Efficient big seismic data assimilation through sparse representation

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Big data assimilation with sparse representation

• Background (big data assimilation in seismic history matching)

• Proposed framework

• Numerical examples

• Discussion and conclusion
Background

What is history matching about?

Effect – observed data

Cause – Petro-physical parameters (PERM, PORO)

Detectives – history matching algorithms

Who did this?

History matching aims to find proper values of petro-physical parameters to explain observed data.
Background

Data in history matching

- Production data
- Seismic data
- Electromagnetic (EM) data
- Well logs
- Others
Seismic data

- Amplitude versus angle (AVA);
- or raw seismic data
- Saturation and pressure maps
- Impedances ($I_p$, $I_s$);
- or velocities ($v_p$, $v_s$) and density

Background

Relation between reservoir petro-physical parameters and seismic data at different levels

AVA data
(Raw seismic)

Impedance
\( (v_p, v_s, \rho) \)

Saturation
Pressure

Petrophysical
parameters

Rock physics
model

Forward simulation

AVA (full waveform)
simulation

Impedance
\( (v_p, v_s, \rho) \)

Saturation
Pressure

Reservoir
simulation

Inversion

Petrophysical
parameters
Our focus in this talk is to history match **AVA data**
Background

Challenge in history-matching seismic data

Conventional history matching
- Small to moderate data
- Data size < model size
- Moderate demand of computing power and memory

Seismic history matching
- Big data
- Data size ≥ model size
- High demand of computing power and memory, if without an efficient method
- Extra computational issues
Big data assimilation with sparse representation

- Background
- Proposed framework
- Numerical examples
- Discussion and conclusion
Use wavelet-based sparse data representation to address the big data problem in seismic history matching.
Proposed framework

Workflow

- Reservoir model
- AVA simulation
- Simulated AVA data
- Observed AVA data
- Sparse representation
- Leading wavelet coefficients
- Leading wavelet coefficients
- History matching
Proposed framework
Wavelet-based sparse representation


Noisy AVA data (noise lv = 30%)

Reference AVA data

Proposed framework

Illustration: 2D data

- Leading coefficients used in history matching
- Number of leading coefficients is about 6% of the original
- True noise STD = 0.0148; estimated noise STD = 0.0141

Wavelet transform

Thresholding

Inverse transform
Big data assimilation with sparse representation

- Background
- Proposed framework
- Numerical examples
- Discussion and conclusion
Numerical example I: A 2D Norne field model

3D Norne field model

PERMX filed of the 2D model

(The 2D model is kindly provided by Dr. Mohsen Dadashpour)
## Experimental settings

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>Model size</td>
<td>39x1x26, with 739 out of 1014 being active gridcells</td>
</tr>
<tr>
<td>Parameters to estimate</td>
<td>PORO, PERMX. Total number is 2x739 = 1478</td>
</tr>
<tr>
<td>Production data (~10 yrs)</td>
<td>BHP, GOR, OPT, WCT. Total number is 135</td>
</tr>
<tr>
<td>4D seismic data (1 Base + 2 monitor surveys)</td>
<td>AVA intercept and gradient. Total number is 46686</td>
</tr>
<tr>
<td>Leading wavelet coefficients</td>
<td>Total number is 2746</td>
</tr>
<tr>
<td>History matching algorithm</td>
<td>Iterative ensemble smoother*</td>
</tr>
</tbody>
</table>

Numerical example I: A 2D Norne field model

Results when both production and seismic data are used (more results in SPE Journal paper SPE-180025-PA*)

**Numerical example II: 3D Brugge field model**

### Experimental settings

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<tbody>
<tr>
<td><strong>Model size</strong></td>
<td>139x48x9, with 44550 out of 60048 being active gridcells</td>
</tr>
<tr>
<td><strong>Parameters to estimate</strong></td>
<td>PORO, PERMX, PERMY, PERMZ. Total number is 4x44550 = 178,200</td>
</tr>
<tr>
<td><strong>Production data (~10 yrs)</strong></td>
<td>BHP, OPR, WCT. Total number is 1400</td>
</tr>
<tr>
<td><strong>4D seismic data (1 Base + 2 monitor surveys)</strong></td>
<td>Near and far-offset AVA data. Total number is ~ 7 x 10^6 (needing too much computer memory to be used directly)</td>
</tr>
</tbody>
</table>

#### Leading wavelet coefficients

- **Two cases:**
  - **1.** Total number is 178,332 (~2.5%); **100K case**
  - **2.** Total number is 1665 (~0.02%); **1K case**

| **History matching algorithm** | Iterative ensemble smoother* |

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Numerical example II: 3D Brugge field model

Results when both production and seismic data are used (more results presented in ECMOR*)

Reference PORO (at layer 2)

Mean PORO (at layer 2) of initial guess

Mean PORO (at layer 2) after history matching (100K)

Mean PORO (at layer 2) after history matching (1K)

Big data assimilation with sparse representation

- Background
- Proposed framework
- Numerical examples
- Discussion and conclusion
Discussion and conclusion

Advantages in using wavelet-base sparse representation
In seismic history matching

- Efficient reduction of data size
- Intrinsic noise estimation in the data
- Applicability to various types of data (AVA, impedance, saturation map etc.)


Discussion and conclusion

Ongoing and future investigations

Field case studies (with preliminary results)$

Localization*

Adaptive sparse representation


Acknowledgements / Questions

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