Bayesian signal separation applied to ground-roll removal

Two adaptive separation schemes
Many Problems

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Adaptive Subtraction Schemes

- Block Coordinate Relaxation (BCR)
  - Introduced by Starck, Elad, Donoho 2004.
  - Modified for seismic images using curvelets to separate multiples by Herrmann, Boeniger and Verschuur, 2007.
  - Used for ground roll removal by Yarham, Boeniger and Herrmann, 2006.
- Bayesian Separation
  - Developed at SLIM by Saab, Wang, Yilmaz and Herrmann, 2007.
  - Adapted to Multiple and Ground Roll Separation.

Adaptive Subtraction Schemes

Formulate The Problem...

$\mathbf{b}$	Recorded Data	$\mathbf{b} = \mathbf{s}_1 + \mathbf{s}_2 + \mathbf{n}$
$\mathbf{s}_1$	Signal 1 (Reflectors)	
$\mathbf{s}_2$	Signal 2 (Surface Wave)	$N = 2$ Signals

$$\mathbf{s}_i = \mathbf{A}_i \mathbf{x}_i + \mathbf{n}_i \qquad i \ldots N$$

A_i Sparsity Promoting Transform

$\mathbf{b}_1$	Predicted Reflectors	$\mathbf{b} = \mathbf{b}_1 + \mathbf{b}_2$
$\mathbf{b}_2$	Predicted Surface Wave	

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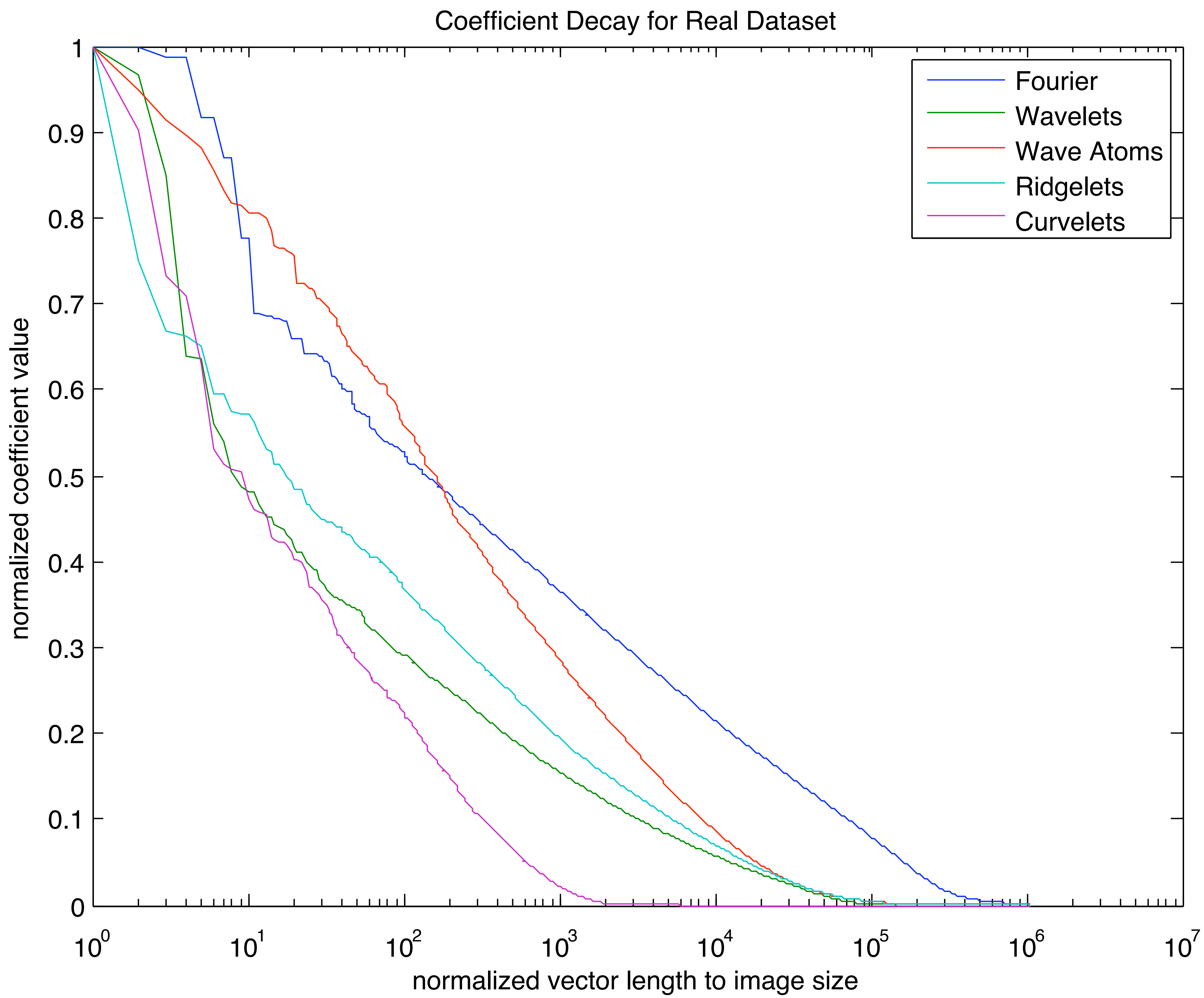
Adaptive Subtraction Schemes

Sparsity

A Sparsity Promoting Transform



Curvelets are the most sparse representation of seismic data.

How do we take advantage of this?

We apply weights to the thresholds that define the 1-norm minimization

Adaptive Subtraction Schemes

Block Coordinate Relaxation

$$\min_x ||x||_{\mathbf{w},1} \quad \text{subject to} \quad ||\mathbf{b} - \mathbf{A}\mathbf{x}||_2 \leq \epsilon$$

$$\hat{\mathbf{b}}_1 = \mathbf{A}_i \hat{\mathbf{x}}_i \quad i \ldots N$$

$$\text{given:} \quad \mathbf{b}_1 \quad \text{and} \quad \mathbf{w}(\mathbf{b}, \mathbf{b}_1)$$

$$\hat{\mathbf{x}}_j = \arg\min_{\mathbf{x}_j} \frac{1}{2} |||]\mathbf{b} - \mathbf{A}_j \mathbf{x}_j - \sum_{i \neq j} \mathbf{A}_i \mathbf{x}_i||_2^2 + ||\mathbf{x}_j||_{1,\gamma \cdot \mathbf{w}_j}$$

Algorithm derived in paper:
Nonlinear primary-multiple separation with directional curvelet frames
F. J. Herrmann and U. Boeniger and D. J. Verschuur, 2007

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Adaptive Subtraction Schemes

Bayesian Formulation

$\mathbf{n}$ Recorded Noise

$\mathbf{n}_1$ Reflector Prediction Noise

$$\mathbf{n} = \mathbf{n}_1 + \mathbf{n}_2 \qquad N(0, \sigma_2^2)$$

Rewrite surface wave and reflectors as:

$$\mathbf{b}_2 = \mathbf{A}\mathbf{x}_2 + \mathbf{n}_2$$

$$\mathbf{b}_1 = \mathbf{A}\mathbf{x}_1 + \mathbf{n} - \mathbf{n}_2$$

Adaptive Subtraction Schemes

Bayesian Formulation

We need to find the curvelet vectors that maximize the posterior probability

$$P(\mathbf{x}_1, \mathbf{x}_2 | \mathbf{b}_1, \mathbf{b}_2) = \frac{P(\mathbf{x}_1, \mathbf{x}_2) P(\mathbf{b}_1 | \mathbf{x}_1, \mathbf{x}_2) P(\mathbf{b}_2 | \mathbf{b}_1, \mathbf{x}_1, \mathbf{x}_2)}{P(\mathbf{b}_1, \mathbf{b}_2)}$$

We have independent and identically distributed white gaussian noise distributions with a priori information in the form of predictions

$$\arg\max_{x_1, x_2} P(x_1, x_2 | b_1, b_2) = \arg\min_{x_1, x_2} f(x_1, x_2)$$

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Adaptive Subtraction Schemes

Bayesian Formulation

Minimize the function:

$$f(\mathbf{x}_1, \mathbf{x}_2) = \lambda_1 ||\mathbf{x}_1||_{1,\mathbf{w}_1} + \lambda_2 ||\mathbf{x}_2||_{1,\mathbf{w}_2}$$
$$+||\mathbf{A}\mathbf{x}_2 - \mathbf{b}_2||_2^2 + \eta ||\mathbf{A}(\mathbf{x}_1 + \mathbf{x}_2) - \mathbf{b}||_2^2$$

Algorithm is derived in technical report:
Bayesian wavefield separation by transform-domain sparsity promotion
Deli Wang, Rayan Saab, Ozgur Yilmaz and Felix J. Herrmann, 2008

η	Confidence parameter
λ_1	Reflector expected sparsity parameter
λ_2	Surface wave expected sparsity parameter

Adaptive Subtraction Schemes

Parameters

Block Coordinate Relaxation:

c_1 Reflector 1-norm minimization threshold decay rate

c_2 Surface wave 1-norm minimization threshold decay rate

Bayesian Formulation:

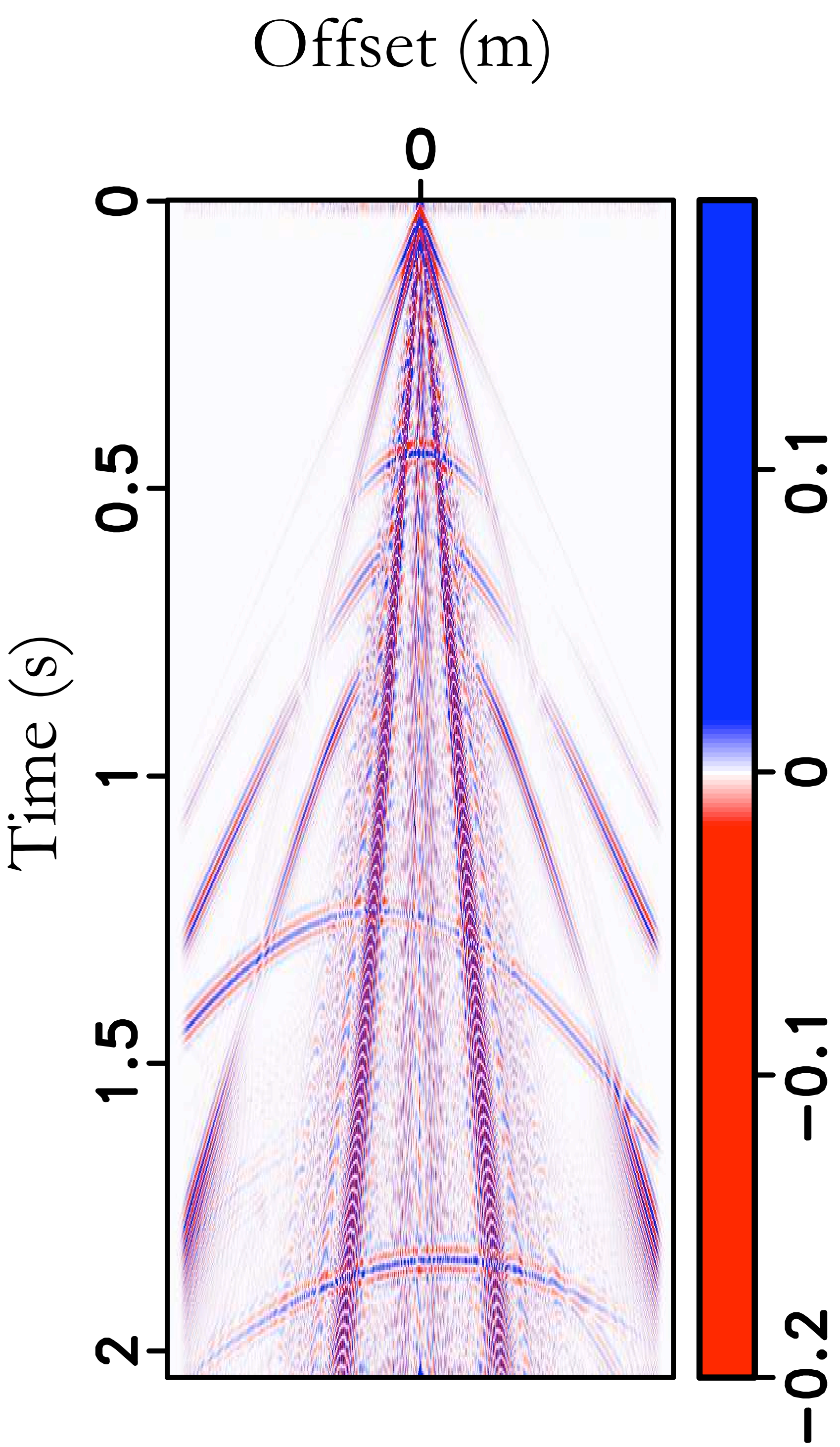
η Confidence parameter

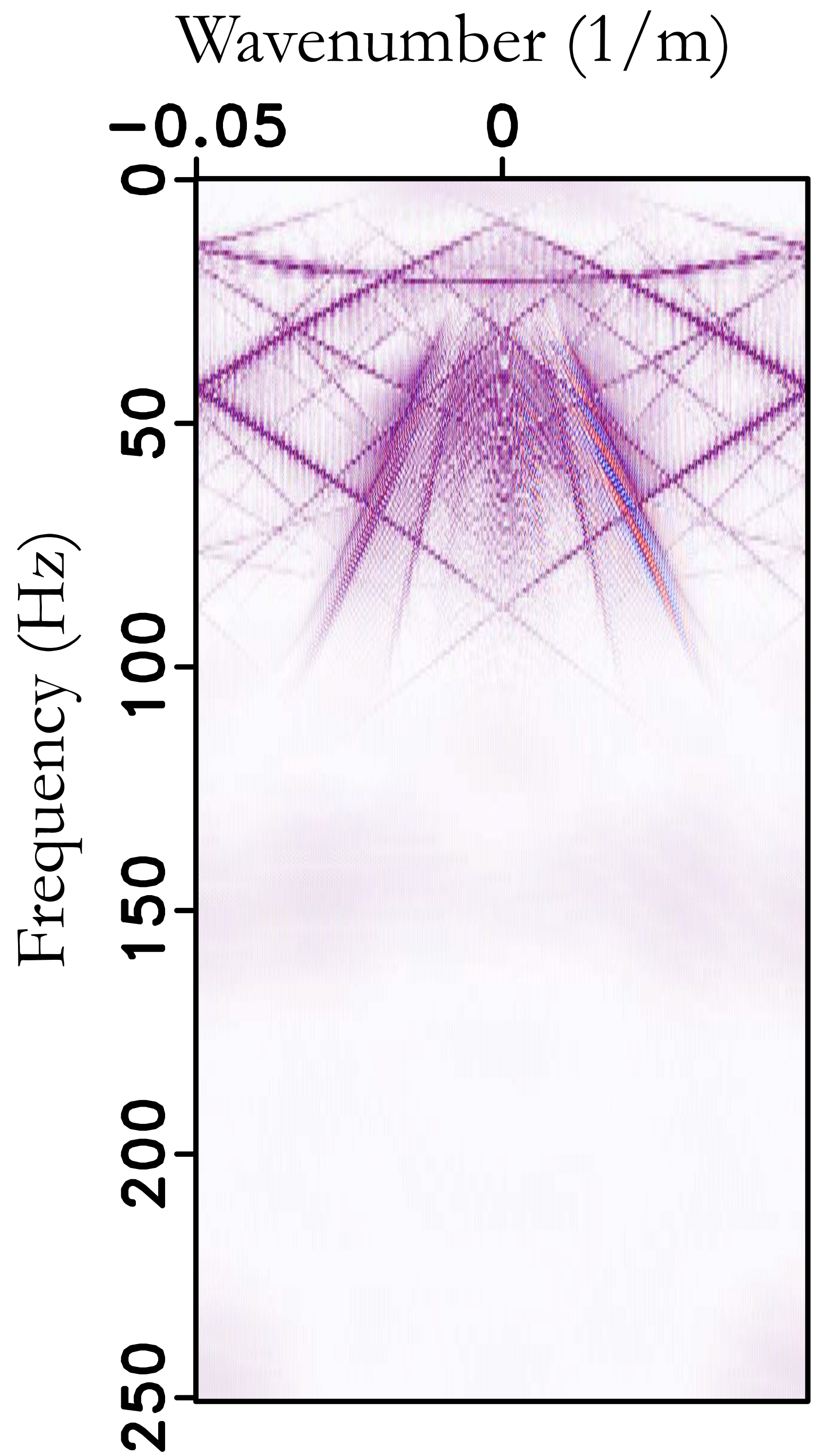
λ_1 Reflector expected sparsity parameter

λ_2 Surface wave expected sparsity parameter

Synthetic Example

Data - Elastic Finite Difference

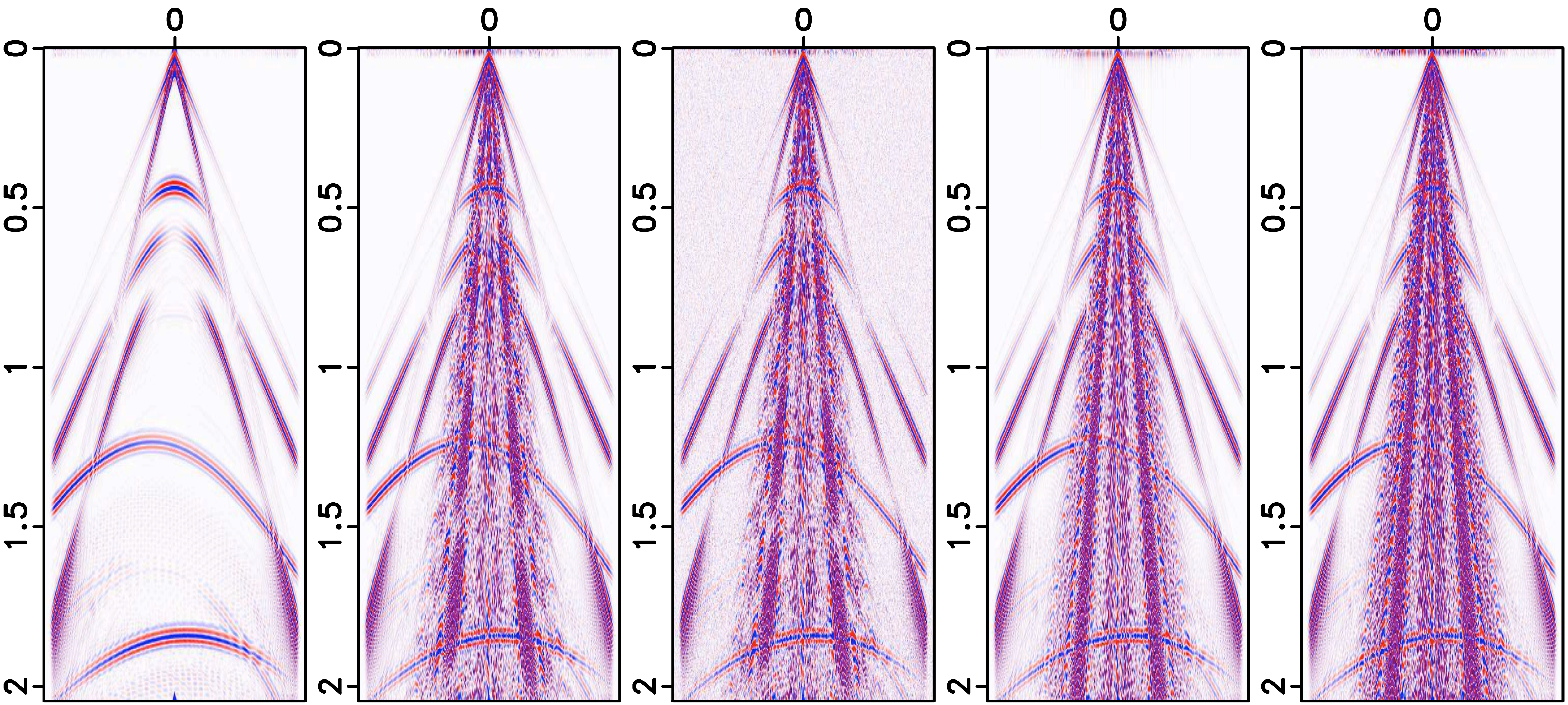




- Reflectors
  - 10m grid
  - 3 Reflectors
    - 500 (m) flat
    - 1500 (m) dipping right
    - 2650 (m) dipping left
- Surface Wave
  - 1m Grid
  - 25m Surface Layer
    - Linear Increase in parameters

Synthetic Example

Benchmark Tests - Predictions



Exact | 5% Model Error | 5% model error with noise | Hilbert transform | Exact inverse

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Synthetic Example

Benchmark Tests - Results

Noise Prediction	Initial SNR	Subtraction	Bayesian	Block Coordinate Relaxation
Exact Noise	-1.673	147.960	17.922	15.504
5% Model Error	-1.673	-4.377	9.592	9.424
5% Model Error + Noise	-1.923	-4.515	9.470	3.528
Hilbert Transform	-1.673	-4.670	13.103	13.331
Phase Inverse	-1.673	-7.694	14.083	13.099

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Synthetic Example

Parameter Sensitivity - Bayesian Solver

SNR (dB)	$0.1 \cdot (\lambda_1^*, \lambda_2^*)$	$2 \cdot \lambda_1^*, \lambda_2^*$	λ_1^*, λ_2^*	$\lambda_1^*, 2 \cdot \lambda_2^*$	$10 \cdot (\lambda_1^*, \lambda_2^*)$
$0.1 \cdot \eta^*$	8.349	3.331	4.457	4.458	1.558
$0.5 \cdot \eta^*$	1.860	5.828	8.875	9.001	3.332
η^*	1.758	6.925	9.592	9.023	4.454
$2 \cdot \eta^*$	-3.899	6.479	1.266	2.782	5.974
$10 \cdot \eta^*$	-4.280	-2.561	-3.384	-3.180	8.052

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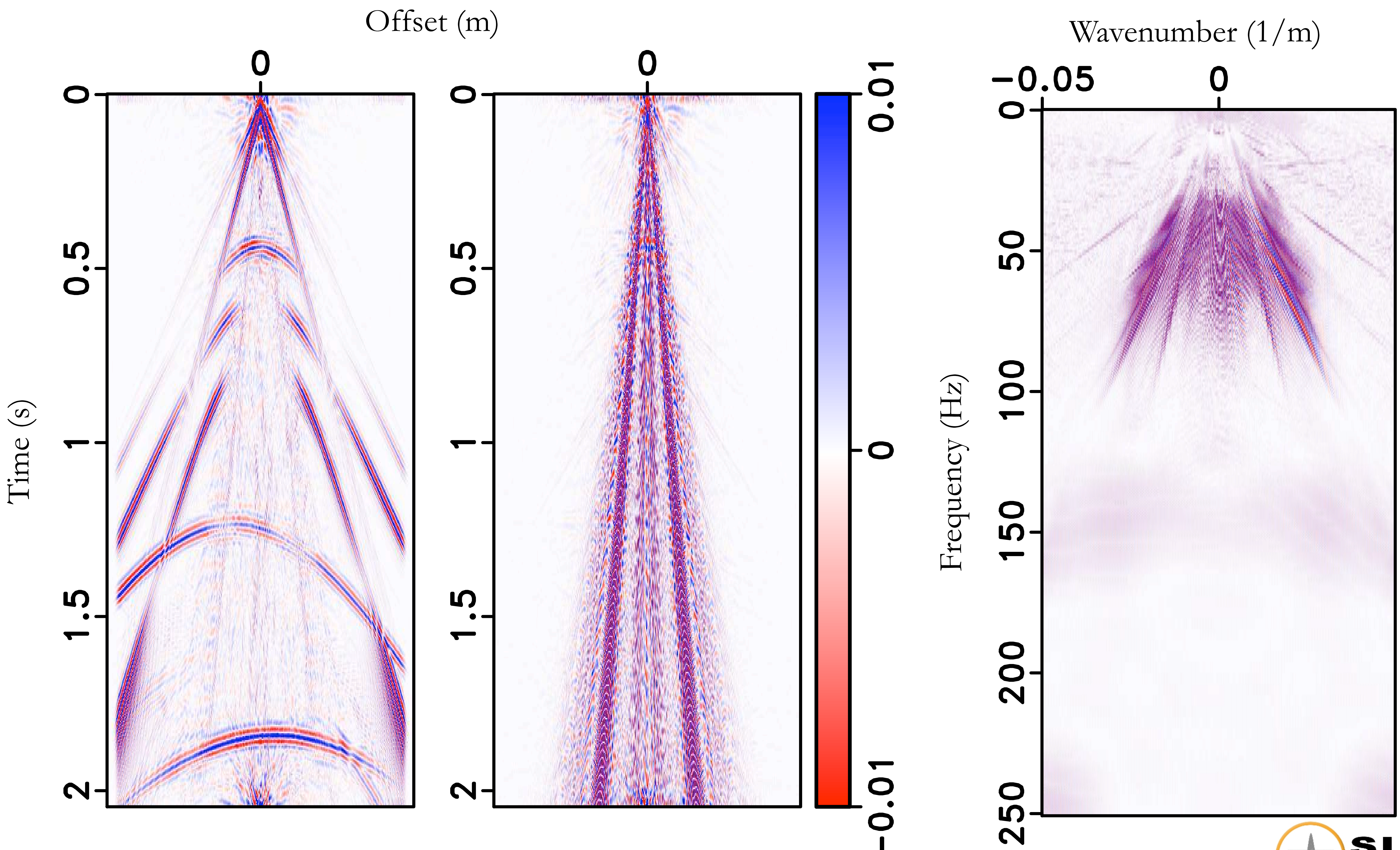
Synthetic Example

Parameter Sensitivity - BCR Solver

SNR (dB)	$0.1 \cdot c_1^*$	$0.5 \cdot c_1^*$	c_1^*	$2 \cdot c_1^*$	$10 \cdot c_1^*$
$0.1 \cdot c_2^*$	6.242	0.353	2.995	-1.566	-1.672
$0.5 \cdot c_2^*$	4.085	8.829	0.618	-1.348	-1.659
c_2^*	2.995	5.011	9.414	-0.556	-1.240
$2 \cdot c_2^*$	1.658	2.468	4.021	7.846	8.420
$10 \cdot c_2^*$	0.002	0.005	0.121	0.145	0.211

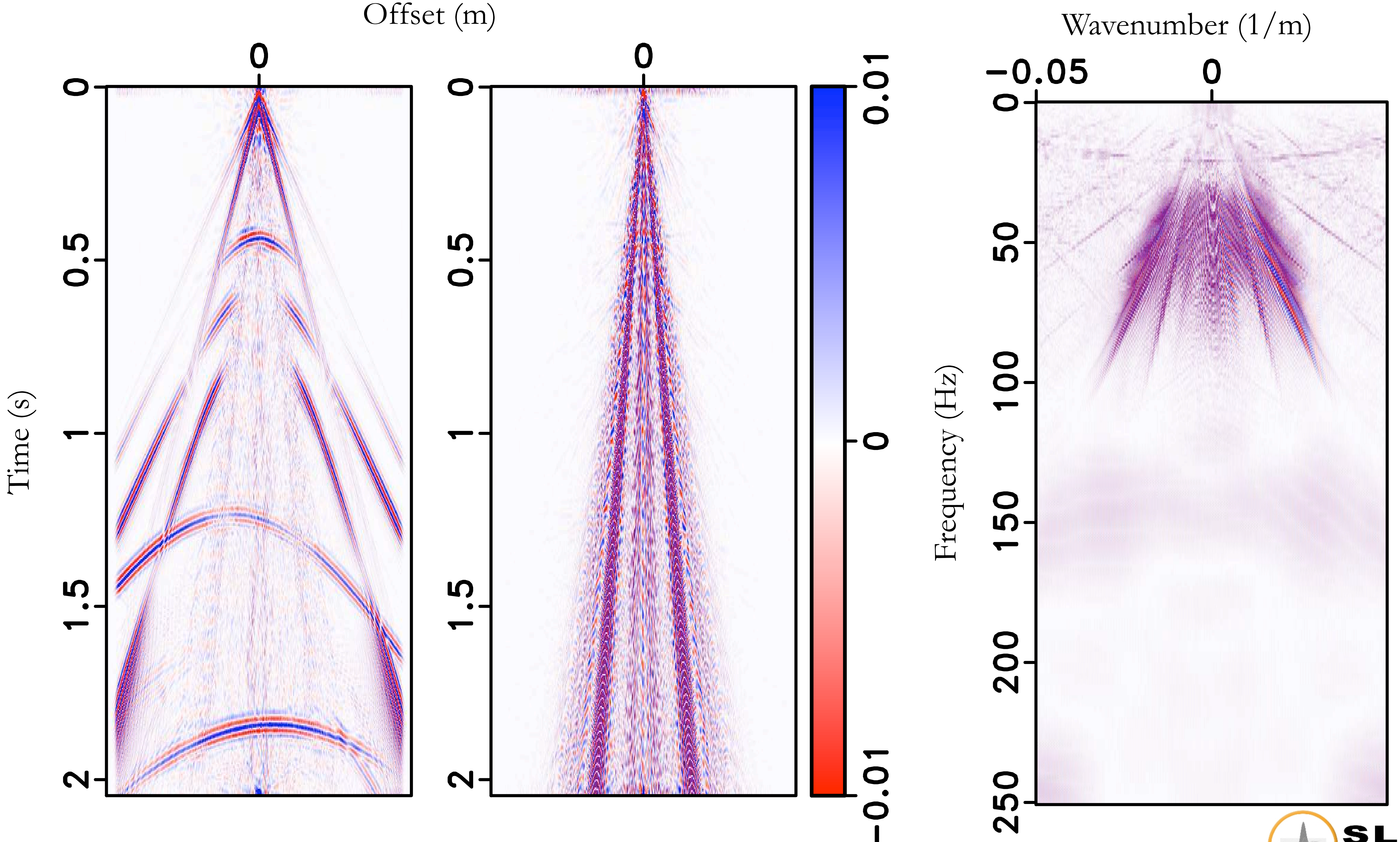
Synthetic Example

Results - Block Coordinate Relaxation



Synthetic Example

Results - Bayesian Formulation



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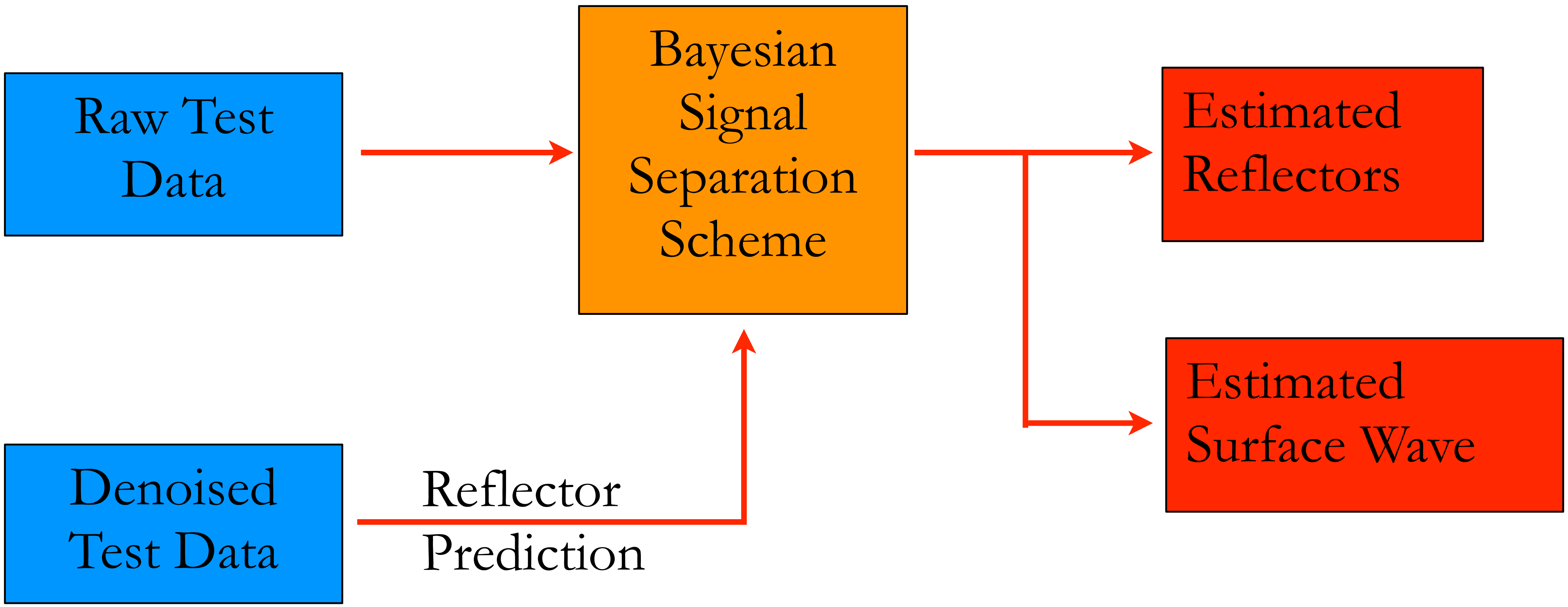
Real Data Example

Shell Test Data



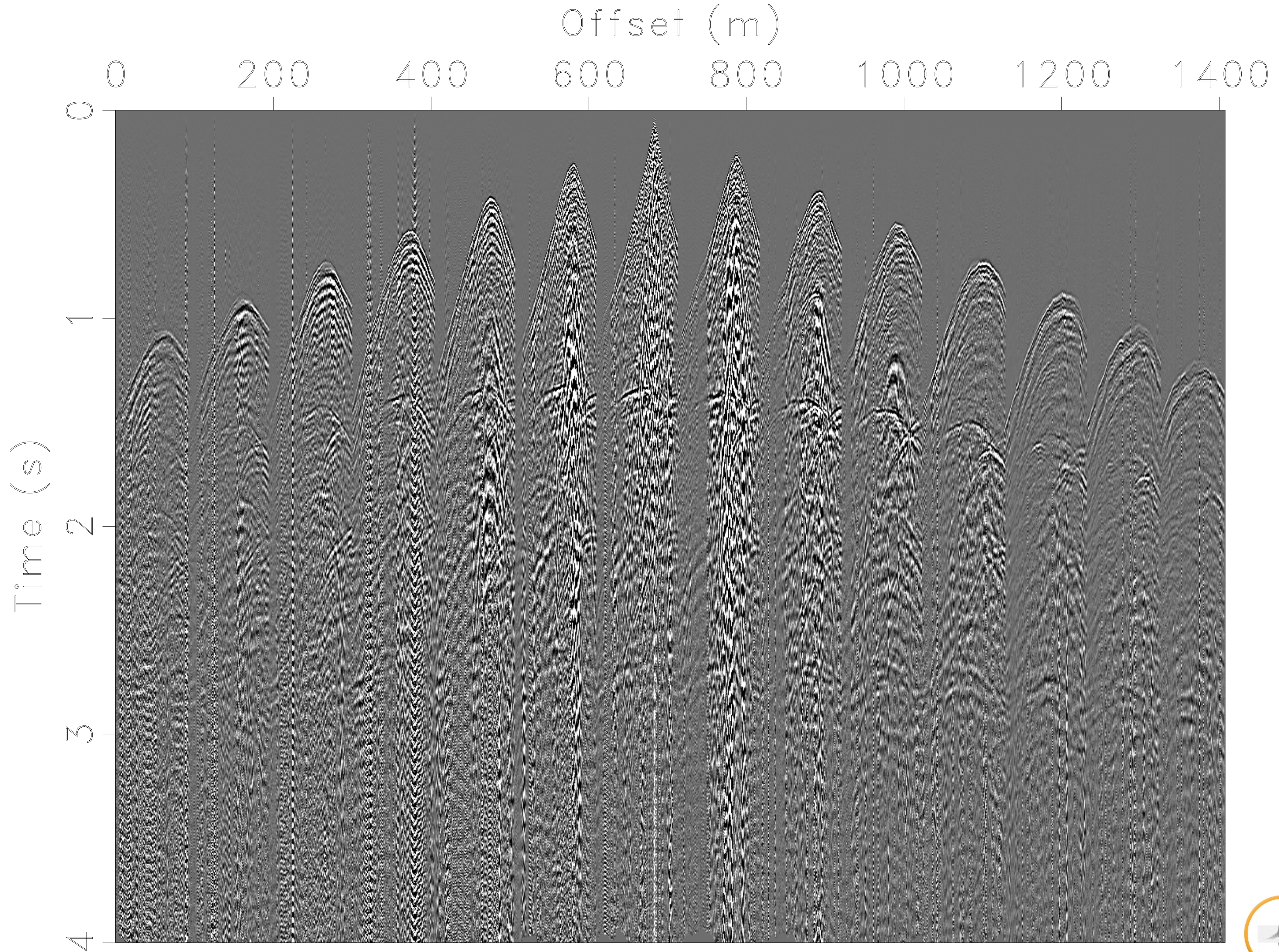
η Prediction Confidence Parameter - Set to 2.0

λ_1 Reflector Sparsity Parameter - Set to 1.0

λ_2 Surface Wave Sparsity Parameter - Set to 1.0

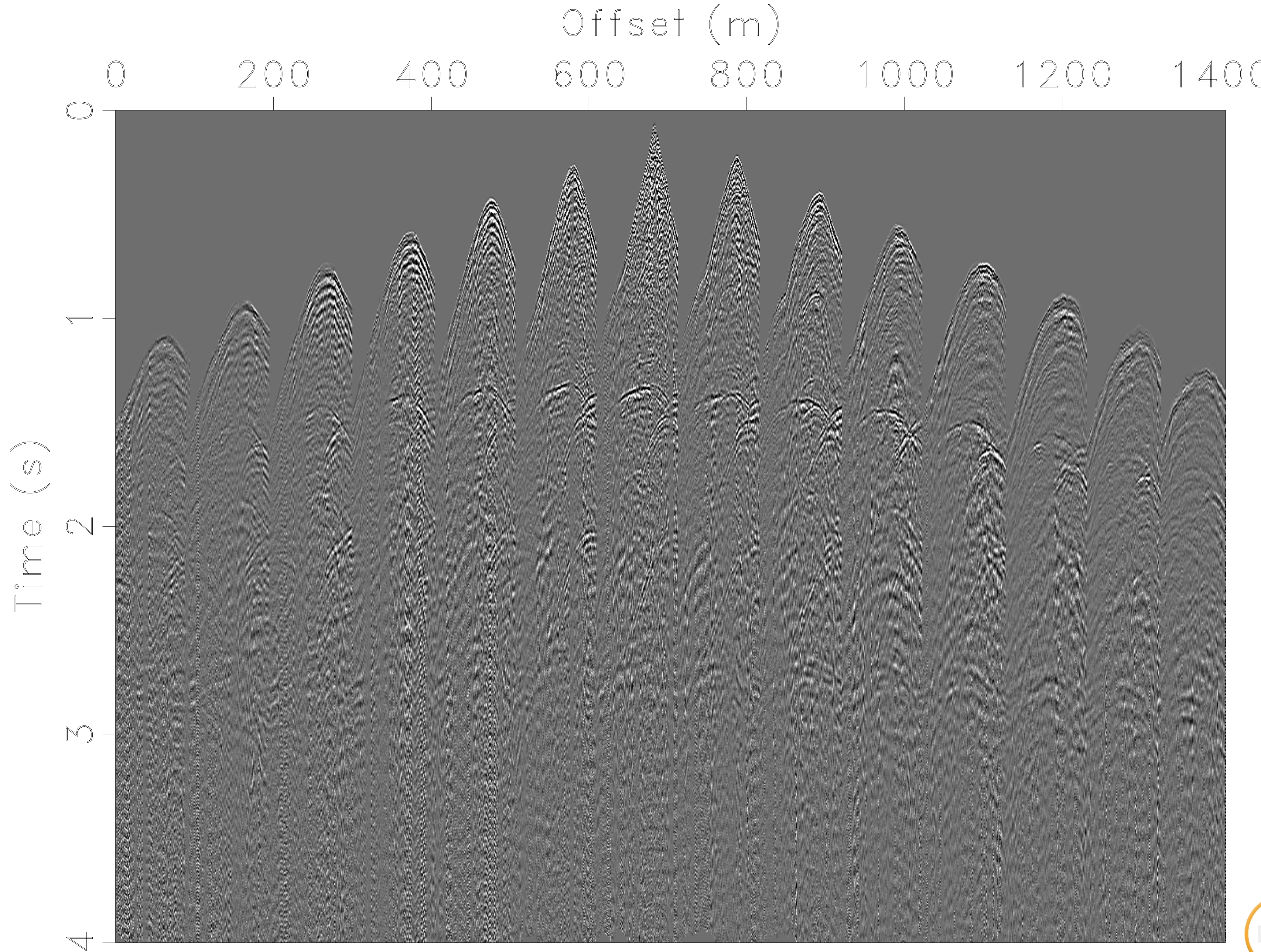
Real Data Example

Shell Test Data



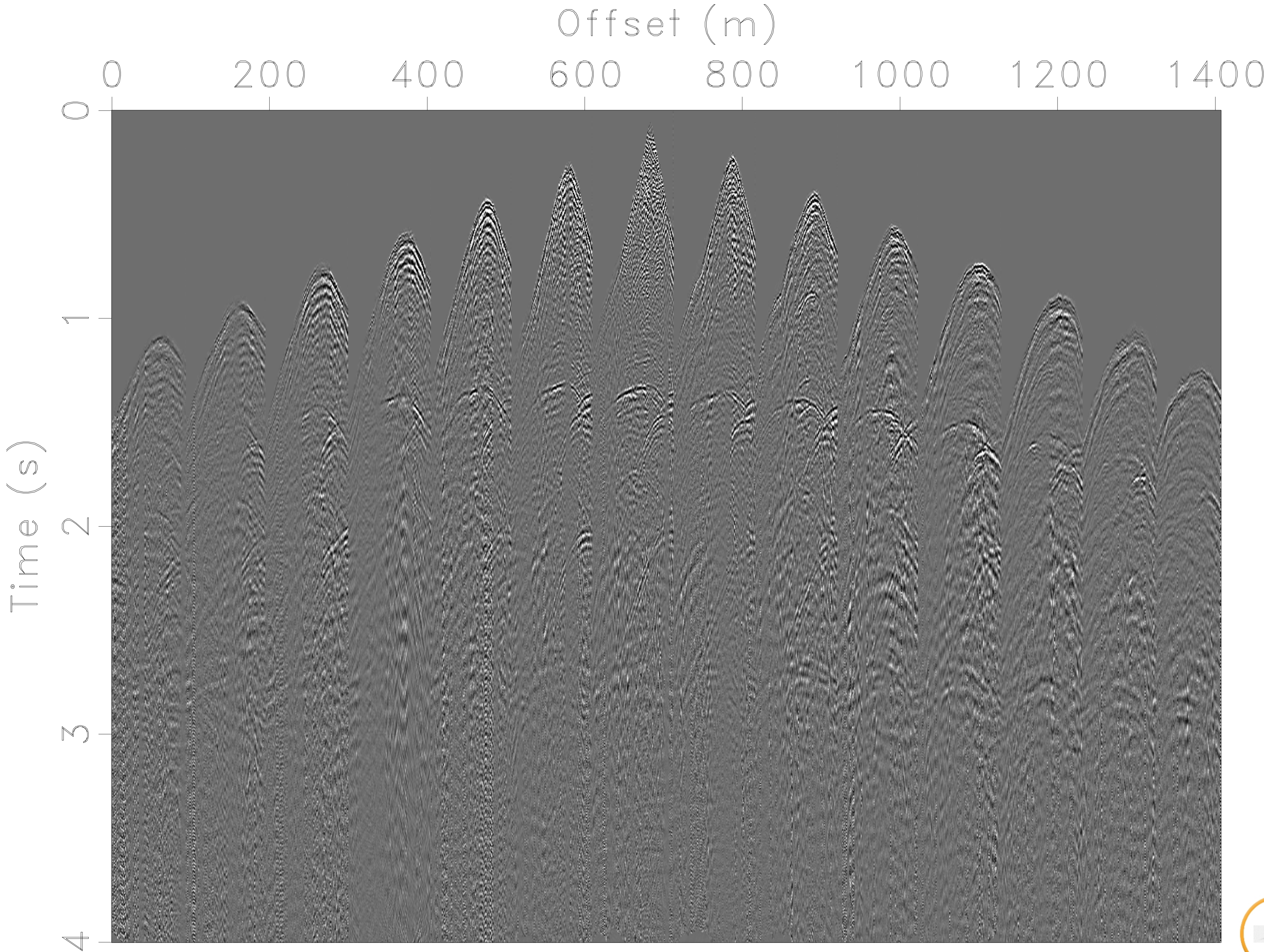
Real Data Example

Provided Reflectors



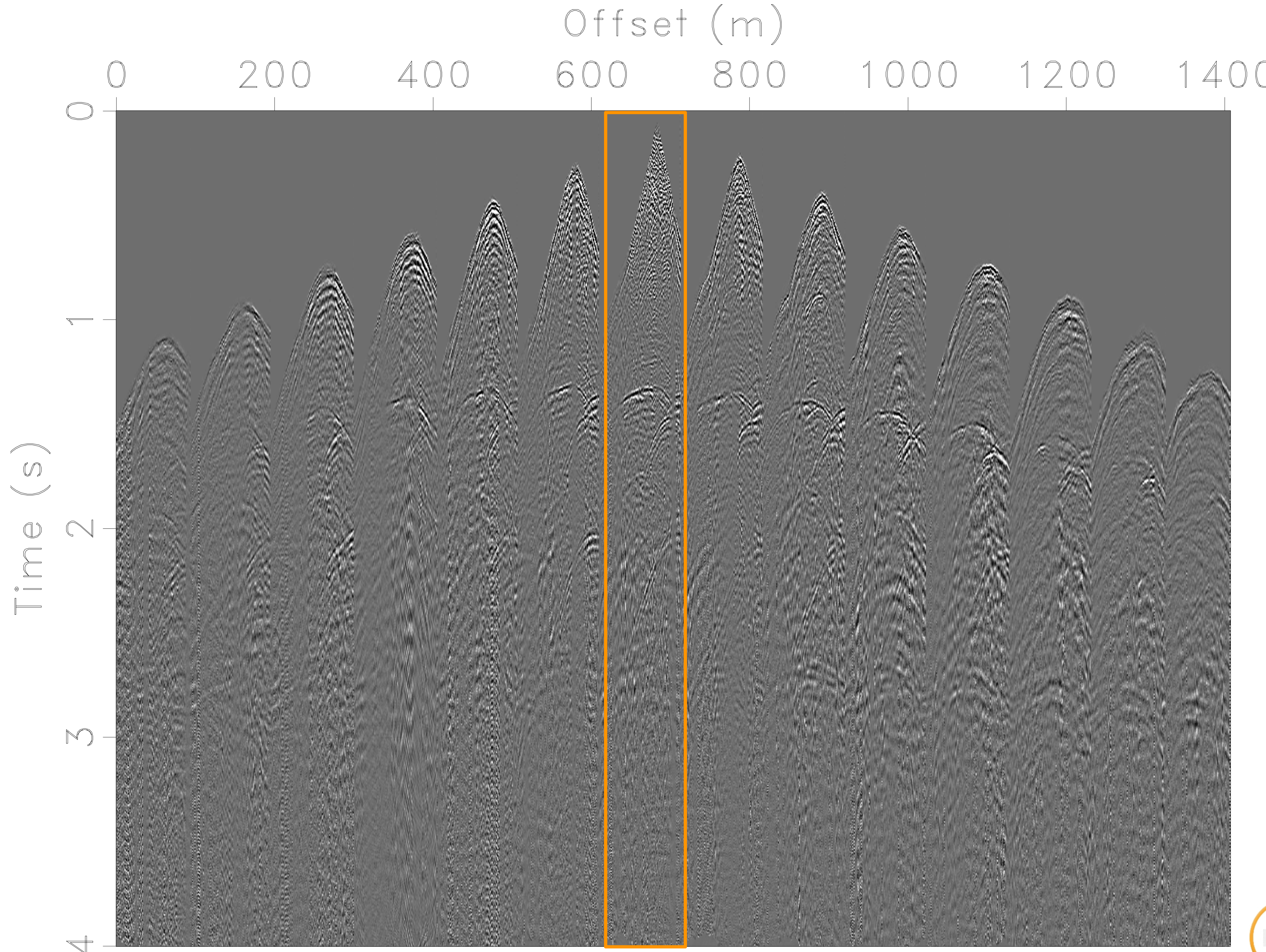
Real Data Example

Estimated Reflectors



Real Data Example

Estimated Reflectors



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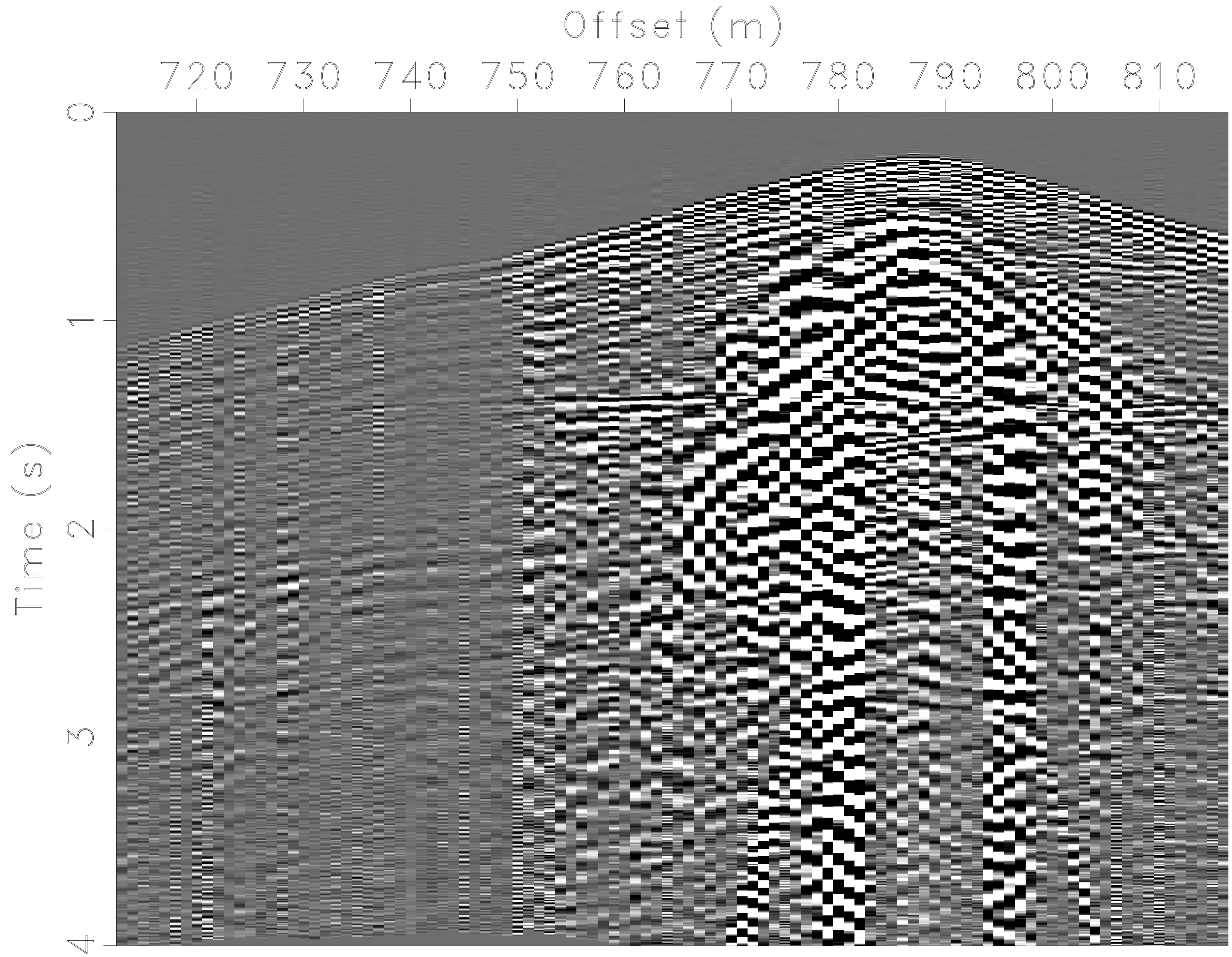
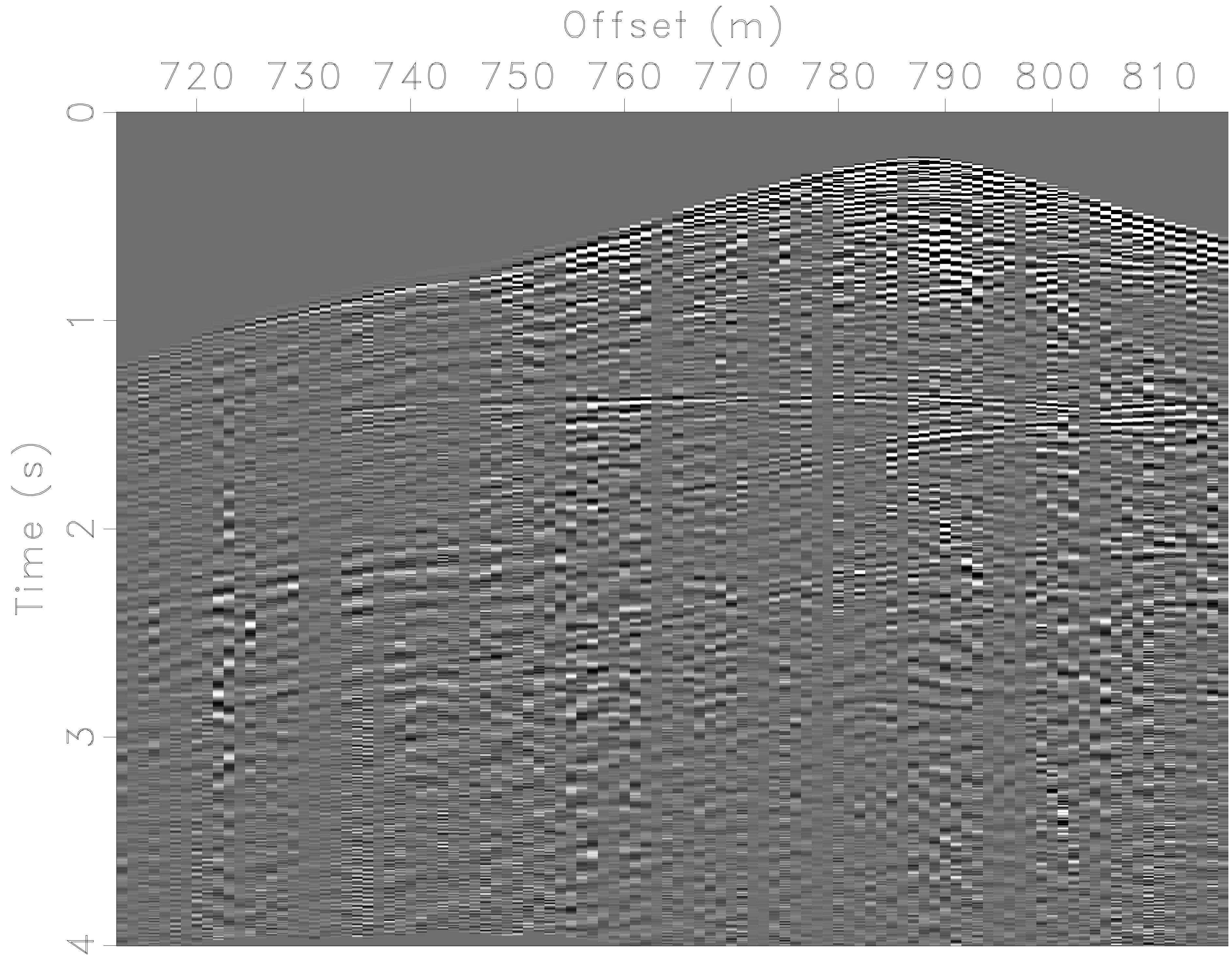
Real Data Example

Raw Data



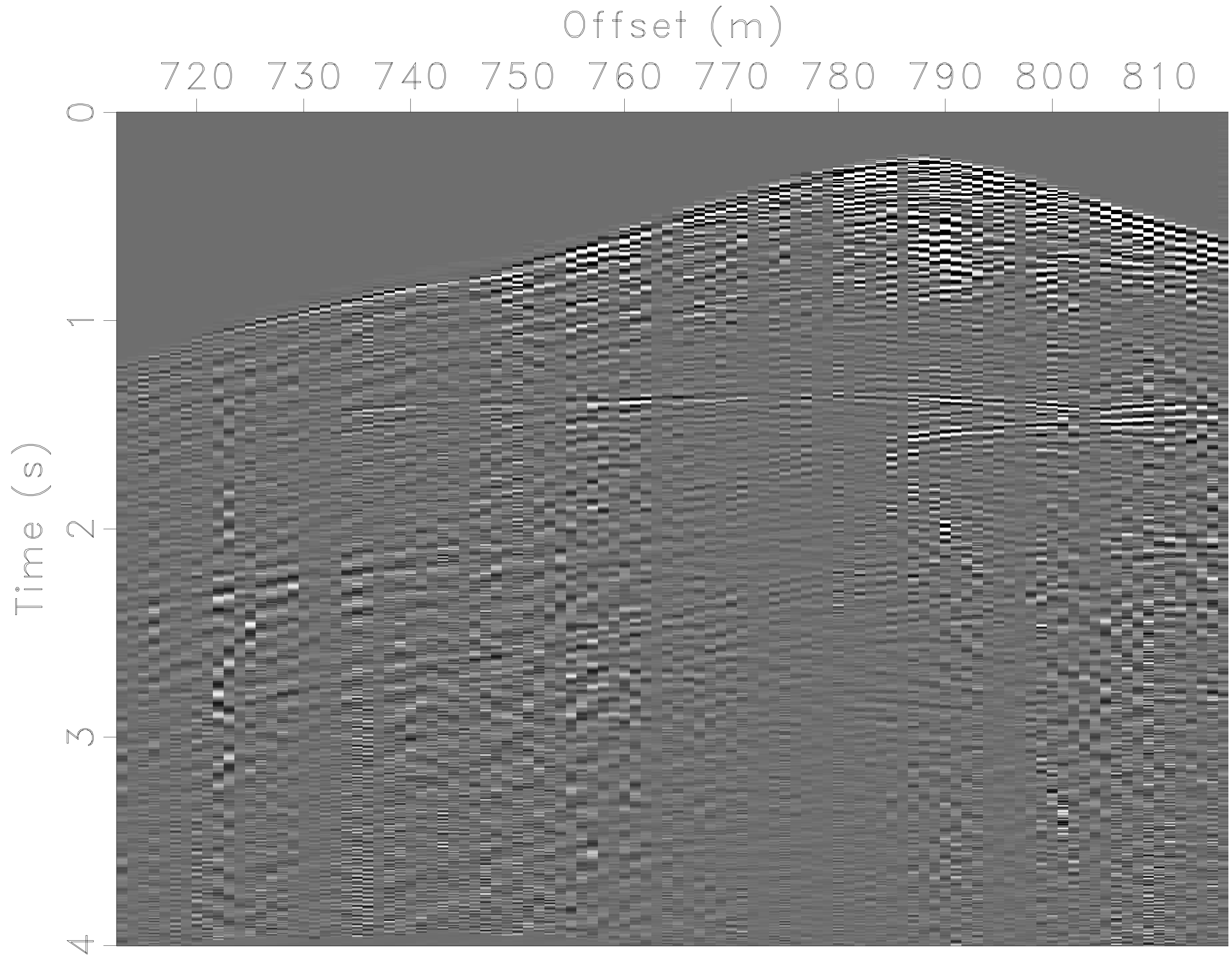
Real Data Example

Provided Reflectors



Real Data Example

Estimated Reflectors



Conclusions

- Two signal separation schemes for surface wave removal
  - Block coordinate relaxation
    - More sensitive parameters
    - Might degrade small amount of reflector information
  - Bayesian Formulation
    - Less sensitive
    - More control over separation
    - Less effect on reflector information than block coordinate relaxation scheme
- Both methods effective on synthetic data.
- Bayesian method shown on real data.
- SLIMpy user demos now contains a demo with the synthetic example and an example with the Oz25 data set.
- Future Work:
  - Full 3D data
  - Interferometric Predictions.

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