Application of surface-consistent matching filters (SCMF) to time-lapse data set

Mahdi Almutlaq and Gary F. Margrave

University of Calgary, Department of Geoscience, CREWES

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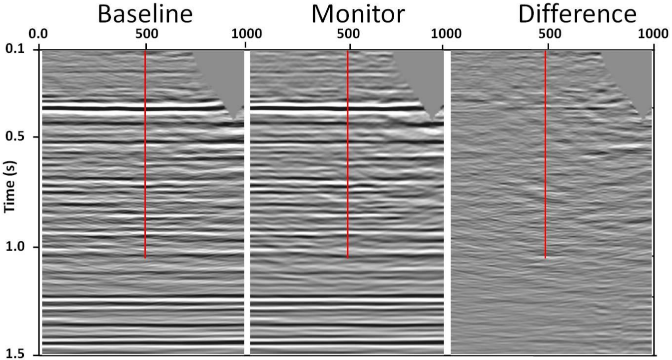
What is the purpose of this study?



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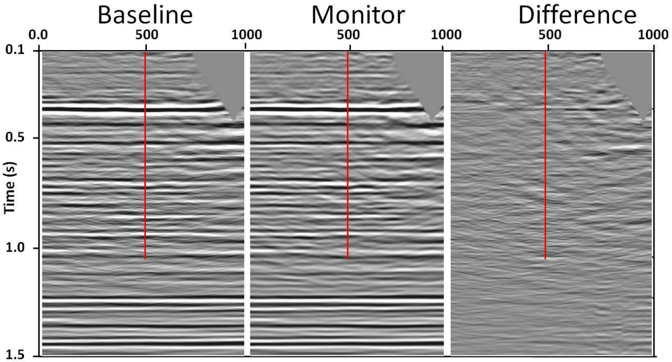

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- scale data to same amplitude level

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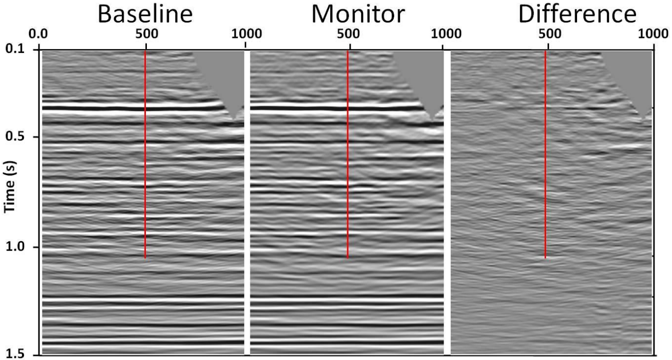

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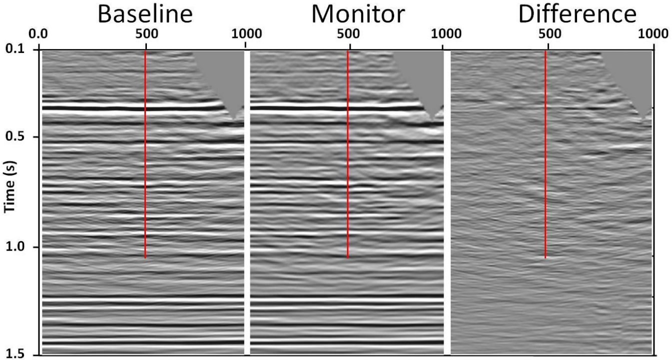

Our goal is to design matching filters that

- scale data to same amplitude level
- equalize phase and bandwidth
- compensate for time-shifts

Outline

Surface-consistent model

Surface-consistent model

The seismic trace can be modeled as

$$d_{ij}(t) = s_i(t) * r_j(t) * h_k(t) * y_l(t)$$

where

- d_{ij}: *seismic trace*
- s_i : *source response at location* i
- r_j : *receiver response at location* j
- h_k: *offset response at location* k; $k = |i - j|$
- y_l : *subsurface response at* l; $l = \frac{(i+j)}{2}$

Matching filters

Time domain:

$$m * s1 = s2 \tag{1}$$

Fourier domain:

$$M(\omega) = \frac{S_2(\omega)}{S_1(\omega)}. \tag{2}$$

Matching filters

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- a perfect matching filter is a spectral ratio; however
- spectral ratio is unstable in presence of noise; and

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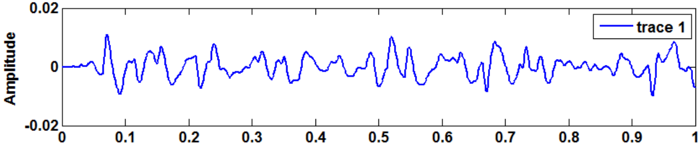
What do we do?

- We solve time-domain (equation 1) in LSQ sense and Fourier transform the solution which is a good approximation to the spectral ratio method.

Matching filters



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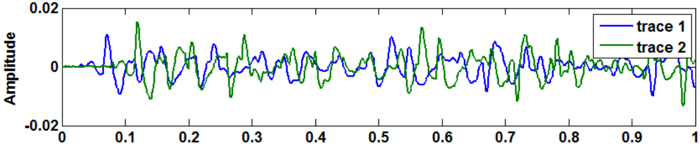

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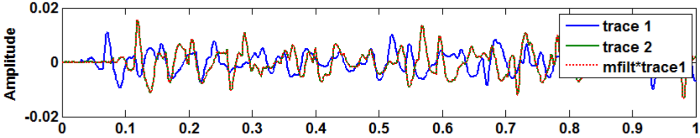
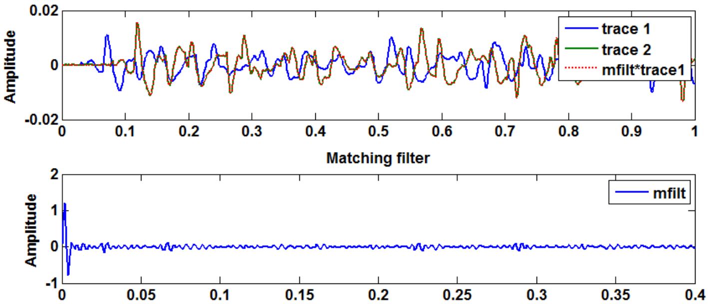
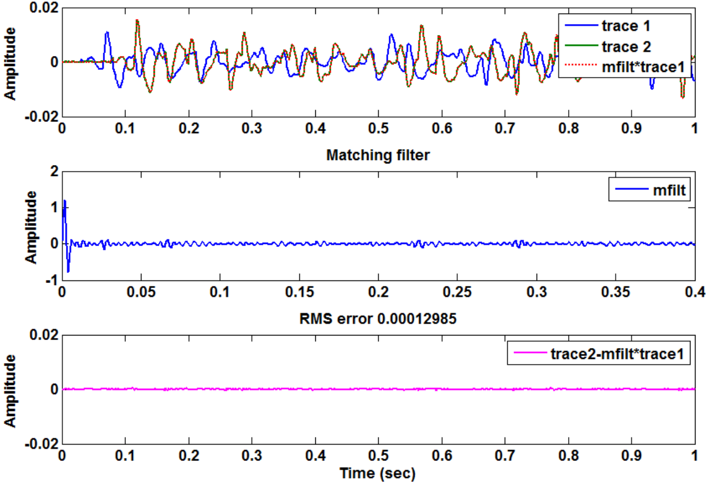


Matching filters



Matching filters



In time-lapse we normally have 2 data sets:

- Baseline survey; and
- Monitoring survey

Their surface-consistent model is:

$$
\begin{aligned}
d1_{ij}(t) &= s1_i(t) * r1_j(t) * h1_k(t) * y1_l(t) \\
d2_{ij}(t) &= s2_i(t) * r2_j(t) * h2_k(t) * y2_l(t)
\end{aligned}
\tag{3}
$$

Surface-consistent matching filters

Several steps to obtain a SCMF:

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- design $\mathbf{m}$ such that

$$\mathbf{d1} = \mathbf{D2m}, \tag{4}$$

  where $\mathbf{D2}$ is the convolution matrix formed from $\mathbf{d2}$

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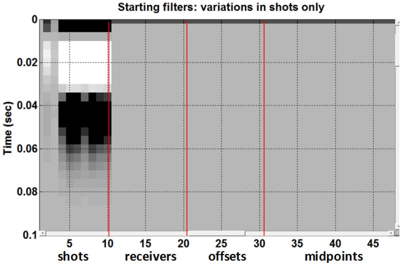
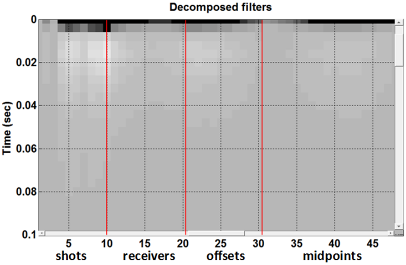
The above are trace-by-trace process. Once that complete, we

- decompose the log(FFT($\mathbf{m}$)) into four-components

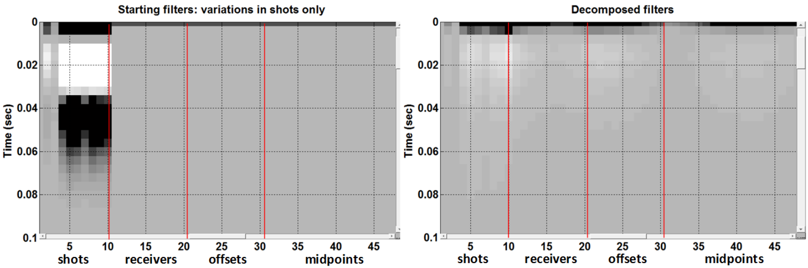
1D example: variations in source





- variation in input shot filters only

1D example: variations in source



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- decomposed filters show variation in all components

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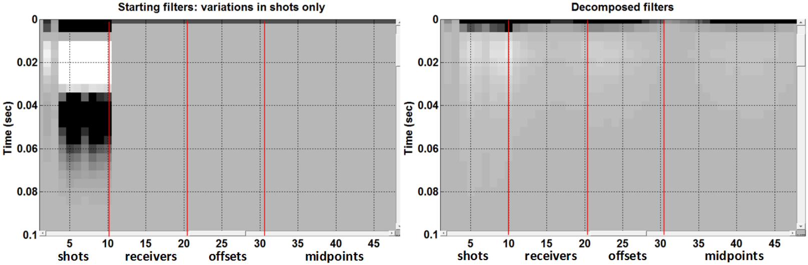
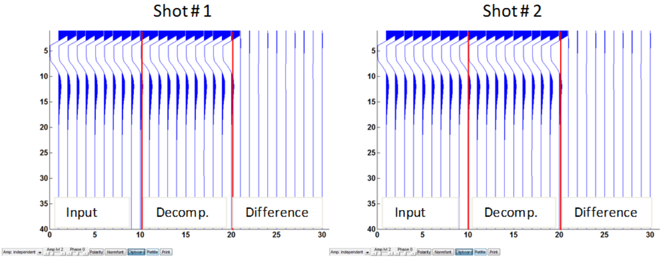
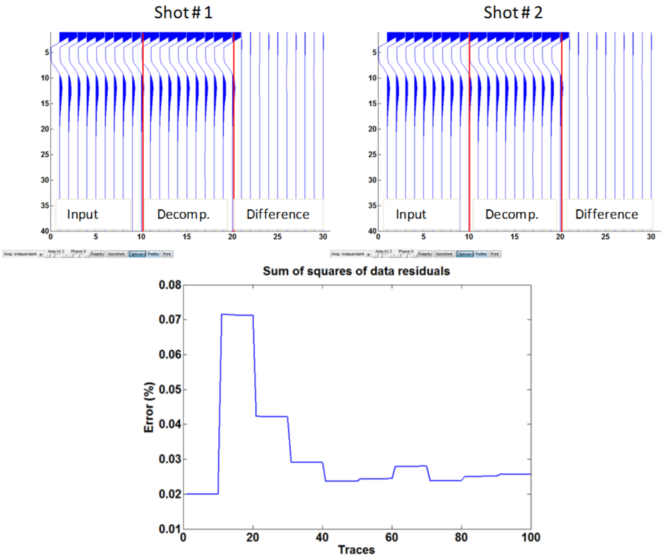


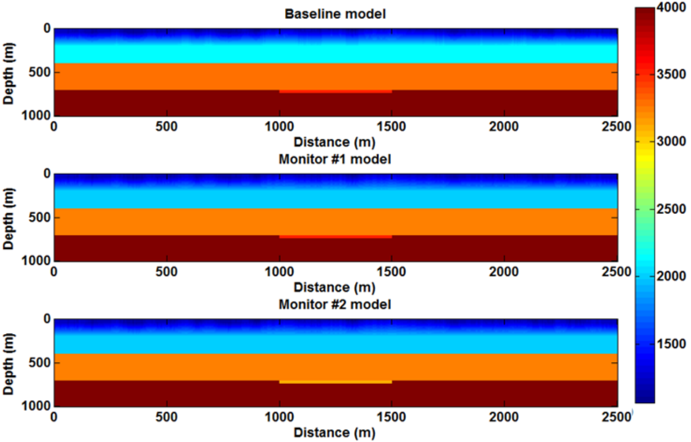
- variation in input shot filters only
- decomposed filters show variation in all components
- comparing the input data with the decomposed data we see the following:

1D example: variations in source

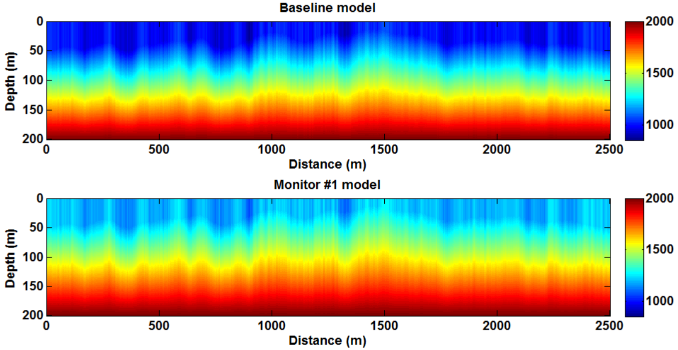


1D example: variations in source

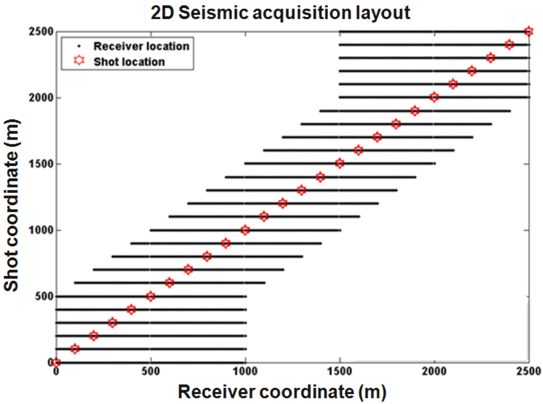



Baseline model
Monitor #1 model
Monitor #2 model
Depth (m)
Distance (m)
0
500
1000
1500
2000
2500
4000
3500
3000
2500
2000
1500

Zoom in:

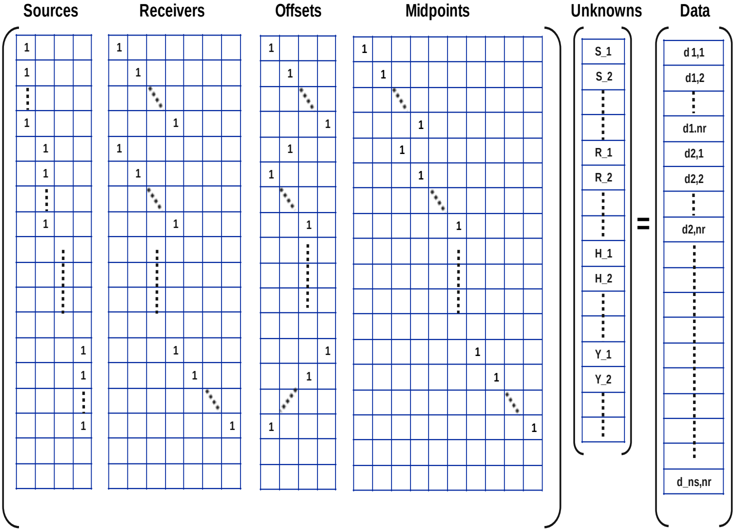

Baseline model
Depth (m)
0
50
100
150
200
0
500
1000
1500
2000
2500
Distance (m)
2000
1500
1000
Monitor #1 model
Depth (m)
0
50
100
150
200
0
500
1000
1500
2000
2500
Distance (m)
2000
1500
1000

Data acquisition



shot spacing = 100m
receiver spacing = 10m
total number of shots = 26
101 receivers per shot

How do we get the SCMF?



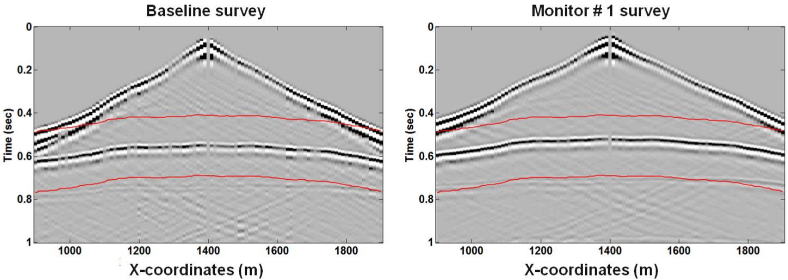
How do we construct the SCMF?

$$\mathbf{G}\mathbf{x} = \mathbf{p}, \tag{6}$$

where $\mathbf{G}$ is the geometry matrix and $\mathbf{x}$ contains the unknown parameters. Recall that we have the $\log(\mathrm{FFT}(\mathbf{m}))$, we denote it $\mathbf{p}$, and the decomposition is:

$$\mathbf{x} = (\mathbf{G}^T\mathbf{G} + \alpha^2\mathbf{I})^{-1}\mathbf{G}^T\mathbf{p}, \tag{7}$$

Constructing the SCMF



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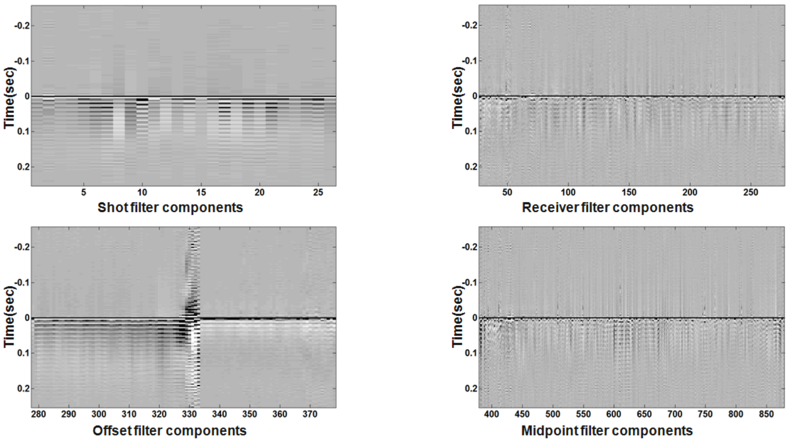
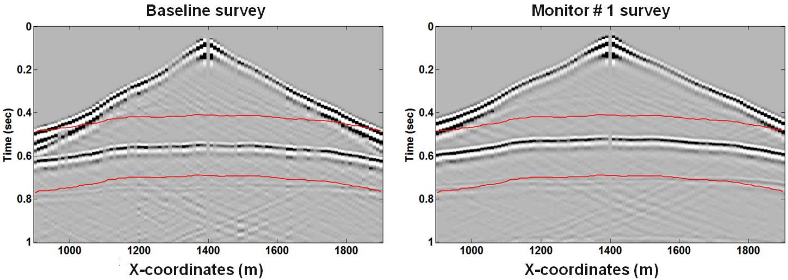


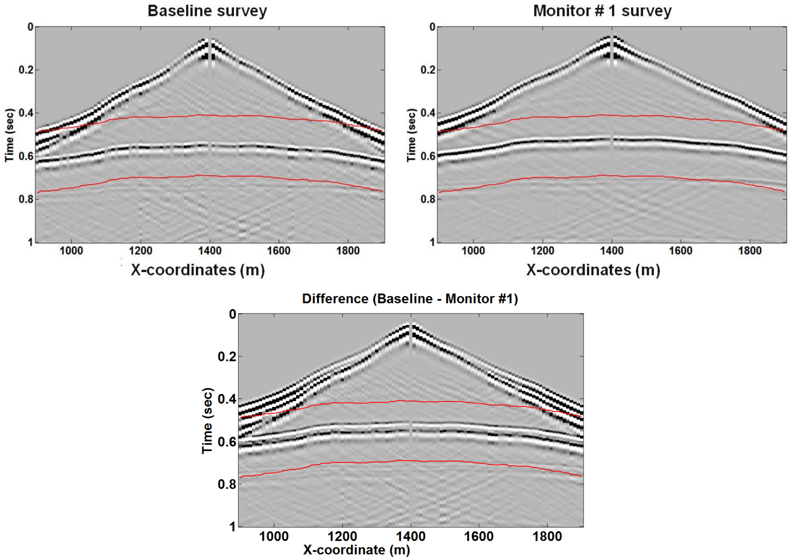
We will show two examples:

1. matching monitor # 1 survey to baseline survey
2. matching monitor # 2 survey to monitor # 1 survey

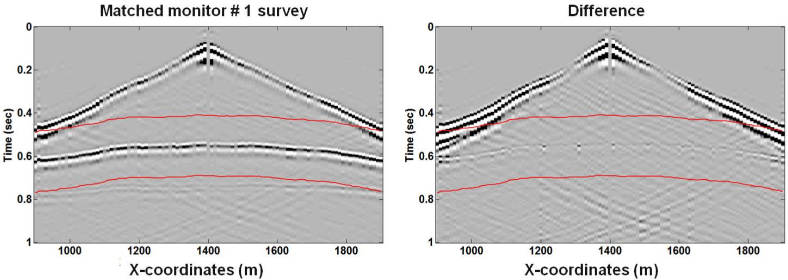
2D example 1


Baseline survey
Monitor # 1 survey
Time (sec)
0
0.2
0.4
0.6
0.8
1
1000
1200
1400
1600
1800
X-coordinates (m)

2D example 1


Baseline survey
Time (sec)
X-coordinates (m)
Monitor # 1 survey
Time (sec)
X-coordinates (m)
Difference (Baseline - Monitor #1)
Time (sec)
X-coordinate (m)

2D example 1

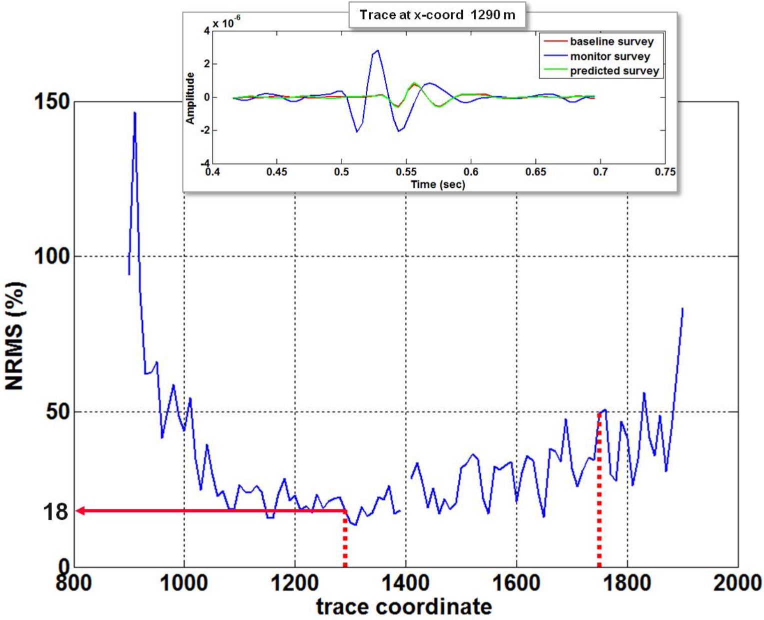

Matched monitor # 1 survey
Difference
Time (sec)
0
0.2
0.4
0.6
0.8
1
1000
1200
1400
1600
1800
X-coordinates (m)

What is NRMS?

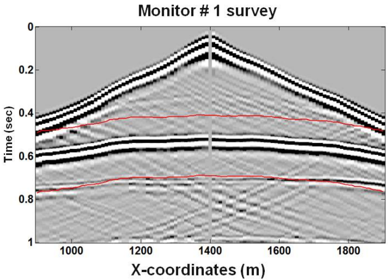
Nrms is considered as the metric system that measures the repeatability between two traces a_t and b_t in a time gate:

$$NRMS = 2\frac{RMS(a_t - b_t)}{RMS(a_t) + RMS(b_t)}. \tag{8}$$

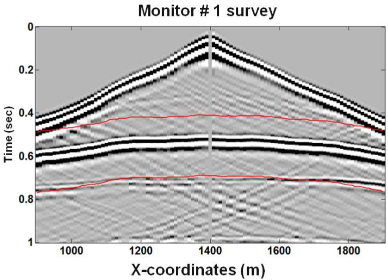
2D example 1: NRMS



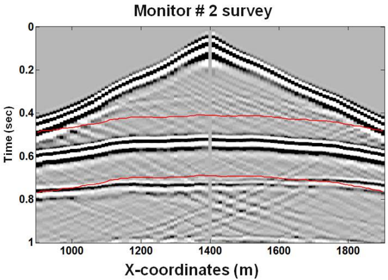
2D example 2


Monitor # 1 survey
Monitor # 2 survey
Time (sec)
0
0.2
0.4
0.6
0.8
1
1000
1200
1400
1600
1800
X-coordinates (m)

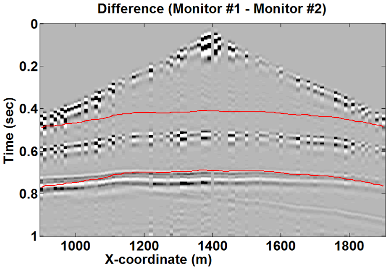
2D example 2



Monitor # 1 survey
0
0.2
0.4
0.6
0.8
1
Time (sec)
1000
1200
1400
1600
1800
X-coordinates (m)

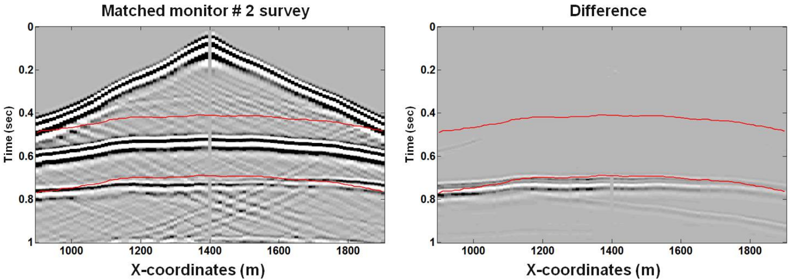


Monitor # 2 survey
0
0.2
0.4
0.6
0.8
1
Time (sec)
1000
1200
1400
1600
1800
X-coordinates (m)

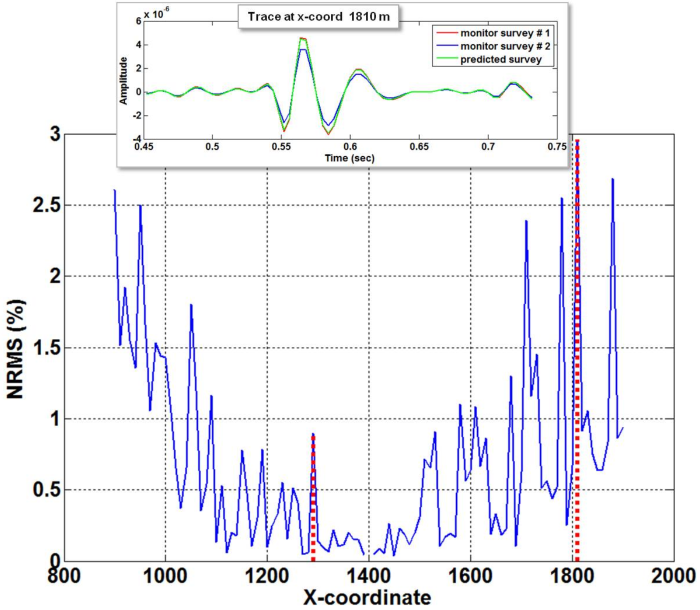


Difference (Monitor #1 - Monitor #2)
0
0.2
0.4
0.6
0.8
1
Time (sec)
1000
1200
1400
1600
1800
X-coordinate (m)

2D example 2


Matched monitor # 2 survey
Difference
Time (sec)
0
0.2
0.4
0.6
0.8
1
1000
1200
1400
1600
1800
X-coordinates (m)

2D example 2: NRMS



Conclusions

- We've deomonstrated the theory of surface-consistent matching filters
- It's analogous to surface-consistent deconvolution **except** we consider **two** data set
- Synthetic time-lapse data sets: baseline, first monitor survey, second monitor survey
- Constructed the 4-component surface-consistent matching filters
- Applied the matching filters to two time-lapse examples
- Balanced amplitudes, equalized phase and bandwidth and compensated for time-shifts

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Thank you ...
Questions?