

Recent Results on Seismic Deconvolution

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Outline

- Introduction & Background
 - Motivation
 - Detection-Estimation Algorithm [ChaRM]
- Recent results
 - Spiky Deconvolution
 - Stagewise Orthogonal Matching Pursuit(StOMP)
 - Multiscale Newton Method and Estimation
- Future work
 - Sensitivity analysis
 - Higher Dimensions
 - Well tie via percolation & IAM

Credits

- Sparse spike Decon.^[Mallat'05] :
 - Stéphane Jaffard (Univ. of Paris)
 - Béatrice Vedel (Univ. De Picardie)
 - Ozgur Yilmaz (Math. Dept., UBC)

- Percolation model^[H&B'04] & well tie :
 - Yves BernabÉ (MIT)

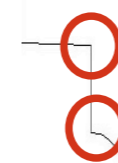
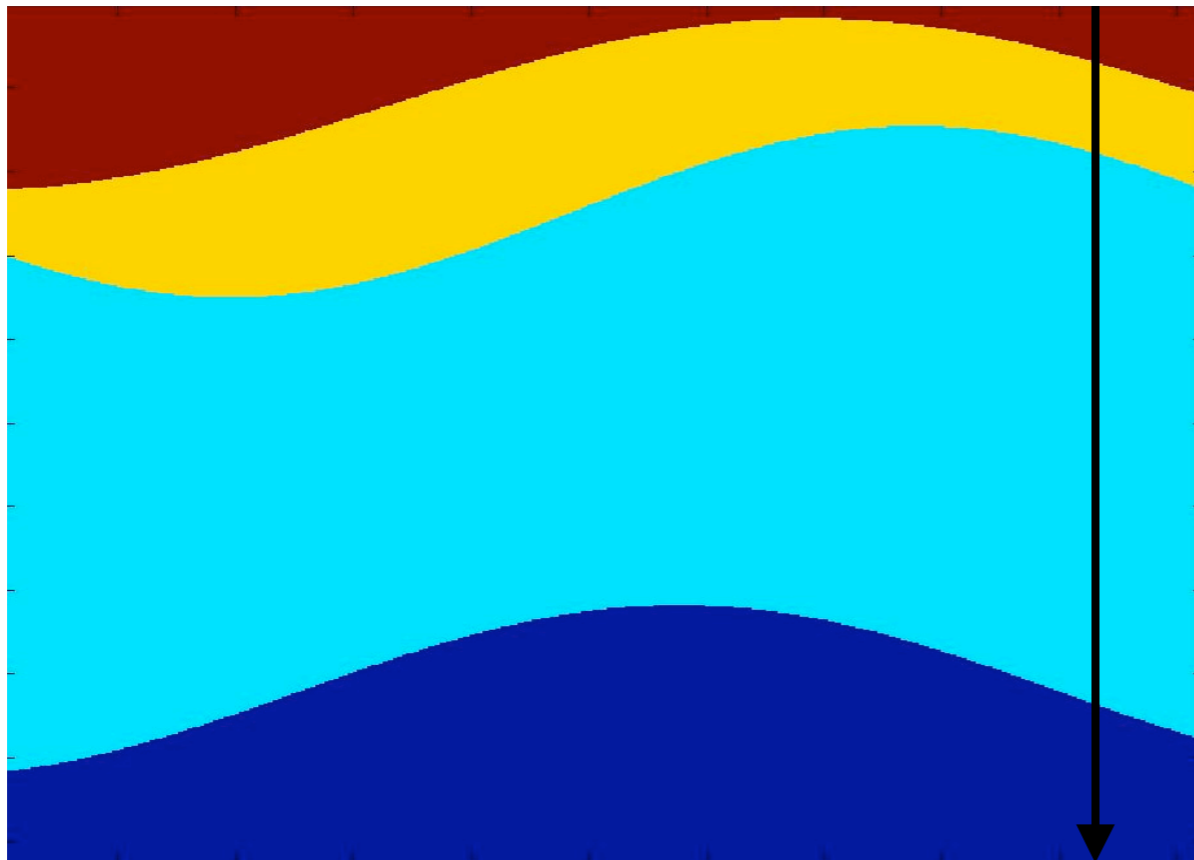
Introduction to Previous works

ChaRM Project

Model for Seismic Transition

$$\text{Causal: } \chi_+^\alpha(x) = \begin{cases} 0 & \text{if } x < 0 \\ \frac{x^\alpha}{\Gamma(\alpha+1)} & \text{if } x \geq 0 \end{cases},$$

$$\text{Anticausal: } \chi_-^\alpha(x) = \begin{cases} \frac{(-x)^\alpha}{\Gamma(\alpha+1)} & \text{if } x \leq 0 \\ 0 & \text{if } x > 0 \end{cases}$$



$$\longrightarrow \alpha = 0$$

$$\longrightarrow \alpha = 0.5$$

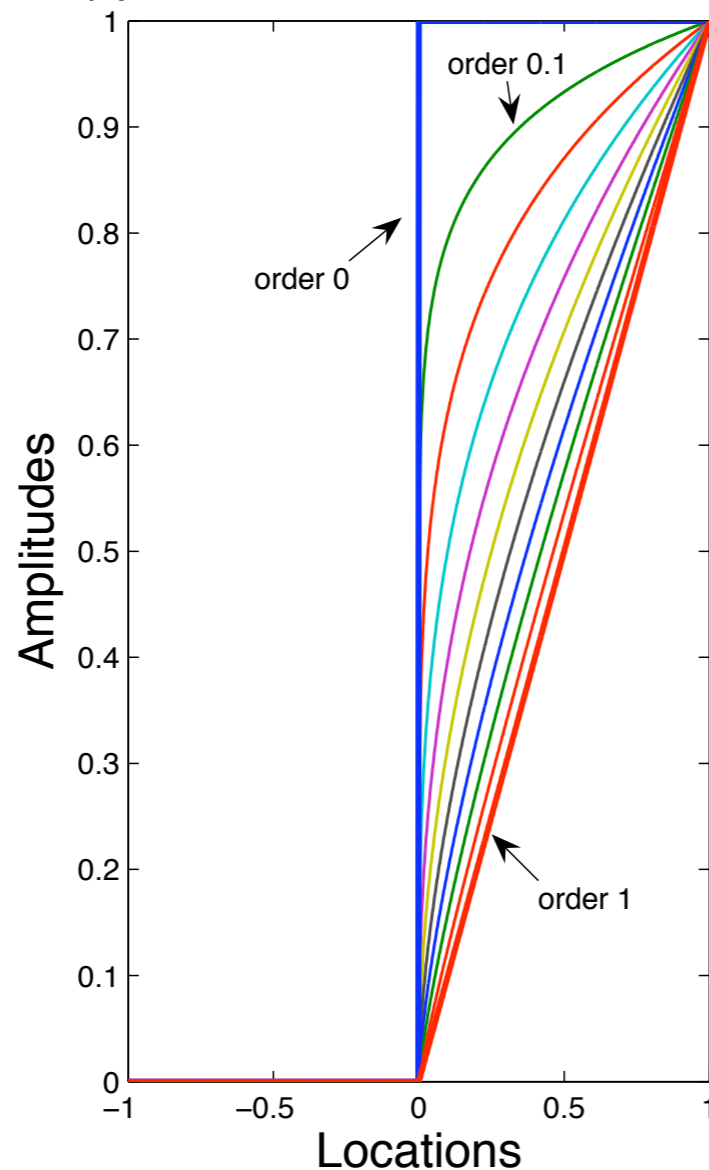
$$f(z) = \sum_i a_i \chi_{\pm}^{\alpha_i}(z - z_i),$$

$$\longrightarrow \alpha = 1$$

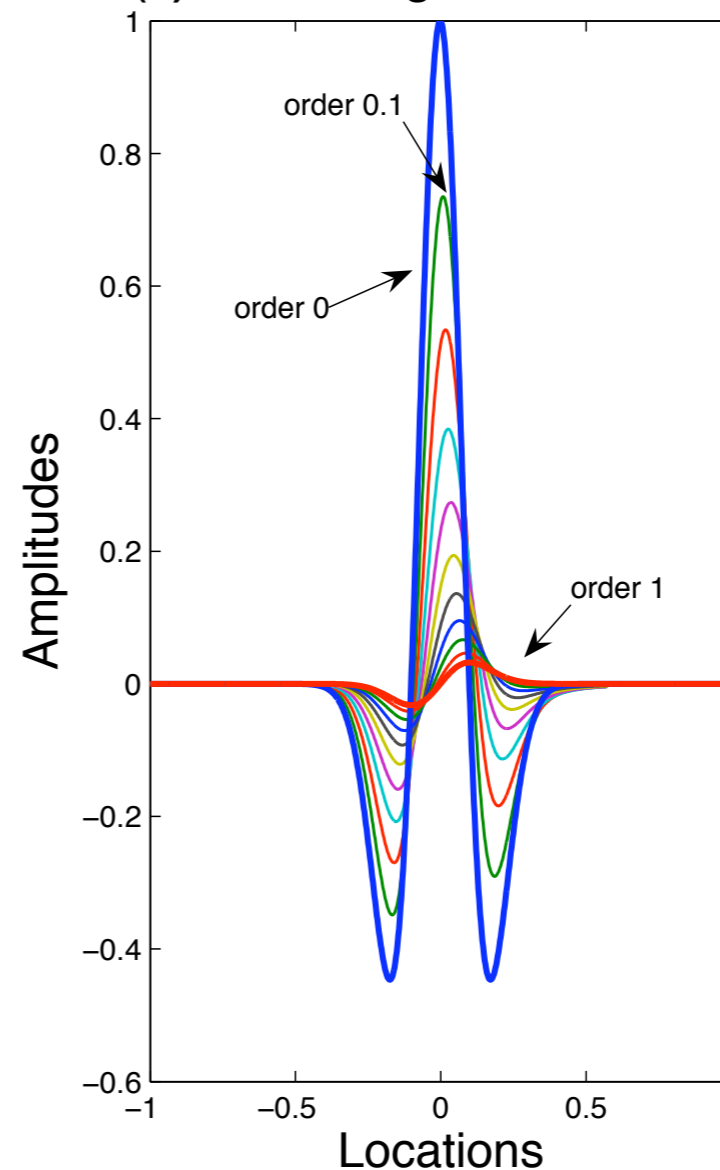
Reflectivity Models

$$r(z) = \sum_{i \in \Lambda_C} K_i \chi_+^{\alpha_i - 1}(z - z_i) - \sum_{i \in \Lambda_A} K_i \chi_-^{\alpha_i - 1}(z - z_i),$$

(a) Transitions: α between 0 and 1

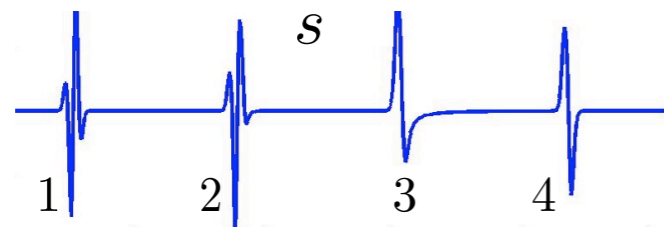


(b) Seismic signals with Ricker



$$s(t) = (r * \psi)(z)$$

Detection-Estimation method



Looking for components of dictionary that are best correlated to data

↓ 4.1



↓ 4.2

↓ 4.2

↓ 4.2

↓ 4.2

ESTIMATION

ESTIMATION

ESTIMATION

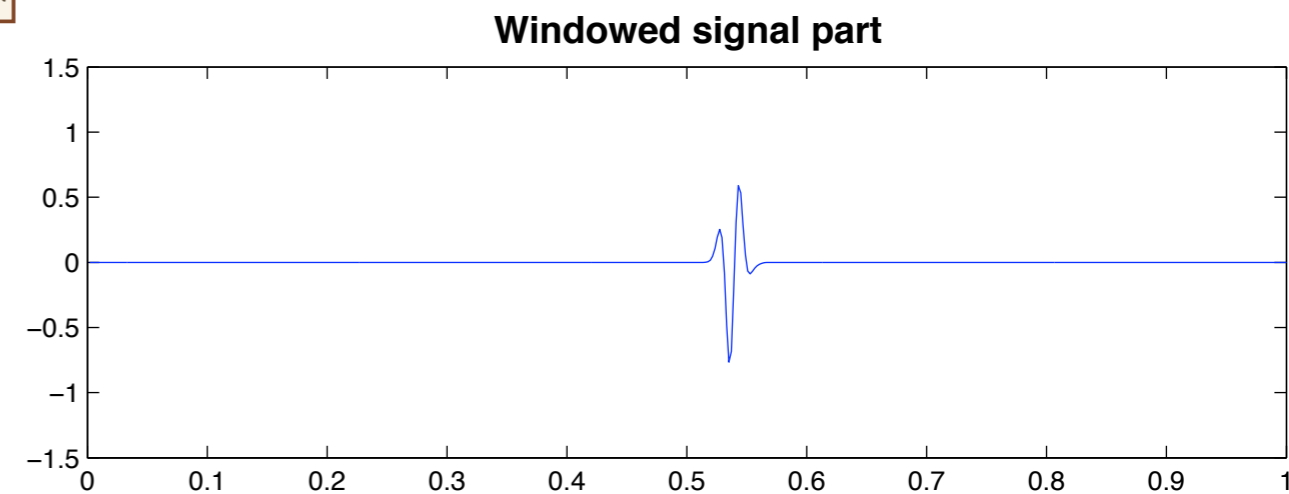
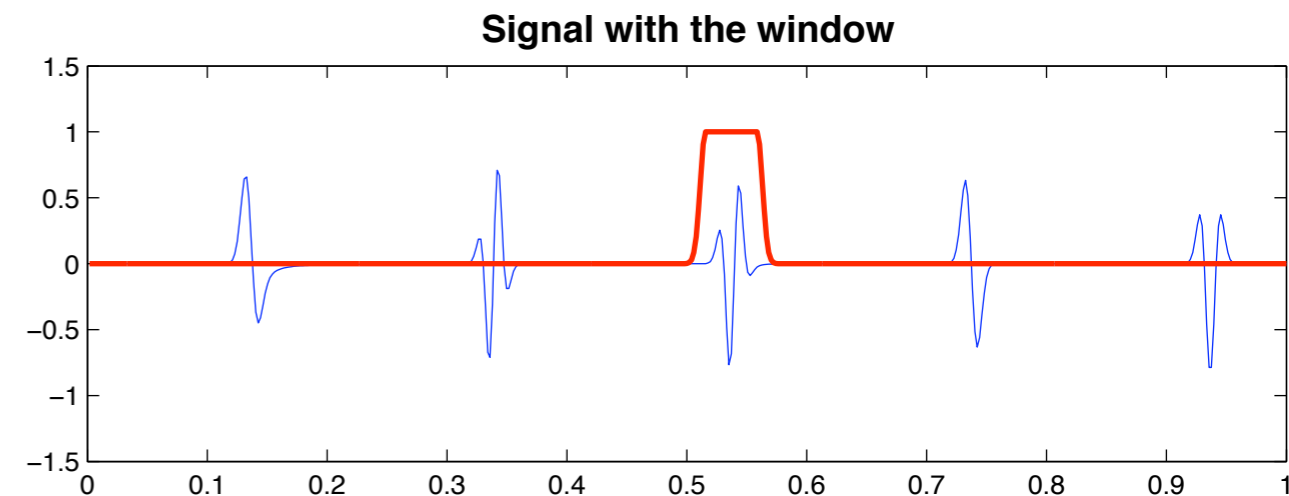
ESTIMATION

↓
 α_1

↓
 α_2

↓
 α_3

↓
 α_4



- Detect the events (D_D)
- Isolate the events
- Characterize windowed events (D_E)

Brief history

- Introduced a two-stage detection-estimation approach [C.M.Dupuis & F. Herrmann'05]
 - **Detection** \Leftrightarrow spiky decon. for non-spiky reflectivity
 - detect and ***isolate*** the main reflection events
 - **Estimation** \Leftrightarrow characterization of reflectors
 - scale exponents
 - elastic properties end-members binary members
 - percolation threshold and exponent
- Worked on new *estimation* methods to characterize the fine-structure of reflectors

Sparse Spike Deconvolution

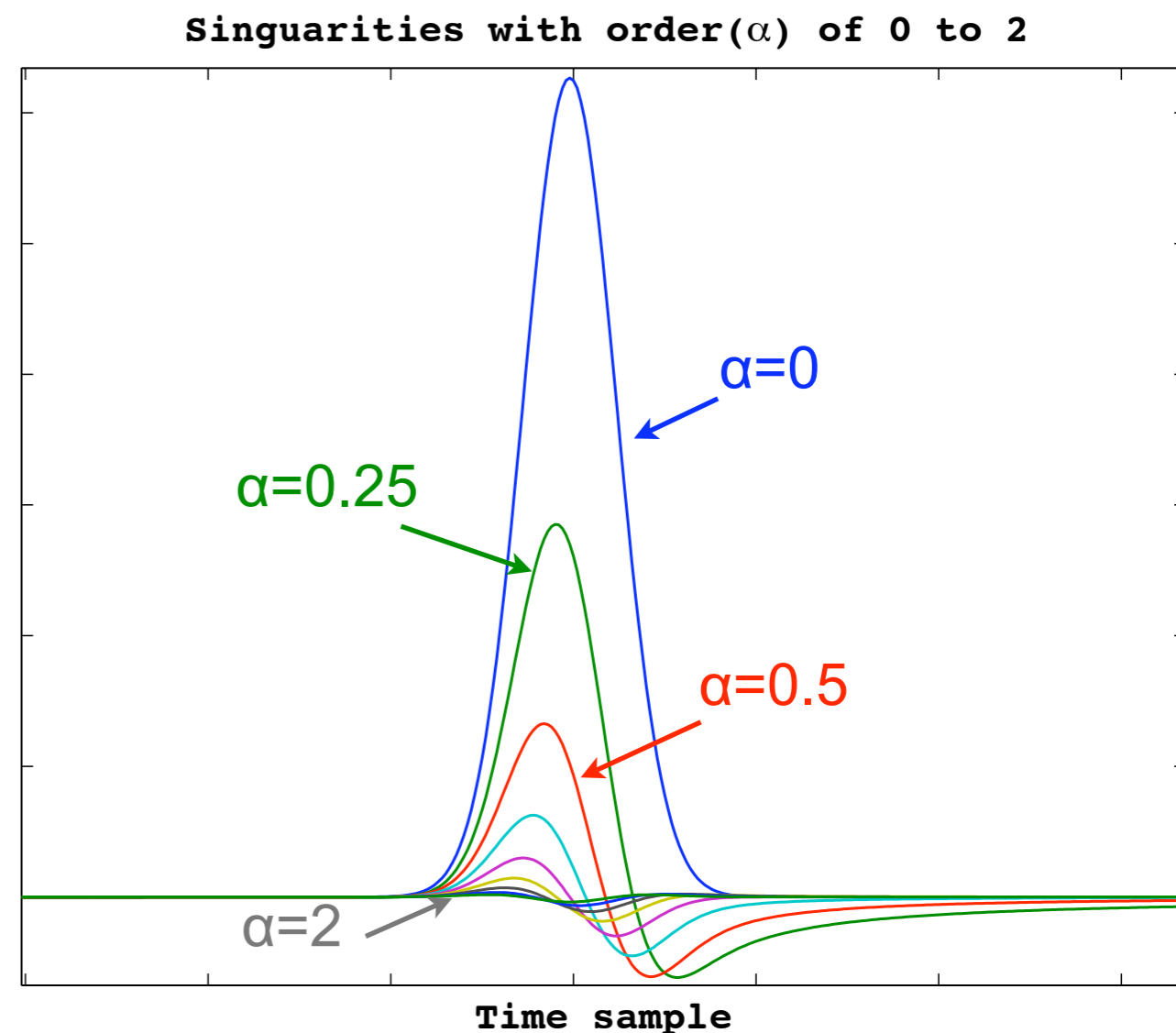
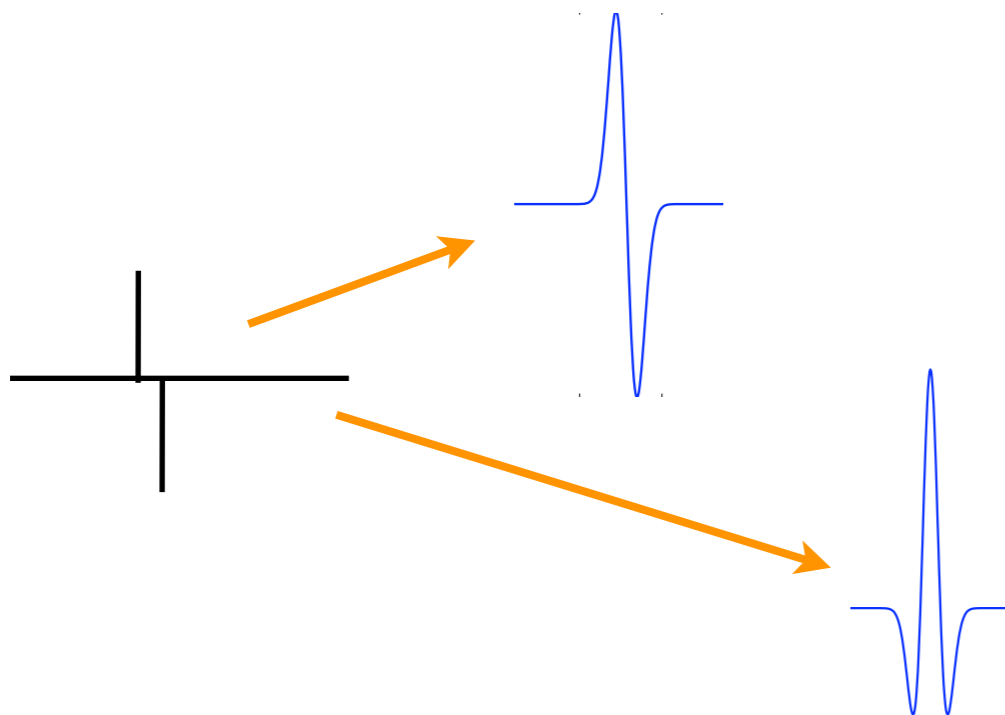
[Dossal and Mallat '05]

for Detection

[ChaRM]

Utilizing Spike Decon.

- Used as a part of our Detection-Estimation approach
- Need of **accurate (not exact)** recovery
 - Detecting major events (main cluster)
- fractional order of differentiation
 - two wavelet next to each other
 - one derivative of wavelet



Deconvolution Method

- Widely used in geophysical inversion
- Singularity order of one ($\alpha=0$)
- Efficiency analysis for seismic data [Dossal-Mallat]

$$Y = \psi \star R + W.$$

$$R = \sum_{i \in S} a_i \delta_i$$

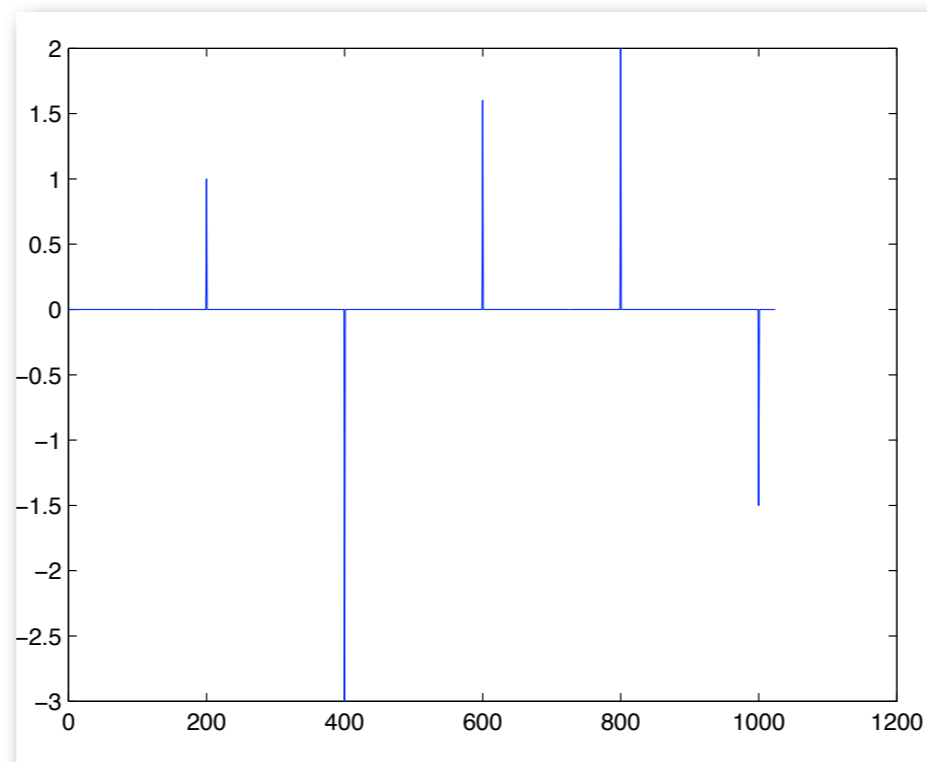
$$R = \arg \min_f \frac{1}{2} \|Y - \psi \star f\|_2^2 + \gamma \|f\|_1.$$

Efficiency Analysis

- Deconvolution without noise
 - Similar analysis for noisy data
- Minimum scale

$$\Delta = \min_{(i,j) \in S^2} \|i - j\|.$$

$$R = \arg \min \|f\|_1 \quad \text{with} \quad \psi \star f = Y.$$



Efficiency Analysis (cont'd)

- *Dictionary* = Matrix whose Columns are:

$$\mathbf{D} = [g_i = \psi \star \delta_i \quad \text{for } 1 \leq i \leq N].$$

- *Weak Exact Recovery Coefficient (WERC)*

$$WERC(S) = \frac{\beta}{1 - \alpha}, \text{ where } S \subset \{1, \dots, N\}.$$

$$\alpha(S) = \sup_{i \in S} \sum_{k \in S, k \neq i} |\langle g_k, g_i \rangle| \leq 2 \sum_k \phi(k\Delta_0)$$

$$\beta(S) = \sup_{j \notin S} \sum_{k \in S} |\langle g_k, g_j \rangle| \leq \max_{j \leq \Delta_0} (\phi(j) + \phi(\Delta_0 - j)) + \alpha(S)$$

StOMP: a fast L1 solver

[Donoho et. al. 06]

L0 - L1 Equivalency

- Strong equivalence of Pf_0 and Pf_1
 - for given \mathbf{A} , $\forall x_0$ $P1(y, \mathbf{A}) \rightarrow$ Unique sparsest Solution

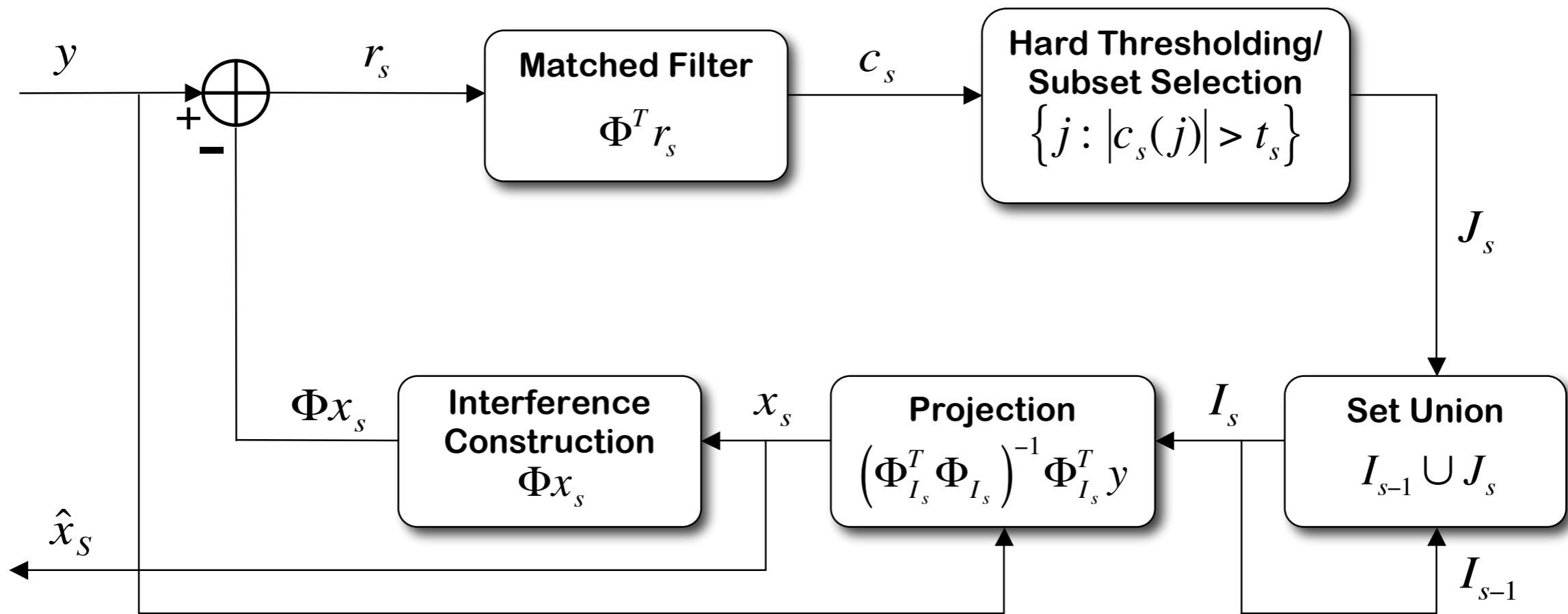
- Weak equivalence of Pf_0 and Pf_1
 - equivalence holds for the typical sparse x_0

$$\|x\|_0 < \frac{1}{2} \sqrt{N}$$

StOMP Solver

- For (under)determined systems of equations
- Assumes additive Gaussian noise for non-zero entries
- Numerous terms enter at each thresholding stage and have fixed number of staged.
- Approximation to the sparsest solution over a region of the sparsity/indeterminacy plane
- ◆ Our Case
 - Determined System : $A_{(N \times N)}$
 - Mixing by random spike train
 - Random locations
 - Random amplitudes

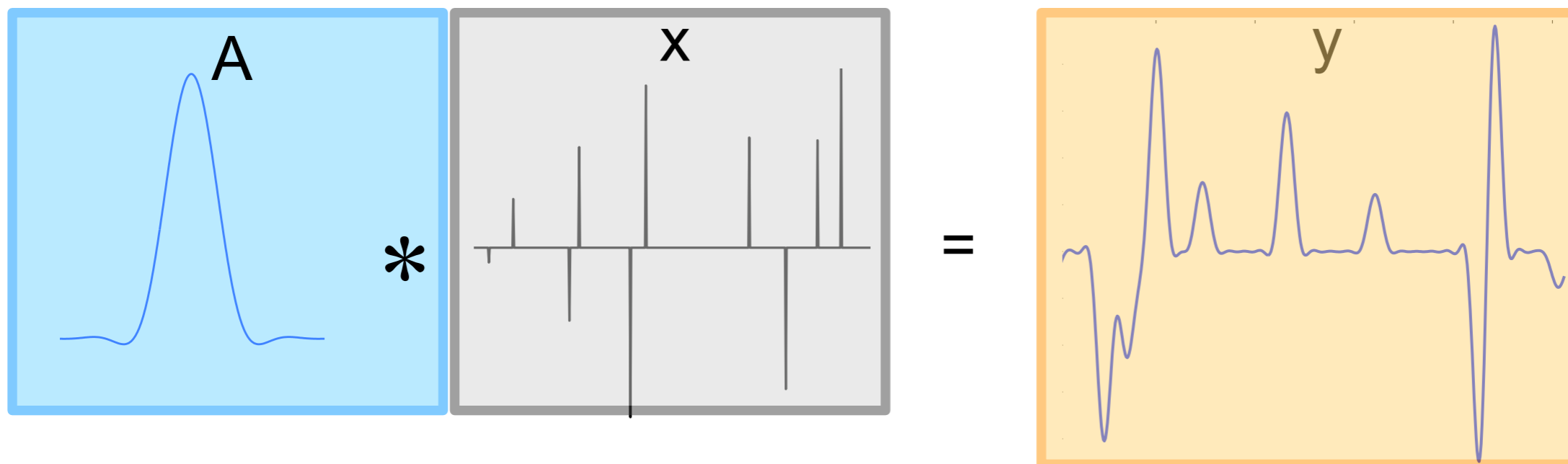
Algorithm Flowchart



$$\mathbf{J}_s = \{j : |c_s(j)| > t_s \sigma_s\}$$

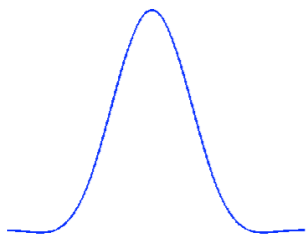
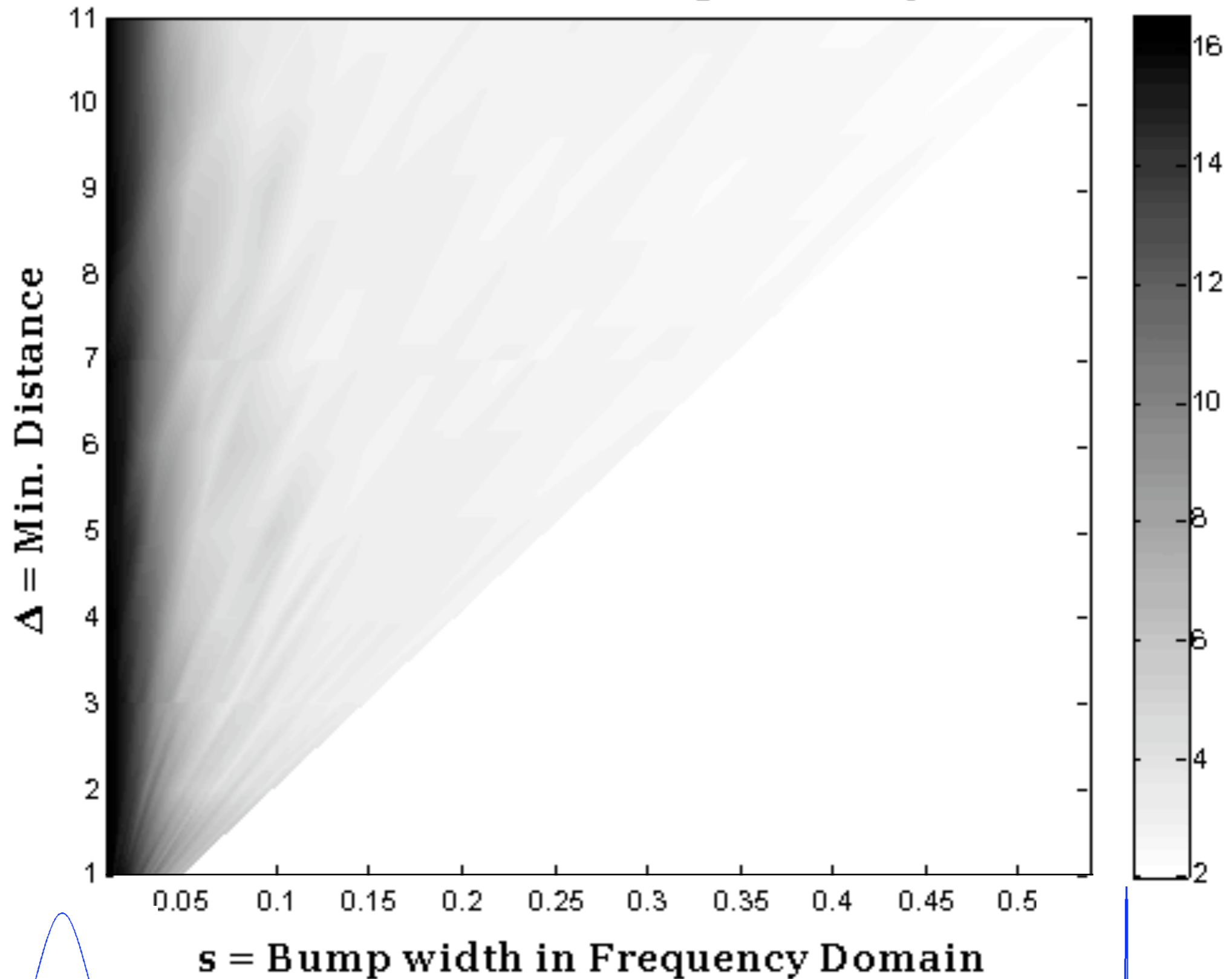
Recovery Phase Diagram

- Test Settings:
 - A: Convolution with cosine bump
 - Signal length : 512
 - No. of spikes (K) : 20
 - Dynamic range setting
 - Δ values : 13
 - scale values : 30
- L0 norm to show the error
 - L2 could also be used



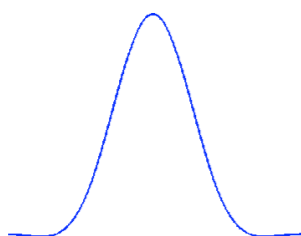
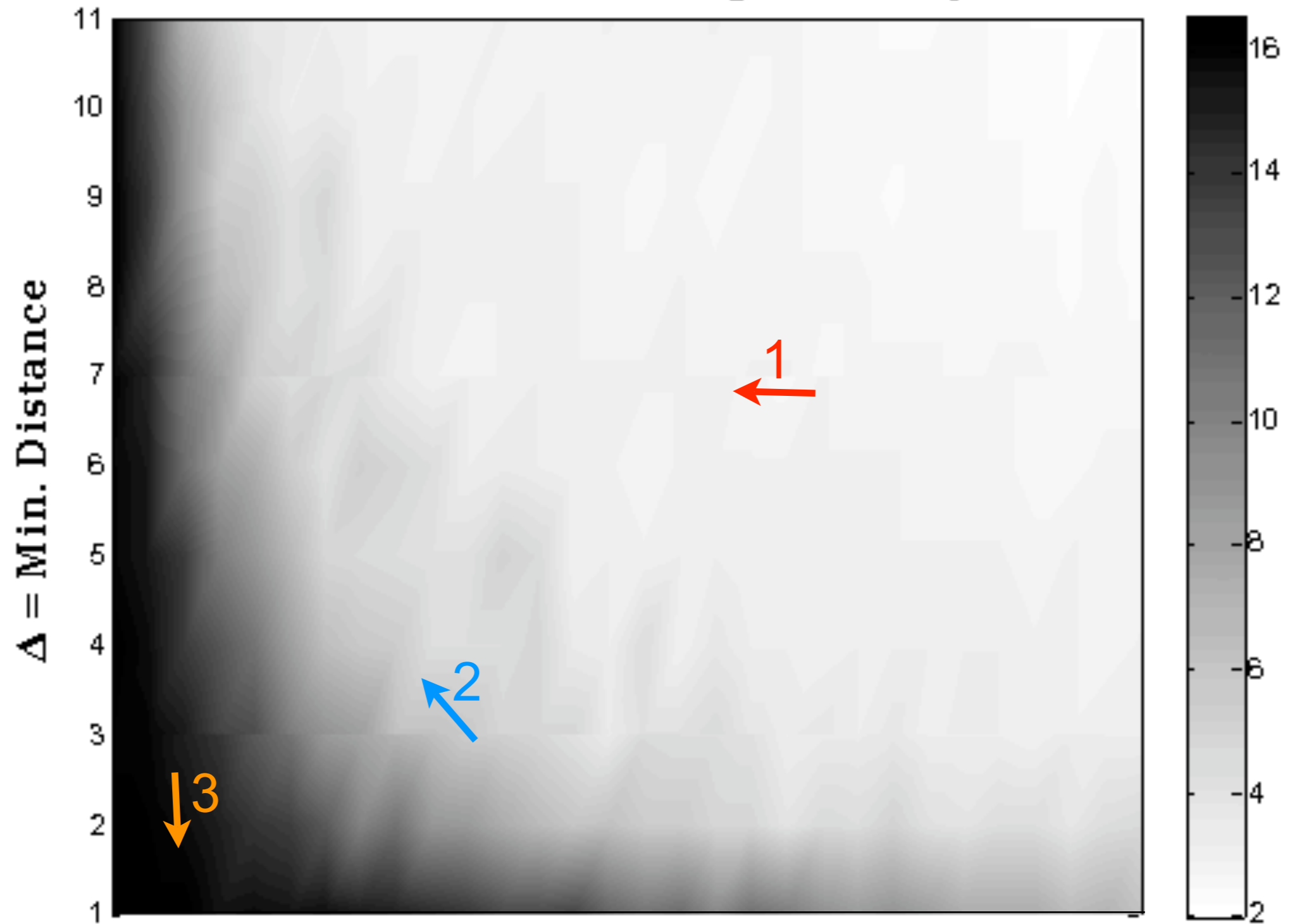
Sample Phase Diagram

Wavelet :bconv N = 512 K = 29



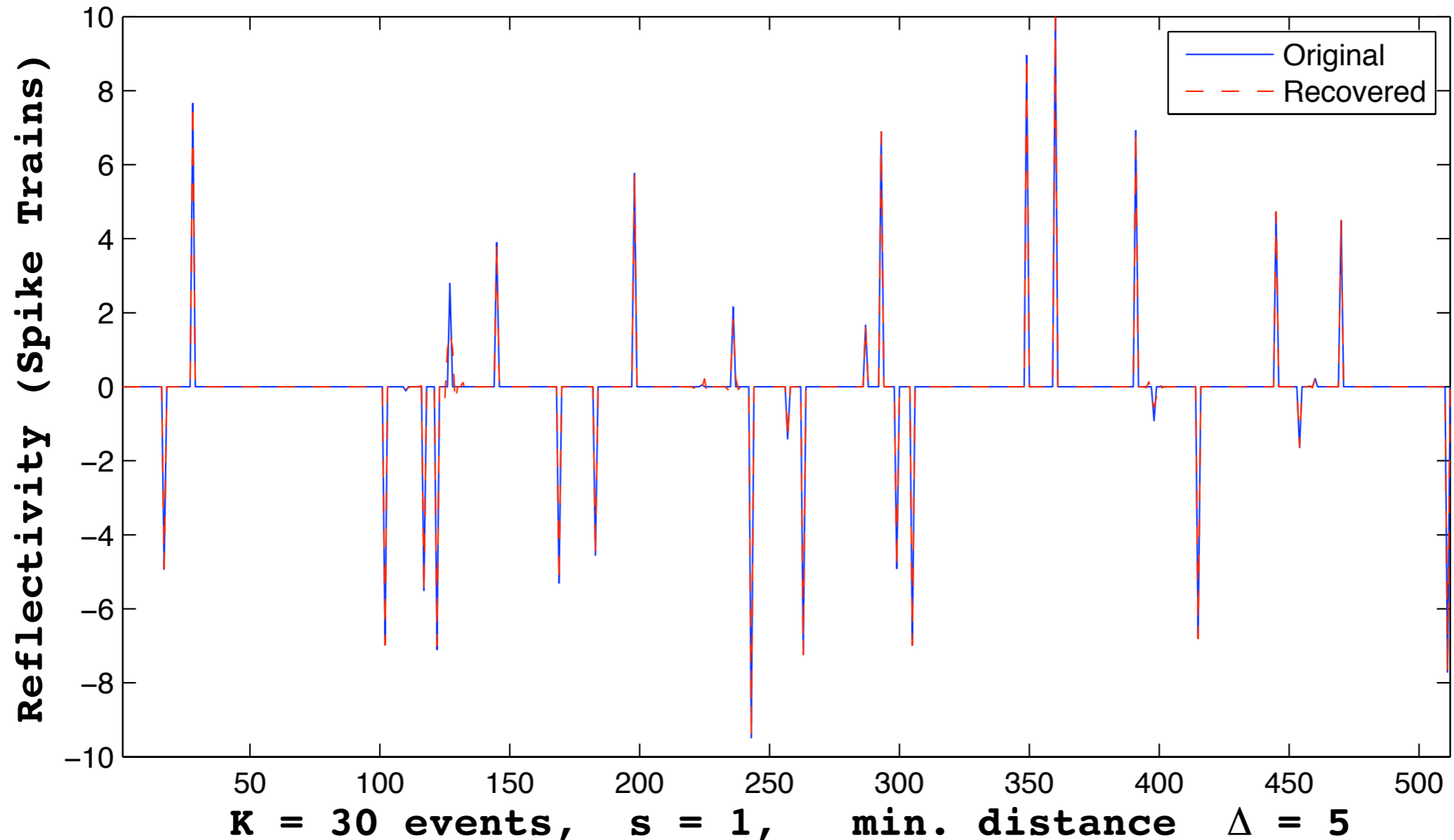
Sample Phase Diagram

Wavelet :bconv N = 512 K = 29



1: Accurate Recovery

Cosine Bump Convolution with Spike Train (StOMP), N=512

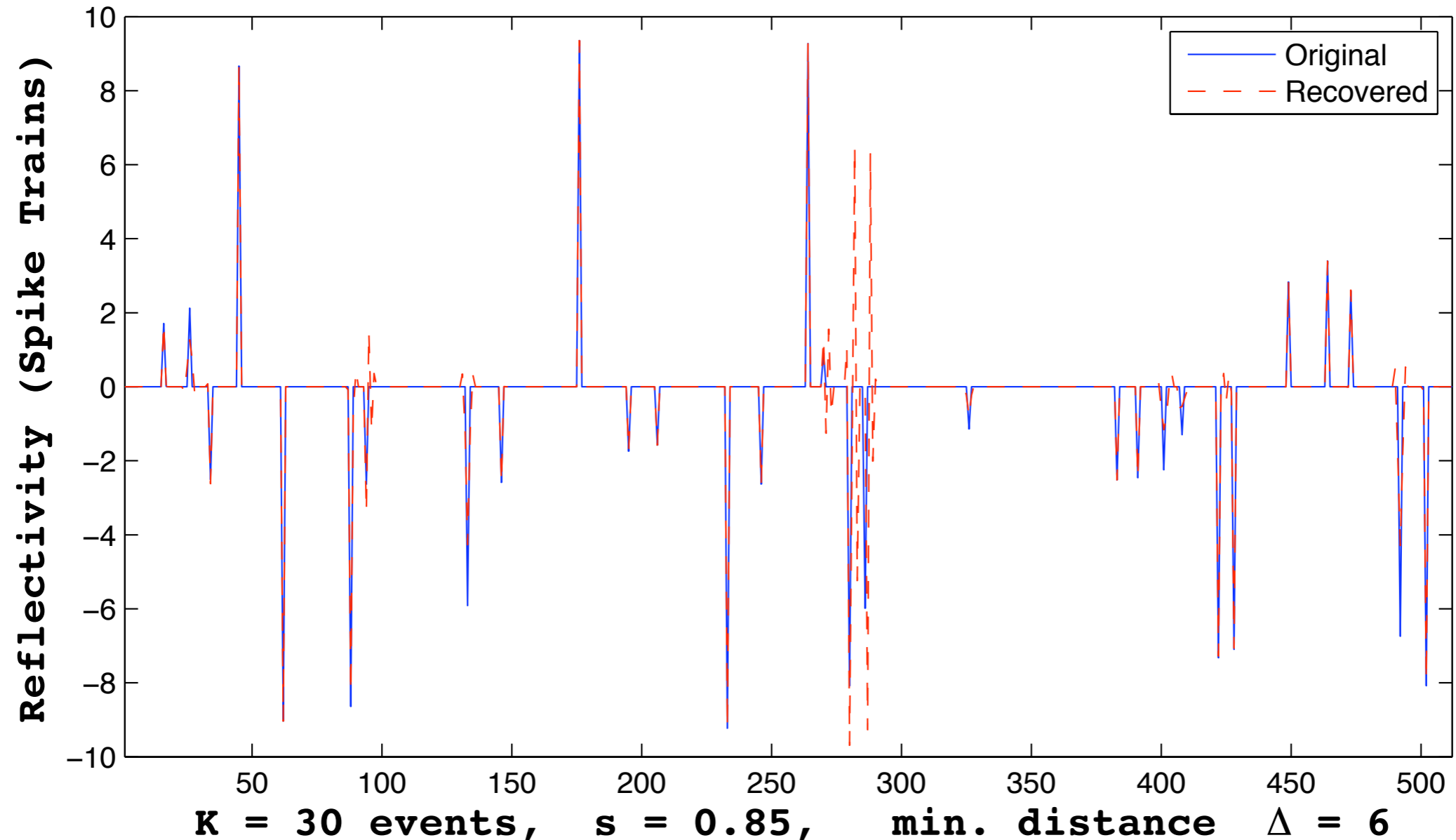


Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 5,74
Bump/Wavelet Scale : 1
Regular , Uniform : 0,0

StOMP Solving Time : 1.6
StOMP Stage : 12
L2 Nrom(x) : 31.13
% L0 Error : 1.867
% L2 Error : 0.07104

2 : Partial Recovery

Cosine Bump Convolution with Spike Train (StOMP), N=512

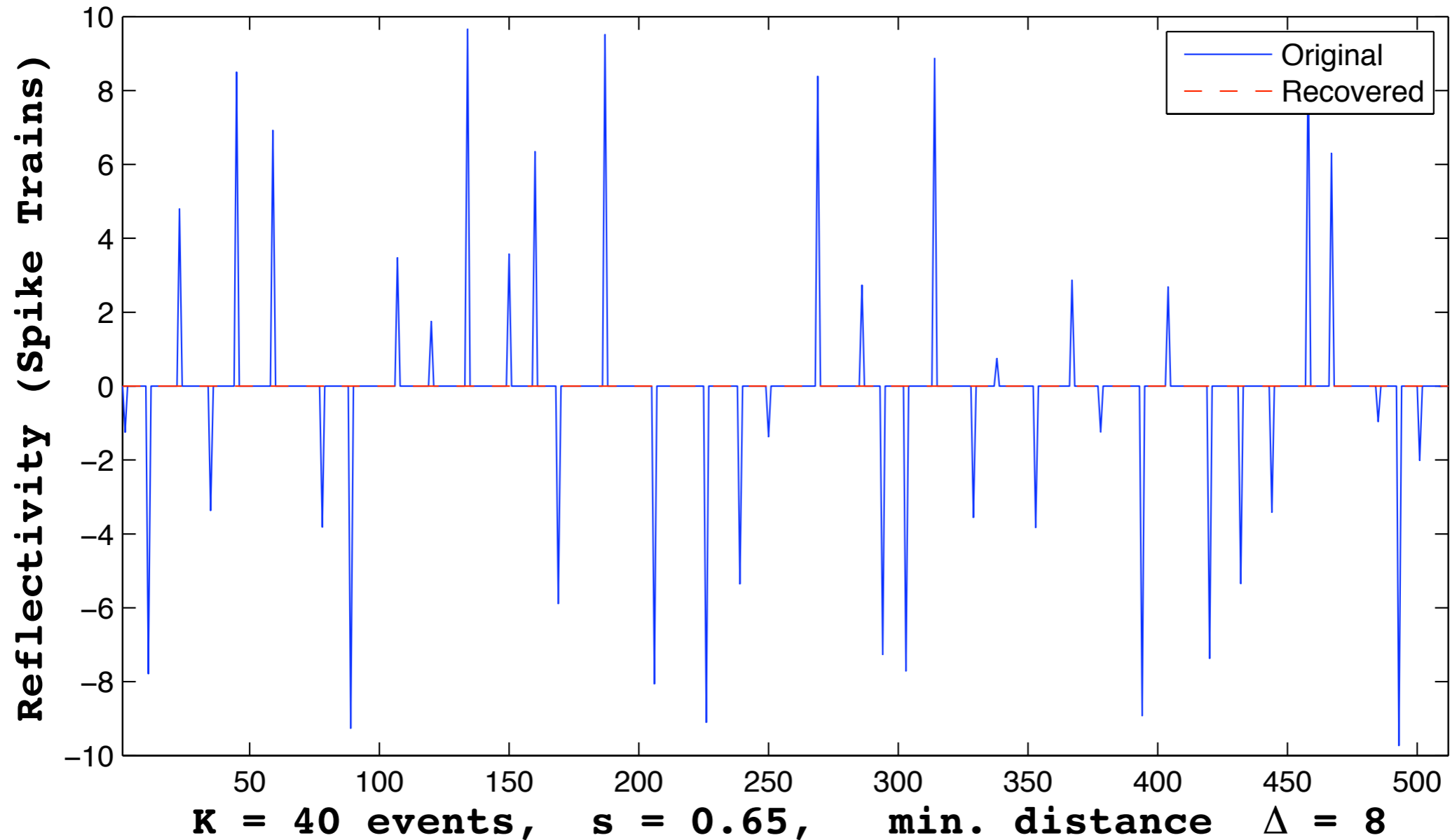


Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 6,57
Bump/Wavelet Scale : 0.85
Regular , Uniform : 0,0

StOMP Solving Time : 1.75
StOMP Stage : 10
L2 Norm(x) : 30.47
% L0 Error : 2.3
% L2 Error : 0.5451

3: Unrecoverable

Cosine Bump Convolution with Spike Train (StOMP), N=512



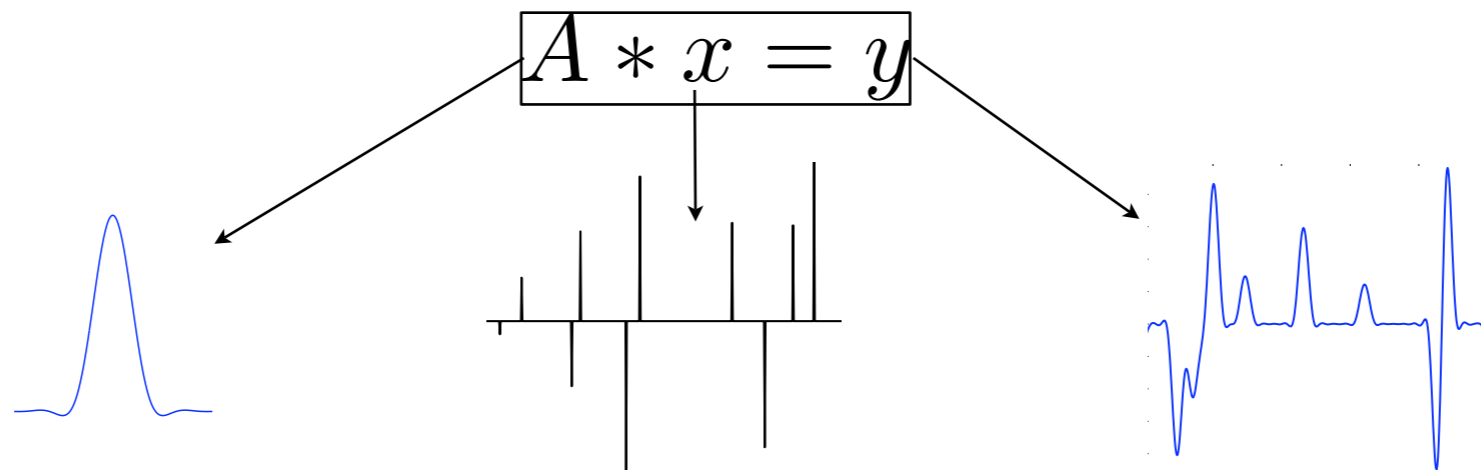
Length of Signal : 512
Number of Spikes : 40
Min & Max Spacing : 8,20
Bump/Wavelet Scale : 0.65
Regular , Uniform : 0,0

StOMP Solving Time : 0.01
StOMP Stage : 2
L2 Norm(x) : 38.67
% L0 Error : 1
% L2 Error : 1

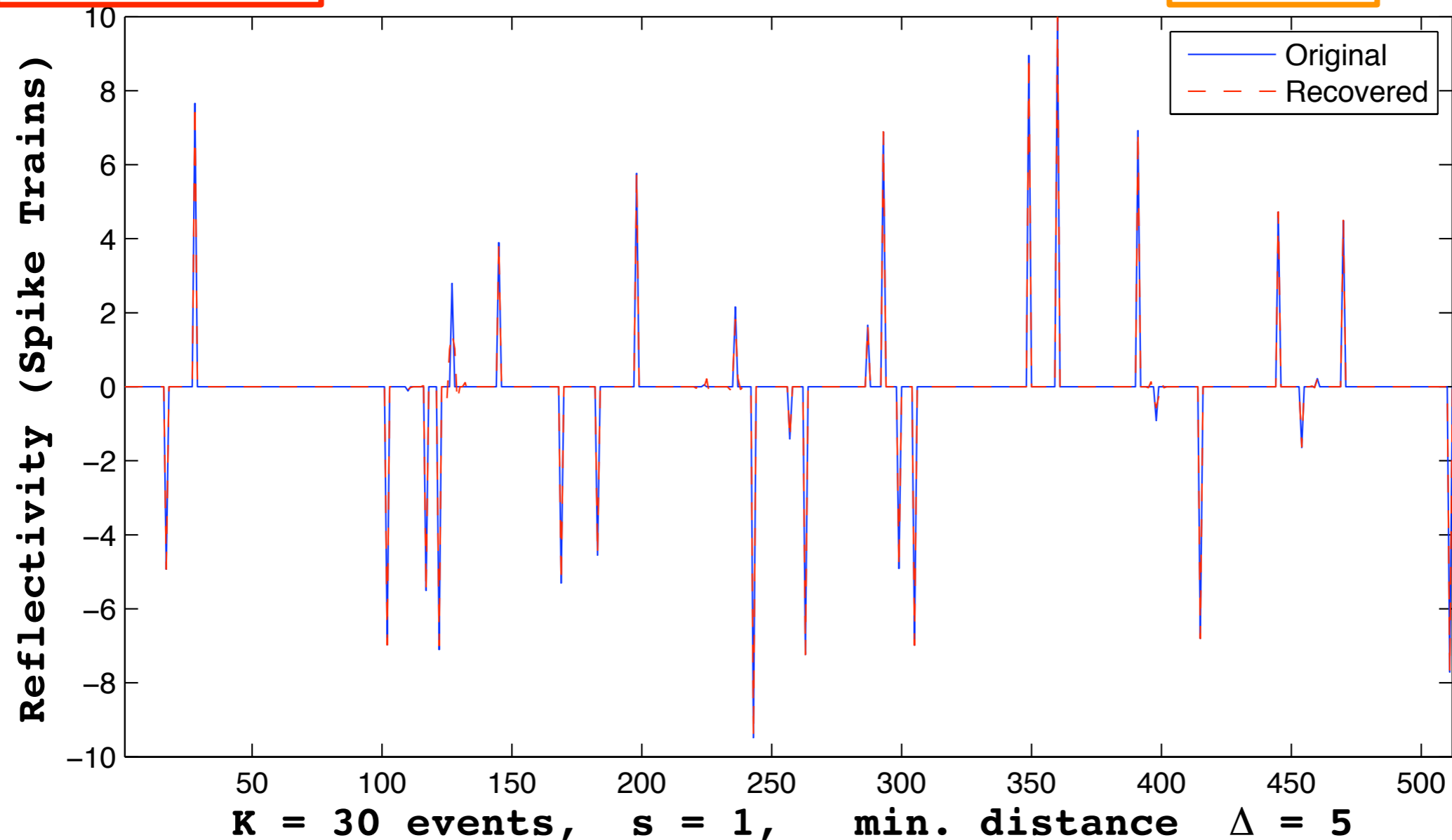
Spike Decon. Analysis Scheme

Analysis w.r.t.

- wavelet type
- wavelet width/scale
- Minimum distance (Δ)
- Solver
 - Stagewise Orthogonal Matching Pursuit (StOMP)
 - Basis Pursuit (BP)
- Different synthesis and analysis wavelets



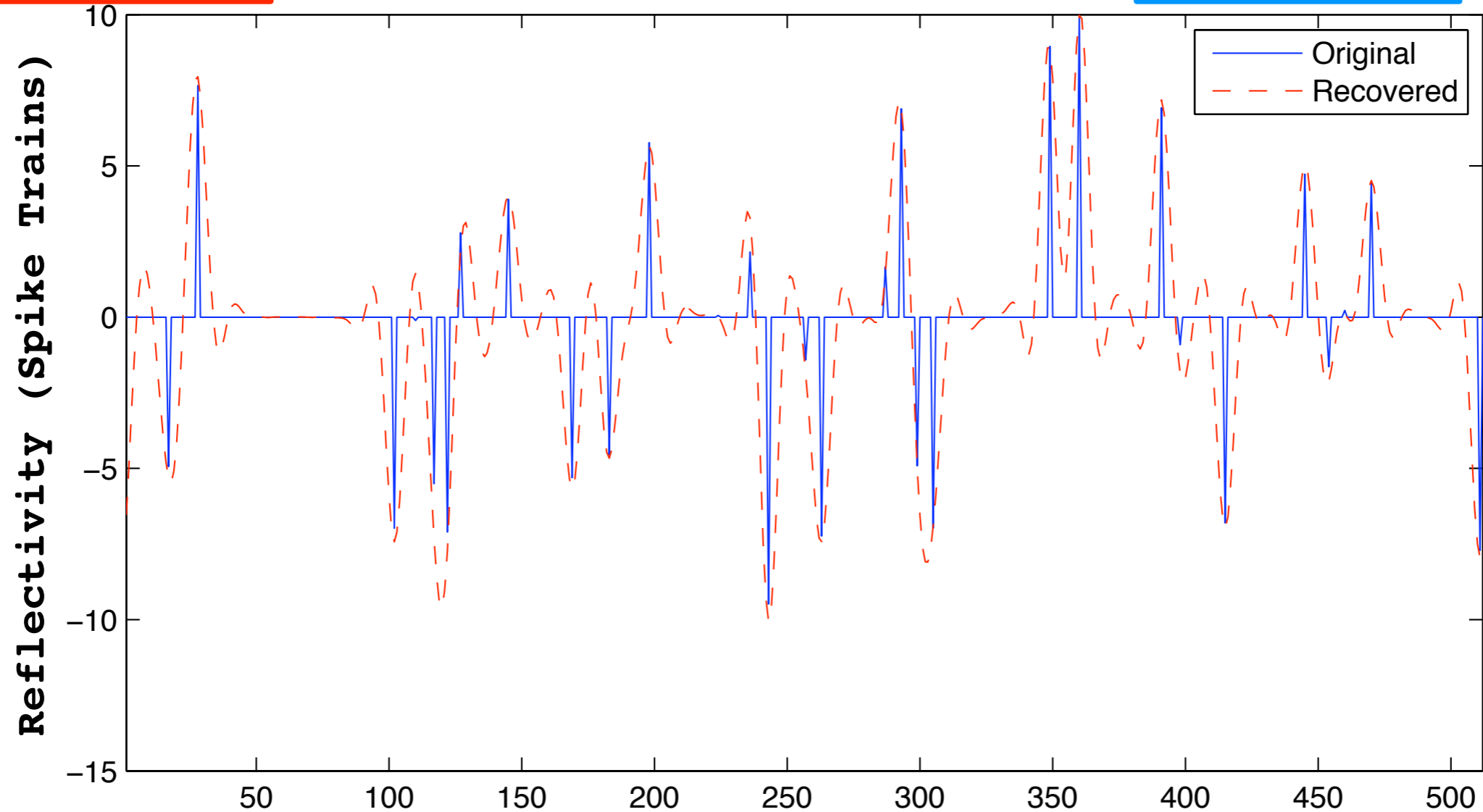
Cosine Bump Convolution with Spike Train (StOMP), N=512



Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 5,74
Bump/Wavelet Scale : 1
Regular , Uniform : 0,0

StOMP Solving Time : 1.6
StOMP Stage : 12
L2 Norm(x) : 31.13
% L0 Error : 1.867
% L2 Error : 0.07104

Cosine Bump Convolution with Spike Train (Scaled BP), N=512

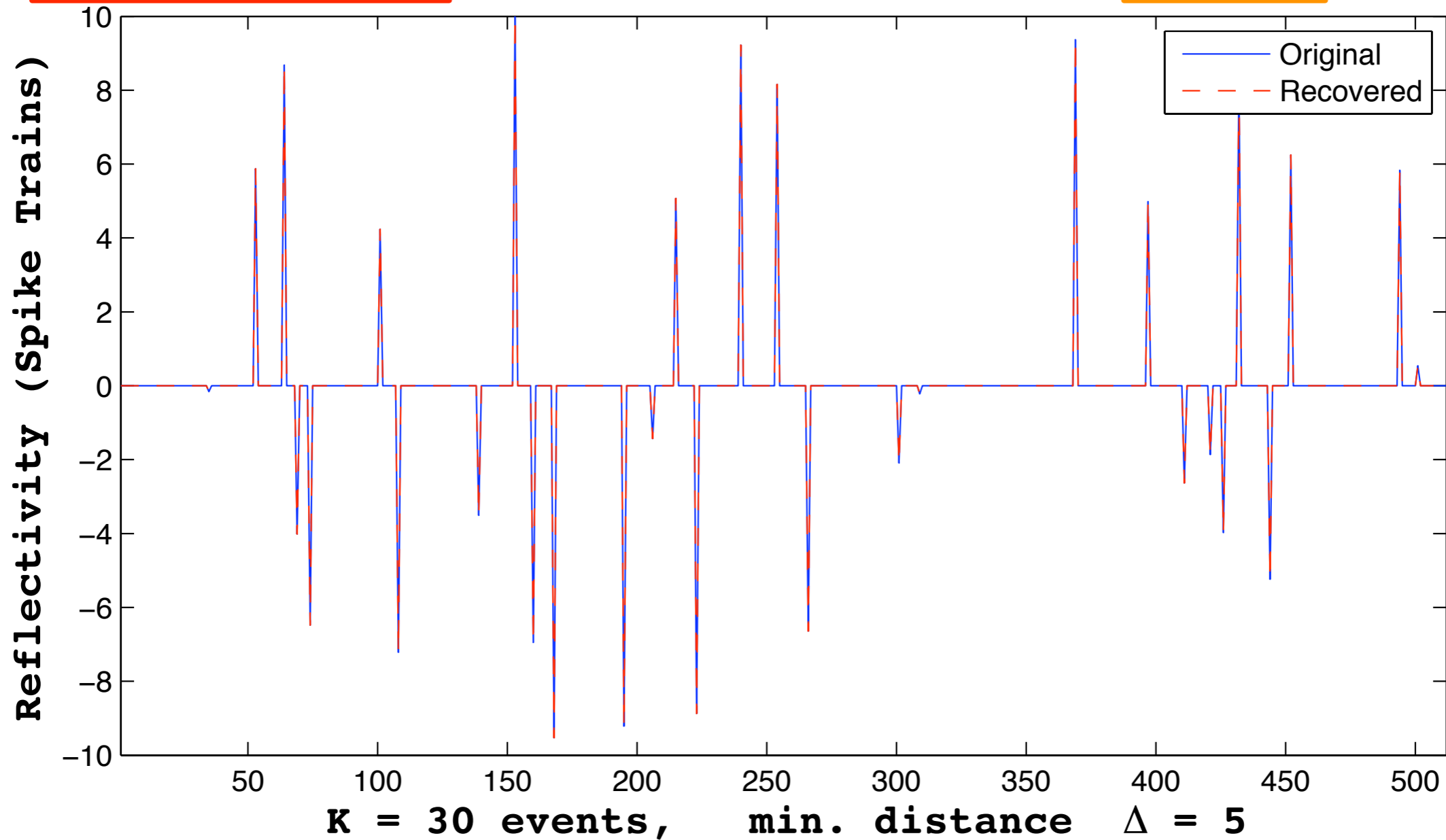


K = 30 events, s = 1, min. distance $\Delta = 5$

Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 5,74
Bump/Wavelet Scale : 1
Regular , Uniform : 0,0

BP Solving Time : 0.15
L2 Norm(x) : 31.13
% L0 Error : 16.07
% L2 Error : 0.9992

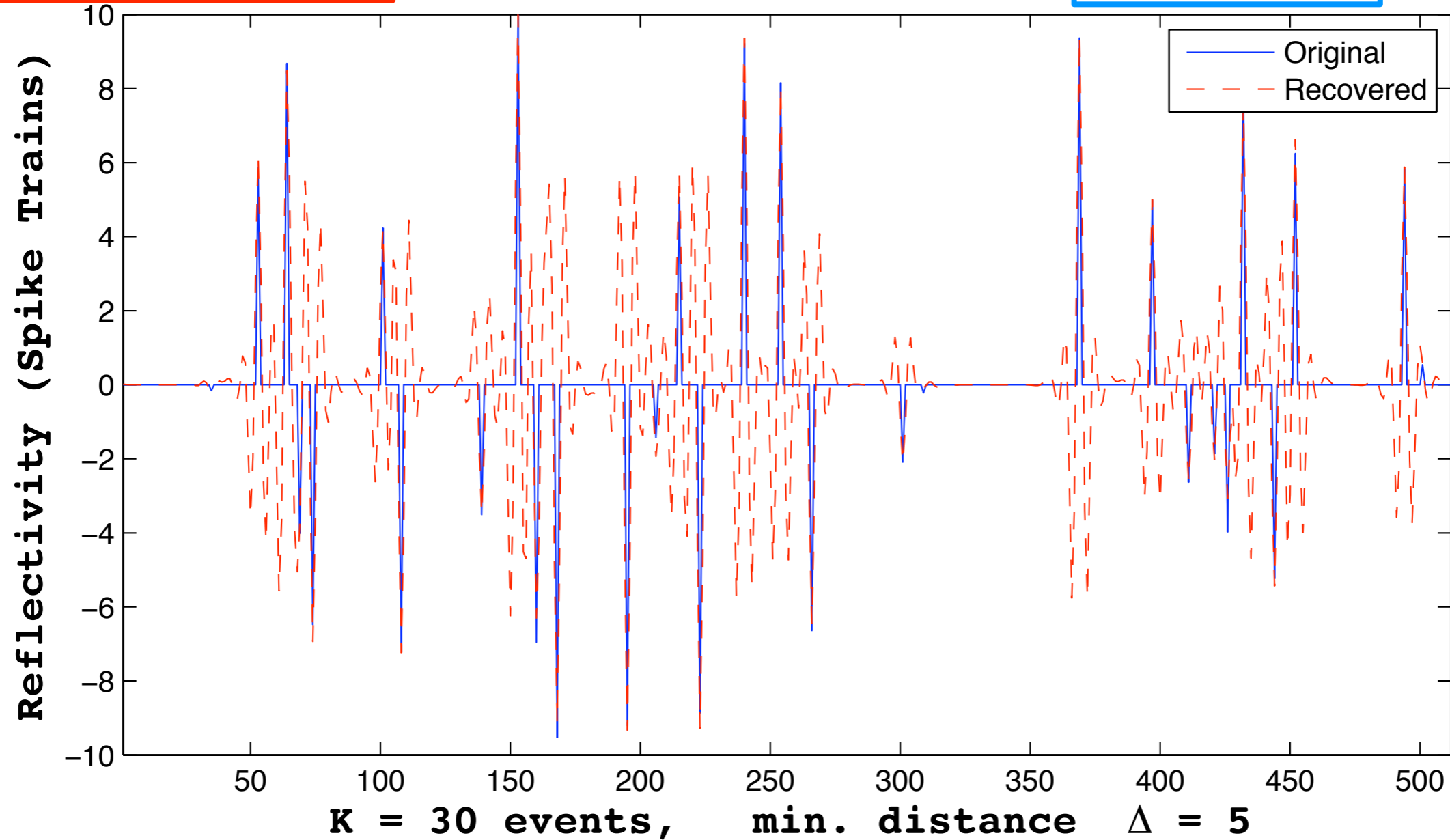
Ricker Wavelet Conv. with Spike Train (StOMP), N=512



Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 5,60
Bump/Wavelet Scale : 1
Regular , Uniform : 0,0

StOMP Solving Time : 0.55
StOMP Stage : 5
L2 Norm(x) : 34.48
% L0 Error : 0.8667
% L2 Error : 4.568e-16

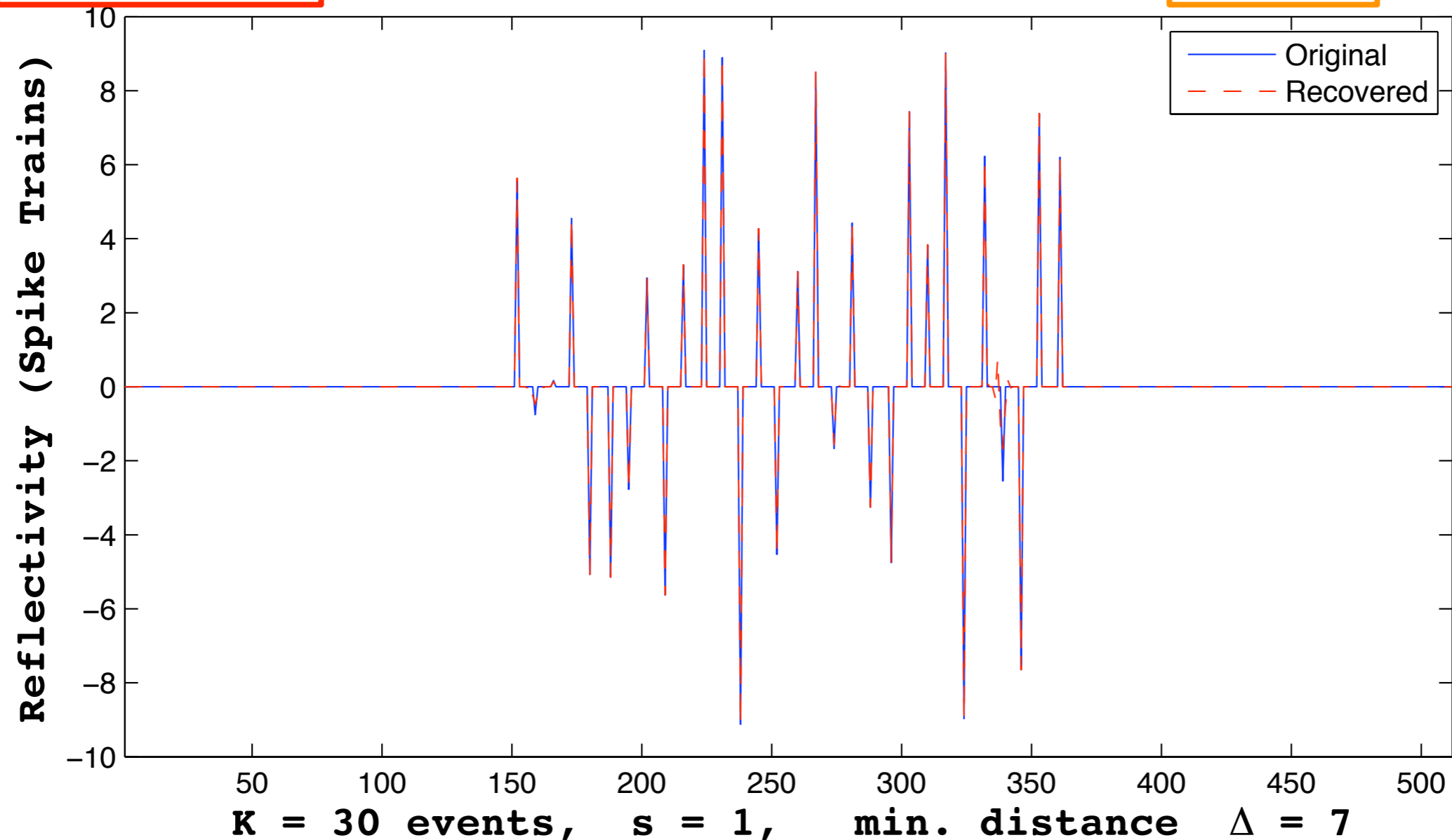
Ricker wavelet Conv. with Spike Train (Scaled BP), N=512



Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 5,60
Bump/Wavelet Scale : 1
Regular , Uniform : 0,0

BP Solving Time : 0.34
L2 Norm(x) : 34.48
% L0 Error : 16.07
% L2 Error : 0.9993

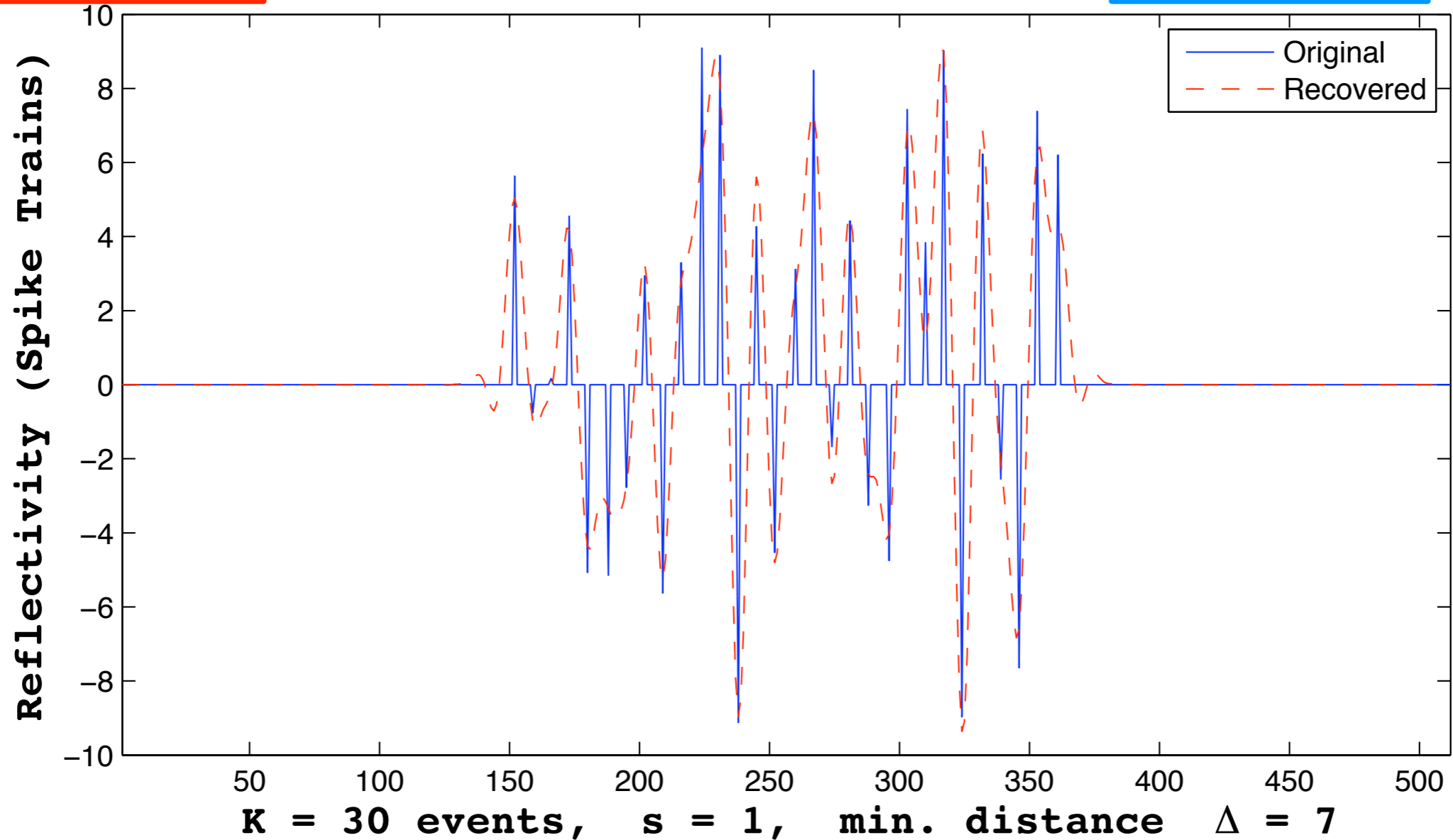
Cosine Bump Convolution with Spike Train (StOMP), N=512



Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 7, 8
Bump/Wavelet Scale : 1
Regular , Uniform : 1, 0

StOMP Solving Time : 1.45
StOMP Stage : 12
L2 Norm(x) : 31.83
% L0 Error : 1.467
% L2 Error : 0.05429

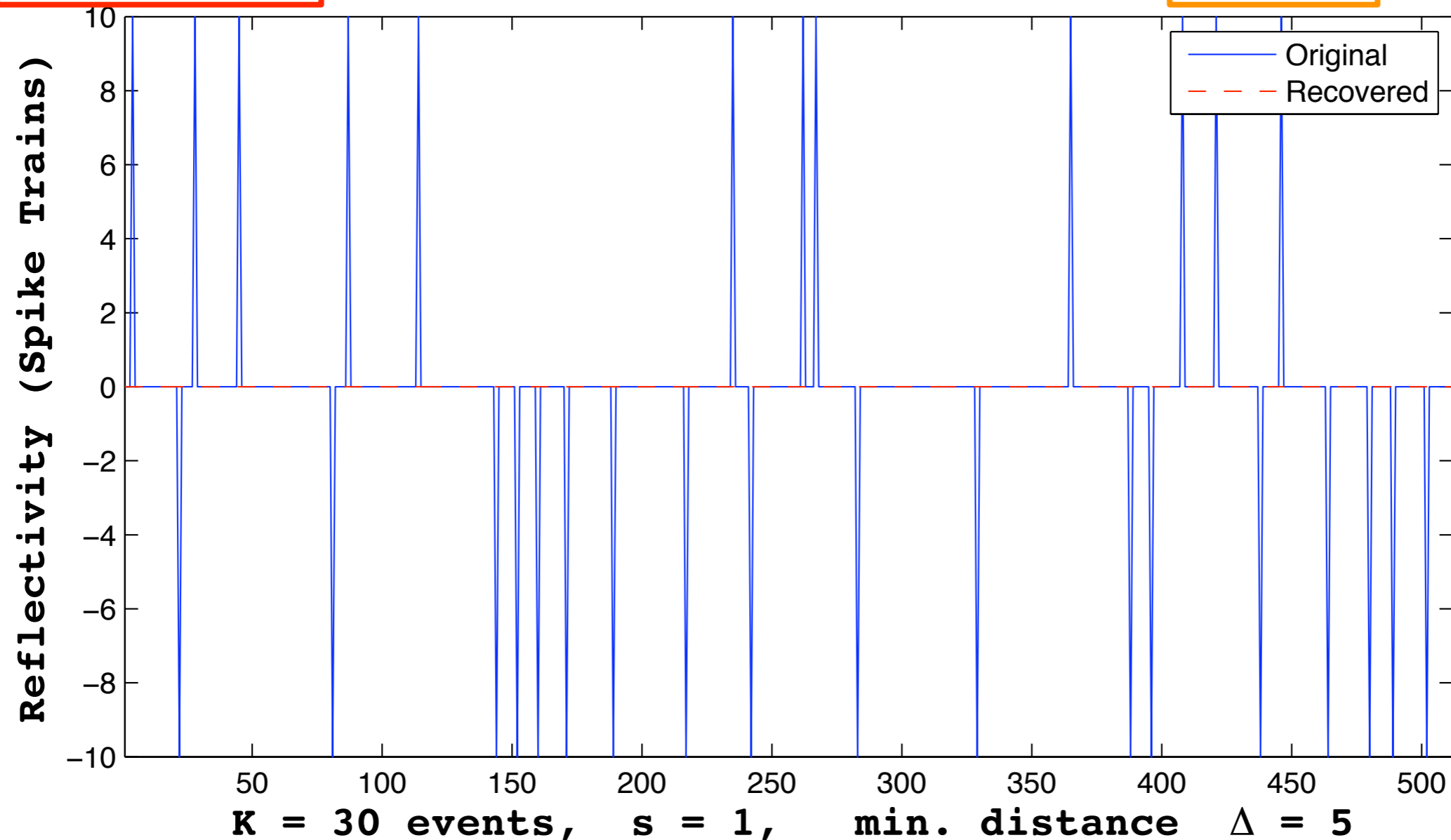
Cosine Bump Convolution with Spike Train (Scaled BP), N=512



Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 7, 8
Bump/Wavelet Scale : 1
Regular , Uniform : 1, 0

BP Solving Time : 0.1
L2 Norm(x) : 31.83
% L0 Error : 16.07
% L2 Error : 0.9992

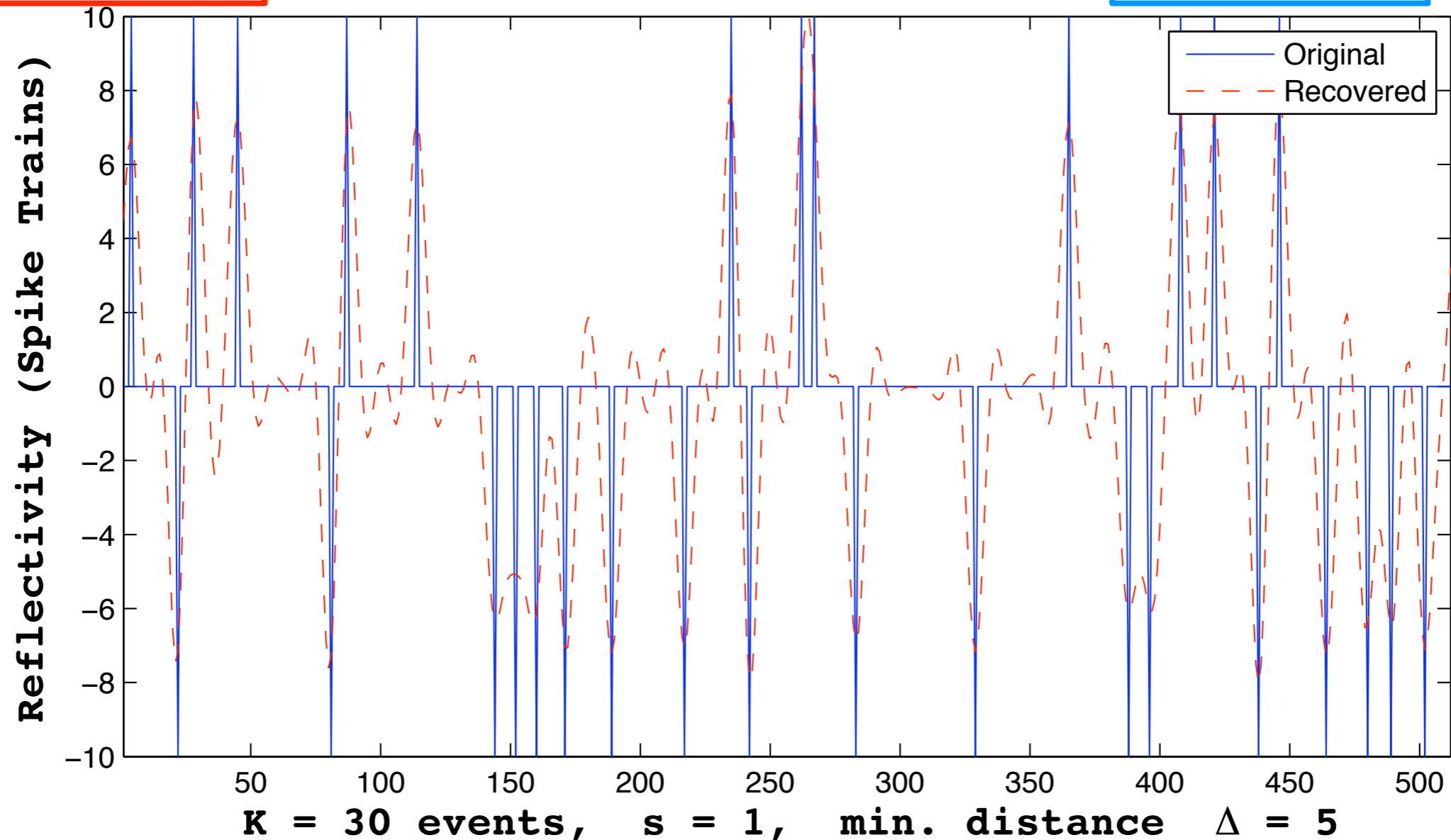
Cosine Bump Convolution with Spike Train (StOMP), N=512



Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 5, 46
Bump/Wavelet Scale : 1
Regular , Uniform : 0, 1

StOMP Solving Time : 0.01
StOMP Stage : 2
L2 Norm(x) : 54.77
% L0 Error : 1
% L2 Error : 1

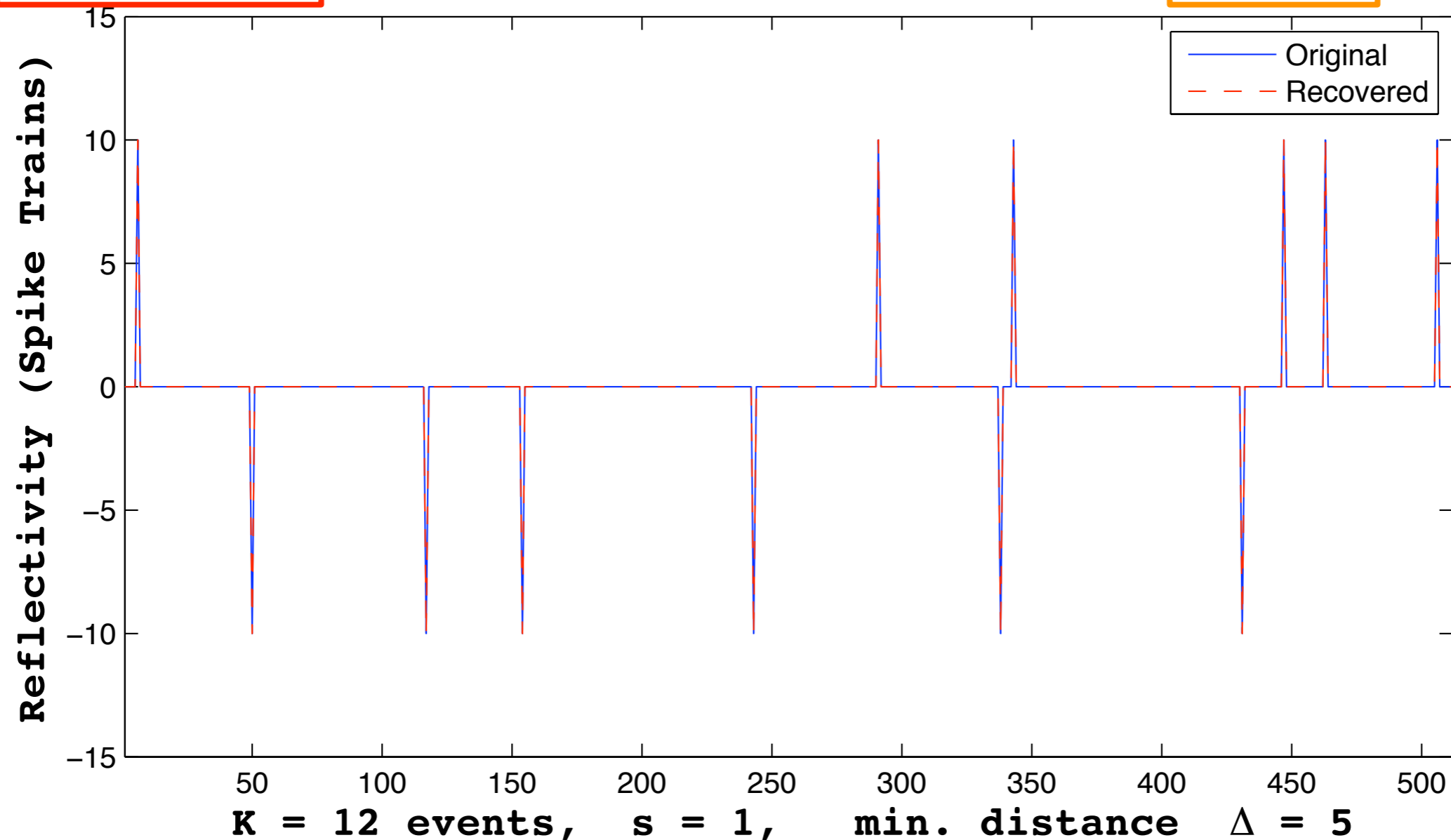
Cosine Bump Convolution with Spike Train (Scaled BP), N=512



Length of Signal : 512
Number of Spikes : 30
Min & Max Spacing : 5, 46
Bump/Wavelet Scale : 1
Regular , Uniform : 0, 1

BP Solving Time : 0.11
L2 Norm(x) : 54.77
% L0 Error : 16.07
% L2 Error : 0.9992

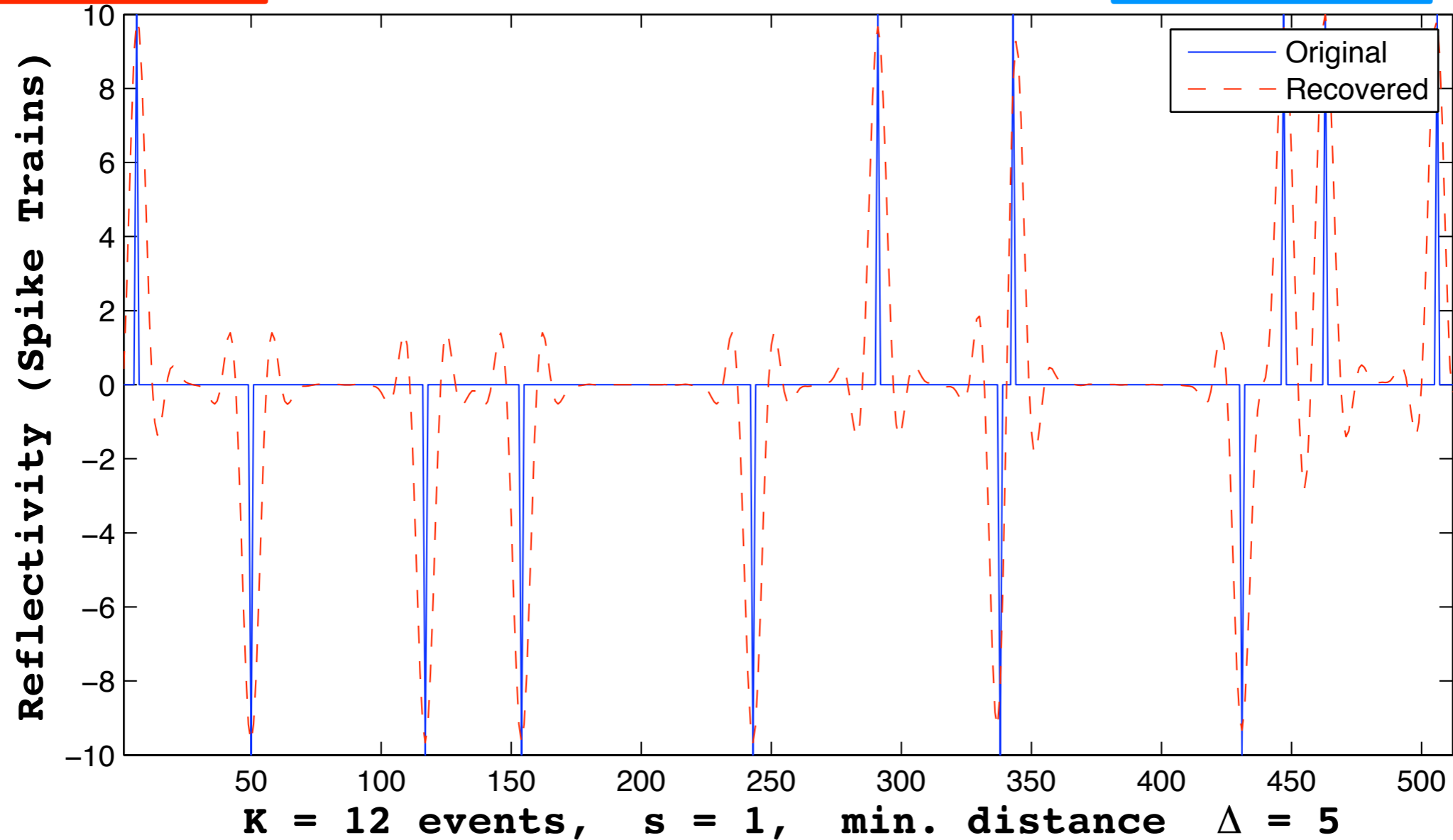
Cosine Bump Convolution with Spike Train (StOMP), N=512



Length of Signal : 512
Number of Spikes : 12
Min & Max Spacing : 5, 89
Bump/Wavelet Scale : 1
Regular , Uniform : 0, 1

StOMP Solving Time : 0.08
StOMP Stage : 3
L2 Norm(x) : 34.64
% L0 Error : 0.5
% L2 Error : 8.075e-14

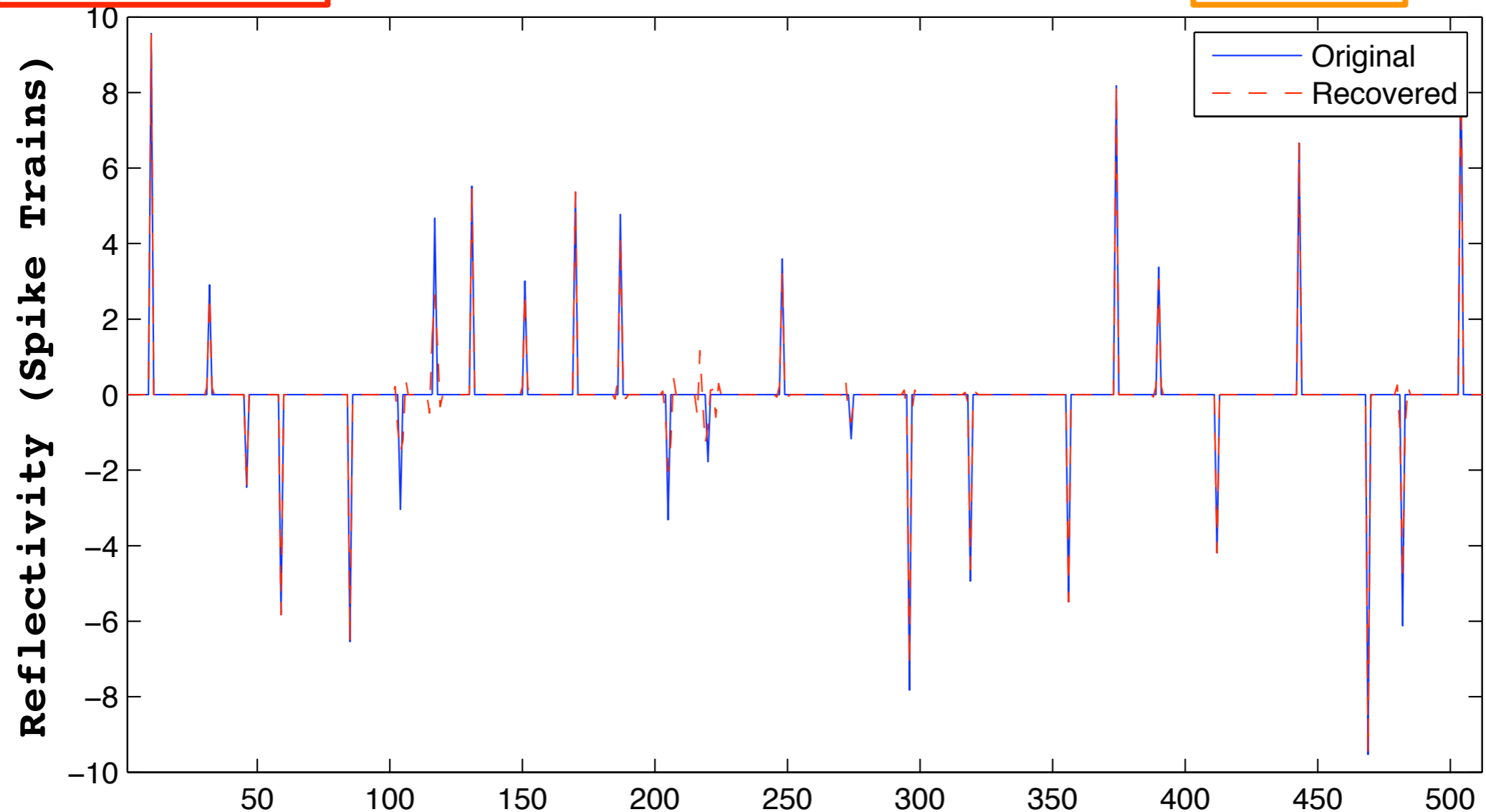
Cosine Bump Convolution with Spike Train (Scaled BP), N=512



Length of Signal : 512
Number of Spikes : 12
Min & Max Spacing : 5, 89
Bump/Wavelet Scale : 1
Regular , Uniform : 0, 1

BP Solving Time : 0.11
L2 Norm(x) : 34.64
% L0 Error : 41.67
% L2 Error : 0.9992

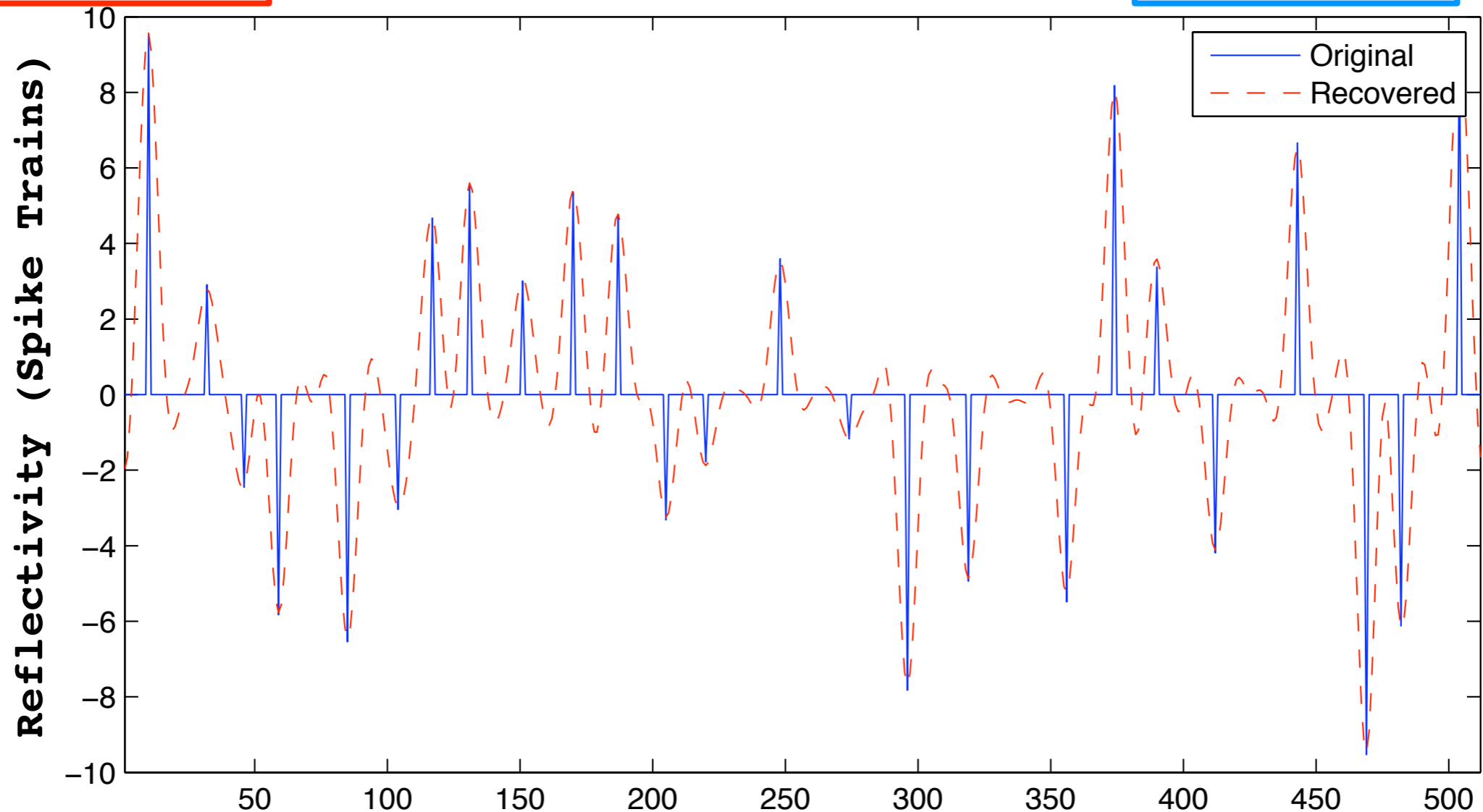
Cosine Bump Convolution with Spike Train (StOMP), N=512



K = 25 events, s = 0.66667, min. distance $\Delta = 13$

Length of Signal : 512	StOMP Solving Time : 1.43
Number of Spikes : 25	StOMP Stage : 9
Min & Max Spacing : 13, 37	L2 Norm(x) : 28.35
Bump/Wavelet Scale : 0.667	% L0 Error : 3.16
Regular , Uniform : 0, 0	% L2 Error : 0.1873

Cosine Bump Convolution with Spike Train (Scaled BP), N=512



K = 25 events, s = 0.66667, min. distance $\Delta = 13$

Length of Signal : 512	BP Solving Time : 0.13
Number of Spikes : 25	L2 Norm(x) : 28.35
Min & Max Spacing : 13, 37	% L0 Error : 19.48
Bump/Wavelet Scale : 0.667	% L2 Error : 0.9992
Regular , Uniform : 0,0	

Deconv. Summary

- Signal with length of 512 samples

Wavelet	Scale	K	Δ	Recovery
Cosine Bump	1	30	5	+
Ricker wavelet	1	30	5	+
Cosine Bump, Regularly spaced	1	30	7	+
Cosine Bump, Uniform Amp.	1	30	5	0
Cosine Bump, Uniform Amp.	1	12	5	+
Cosine Bump	2/3	25	13	0

Multiscale Newton Method

[ChaRM Estimation]

Mohammad Maysami

Image Manifolds [Wakin'06]

- Varying Parameter: $\theta \in \Theta$ (Dimension: d)
- Image function model: $f_\theta : \mathbb{R}^d \mapsto \mathbb{R}$
- IAM : $\mathbf{F} = \{f_\theta : \theta \in \Theta\}$.
 - 1-to-1 $\theta \mapsto f_\theta$ Relation
 - \mathbf{F} is Square integrable: $\mathbf{F} \subset L^2(\mathbb{R}^2)$
- Non-Lipschitz relation \rightarrow manifolds with Φ_s , $s > 0$

$$F_s = \{ \Phi_s f_\theta : \theta \in \Theta, s > 0 \}$$

$$\Phi_s f = \phi_s * f, \text{ where } \phi_s(x) = \frac{1}{2\pi s^2} \exp\left\{-\frac{\|x\|^2}{2s^2}\right\}$$

$$T(s, \theta^{(0)}; \mathbf{F}) = T_{f_{\theta^{(0)}, s}}(\mathbf{F}_s)$$

Multiscale Newton Method

- Local tangent vectors on \mathbf{F}_{s_k}

$$\tau_{\theta^{(k)}, s_k}^i = \left. \frac{\partial}{\partial \theta_i} f_{\theta, s_k} \right|_{\theta = \theta^{(k)}}, \quad i = 0, 1, \dots, d-1.$$

- Project estimation error

$$J_i = 2 \langle f_{\theta^{(k)}, s_k} - I_{s_k}, \tau_{\theta^{(k)}, s_k}^i \rangle$$

- products of tangent vectors

$$H_{ij} = 2 \langle \tau_{\theta^{(k)}, s_k}^i, \tau_{\theta^{(k)}, s_k}^j \rangle$$

$$\langle \tau_{s_0}^i, \tau_{s_1}^j \rangle = c_{s_0, s_1} \delta_{i,j}$$

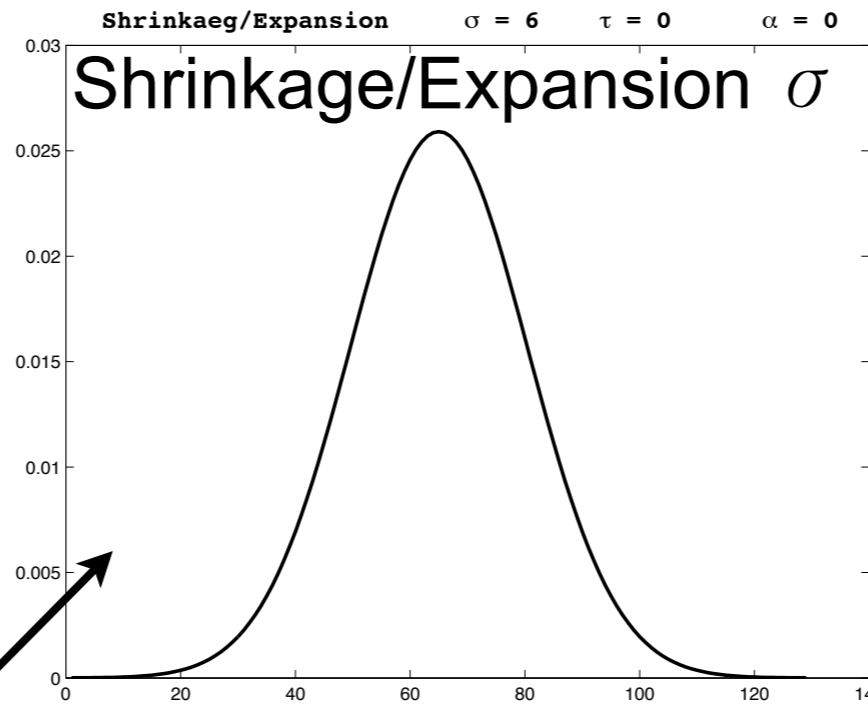
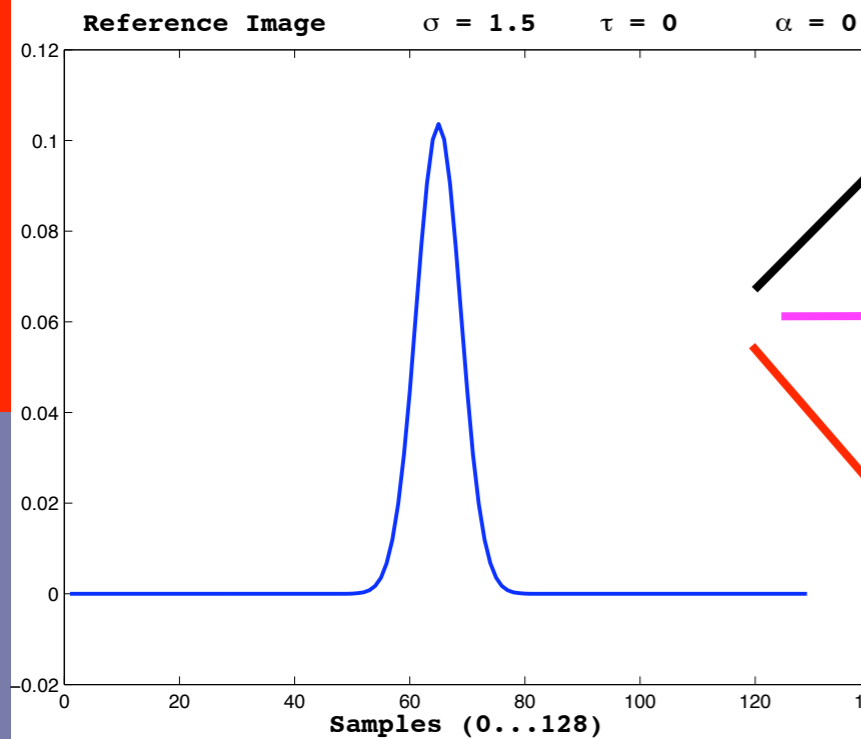
- Update estimation

$$\theta^{(k+1)} \leftarrow \theta^{(k)} + H^{-1} J.$$

Form IAM for Gaussians

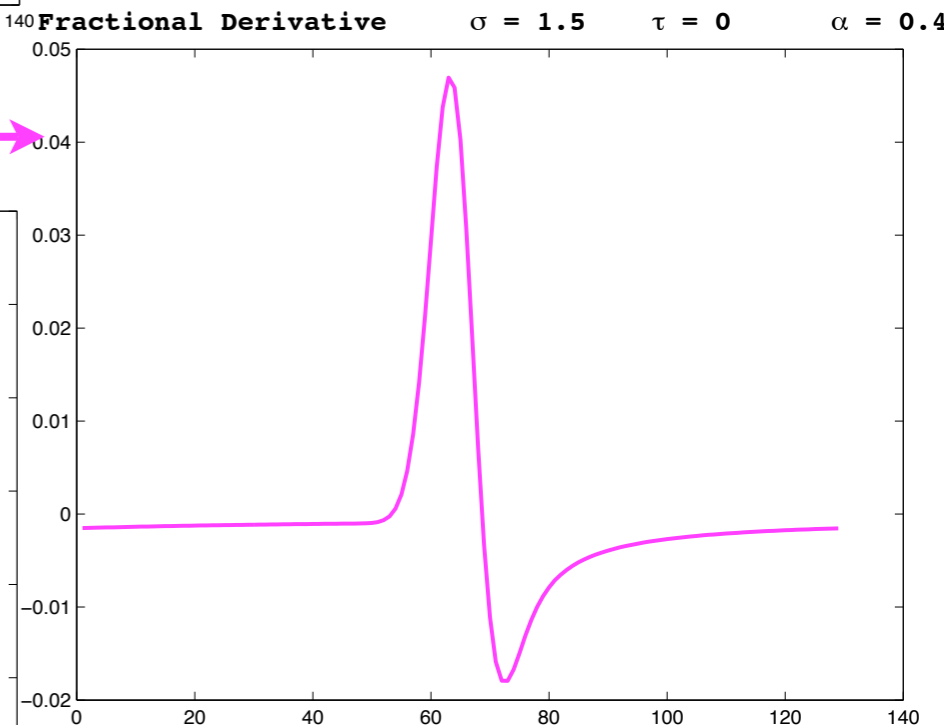
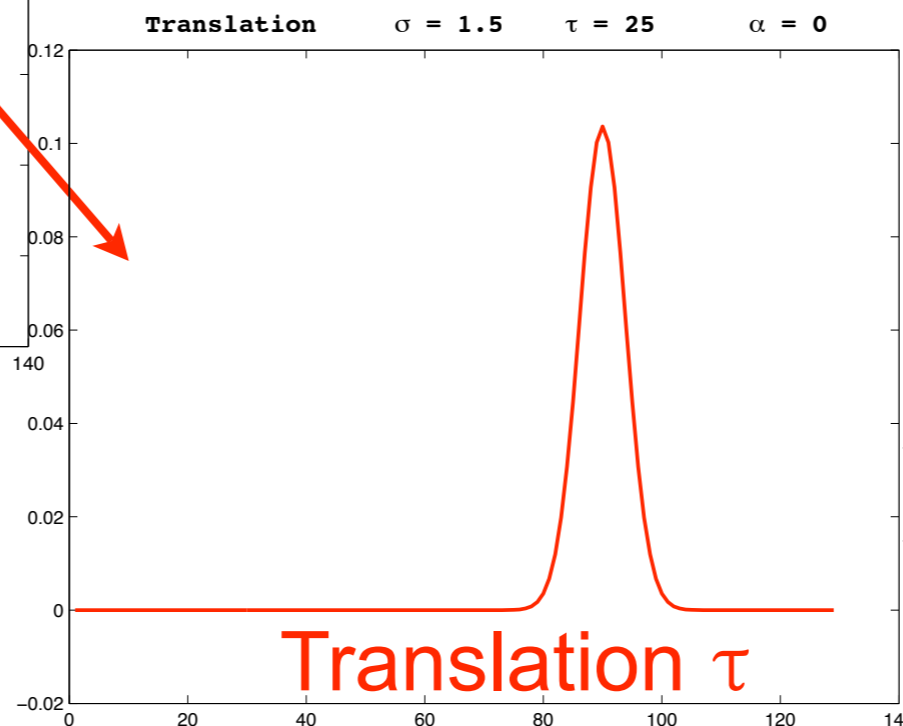
$$\theta = [\sigma, \tau, \alpha, \gamma]$$

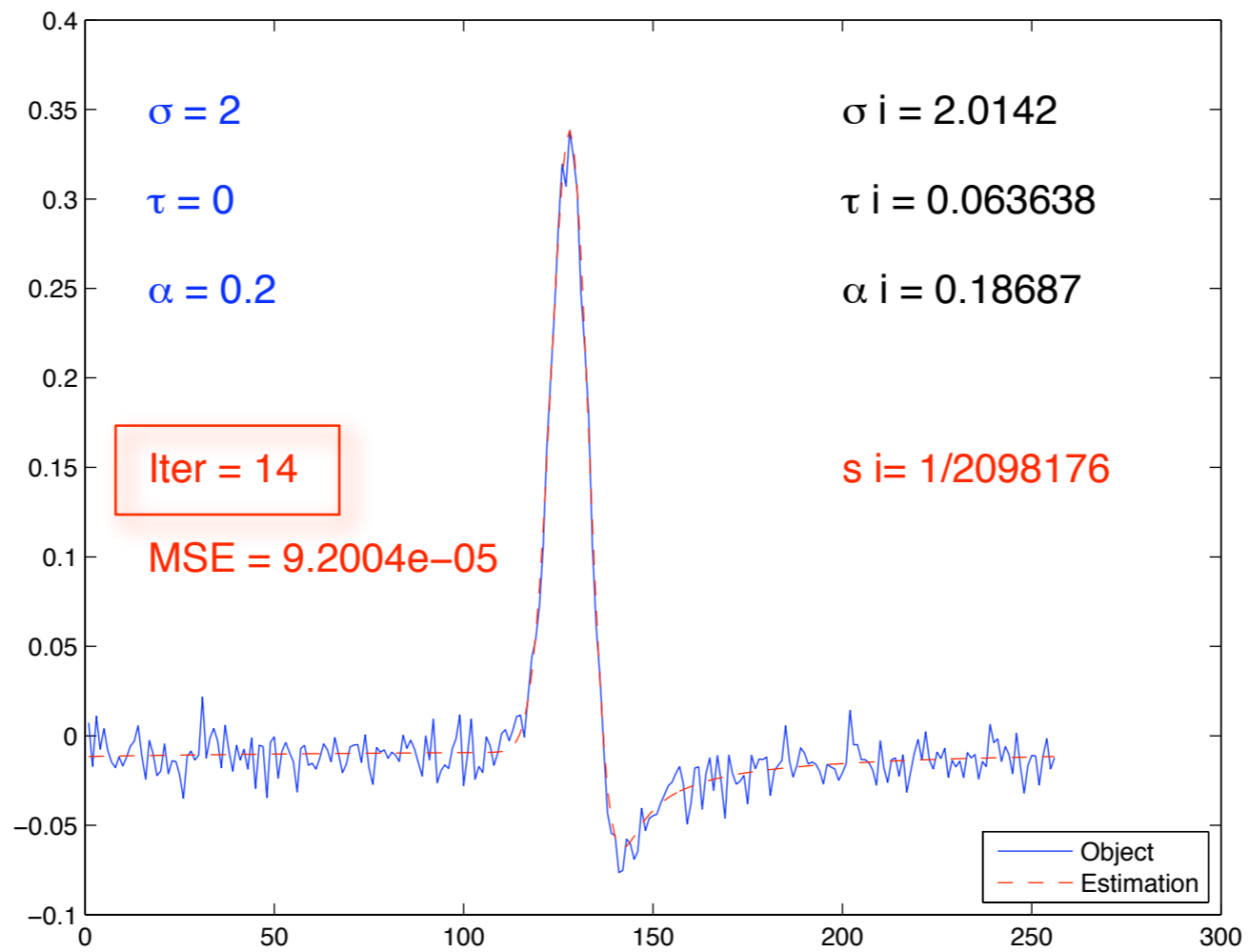
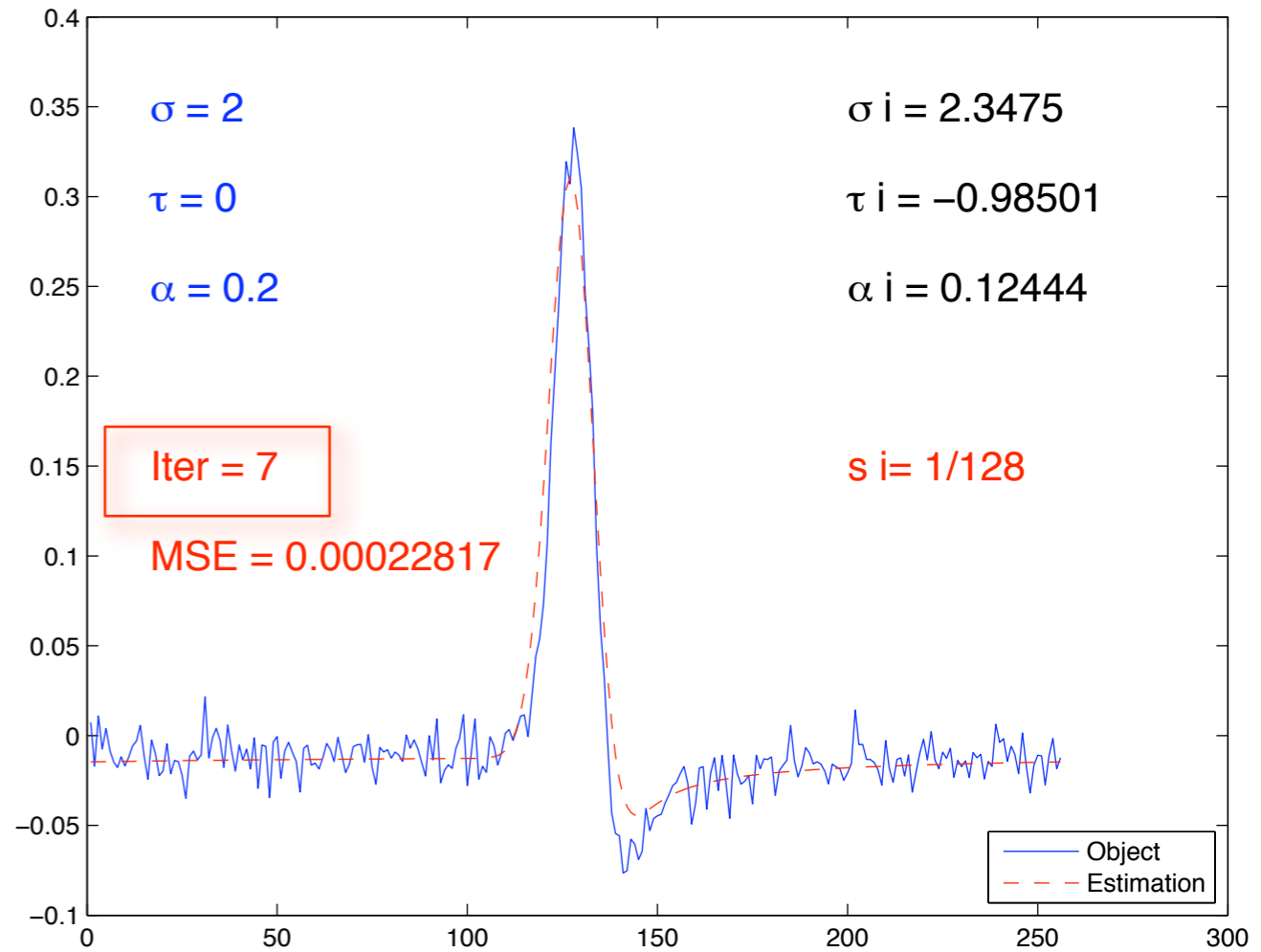
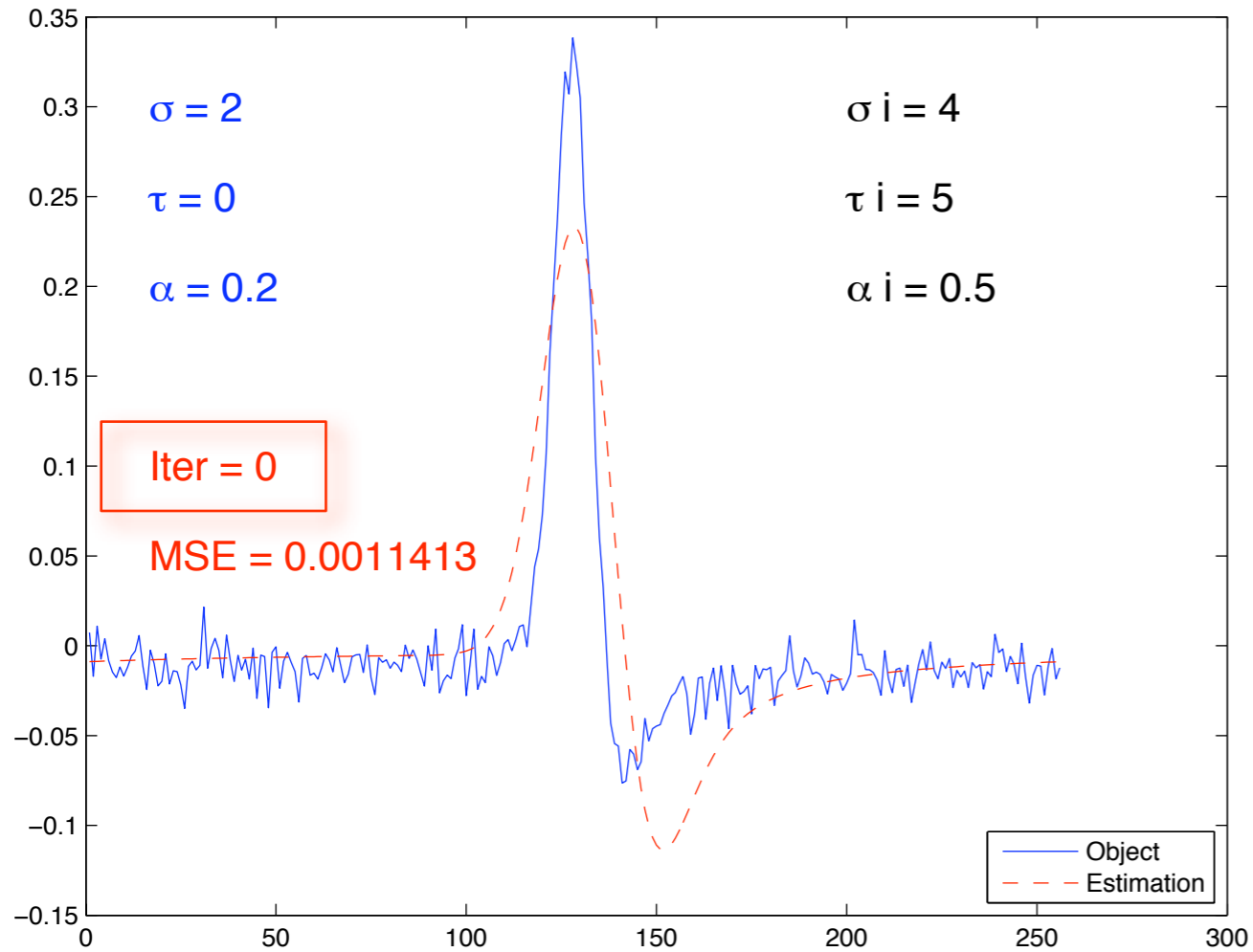
Reference Object



Phase Shift γ :
To be added

Fractional Derivative α

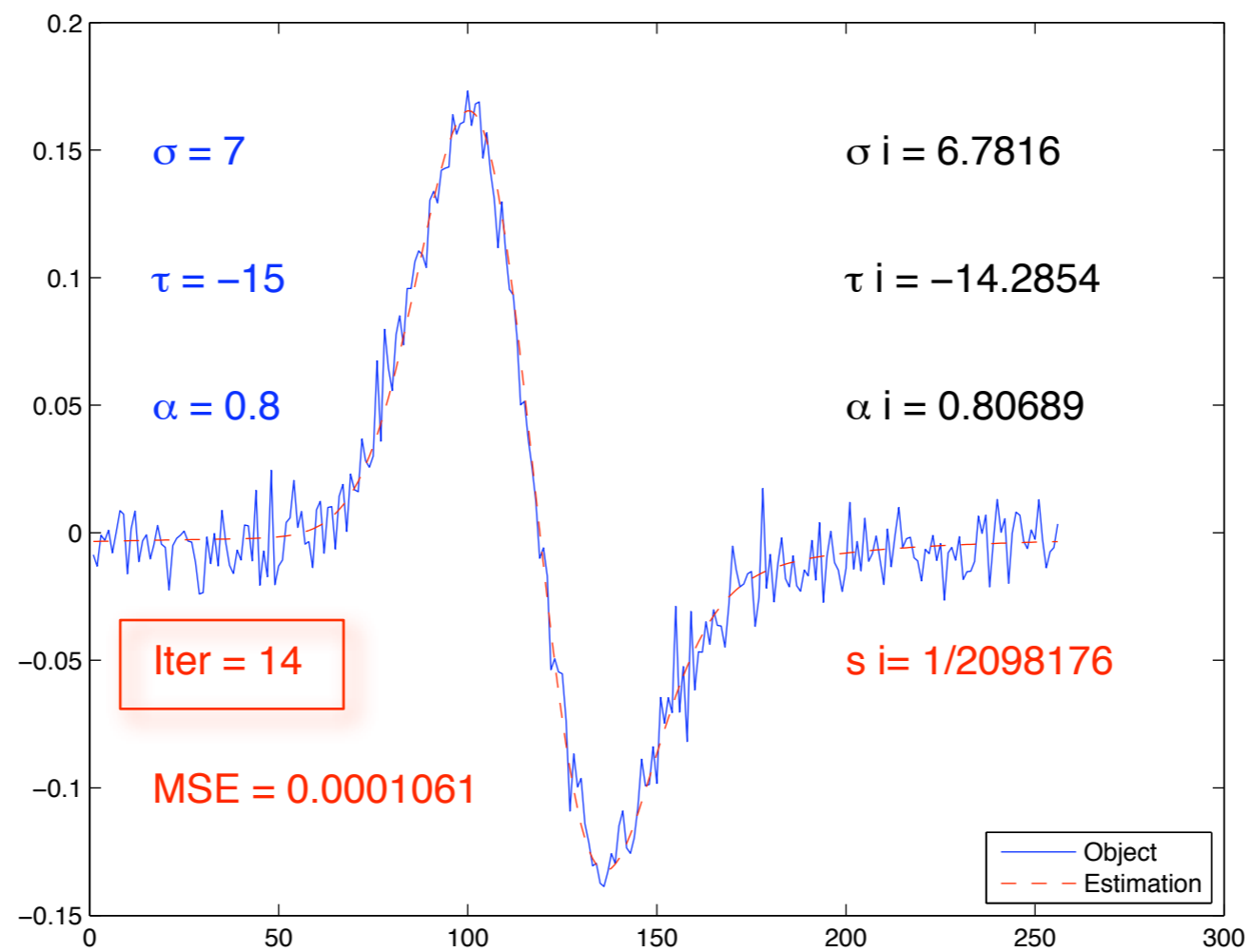
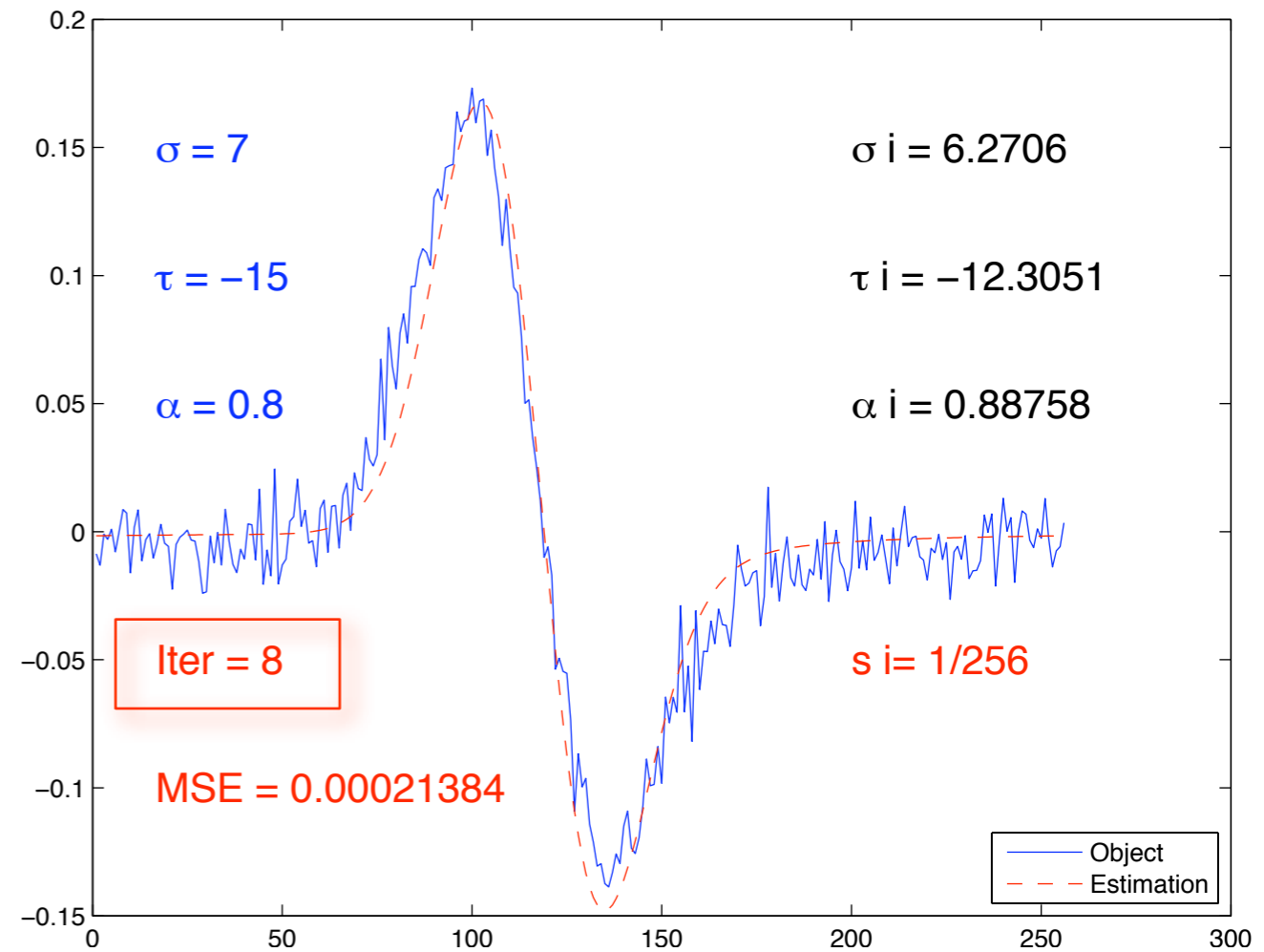
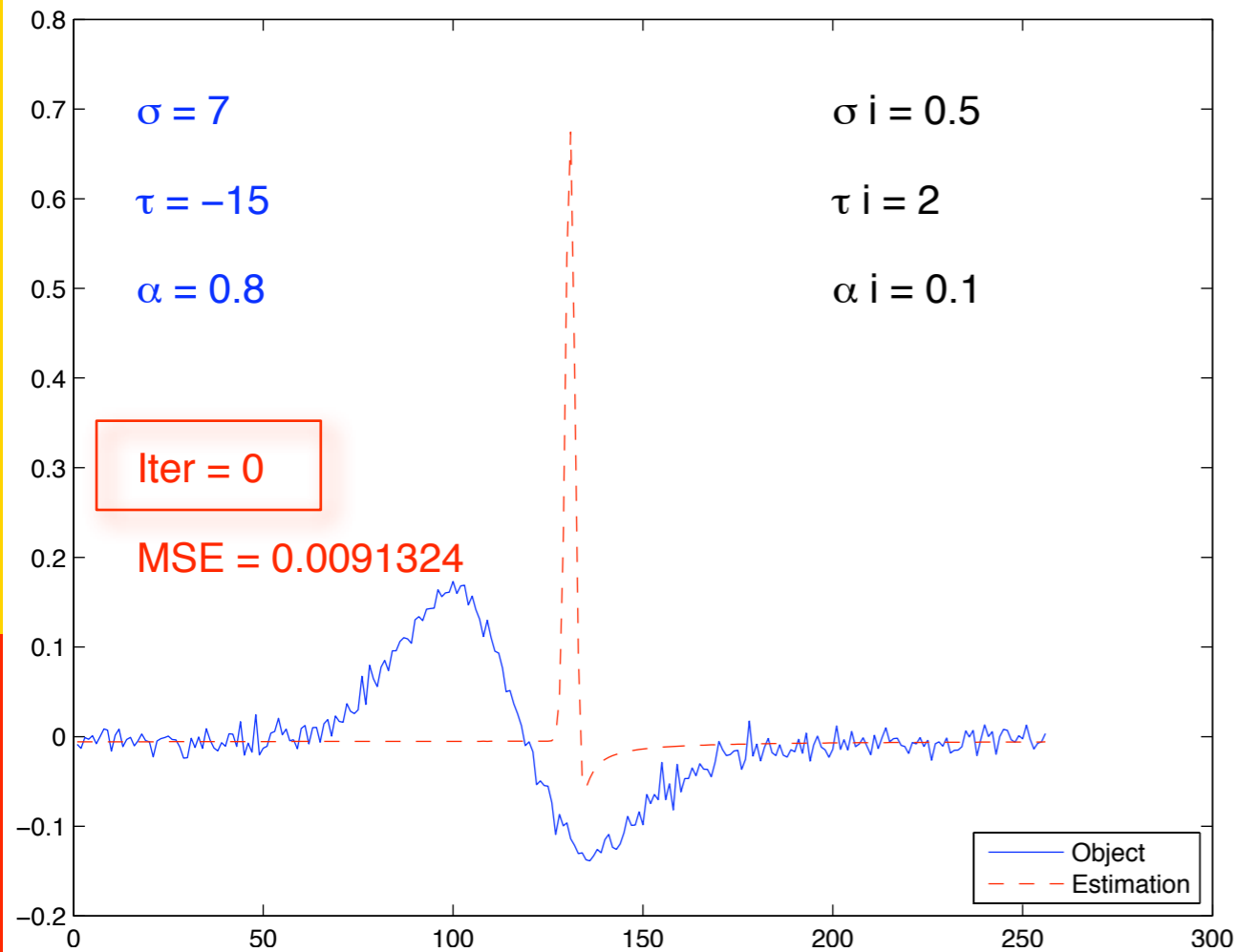




Result statistics - Case 1

	Actual	Initial Guess	Estimated
Sigma	2	4	2.0142
Tau	0	5	0.0636
Alpha	0.2	0.5	0.1869

Noise Variance	8.01E-06
Iter. No.	14
MSE	9.20E-04
Elapsed Time	0.42



Result statistics - Case 2

	Actual	Initial Guess	Estimated
Sigma	7	0.5	6.6911
Tau	-15	2	-14.025
Alpha	0.8	0.1	0.8066

Noise Level	3.522E-08
Iter. No.	14
MSE	1.06E-04
Elapsed Time	0.31

Multiscale Newton method

- Replace the **slow** redundant dictionary technique with a multiscale Newton method
- Resolve problem with the **non-differentiability** of the parametrization => stable
- Good initial guess provided by detection step
- Convergence rate
- robust under noise and incomplete data
- Smoothing Sensitivity

Percolation model and Well tie

[Herrmann-Bernabe'05]

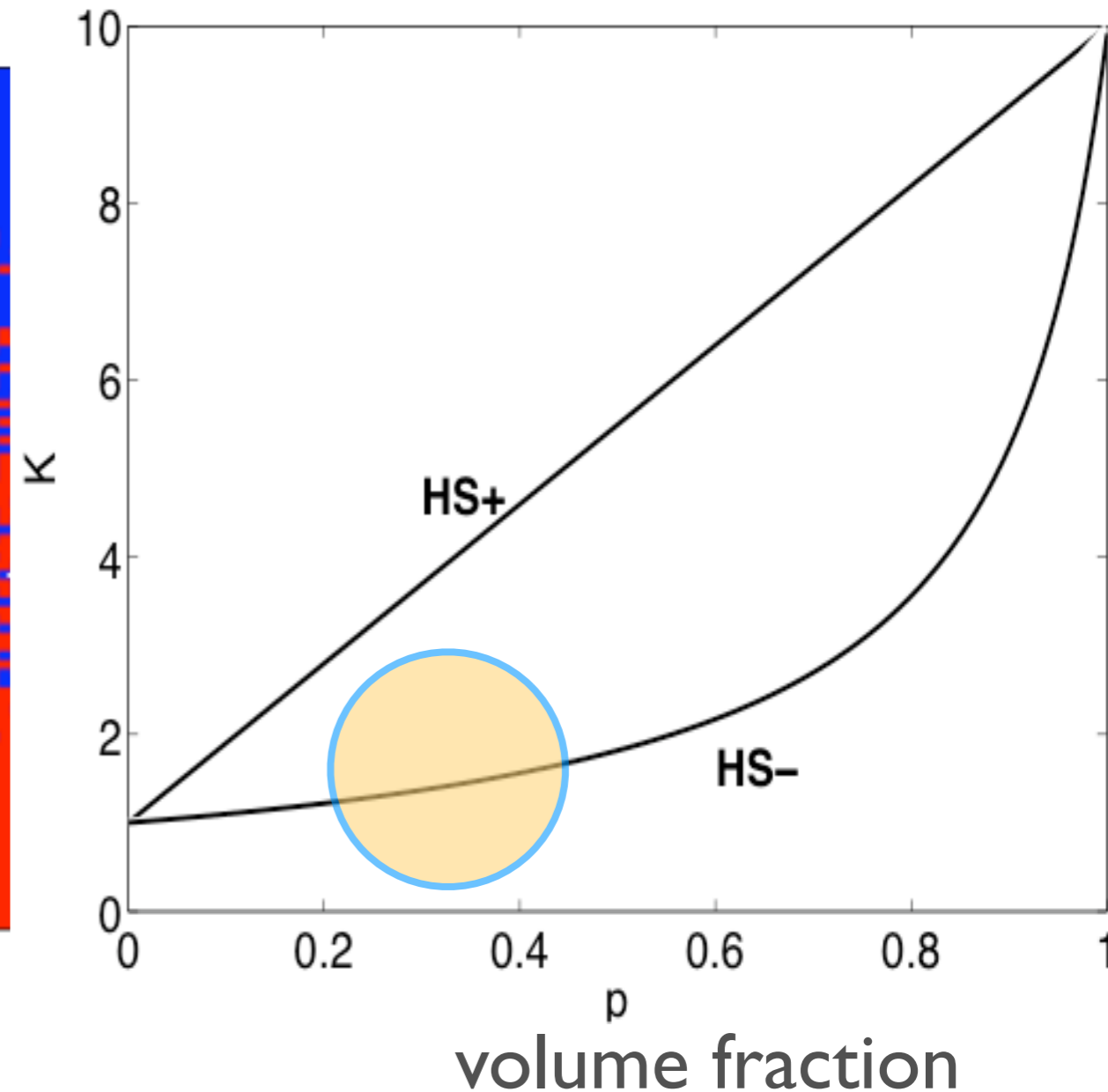
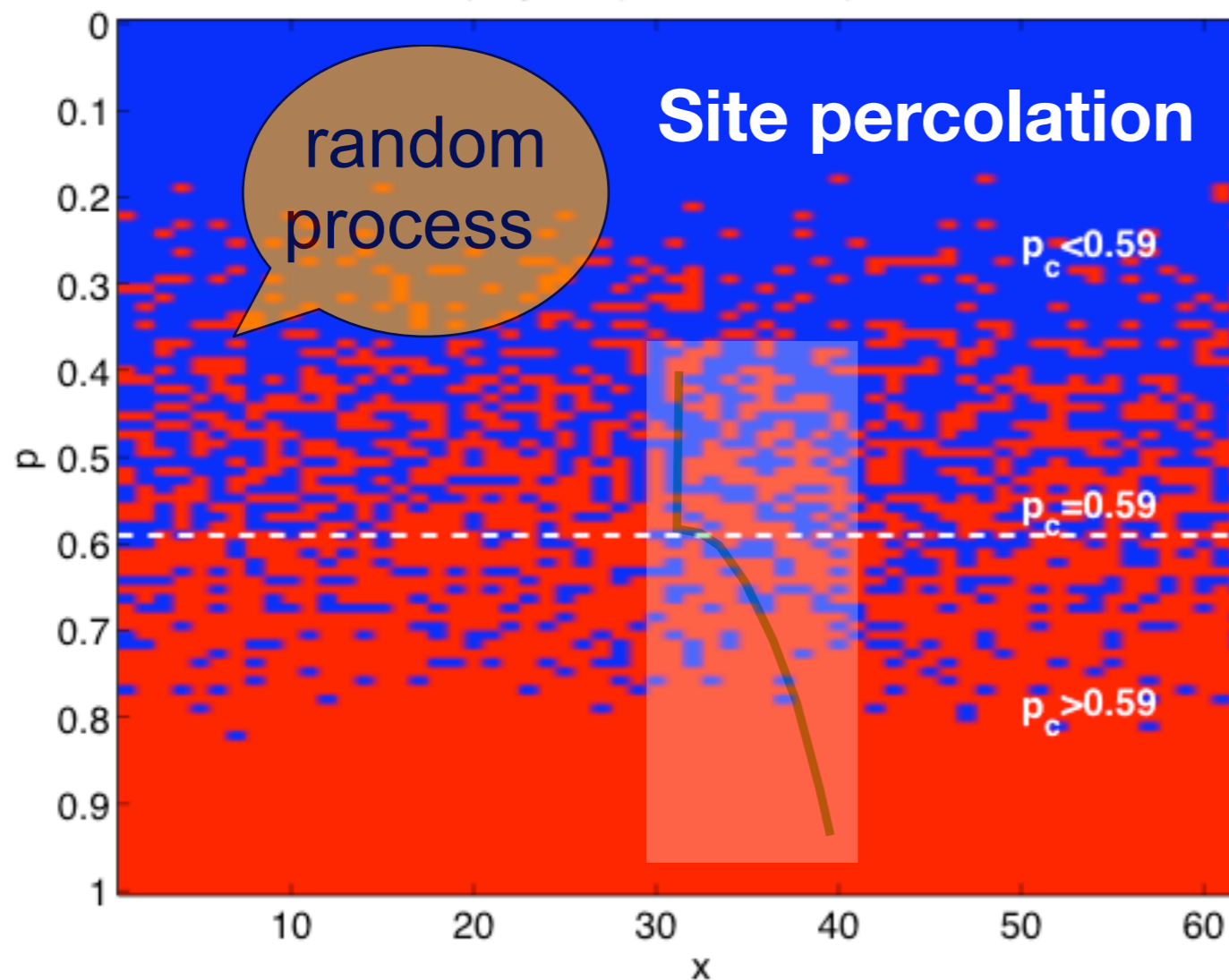
Discontinuity modeling

binary mixtures

LP  olivine HP  β -spinel

elastic properties

Varying composition binary mixture



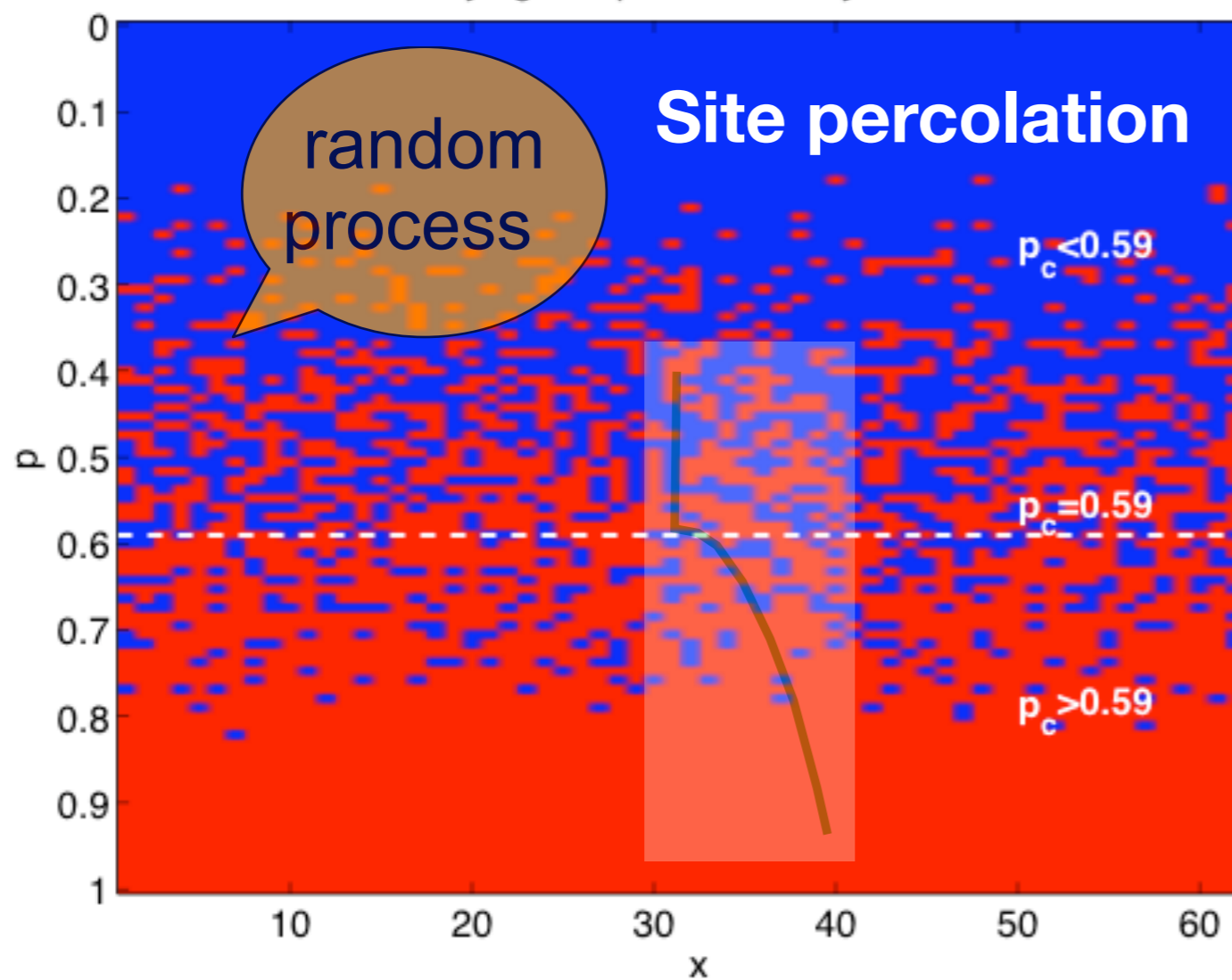
HP: high porosity
LP: low porosity

Discontinuity modeling

binary mixtures

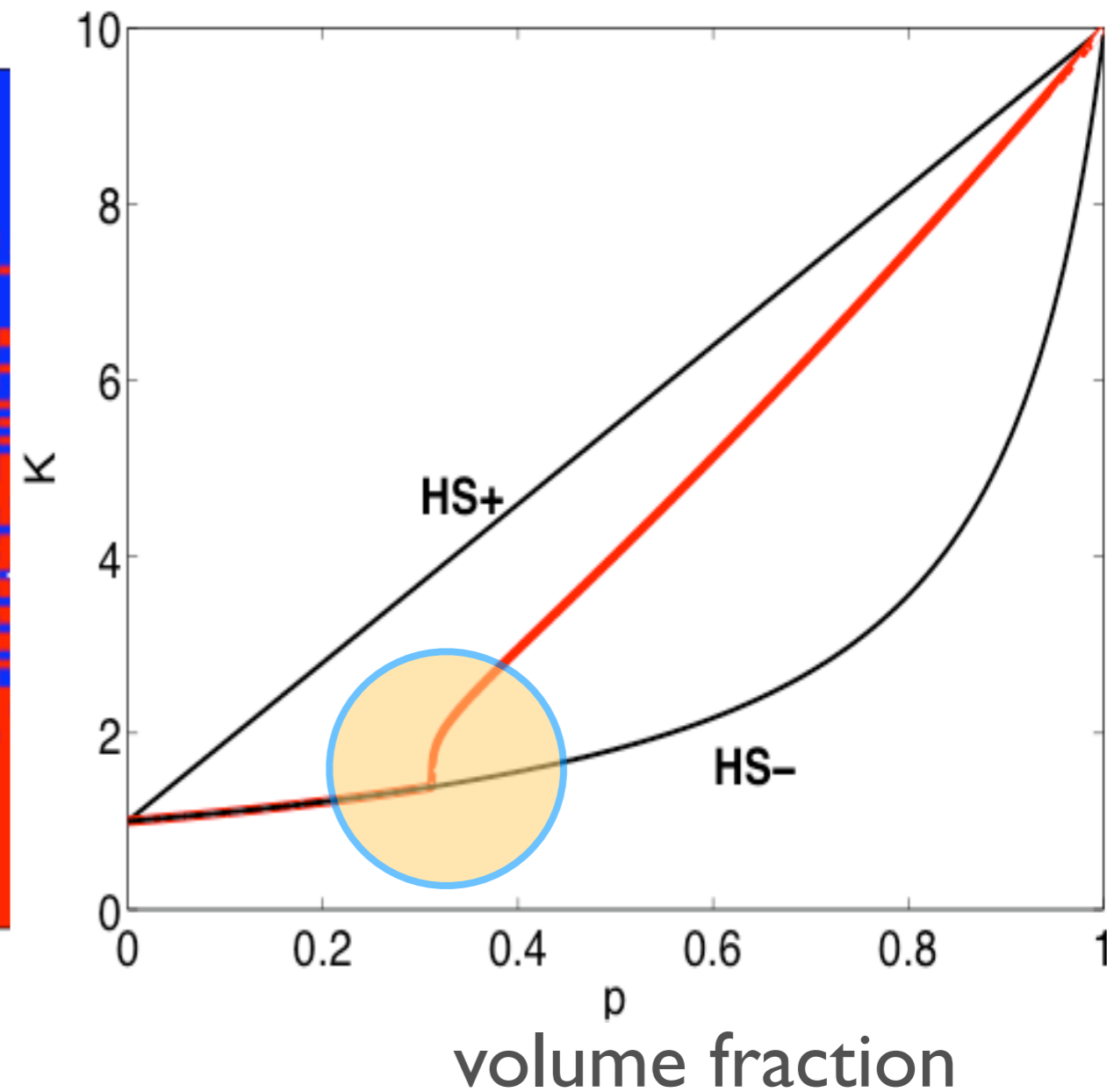
LP  olivine HP  β -spinel

Varying composition binary mixture



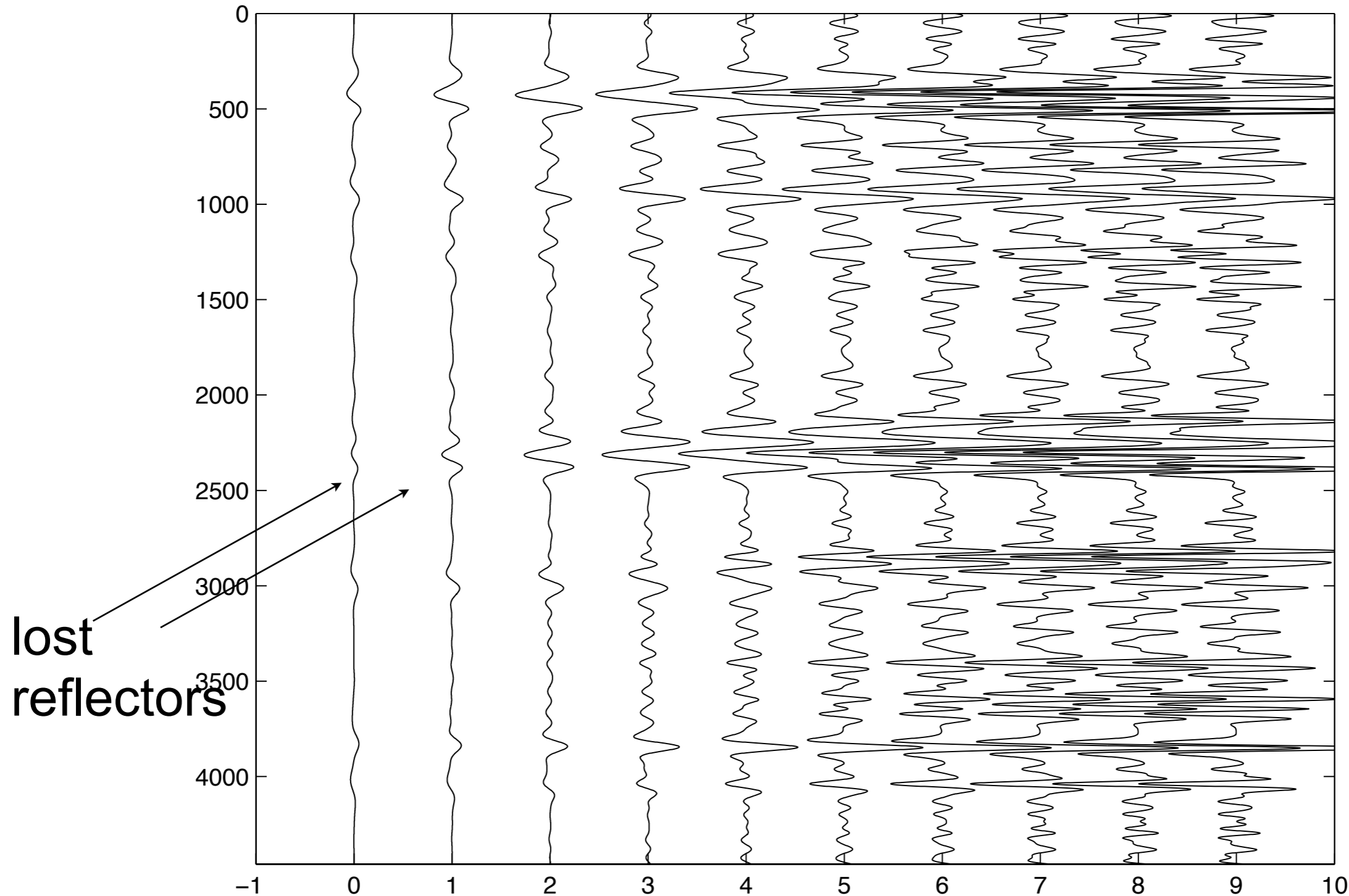
HP: high porosity
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elastic properties



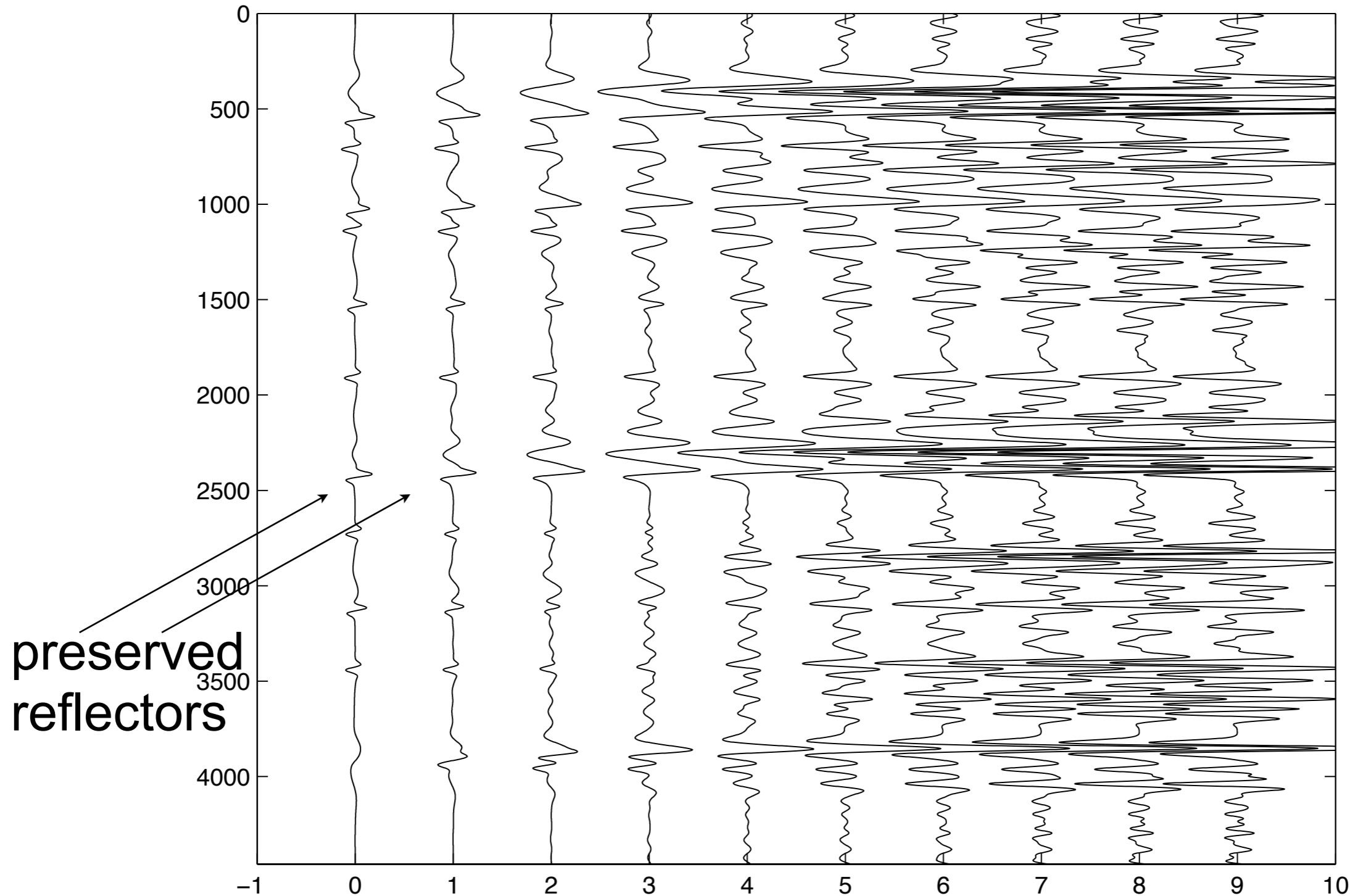
Upscaling: EM upscaled reflectivity

Reflectivity for the Equivalen medium model



Upscaling: Perc. upscaled reflectivity

Reflectivity for the Percolation model



Upscaling: lithology

- Use the volume fractions, p , to compute
 - **density** via a **linear** relation
 - **velocity** via a **nonlinear** & **singular** (switch) relation
- Upscaling by smoothing p and not the velocity
- preserves singularities because of the switch
- **singularities** from p or **switch**

Using IAMs for Well tie

- Percolation Model
 - P_c
 - β
- Match well-log (P) to seismic reflectivity
 - Parametrizing by IAM
 - solve for inverse problem
- Model mixtures as binary mixtures

Future plans

[ChaRM]

ChaRM Detection

- Use recent results on spiky decon (Mallat) to make the detection unique given minor information on the seismic wavelet
 - insensitivity to estimated wavelet and spike assumption
- Extend these results to higher dimensions
 - multidimensional reflector detection
 - solve spike decon. for curvelet
 - Joint work with Yilmaz, Jaffard, Vedel
- Characterization depends on an sufficiently accurate event detection

ChaRM Characterization

- Develop the multiscale Newton method
- Extend to higher dimensions
- Make robust under noise and missing data
- Extend the multiscale Newton technique to invert for (given the end members)
 - the percolation threshold and exponent
 - the extend of the lithological transition (the width of a layer in the composition)
- Joint work with Yves Bernabé

ChaRM Upscaling and well tie

- Study well-defined binary mixtures (e.g. Opal, gas-hydrates etc.)
- Develop upscaling techniques that preserve singularities
- Provide new insights in the well-seismic tie
- Joint work with Yves Bernabé

Questions ?

Comments ?

