# Full waveform microseismic inversion using differential evolution algorithm

#### Lijun Zhu, Entao Liu, and James McClellan

CeGP, Georgia Tech

December 11, 2015





1 Introduction



**3** Synthetic Simulation

#### 4 Conclusion

1 Introduction



**3** Synthetic Simulation



## Surface monitoring during hydraulic fracturing



# Summary

- Low oil price urges for cost-effective long-term monitoring
- Increasing interests on surface geophone array monitoring
  - Low cost comparing to wellbore array
  - Good azimuth angle coverage
  - Long term monitoring
- Microseismic events is a good indicator of subsurface structure changes
  - Event location
  - Source mechanism
- Processing pipeline
  - Pre-processing (QC and de-noise)
  - Event detection
  - Event localization
  - Finding source mechanism

## Previous work on event localization

- Digitize the entire monitoring space into small blocks (grid nodes)
- Semblance [Gharti et al., 2010, Frantiek\* et al., 2014]
  - Search all possible grid nodes using simple but fast method.
  - Rely on the coherent signal energy across the receiver array.
  - Low computation requirement, but might give misleading or imprecise results.
- Back-propagation
  [Gajewski and Tessmer, 2005, Haldorsen et al., 2012]
  - Reverse time and back propagate wave field in digitized grids based on wave equations.
  - Take advantage of full waveform information.
  - Effective but expensive (time and memory), especially for 3D elastic wave.
  - Sensitive to model error, can have poor focusing.
- Both methods were developed using single component data

## Example of traditional methods



Figure 1 : Event localization from (a)semblance based method and (b) reverse-time based method.

## 3-component data and source mechanism

- 3-component(3-C) data is becoming popular
- Source mechanism is also important in reservoir monitoring
- Identify the source mechanism along with the localization becomes possible



Beachball	Moment tensor	Beachball
	$-\frac{1}{\sqrt{3}} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$	$\bigcirc$
$\bullet$	$\frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$	
$\bigcirc$	$\begin{array}{ccc} \frac{1}{\sqrt{2}} \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & -1 & 0 \end{pmatrix}$	
$\bigcirc$	$\frac{1}{\sqrt{2}} \begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$	
	$\frac{1}{\sqrt{6}} \begin{pmatrix} -2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$	
0	$-\frac{1}{\sqrt{6}} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -2 \end{pmatrix}$	$\bigcirc$
		$ \begin{array}{ c c c c c c c } & & & & & & & & \\ \hline & & & & & & \\ \hline & & & &$

(b) Moment tensor









#### Assumptions

- Event origin time is given by event detection
- Source waveform is available through wavelet estimation
- Only AWGN is considered after pre-processing
- Isotropic lossless layered velocity model
- Forward modelling of 3-C data
  - For complicated model, Finite-difference is used to compute Green's function
  - For layered velocity model, Green's function for *p*-wave and s-wave can be obtained by Generalized Ray Theory [Ben-Menahem and Singh, 2012]
  - Separate moment tensor and wave propagation due to isotropy of the media

# Problem setup (cont.)

#### Physical model

For  $i^{\text{th}}$  source and receiver pair, a Green's function g[i] satisfies

$$\mathbf{u}[i] = g[i] * w \times \mathbf{m}$$

where  $\mathbf{u}[i]$  is the data received, w is the source wavelet and  $\mathbf{m}$  is the moment tensor.

■ Denote the convolution by G[i] ≜ g[i] \* w. Stack G[i] into a big matrix G and data matrix u[i] into u, we have

$$\mathbf{u} = \mathbf{G}\mathbf{m} \tag{1}$$

where both **G** and **m** are unknown.

For a set of receiver locations, fixed velocity model and source wavelet, G is only a function of source location s, thus

$$\mathbf{u} = \mathbf{G}(\mathbf{s})\mathbf{m} \tag{2}$$

## Minimization problem

#### Original problem

$$\underset{\mathbf{s},\mathbf{m}}{\mathsf{Minimize}} \|\mathbf{u} - \mathbf{G}(\mathbf{s})\mathbf{m}\|$$

For a fixed s, m can be estimated by least squares

$$\hat{\mathbf{m}}(\mathbf{s}) = (\mathbf{G}^{H}(\mathbf{s})\mathbf{G}(\mathbf{s}))^{-1}\mathbf{G}^{H}(\mathbf{s})\mathbf{u}$$
(3)

New problem

$$\underset{s}{\text{Minimize } J(s) \triangleq \| u - G(s)\hat{m}(s)\|}$$
(4)

In most cases, J(s) is a highly non-linear, non-convex function of s.

# Search for the minimum

#### Grid search

- Small model, coarse grid
- Green's function of every source-receiver pair is evaluated
- Minimum is guaranteed
- Differential Evolution algorithm (DE)
  - A smart way to sample the parameter space by population
  - Mutation is introduced for each generation(iteration) based on the current population
  - Selected mutants are compared with current population, the better one goes into the next generation
  - Requires fewer evaluations of forward modelling (computation of Green's function)

## Differential evolution

- Initialization: randomly select an initial population of D agents consisting a set of parameters
- Mutation **v**<sub>p</sub>:

$$\mathbf{v}_p = \mathbf{x}_{p1} + F(\mathbf{x}_{p2} - \mathbf{x}_3) \tag{5}$$

where  $F \in [0, 2]$ ,  $\mathbf{x}_{p1}$  to  $\mathbf{x}_{p3}$  are distinct and randomly selected from current population.

Crossover:

$$u_j = \begin{cases} v_j & \text{if } p_j \leq C \text{ or } j = RI \\ x_j & \text{otherwise} \end{cases}$$
(6)

where  $p_j \sim U(0,1)$ ,  $C \in [0,1]$ , and random index(*RI*) is among  $\{1, \cdots, D\}$ .

Selection: Choose between u<sub>i</sub> and x<sub>i</sub> and keep the one with lower cost function J(s).









15 × 15 surface geophone array, double-couple moment sensor shown below:

$$MT = \begin{bmatrix} 0.4330 & -0.2500 & 0.7500 \\ -0.2500 & -0.4330 & 0.4330 \\ 0.7500 & 0.4330 & 0.0000 \end{bmatrix}$$
(7)

• Use **PSNR** as the measurement of noise level:

$$\mathsf{PSNR} = 20 \log_{10} \frac{D_{\mathsf{max}}}{\sigma} \tag{8}$$

where  $D_{\max}$  is the maximum magnitude of a trace and  $\sigma$  is the standard deviation of AWGN.

• The model size is of  $30 \times 30 \times 15$  grid points with 40m spatial resolution

## Simulation setup



Figure 2 : Simulation setup: (i)array geometry and (ii)sample data with 25dB PSNR: (a)x, (b)y, (c)z components.

## Details about DE algorithm

- Off-grid point
  - Move to the nearest grid node
  - Green's function of each node will only be evaluated once in the simulation
- Population size
  - Rule of thumb: population size is 5 to 10 times the dimension of parameter space
  - In our example, the dimension of parameter space is three (x,
    - y, z): population size is 30
- Accuracy measurement
  - The spatial resolution is 40m, the half diagonal distance is about 30m  $(20\sqrt{2})$
  - 60m error will be acceptable, 30m error will be a good estimation
- Terminal condition
  - DE program can be restart at any iteration as long as the population is saved
  - Gradually increase the number of iteration until the cost function is stable



### Population convergence as iteration increases

- Population converges slower than the estimated error
- Dot color and size indicate number of iterations



# Simulation results

#### Accuracy

- acceptable accuracy (60m error) within 40 iteration
- good accuracy (30m error) within 60 iteration
- Robustness
  - Reach good accuracy in 100 iteration down to 0 dB PSNR
  - Event detection will break before the localization algorithm
- Computation requirement
  - Grid search:  $30 \times 30 \times 15 \times 225 = 3,037,500$  evaluation of Green's function
  - DE algorithm(C = 0.5):  $15 + 0.5 \times 30 \times 60 \times 225 = 205,875$ evaluation of Green's function
  - DE evaluates only 6.7% of all the grid nodes









- The proposed method integrates moment tensor inversion and event localization
- Reduce the dimension of parameter space from 9 to 3 using proposed scheme
- Synthetic simulation illustrates a good accuracy of proposed method within reasonable number of iterations
- Differential evolution method evaluates significantly fewer Green's functions than grid search method

## References

- Ben-Menahem, A., and S. Singh, 2012, Seismic waves and sources: Springer New York.
  - Frantiek\*, S., J. Valenta, D. Anikiev, and L. Eisner, 2014, Semblance for microseismic event detection: SEG Technical Program Expanded Abstracts 2014, 2178–2182.

Gajewski, D., and E. Tessmer, 2005, Reverse modmodel for seismic event characterization: Geophysical Journal International, **163**, 276–284.



Gharti, H. N., V. Oye, M. Roth, and D. Khn, 2010, Automated microearthquake location using envelope stacking and robust global optimization: GEOPHYSICS, **75**, MA27–MA46.



Haldorsen, J., M. Milenkovic, N. Brooks, C. Crowell, and M. Farmani, 2012, Locating microseismic events using migration-based deconvolution: SEG Technical Program Expanded Abstracts 2012, 1–5.

# Thanks for your attention!

This work is supported by the Center for Energy and Geo Processing (CeGP) at Georgia Tech and by King Fahd University of Petroleum and Minerals (KFUPM).