SINBAD Consortium 2010

Leveraging **informed blind deconvolution** techniques for **EPSI**

Tim Lin

SLIM
University of British Columbia

EPSI

Estimation of Primaries by Sparse Inversion (van Groenestijn and Verschuur, 2009)

-based on Amundsen inversion, division of up/down going wavefields

recorded data — predicted data from primary IR

$$\mathbf{P}^- = \mathbf{X}_\mathbf{o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)$$

$\mathbf{P}$ total up-going wavefield

$\mathbf{Q}$ down-going source signature

$\mathbf{R}$ reflectivity of free surface (assume -1)

$\mathbf{X}_\mathbf{o}$ primary impulse response

(all single-frequency data volume, implicit ω)

SLIM

EPSI

Estimation of Primaries by Sparse Inversion (van Groenestijn and Verschuur, 2009)

-based on Amundsen inversion, division of up/down going wavefields

recorded data   predicted data from primary IR

$$\mathbf{P}^- = \mathbf{X_o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)$$

$$f(\mathbf{X_o}, \mathbf{Q}) = ||\mathbf{P}^- - \mathbf{X_o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)||_2^2$$

EPSI

Estimation of Primaries by Sparse Inversion (van Groenestijn and Verschuur, 2009)

-based on Amundsen inversion, division of up/down going wavefields

recorded data   predicted data from primary IR

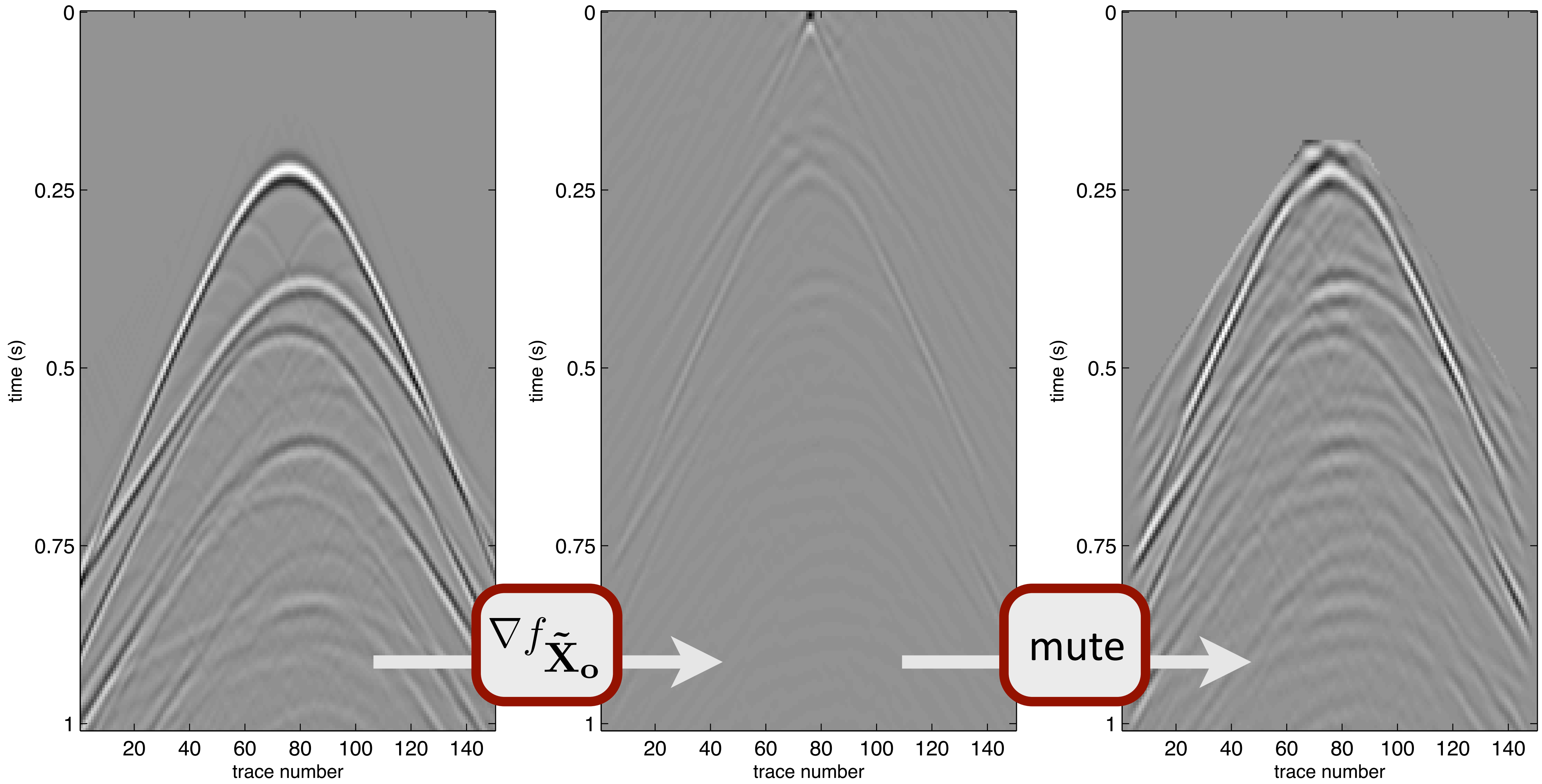
$$\mathbf{P}^{-} = \mathbf{X_o}(\mathbf{Q}^{+} + \mathbf{R}\mathbf{P}^{-})$$

$$f(\mathbf{X_o}, \mathbf{Q}) = ||\mathbf{P}^{-} - \mathbf{X_o}(\mathbf{Q}^{+} + \mathbf{R}\mathbf{P}^{-})||_2^2$$

$$\nabla f_{\tilde{\mathbf{X}}_\mathbf{o}} = \left(\mathbf{P}^{-} - \tilde{\mathbf{X}}_\mathbf{o}(\mathbf{Q}^{+} + \mathbf{R}\mathbf{P}^{-})\right)(\mathbf{Q}^{+} + \mathbf{R}\mathbf{P}^{-})^{H}$$

EPSI

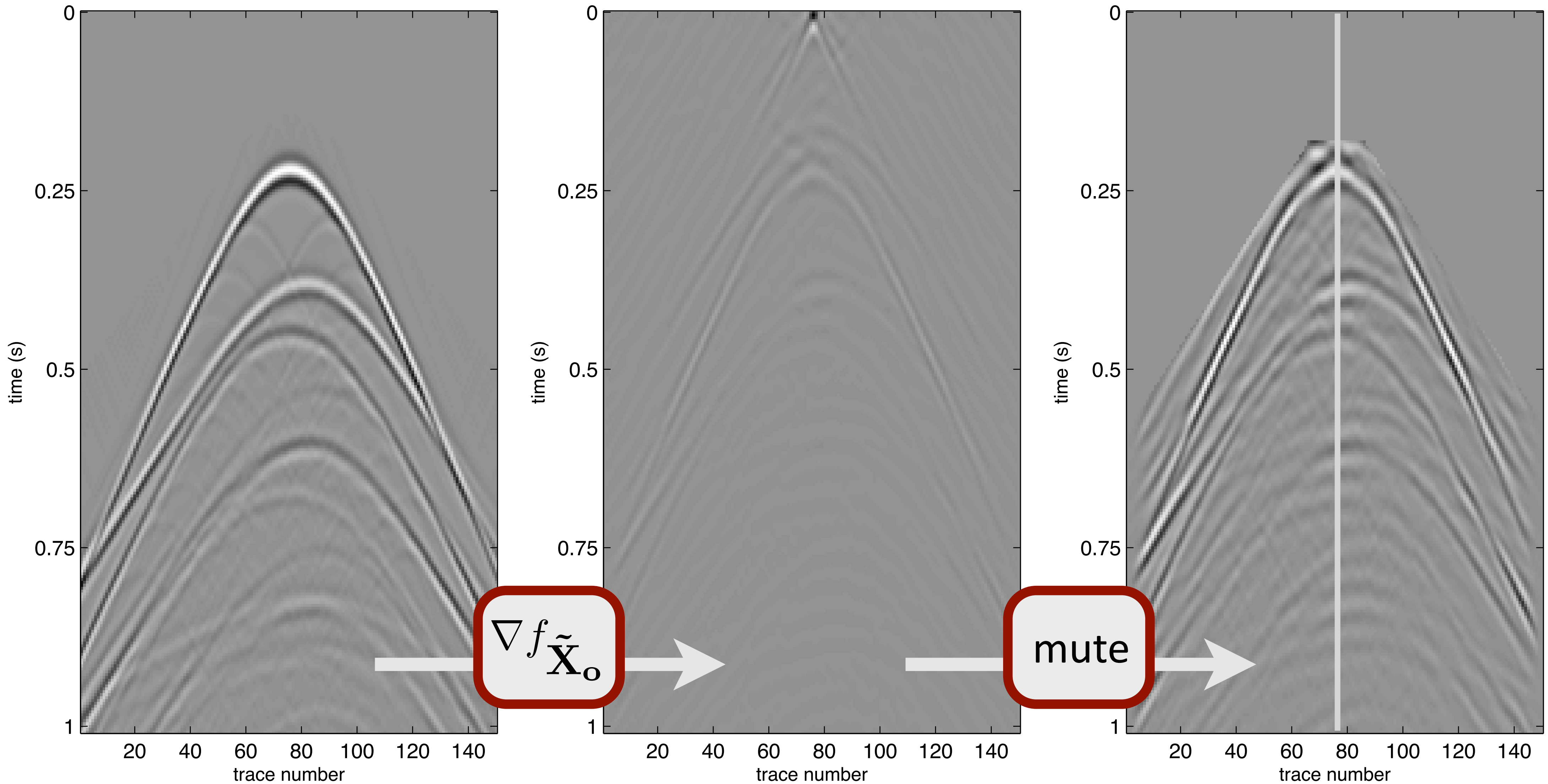
Primary event estimation step



input data gradient muted gradient

EPSI

Primary event estimation step

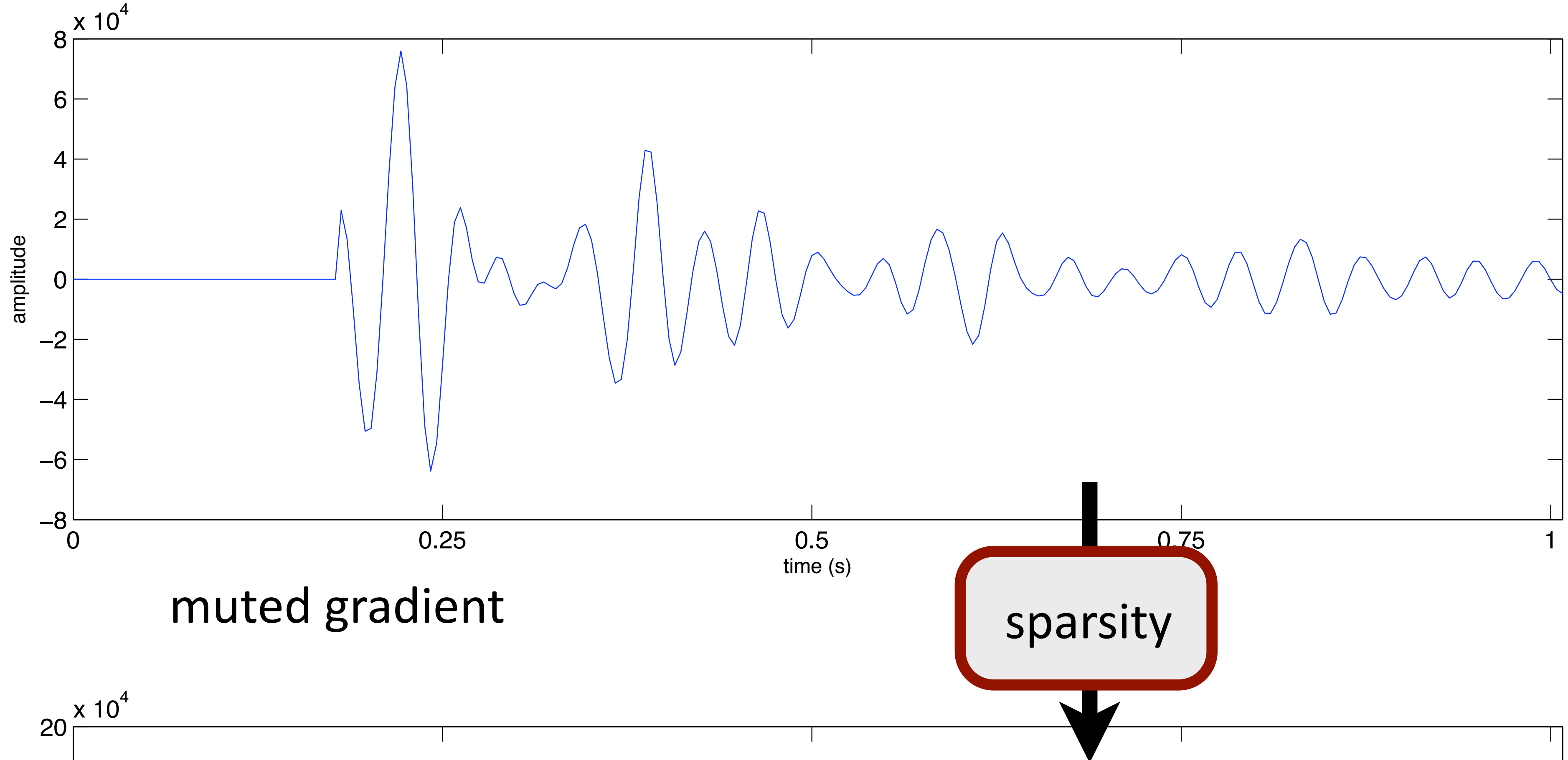


input data

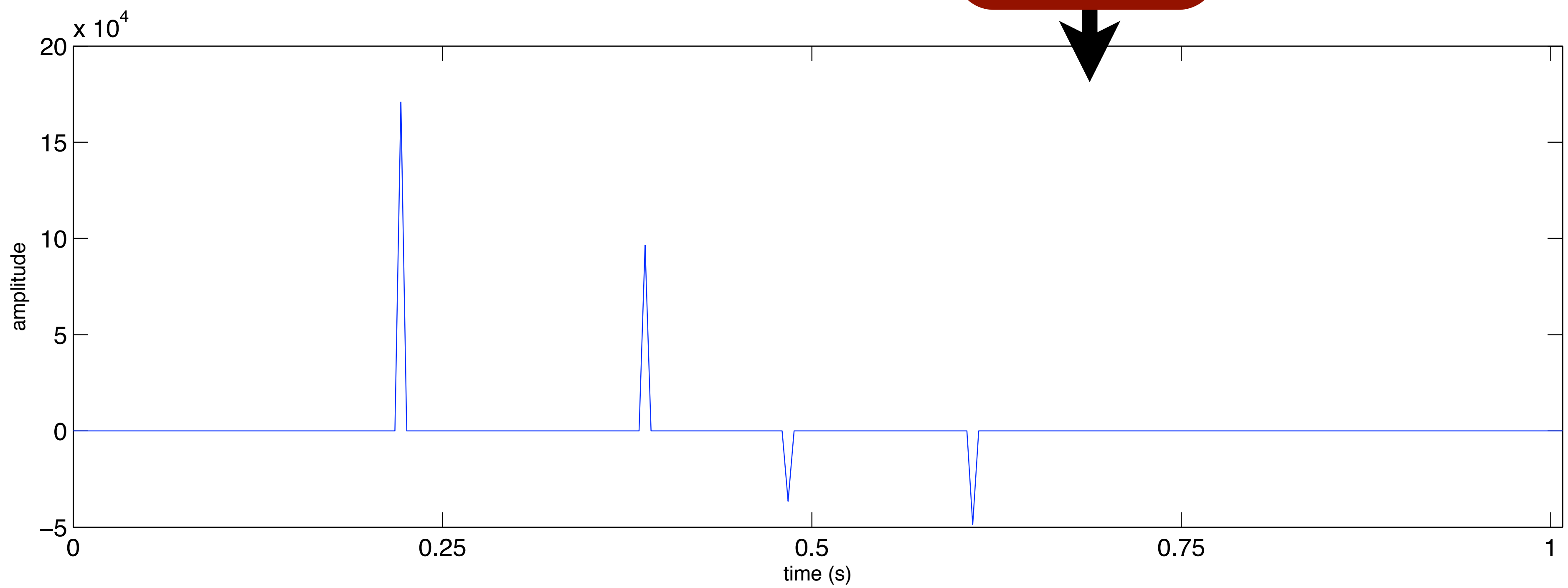
gradient

muted gradient

EPSI Primary event estimation step



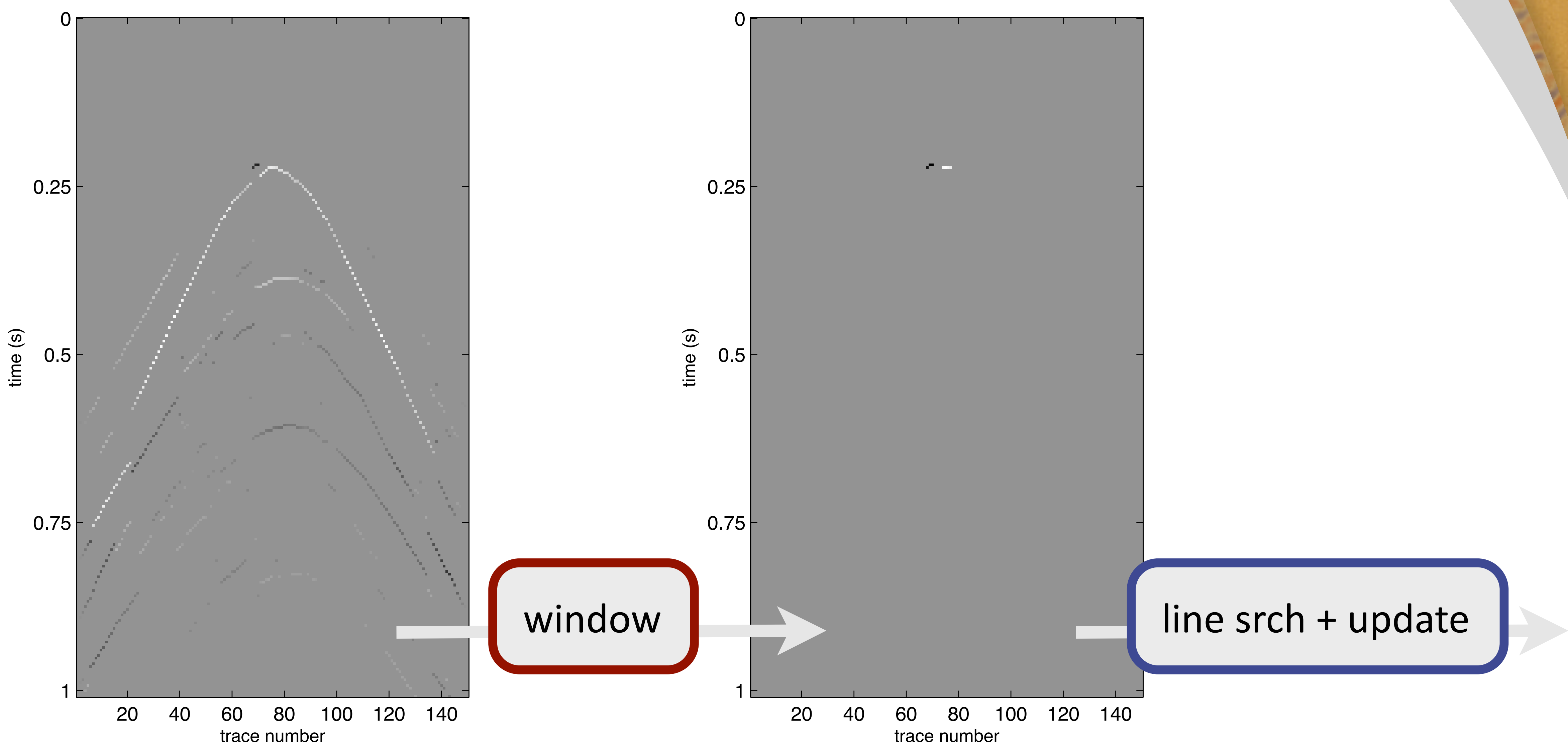
muted gradient



4 events picked (per trace)

EPSI

Primary event estimation step



4 events picked (per trace)

windowed picked events

EPSI

Wavelet matching step

$$\mathbf{P}^- = \mathbf{X_o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)$$

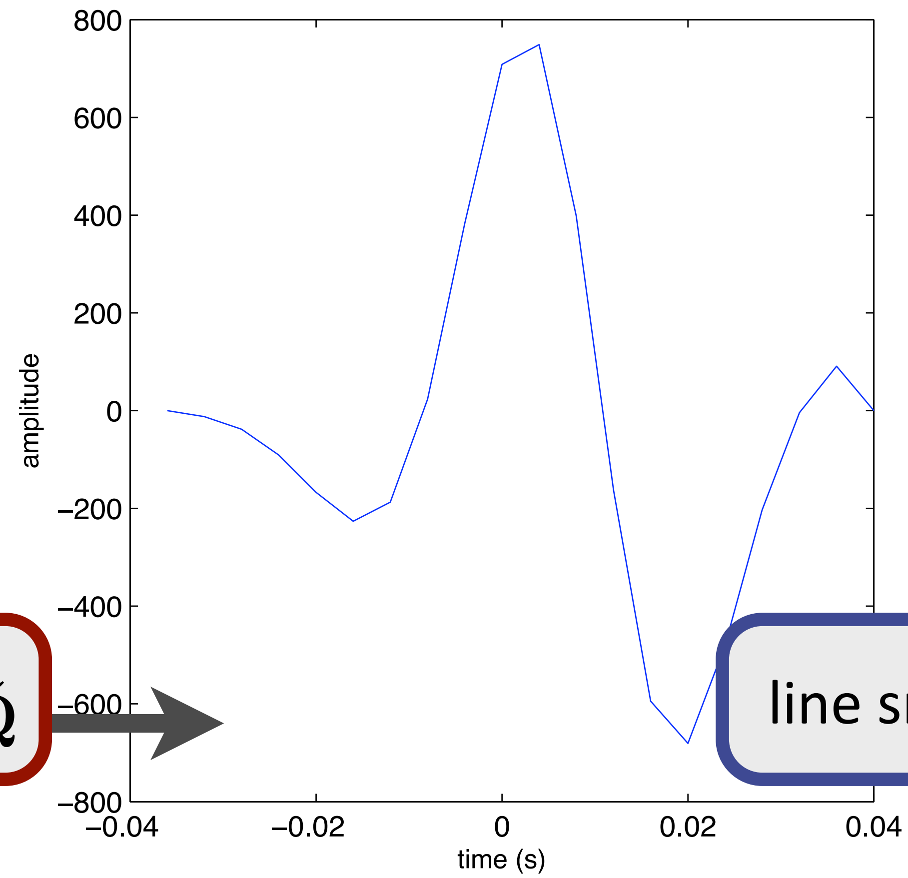
$$f(\mathbf{X_o}, \mathbf{Q}) = ||\mathbf{P}^- - \mathbf{X_o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)||_2^2$$

$$\nabla f_{\tilde{\mathbf{Q}}} = \mathbf{X_o}^H \left(\mathbf{P}^- - \mathbf{X_o}(\tilde{\mathbf{Q}}^+ + \mathbf{R}\mathbf{P}^-)\right)$$

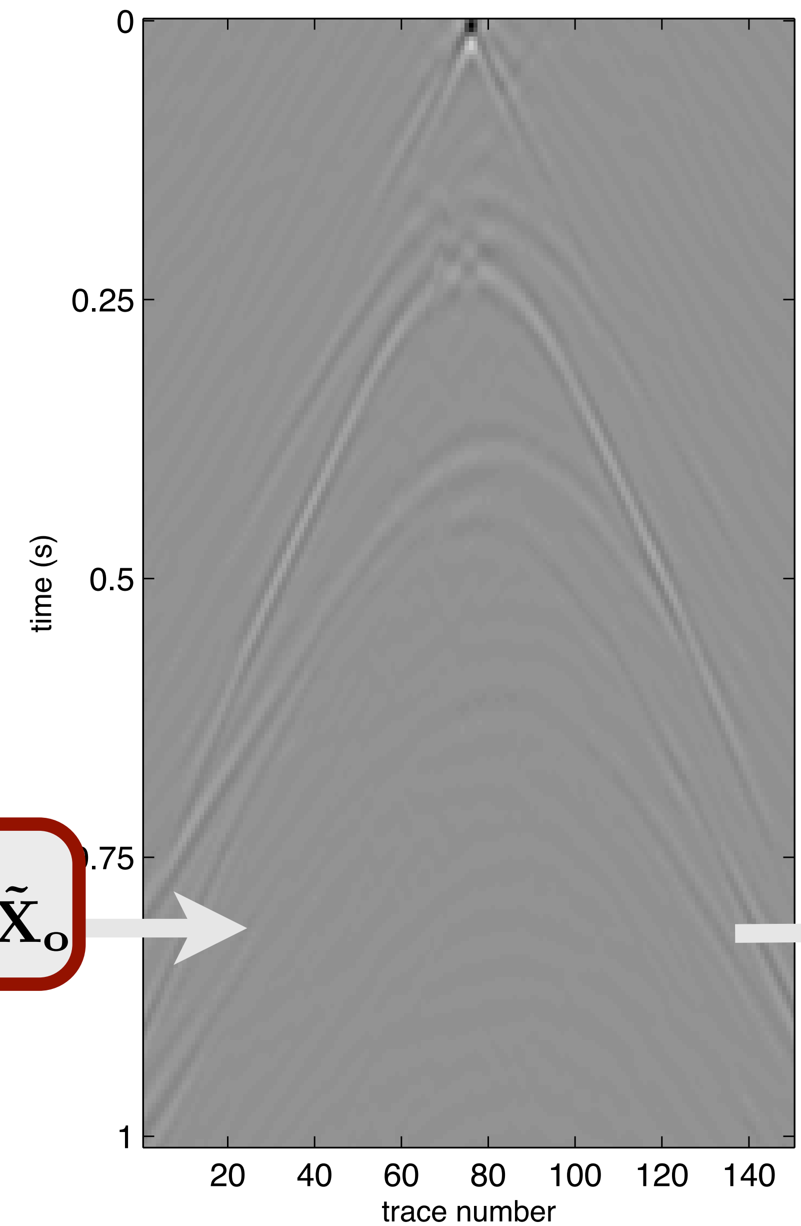
EPSI

Wavelet matching step

$\nabla f_{\tilde{\mathbf{Q}}}$ → line srch + update → $\nabla f_{\tilde{\mathbf{X}}_o}$ → mute → etc...



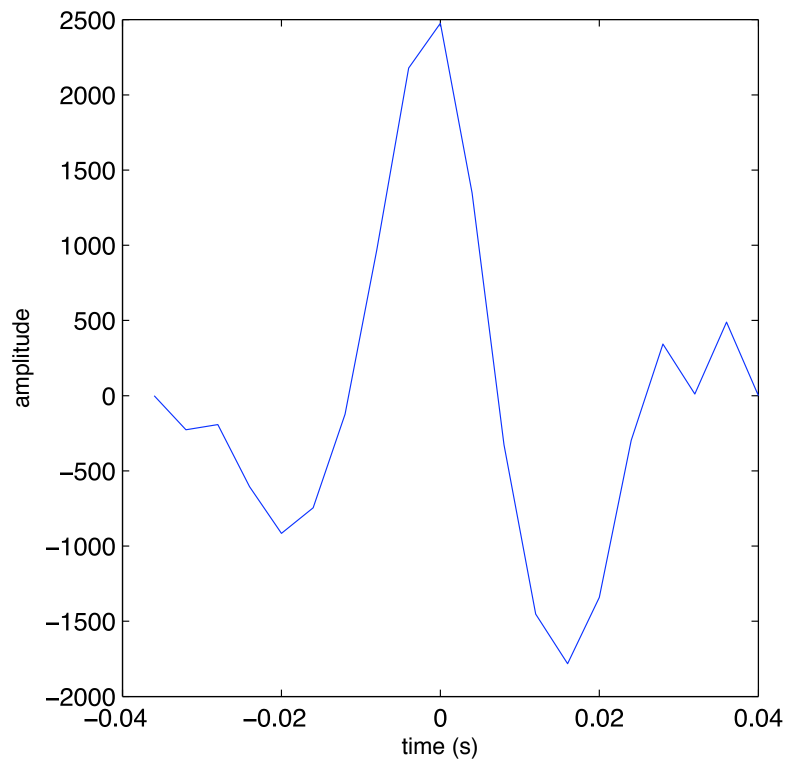
1st wavelet matching gradient



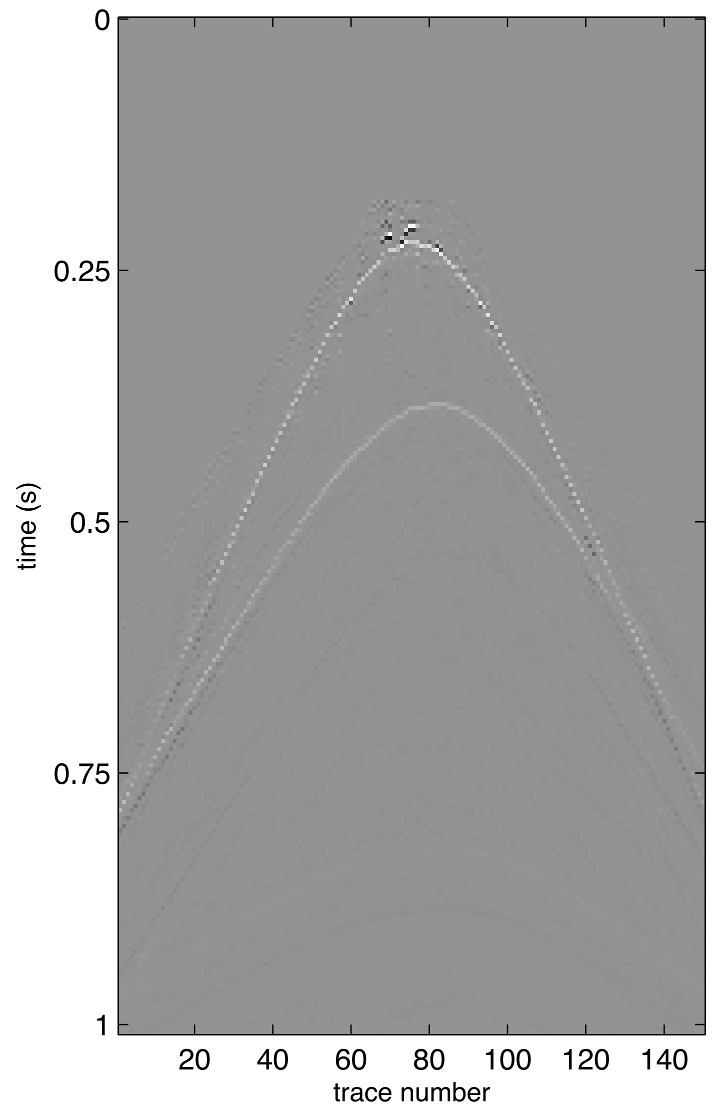
2nd Xo Gradient

EPSI

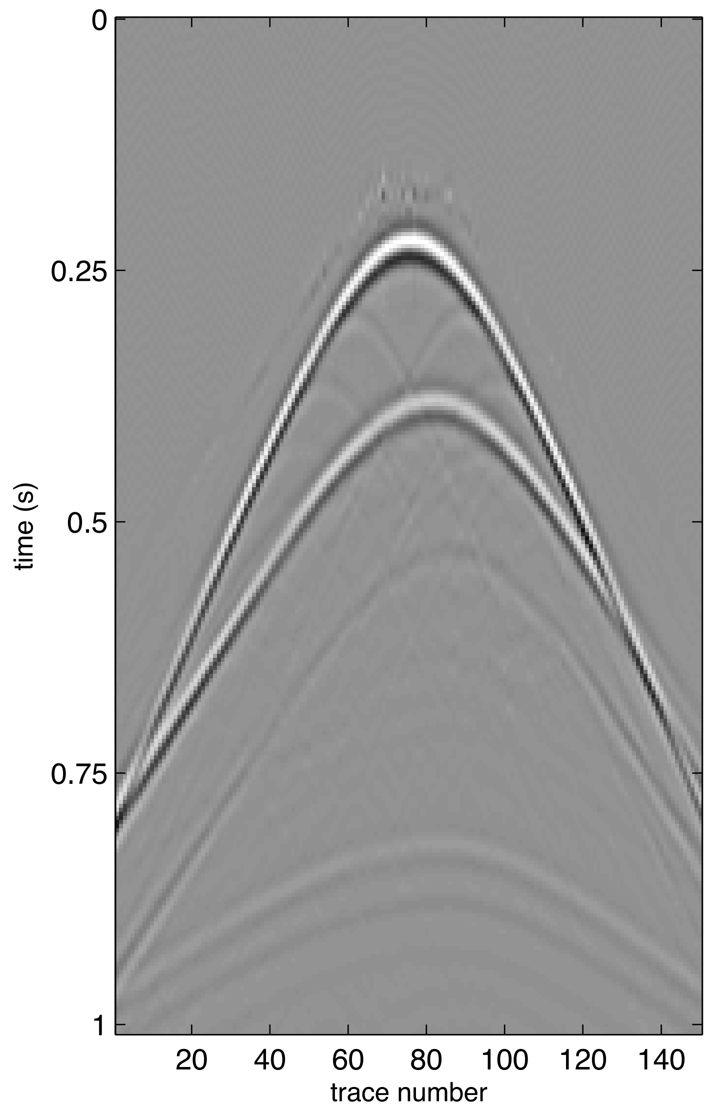
Final results (60 iterations)



Final wavelet



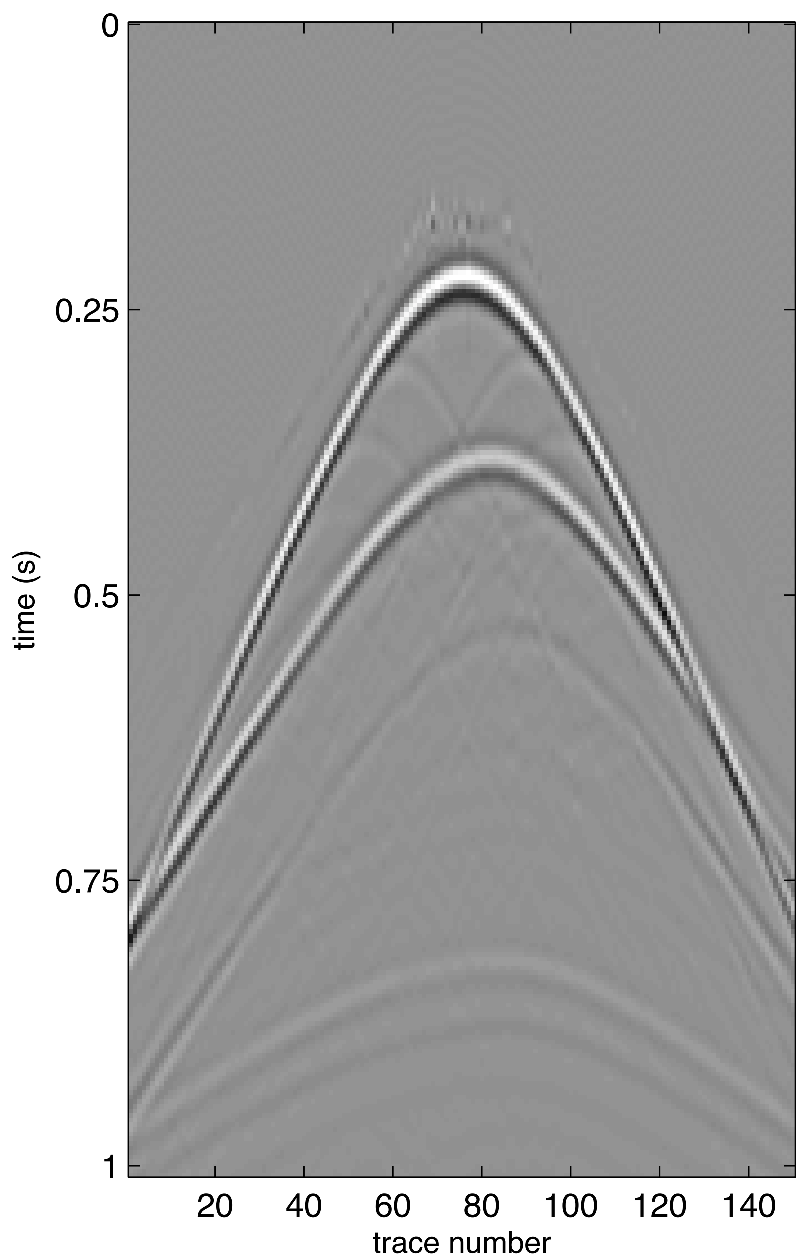
Final Green's function



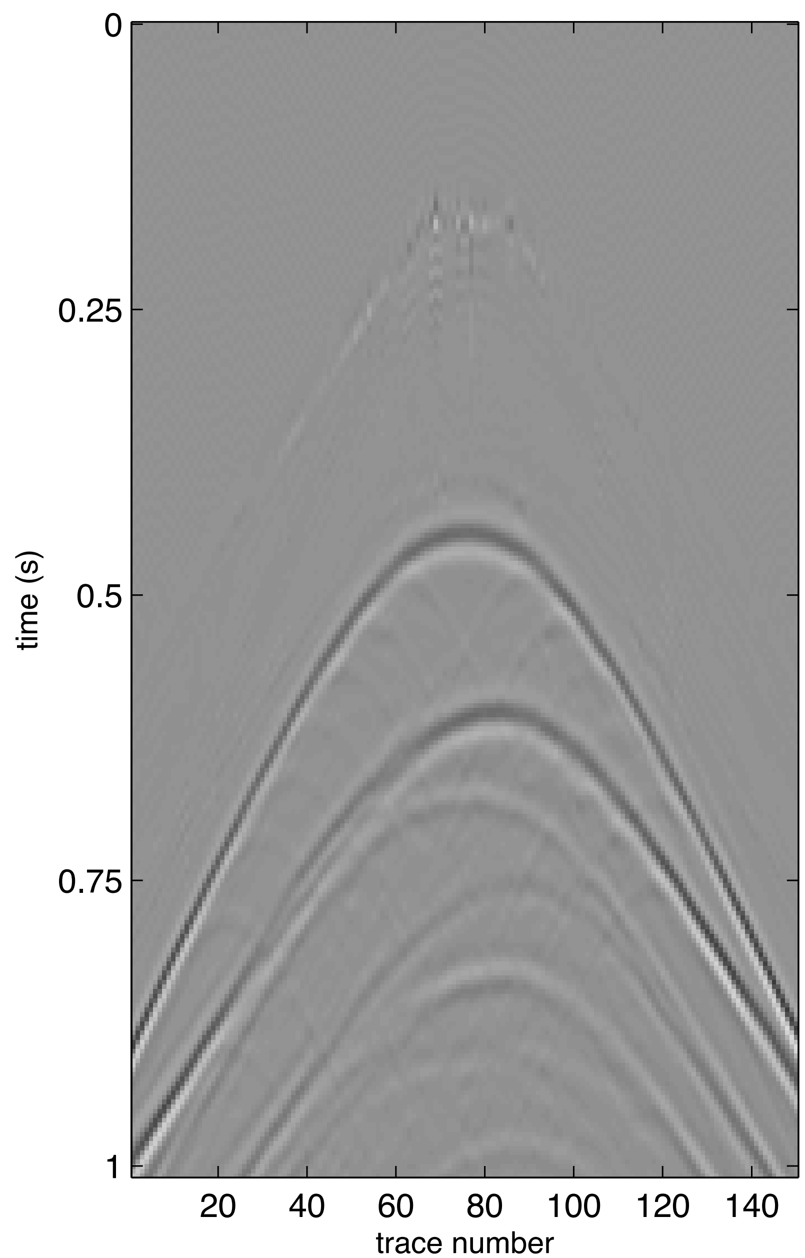
Final estimated primary

EPSI

Final results (60 iterations)



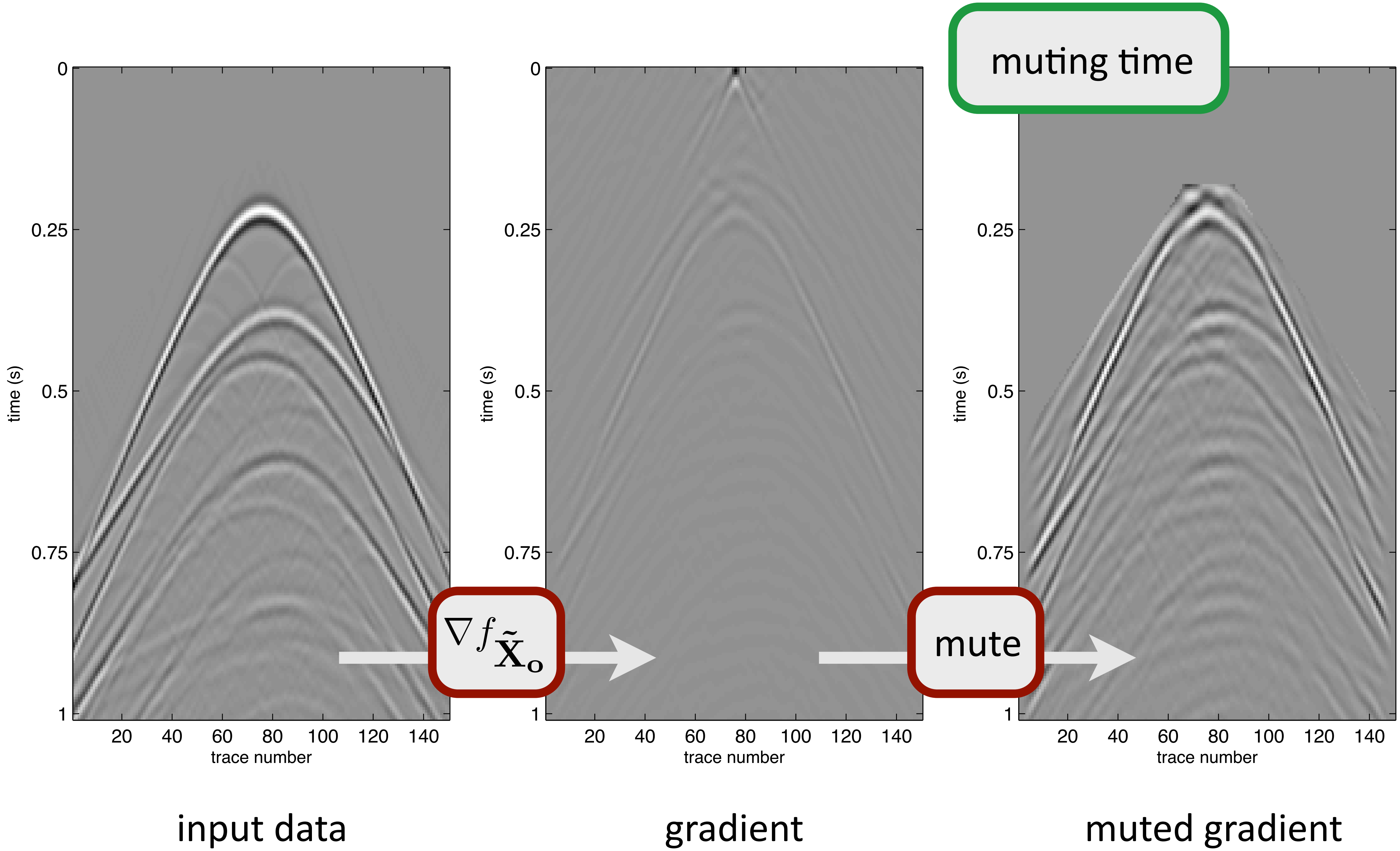
Final estimated primary



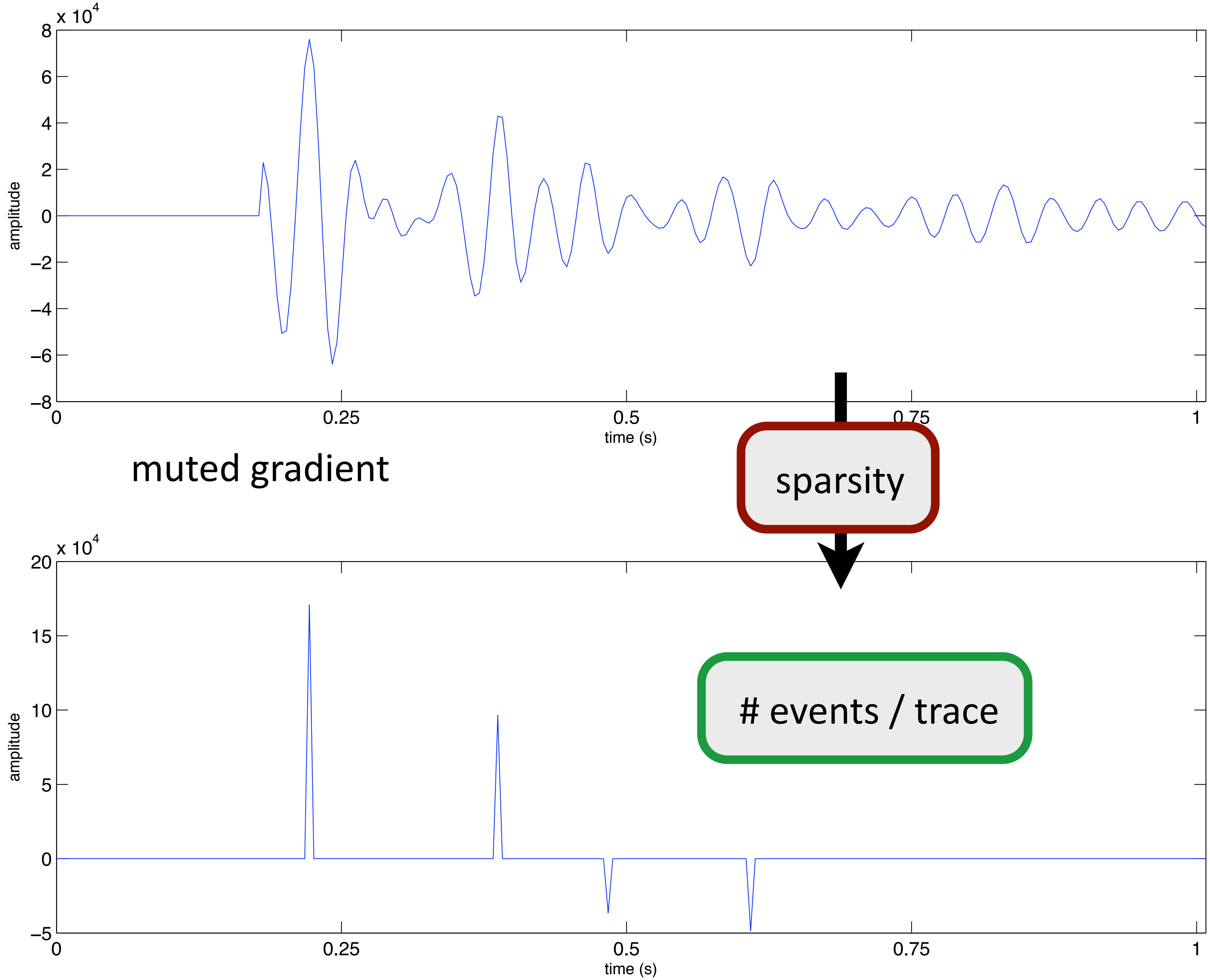
Data minus estimated primary

EPSI

Primary event estimation step



EPSI Primary event estimation step

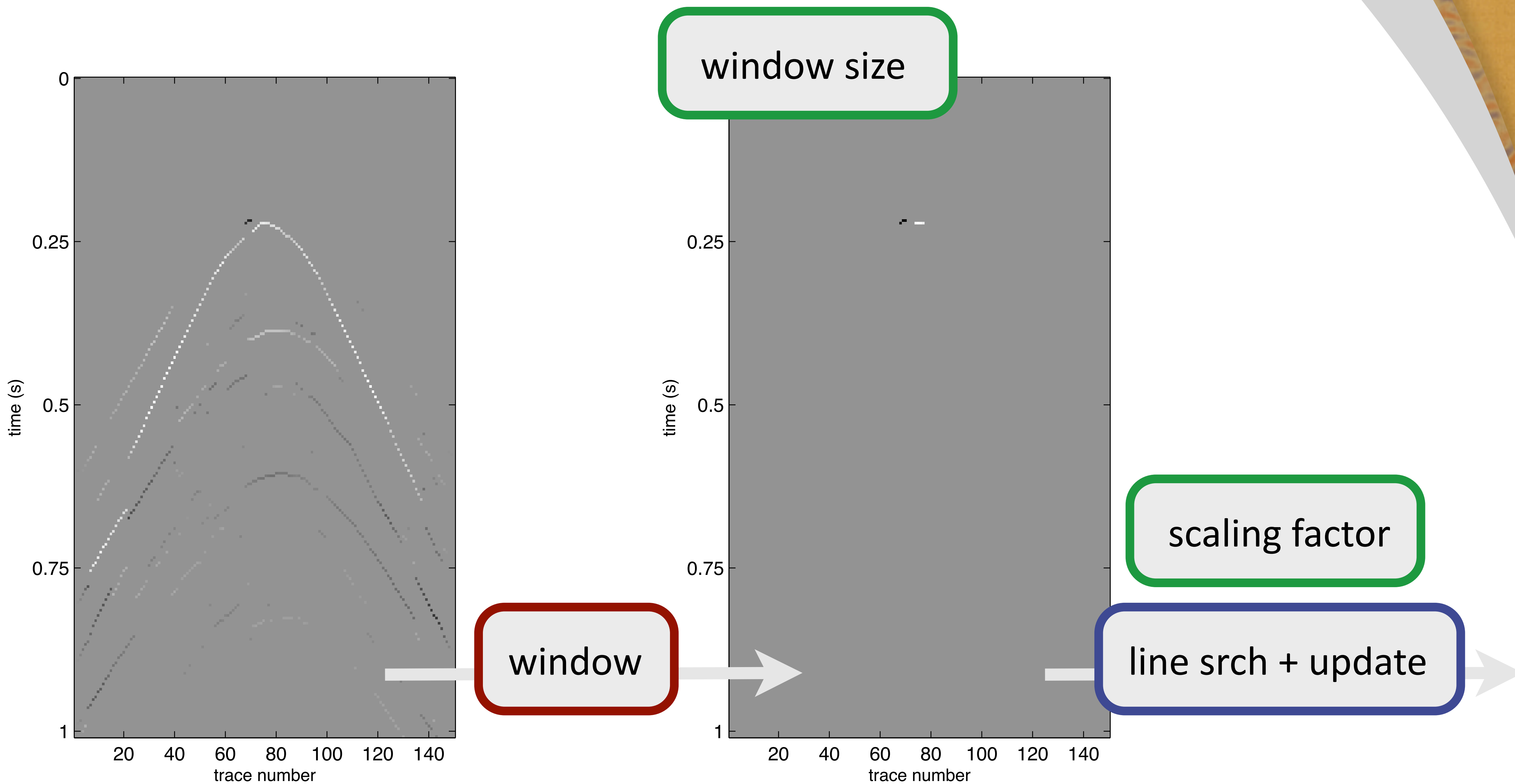


muted gradient

4 events picked (per trace)

EPSI

Primary event estimation step



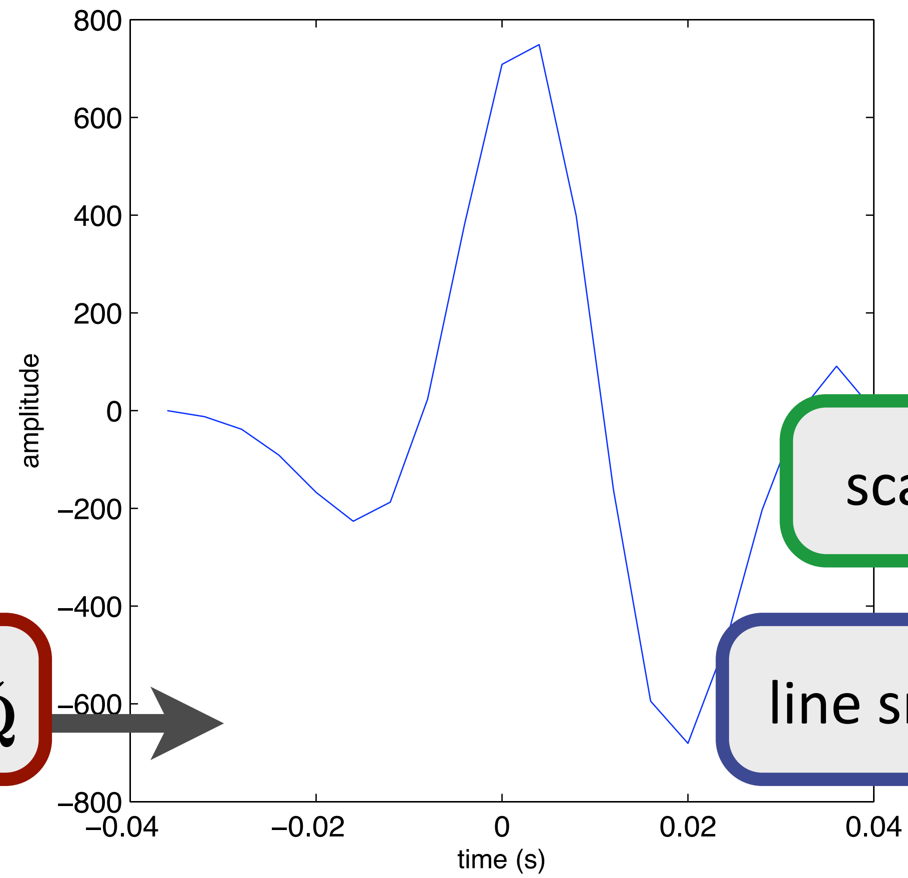
4 events picked (per trace)

windowed picked events

EPSI

Wavelet matching step

$\nabla f_{\tilde{\mathbf{Q}}}$

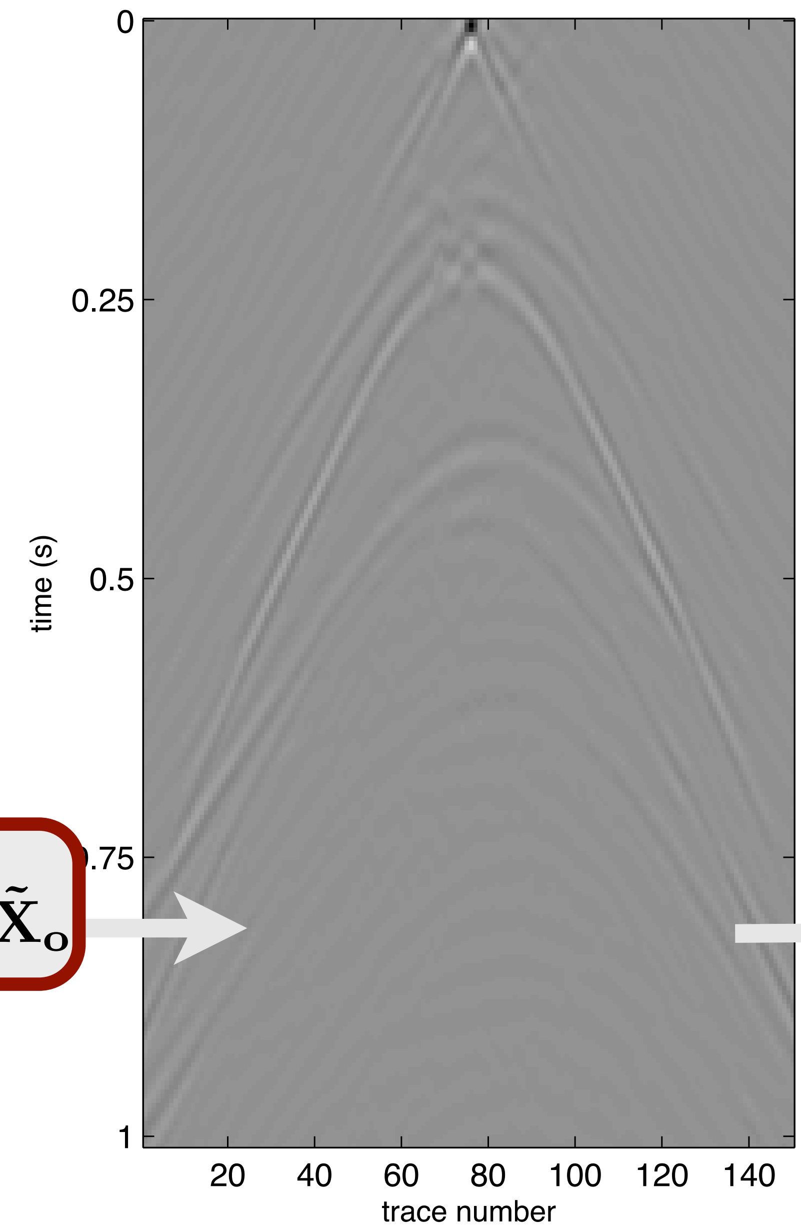


1st wavelet matching gradient

scaling factor

line srch + update

$\nabla f_{\tilde{\mathbf{X}}_o}$



2nd Xo Gradient

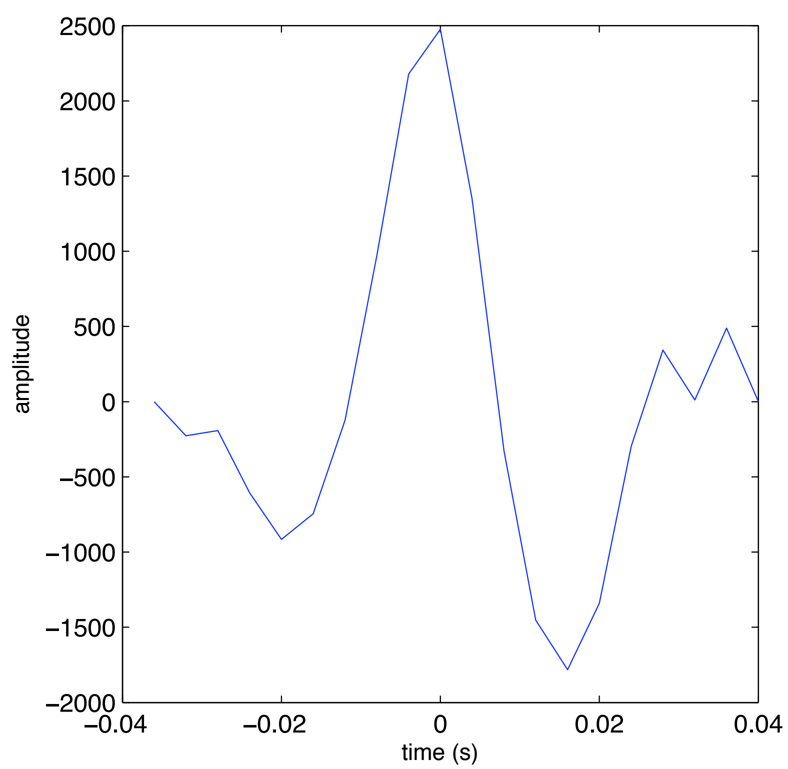
mute

etc...

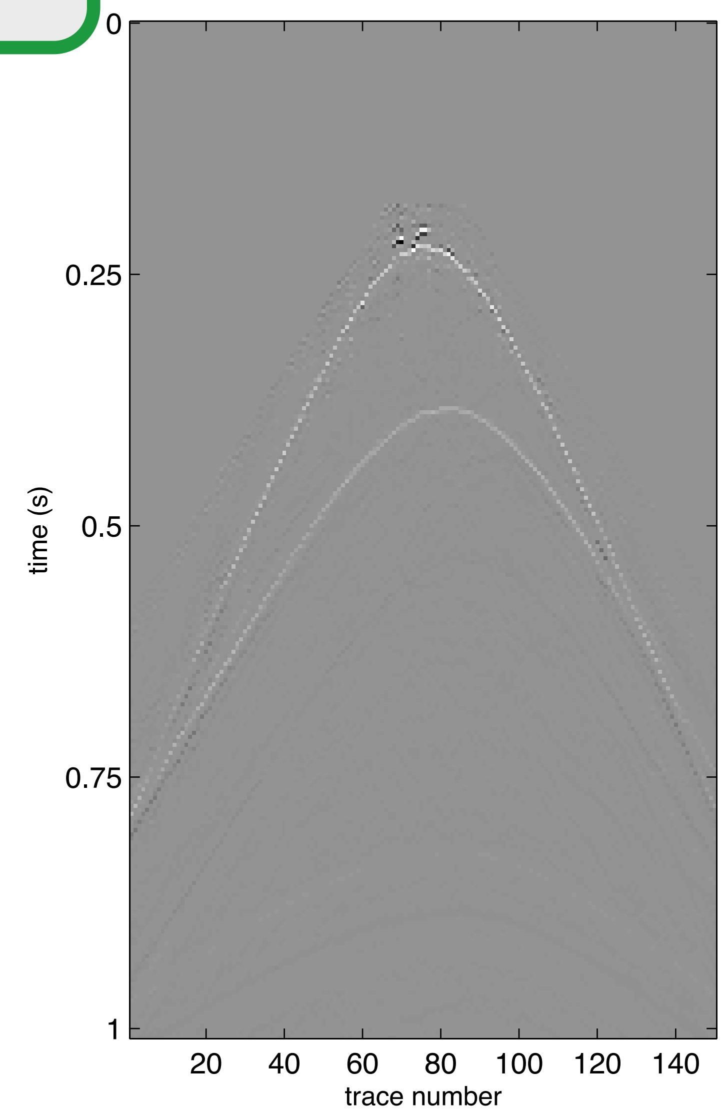
EPSI

Final results (60 iterations)

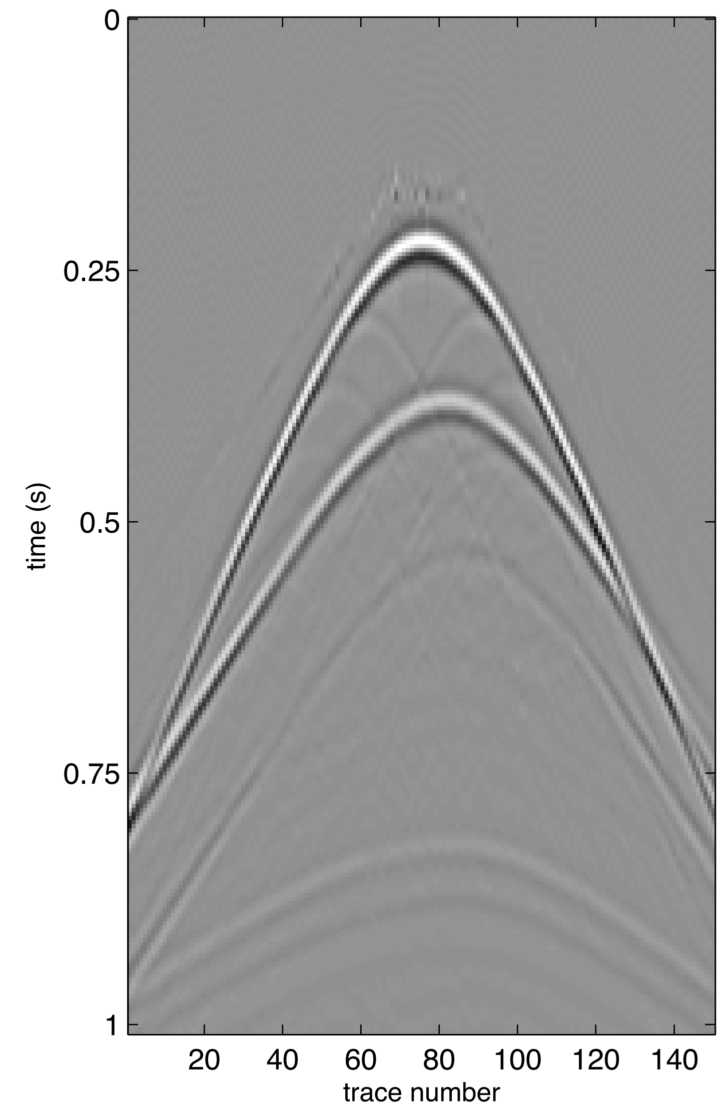
stopping criterion



Final wavelet



Final Green's function



Final estimated primary

EPSI

Uses sparsity assumption on $\mathbf{X_o}$

$$\underset{\mathbf{X_o}, \mathbf{Q}^+ \in \mathbf{Q}_\Lambda}{\textbf{minimize}} \quad \mathrm{nnz}(\mathbf{X_o}) \quad \textbf{s.t.} \; ||\mathbf{P}^- - \mathbf{X_o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)||_2^2 \leq \sigma$$

But approximates the solution with k iterations of projected gradient

$$\underset{\mathbf{X_o}, \mathbf{Q}^+ \in \mathbf{Q}_\Lambda}{\textbf{minimize}} \quad ||\mathbf{P}^- - \mathbf{X_o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)||_2^2 \; \textbf{s.t.} \; \mathrm{nnz}(\mathbf{X_o}) \leq \tau$$

This is an NP-hard problem:

- existence of local minima
- no convergence guarantees

τ number. spike per iteration

$\mathbf{Q}_\Lambda$ short time-windowed wavelet (implies smooth spectrum)

Convex relaxation

Use L1-norm relaxation for the sparsity objective

$$\underset{\mathbf{X_o},\, \mathbf{Q}^+ \in \mathbf{Q}_\Lambda}{\textbf{minimize}} \quad ||\mathbf{X_o}||_1 \quad \textbf{s.t.} \quad ||\mathbf{P}^- - \mathbf{X_o}(\mathbf{Q}^+ + \mathbf{R}\mathbf{P}^-)||_2^2 \leq \sigma$$

Bi-convex problem, but turns into two convex problems we know how to solve via alternating optimization

-Standard approach in blind image deconvolution

-no need for windowing primary events at each iteration

Alternating optimization

Use L1-norm relaxation for the sparsity objective

$$\underset{\mathbf{X_o}}{\textbf{minimize}} \quad ||\mathbf{X_o}||_1 \quad \textbf{s.t.} \quad ||\mathbf{P}^- - \mathbf{X_o}(\mathbf{Q_k^+} + \mathbf{R}\mathbf{P}^-)||_2^2 \leq \sigma$$

Fix source signature, turns into ℓ_1- minimization

Operator form

$$\mathbf{P}^- = \mathbf{X_o}(\mathbf{S}^+ + \mathbf{R}\mathbf{P}^-)$$

Define linear operator A that maps Green's func to up-going wavefield

$$\mathbf{A}\mathbf{x_o} := \mathcal{F}_\mathrm{t}^* \mathrm{BlockDiag}_\omega[(\mathbf{Q}^+ - \mathbf{P}^-)^* \otimes \mathbf{I}]\mathcal{F}_\mathrm{t}\mathbf{x_o} = \mathbf{p}^-$$

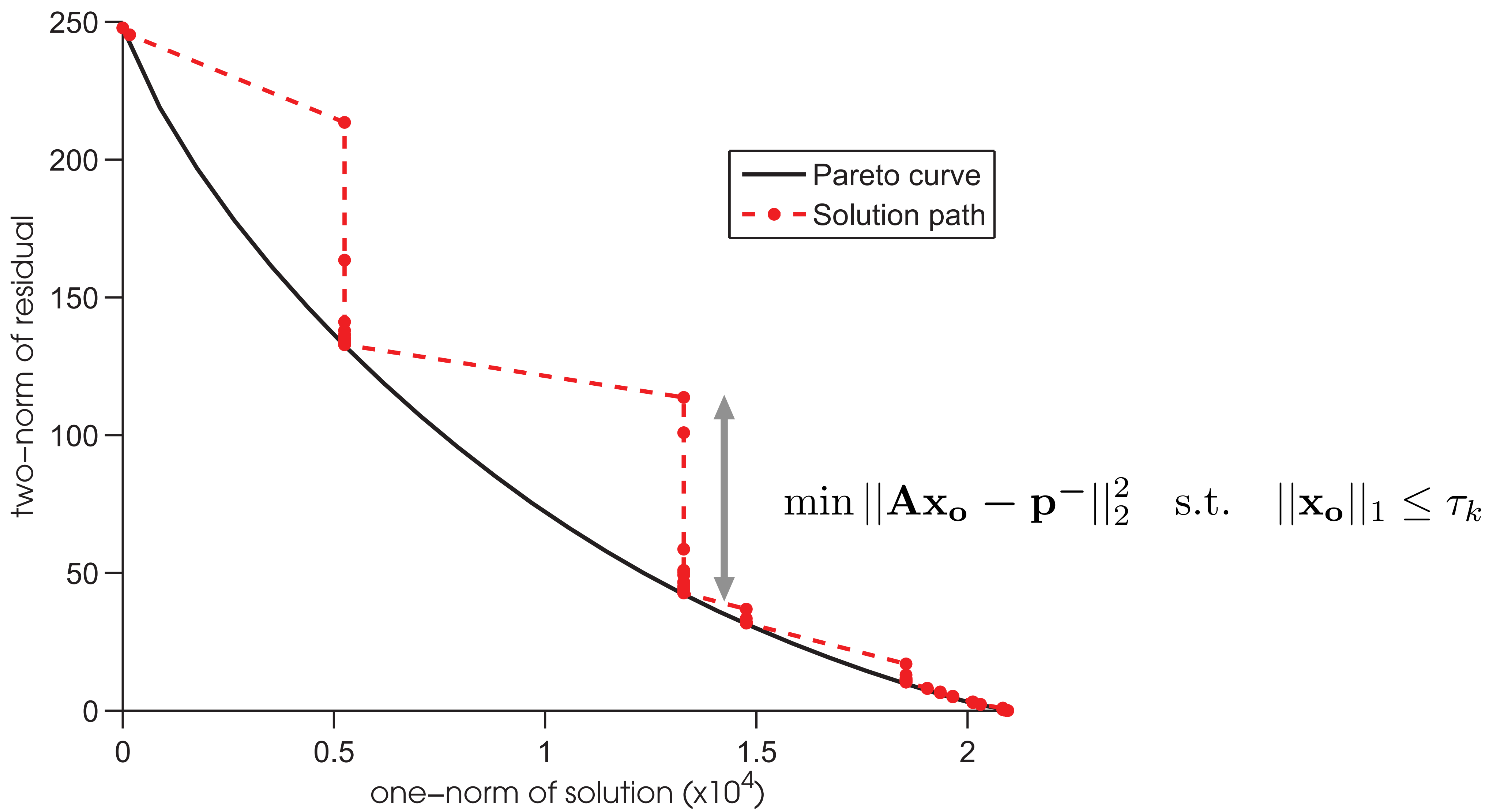
$$\mathbf{p}^- := \mathrm{vec}(\mathbf{P}^-)$$
$$\mathbf{x_o} := \mathrm{vec}(\mathbf{X_o})$$

L1 minimization

$$\min ||\mathbf{x_o}||_1 \quad \text{s.t.} \quad ||\mathbf{p}^- - \mathbf{A}\mathbf{x_o}||_2^2 \leq \sigma$$

Use SPGl1 (van den Berg, Friedlander, 2008)

- a projected gradient based method (seismic data-volumes are huge)
- uses root-finding to find the final one-norm

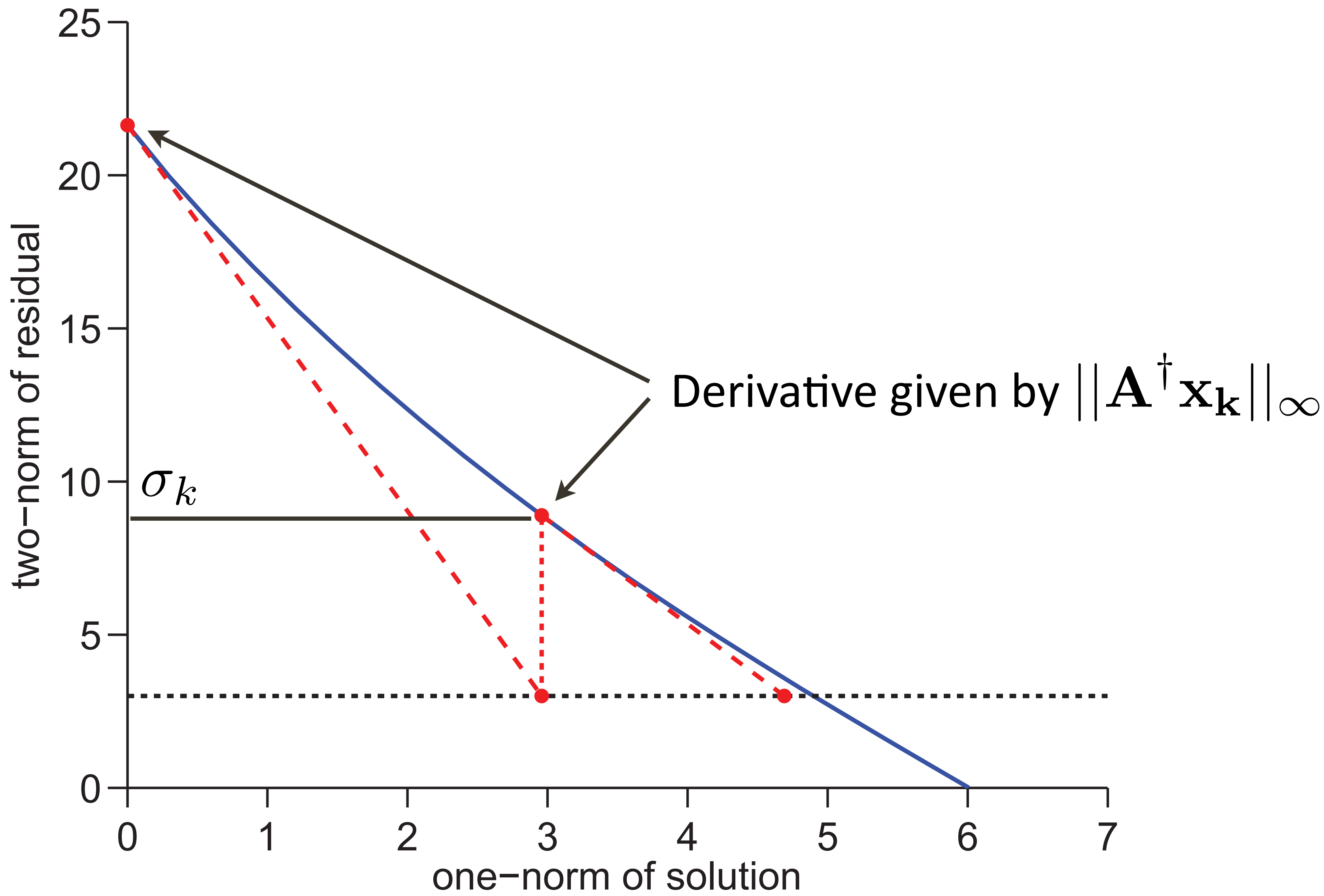


L1 minimization

$$\min ||\mathbf{x_o}||_1 \quad \text{s.t.} \quad ||\mathbf{p}^- - \mathbf{A}\mathbf{x_o}||_2^2 \leq \sigma$$

Use SPGl1 (van den Berg, Friedlander, 2008)

- a projected gradient based method (seismic data-volumes are huge)
- uses root-finding to find the final one-norm



Alternating optimization

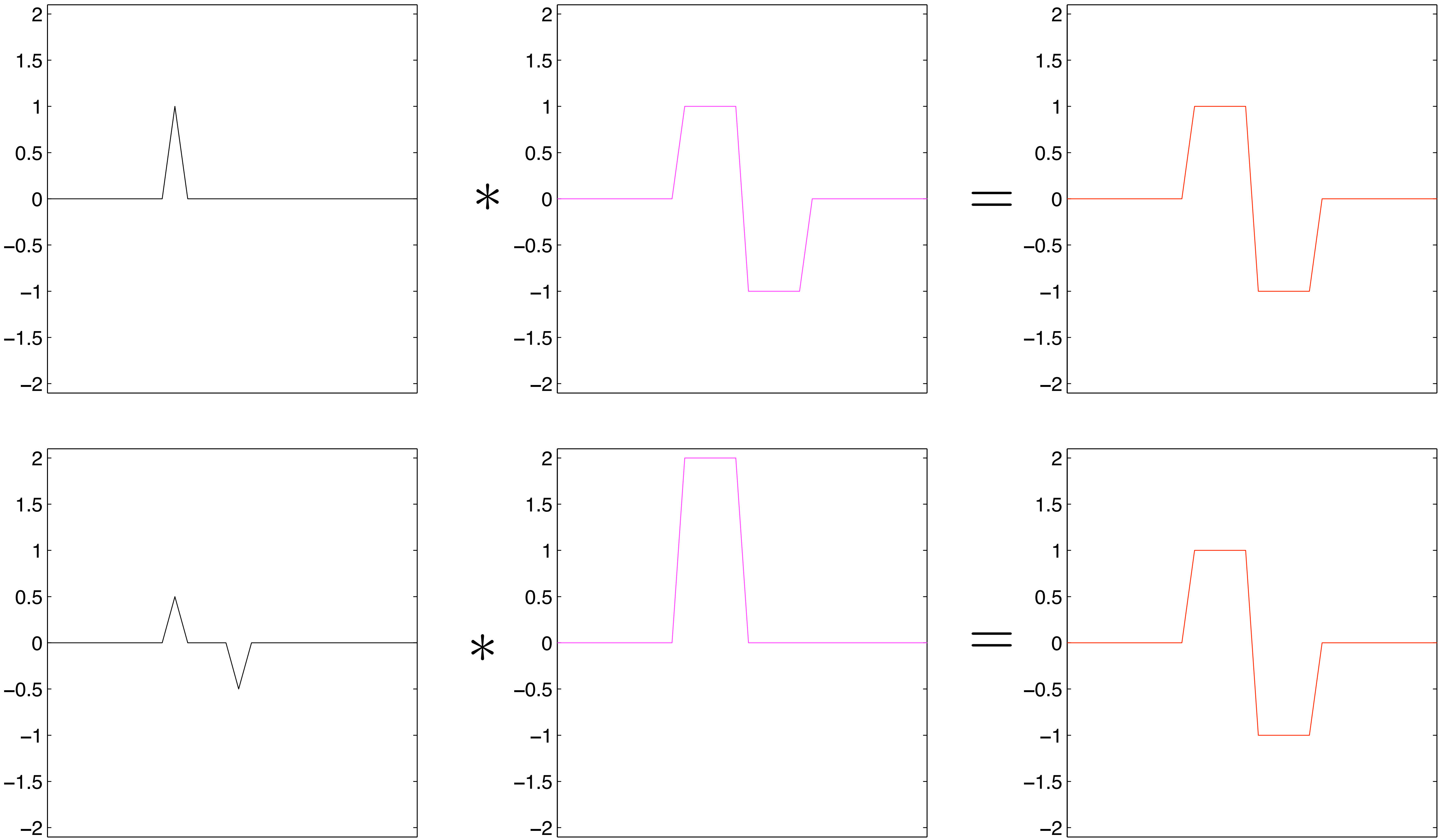
Wavelet matching at Pareto curve

minimize $\quad ||\mathbf{X}_{\mathbf{O}k}||_1$ **s.t.** $||\mathbf{P}^{-} - \mathbf{X}_{\mathbf{O}k}(\mathbf{Q}^{+} + \mathbf{R}\mathbf{P}^{-})||_2^2 < \sigma_k$

$\mathbf{Q}^{+} \in \mathbf{Q}_{\Lambda}$

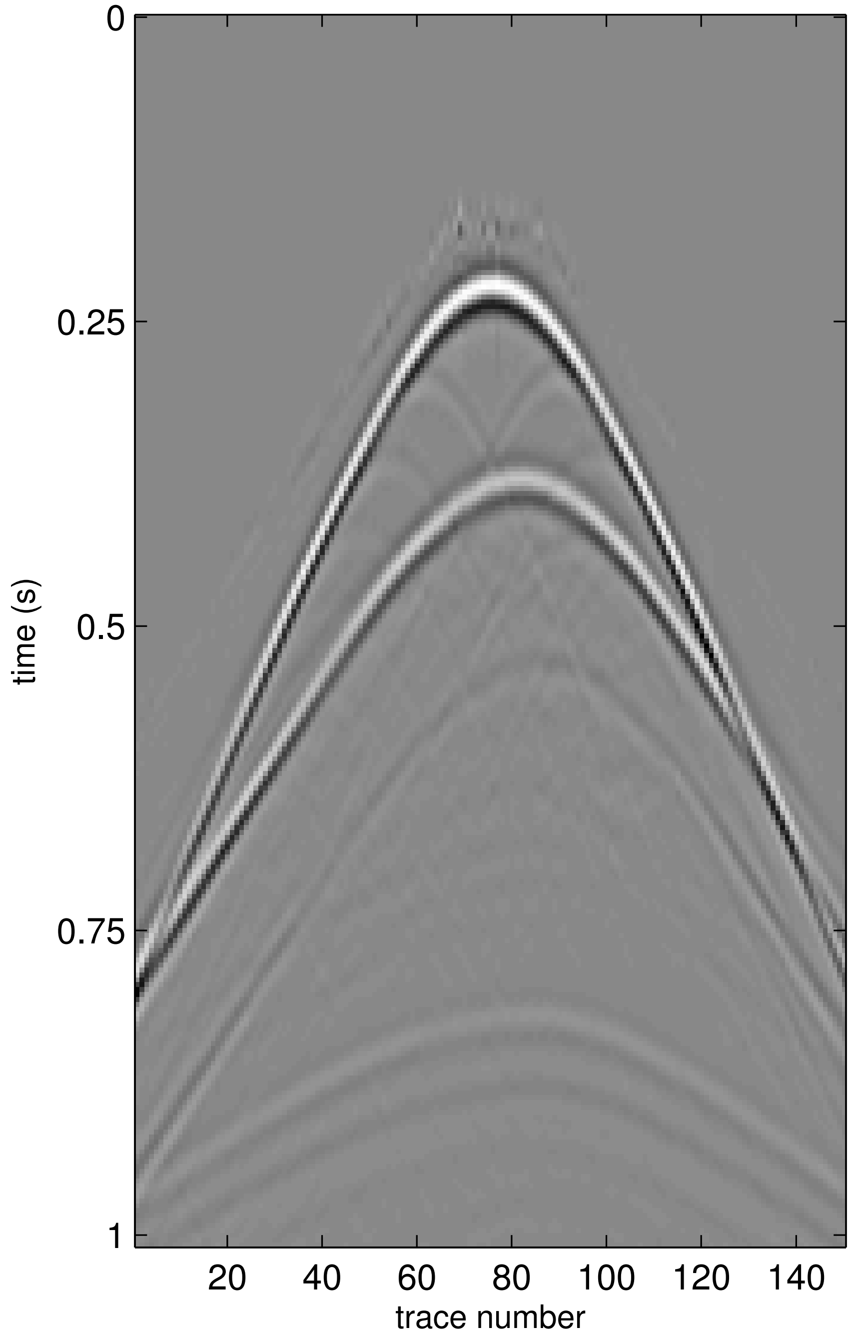
Fix primary impulse response, get least-squares matching for $\mathbf{Q}^{+}$ past ℓ_2 mismatch tolerance σ_k

Wavelet ambiguity

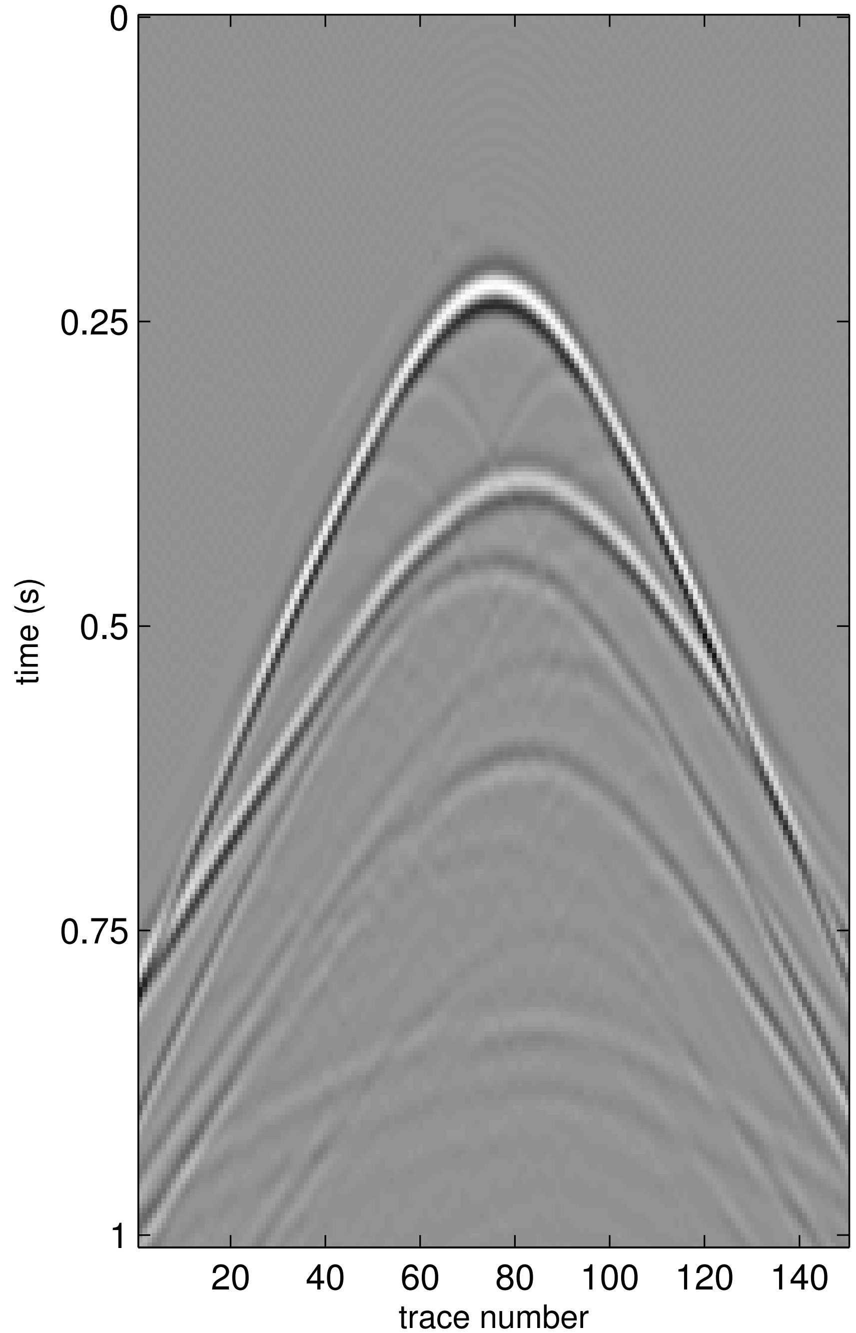


same ℓ_1 norm

Wavelet scaling

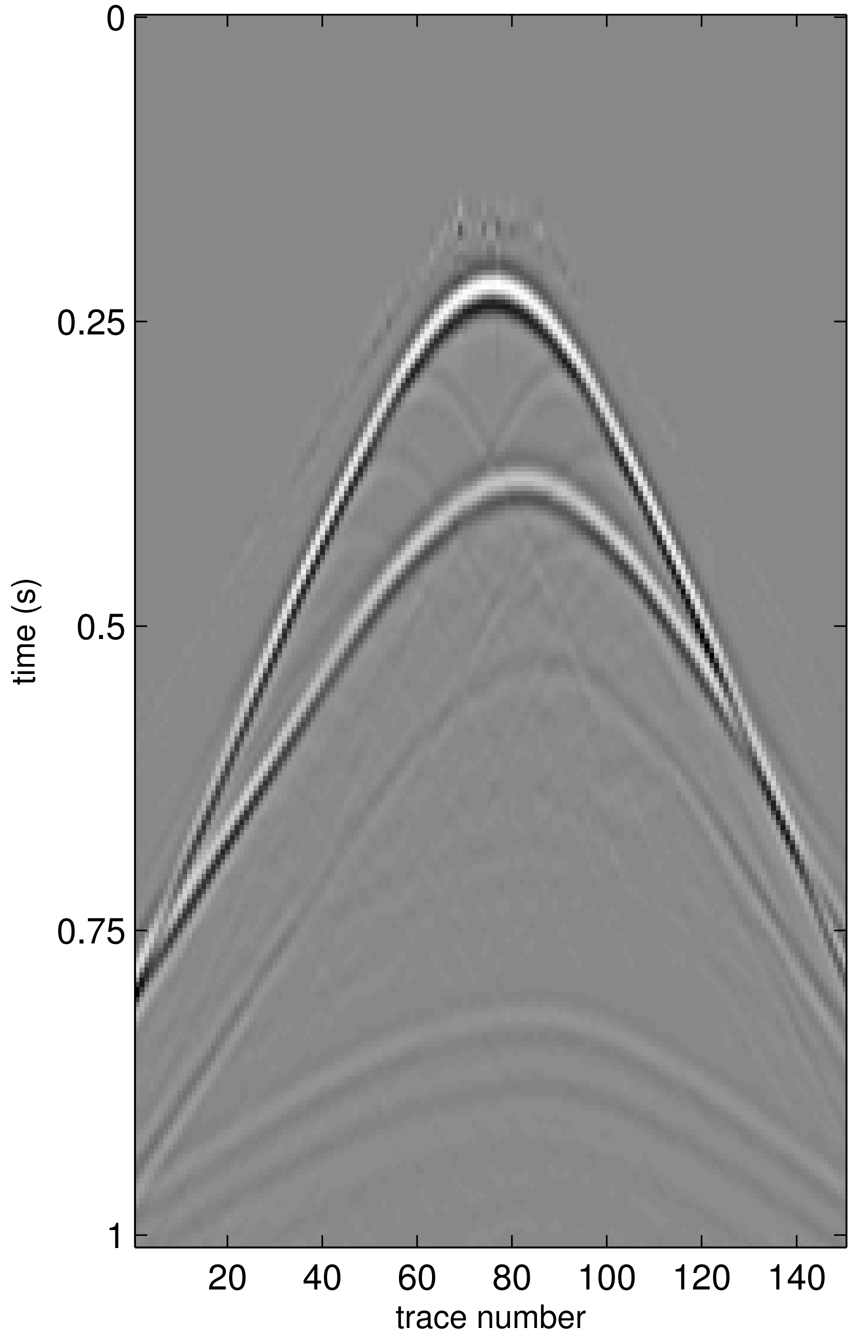


wavelet well-scaled

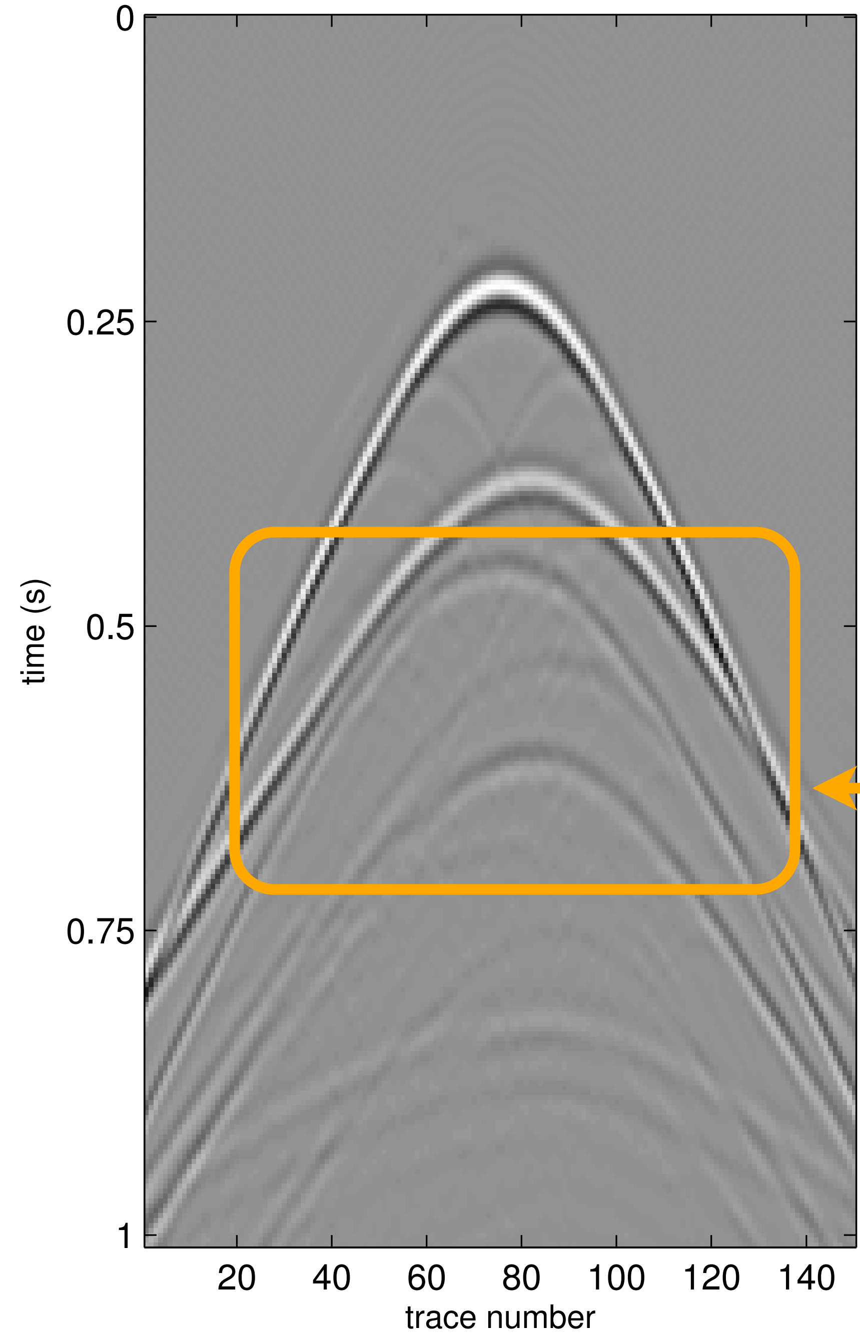


wavelet scale too high

Wavelet scaling



wavelet well-scaled



wavelet scale too high

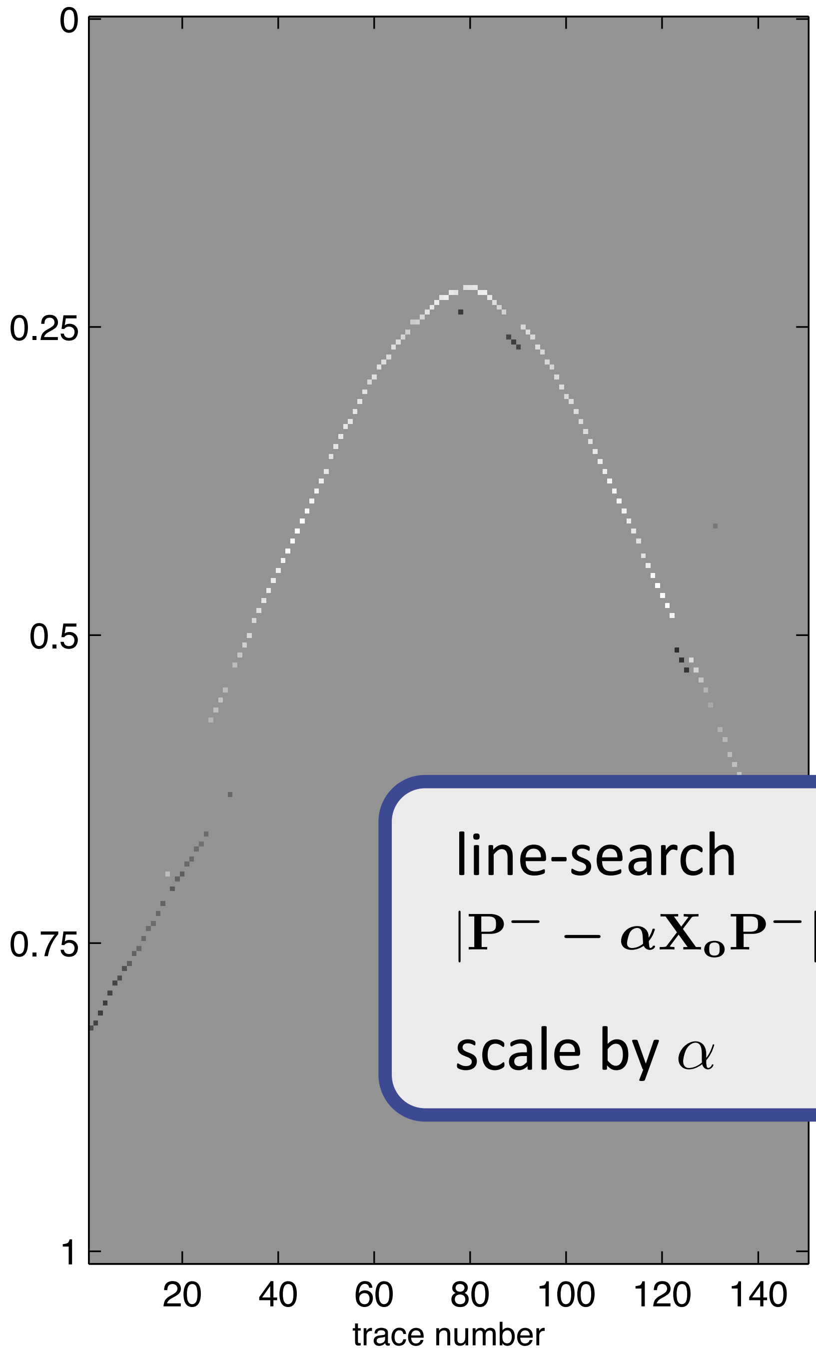
in this section, multiples show up because

$$\delta \mathbf{X}_o \mathbf{Q}^+ > \delta \mathbf{X}_o \mathbf{P}^-$$

Decrease objective

Increase objective

Wavelet ambiguity

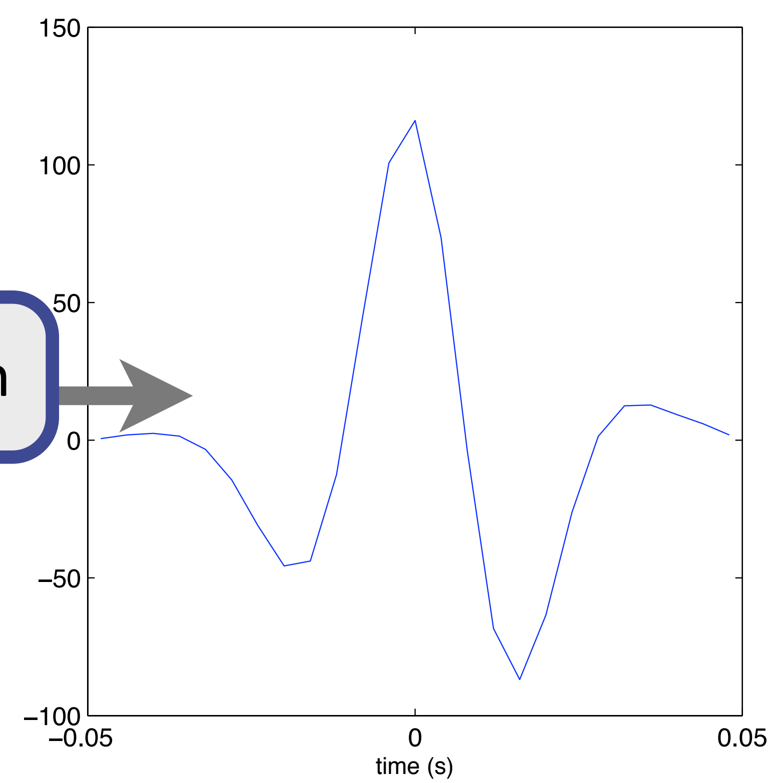


pick only max event

line-search
$|\mathbf{P}^{-} - \alpha \mathbf{X}_{\mathrm{o}} \mathbf{P}^{-}|_2$

scale by α

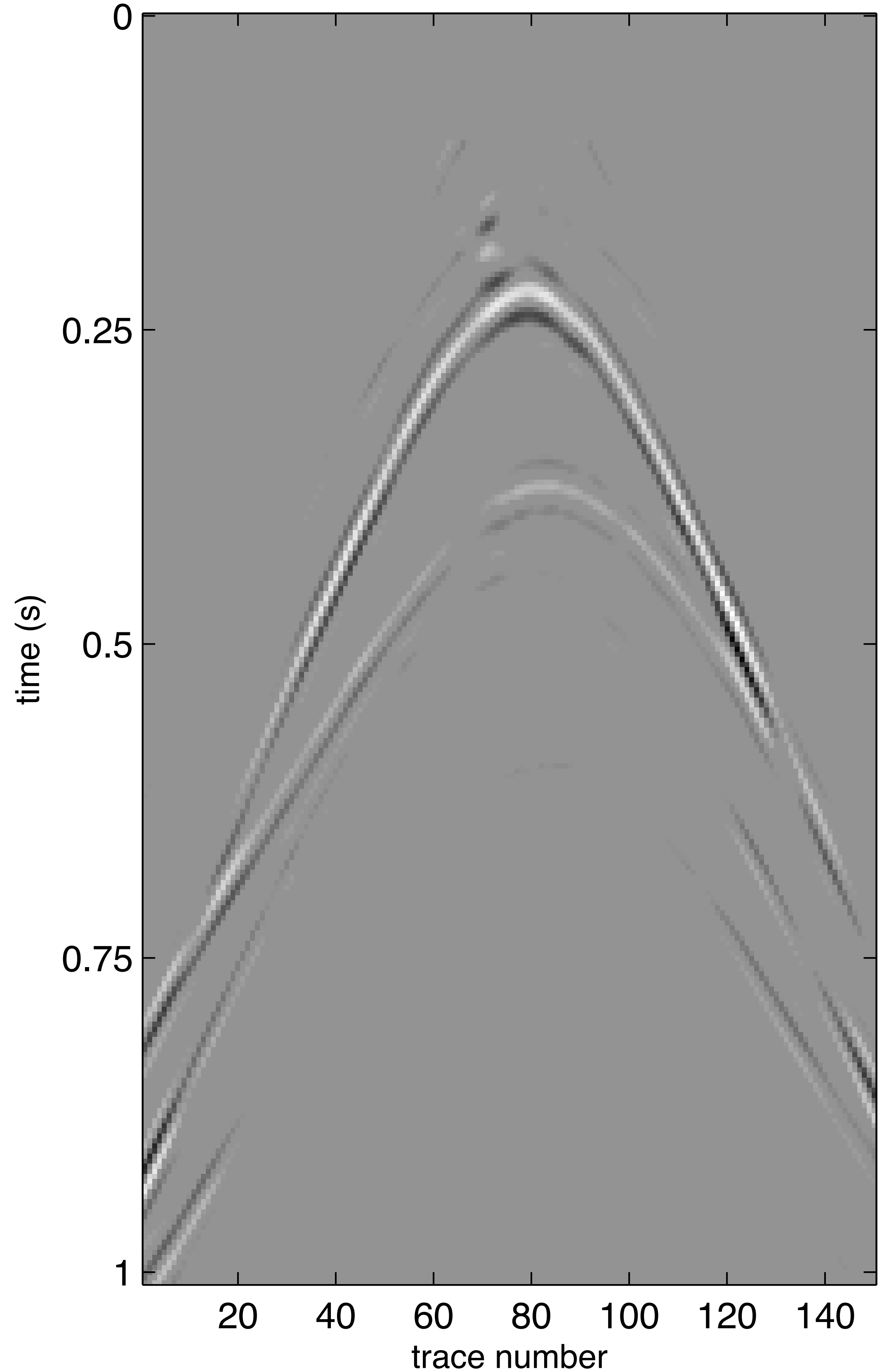
→ wavelet match →



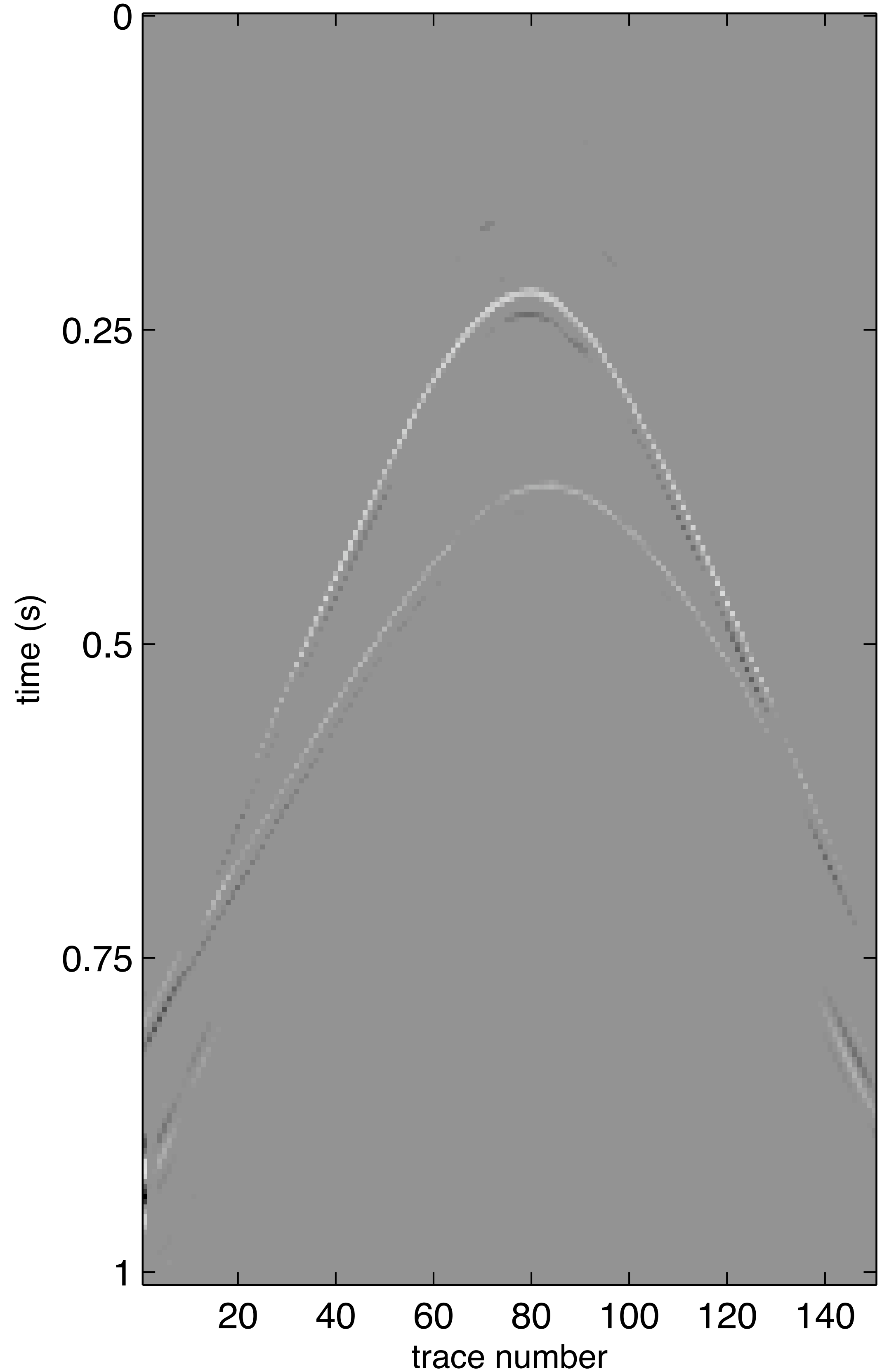
$= \mathbf{Q}^{+}_{k=1}$

reset Green's Func → $\mathbf{x}_{k=1} =$ zero vector

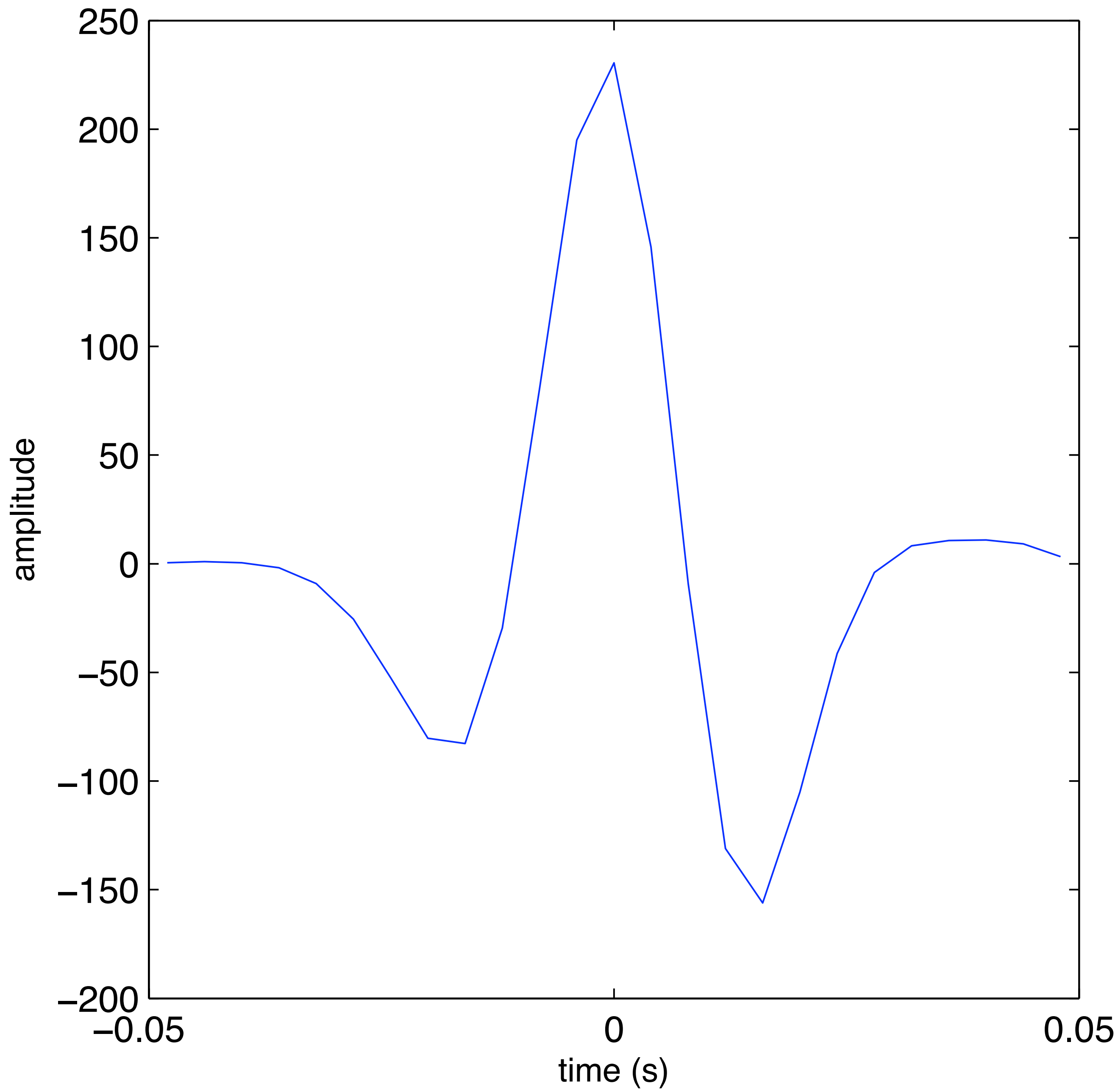
IR estimation 1 - start



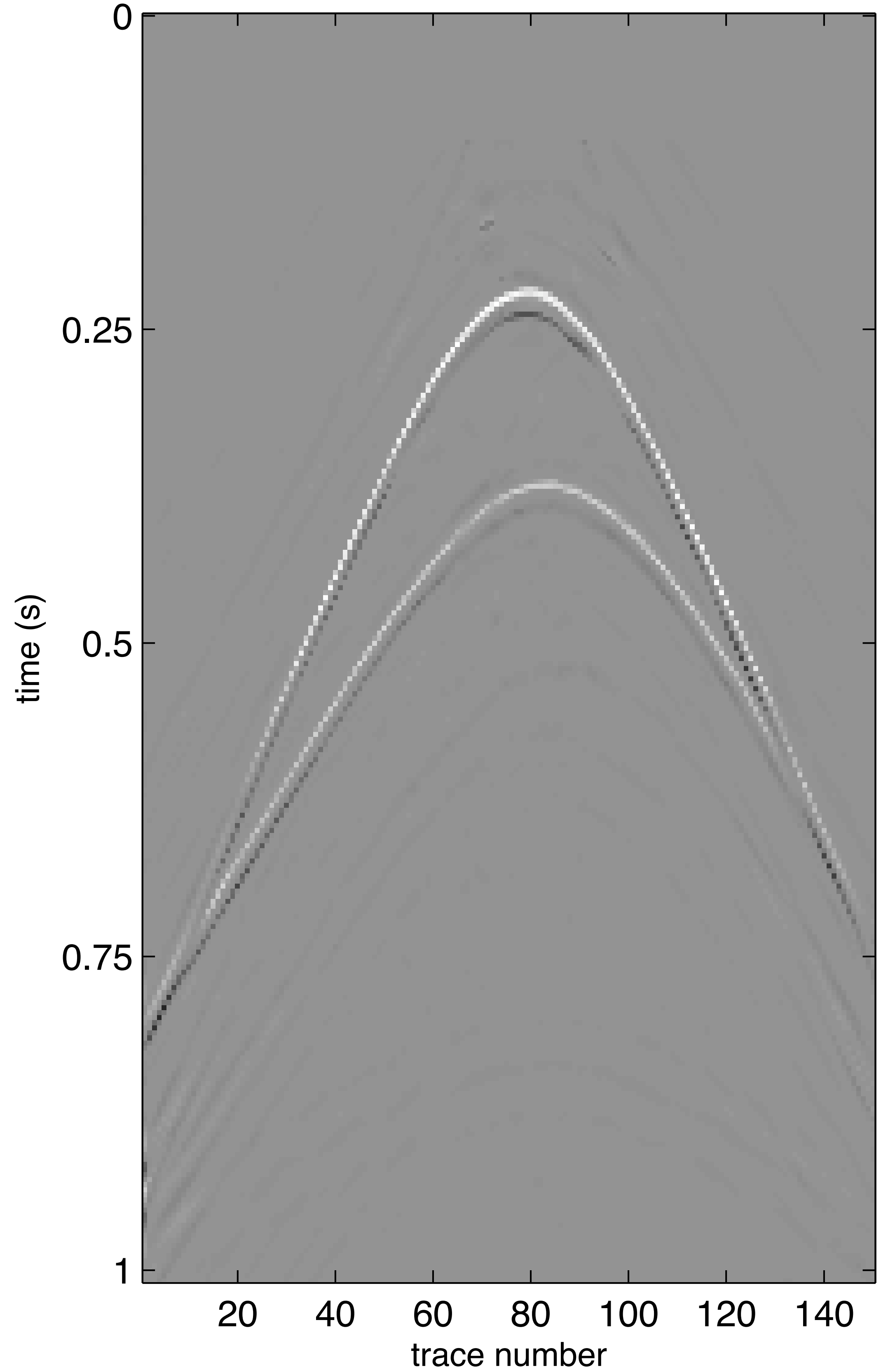
IR estimation 1 - Pareto



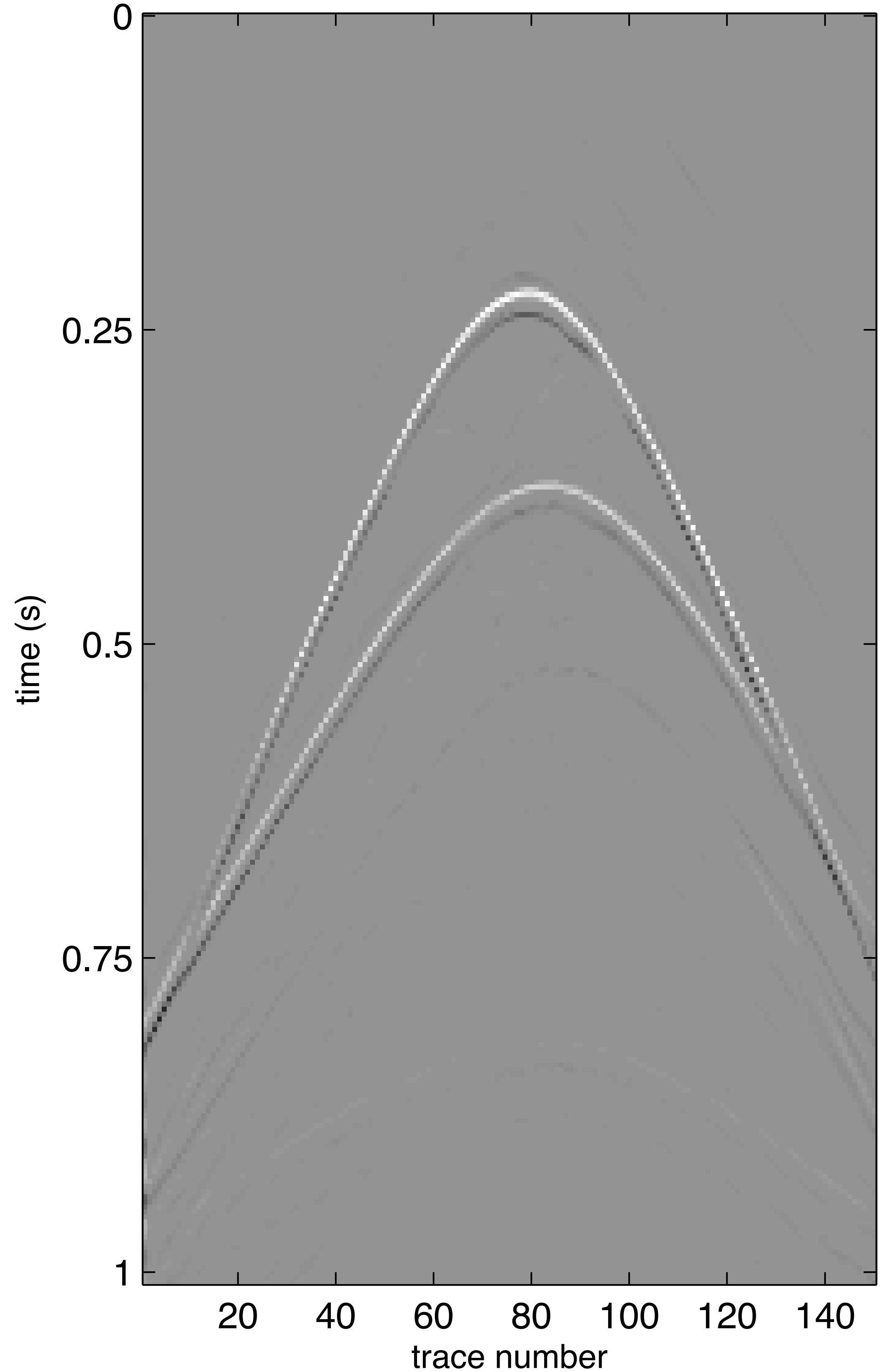
Wavelet matching 2



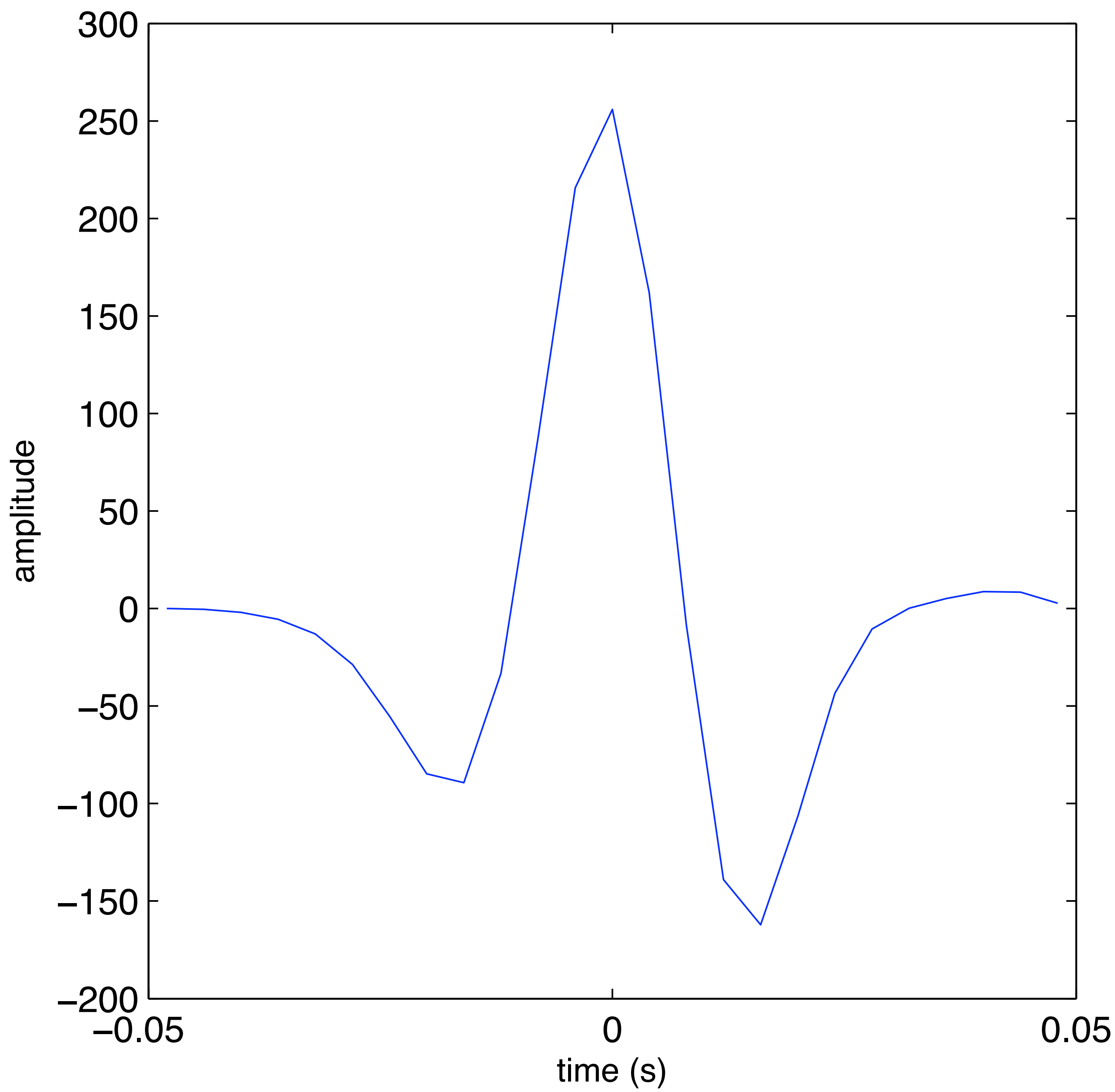
IR estimation 2 - start



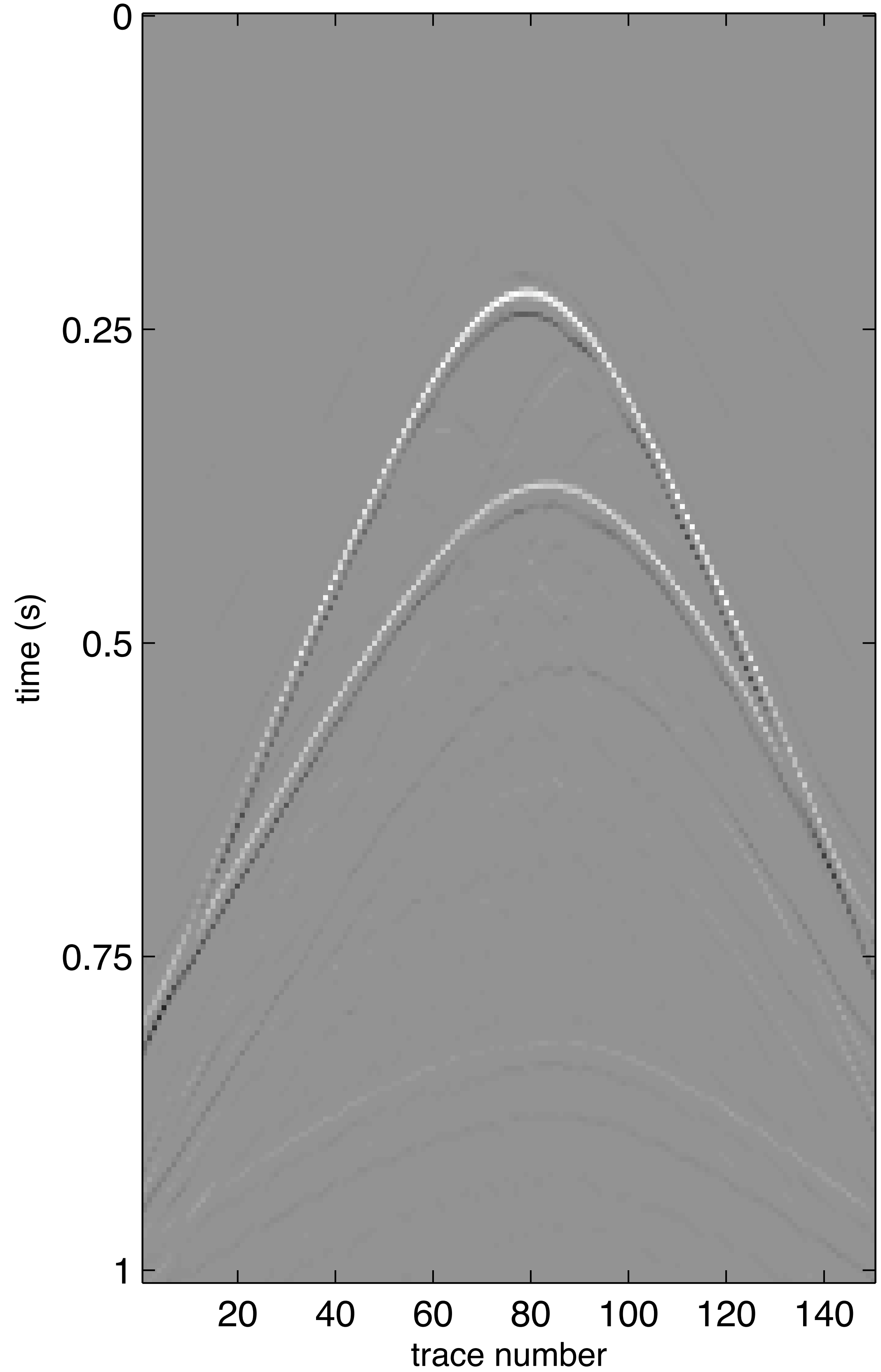
IR estimation 2 - Pareto



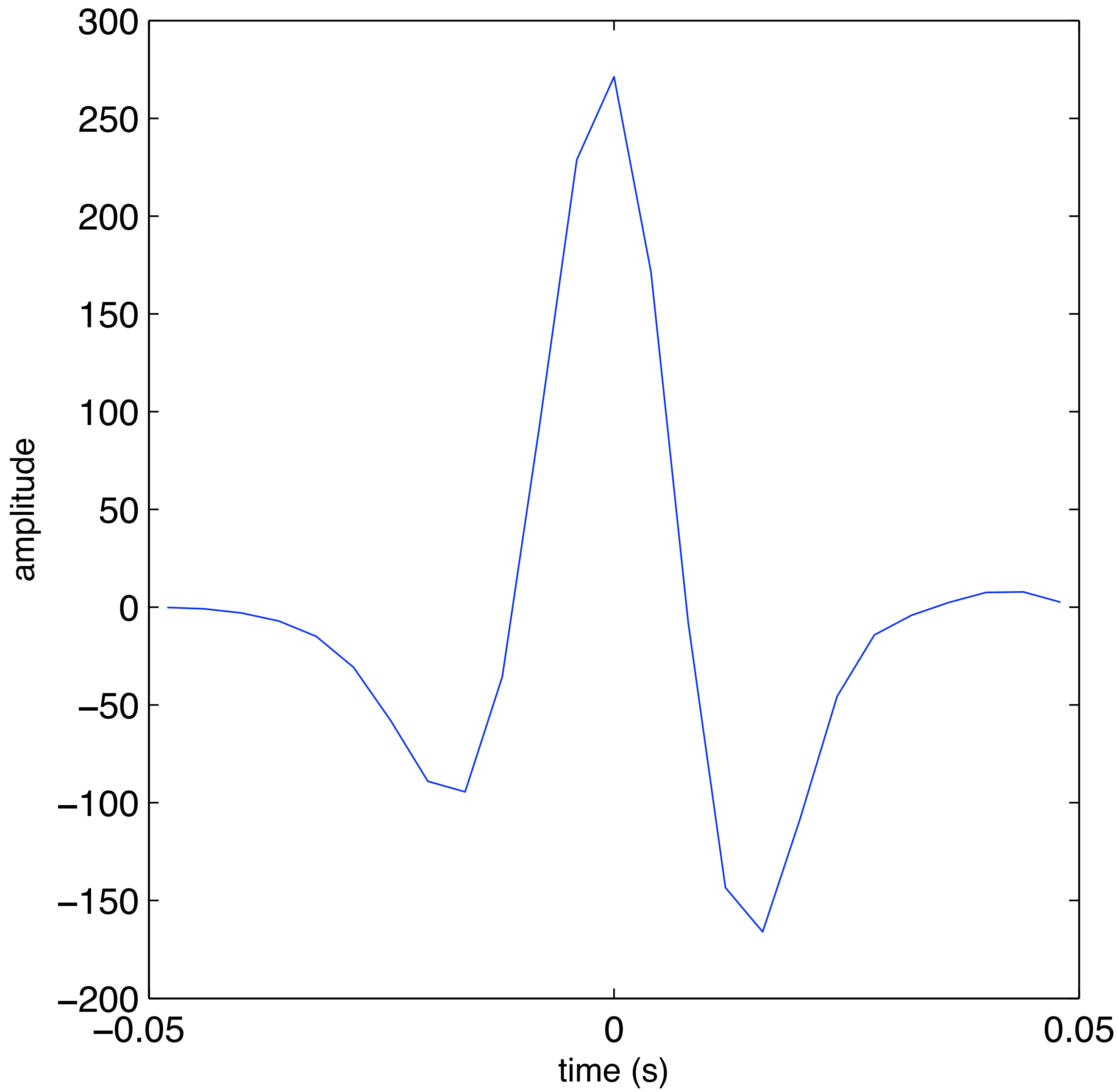
Wavelet matching 3



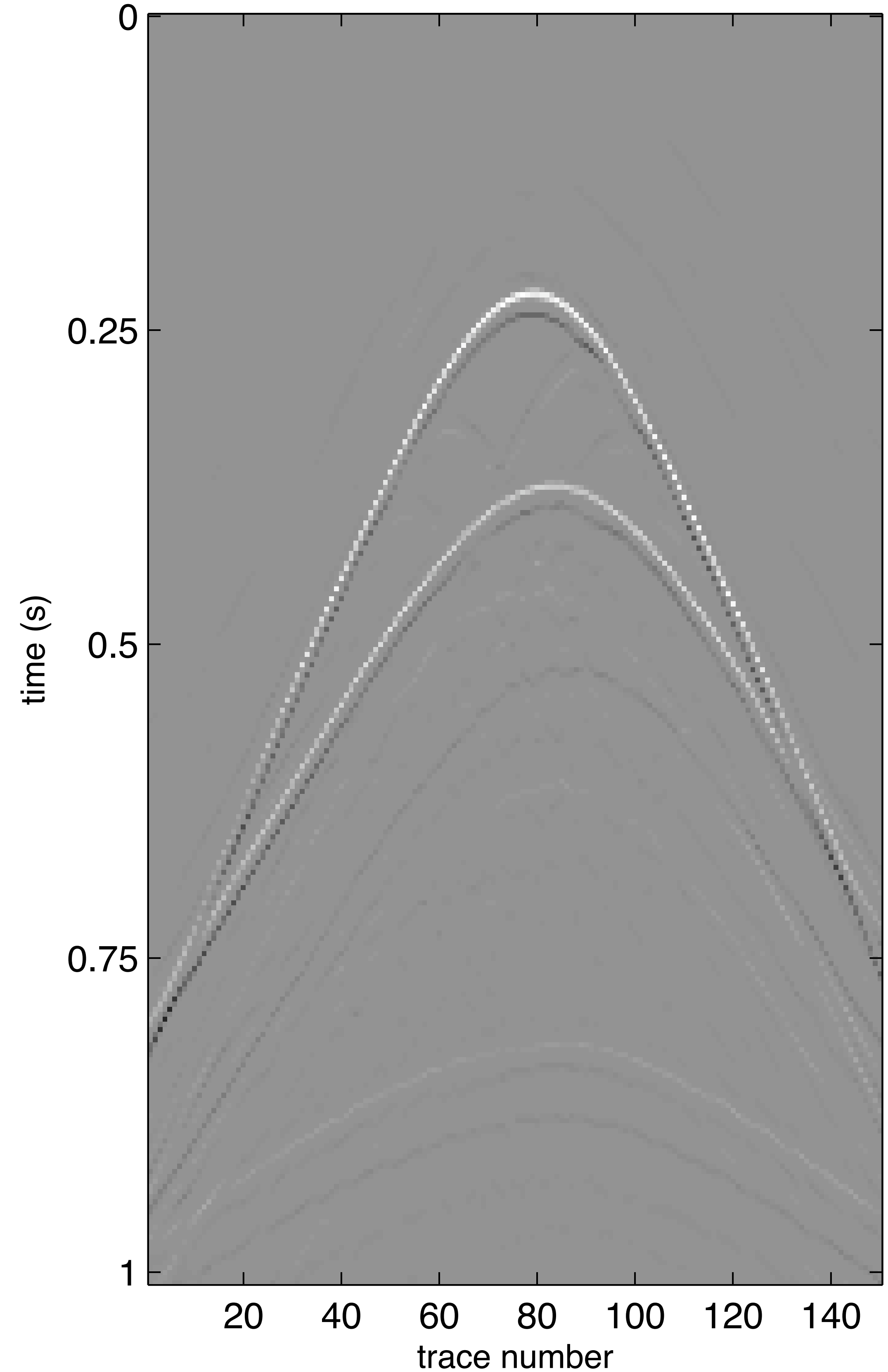
IR estimation 3 - Pareto



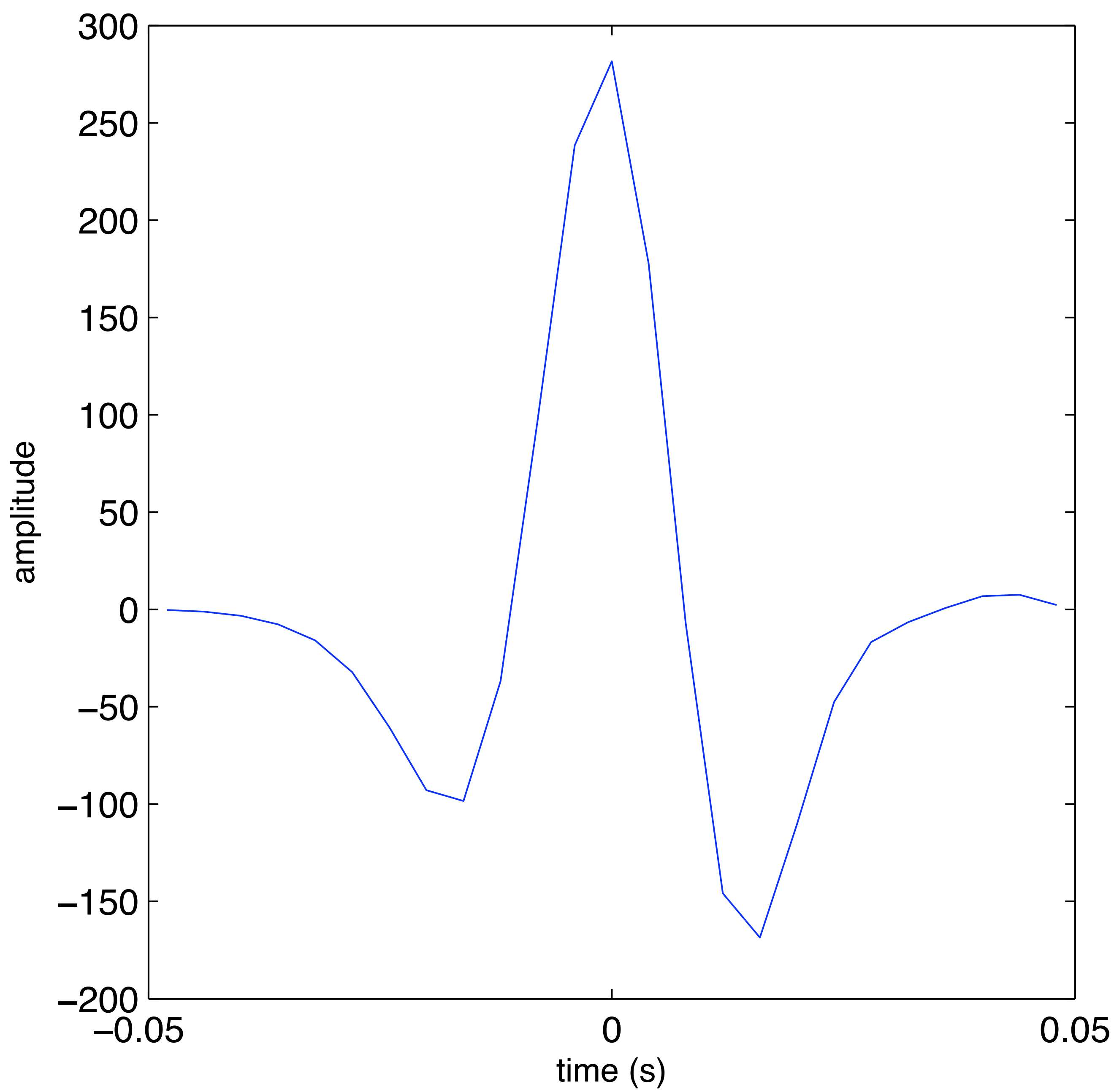
Wavelet matching 4

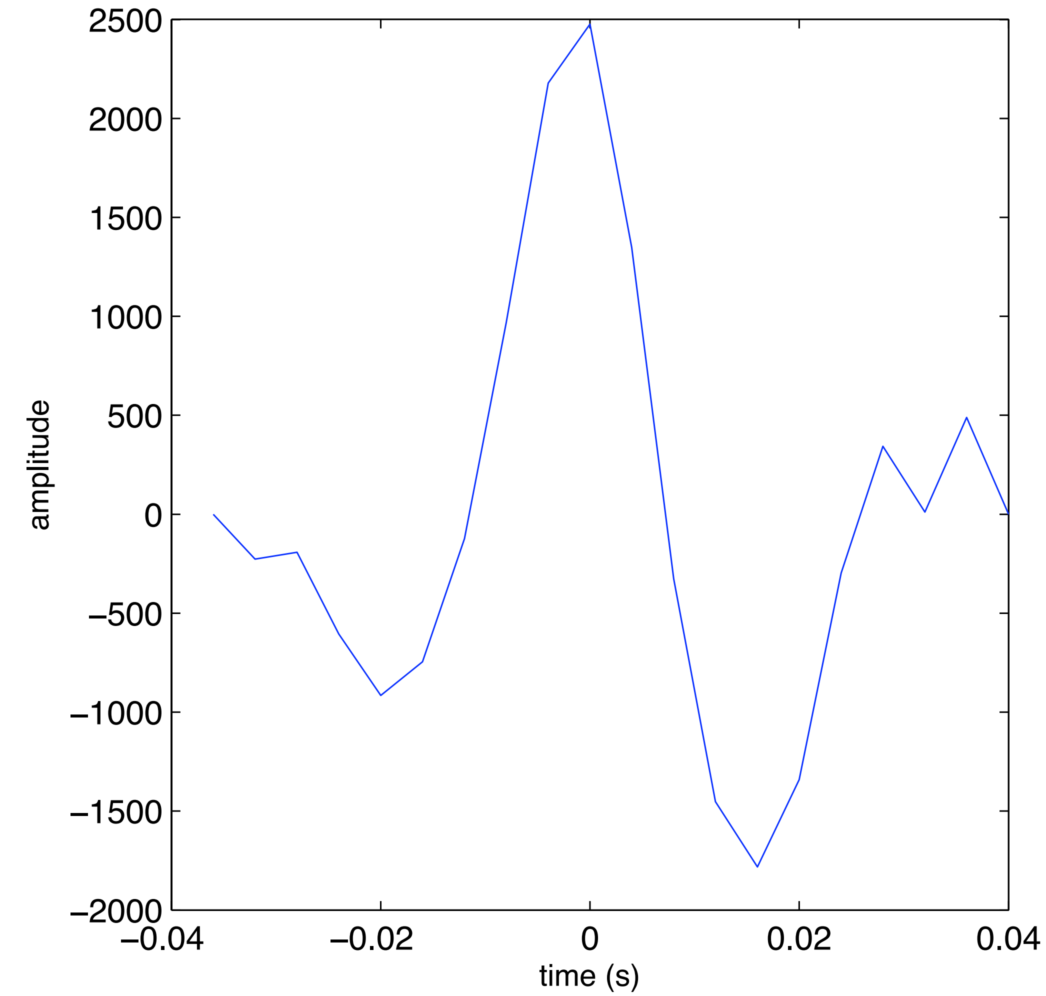


IR estimation 4 - Pareto



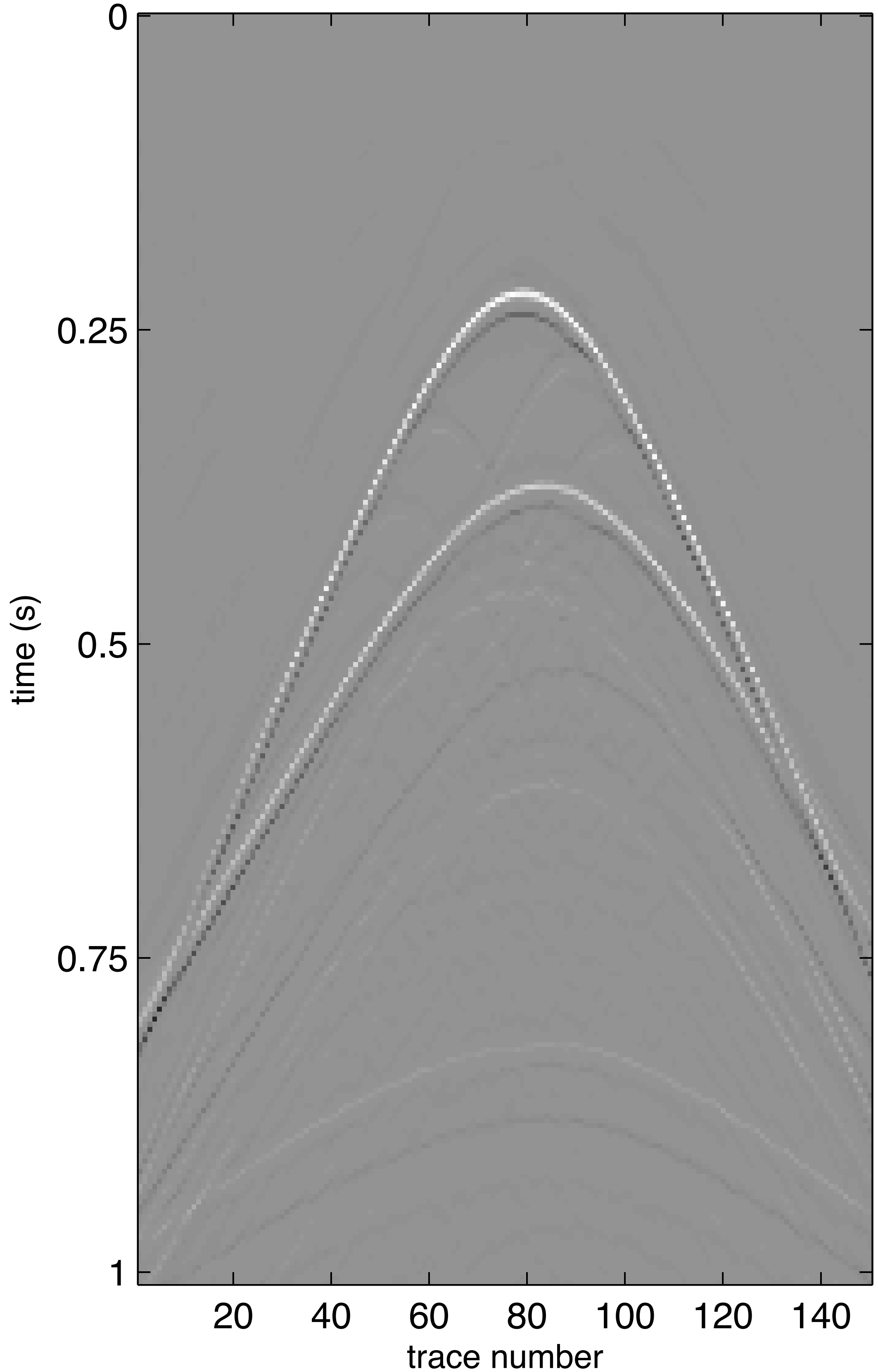
Wavelet matching 5





EPSI result (scaled differently)

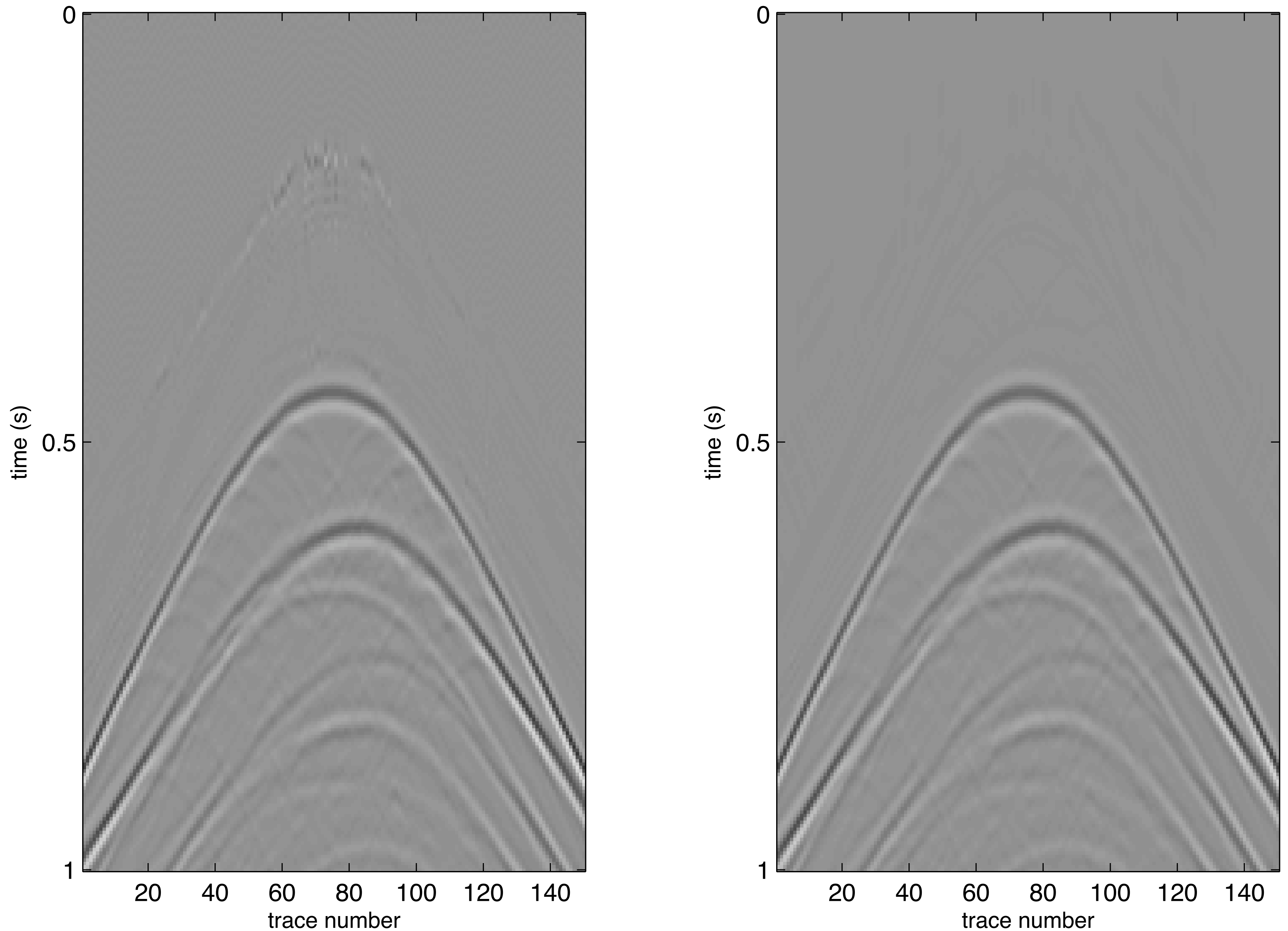
IR estimation 5 - Pareto



total ~60 gradient updates

Sparsity vs L1

Data minus estimated primary
(one shot)

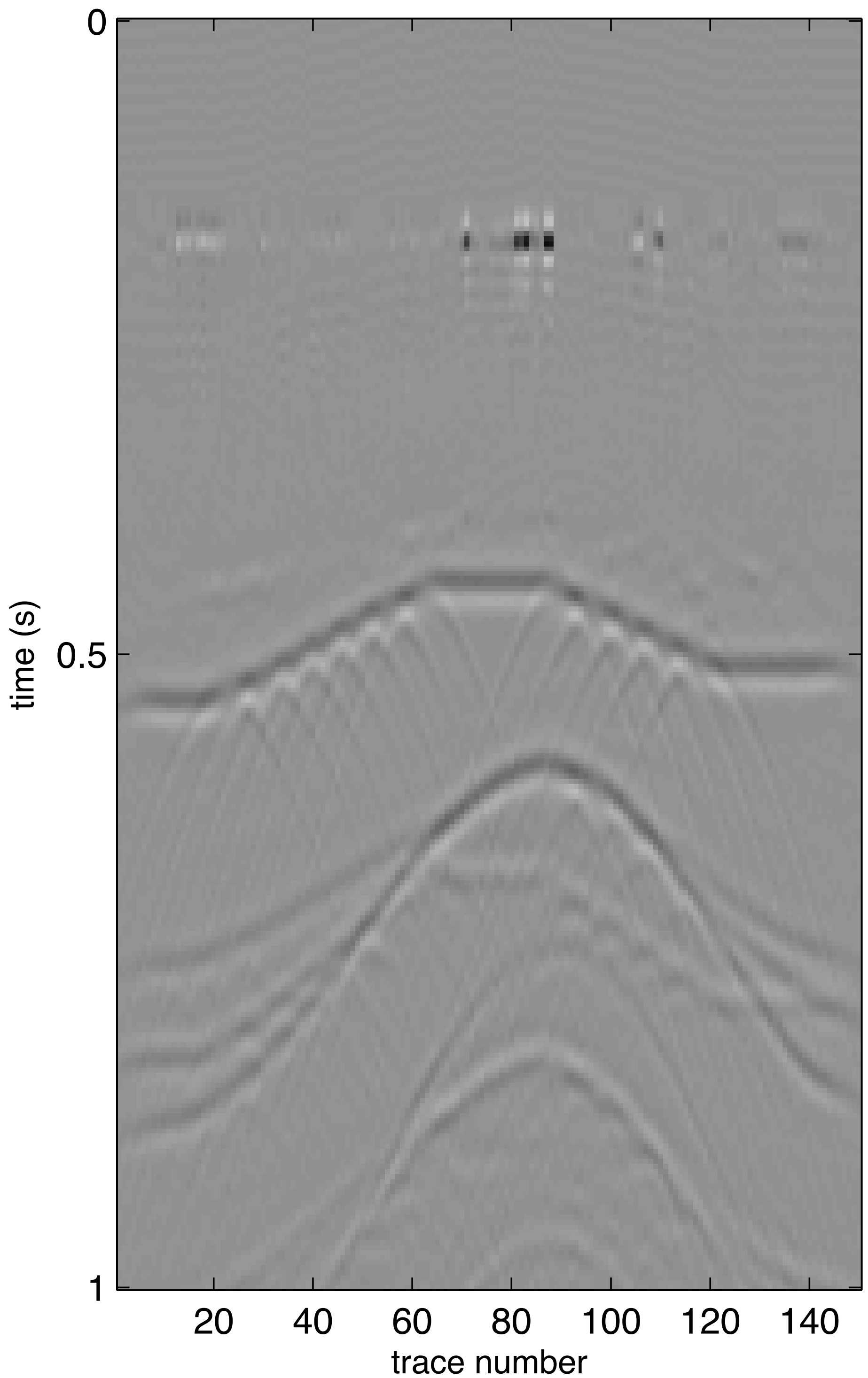


Sparse EPSI

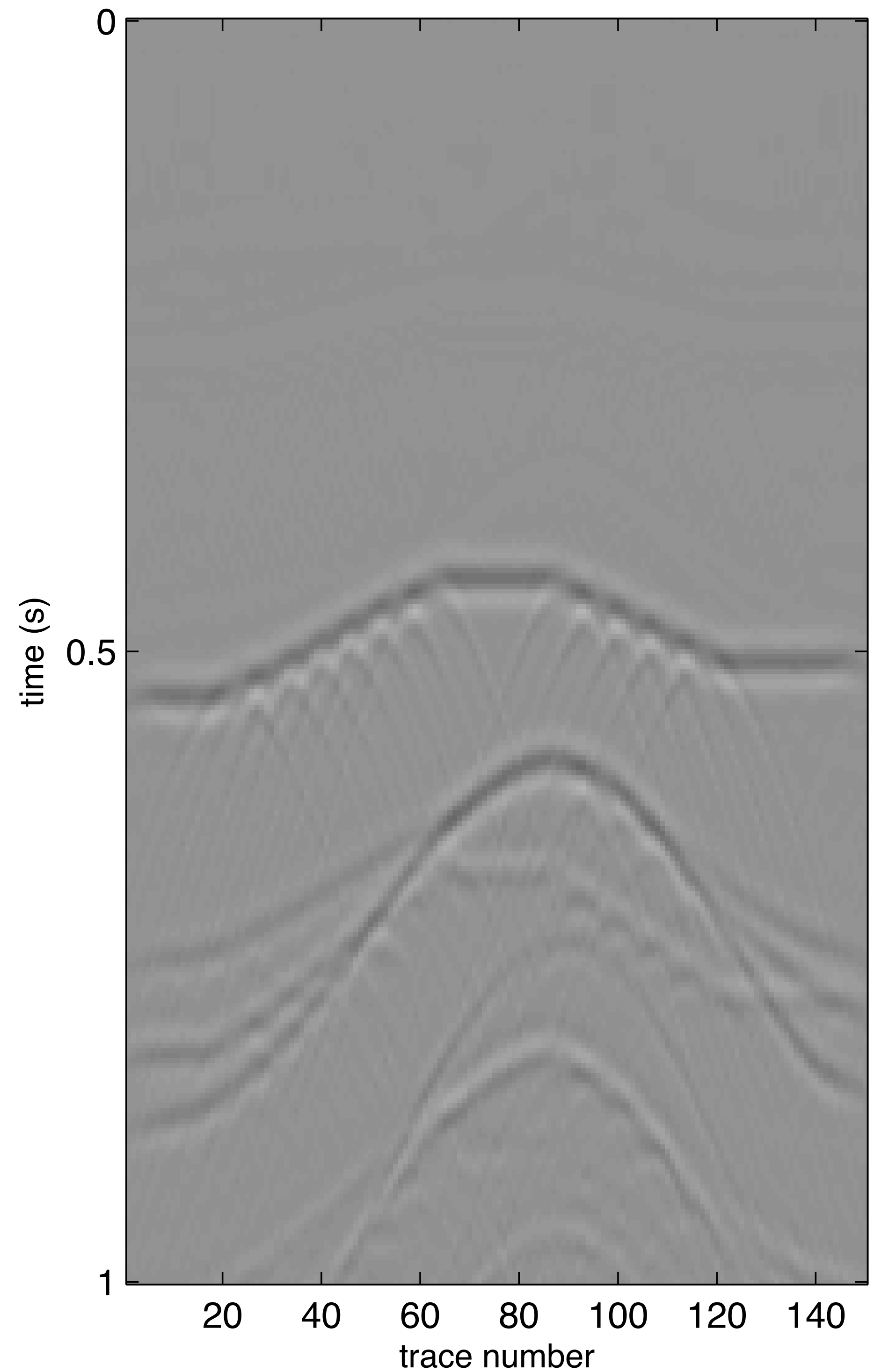
ℓ_1 EPSI

Sparsity vs L1

Data minus estimated primary
(zero-offset)



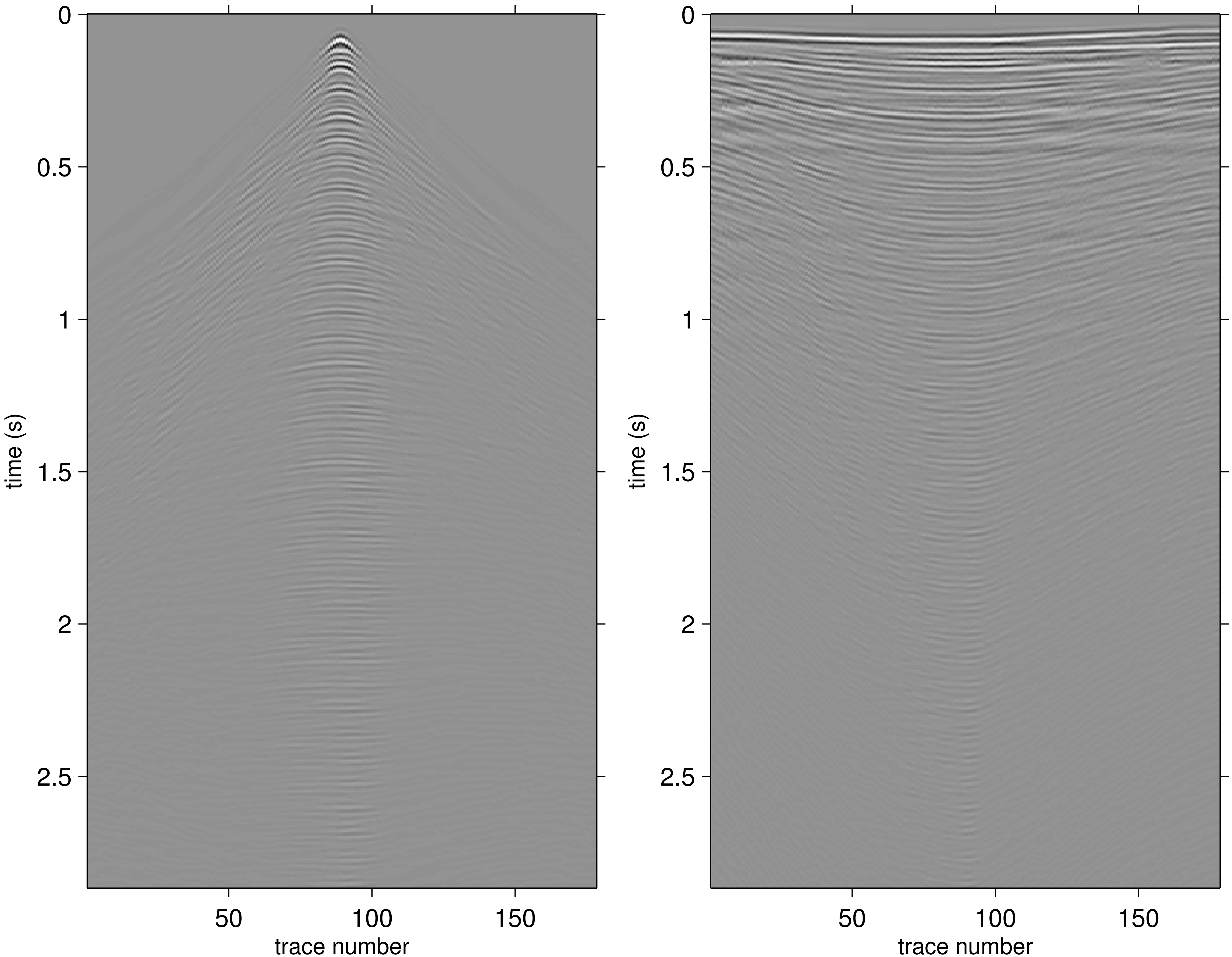
Sparse EPSI



ℓ_1 EPSI

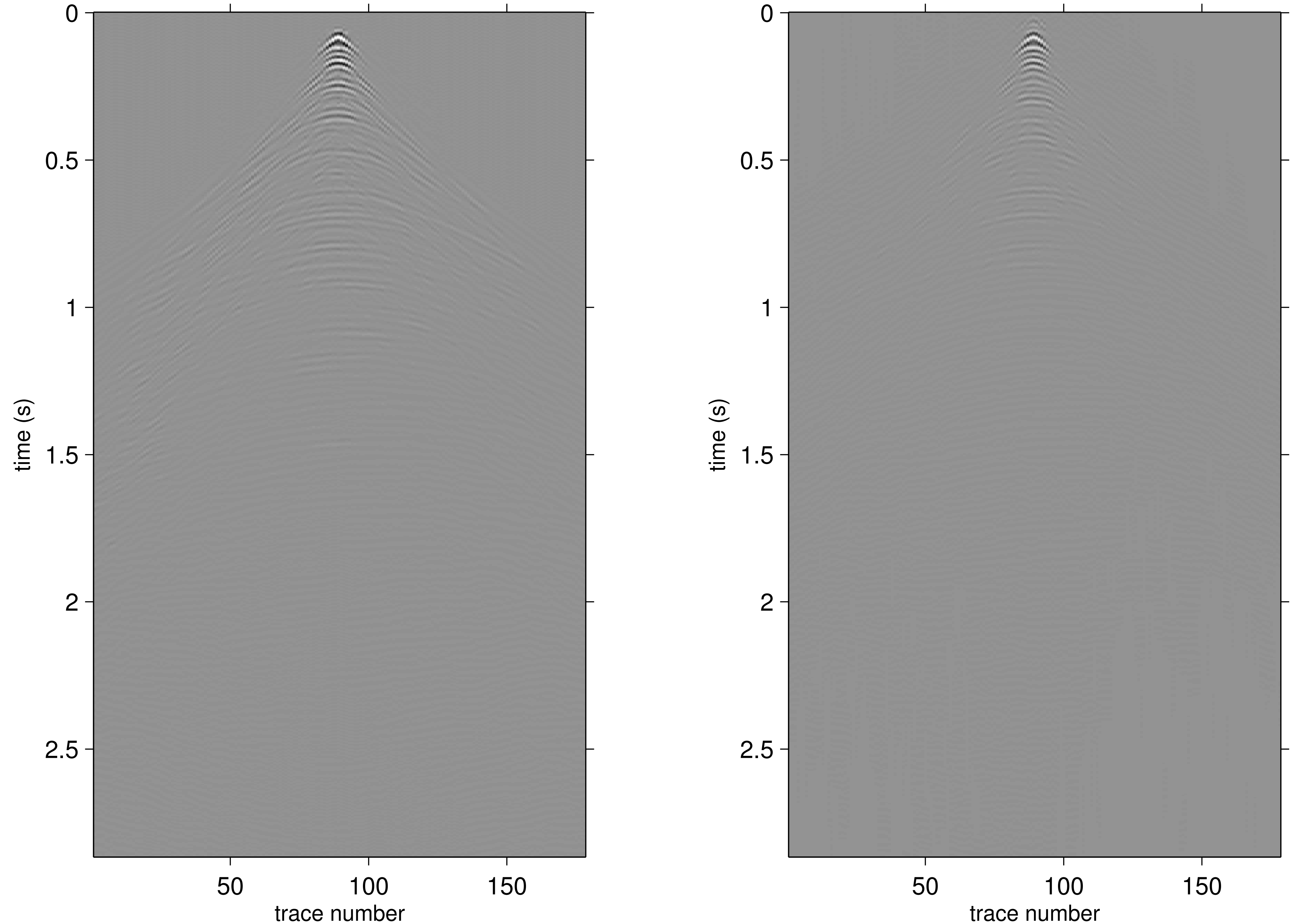
Sparsity vs L1

Gulf of Suez



Sparsity vs L1

Gulf of Suez
(one shot)

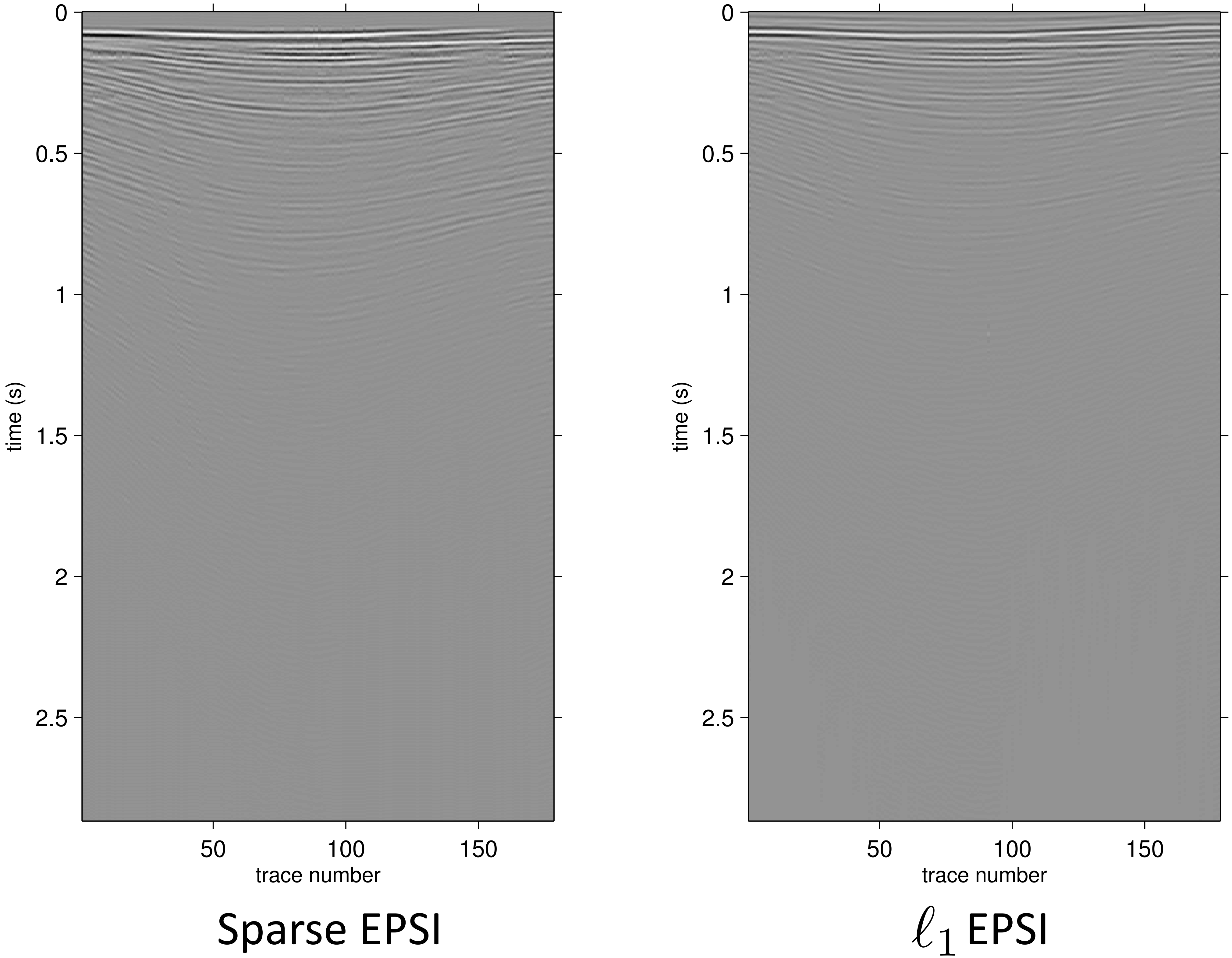


Sparse EPSI

ℓ_1 EPSI

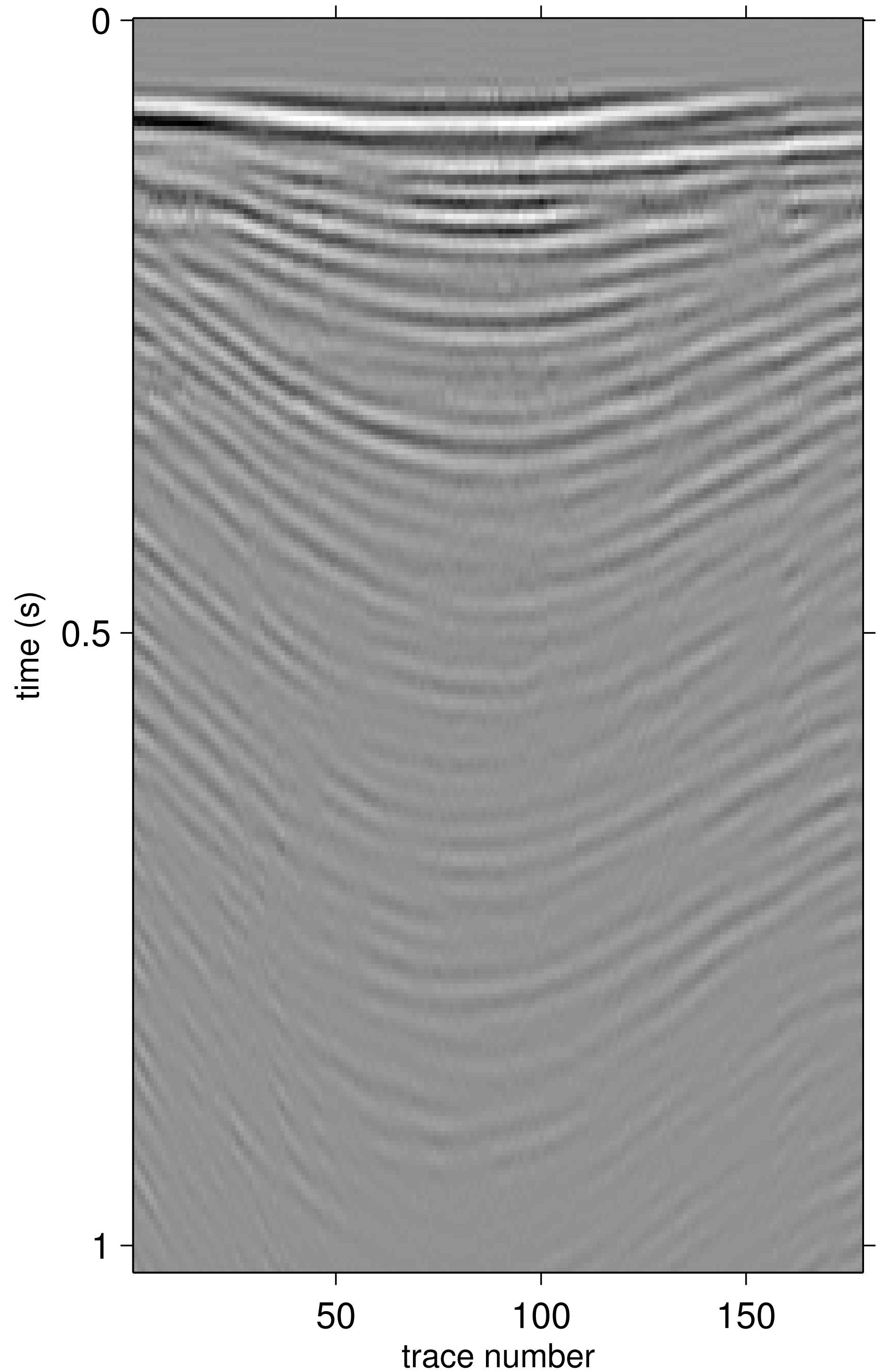
Sparsity vs L1

Gulf of Suez
(zero-offset)

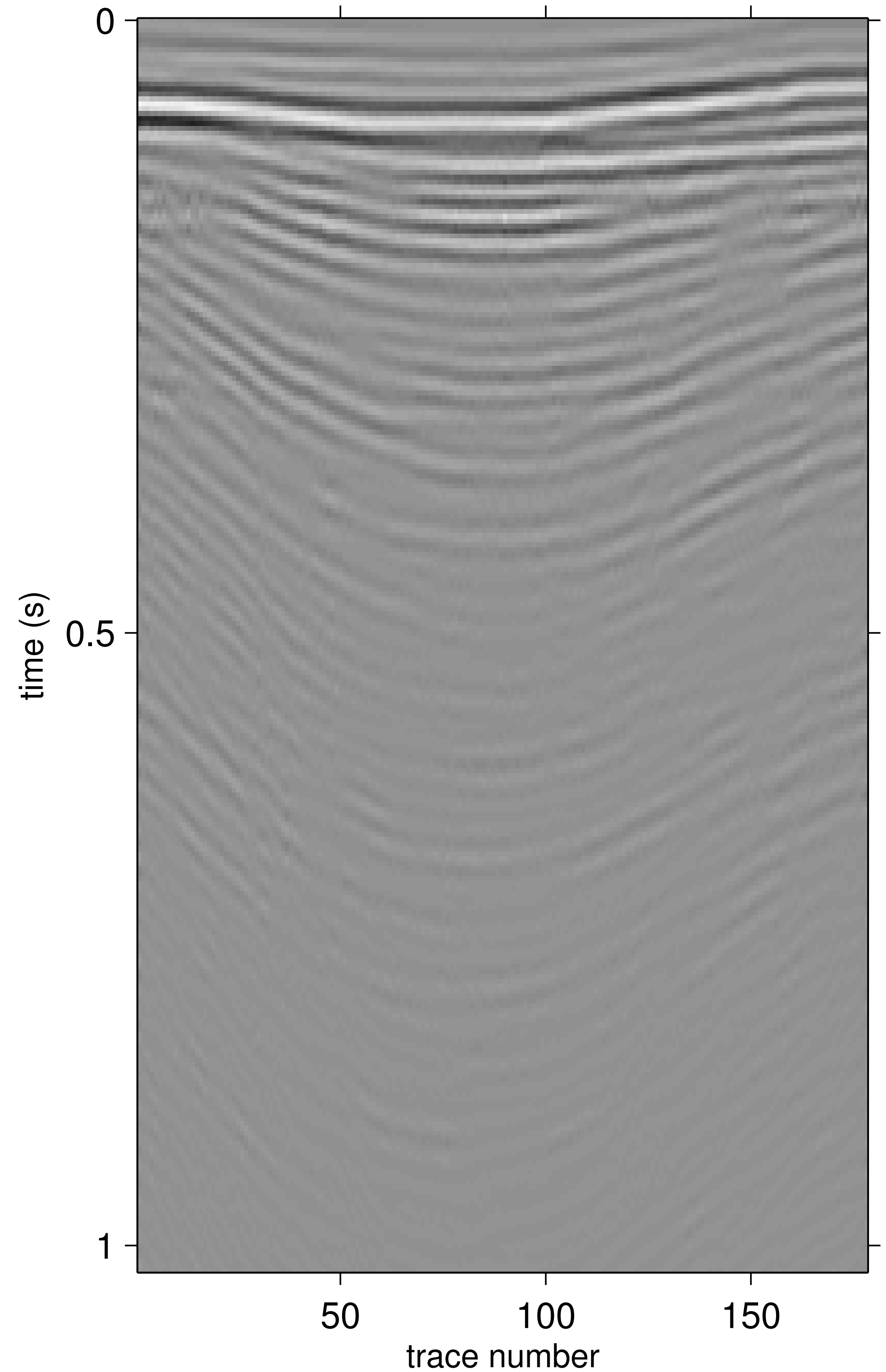


Sparsity vs L1

Gulf of Suez
(zero-offset zoomed)



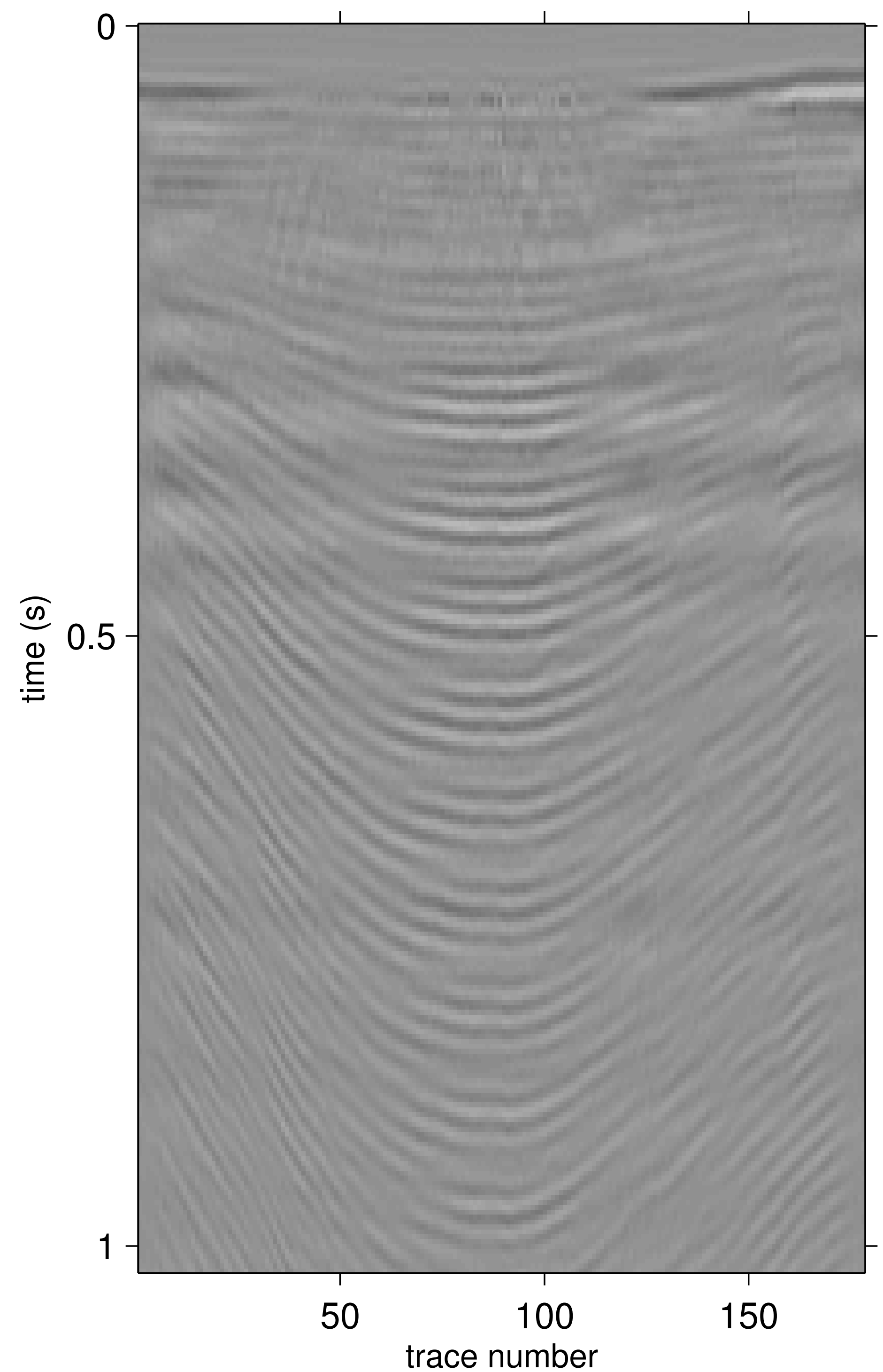
Sparse EPSI



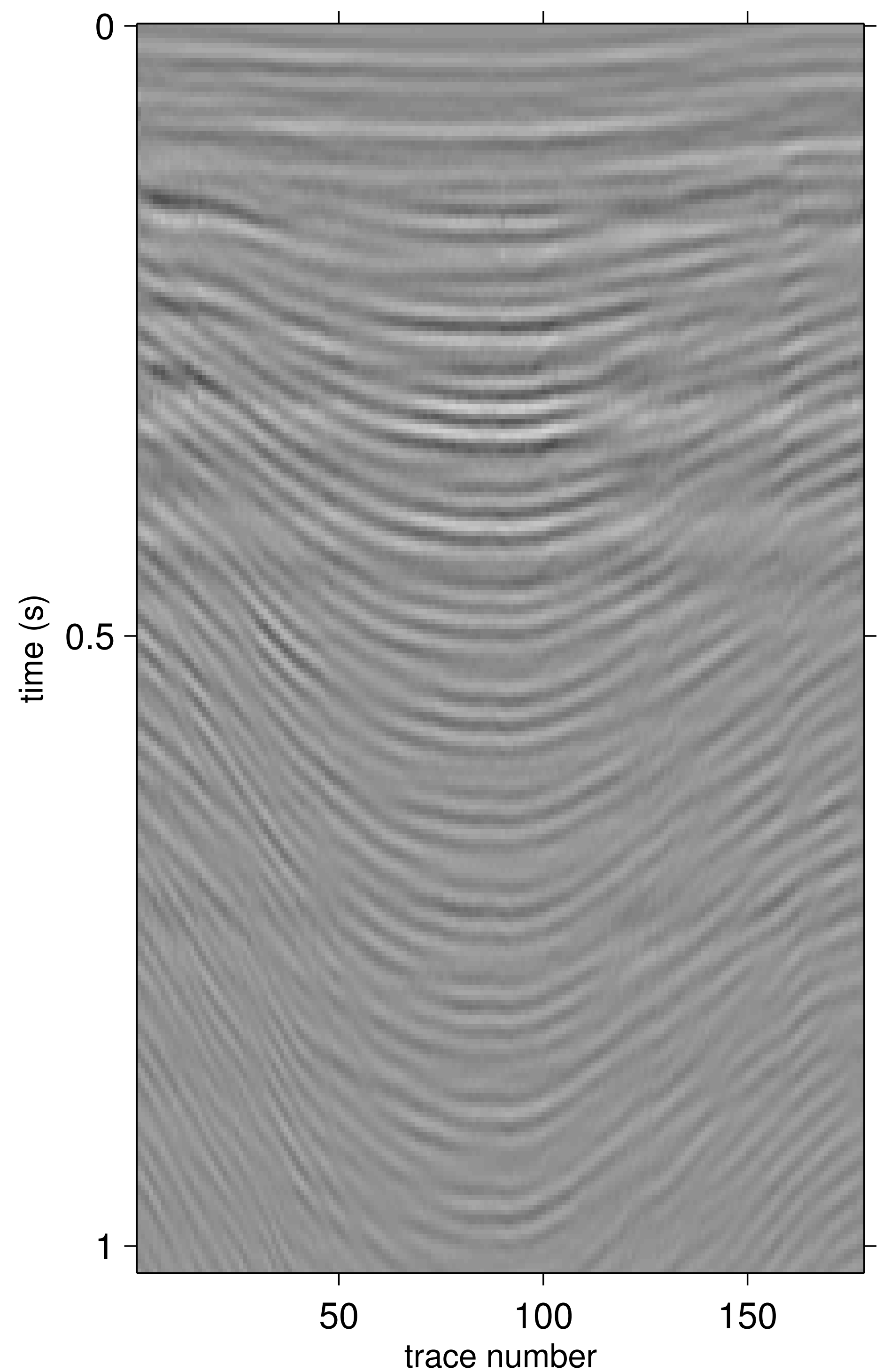
ℓ_1 EPSI

Sparsity vs L1

Data minus estimated primary
(zero-offset)



Sparse EPSI



ℓ_1 EPSI

EPSI requires

- tight muting window
- physical locations of the primaries (window at each gradient update)
- number of reflection events inside this window
- source wavelet length

L1 reformulation

- ~~tight muting window~~
- ~~physical locations of the primaries (window at each gradient update)~~
- ~~number of reflection events inside this window~~
- noise level in input data (use GCV in the future)
- source wavelet length

conclusions

- **less** parameters to tweak
- **improved convergence** properties of EPSI by convex relaxation
- **improved quality** of first arrivals
- cast EPSI into blind deconvolution **framework** using alternating optimization
- **removed gradient scaling issues** btw wavelet matching and IR estimation
- future work on intelligently setting σ (GCV)

gotchas

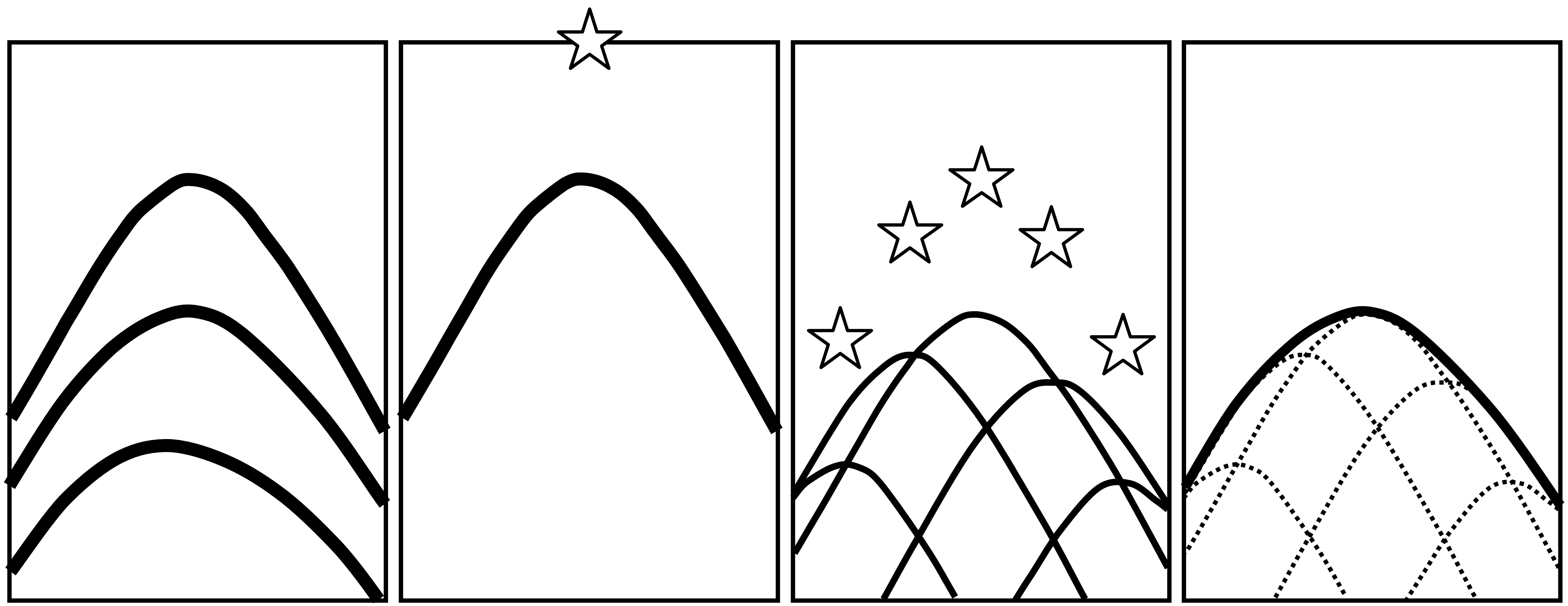
- out-of-plane scattering
- see Mufeed's work

Acknowledgements

Special thanks to G.J. van Groenestijn, Eric Verschuur, and the rest of the members of DELPHI

SINBAD
NSERC CRSNG

This work was in part financially supported by the Natural Sciences and Engineering Research Council of Canada Discovery Grant (22R81254) and the Collaborative Research and Development Grant DNOISE II (375142-08). This research was carried out as part of the SINBAD II project with support from the following organizations: BG Group, BP, Chevron, ConocoPhillips, Petrobras, Total SA, and WesternGeco.



(van Groenestijn and Verschuur 08)