. A second source wavelet was simply inferred from the stack of the direct wave. A third source wavelet was inferred by linear least-squares waveform inversion of the direct wave in the frequency domain (Pratt, 1999, his equation 17). A homogeneous medium representing the water column was used during the source estimation by linear inversion. The three source wavelets and their amplitude spectrum, inferred from the three methods just described, are shown in Figure 18. We show a good overall agreement between the three source signatures, although the source wavelets inferred from the direct wave have a higher low-frequency content and a lower high-frequency content than the wavelet inferred from the near-field measurement. In the following, we shall use the wavelet obtained by linear least-squares waveform inversion of the direct wave in the frequency domain (Pratt, 1999, his equation 17). A homogeneous medium representing the water column was used during the source estimation by linear inversion. The three source wavelets and their amplitude spectrum, inferred from the three methods just described, are shown in Figure 18. We show a good overall agreement between the three source signatures, although the source wavelets inferred from the direct wave have a higher low-frequency content and a lower high-frequency content than the wavelet inferred from the near-field measurement. In the following, we shall use the wavelet obtained by linear inversion of the water wave to perform the postprocessing. During postprocessing of the migrated image, we have selected one trace every $x = 250$ m, and we have tested approximately 200,000 models for each trace in the VFSA inversion. The initial temperature and the cooling factor were fixed to $T_0 = 0.01$ and $\alpha = 0.0001$, respectively. One sequential run of the VFSA took 97 s on a 2.4-GHz dual core Opteron biprocessor computed for approximately 200,000 models. For uncertainty analysis, we performed 20 runs of VFSA. The multiple runs of VFSA for uncertainty analysis are uncoupled and therefore can be easily performed in parallel.

Results are summarized in Figure 19, which shows a close-up centered on the décollement of the ray + Born migrated image (Figure 19a) and the mean LPMs with superimposed standard deviation (Figure 19b and c). We show that different reflector signatures in the ray + Born migrated image translate into significant structural variations of the décollement in the LPMs. However, negative velocity contrasts between the décollement layer and straddling rocks is a constant feature in

Figure 16. Marmousi example. (a and b) Maps of the number of visits of each velocity-depth cell that samples the model space for a velocity profile located at a distance of 8.0 km. These maps were obtained using the true-perturbation model and the final ray + Born migrated image as input data in the VFSA inversion, respectively. (c and d) Standard deviations inferred from the maps shown in panels (a and b), respectively.
most of the LPDs. Identification of these negative velocity contrasts is not obvious from the band-limited migrated images alone. Two close-ups of the images of the décollement are presented in Figure 19b and c. Zooms of the décollement reflector reveal that it corresponds to a layer with an average thickness of 80 m and with a negative velocity contrast with respect to overlying rocks of approximately –50 m/s that can locally reach –250 m/s. Uncertainties associated with these best-fitting models are presented in Figure 19 (bold-gray zones). In the zone of the décollement, the error is remarkably small. An 80-m-thick décollement layer rather supports a shear band than a single fault plane along the roof thrust of the subduction channel. These lateral velocity variations may reflect intrinsic variations in porosity and therefore fluid content according to the \( V_p \)-porosity empirical relationship by Erickson and Jarrard (1998). A possible interpretation of the relationship between the seismic signature of décollement and fluids is presented in the qualitative diagram of Figure 20, which is in agreement with results presented by Shipley et al. (1994) in the Barbados Ridge. Segments of negative velocity contrast associated with an 80-m-thick décollement layer (Figure 20a) would have slightly higher porosity and therefore higher fluid content than nearby rocks, thus possibly favoring slip along poorly coupled segments of the thrust interface. Zones of the décollement layer with slightly negative velocity contrast, underlain by a zone of positive velocity contrast at the top underlying rocks (Figure 20b), could be associated with areas of fluid diffusion toward the overlying rocks. This situation might be favorable for hydrofracturation, a process that is expected to contribute to basal erosion at active margins (Le Pichon et al., 1993). Other segments of the décollement layer are not associated with detectable amplitude variations and therefore do not show noticeable velocity contrast (Figure 20c). These segments of layers are too thin (<20 m) to be detected or they may be hydrogeologically isolated and possibly drier than surrounding segments of the décollement. In the latter case, the décollement fault would be better coupled locally because of a higher coefficient of friction.
Figure 19. Results of the target-oriented postprocessing applied to the décollement zone on top of the subduction channel. (a) Close-up of the ray + Born migrated image centered on the décollement zone. Two segments of the décollement (1 and 2) with different seismic signature are delineated. (b) Area 1 — Top panel: mean broadband perturbation models with superimposed $\pm$ standard deviation. Bottom panel: migrated image with several superimposed mean broadband perturbation models. (c) Same as in panel (b) for area 2. The arrows point to the velocity variations in the décollement.
CONCLUSIONS

We develop a seismic workflow that combines least-squares migration/inversion and stochastic inversion to derive inferences on the fine-scale P-wave velocity (or impedance) structure of selected targets. The main objective of the stochastic inversion is to build high-resolution velocity models characterized by a layered parameterization from the band-limited migrated images and to estimate the uncertainties of these velocity models by means of a multiple VFSA algorithm. Unlike many workflows used in reservoir characterization, the stochastic inversion is applied to true-amplitude depth-migrated sections. Because the postprocessing is implemented in the poststack domain as a series of 1D optimization problems, an extensive exploration of the model space through multiple runs of VFSA can be performed for uncertainty analysis. In this study, the stochastic inversion was applied to 2D migrated sections. However, the stochastic inversion should extend to 3D problems because it consists of a series of 1D inversions, the forward problem of which is described by a simple convolutional model. The outputs of the ray + Born migration/inversion and the stochastic inversion can be parameterized by velocity or impedance models. Extension to elastic media can be viewed if reliable elastic migrated images can be developed from multicomponent receivers. We have illustrated the applicability of the method to real data with the fine-scale characterization of a detachment zone on top of the subduction channel off the shore of Ecuador. The seismic workflow presented in this study might provide some guidelines for developing methodologies for reservoir and petrophysical characterizations from true-amplitude depth-migrated images.

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REFERENCES
