A stochastic approach of Residual Move Out Analysis in seismic data processing

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Introduction

Analysis of the subsurface geology in order to identify and optimise the production of oil and gas deposits relies on the interpretation of seismic images. The seismic images in the depth's domain are the result of an inversion tool which is called depth migration. Depth migration converts wave field recorded in "time domain" in "depth domain". This conversion requests an accurate knowledge of vertical and horizontal seismic velocity variations. So-called Common-Image-Gathers (CIGs) serve as a tool to verify correctness of velocity models. CIG compute in the surface offset (distance between source and receiver) domain using correct velocity model should show flat event for main reflectors. The curvature of events (Residual MoveOut) present on this CIG is due to the ratio of velocity use for the migration to medium velocity. The main goal of Residual MoveOut analysis is to estimate this ratio which represents the curvature of event for the velocity model updating. Conventional Residual Move Out analysis is based on the scan of events present in the CIG panel. A criterion called semblance is used to pick a curvature which match the most with the event. A stochastic version of this analysis by the mean of Bayesian modelling is discussed in this work. It provides a quantification of the uncertainty which is not currently considered, and which could help in the decisions that will have important social and commercial implications. With the Bayesian setting, prior knowledge about the Residual MoveOut curvature is combined with the information contained in the migrated data in the surface offset domain. The prior knowledge about the curvature is specified by a probability density function where the prior belief and the corresponding uncertainty are defined. The relationship between the curvature parameter and the migrated data in surface offset data is described by the likelihood model. The posterior distribution provides both the most probable curvature and information about the corresponding uncertainty. Since analytical expression for the posterior distribution can not found in our case, Markov Chain Monte Carlo simulation is used to explore it. Data and conventional method of Residual MoveOut analysis is briefly presented in the following section and then the Bayesian approach is presented and illustrated by an example on synthetic and real data.

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Data presentation

The Residual Move Out analysis is performed on offset domain Common Image Gathers which are subsets of the whole image with fixed surface location and function of offset data. Variations between the partial images at the fixed image point are the principal elements of the Residual MoveOut analysis (See figure (1) and(2)).

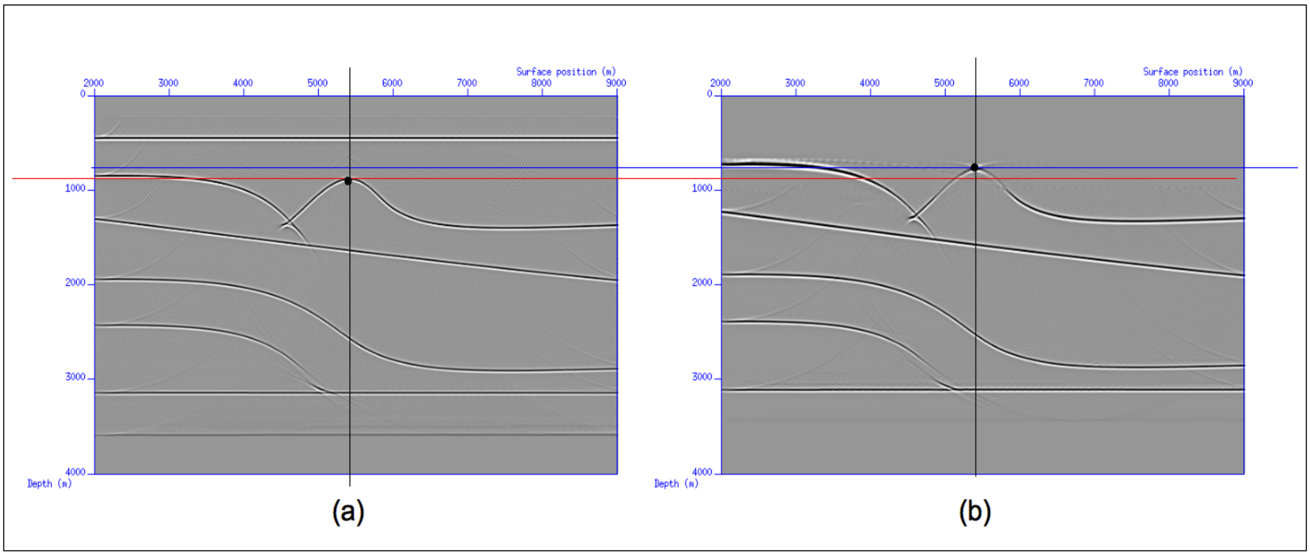


Figure 1: (a) Image at zero-offset (b) Image at offset 2500m of synthetic data . Vertical line represents the surface position at 5425m

For example, in this synthetic data, at the surface position fixed at 5425m, we notice that the summit of the dome represented by the black point on the image (a) and (b) of Figure (1) changes in depth. In other words, if we fix a point of coordinates (x,z) of the image where x is the surface location and z the depth, the corresponding amplitude $a(x,z)$ is not the same on the two images of figure (1). Now if we decide to follow the evolution of the depth z of the summit of the dome according to the offset h, we notice that this one has a hyperbolic geometry (figure(2)). This hyperbolic geometry is given by the following equation: $z(h) = \sqrt{z_0^2 + (\gamma^2 - 1)h^2}$ where z_0 is the depth observe on zero-offset image,$\gamma = \frac{v}{c}$ with v the velocity used for the migration and c the media velocity and h the half-offset . [3] and [1] show how to obtain this equation. In the following section we shall show how this equation is exploited to implement the conventional Residual Moveout Analysis.

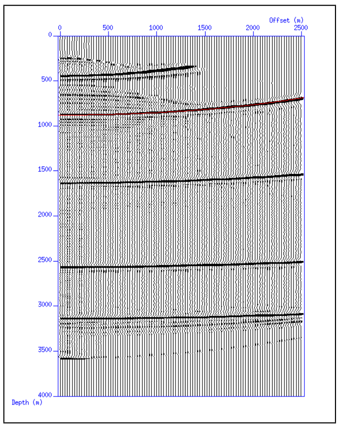


Figure 2: Offset Domain Common Image Gather at surface position 5425m. The line in red represents the depth's evolution according the offset.

Conventional Residual MoveOut Analysis

At fixed z_0, the residual moveout curve is completely determined by the parameter $\gamma = \frac{v}{c}$. The conventional residual moveout analysis algorithm define for each depth z_0 a set of values of γ and so a set of residual moveout curve. A coherence along each residual moveout curve is computed by the mean of the semblance[6] which is widely used in the seismic world for the detection of coherent events in the data . The definition of semblance $S(i_0,\gamma)$ is

$$S(i_0,\gamma)=\frac{\sum_{i=i_0-\frac{W}{2}}^{i_0+\frac{W}{2}}(\sum_{j=1}^{M}a_{i+w(j,\gamma),j})^2}{M\sum_{i=i_0-\frac{W}{2}}^{i_0+\frac{W}{2}}\sum_{j=1}^{M}a^2_{i+w(j,\gamma),j}}, \quad (1)$$

where i_0 is the index which represents z_0 and M is the number of traces contributing to the coherence analysis. The value of $w(j,\gamma)$ describes the sample of the discrete depth on the trace indexed by j which depends on γ value. A depth window of width W is centered about i_0 where the semblance is computed. The index i represents the sample position in the depth window. All amplitudes $a_{i(j,\gamma),j}$ within W enter into the semblance analysis, where $a_{i(j,\gamma),j}$ is calculated by a linear interpolation between the amplitude values associated the two samples next to $w(j,\gamma)$. The sums in the denominator in equation (1) describe the energy in the subset of prestack data used for the semblance analysis while the sums in the numerator yield the energy of the stacks along residual moveout curve shifted in the depth window. Thus, the semblamce coefficient $S(i_0,\gamma)$ gives the normalized ratio of output to input energy which may vary between 0 and 1, where the maximum $S(i_0,\gamma)=1$ is obtained if all considered amplitudes $a_{i(j,\gamma),j}$ are identical, separately for each fixed value of index i. The value of γ in the set of γ values which maximises the semblance criterion give the curvature which match the most with the event. Next section presents the Bayesian approach of this residual moveout analysis.

Bayesian approach

For this part, we keep the same definition as the previous part for the various indexes.

The conventional method of the residual moveout analysis supposes implicitly that the amplitudes are uniformly distributed along the residual moveout curves . It is shown in the literature [2], [4], [5] that the criterion of the semblance is not effective when we are in the presence of variation of the amplitude along the residual moveout curves. To avoid this problem we assume that the amplitudes along the residual moveout are locally uniformly distributed and we use an approximation with Haar wavelet to approximate theses amplitudes. Let's call $\mathbb{A}=(a_{k,j})_{1\leqslant k\leqslant W,1\leqslant j\leqslant M}$ the matrix that designates all amplitudes within the depth window of width W which is centered about i_0 where $k=i+w(j,\gamma)$. Instead of calculating $a_{k,j}$ by interpolation linear as in the conventional method, we shall use a kernel regression to calculate $a_{k,j}$ and so take into account more than the immediate neighbours as it is the case in the conventional method.

Model for data processing

The noise presented in data is assumed to be zero mean Gaussian with variance σ^2 and Independent and identically distributed. The amplitudes $a_{k,j}$ are realisations of $A_{k,j}$ with distribution of $(A_{k,j})|\gamma\sim\mathcal{N}(\boldsymbol{a}_{k,j},\sigma^2)$ where σ^2 and $\boldsymbol{a}_{k,j}$ where $k=i+w(j,\gamma)$ are assumed to be the approximation with the Haar wavelet of amplitudes along residual moveout curve define by γ. Let's $\hat{\boldsymbol{a}}_{k,j}$ be the estimation with Haar wavelet of $\boldsymbol{a}_{k,j}$.

γ is the realisation of Γ with pdf π_θ (θ is a known parameter which describes a prior knowledge on γ).

The likelihood model

Since $A_{k,j}$ are assumed to be independents, the likelihood model for data in the matrix $\mathbb{A}$ is given by

$$\begin{aligned} f_{\mathbb{A}|\Gamma}(a|\gamma) &= \prod_{k=1}^{W}\prod_{j=1}^{M}\frac{1}{2\pi\sigma^2}\exp\left[-\frac{1}{2\sigma^2}\left(a_{k,j}-\boldsymbol{a}_{k,j}\right)^2\right] \\ f_{\mathbb{A}|\Gamma}(a|\gamma) &= \frac{1}{(2\pi\sigma^2)^{\frac{WM}{2}}}\exp\left[-\frac{1}{2\sigma^2}\sum_{k=1}^{W}\sum_{j=1}^{M}\left(a_{k,j}-\boldsymbol{a}_{k,j}\right)^2\right] \end{aligned} \tag{2}$$

Let's recall that k is function of γ.

The prior model

The parameter γ is positive and can vary of a zone from the image to an other one. We shall thus choose to put an uniform prior $U_{[\gamma_{min},\gamma_{max}]}$ on the parameter γ. $0 < \gamma_{min} < \gamma_{max}$.

The posterior model

The posterior distribution of $\Gamma|\mathbb{A}$ is given by

$$f_{\Gamma|\mathbb{A}}(\gamma|a) = \frac{\exp\left[-\frac{1}{2\sigma^2}\sum_{k=1}^{W}\sum_{j=1}^{M}\left(a_{k,j}-\boldsymbol{a}_{k,j}\right)^2\right]\pi_\theta(\gamma)}{\int_{\mathbb{R}^+}\exp\left[-\frac{1}{2\sigma^2}\sum_{k=1}^{W}\sum_{j=1}^{M}\left(a_{k,j}-\boldsymbol{a}_{k,j}\right)^2\right]\pi_\theta(\gamma)d\gamma} \tag{3}$$

The Metropolis Hastings sampler algorithm

The posterior distribution can be explored by MCMC simulation. We choose the Metropolis Hastings sampler for our case. To implement the algorithm, we argue proportionally about the posterior distribution. We have

$$\hat{f}_{\Gamma|\mathbb{A}}(\gamma|a) \propto \exp\left[-\frac{1}{2\hat{\sigma}^2}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(a_{i,j}-\hat{\boldsymbol{a}}_\gamma(z_i,h_j)\right)^2\right]\pi_\theta(\gamma) \tag{4}$$

Applications on synthetic and real data

For the application on synthetic and real data, we choose an uniform prior $U_{[0.6,1.6]}$ for Γ prior distribution. σ^2 which is the variance of noise presented in data is estimated by a deterministic method.

Event with strong variations of amplitude according offset and phase changing

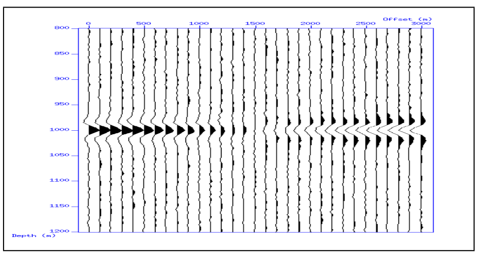


Figure 3: Event on Offset Domain Common Image Gather which presents variation of amplitude according offset.

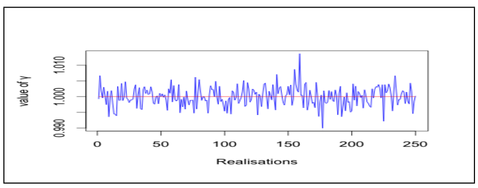
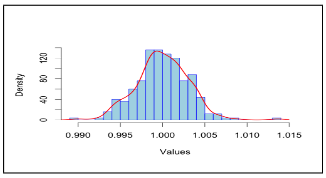


Figure 4: Outcomes of Metropolis Hastings simulation.



Theoretical Value	1.0
Mean value	0.999
Standard deviation	0.003
95% CI	[0.994 ; 1.005]
Median	0.9999529

Figure 5: The histogram of the outcomes shows a posterior distribution of Γ for the event in figure (3).

We see that on the synthetic data with strong variation of amplitude, the Bayesian approach gives satisfying results and brings in more an informations about the uncertainty, what is not the case with the conventional method.

Comparison of conventional method and Bayesian approach of residual moveout analysis on real data

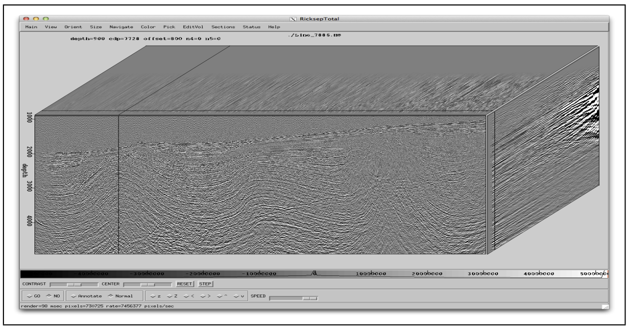


Figure 6: Real data : The vertical axe represents the depth, the horizontal the surface location and the third one represents the offset dimension.

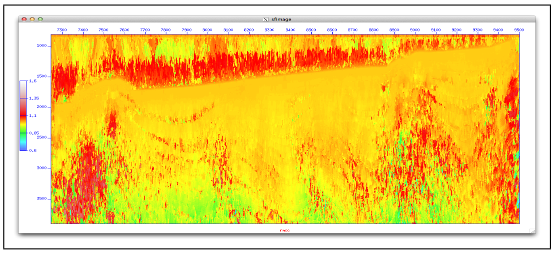


Figure 7: Result of conventional residual moveout analysis

The main difference between the conventional method and the Bayesian approach is that the latter is more precise. It observes on the results of the figure 8 where the geological layers are more visible than the results of the figure 7. The estimation of the uncertainty which motivated this work is translated here by the standard deviation (figure 9). Others Informations like credibility interval can be computed.

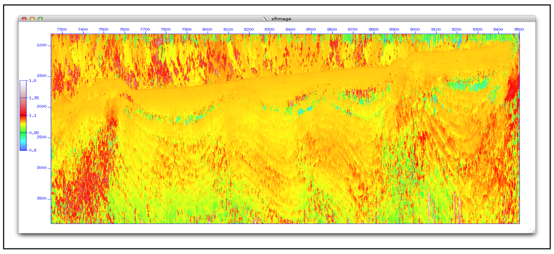


Figure 8: Result of Bayesian approach of residual moveout analysis

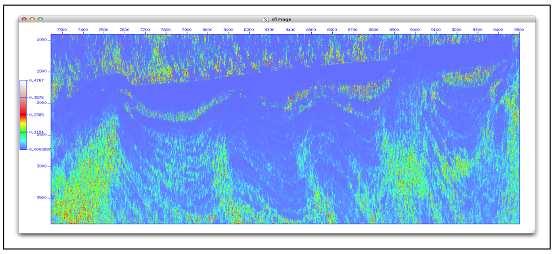


Figure 9: Standard deviation associate with the Bayesian estimation (figure 8) of γ value

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