Probabilistic seismic inversion using pseudo-wells

*Patrick Connolly, PCA Ltd
Outline

ODiSI: probabilistic inversion algorithm for the estimation of lithofacies and reservoir properties

• Context
• Algorithm
• Uncertainty
• Examples

ODiSI:
• developed by BP
• re-engineered by Cegal

Stochastic inversion by matching to large numbers of pseudo-wells, 2016,
Patrick Connolly and Matthew Hughes, Geophysics
Reservoir Geological Model Elastic Properties Ideal Seismic Real Seismic

Geology & petrophysics Rock Physics Modelling & Inversion Acquisition & processing

inversion to elastic props.
inversion to reservoir properties
rock physics models
gerological models

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Rocks

Geological Model

Elastic Properties

Ideal Seismic

Real Seismic

prior

likelihood

integration

posterior
Solving Bayes

1) Analytic
2) Monte Carlo rejection sampling
3) Markov chain Monte Carlo
Samples

Vertical stratigraphic profiles

Pseudo-wells

Seismic

Rock physics models

lithofacies  shale  porosity  shear  dry-frame  Vp  Vs  bulk
volume  modulus  modulus  density

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One Dimensional Stochastic Inversion (ODiSI)

Input seismic → match & accept/reject → Best-match synthetics

Thousands of pseudo-wells for each trace

Corresponding lith columns

Lithofacies probabilities

Probabilities

Mean net sand fraction

Input seismic

Thousands of pseudo-wells for each trace

Best-match synthetics

Corresponding lith columns

Lithofacies probabilities

Probabilities

Mean net sand fraction
**Bed thickness statistics**

- **Bed thicknesses**
- Very similar distributions for any clastic depositional system

**Sand**
- \( \lambda = 0.18 \)
- Mean bed thickness = 5.5ms

**Shale**
- \( \lambda = 0.15 \)
- Mean bed thickness = 6.6ms

Straight line on log-linear plot implies an exponential distribution.

Proportion of beds > x (complementary cumulative distribution function - CCDF)

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**Lithofacies column**

<table>
<thead>
<tr>
<th></th>
<th>ss</th>
<th>sh-ss</th>
<th>cs</th>
<th>sh</th>
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<tbody>
<tr>
<td>Clean sand</td>
<td>0</td>
<td>0.9</td>
<td>0.1</td>
<td>0</td>
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<tr>
<td>Shaley-sand</td>
<td>0.5</td>
<td>0</td>
<td>0</td>
<td>0.5</td>
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<tr>
<td>Cem. sand</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Shale</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
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</table>

Transition probabilities

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**Deterministic macro-layers**
- Overburden
- Sheet sand
- Intra-reservoir
- Channel sand
- Basal lag
- Underburden

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**Stochastic micro-layers**

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**Continuous time Markov chain**

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**Exponential distribution CDF**

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**Deterministic macro-layers**
Prior net-to-gross

Sheet sand: high net-to-gross

Intra-reservoir: low net-to-gross

Channel sand: mostly high net-to-gross, some cemented sands

Basal lag: high net-to-gross, a lot of cemented sands

Prior expectation of net-to-gross for each macro-layer
Lithofacies proportions

Low net-to-gross

High net-to-gross

Parameterisation

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Lithofacies modelling - sands

Porosity/depth trend

Porosity/moduli relationships

Fluid substitution

Porosity

dry frame modulus

shear modulus

porosity
Lithofacies modelling - shales

Vp/depth trend

Vp / Vs and Vp / ρ correlations

Shaley sand mixing laws & other lithologies
Pseudo-wells

pseudo-well

real well

<table>
<thead>
<tr>
<th>lithofacies</th>
<th>shale volume</th>
<th>porosity</th>
<th>shear modulus</th>
<th>dry-frame modulus</th>
<th>Vp</th>
<th>Vs</th>
<th>bulk density</th>
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Matching

• The process is 1D.

• Thousands of pseudo-wells are created for each trace.

• EEI synthetics are generated with consistent wavelet and chi-angle.

• ~1% of pseudo-wells with lowest residual energy are selected.
Back to Bayes

Prior information

- geology (deposition/environment)
- well logs
- rock property correlations
- stratigraphy
- vertical statistics
- depth trends
- fluid contacts

Specific prior

Data

Posterior

Mean VSh of all pseudo-wells

accept/reject

Mean VSh of best-match pseudo-wells
**Algorithm stability**

- Stability; lateral continuity
- Better results with more pseudo-wells

\[ \text{BMPWs} = \frac{\text{PWs}}{100} \]
Simultaneous inversion

CI gradient (lithology)

CI chi 15 (fluid)

Matching

Most likely lithofacies

Mean net sand fraction

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Simultaneous inversion

Cl gradient (lithology)

Cl chi 15 (fluid)

Matching

QC

synthetic

residual
Validation

Blind well ties: offshore Angola

- **Red**: well data.
- **Blue**: ODiSI prediction

![Blind well tie diagram](image)
**Percentiles**

Usually the best-match pseudo-wells are averaged to obtain a mean and standard deviation of the property to be estimated. But if we sort the BMPWs...

<table>
<thead>
<tr>
<th>Layer</th>
<th>Time (ms)</th>
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<tbody>
<tr>
<td>1</td>
<td>-1600</td>
</tr>
<tr>
<td>2</td>
<td>-1550</td>
</tr>
<tr>
<td>3</td>
<td>-1500</td>
</tr>
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</table>

Decreasing match quality
Percentiles

By selecting a number of traces around a selected percentile, different cases with *approximate percentiles* can then be calculated.

20 BMPWs centred around the P10 trace

Increasing net-to-gross
Percentiles

By selecting a number of traces around a selected percentile, different cases with *approximate percentiles* can then be calculated.

20 BMPWs centred around the P50 trace

Increasing net-to-gross
Percentiles

By selecting a number of traces around a selected percentile, different cases with *approximate percentiles* can then be calculated.

20 BMPWs centred around the P90 trace

Increasing net-to-gross
Uncertainty quantification

Measured uncertainties:

- Is the relationship linear or higher order?
- How many components; 1 shale or 2?
- Is the data noisy? Should we decrease the variance?
- Is the data representative of the entire reservoir? Should we increase the variance?

The measured variance will depend on the model we choose.
Quantitative Interpretation

- Bayesian methods require uncertainties to be quantified.
- Uncertainty values determine the results; mean & variance
- But, all uncertainties are subjective.
- Your inversion result is an interpretation.
Nile Delta example

Layer 1 net-to-gross

Layer 2 net-to-gross

Blue: ODiSI prediction
Red: well data.

<table>
<thead>
<tr>
<th>Layer 1 net-to-gross</th>
<th></th>
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</thead>
<tbody>
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<td>ODiSI prediction</td>
<td>0.40</td>
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<tr>
<td>Actual</td>
<td>0.41</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Layer 2 net-to-gross</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ODiSI prediction</td>
<td>0.54</td>
</tr>
<tr>
<td>Actual</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Stochastic Inversion by Trace Matching - Reservoir Property Prediction Case Studies, EAGE 2016, S.R. Grant (BP) & B.J. Dutton (Cegal Ltd)
North Sea example

Upper Jurassic Fulmar reservoir flanked by Triassic shales and underlain by Triassic shales and Zechstein evaporites.

Central North Sea, Upper Jurassic Fulmar Inversion Case Study. Utilising Blueback ODiSI, 2016
L. Casteleyn¹, P. Ashton², A. D’Alessandria², P. Connolly³ and J. Sayer¹.

1. Cegal Limited, Aberdeen UK.
2. Repsol-Sinopec Resources UK Limited, Aberdeen UK.
North Sea example
Performance

Full probabilistic $10^6$ trace inversion

~ 2,000 pseudo-wells per trace

= $2 \times 10^9$ pseudo-wells

• ~8 hours on a standard workstation
• 25 mins on the cloud
Transparency

“Algorithms, when they are not transparent, can lead to a distortion of our perception.”
— Angela Merkel

Monte Carlo rejection sampling
• conceptually simple
• easy to understand
• highly transparent
**ODiSI Summary**

- Full probabilistic inversion to facies probabilities and reservoir properties.
- Efficient, stable, transparent algorithm with results validated on multiple fields.
- Posterior uncertainties are captured.
- Uncertainty quantification is inherently subjective; any inversion is an interpretation.