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OPPORTUNITIES PRESENTED BY THE ENERGY TRANSITION

2018 EAGE ANNUAL

80TH CONFERENCE + EXHIBITION

COPENHAGEN | DENMARK

wintershall

11-14 JUNE 2018

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Accounting for Processing Errors in AVO/AVA Data

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14th of June

Outline

- Motivation
  - AVO data
  - Processing
- Processing/modeling errors
  - One processing error realization
  - Estimation of processing error
- Inversion
  - Linear Bayesian Inversion
  - Accounting for modeling error
  - Results
- Conclusions

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AVO data

Convolutional model

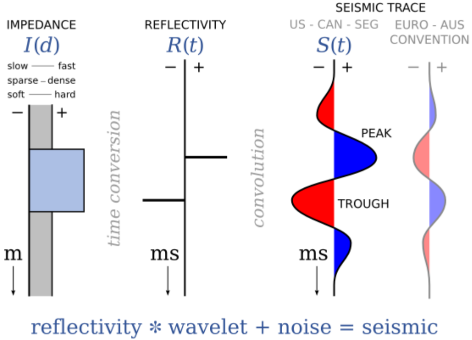
- Seismic traces can be emulated by the convolution of a seismic reflectivity series and a wavelet
  - Reflectivities come from Zoeppritz equations or approximations hereof
  - Wavelet can be e.g. be estimated from well logs

AVO data

Convolutional model

$$S(t) = W(t) * R(t)$$
$$\equiv \int_0^{t_s} W(\tau) R(t-\tau)\, \mathrm{d}\tau \qquad (1)$$

- where $S(t)$ is the seismic trace, $R(t)$ is the reflectivity series (earth response) such as given in for example Zoeppritz equations, and $W(t)$ is the wavelet (source-time function) where t_s is the duration of the source input



AVO data

AVO data assumptions

- Layers are:
  - Flat
  - Homogeneous
  - Isotropic

AVO data

AVO data benefits

- Gives rise to the discipline of AVO analysis ("the search for bright/dim spots")
- Use fast convolutional model as forward model in inversion
- Data reduction

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AVO data

AVO data benefits

- Gives rise to the discipline of AVO analysis ("the search for bright/dim spots")
- Use fast convolutional model as forward model in inversion
- Data reduction
- How does one go from seismic raw data to seismic AVO data?
- Processing!

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Processing

Goals

- Raw seismic data $\rightarrow$ AVO (AVA) seismic data
- AVO: Amplitude Variation with Offset
  - Follow the assumptions of Zoeppritz equations, e.g. flat layers, plane wave
- Process preserve seismic amplitudes and accurately determine the spatial coordinates of each sample

Processing

Factors affecting AVO data

multiple interference temporal tuning mode conversions transmission losses effect of overburden reflector curvature spherical divergence phase changes with offset noise and interference attenuation, dispersion, absorption	array effects instrumentation source strength & consistency receiver coupling RNMO processing algorithms NMO stretch geology ground roll random noise

Table1: Factors which influence AVO

Figure: Table taken from: Downton et al. 2000, AVO for managers : pitfalls and solutions, Crewes Research Report 12

- Trade-off: Noise suppression and isolation of reflectivities / biasing or corrupting the reflectivity variations

Processing

Issues

- Heuristic procedure $\rightarrow$ error prone (Human errors?)
- Introduction of biases/errors?
- Motivation:
  - How big are these biases/errors? (Inability to process raw data in accordance with AVO assumptions)
  - Is it significant?
  - Can it be quantified and estimated?

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One processing error realization

- Consider one subsurface realization $\mathbf{m}$
- To generate one processing error we compare two ways of obtaining the forward response for this realization
- Convolutional model: $\mathbf{d}_{\text{obs,conv}} = g_{\text{conv}}(\mathbf{m}) = \mathrm{G}\mathbf{m}$
- Processing raw data: $\mathbf{d}_{\text{obs,proc}} = g_{\text{proc}}(\mathbf{m})$
  - g_{proc}: Generate raw data from $\mathbf{m}$ $\rightarrow$ process to AVA data
- Modeling (processing) error: $\mathbf{d}_{\text{e}} = \mathbf{d}_{\text{obs,conv}} - \mathbf{d}_{\text{obs,proc}}$

One processing error realization

Well log $\mathbf{m}$

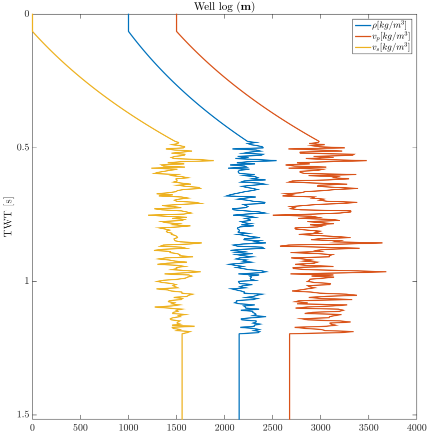


Figure: Synthetic log. Known synthetic velocity model of the subsurface which enables ideal conditions for processing

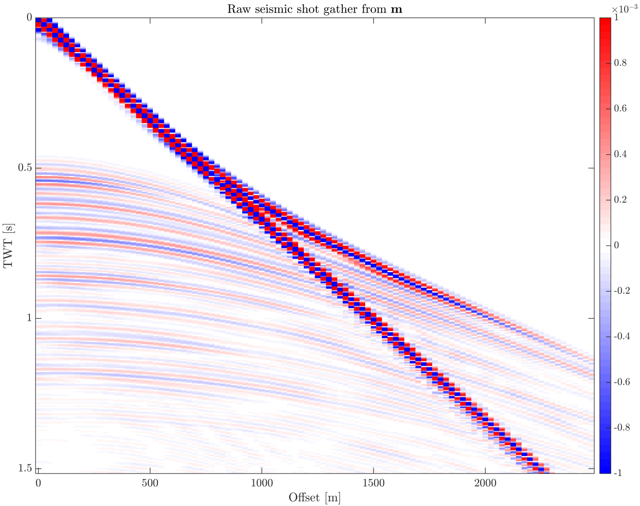
One processing error realization

Well log $\mathbf{m} \rightarrow$ raw data

- Finite difference solver is used to do full waveform modeling
- Staggered grid fourth order space, second order time based on (Levander, 1988; Virieux, 1986).
- Absorbing boundary conditions (weak multiples) the PML strategy is adapted from (Collino & Tsogka, 2001).
- Basically noise-free (except for modeling errors from the finite difference scheme)
- Wavelet can be extracted relatively exactly from the finite difference solution.

One processing error realization

Raw seismic data from **m**



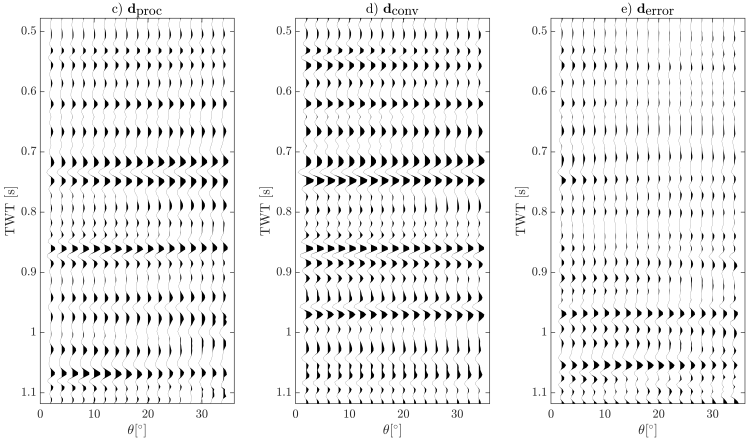
One processing error realization

Processing sequence

- Processing done in Promax software
  - Load raw seismic data
  - Spherical divergence (constant velocity plus 6 dB/sec)
  - NMO-correction (with known background velocity model)
  - FK-filtering (apparent velocity = 1500 m/s)
  - Offset to angle conversion

Processing sequence

Modeling error



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Estimation of processing error

Gaussian covariance model

Consider a sample consisting of N realizations of the modeling error $(\mathbf{d}_e^1, \mathbf{d}_e^2, \ldots, \mathbf{d}_e^N)$. This sample is setup in matrix form as:

$$\mathbf{D}_e = [\mathbf{d}_e^1, \mathbf{d}_e^2, \ldots, \mathbf{d}_e^N] \tag{2}$$

The mean modeling error is estimated for each individual point j as:

$$d_{T_{app}}^j = \frac{1}{N} \sum_{i=1}^{N} \mathbf{D}_e^{i,j} \tag{3}$$

where the mean for the jth data point is the arithmetic mean of all $i = 1, \ldots, N$ realizations from the sample.

Estimation of processing error

Gaussian covariance model

$$\mathbf{d}_{\mathrm{Tapp}} = \left[\mathrm{d}^{1}_{\mathrm{T}_{\mathrm{app}}}, \mathrm{d}^{2}_{\mathrm{T}_{\mathrm{app}}}, \ldots, \mathrm{d}^{\mathrm{N_d}}_{\mathrm{T}_{\mathrm{app}}}\right] \tag{4}$$

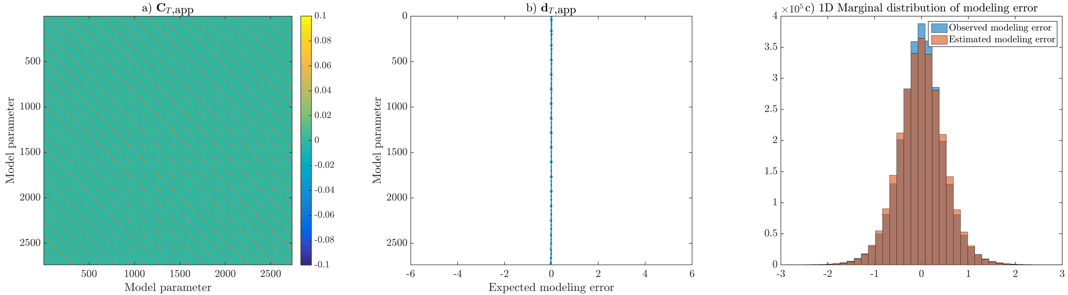
The covariance of the modeling error is estimated as:

$$\mathbf{C}_{\mathrm{Tapp}} = \frac{1}{\mathrm{N}}\left[\mathbf{D}_{\mathrm{e}} - \mathbf{D}_{\mathrm{Tapp}}\right]\left[\mathbf{D}_{\mathrm{e}} - \mathbf{D}_{\mathrm{Tapp}}\right]^{\mathrm{T}} \tag{5}$$

where $\mathbf{D}_{\mathrm{T}_{\mathrm{app}}} = \left[\mathbf{d}^{\mathrm{T}}_{\mathrm{T}_{\mathrm{app}}}, \mathbf{d}^{\mathrm{T}}_{\mathrm{T}_{\mathrm{app}}}, \cdots, \mathbf{d}^{\mathrm{T}}_{\mathrm{T}_{\mathrm{app}}}\right]$ is a matrix containing N repetitions of the mean vector of Equation 4.

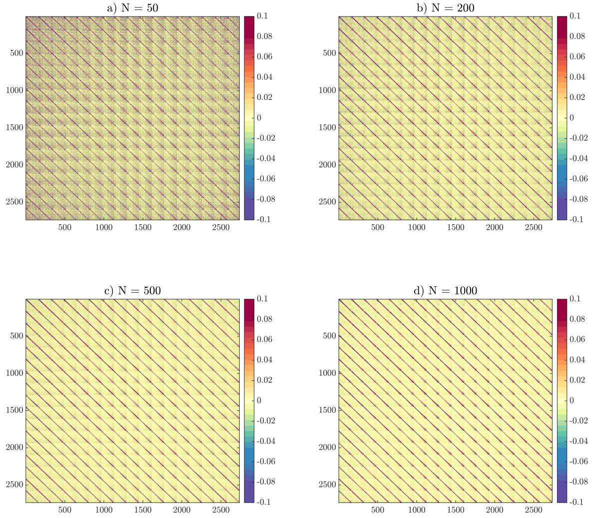
Estimation of processing error

Gaussian model



Estimation of processing error

Sample size



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Linear Bayesian Inversion

Posterior

The posterior probability density of the model parameters $\widetilde{\mathbf{m}}$ is described as a Gaussian probability distribution $\mathcal{N}(\widetilde{\mathbf{m}}, \widetilde{\mathbf{C}}_\mathrm{M})$ with mean:

$$\widetilde{\mathbf{m}} = \boldsymbol{\mu}_\mathrm{M} + (\mathbf{WADC}_\mathrm{M})^\mathrm{T}\mathbf{C}_\mathrm{D}^{-1}(\mathbf{d}_\mathrm{obs} - \mathbf{WAD}\boldsymbol{\mu}_\mathrm{M}) \tag{6}$$

and covariance:

$$\widetilde{\mathbf{C}}_\mathrm{M} = \mathbf{C}_\mathrm{M} - (\mathbf{WADC}_\mathrm{M})^\mathrm{T}\mathbf{C}_\mathrm{D}^{-1}\mathbf{WADC}_\mathrm{M} \tag{7}$$

where $\mathbf{d}_\mathrm{obs}$ is the observed data. Here we use $\mathbf{d}_\mathrm{obs,proc}$

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Accounting for modeling error

- Consider three noise models:
  - Case 1: Account for modeling (processing) error: $\mathbf{C}_{\mathrm{D}} = \mathbf{C}_{\mathrm{Tapp}}$
  - Use uncorrelated noise model: $\mathbf{C}_{\mathrm{D}} = \mathbf{C}_{\mathrm{d}}$
    - Case 2: Assume low noise on data ($\mathrm{S/N} = 9$)
    - Case 3: Assume high noise on data ($\mathrm{S/N} = 0.4$)

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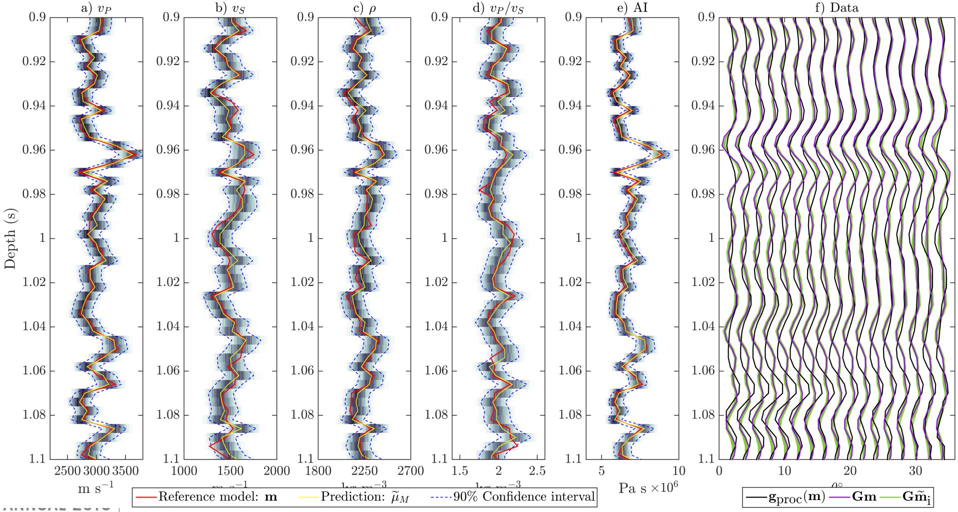
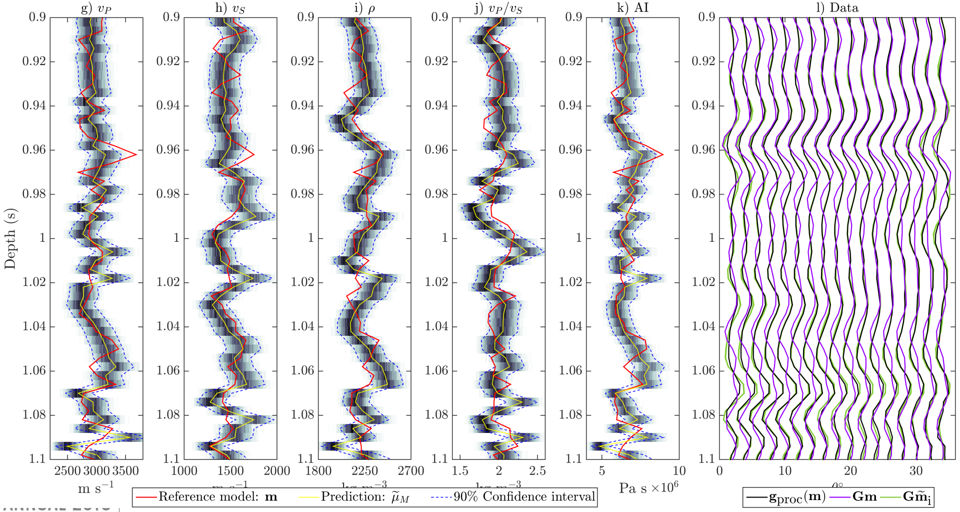
Inversion

Case 1: $\mathbf{C}_{\text{Tapp}}$



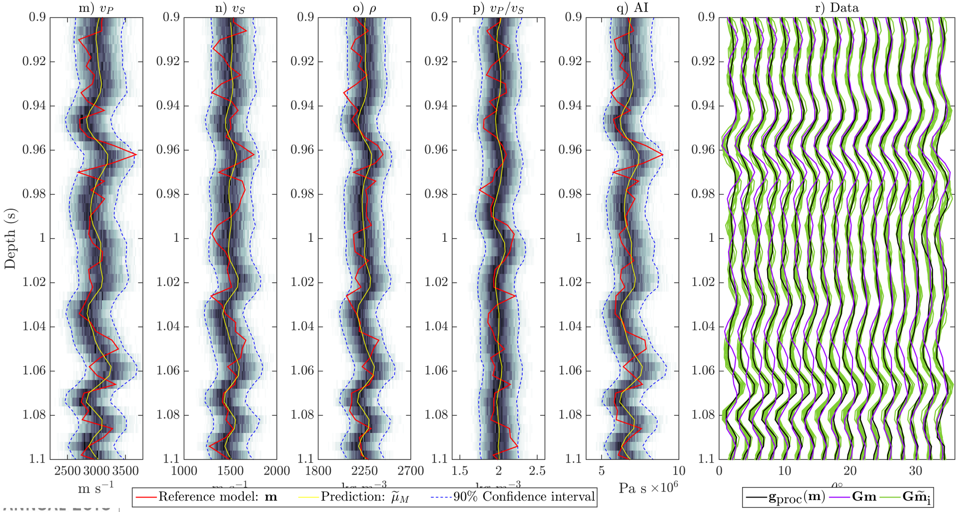
Inversion

Case 2: $\mathbf{C}_\mathrm{d}$ (S/N = 9)



Inversion

Case 3: $\mathbf{C}_\mathrm{d}$ (S/N = 0.4)



Inversions summarized

Model	RMSD	Entropy (H)	Log-likelihood
$\mathbf{C}_D = \mathbf{C}_{Tapp}$	0.0306	-1135.1	-243.7
$\mathbf{C}_D = \mathbf{C}_d$ (S/N=9)	0.0734	-1155.4	-50760.3
$\mathbf{C}_D = \mathbf{C}_d$ (S/N=0.4)	0.0582	-790.9	-248.7

Table: rmsd, entropy and log-likelihood for inversion cases

Conclusions

- Substantial significance of processing error (S/N=2)
  - Even in "Best-case" scenario (known velocity model, noise-free raw data etc.)
- Processing (+ simulation) error can in this case be reasonably described by a Gaussian covariance model
  - Qualitative visual results + 1D marginals
  - Takes roughly 500+ samples to reasonably estimate error
- Inversion results improves
  - Prediction
  - Resolution
- Offers a computationally efficient setup compared with running metropolis sampler with full waveform forward ($\sim 500 \ll \sim 1.000.000$)

- Questions

Quantifiable measures

- Entropy

$$\mathrm{H} = \frac{n_m}{2} + \frac{n_m}{2}\ln(2\pi) + \frac{n_m}{2}\ln(|\widetilde{\mathbf{C}}_{\mathrm{M}}|) \tag{8}$$

n_m is the dimensionality of the model parameters

- RMSD

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathbf{m}_{\mathrm{i}} - \widetilde{\mathbf{m}}_{\mathrm{i}})^2}{\mathrm{n}}} \tag{9}$$

- Likelihood

$$f(\mathbf{m}_{\mathrm{ref}}|\mathcal{N}(\widetilde{\mathbf{m}}, \widetilde{\mathbf{C}}_{\mathrm{M}})) \sim \exp(-0.5\,(\mathbf{m}_{\mathrm{ref}} - \widetilde{\mathbf{m}})^{\mathrm{T}}\,\widetilde{\mathbf{C}}_{\mathrm{M}}^{-1}\,(\mathbf{m}_{\mathrm{ref}} - \widetilde{\mathbf{m}})) \tag{10}$$