Randomized sampling without repetition in time-lapse seismic surveys

Felix Oghenekohwo

Collaborators : Haneet Wason, Ernie Esser, Felix J. Herrmann

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University of British Columbia

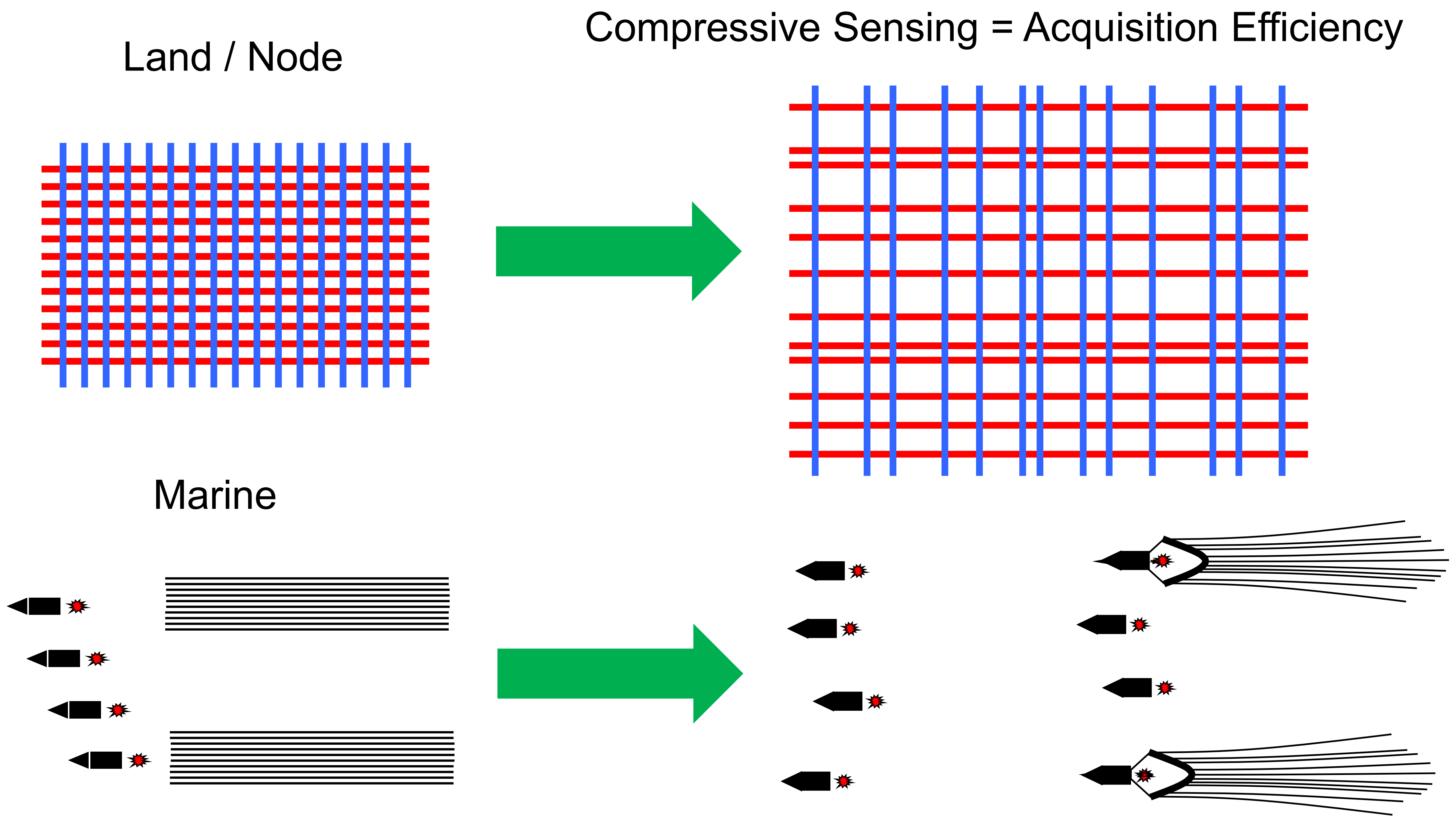
Mosher, C. C., Keskula, E., Kaplan, S. T., Keys, R. G., Li, C., Ata, E. Z., ... & Sood, S. (2012, November). Compressive Seismic Imaging. In *2012 SEG Annual Meeting*. Society of Exploration Geophysicists.

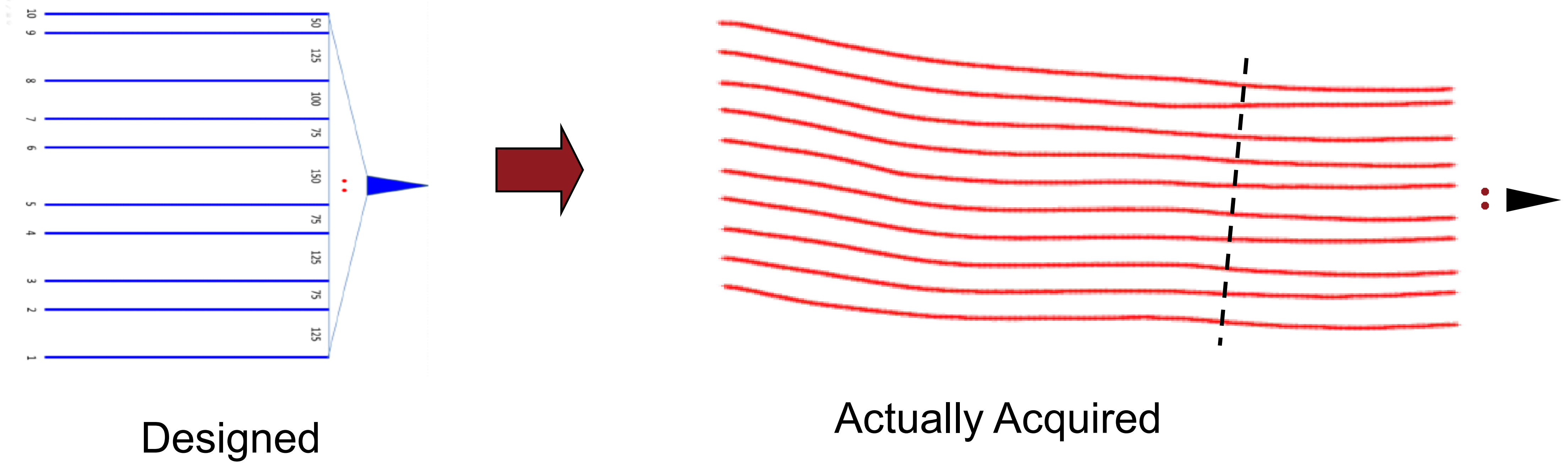
Randomized undersampling

– examples from industry (ConocoPhilips)

Deliberate & natural randomness in acquisition

(thanks to Chuck Mosher)





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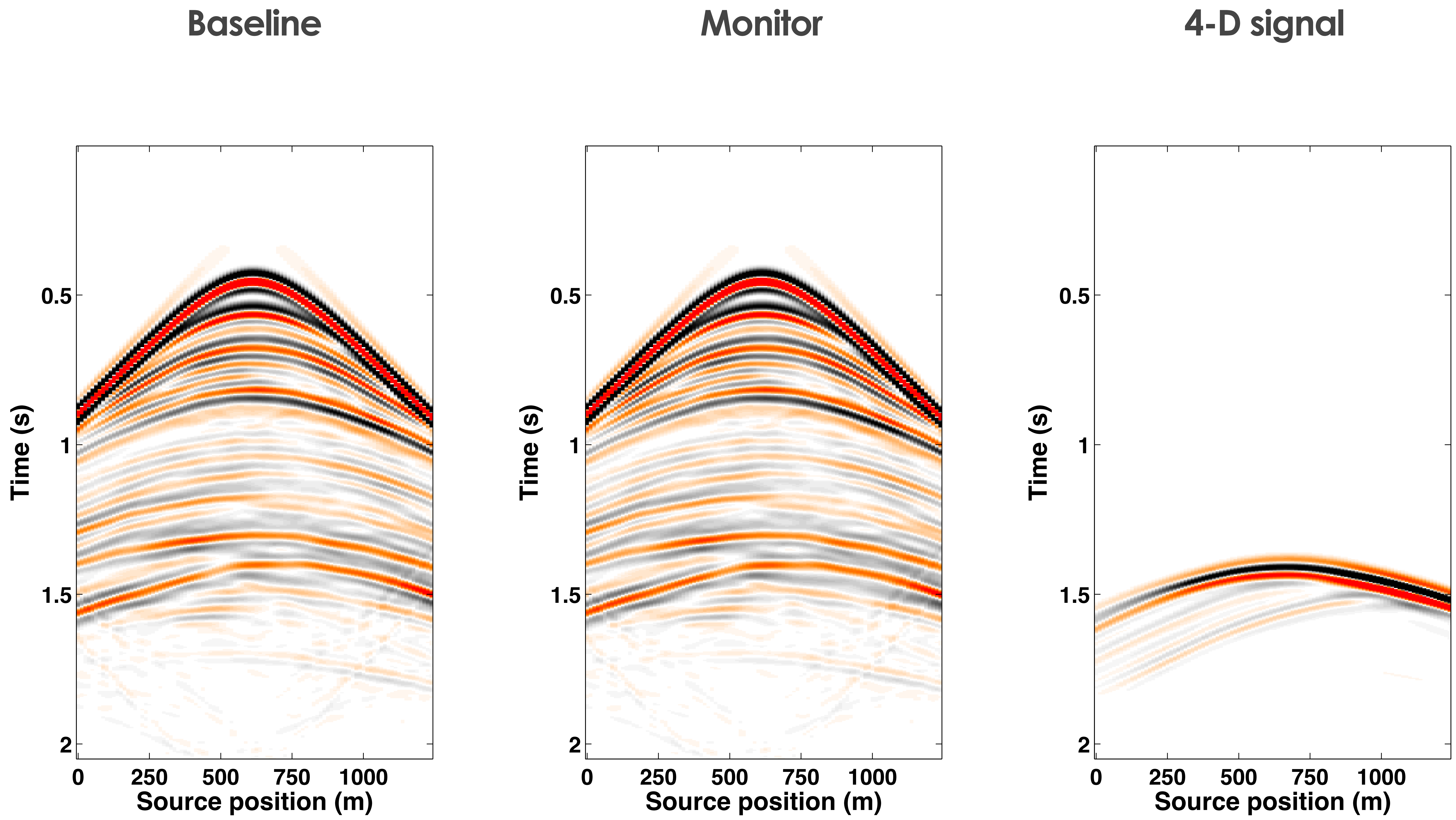
  - *exploits* insights from *distributed* compressive sensing



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sampling
time: **4.0 ms**
receiver: **12.5 m**
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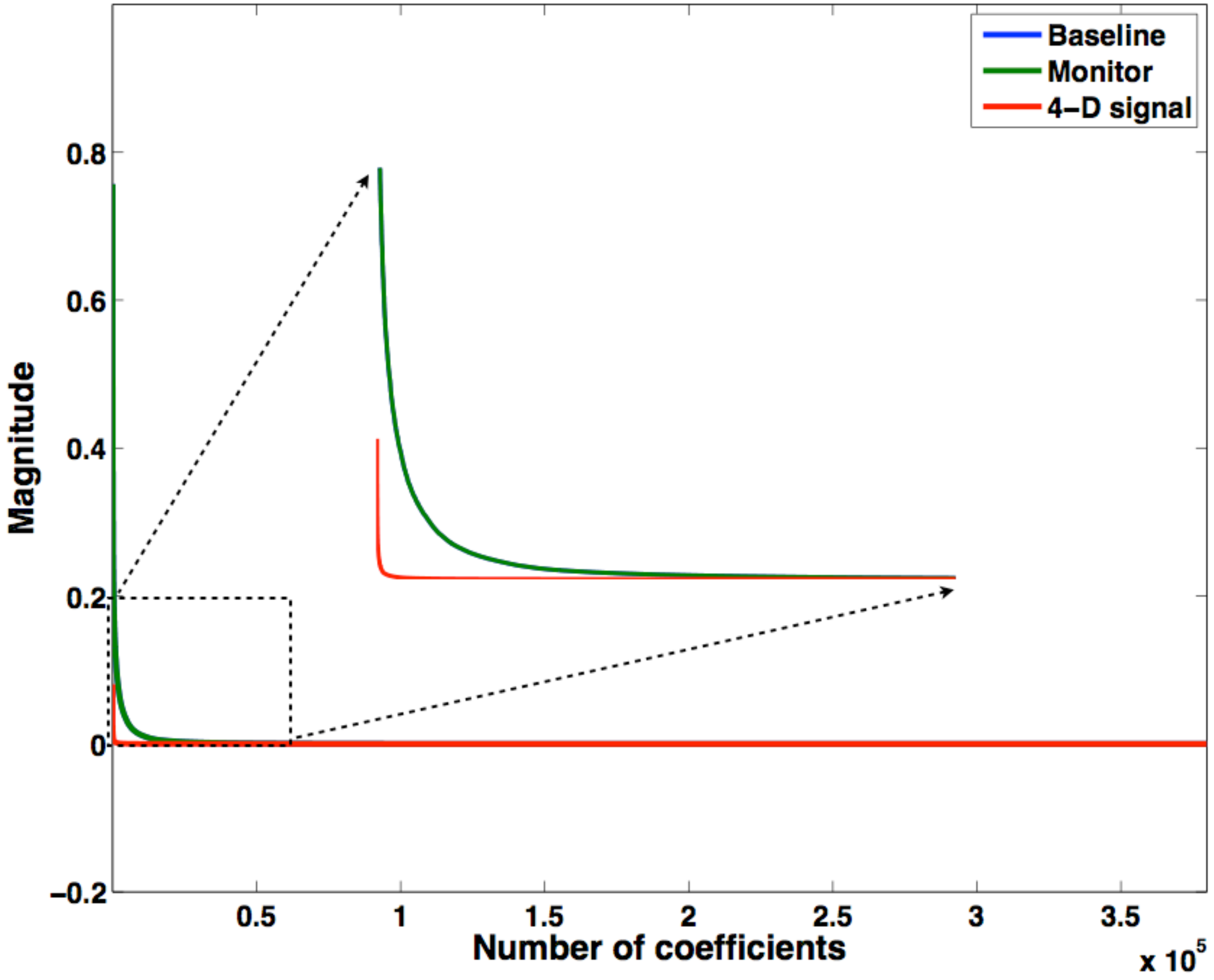
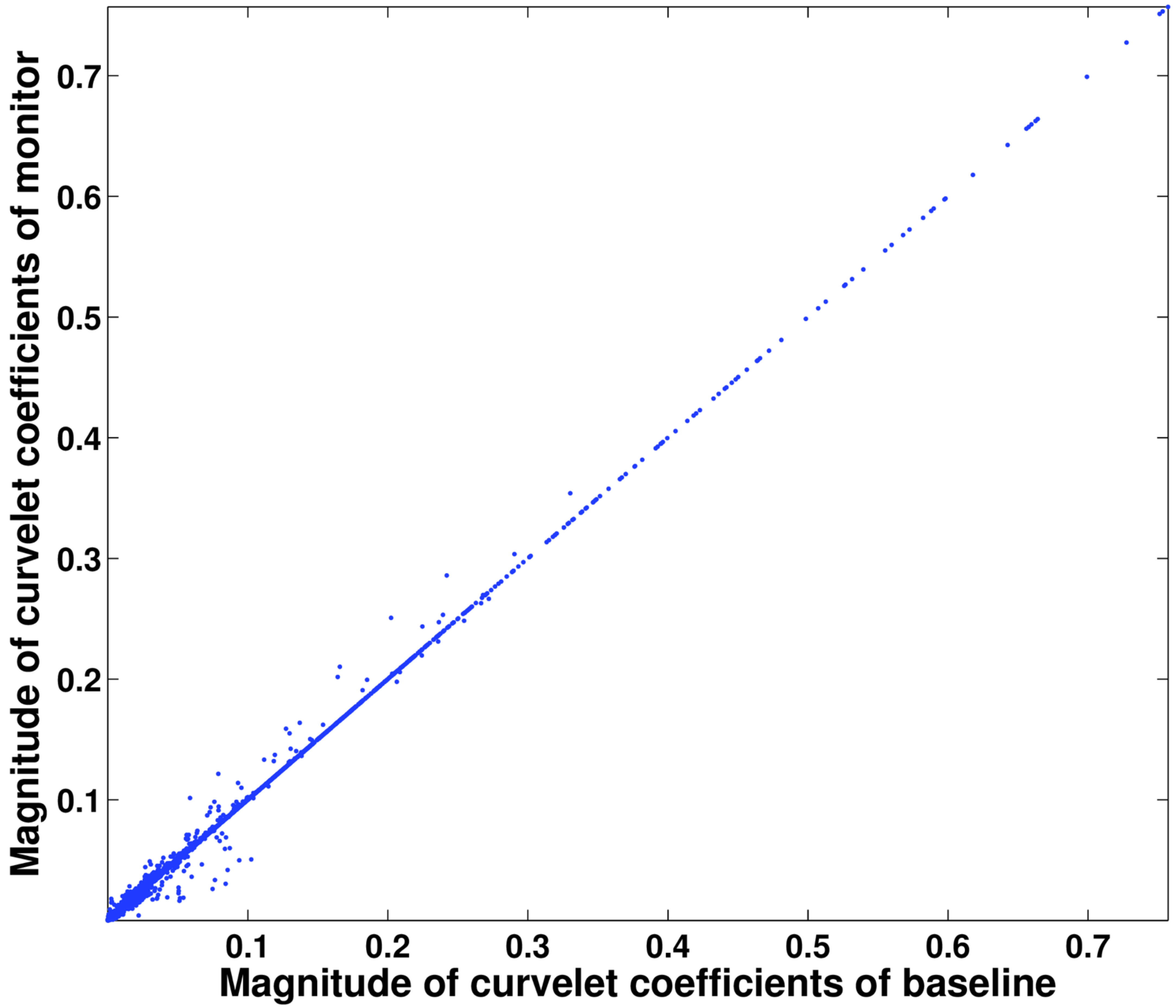
Structure - curvelet representation





Dror Baron , Marco F. Duarte , Shriram Sarvotham , Michael B. Wakin , Richard G. Baraniuk. An Information-Theoretic Approach to Distributed Compressed Sensing (2005)

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Distributed compressive sensing

– *joint* recovery model (JRM)

vintages

$$\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$$
$$\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$$

differences

common **component**

$$\overbrace{\begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix}}^{\mathbf{A}} \overbrace{\begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}}^{\mathbf{z}} = \overbrace{\begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{bmatrix}}^{\mathbf{b}}$$

baseline

monitor

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baseline

monitor

- **Key idea:**
  - use the fact that *different* vintages *share* common information
  - invert for *common* components & *differences* w.r.t. the *common* components with *sparse* recovery

Sparsity-promoting recovery

$$\tilde{\mathbf{z}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad \text{subject to} \quad \mathbf{A}\mathbf{z} = \mathbf{b}$$

$\mathbf{A}$ *measurement operator/sampling matrix*

$\mathbf{b}$ *observed data*

$\tilde{\mathbf{z}}$ *estimated representation of true data*

Interpretation of the model
– w/ & w/o repetition

- **In an *ideal* world** $(\mathbf{A}_1 = \mathbf{A}_2)$
  - JRM *simplifies* to recovering the *difference* from $(\mathbf{b}_2 - \mathbf{b}_1) = \mathbf{A}_1(\mathbf{x}_2 - \mathbf{x}_1)$
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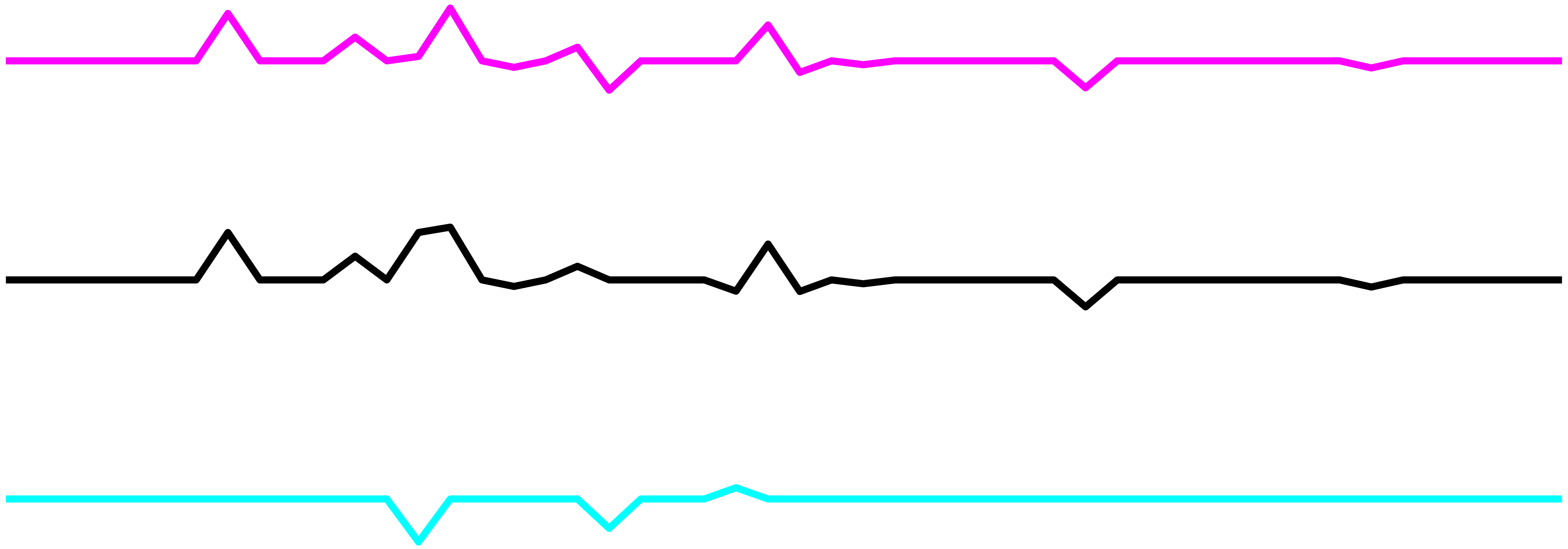
- **In the *real* world** $(\mathbf{A}_1 \neq \mathbf{A}_2)$
  - no absolute *control* on *surveys*
  - *calibration* errors
  - noise...

Stylized Examples

Sparse baseline, monitor & time-lapse signals

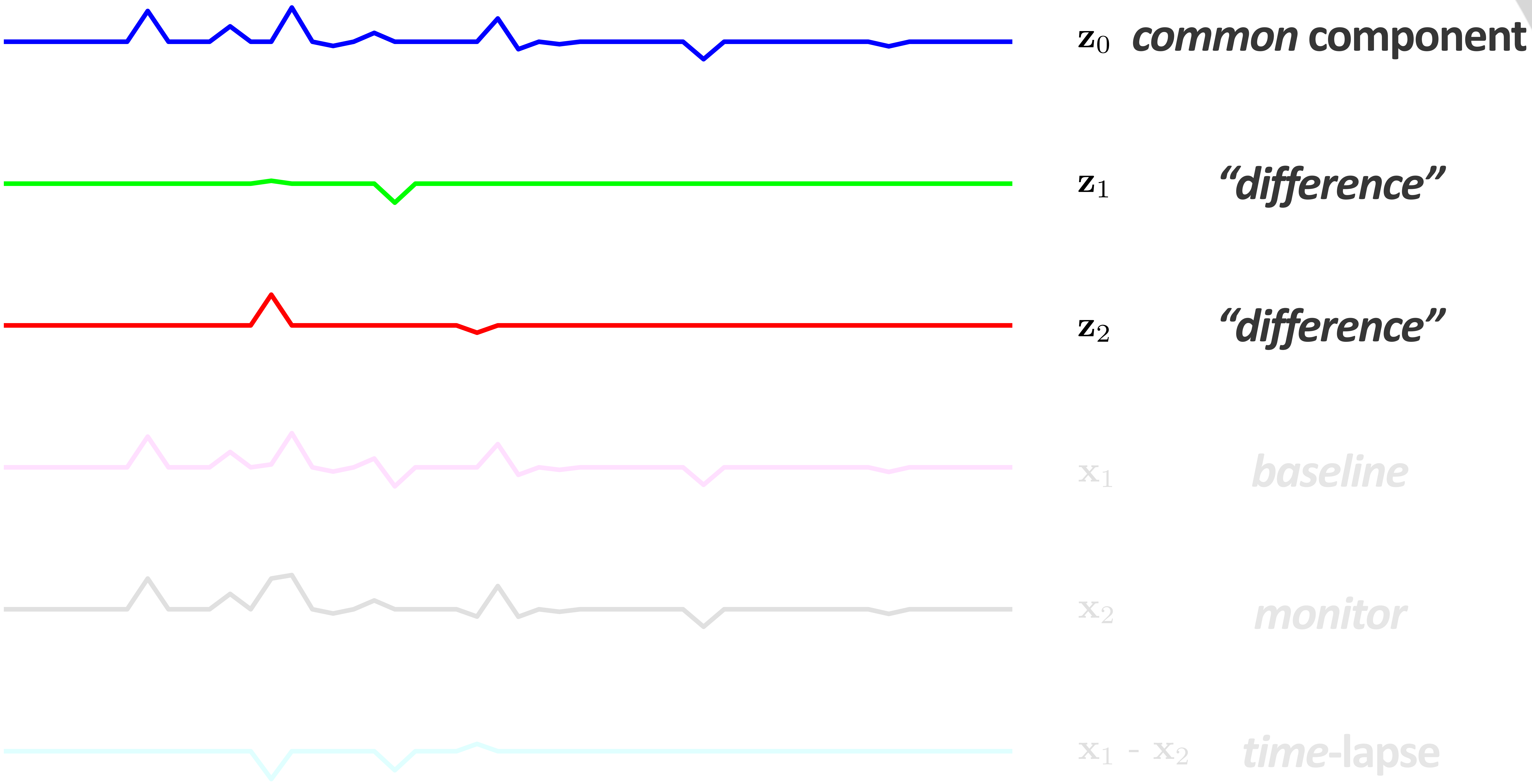


$\mathbf{x}_1$ ***baseline***

$\mathbf{x}_2$ ***monitor***

$\mathbf{x}_1 - \mathbf{x}_2$ ***time*-lapse**

Sparse Joint Recovery Model (JRM)



Signal length $N = 50$

Stylized experiments

Conduct *many* CS experiments to compare

- *joint* vs *parallel* recovery of signals and the difference

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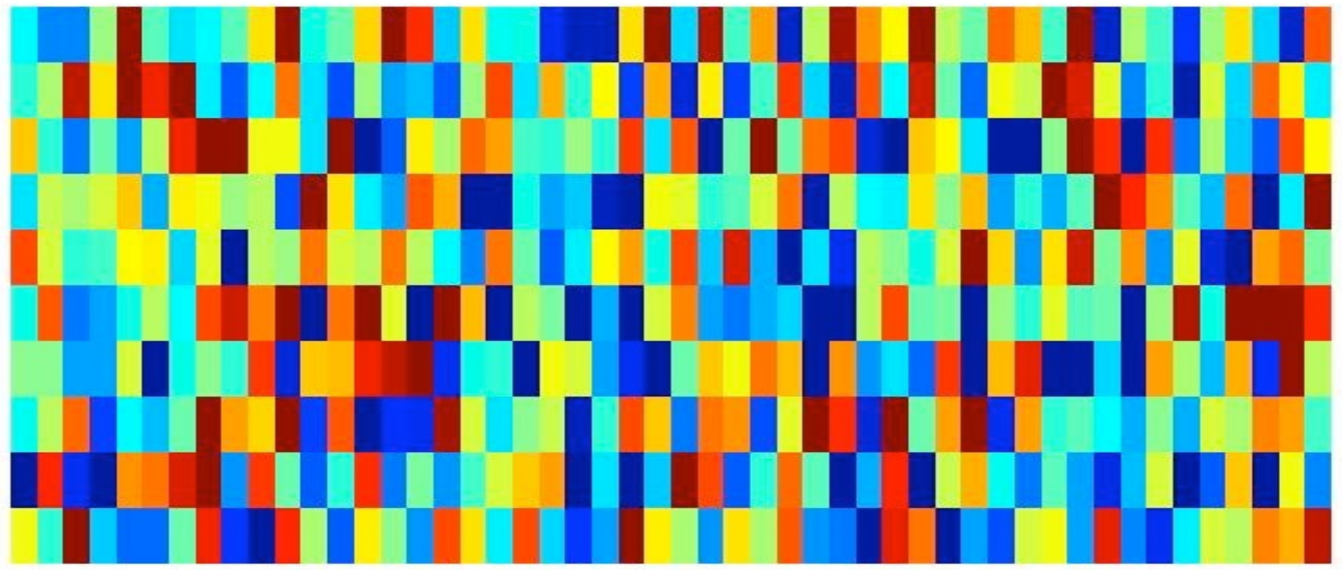
$\mathbf{A}_1$

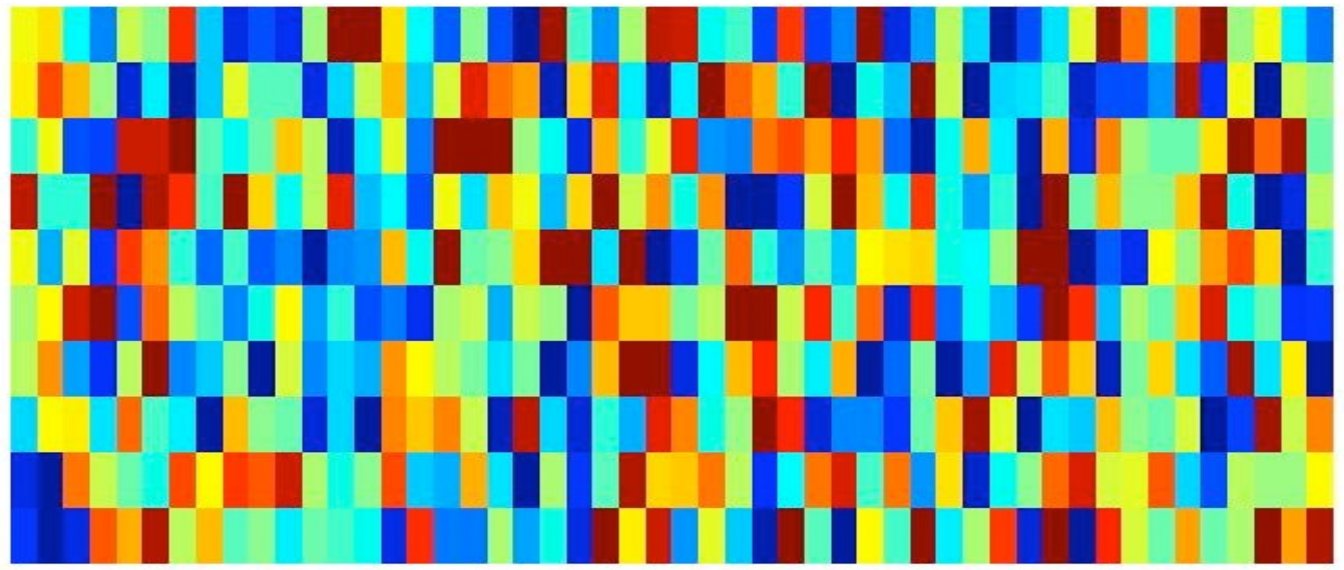
$\mathrm{n} = 10$

$\mathbf{A}_2$

n



n



N

N

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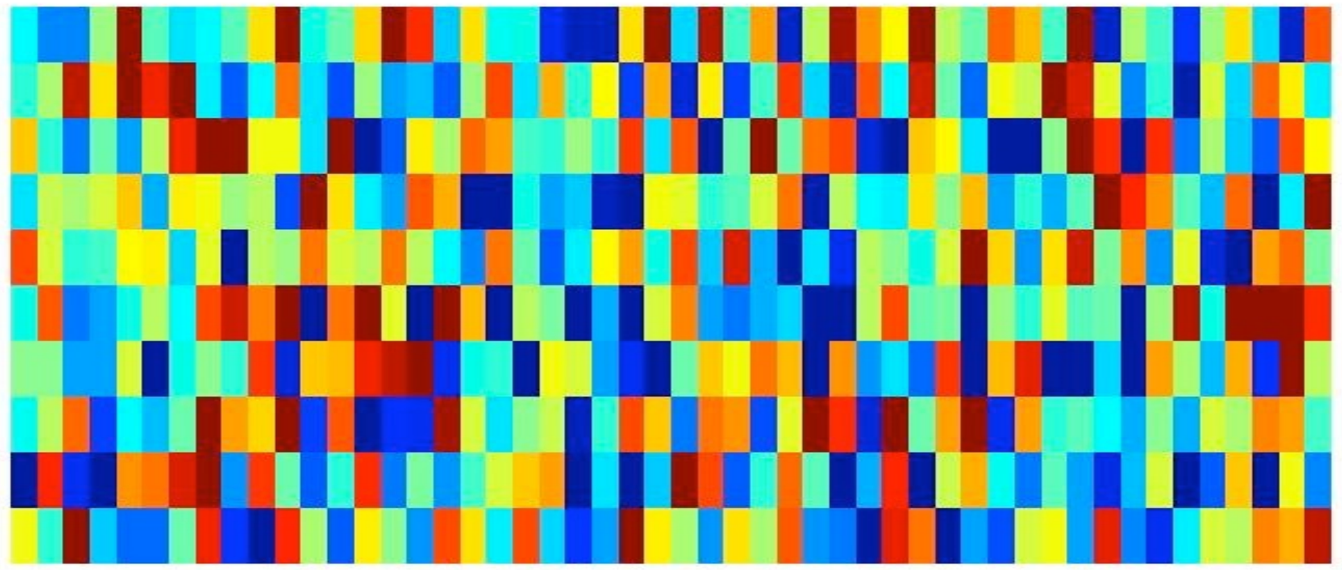

n

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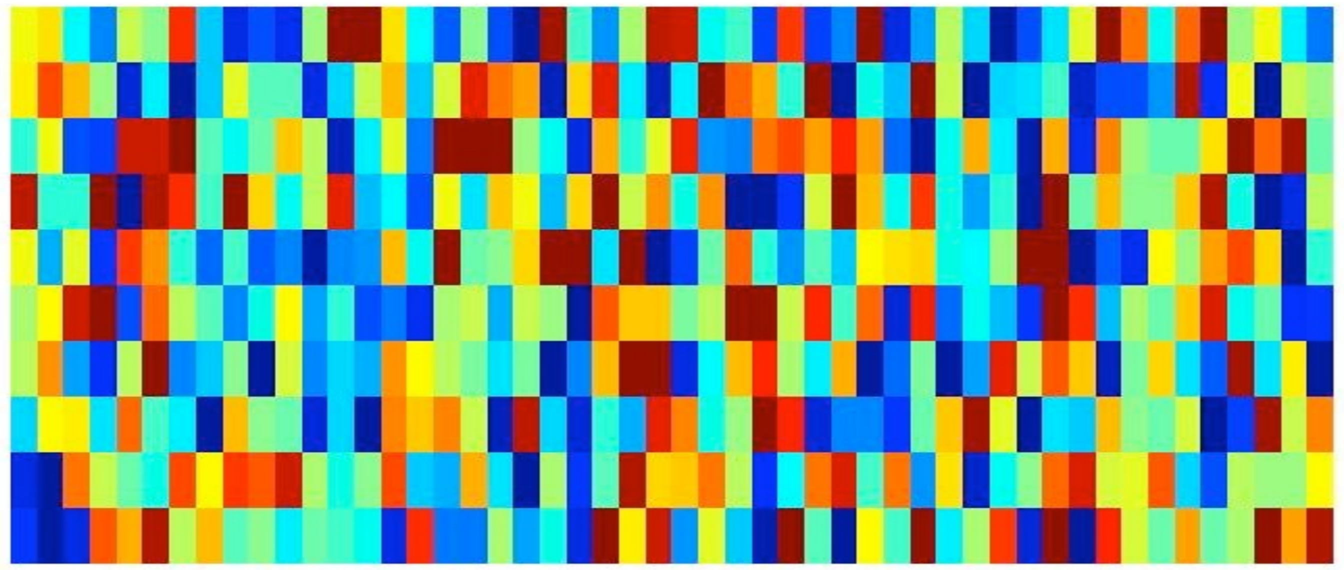

n

N

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Run 1000 different experiments

Stylized experiments

Conduct *many* CS experiments to compare

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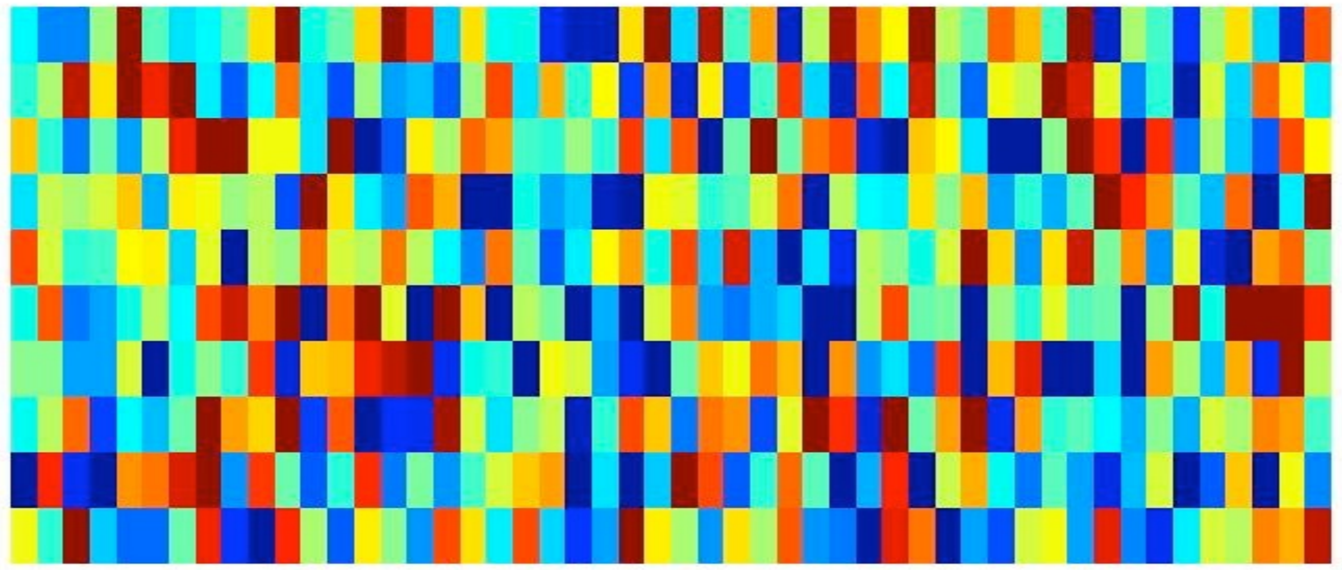

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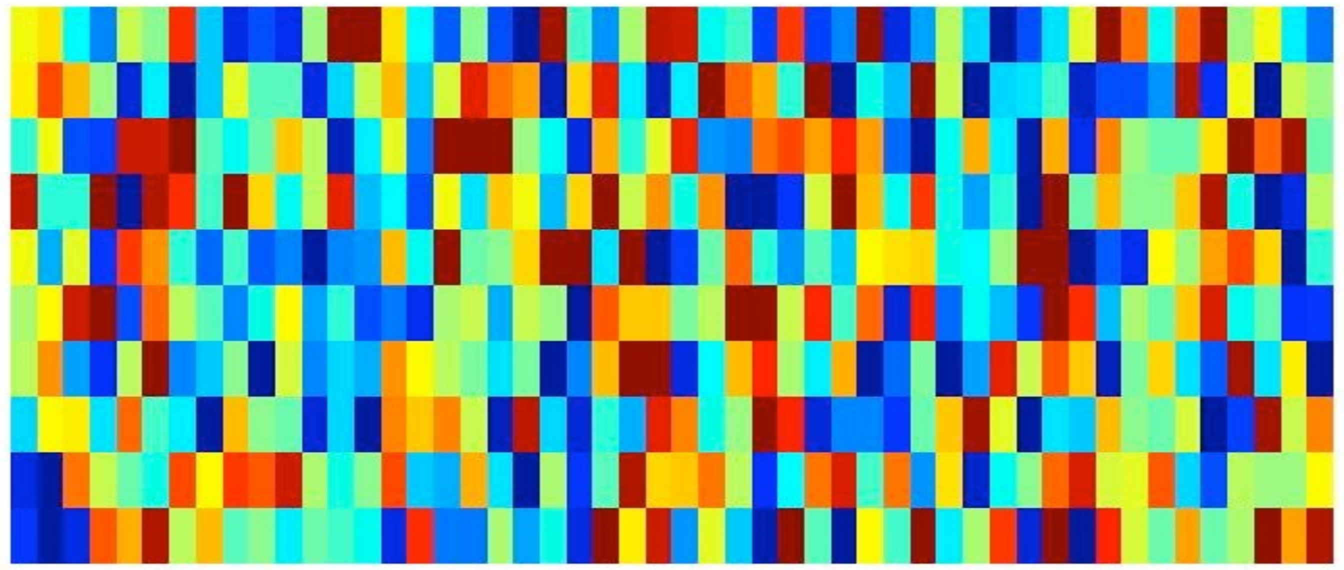

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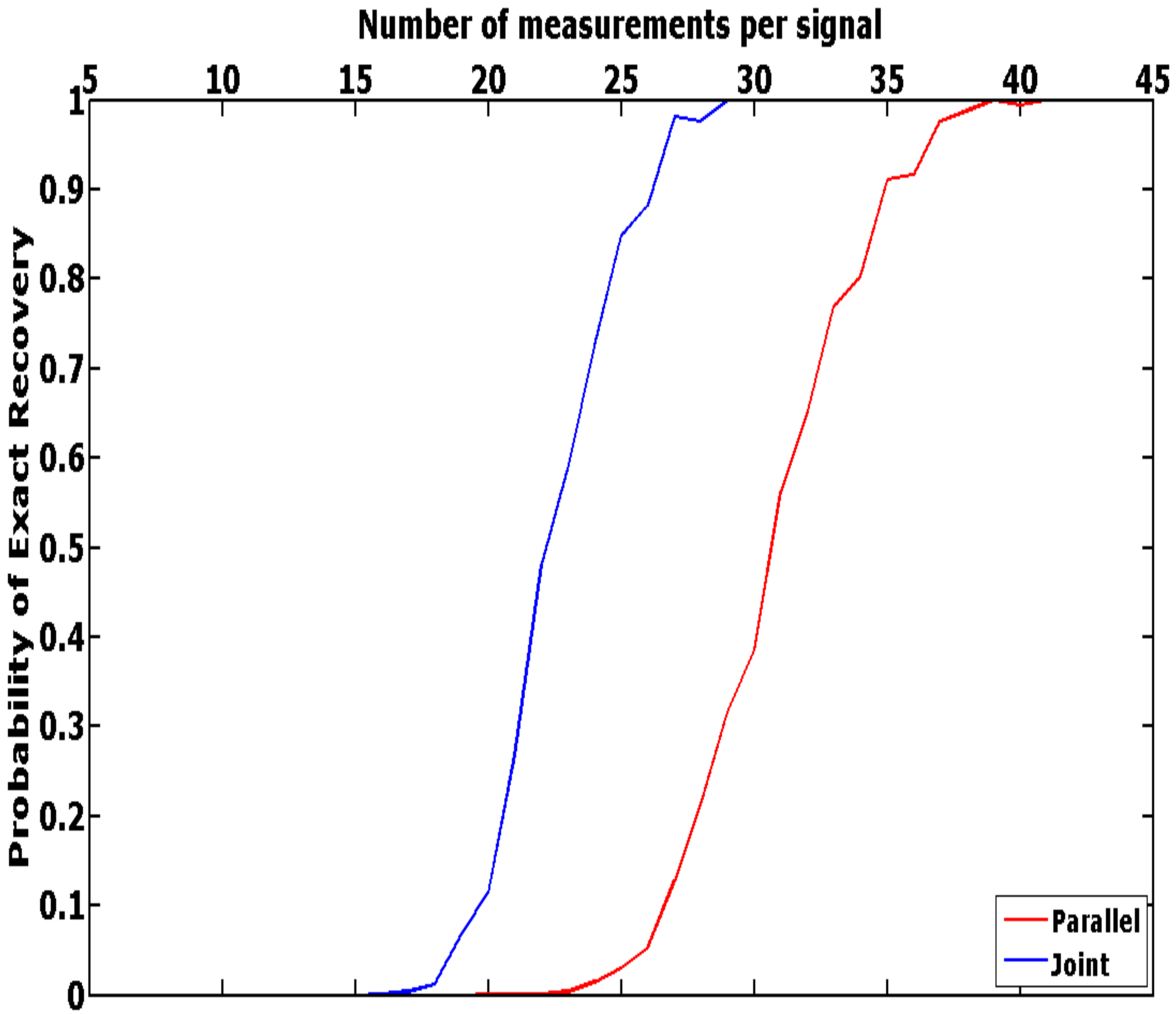
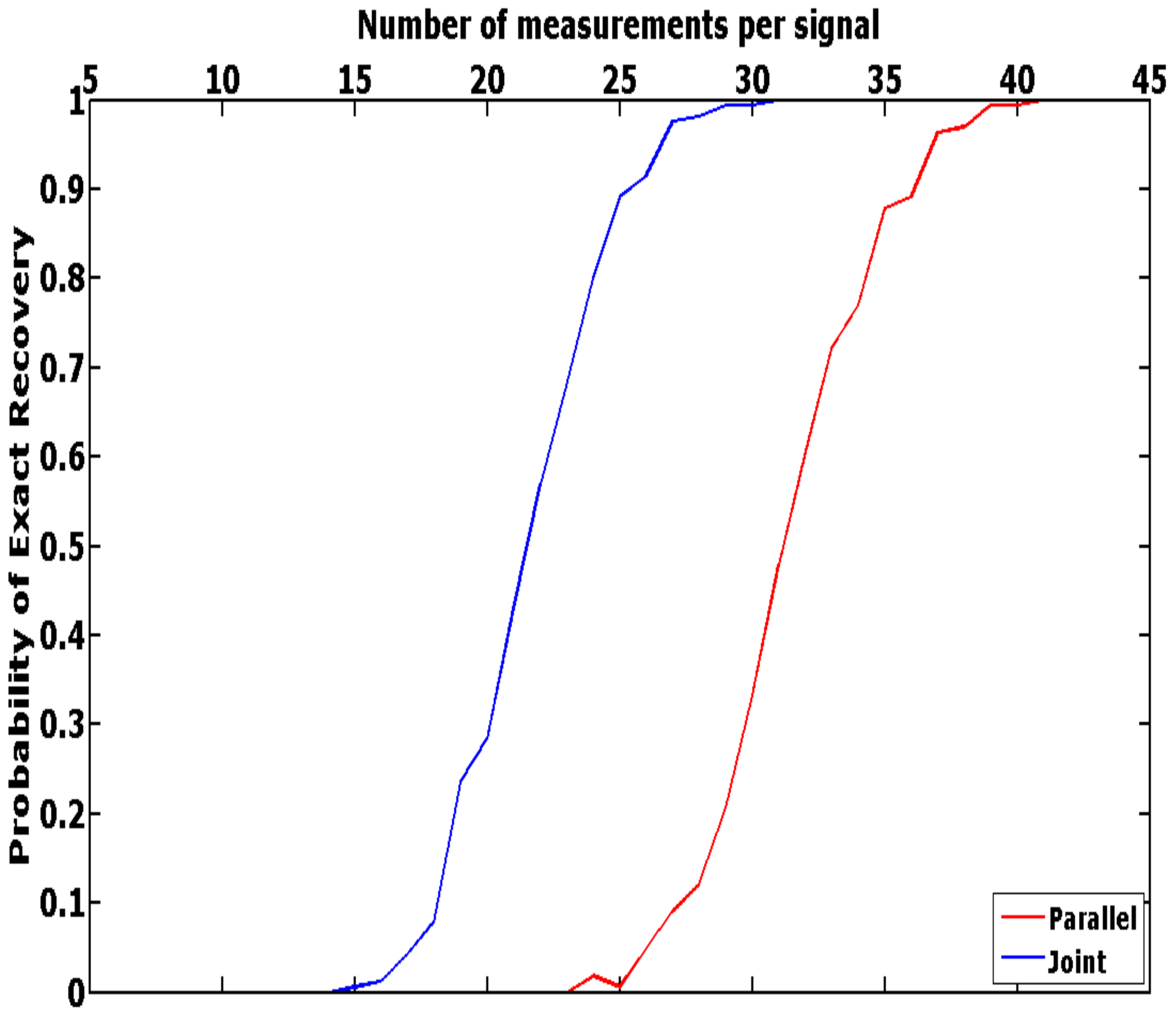
Compute Probability of recovery

Results : *parallel* versus *joint* recovery



Recovery of the vintages



Recovery of the difference

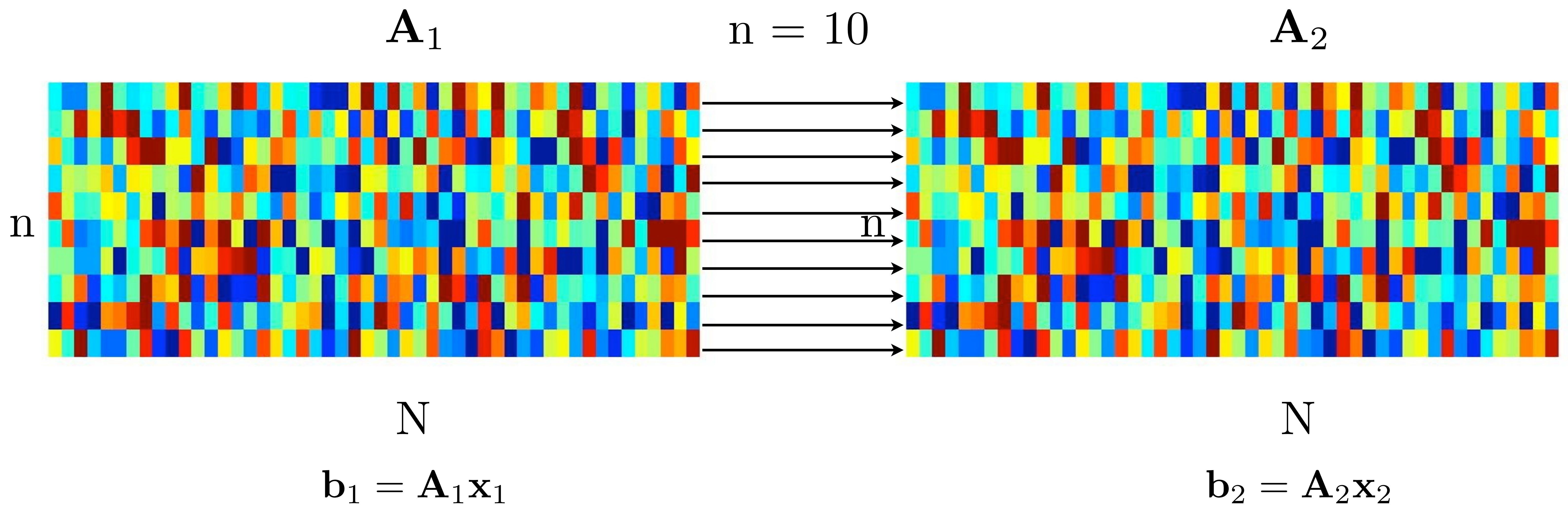
Observations

Joint recovery method is better than parallel because it exploits the shared information in the data

Fewer samples required with joint recovery

With exact repetition

$$\mathbf{A}_1 = \mathbf{A}_2$$



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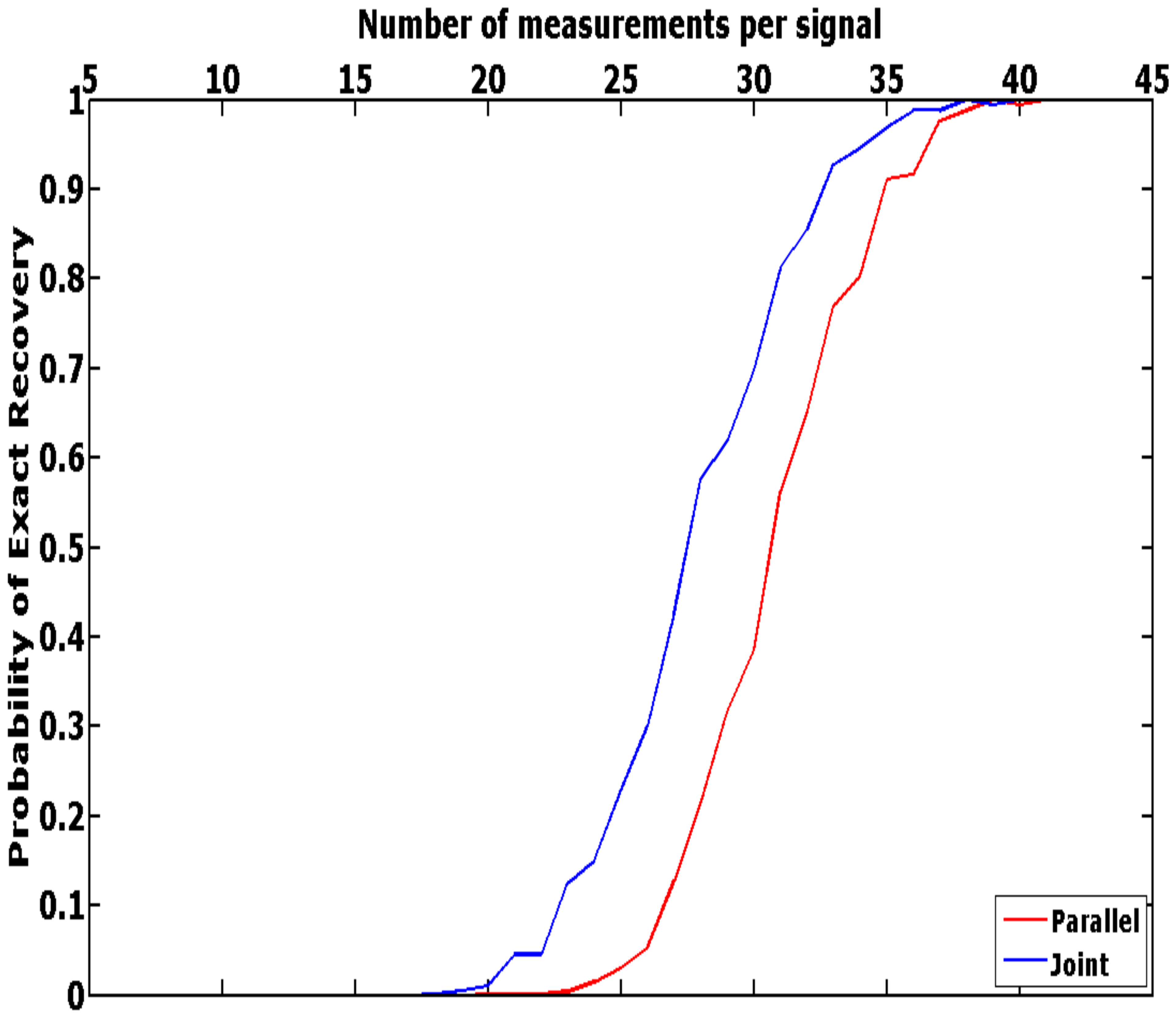

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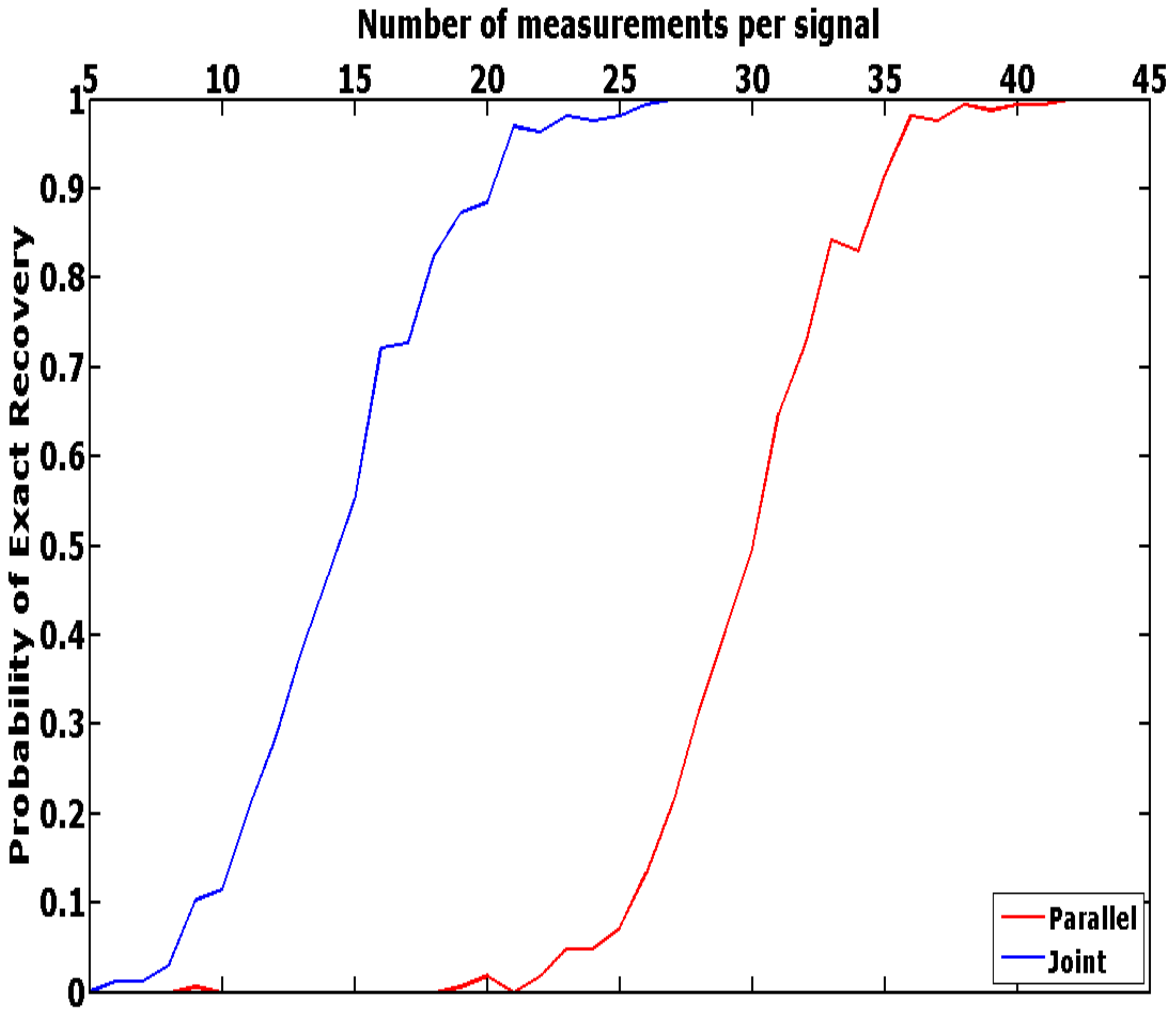

Recovery of the difference

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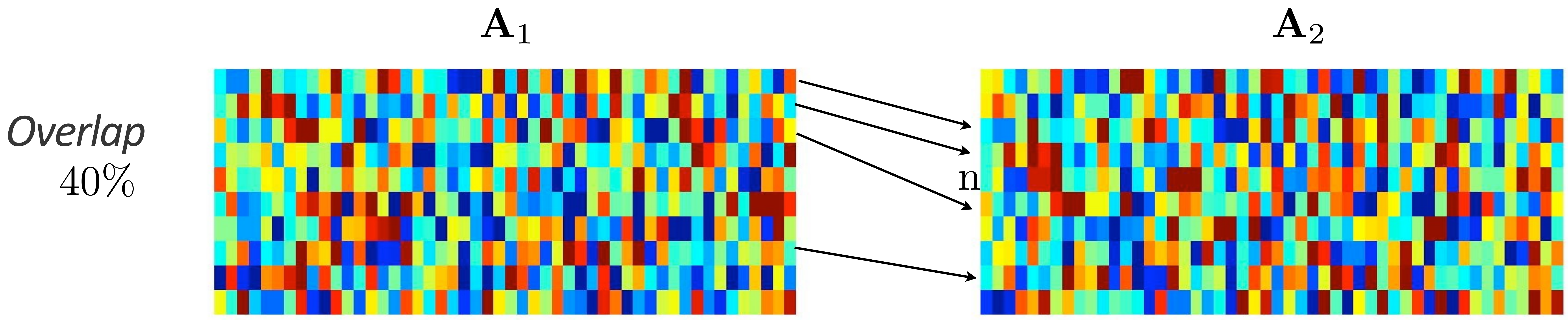
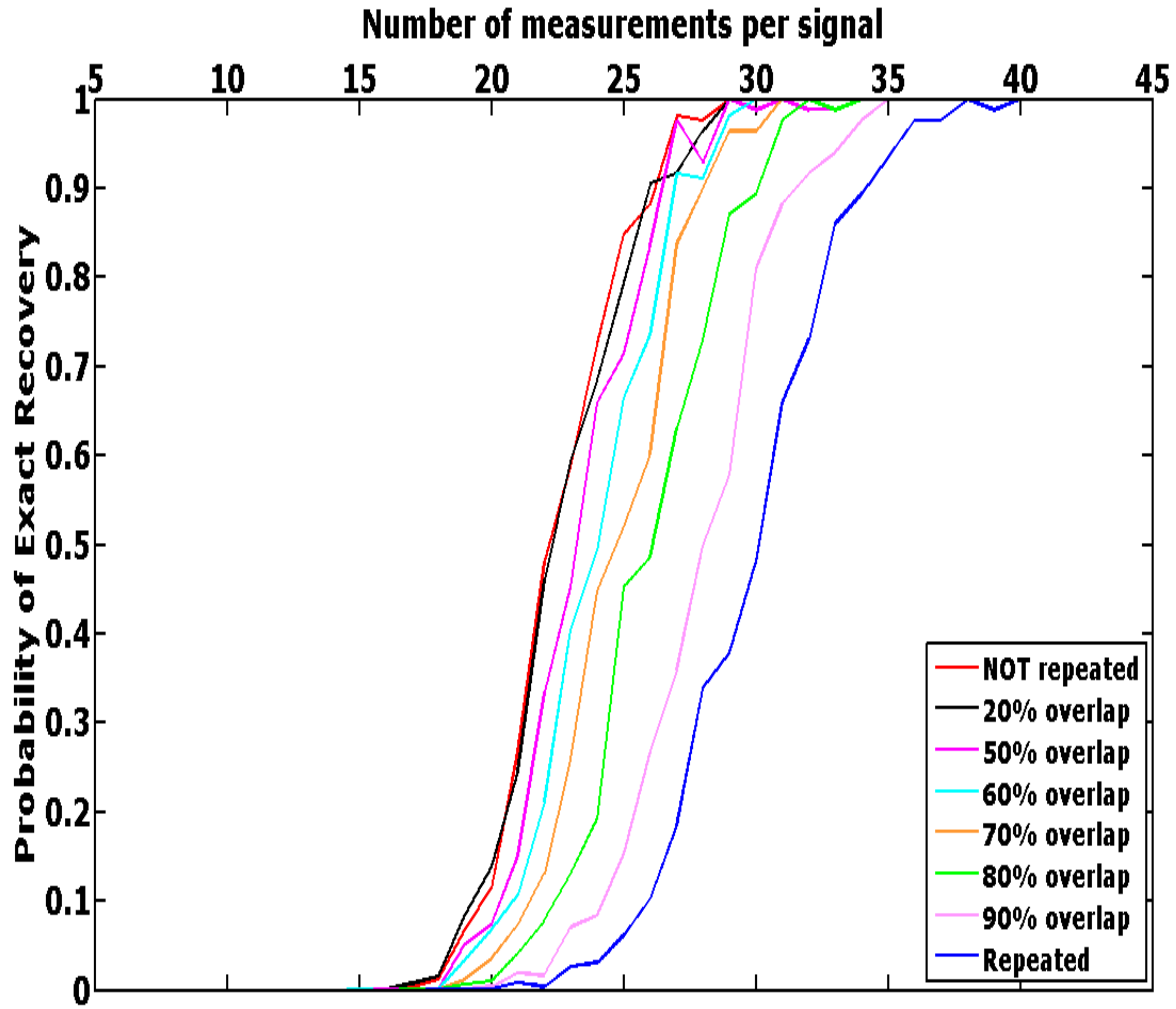


Results : recovery and overlap dependency



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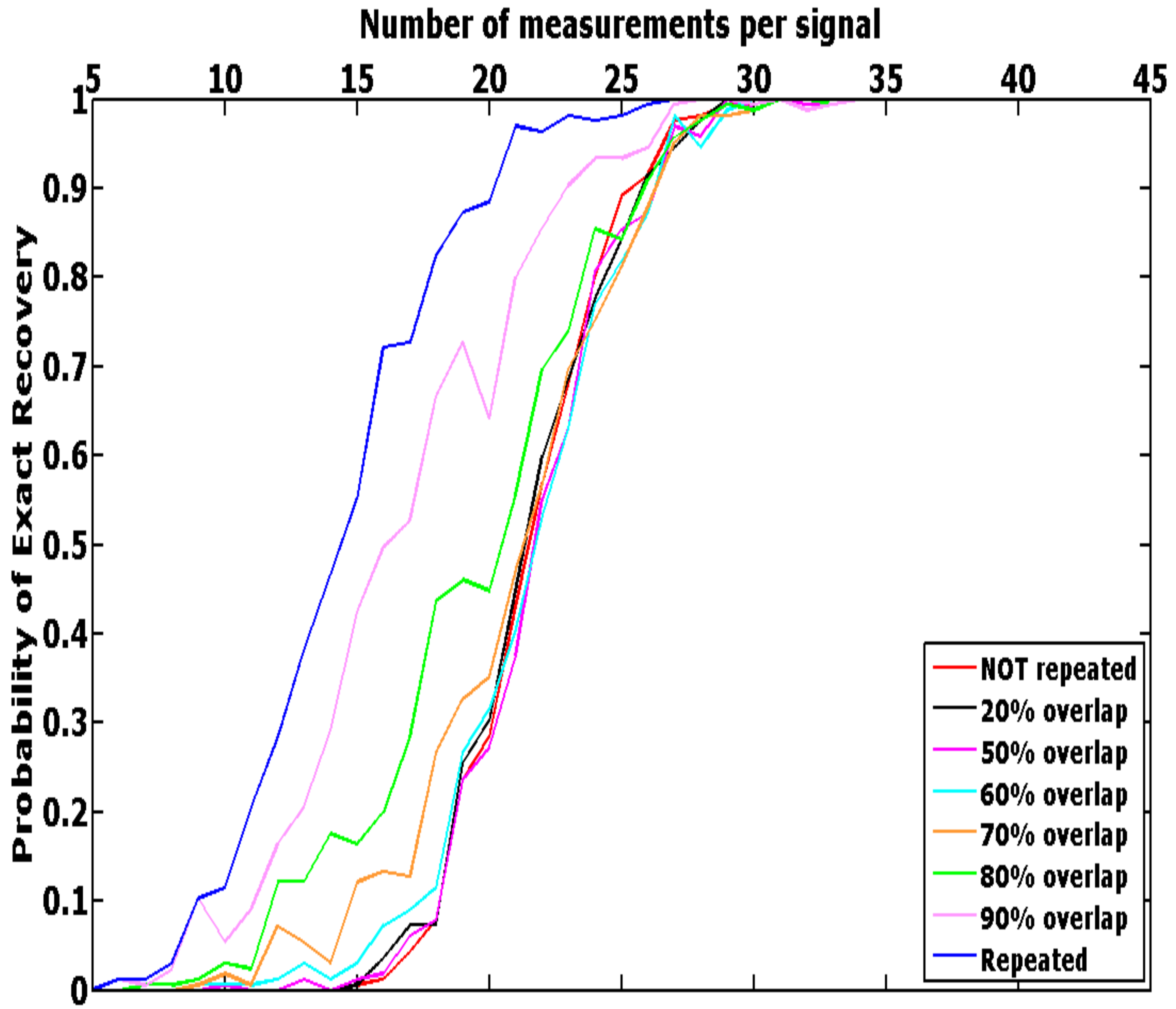

Recovery of the difference

Interpretation from the stylized example

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- *Joint recovery model (JRM) is always superior to the independent or parallel method*
- *As the degree of overlap between the sampling increases, the recovery of the signals gets worse.*
- *Time-lapse signal recovery benefits from some overlap*

Time-jittered marine acquisition

- Application to time-lapse seismic

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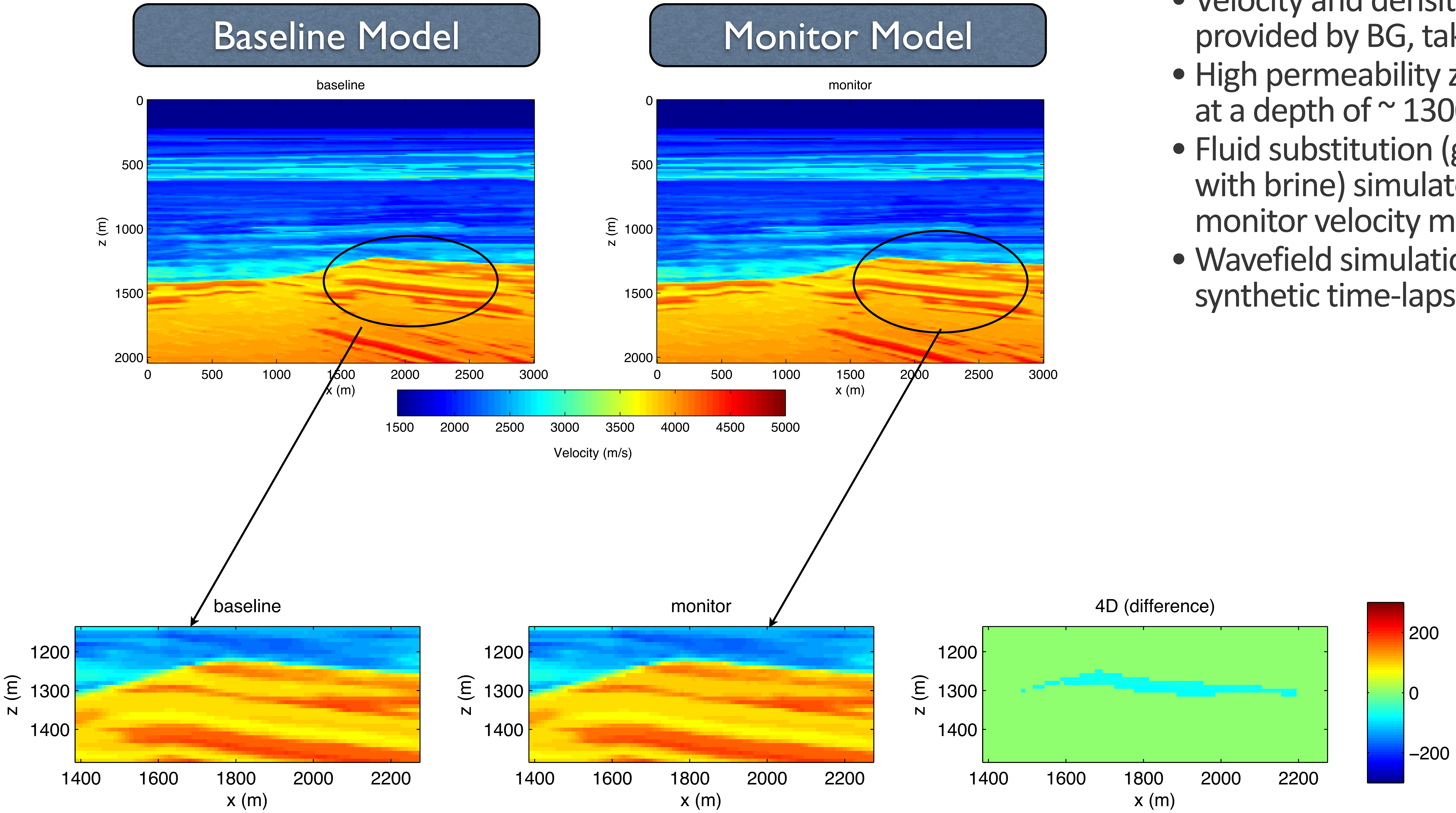
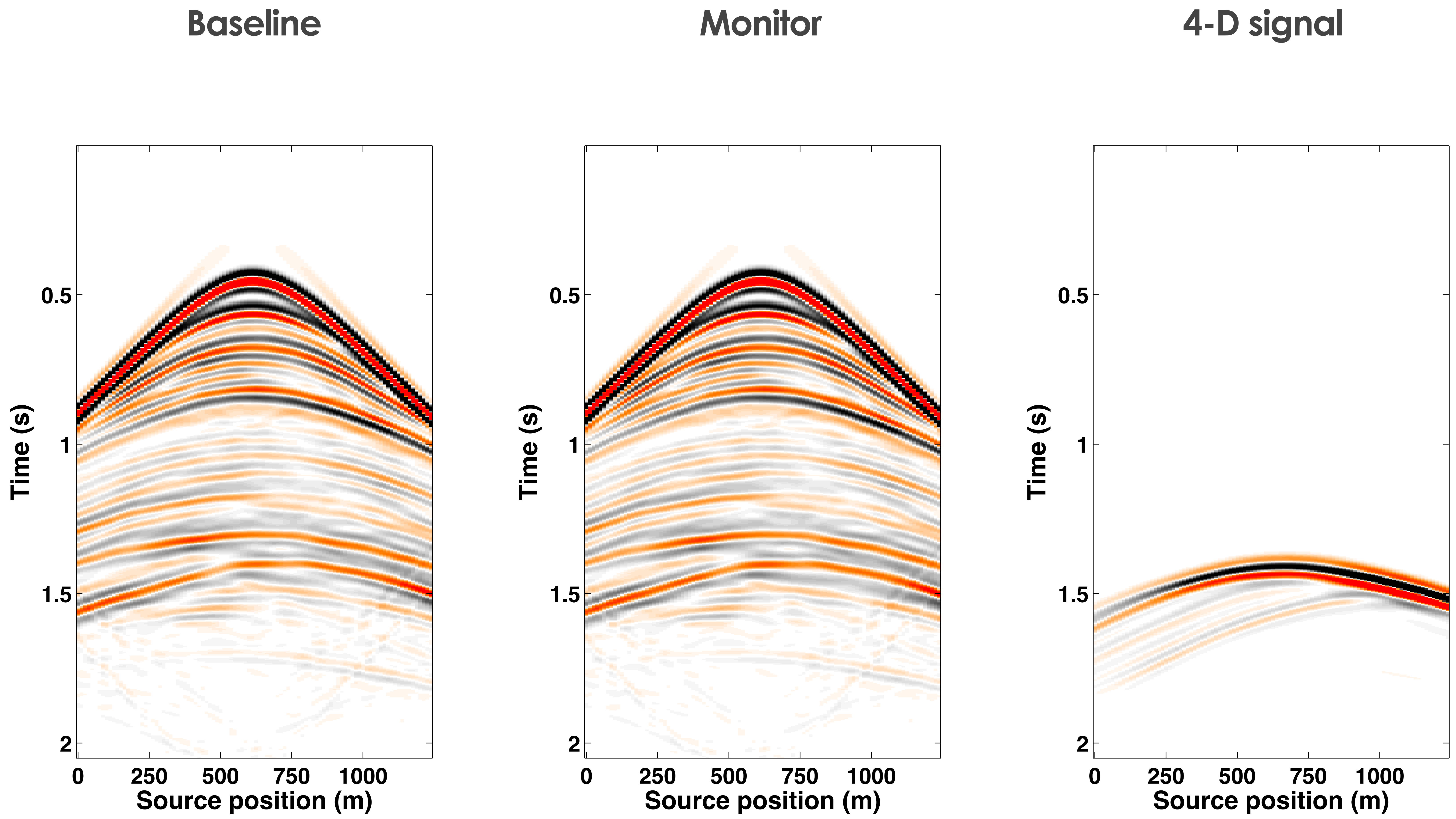


Method

- Velocity and density model provided by BG, taken as baseline
- High permeability zone identified at a depth of ~ 1300m
- Fluid substitution (gas/oil replaced with brine) simulated to derive monitor velocity model
- Wavefield simulation to generate synthetic time-lapse data

Simulated original data
– time-domain finite differences



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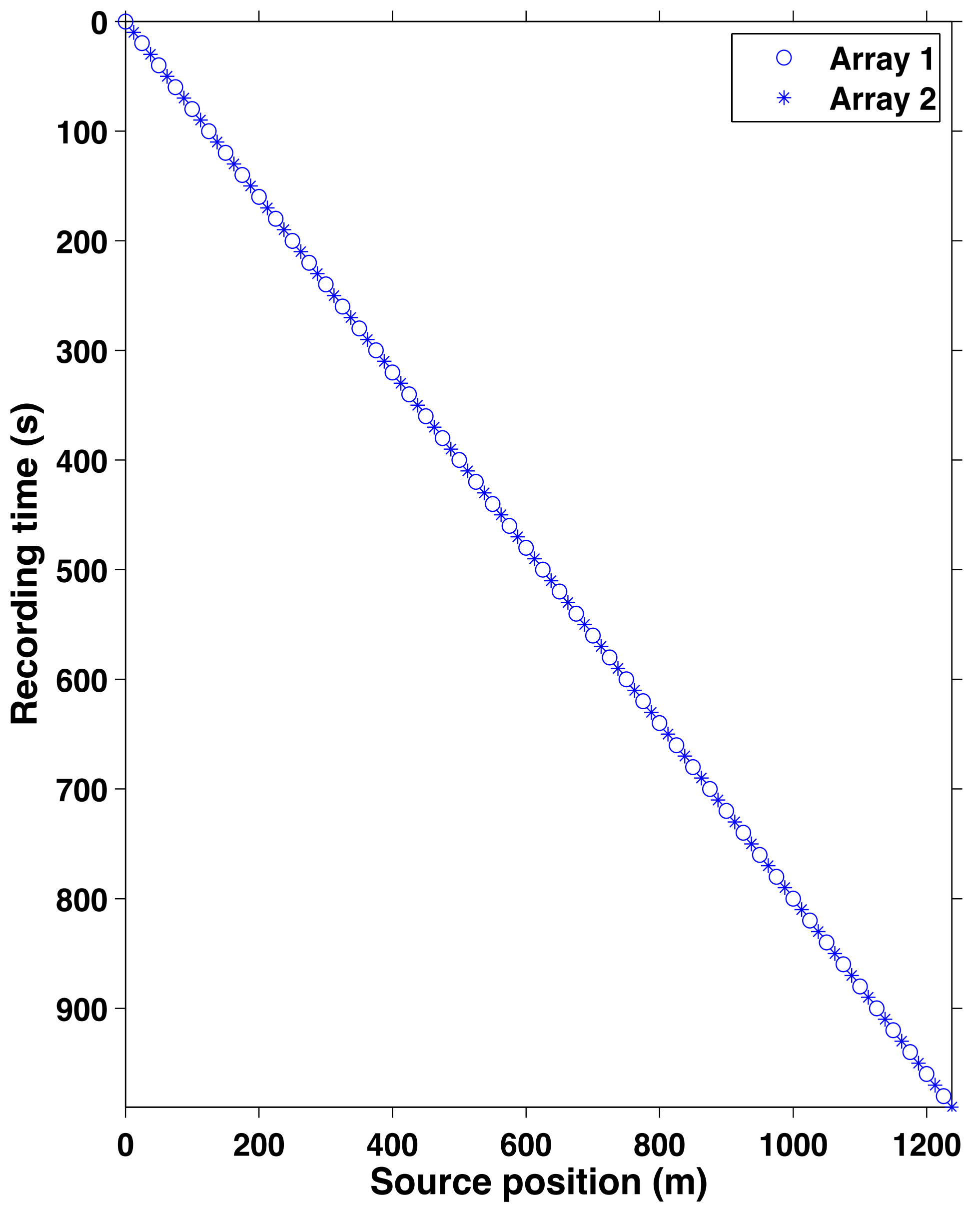
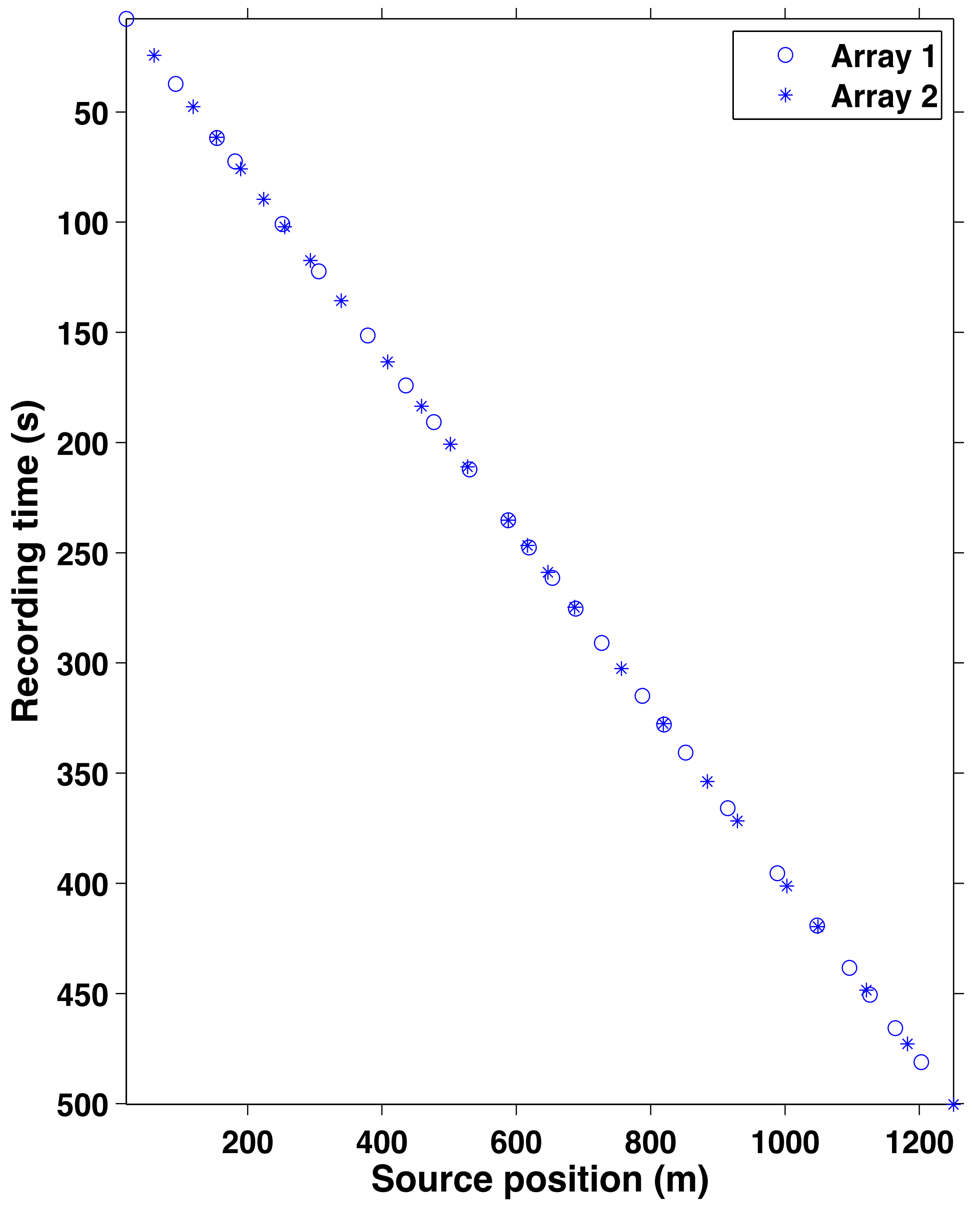
Conventional vs. *time-jittered* sources

– *undersampling* ratio = 2, 2 source arrays

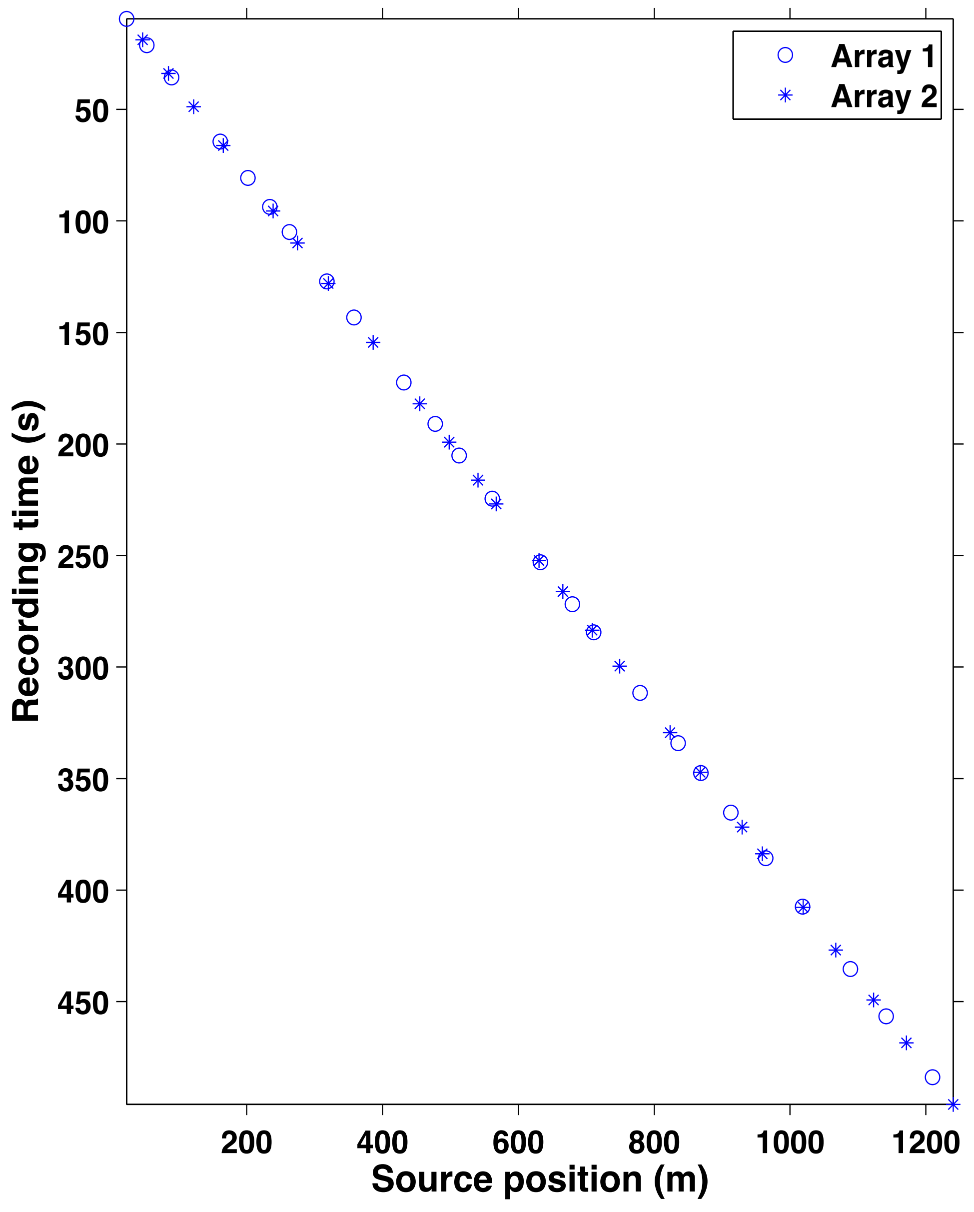
conventional



jittered acquisition 1
(for baseline)



jittered acquisition 2
(for monitor)



shorter acquisition time

geometry is not the same

Sample baseline and monitor randomly and independently

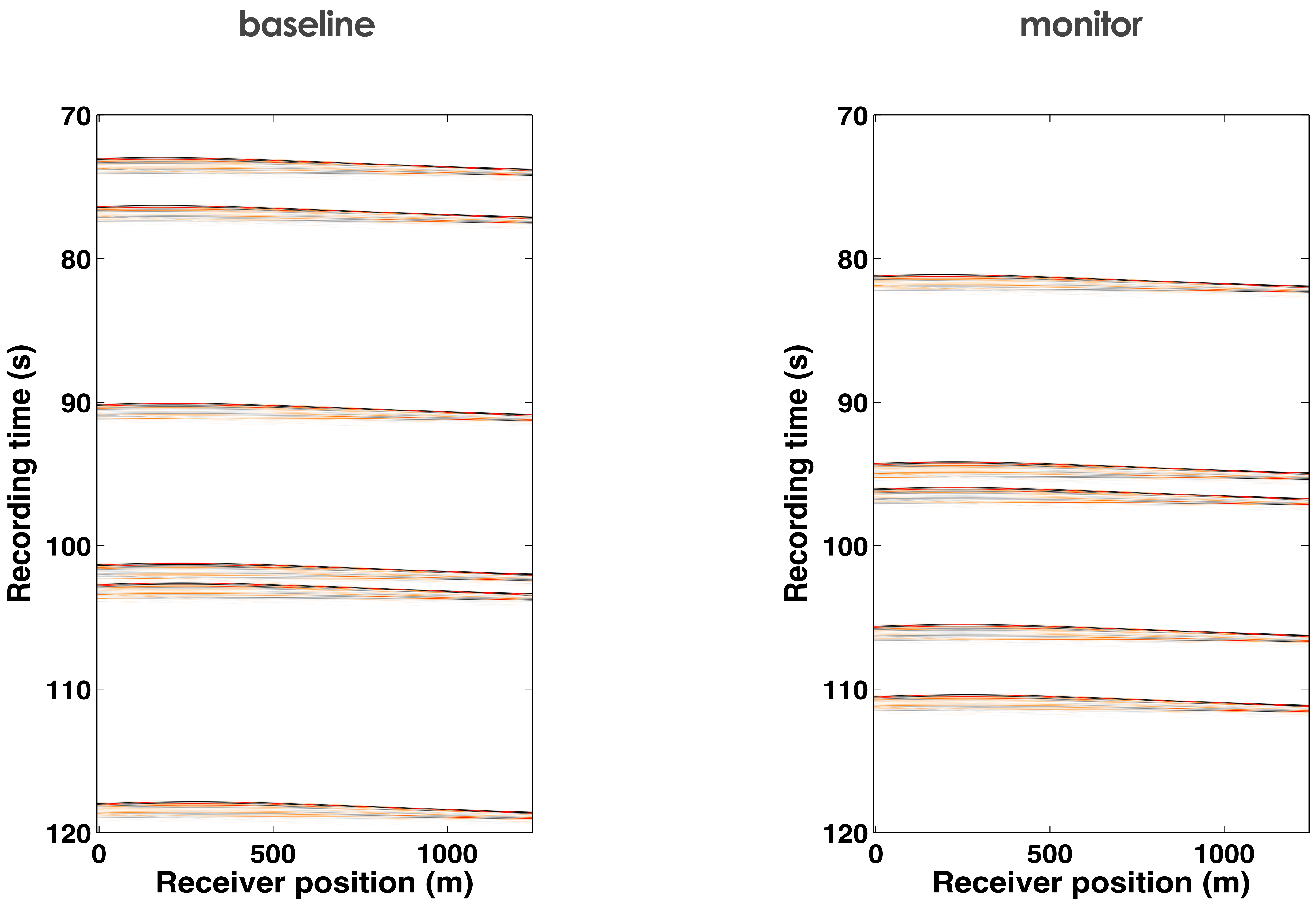
Parallel processing

Joint processing

Compare results

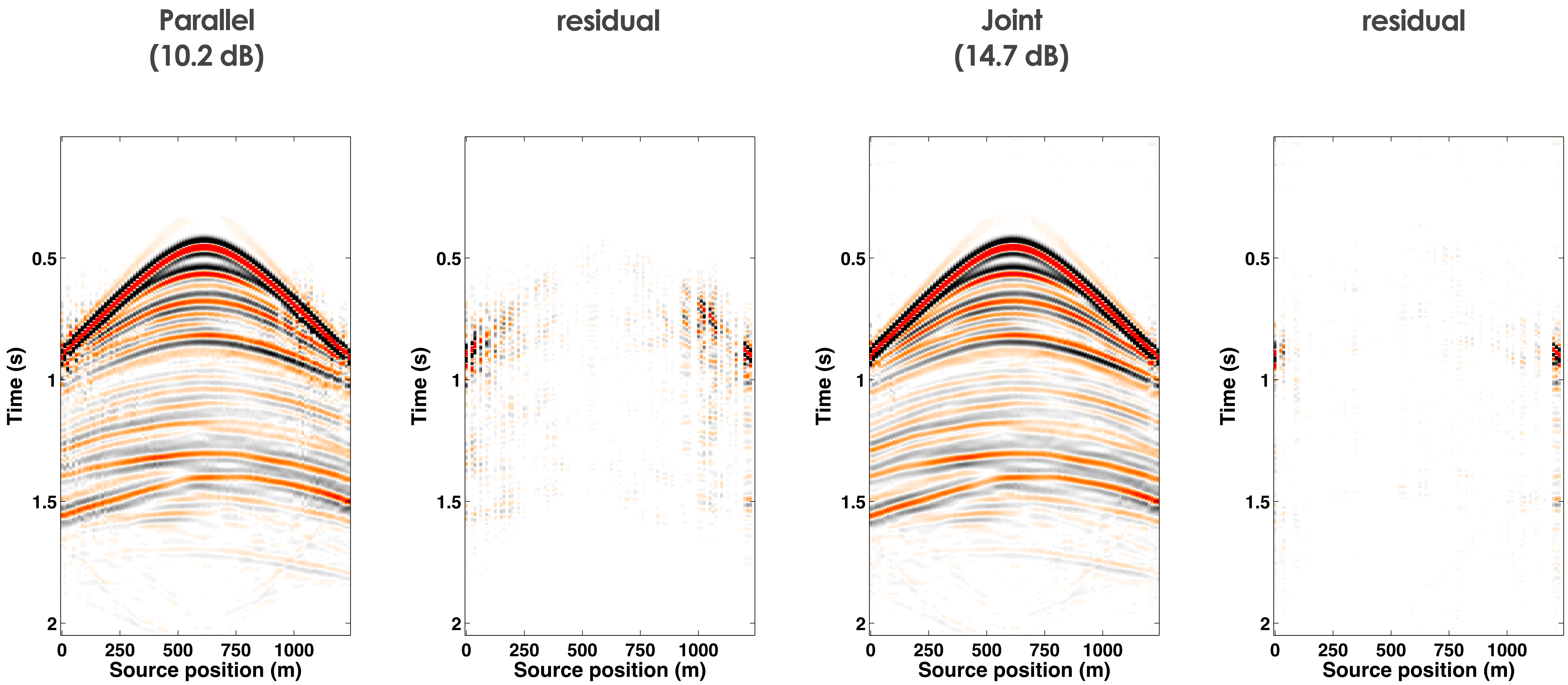
Repeat experiment for different overlap in source points

Measurements
– *undersampled* and *blended*



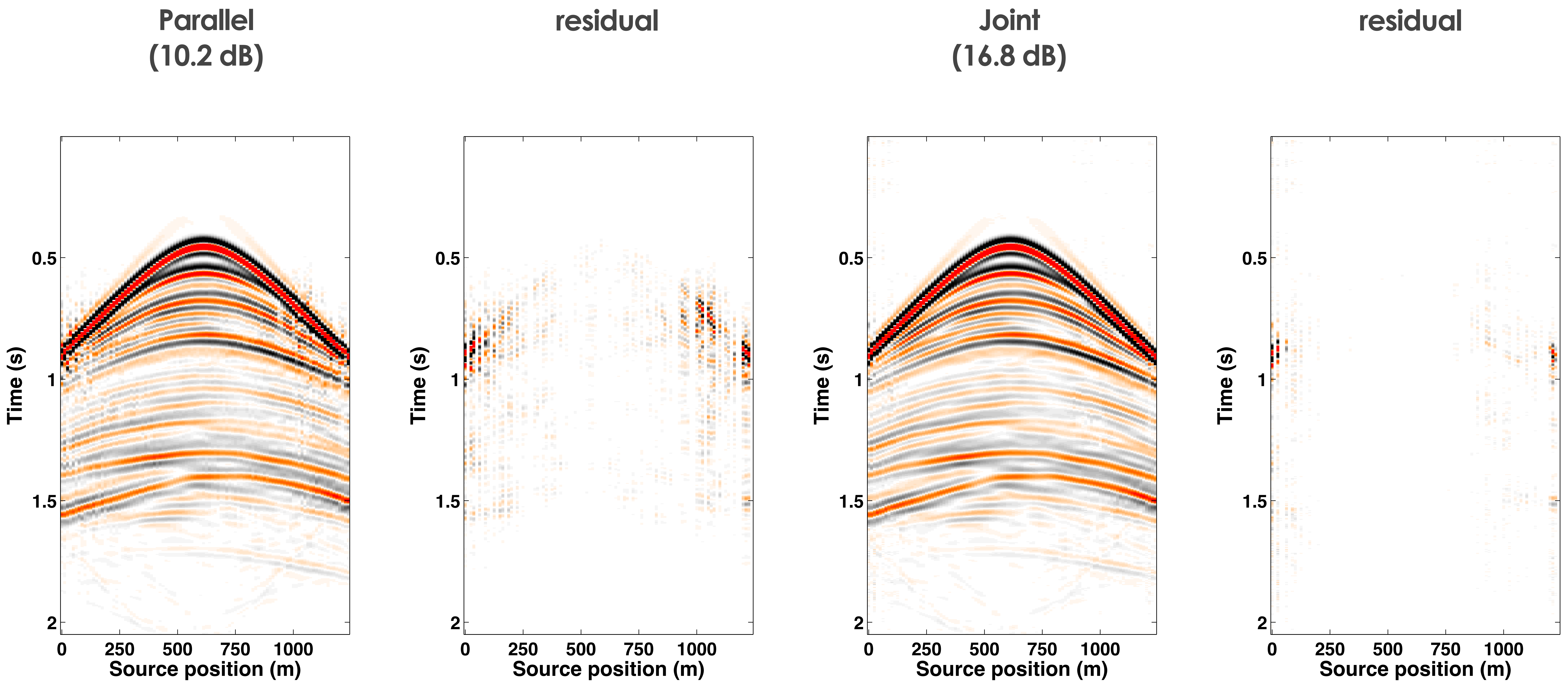
Baseline recovery

– 50% overlap in *acquisition* matrices

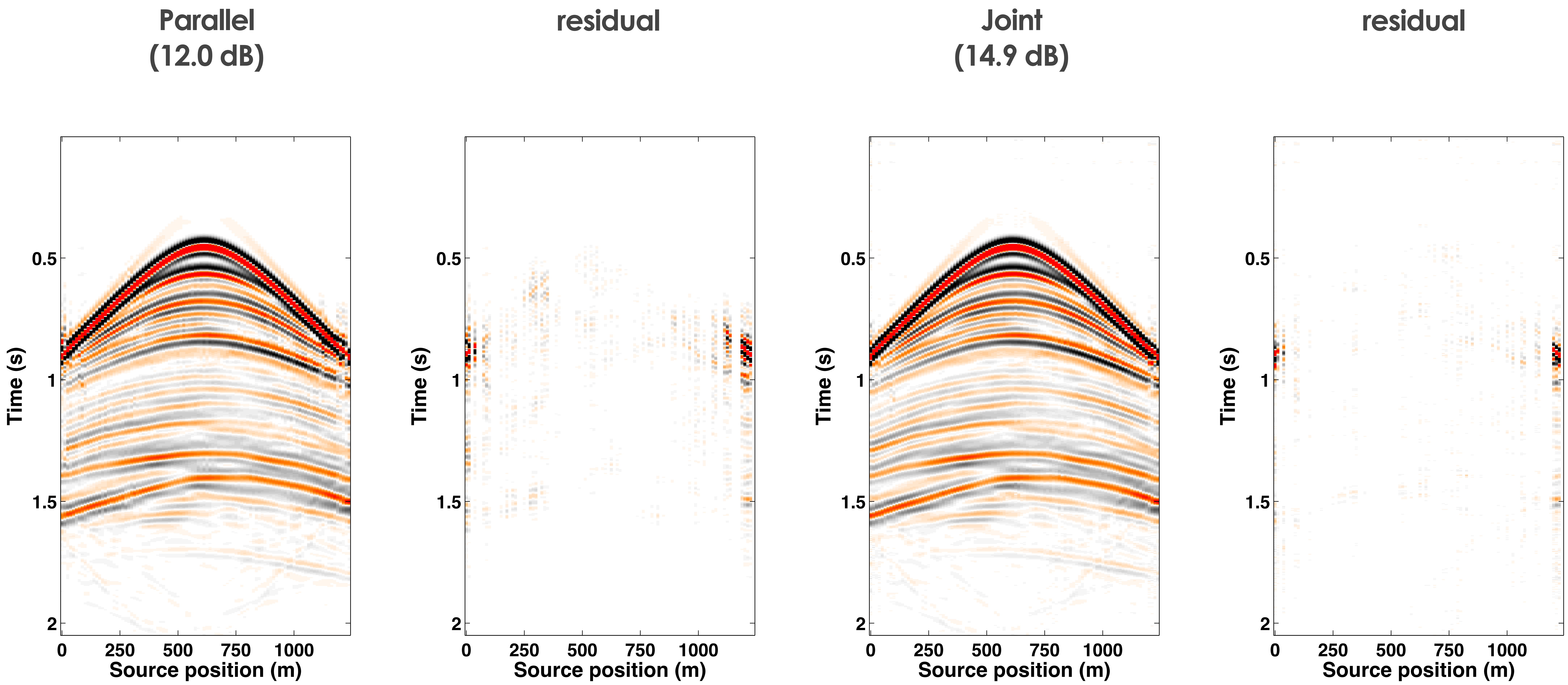


Baseline recovery

– 20% overlap in *acquisition* matrices



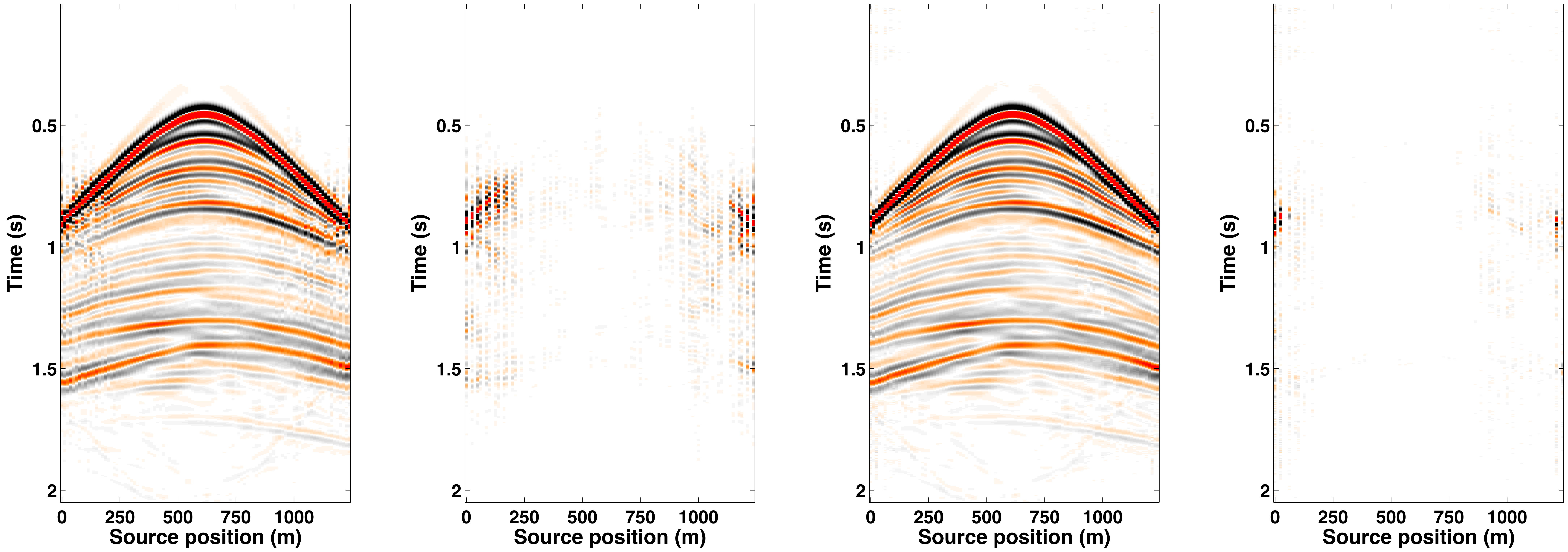
Monitor recovery
– 50% overlap in *acquisition* matrices



Monitor recovery

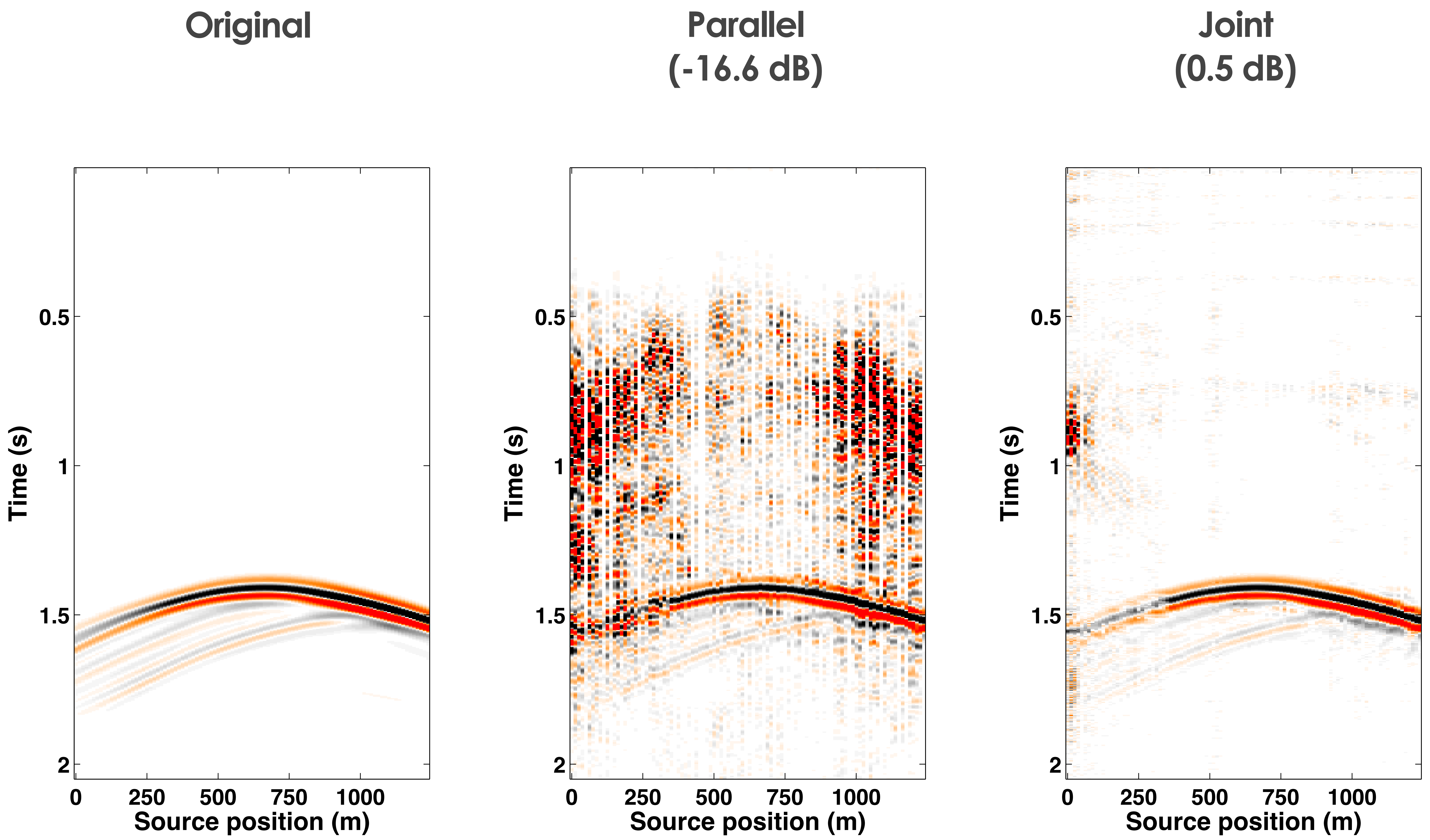
– 20% overlap in *acquisition* matrices

Parallel (10.2 dB) | residual | Joint (16.7 dB) | residual



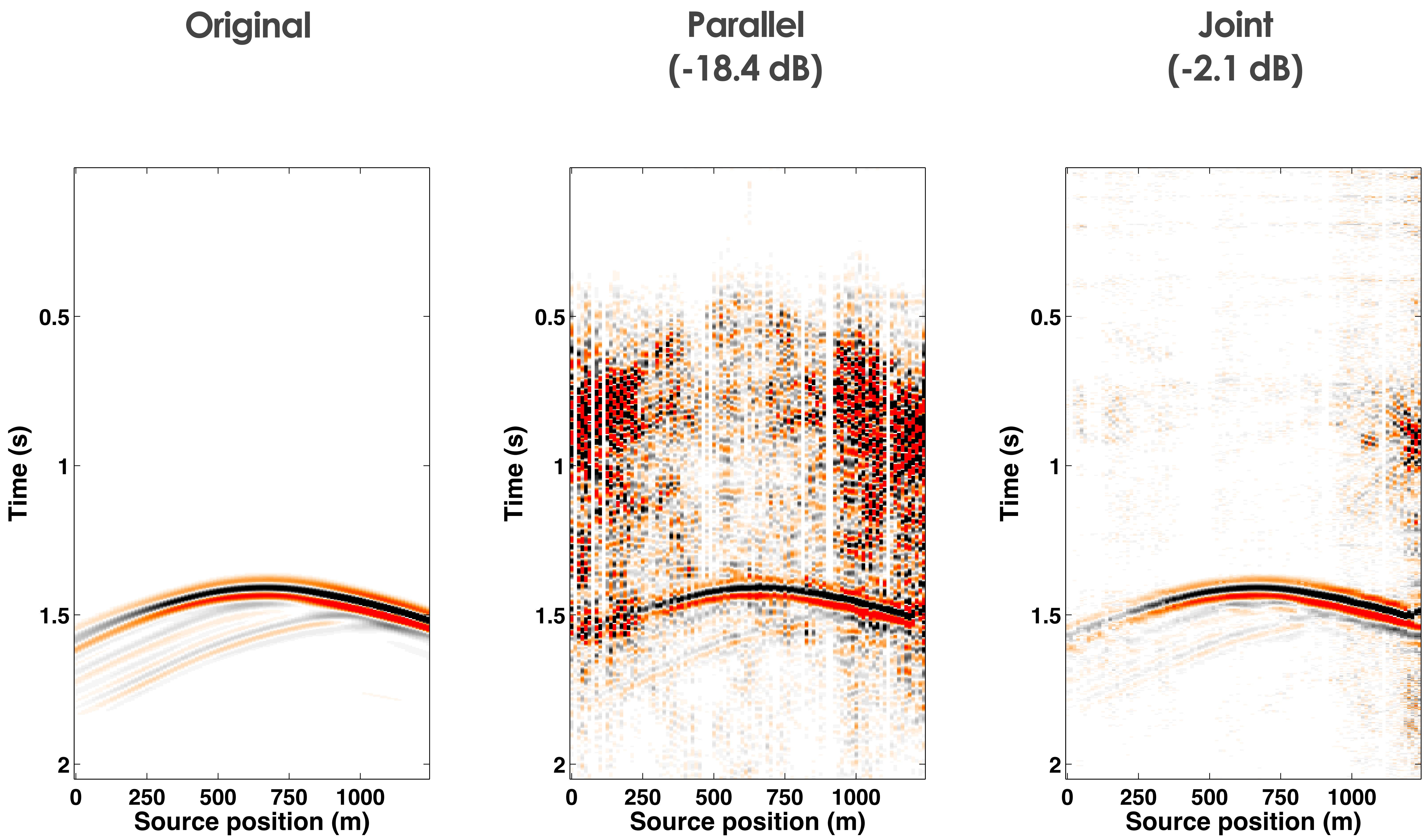
4-D recovery

– 50% overlap in *acquisition* matrices

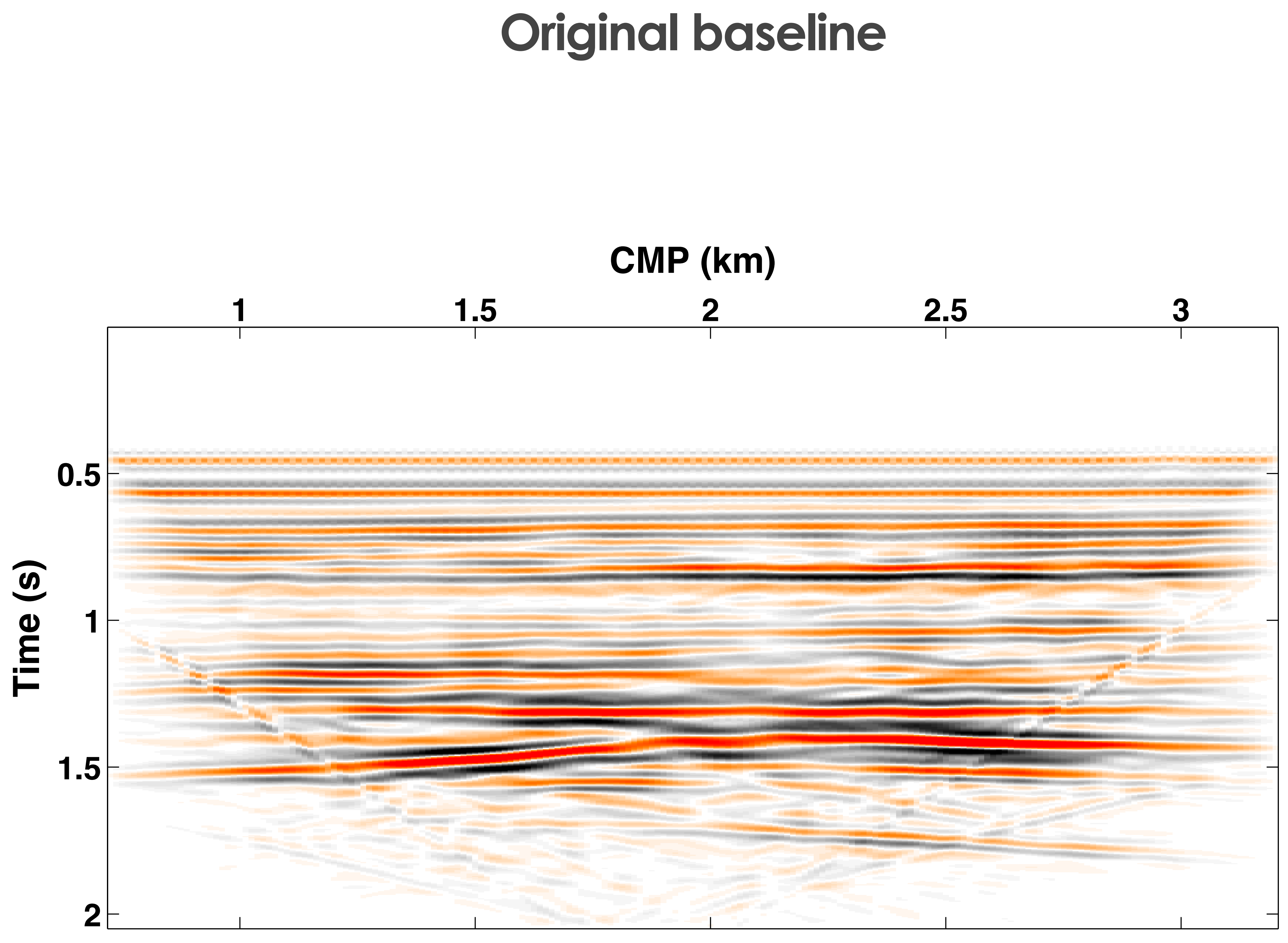


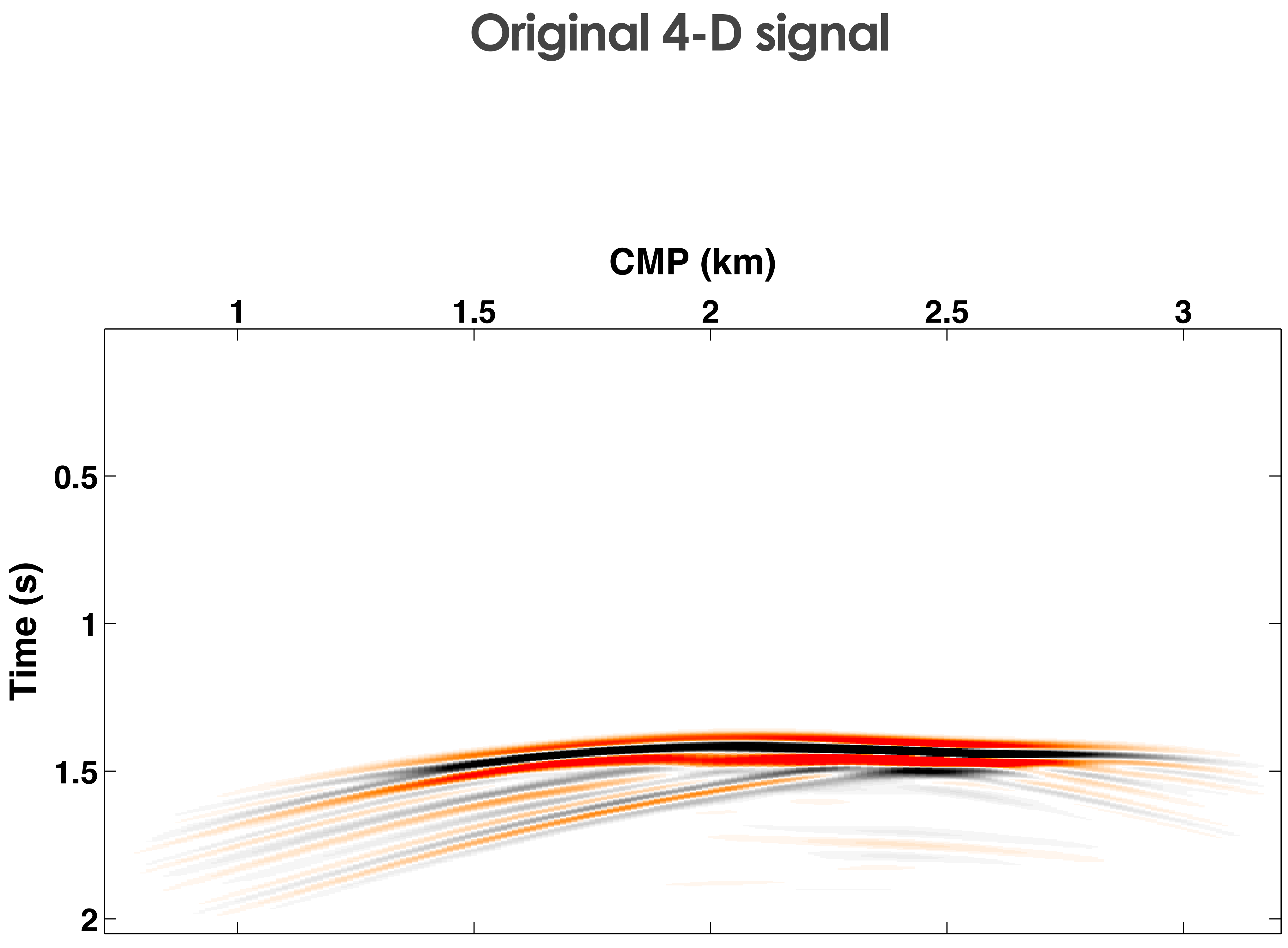
4-D recovery

– 20% overlap in *acquisition* matrices

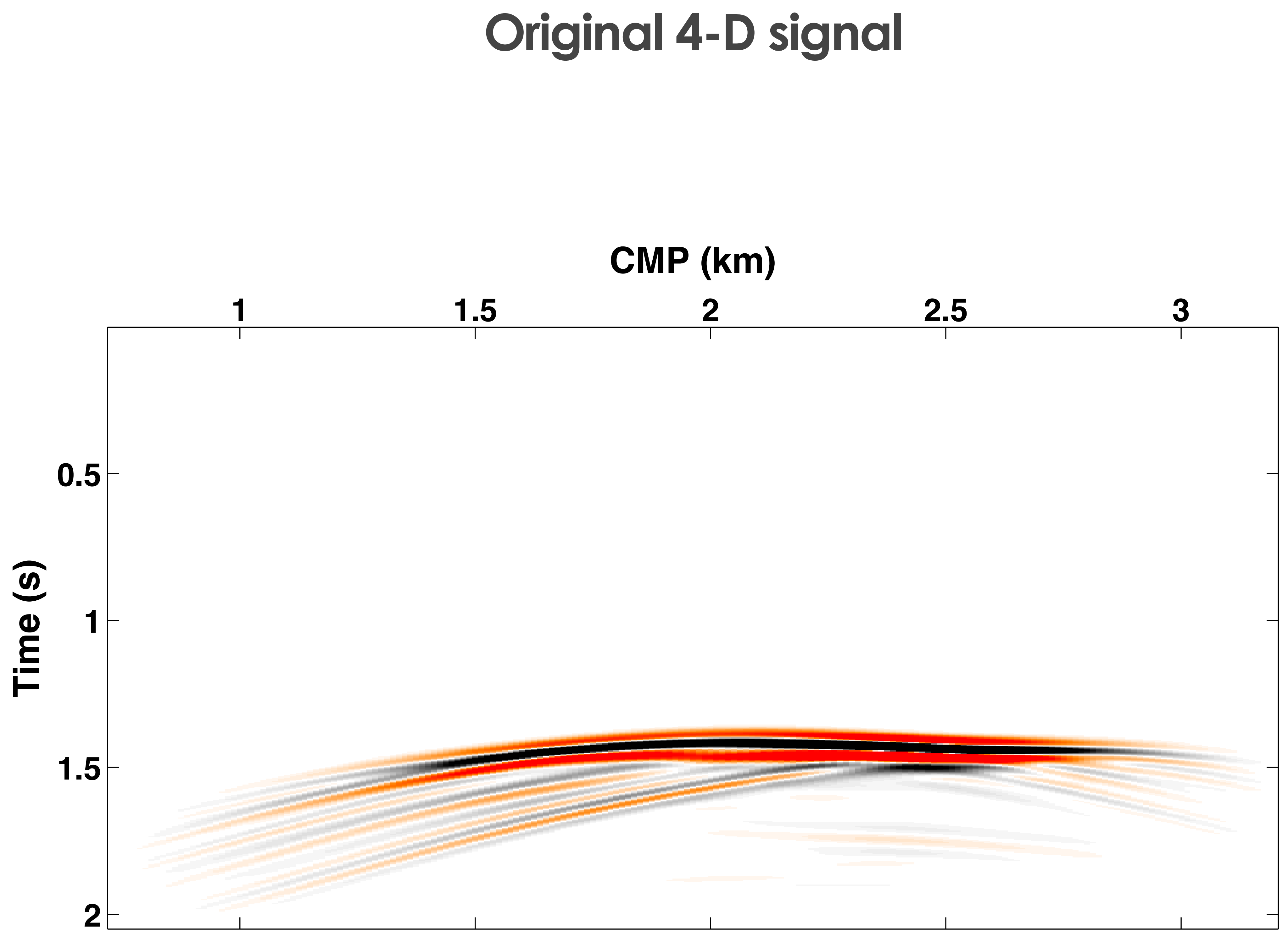


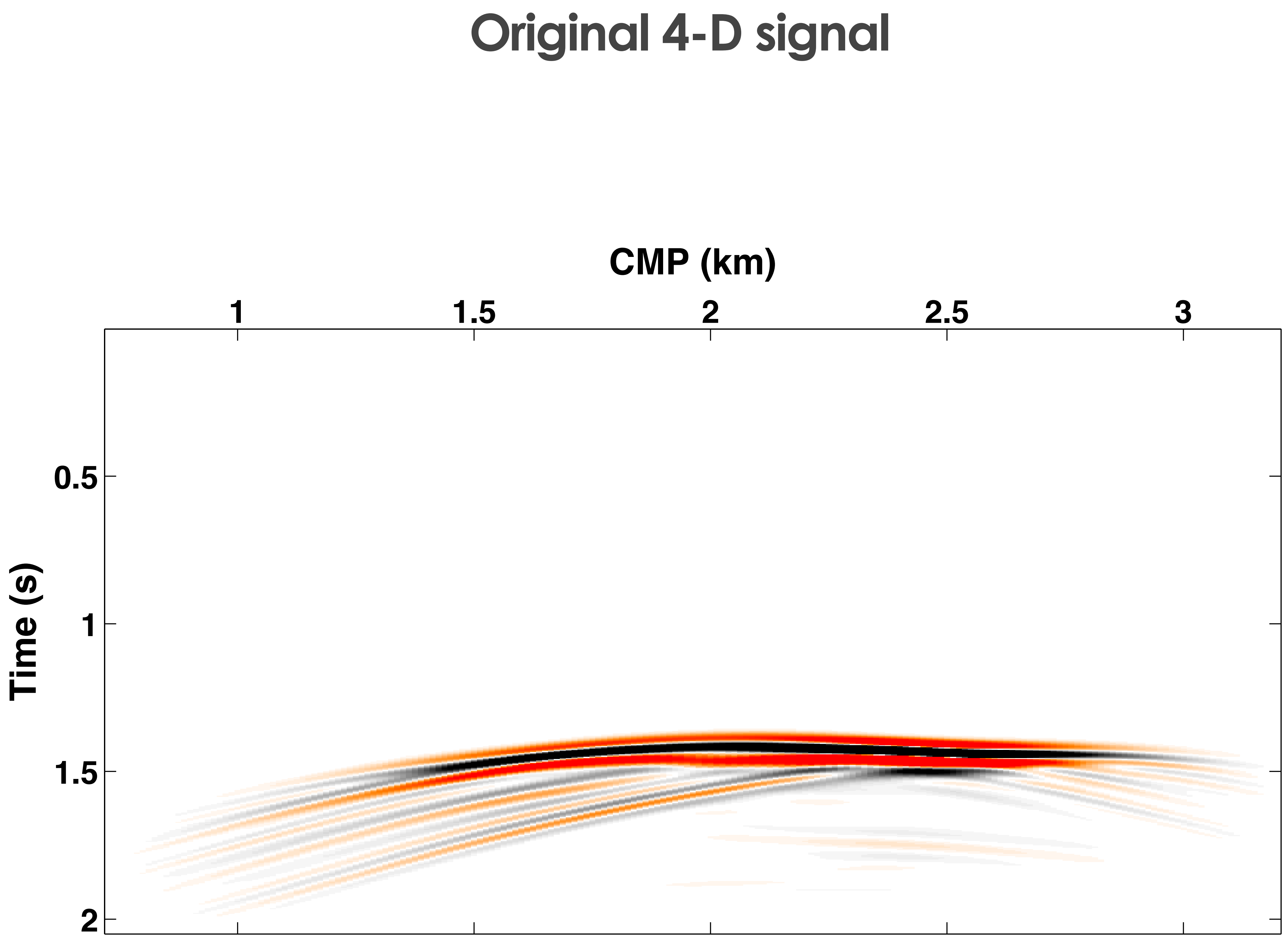
Stacked sections





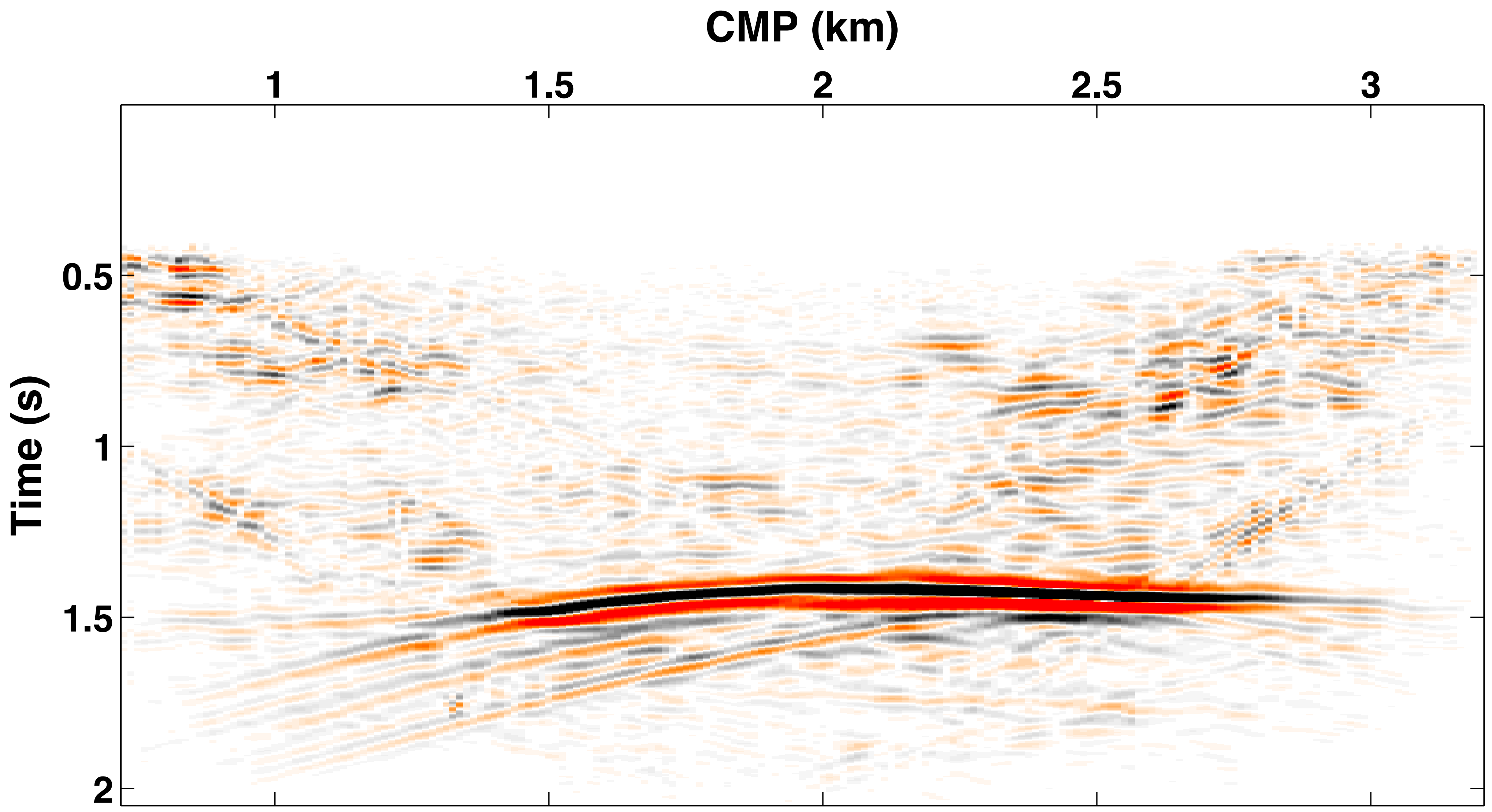
Stacked sections



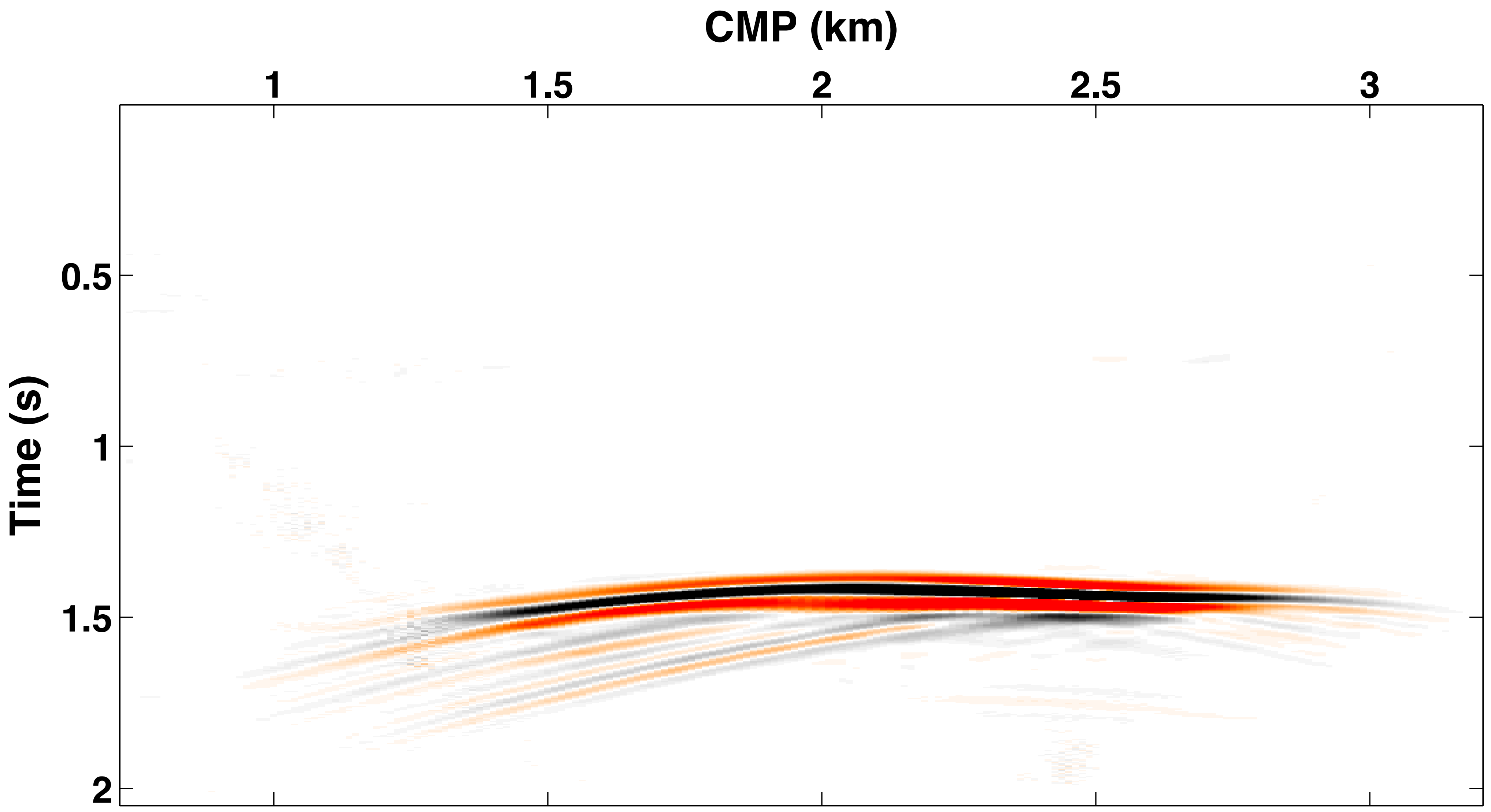


Stacked sections
– 50% overlap in *acquisition* matrices

Parallel
(9.7 dB)



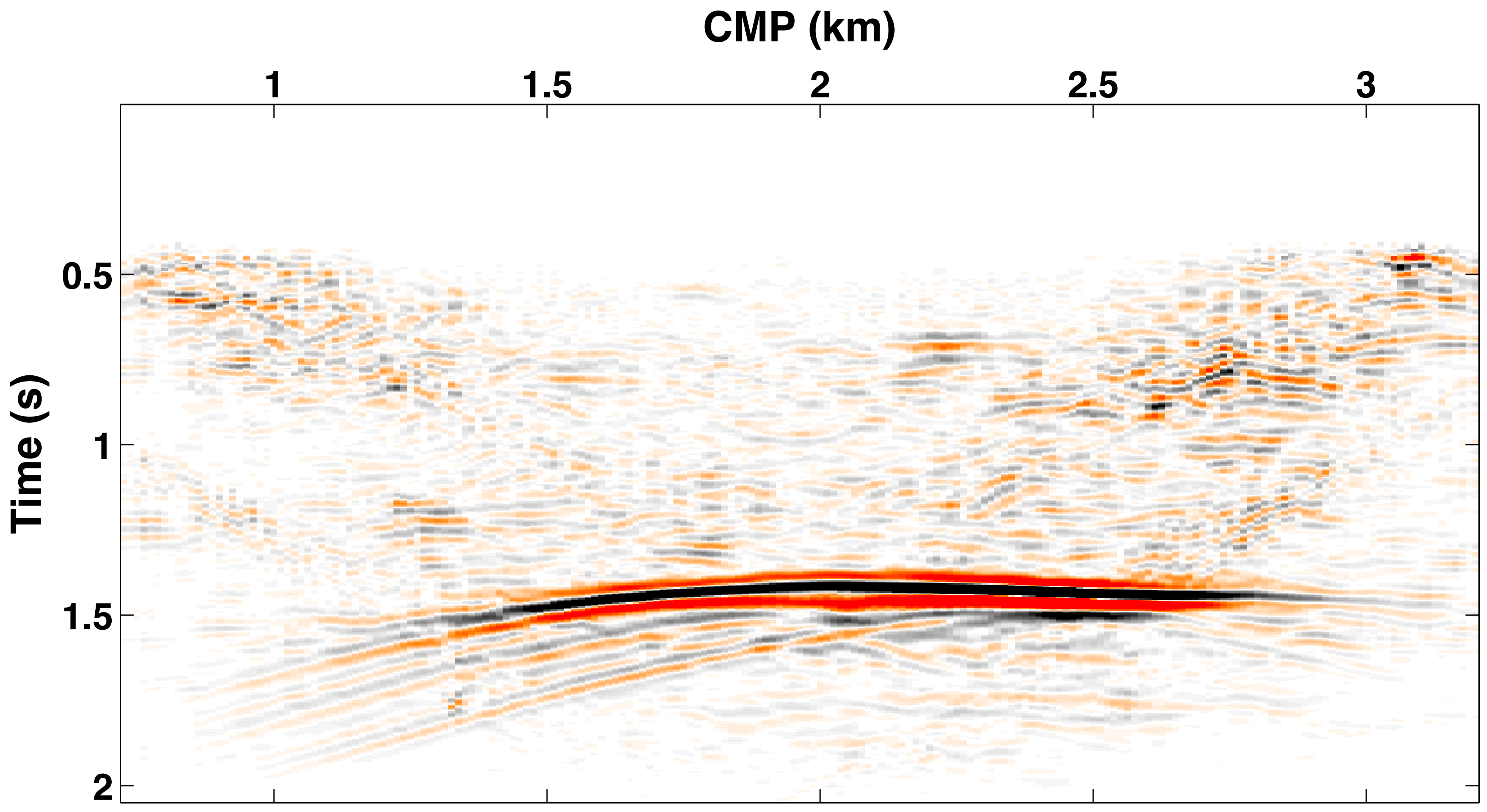
Joint
(18.2 dB)



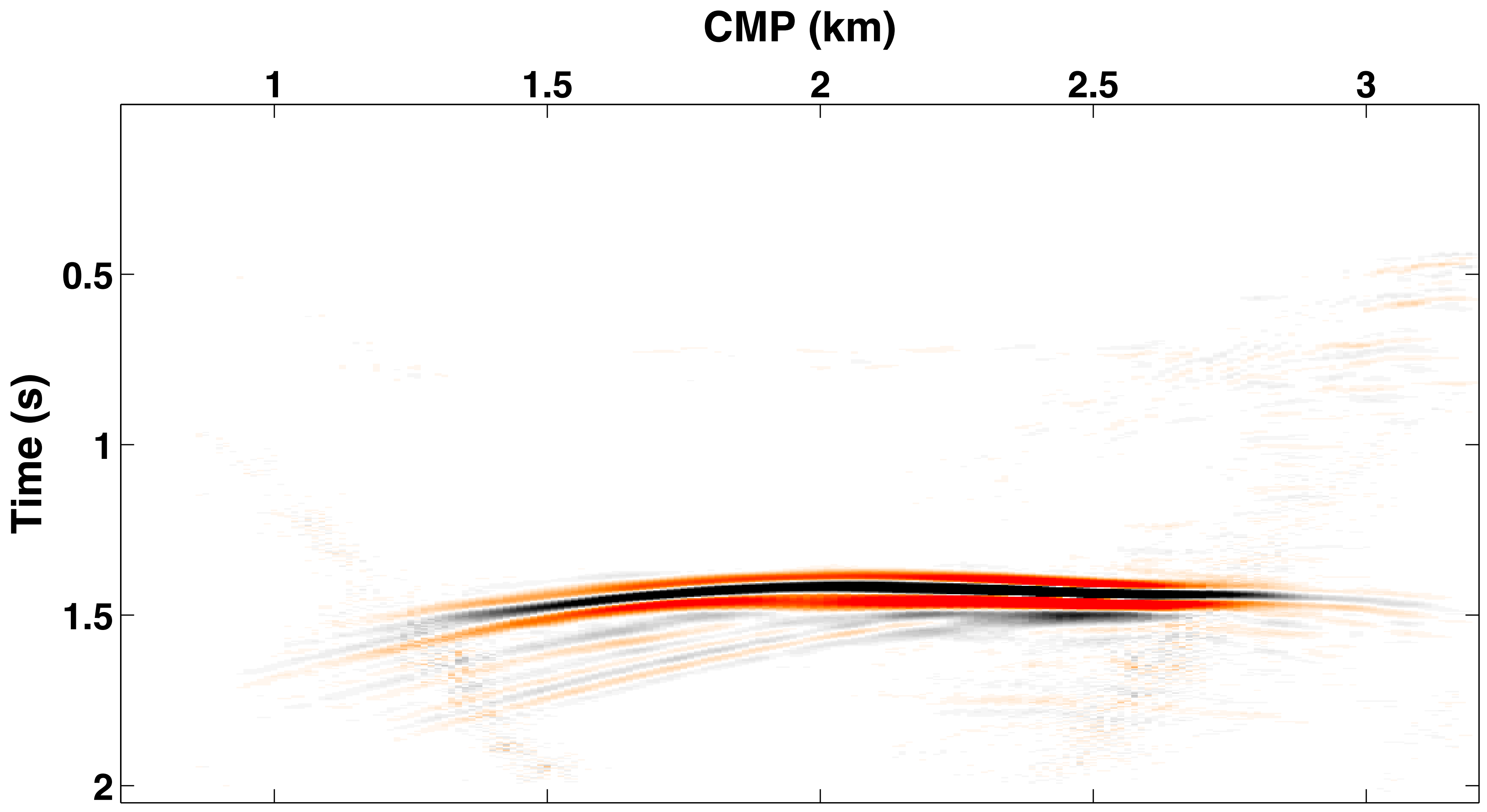
Stacked sections

– 20% overlap in *acquisition* matrices

Parallel
(10.2 dB)



Joint
(14.7 dB)



Summary (SNR (dB))

overlap	baseline		monitor		4-D signal	
	IRS	JRM	IRS	JRM	IRS	JRM
100%	23	21.6	23.1	21.7	22.7	22.4
50%	23	28.9	25.5	28.9	9.7	18.2
20%	23	31.8	23.5	31.9	10.2	14.7

Conclusions

- Randomized sampling techniques can be extended to time-lapse surveys
- It is better to process time-lapse data jointly than independently, in order to exploit shared information
- We can save cost via cheap randomized acquisition designs
- Resolving time-lapse signal from seismic data depends on the degree of repeatability, when the data is "highly" under-sampled
- Method can be extended to multiple surveys where we can use fewer measurements

Future Plan

- Detection of weak and strong 4D changes in noisy environments with high subsampling ratios
- Asymmetric measurement rates - skewed acquisition scenarios
- Incorporate joint reconstruction into wave-equation based inversion
- Extension to time-jittered marine surveys on a non-uniform sampling grid
- Performance of recovery method on noisy data

Acknowledgements

We need 4D data !

Thank you for your attention !

https://www.slim.eos.ubc.ca/

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