Integrated Reservoir Characterization for Unconventional Reservoirs using Seismic, Microseismic and Well Log Data

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PhD Defense

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Outline

- Introduction
- Advanced multiphase autopicker design and implementation workflow
- Attribute studies based on conventional seismic data
- Passive seismic based geomechanical property estimation
- Hybrid FZI* attributes
- Integrated analysis
- Conclusions

* Fracture Zone Identifier
Part 1

Introduction

Problem definition
Background
Workflow
Increasing stress on conventional oil resources has compelled us to look into unconventional oil & gas and other subsurface energy resources.
Seismic and microseismic surveys have become increasingly common. Lowering acquisition costs, improvements in capabilities and new techniques for improved reservoir characterization have all led to the abundance of such geophysical studies.

**Geophysical tools employed...**

**Reflection seismology** *(Nissen, 2007)*

**Passive seismology** *(Calvez, 2005; ESG Solutions)*
Background

4. AVAZ analysis on pre-stack data for fracture characterization
Background

5. Complex hydraulic fracture geometry compared with MEQ cloud and modeled 20 year pressure depletion for un-propped zones

Urbancic et al., 2002
Maxwell et al., 2011
Cipolla et al., 2012
Wessels et al., 2011
Cipolla et al., 2012
Study area

Geothermal
Sedimentary
Fluvial deltaic
Faulted tectonic
Compartmentalized

Introduction
Autopicking
Geomechanical property estimation
Seismic attribute studies
FZI attributes
Integrated analysis
Conclusions
Problem definition

Motivation?

- Enhanced cross-disciplinary technology applications.
- How to work in highly data constrained & geologically challenging environments?
- Novel workflows to tackle said challenges.
- Maximize/ optimize use of available data.
- Improved algorithms to support analysis.

- Fracture zone characterization
- MEQ – Seismic joint interpretation
- Improved velocity models
- Discontinuity mapping
- 4D characterization framework

Introduction | Autopicking | Geomechanical property estimation | Seismic attribute studies | FZI attributes | Integrated analysis | Conclusions
Integrated characterization workflow

- **A-priori information on fracture zones**
- **Image logs/production data, etc.**

**ANN classification algorithm**

- **Well Logs**
- **3D seismic**
  - Data conditioning
  - Dip steered filtering
  - Well to seismic ties
  - Seismic attribute analysis
  - Multi-attribute/ANN
  - Reservoir property estimates

- **Passive seismic**
  - Data formatting
  - Auto-picking
  - Phase detection
  - Event locations
  - Tomographic inversion
  - COSGSIM
  - $V_p$ & $V_s$ (high resolution)

**Fracture zone identification framework**

**FZI maps**

**Rock properties**

**Inversion uncertainty**

**Estimation uncertainty**
Part 2

Advanced multiphase autopicker

Background
Motivation
Workflow
Implementation
Results
Background

Available methods based on previous work

**STA/LTA**
- Allen, 1978

**Wavelet transformation**
- Kanwaldip et al., 1978

**Energy change**
- Coppens, 1985

**AIC**
- Maeda et al., 1985
- Sleeman et al., 1999
- Leonard et al., 1999

**Skewness/ Kurtosis**
- Saragiotis et al., 2002

**Cross-correlation**
- Rowe et al., 2002
- Begnaud et al., 2007

**ANN**
- Zhao et al., 1999

**Fractal**
- Boschetti et al., 1996
- Chang et al., 2002

**Statistics**
- Wagner et al., 1996
Initial observations

- Random noise
- Dead/near dead traces
- High frequency harmonics
- Low frequency artifacts

Which pick to choose? What criteria serves as the best?

AIC & STA/LTA methods

Introduction
Autopicking
Geomechanical property estimation
Seismic attribute studies
FZI attributes
Integrated analysis
Conclusions
Motivation

- Ability to handle untested data
- 5 recording stations
- Improved pick accuracy
- Quick phase data generation for near real time applications
- Hydrofrac/Geothermal, etc
ANN autopicker workflow

DMX files

Stacked dataset

Rotate data to have maximized p phase energy projection on vertical component

Apply bandpass filter based on frequency spectrum of individual traces

Attribute selection based on literature/ cross-plotting & window size analysis (sensitivity studies).

Extract ANN picks from the obtained ANN probability map

ANN training using selected attribute maps

Manual picks for ANN training and validation

Iterate to improve attribute selection and reduce total no. of attributes

Extract seismic trace values starting from p phase arrivals (as obtained from first run of the autopicker) : 2 s time window

Apply high pass filter to attenuate low values close to p phase pick (obtained automatically from frequency spectrum)

Obtain final pick locations (p and s phase). Compare results and calibrate workflow as required

Preliminary comparisons with contemporary autopickers and expert validation

Extract ANN picks from the obtained ANN probability map - s phase arrival offsets

ANN training using previously obtained attribute maps (p phase trained ANN)

New attributes

iterate
Theory - ANN

**AbsSum**

\[ A_{1i} = \sum_{i=1}^{i+N} |x_i| \]

**AbsSumMean**

\[ A_{2i} = \frac{1}{N} \sum_{i=1}^{i+N} A_{1i} \]

**AbsSumMax**

\[ A_{3i} = \max \left( \sum_{i=1}^{i+N} A_{1i} \right) \]

**AbsSumVar**

\[ A_{4i} = \text{var} \left( \sum_{i=1}^{i+N} A_{1i} \right) \]

**Skewness**

\[ A_{5i} = \frac{1}{N} \sum_{i=1}^{i+N}(x_i - \bar{x})^3 \]

**Kurtosis**

\[ A_{6i} = -3 + \frac{1}{N} \sum_{i=1}^{i+N}(x_i - \bar{x})^4 \]

**BIC**

\[ A_{7i} = N \times \ln \left( \frac{1}{N} \sum_{i=1}^{i+N}(x_i - \bar{x})^2 \right) + k \times \ln(N) \]

**InstPha**

\[ A_{8i} = \tan^{-1} \frac{H(t)}{x(t)} \]

**InstFreq**

\[ A_{9i} = \frac{d}{dt} A_{8i} \]

**Wavelet**

\[ H = \left\{ \begin{array}{ll} 1 + \sqrt{3} & 3 + \sqrt{3} \\ 4 \times \sqrt{2} & 4 \times \sqrt{2} \end{array} \right. 
G = \left\{ \begin{array}{ll} 3 - \sqrt{3} & -3 + \sqrt{3} \\ 4 \times \sqrt{2} & 4 \times \sqrt{2} \end{array} \right. 
YH(i) = x_{2i} \times G(4) + x_{2i+1} \times G(3) + x_{2i+2} \times G(2) + x_{2i+3} \times G(1) 
YL(i) = x_{2i} \times H(4) + x_{2i+1} \times H(3) + x_{2i+2} \times H(2) + x_{2i+3} \times H(1) 
\text{where } i = 1 \text{ to } M/2 
a_{12i} = \min \left\{ \min \left( YH \left( i - \frac{n}{2} \right) \text{ to } i + \frac{n}{2} \right) \right. 
\left. \min \left( YL \left( i - \frac{n}{2} \right) \text{ to } i + \frac{n}{2} \right) \right\} \]

**FilterCF**

\[ E_i = \frac{x_i^2 + \bar{x}_i^2}{\frac{1}{N} \sum_{i=1}^{i+N-1} E_i} \]

\[ A_{14i} = \frac{1}{5N} \sum_{j=i-5N}^{i-1} E_j \]

**ESM**

\[ A_{10i} = \frac{1}{\log F} \times \log \left( \frac{\max(\Delta x)}{\frac{1}{N} \sum_{i=1}^{i+N/2} (x_i - \bar{x})^2} \right) \]

**BKM**

\[ E_i^2 = x_i^2 + (x_i - x_{i-1})^2 \times \frac{\sum_{j=1}^{i} x_j^2}{\sum_{j=1}^{i} (x_j - x_{j-1})^2} \]

\[ A_{13i} = \frac{E_i^4 - E_{i-1}^4}{\sigma(E_i^4)} \]
ANN autopicker – Implementation

ANN picks for synthetic hydrofrac data under varying SNR

Seismic attribute studies

FZI attributes

Integrated analysis

Conclusions

Introduction

Autopicking

Geomechanical property estimation
Observations

**Speed:** When compared with contemporary (LBNL) autopickers, the ANN autopicker takes similar run times. However, attribute evaluation and manual training data selection can lead to additional computational times.

**Applicability:** The autopicker has been tested with two independent geothermal datasets as well as synthetic hydraulic fracturing data and it has shown good results including in tests with very noisy data.

**Accuracy:** The results compare favorably when compared with two contemporary autopicking algorithms.

**Robustness:** The workflow has shown ability to operate under a wide range of noise and waveform characteristics.
Part 3

Novel MEQ based geomechanical property estimation

Inversion results
High resolution velocity models
Elastic property prediction
Time differential b/w p and s phase used to find the distance to event
Amplitude of the strongest wave used to measure the magnitude of the event

Theory – hypocentral inversion

- Use crustal model to predict arrival time
- Calculate residuals
- Obtain least square inverse of residuals
- Iterate for threshold

Assume event location
Theory - velocity inversion

ART, PB algorithms
Eberhart-Philips, 1990; Zhao et al., 1992; Scott et al., 1994; Eberhart-Philips & Reyners, 1997; Graeber & Asch, 1999

ART + PB algorithms
Thurber, 1983; Eberhart-Philips, 1986

Damped least square solution to residual eq.

Approximate Ray - tracing

ART locations as first estimate

Relocate & repeat velocity inversion

Velocity & location perturbation to model

Iterate for threshold
Hypoinverse results
Hypoinverse results

- Increase array size – improve ray path coverage as well as usable catalog size
- Improved inversion algorithms – TomoDD, etc
- Better understanding of regional geology including the fault systems to understand observed seismicity patterns

Typical raypath coverage

De Natale et al., 1996
Improved array design

1. Ray path focusing to prevent ill conditioned inverse problem based on source – receiver information.

2. Focal mechanism from microseismic moment tensor with inversion stability based on condition number.
Improved array design

\[ QF = W_1 \times QF_1 + W_2 \times QF_2 \quad (W_1 = 1.0 & W_2 = 0.0) \]

\[ QF = W_1 \times QF_1 + W_2 \times QF_2 \quad (W_1 = 0.0 & W_2 = 1.0) \]
Improved array design

\[ QF = W_1 \times QF_1 + W_2 \times QF_2 \quad (W_1 = 1.0 \text{ & } W_2 = 0.0) \]

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SimulPS results

Sample $V_p$ and $V_s$ maps at 1 Km depth level after SimulPS run
Improved velocity modeling – COSGSIM

Better estimate velocity (primary) based on seismic derived impedance (secondary)

Microseismic Data

\[ V_P & V_S \]

Seismic Data

Normal Score Transformed \[ V_P & V_S \]

COSGSIM

Normal Score Transformed \[ V_P & V_S \]

Inverse Normal Score Transformation

Impedance Maps

Secondary Variable

\[ V_P \] Realizations (Gaussian Domain)

Final \[ V_P \] Realizations

\[ V_S \] Realizations (Gaussian Domain)

Final \[ V_S \] Realizations
COSGSIM – inputs & results

PDF & CDF of normal score transformed $V_P$

PDF & CDF of normal score transformed $V_S$

$V_P$ at depth of 1 km

$V_S$ at depth of 1 km

$V_P$ simulation error

$V_S$ simulation error
Here $\mu$ & $\lambda$ are Lame’s parameters. $K$, $E$ & $\sigma$ are the elastic moduli, $V_E$ & $V_K$ are the stress estimates (extensional and hydrostatic), $\Delta_N$ & $\Delta_T$ are the normal and tangential weakness estimates and finally, $F_E$ is the normalized fracture aperture expandability.

$\rho$ is the density estimate, $V_P$ is the compressional while $V_S$ is the shear wave velocity in the medium, $e$ is the crack density in the medium, $b_r$, $b_{max}$ and $\alpha$ are aperture measurements obtained from laboratory tests using empirical rock classification index.
Property estimation

Normalized fracture aperture expandability - $F_E$
Rock physics for characterization

Martakis et al., 2006; Berryman et al., 2002; Berge et al., 2001; Boitnott, 2003, Downton et al., 2008

- **Effective pressure**: \( \uparrow V_p \) & \( K \)
- **Fractures**: \( \downarrow V_p \) & \( V_s \)
- **Fluid Saturation**: \( \downarrow V_s \) or \( \uparrow V_p/V_s \) & \( \sigma \)
- **Fracture opening**: \( \uparrow V_E \) & \( \downarrow K \)
- **Porosity**: \( \downarrow V_p/V_s \) & \( K \)
- **Lithification**: \( \uparrow V_p/V_s, \mu \) & \( K \) or \( \downarrow \sigma \)
- **Pore pressure**: \( \downarrow V_p \)
- **Gas**: \( \downarrow V_p, V_s \) & \( K \)
- **Fracture density**: \( \uparrow \Delta_T \)
**Observations**

<table>
<thead>
<tr>
<th>High resolution models:</th>
<th>Major limitations plague the available MEQ data for this study but we have utilized geostatistical simulation involving seismic derived impedance map as a means to constrain and improve the resolution of inverted phase velocities.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seismic derived density for property estimates:</td>
<td>We have developed a framework for utilizing seismic and log derived density maps to integrate with the velocity estimates to calculate elastic properties for interpretation and use.</td>
</tr>
<tr>
<td>Seismic derived FZI for crack density estimates:</td>
<td>We have used seismic derived FZI maps to estimate crack density (e) by normalizing the FZI values and using it as an estimate for “e” required for weakness estimation.</td>
</tr>
<tr>
<td>Framework for 4D:</td>
<td>We have established the framework for 4D property estimation by using segmented catalogs and inversion to obtain time lapse velocity maps and using baseline seismic derived impedance as a constraint for time lapse high resolution.</td>
</tr>
</tbody>
</table>
Part 4

3D surface seismic data analysis

**Background**

- Seismic/log attributes
- ANN derived discontinuity
- FZI
Attributes

What are seismic attributes?

Different **measurements** derived from the original seismic data to help reveal features, relationships or patterns in the data useful in interpretation.

- **Curvature**
  - Faults and lineaments

- **Instantaneous Frequency**
  - Fracture zone, bed thickness, shale content & edges

- **Absorption Factor (Q)**
  - Absorption characteristics of beds

- **Energy**
  - Stratigraphic features and geo-bodies

- **Coherence**
  - Faults and fractures

- **Relative AI**
  - Porosities, sequence boundaries & unconformities
Seismic and log derived attributes
Discontinuity mapping

ANN derived discontinuity & confidence
Seismic derived FZI maps

Input maps

$FZI_1 = F\{ f_n(t), AI_n, Q_n(t) \}$

$FZI_2 = F\{ f_n(t), AI_n, \phi_n, \rho_n \}$

FZI$_1$ & FZI$_2$ maps

Sample Well

Training data extraction
**Seismic derived log property estimates:** We have used ANN based property prediction workflows from well logs to map usable property volumes such as porosities and densities which we use for characterization.

**ANN based discontinuity mapping:** We have carried out discontinuity mapping and used it as a framework to understand the observed production regimes at specific test wells.

**ANN based FZI mapping:** We have used ANN based mapping to devise new fracture zone identifiers from seismic data which uses either independent (seismic) or integrated (seismic + logs / seismic + logs + MEQ) approach to fracture identification.
Part 5

Hybrid FZI attributes

ANN derived hybrid FZI Interpretations
Hybrid (seismic + log + MEQ) FZI

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Conclusions
Mapped fracture attributes

\[ k_{Fi} \]

\[ \text{FZI}_{3,4} F \quad k_{Fi} = n_{fn} F \text{ZI}_A^{\frac{3}{2}} / 12 \quad n_1 A_{Fn} V_{En} \]

Introduction
Autopicking
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Integrated analysis
Conclusions
FZI$_4$ projections (horizons of interest)
Part 6

Integrated analysis

- Discontinuity maps
- FZI maps
- Edge maps
- Stress maps
- Weakness maps
Fractured intervals ($V_E$, $\Delta_T$ & $FZI_4$)

Horizon 3 (Testing)
Discontinuity integrated FZI$_4$ maps

FZI$_4$ integrated with discontinuity at 500m & 1000m depths
Connectivity using FZI\textsubscript{4} & discontinuity
$V_E$, discontinuity gradient & edge maps
FZI$_4$, stress gradient & edge maps
Concluding remarks

- Seismic and microseismic data is independently processed and analyzed to obtain useful reservoir property estimates (including geometrical, structural & geomechanical attributes) which together form the basis for our novel fracture characterization workflow.

- We have demonstrated:
  - Improved phase detection for poor quality passive seismic datasets
  - High resolution velocity modeling with poor MEQ data quality (using seismic derived constraints).
  - Geomechanical property estimates for fracture zone identification
  - Implementation of newly defined hybrid FZI attributes
  - Integrated analysis and interpretation to better understand reservoir behavior and plan future field development.
QUESTIONS ...