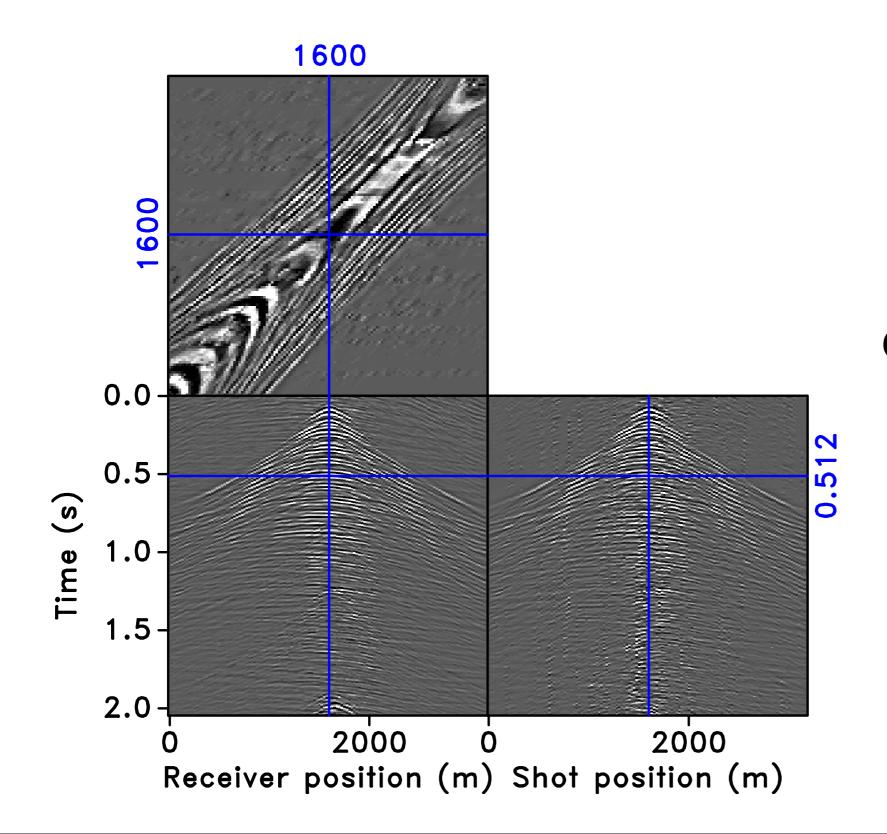
SEG 2011 SAN ANTONIO

Sparsity-promoting recovery from simultaneous data: a compressive sensing approach

Haneet Wason*, Tim T. Y. Lin, and Felix J. Herrmann September 19, 2011

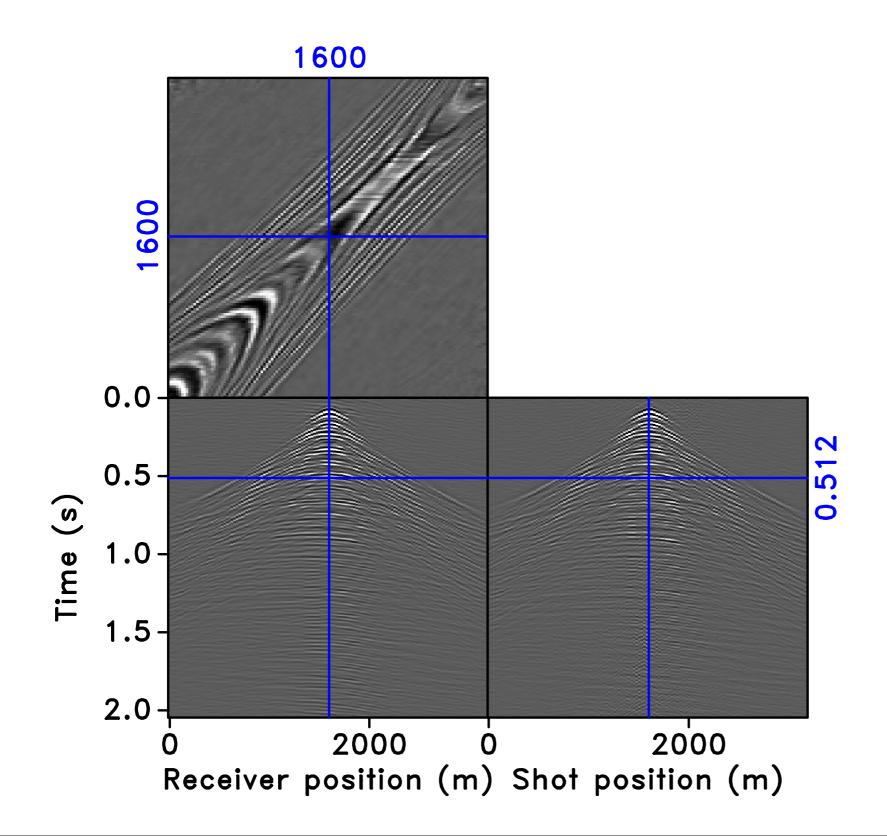


University of British Columbia



Conventional recovery

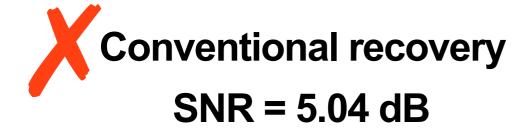
SNR = 5.04 dB



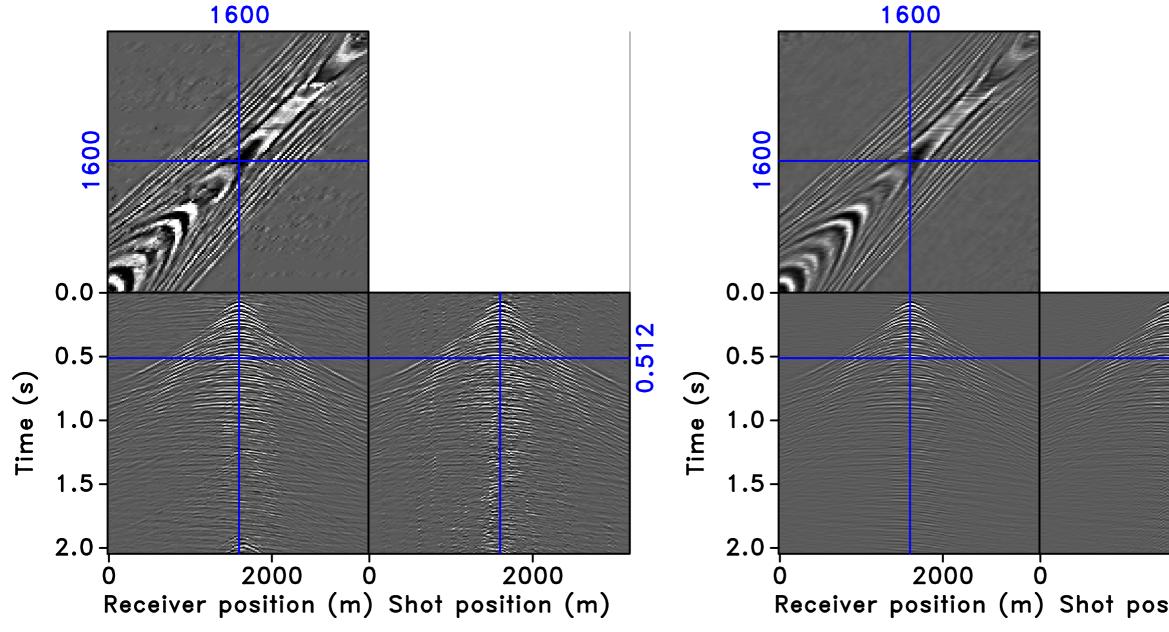
Sparsity-promoting recovery

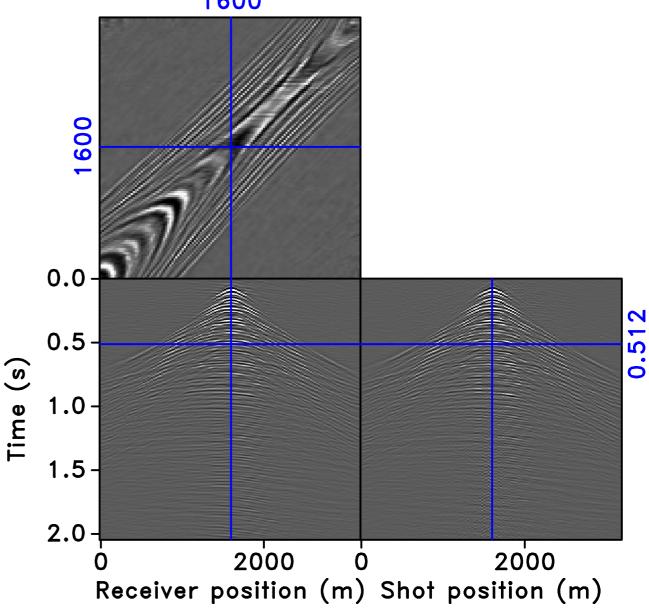
SNR = 9.52 dB













- Opportunity to rethink Marine acquisition
- Concentrate on simultaneous sourcing
- Marine acquisition with ocean-bottom nodes

Outline

- Compressed sensing (CS) overview
 - design
 - recovery
- Design of simultaneous marine acquisition
- Experimental results of sparsity-promoting processing

Problem statement

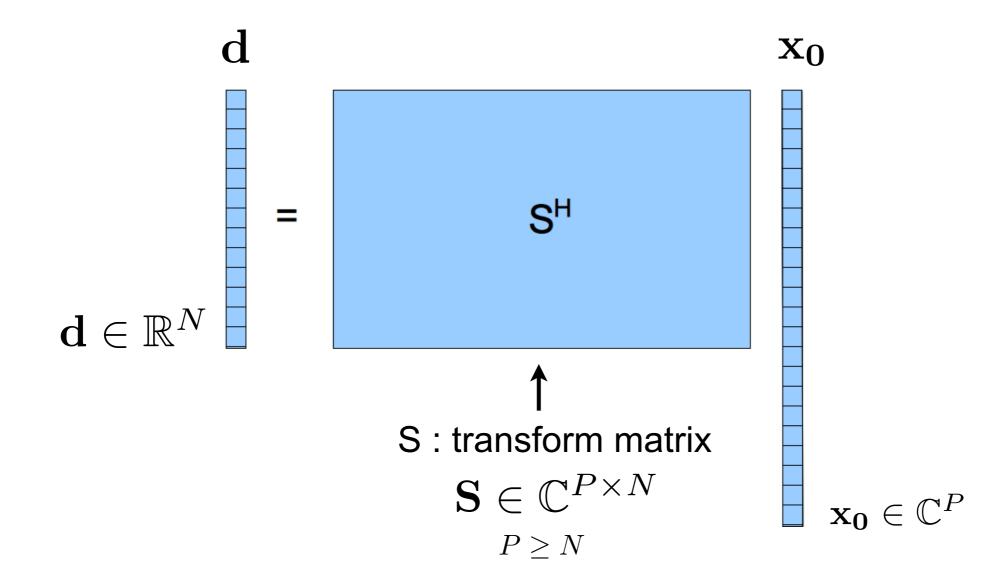
Solve an *underdetermined* system of *linear* equations:

data (measurements /observations)
$$\mathbf{b} \in \mathbb{C}^n \qquad \mathbf{b} \qquad \mathbf{A} \qquad \mathbf{A} \in \mathbb{C}^{n \times P}$$

$$\mathbf{x_0} \longleftarrow \text{unknown} \qquad \mathbf{x_0} \in \mathbb{C}^P$$

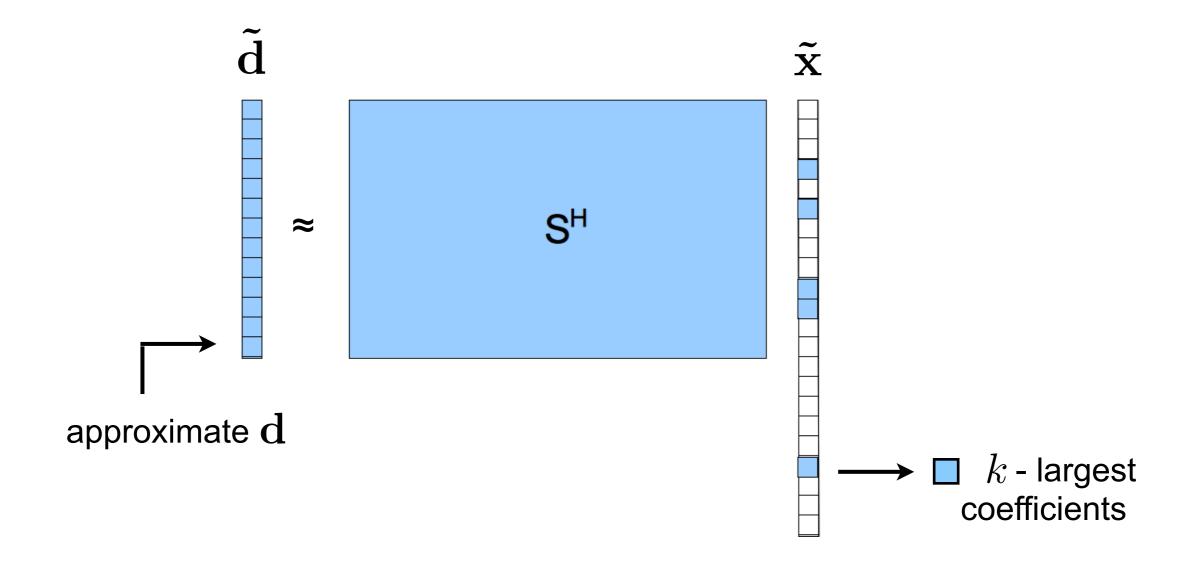
Compressed sensing

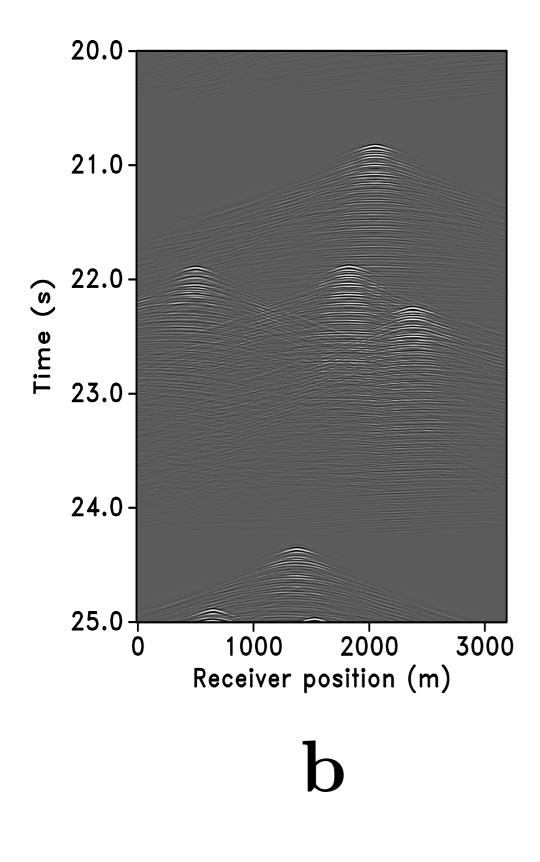
- acquisition paradigm for sparse signals
- in some transform domain

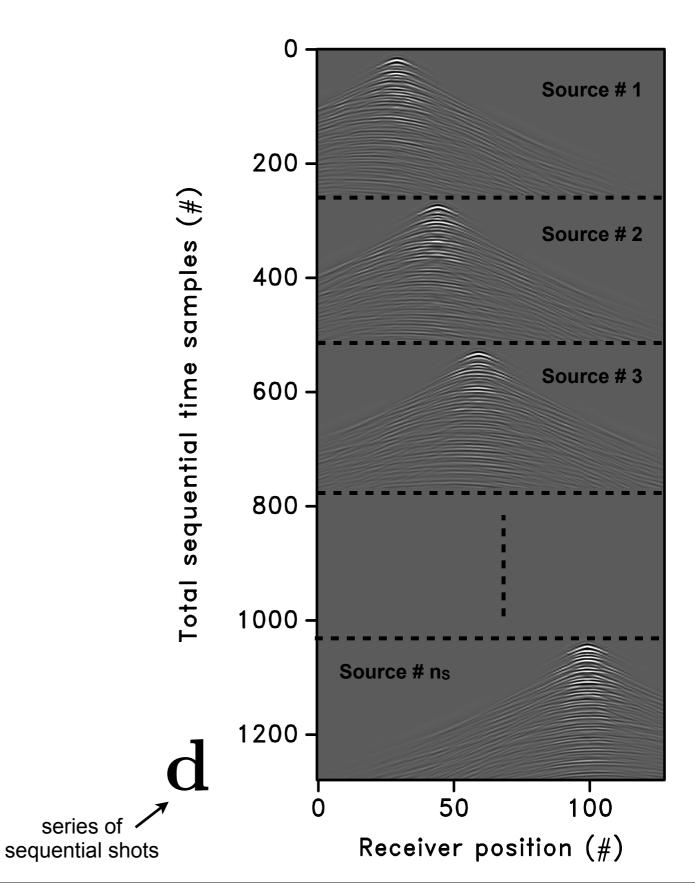


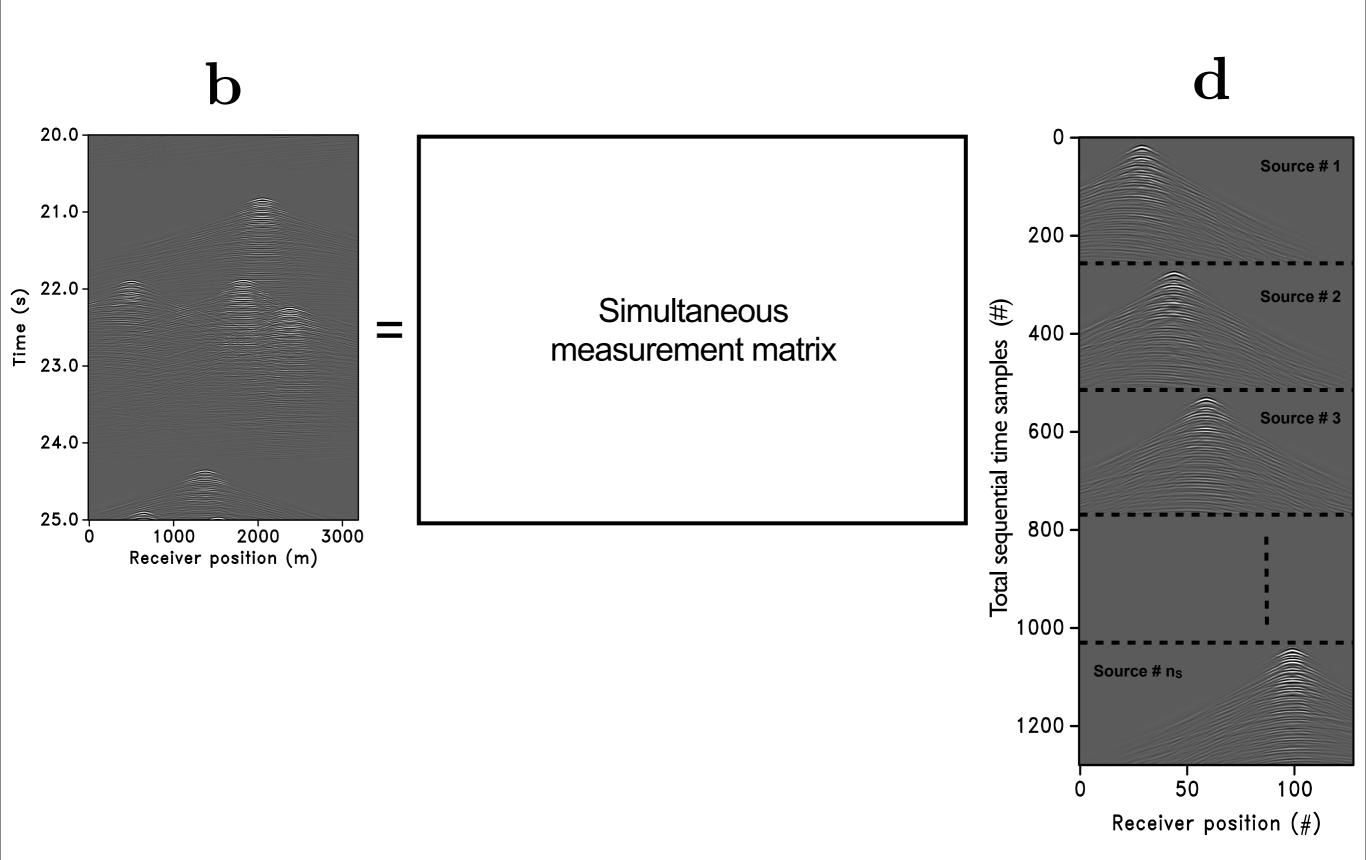
Compressed sensing

- acquisition paradigm for sparse signals
- in some transform domain

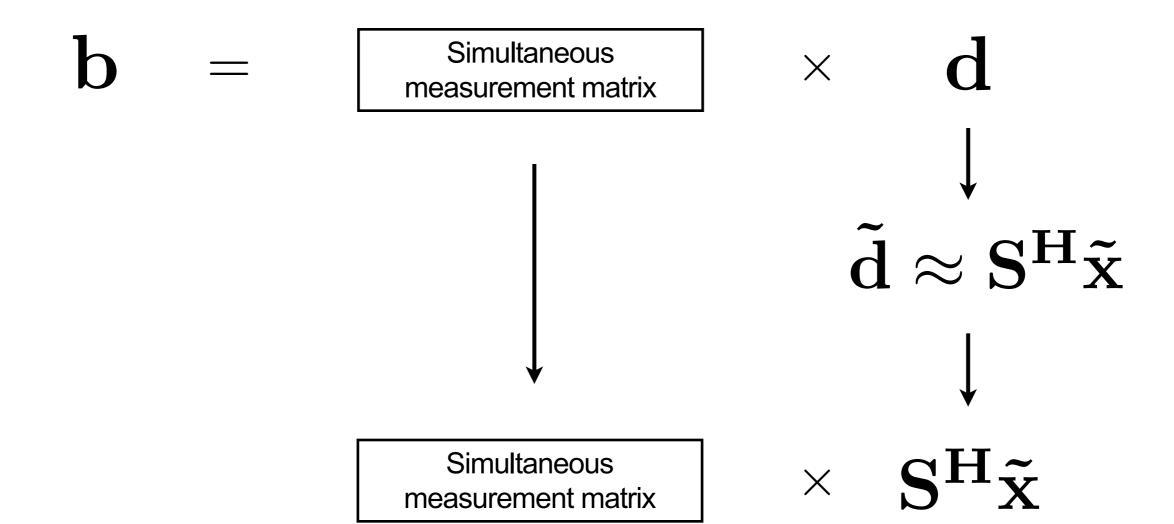


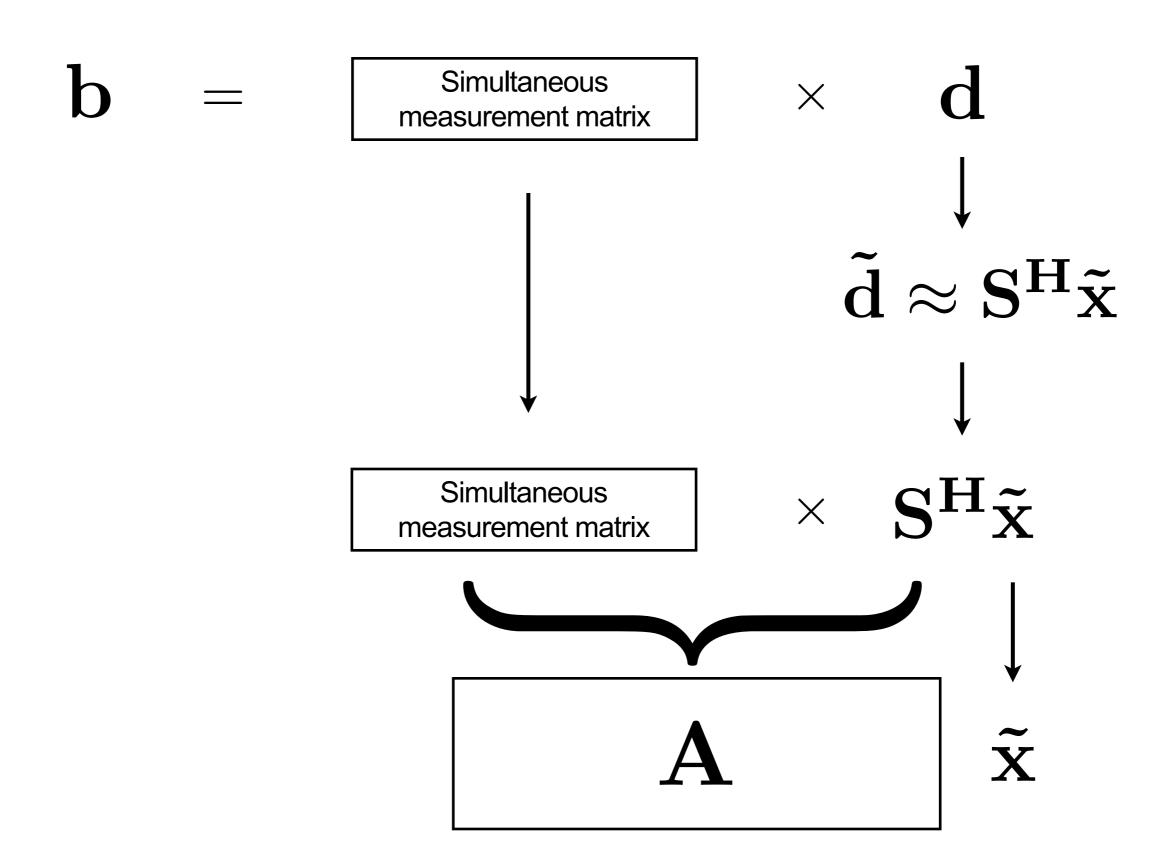






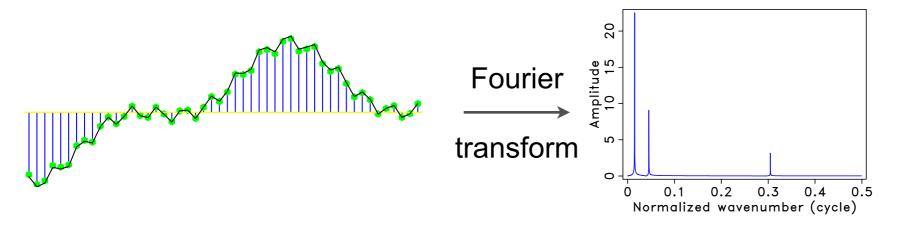
 $\mathbf{b} = egin{array}{ccccc} ext{Simultaneous} & ext{measurement matrix} & ext{} & ext{}$





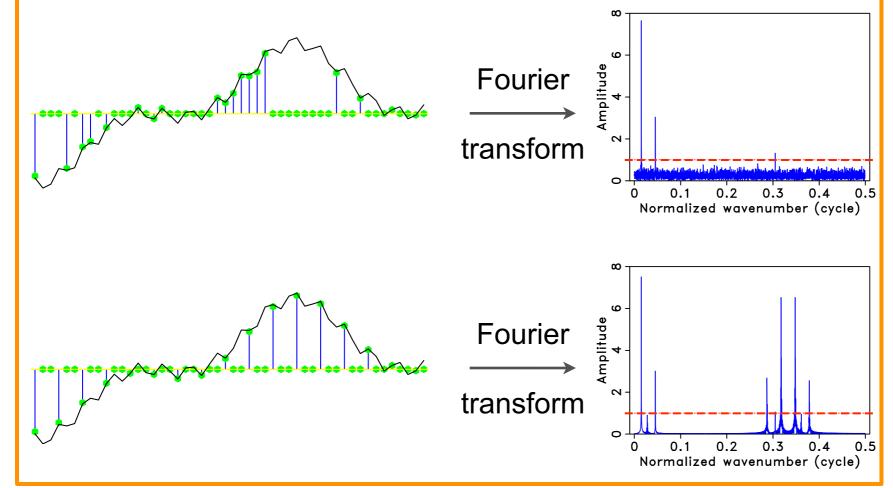


Coarse sampling schemes



few significant coefficients

3-fold under-sampling



significant coefficients detected

X

ambiguity



Mutual coherence

- measures the orthogonality of all columns of A
- equal to the maximum off-diagonal element of the Gram matrix
 - → controlled by compressive sensing via a combination of
 - randomization with
 - spreading of sampling vectors in the sparsifying domain

Restricted isometry property

- lacktriangle indicates whether every group of k columns of ${f A}$ are nearly orthogonal
- restricted isometry constant $0 < \delta_k < 1$ for which

$$(1 - \delta_k) \|\mathbf{x}\|_2^2 \le \|\mathbf{A}\mathbf{x}\|_2^2 \le (1 + \delta_k) \|\mathbf{x}\|_2^2$$

Sparse recovery

Solve the convex optimization problem (one-norm minimization):

$$ilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1$$
 subject to $\mathbf{A}\mathbf{x} = \mathbf{b}$ data-consistent amplitude recovery

Sparsity-promoting solver: $\mathbf{SPG}\ell_1$

[van den Berg and Friedlander, '08]

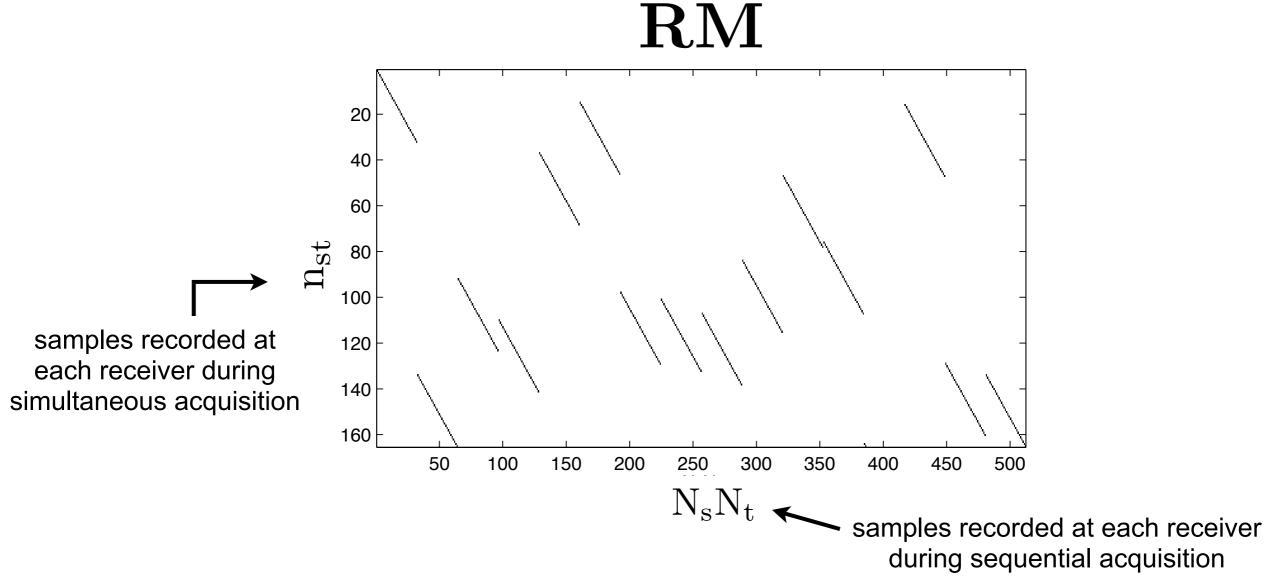
Recover single-source prestack data volume: $\tilde{\mathbf{d}} = \mathbf{S^H}\tilde{\mathbf{x}}$

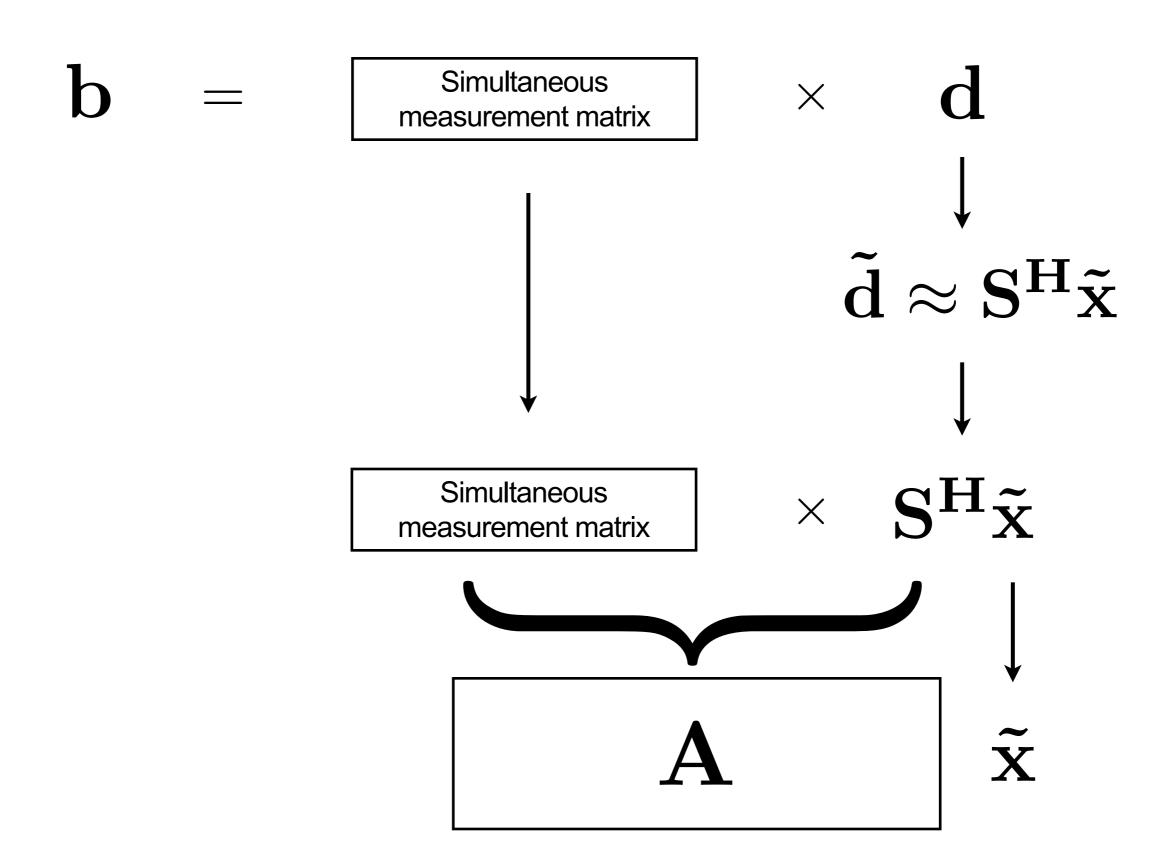
Outline

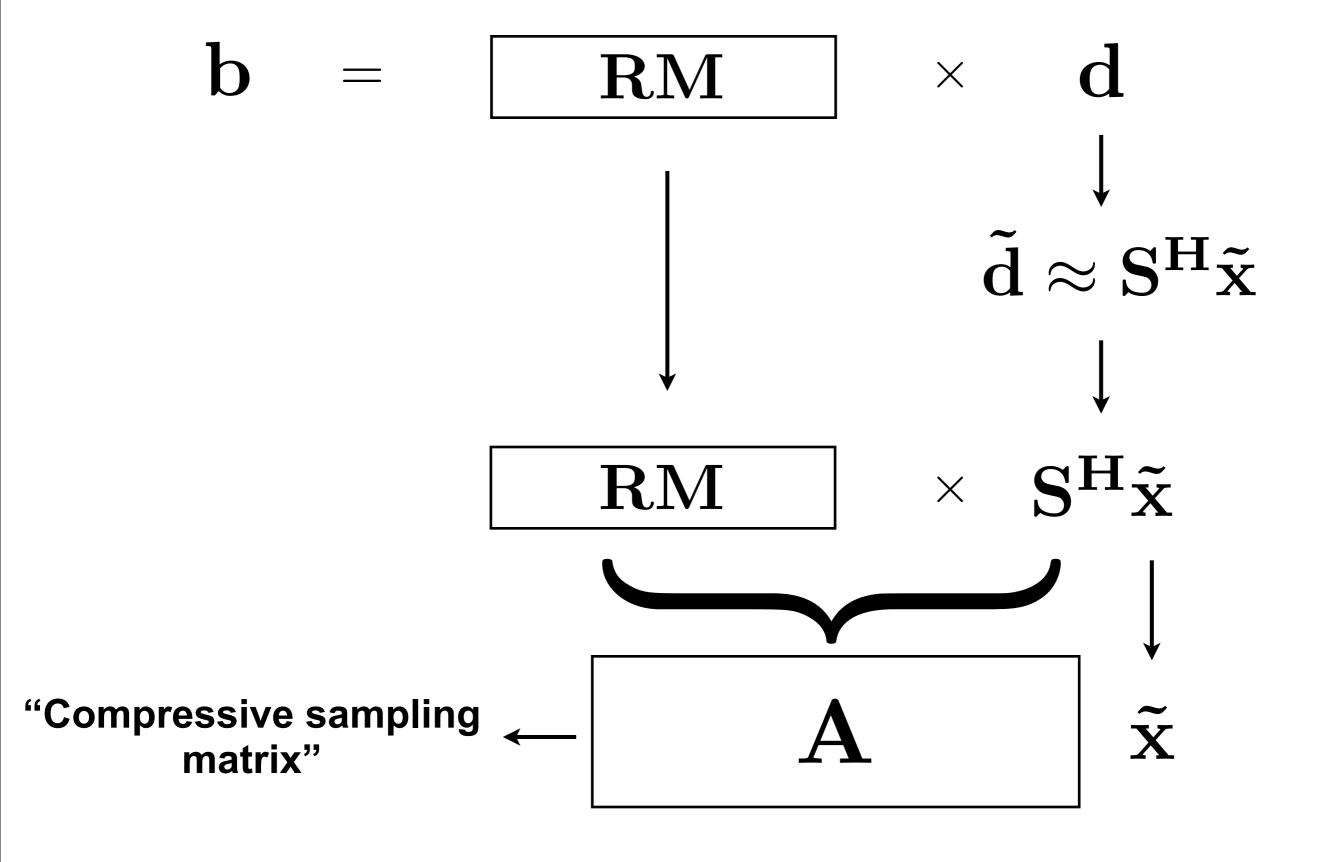
- Compressed sensing (CS) overview
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Simultaneous acquisition matrix

For a seismic line with N_s sources, N_r receivers, and N_t time samples, the sampling matrix is



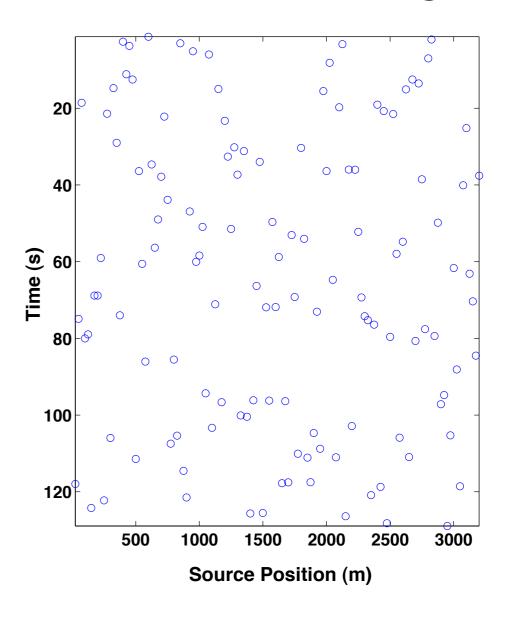




Sequential vs. simultaneous sources

Time (s) Source position (m)

Sampling scheme: Random dithering

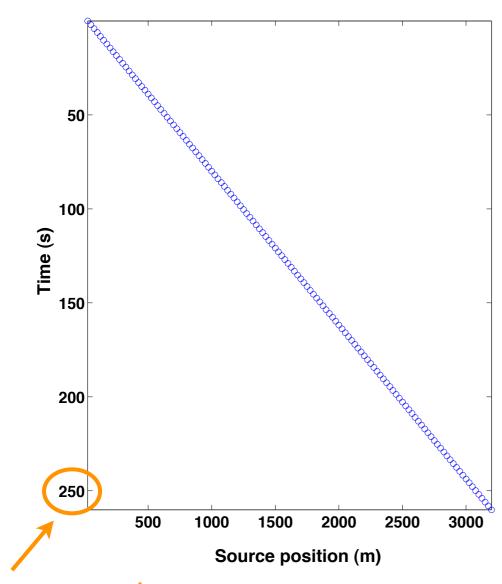


Sequential acquisition

Simultaneous acquisition

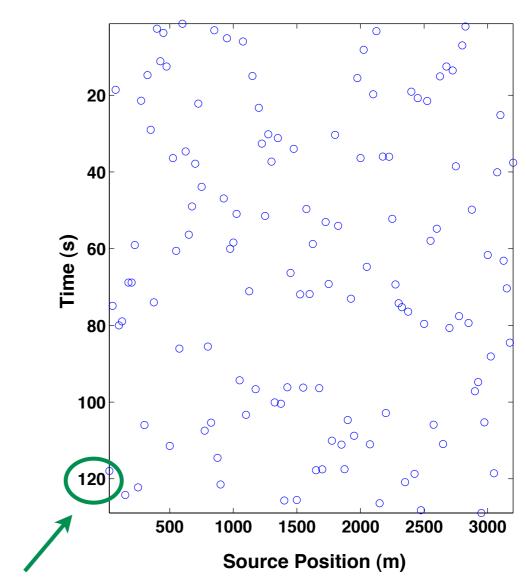
Sequential vs. simultaneous sources

Sampling scheme: Random dithering



Conventional survey time: $t = N_s \times N_t$

Sequential acquisition

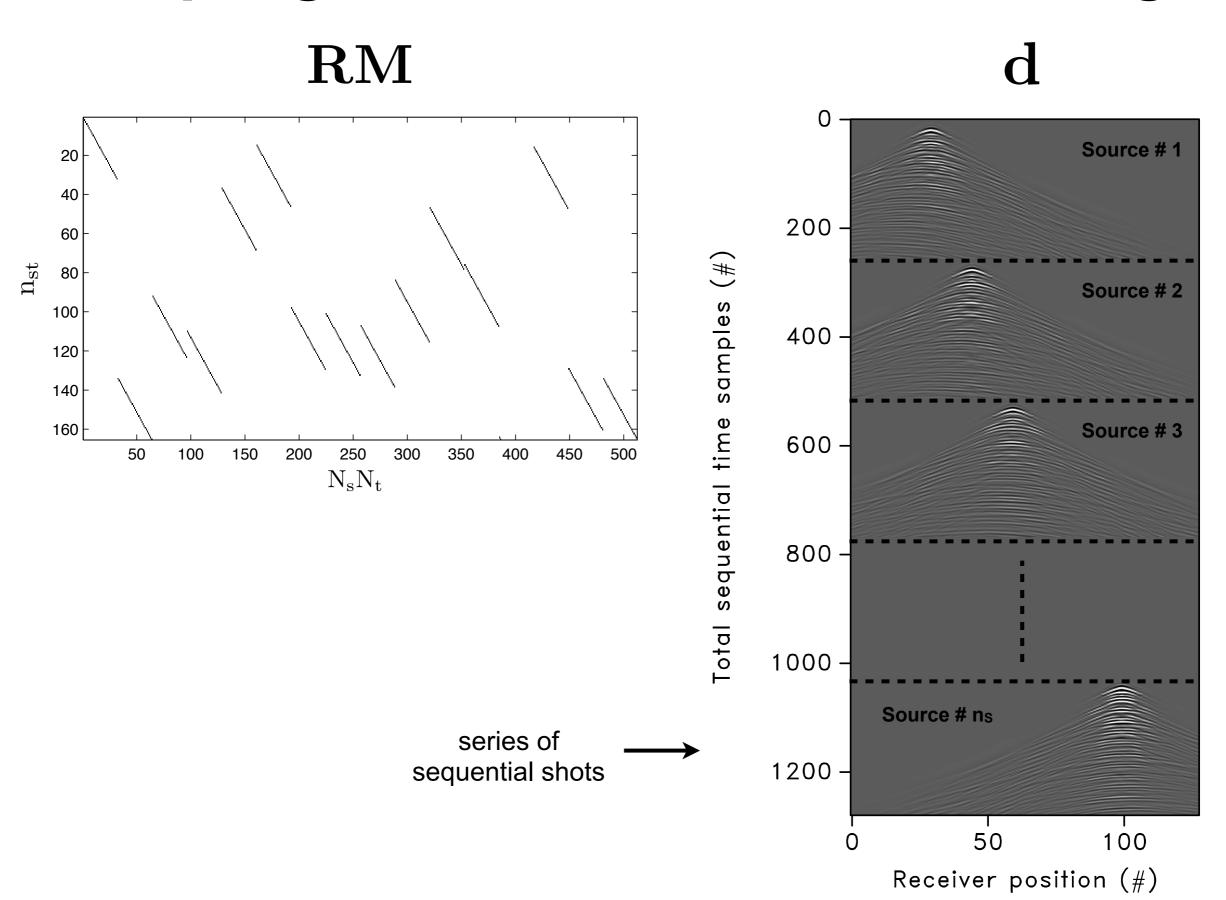


Theoretical survey time:

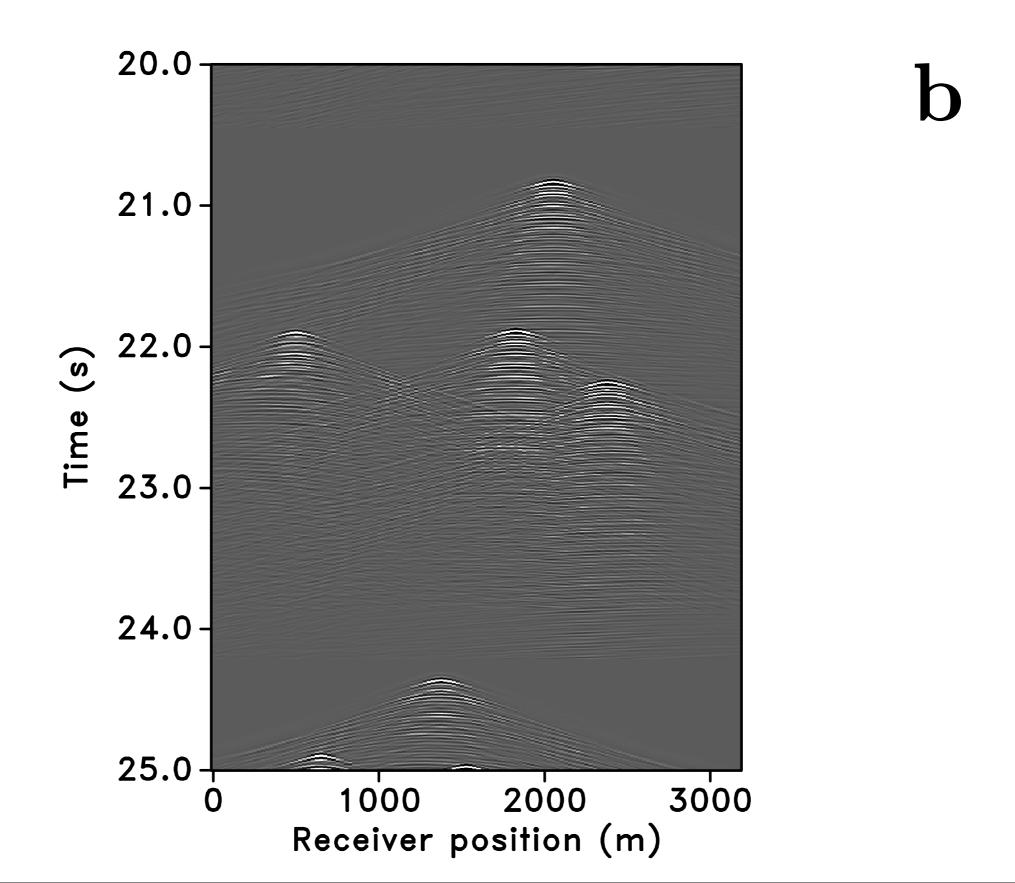
$$t = n_{st} \ll n_s \times N_t$$

Simultaneous acquisition

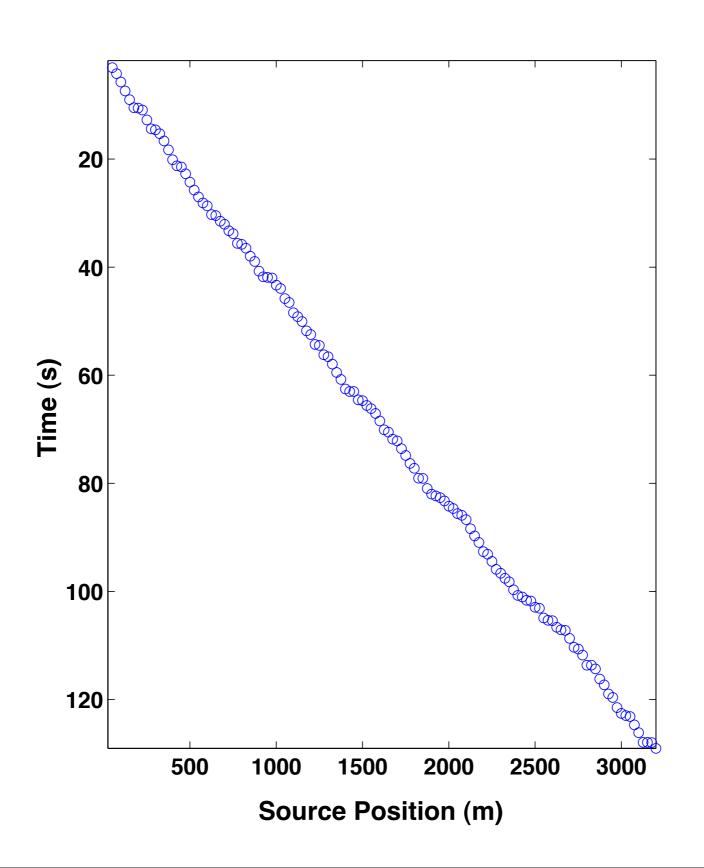
Sampling scheme: Random dithering



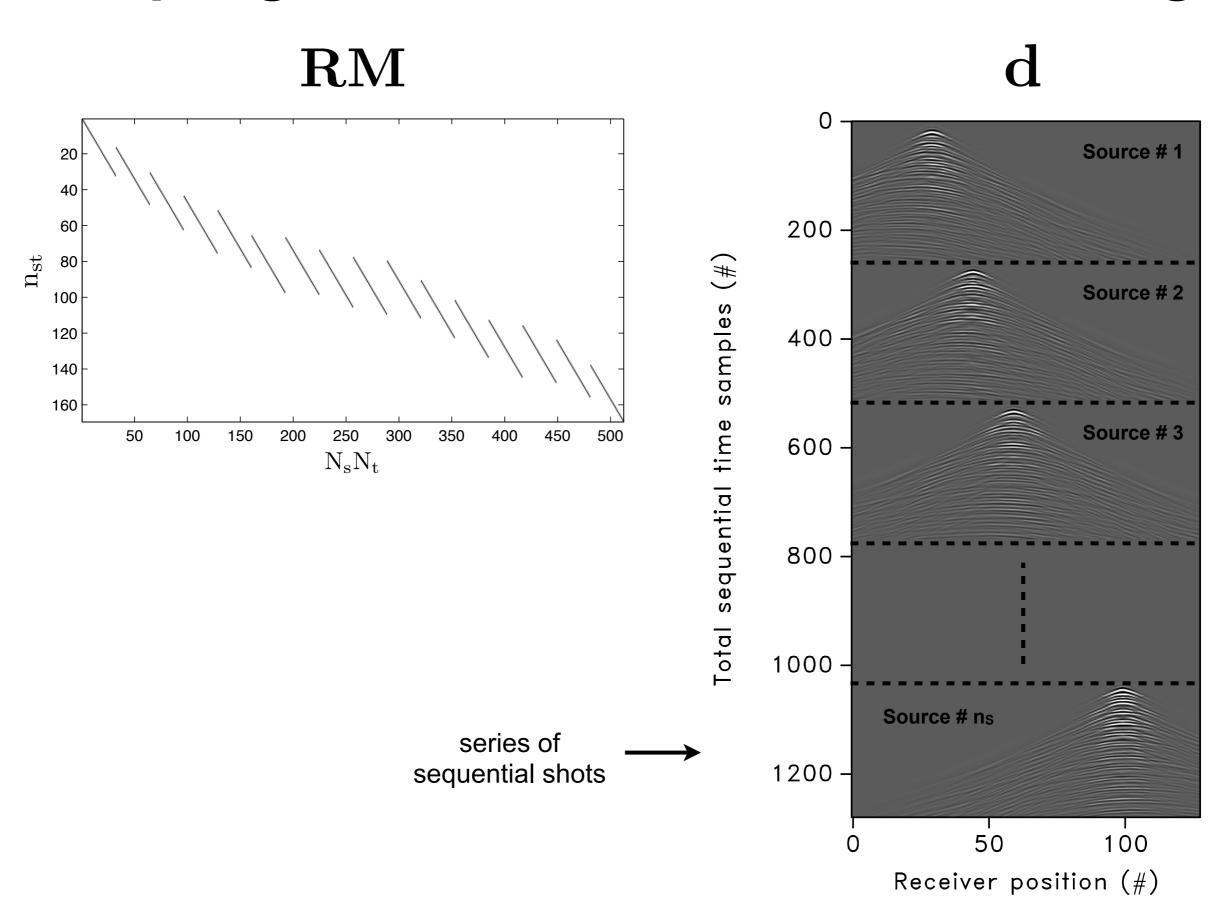
Sampling scheme: Random dithering



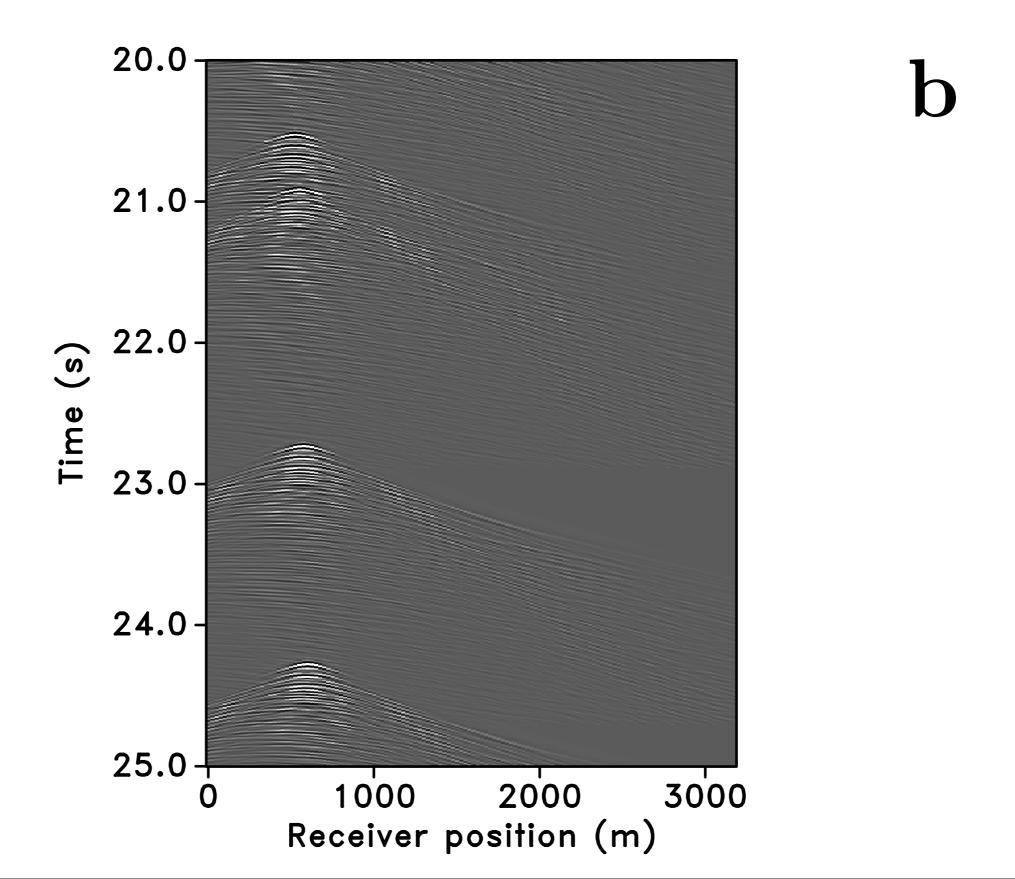
Sampling scheme: Random time-shifting



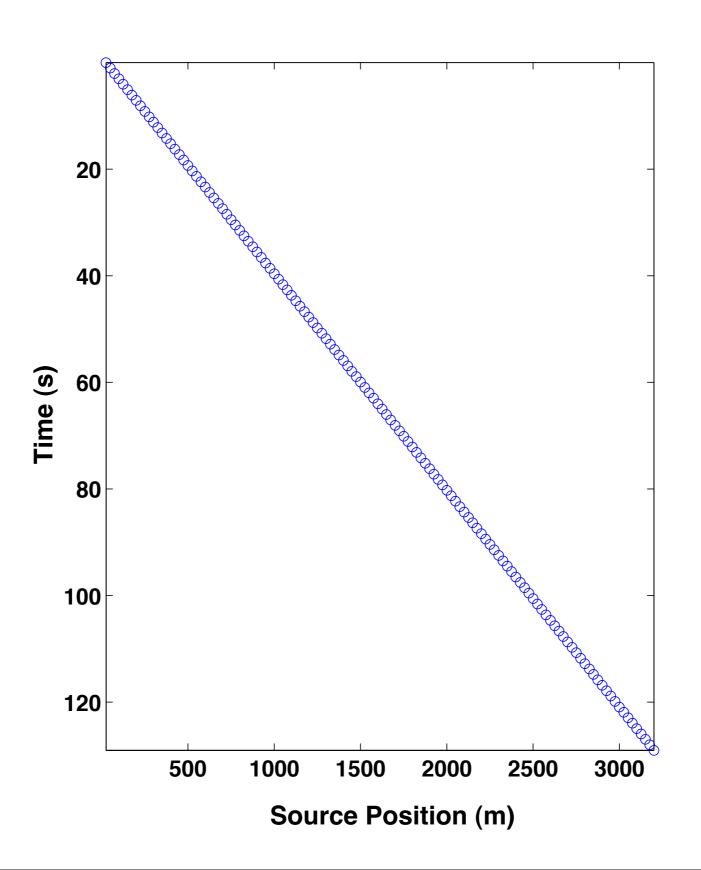
Sampling scheme: Random time-shifting



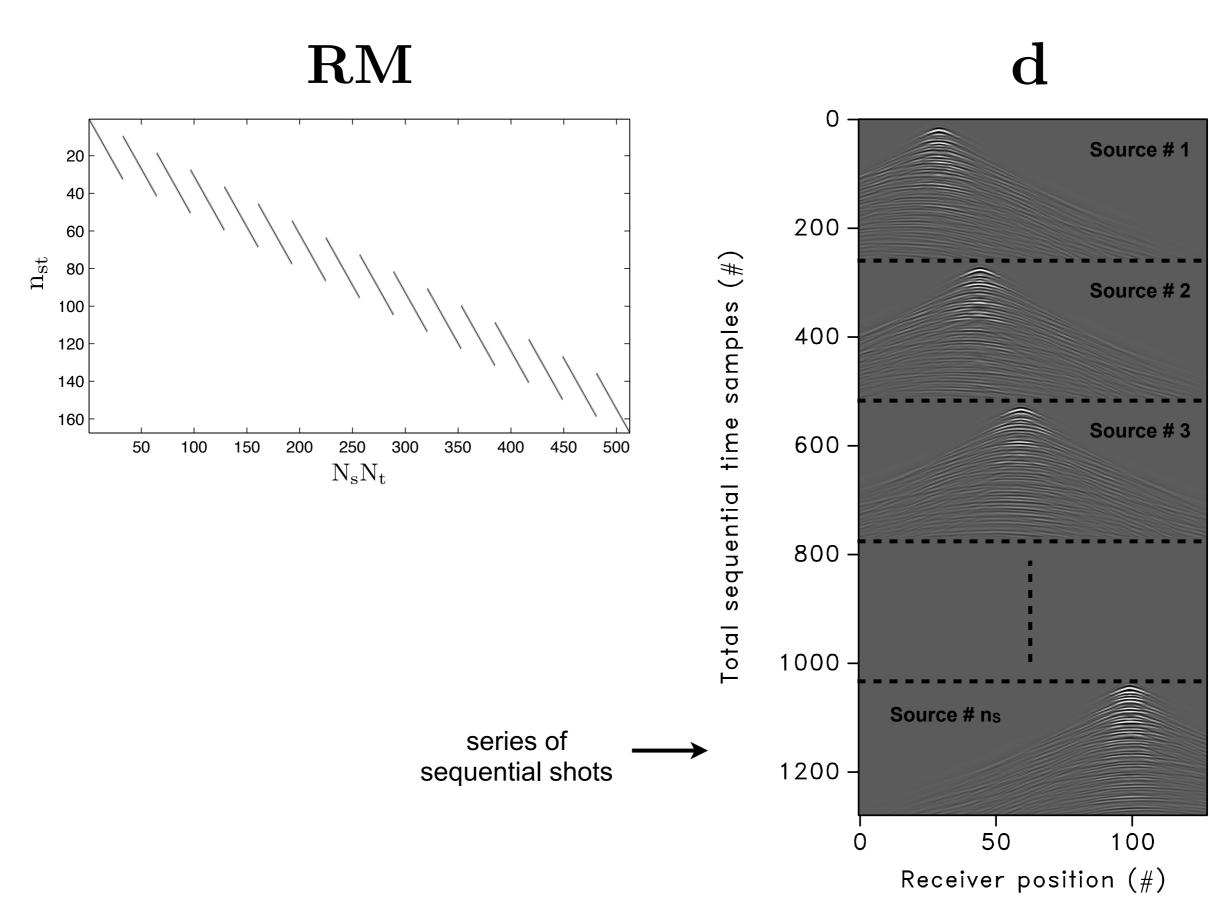
Sampling scheme: Random time-shifting



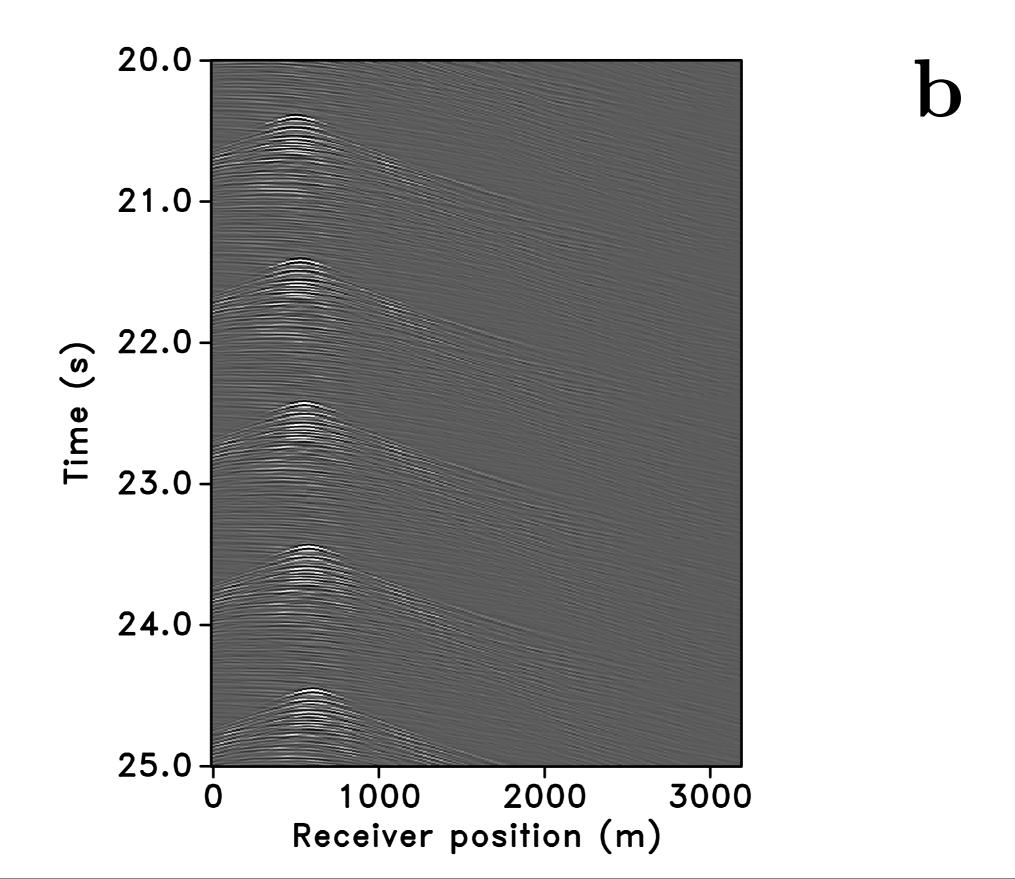
Sampling scheme: Constant time-shifting



Sampling scheme: Constant time-shifting



Sampling scheme: Constant time-shifting



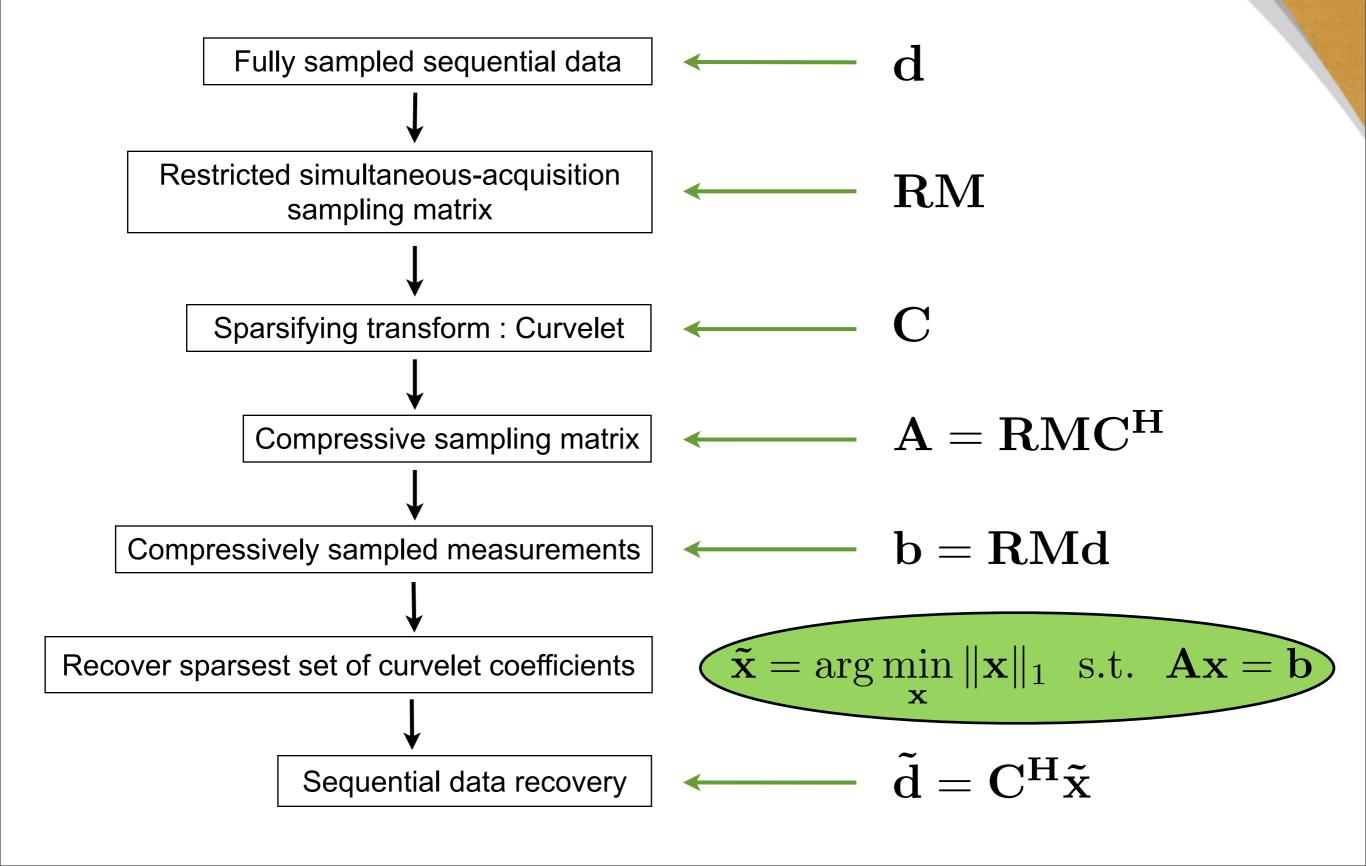
Outline

- Compressed sensing (CS) overview
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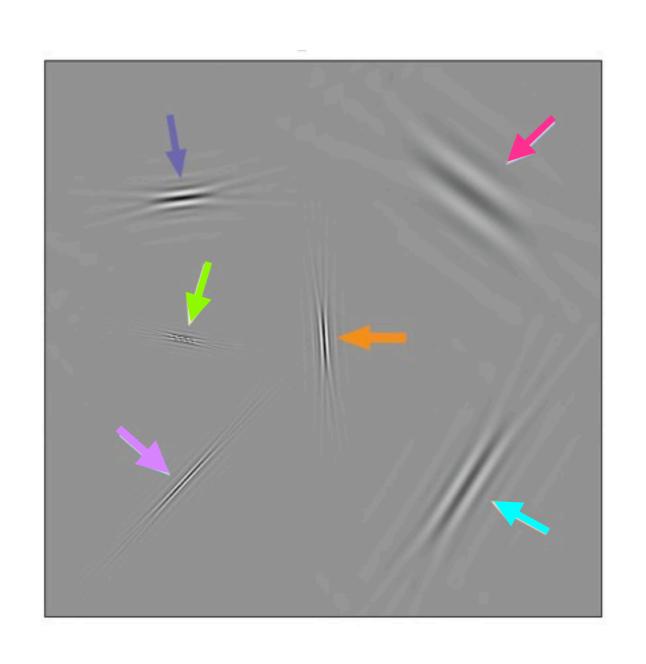
Experimental setup

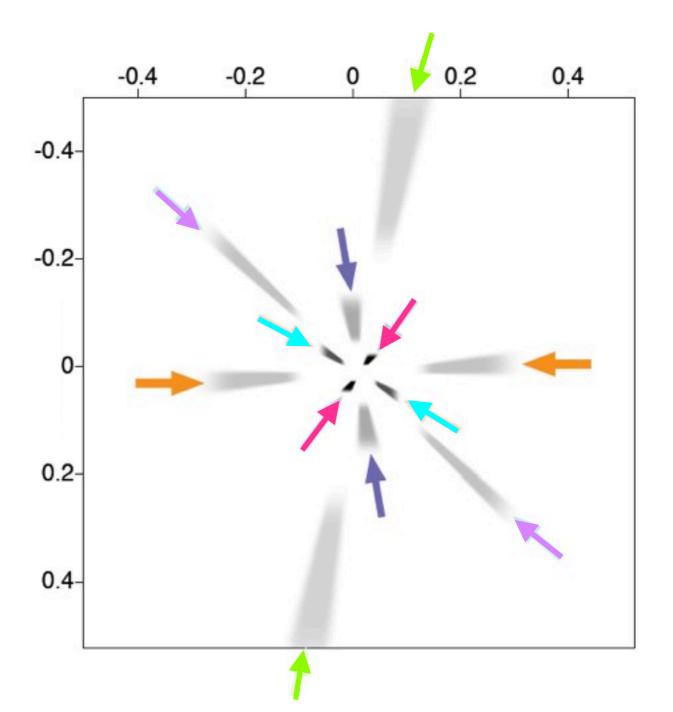
- Three sampling schemes:
 - Random dithering
 - Random time-shifting
 - Constant time-shifting
- Fully sampled sequential data (a seismic line from the Gulf of Suez) with $N_{\rm s}=128$ sources, $N_{\rm r}=128$ receivers, and $N_{\rm t}=512$ time samples
- Subsampling ratio, $\gamma = 0.5$
- ▶ Recover prestack data from simultaneous data
 - ℓ_1 minimization
 - sparsifying transform: 3-D curvelets
- ▶ All sources see the same receivers
 - marine acquisition with ocean-bottom nodes

Algorithm



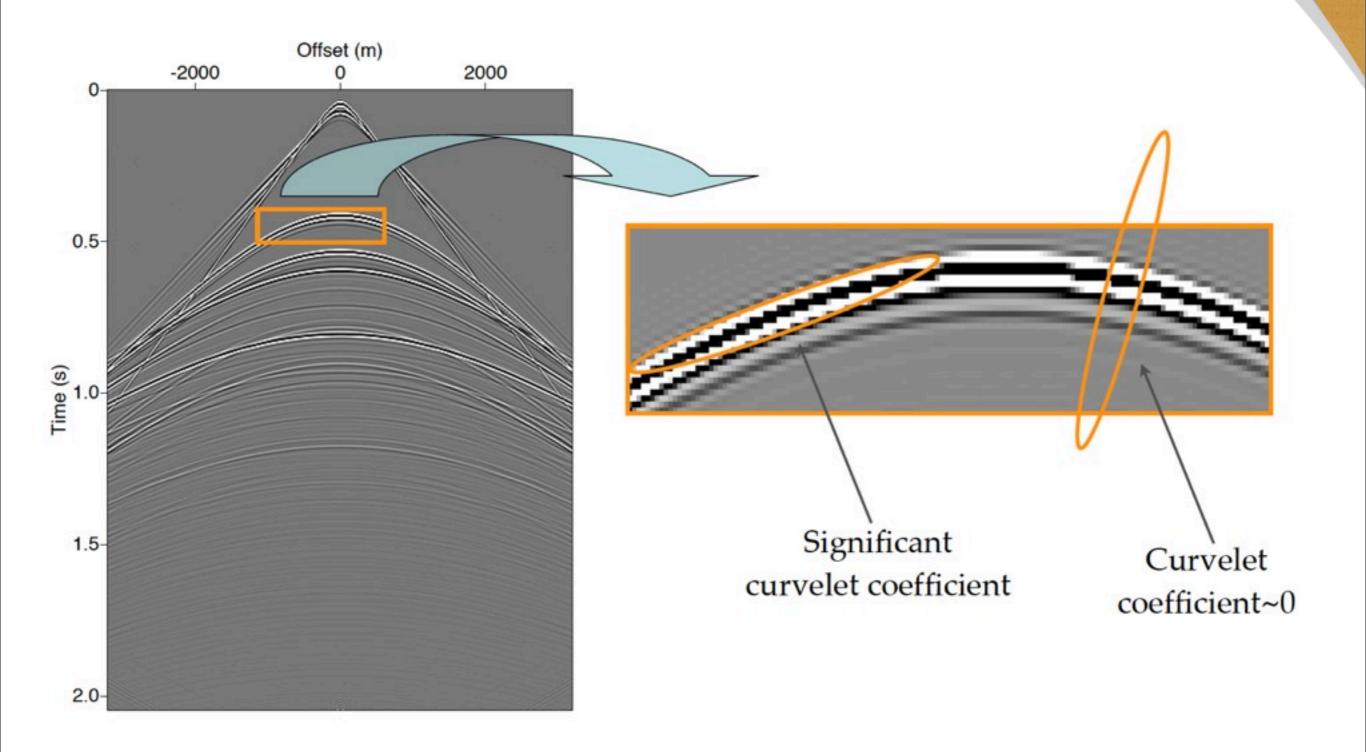
Curvelets



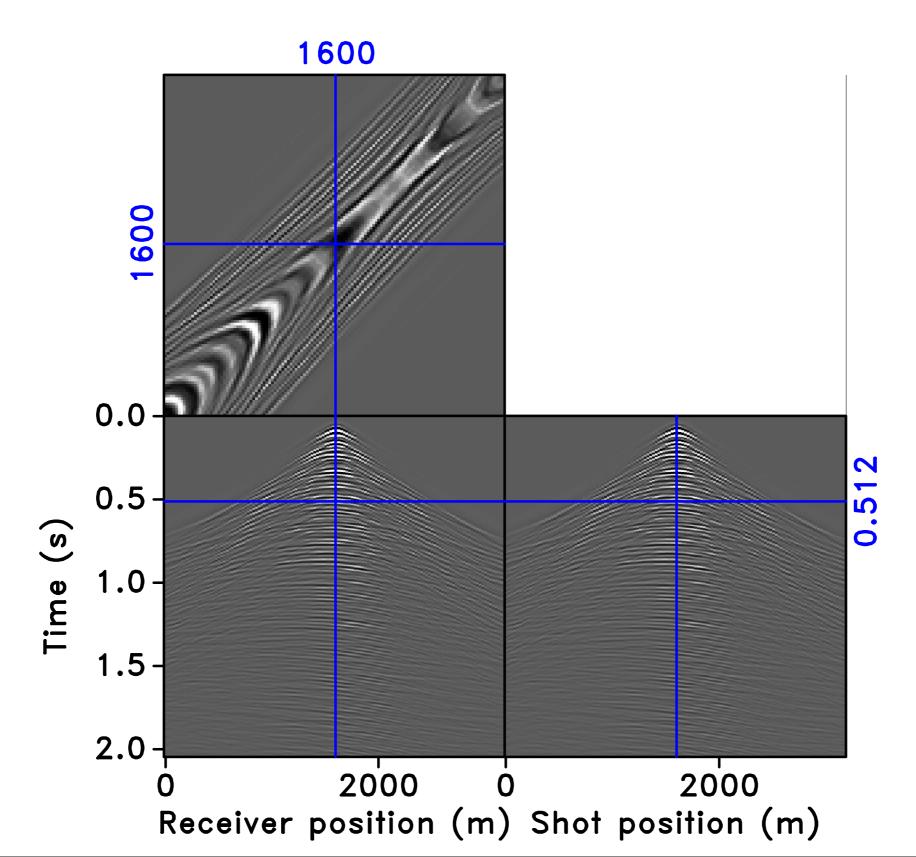




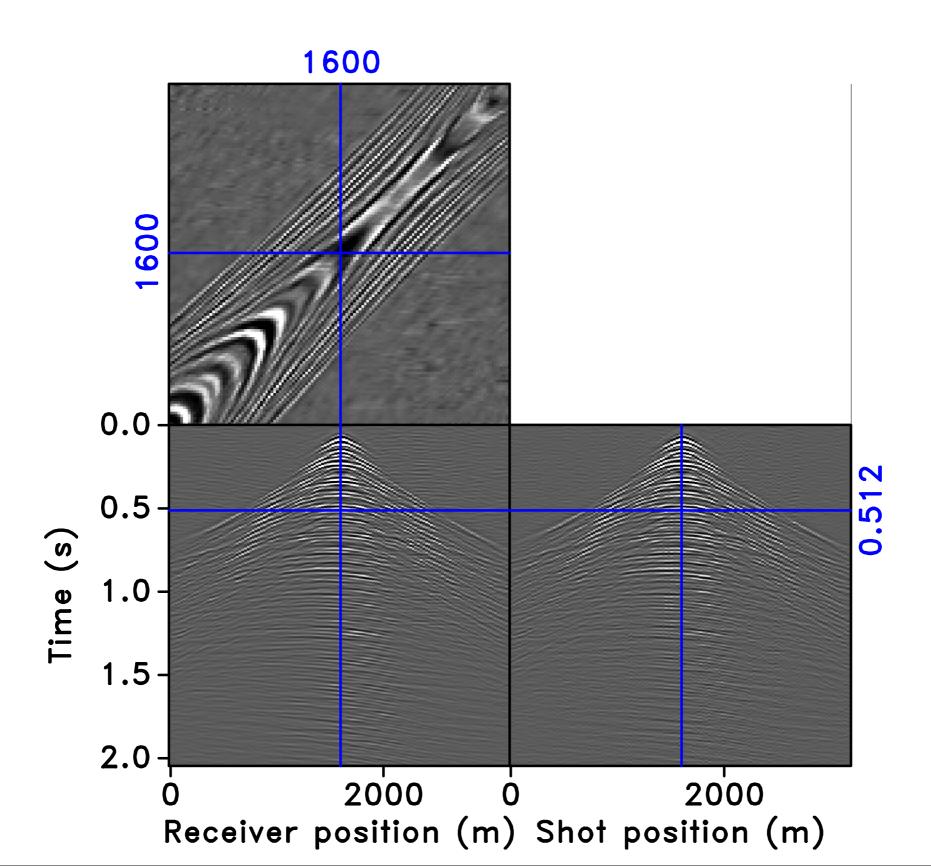
Detect the wavefronts



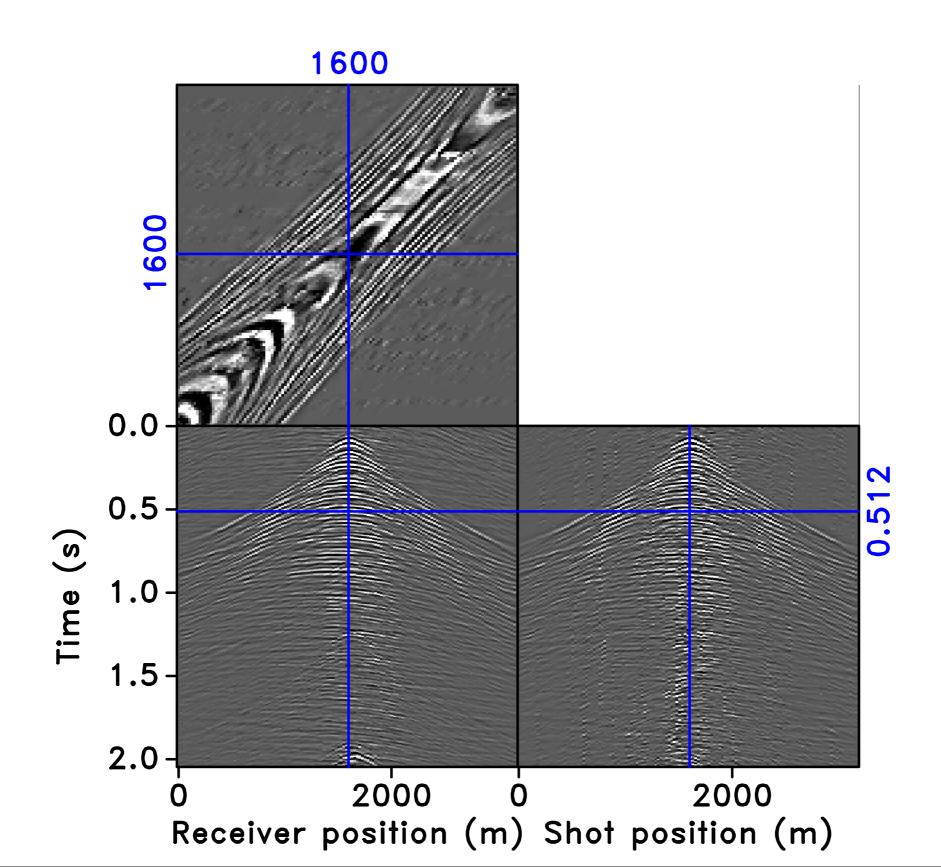
Original data (Sequential acquisition)



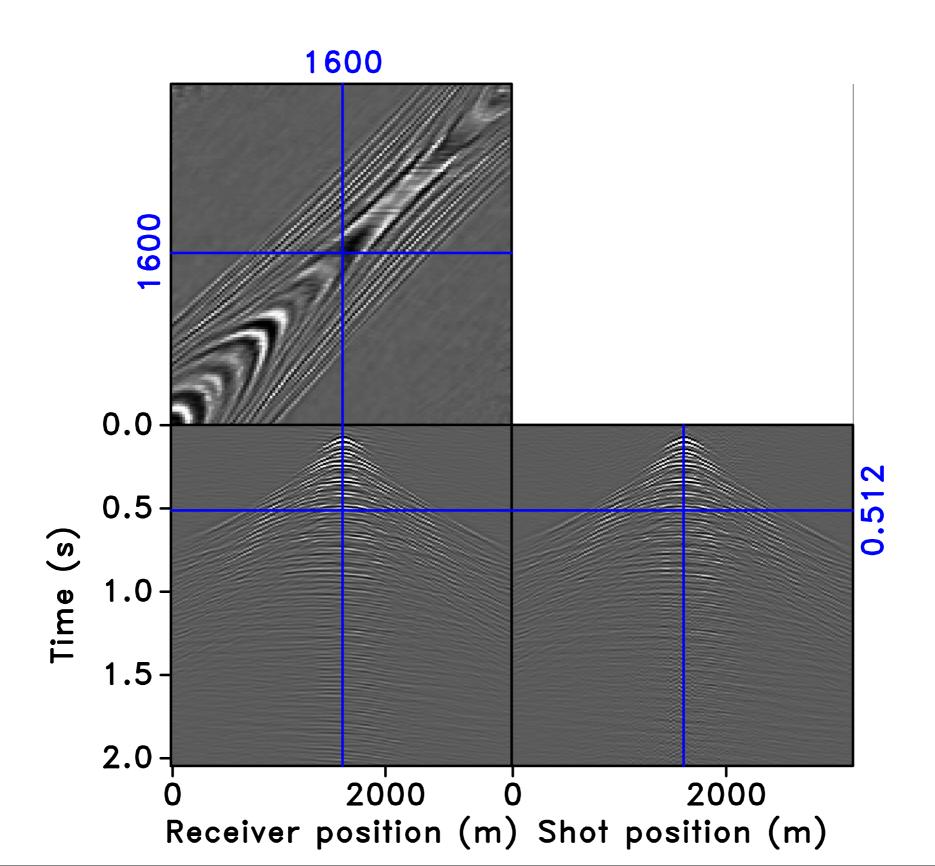
Sparsity-promoting recovery: Random dithering SNR = 10.5 dB



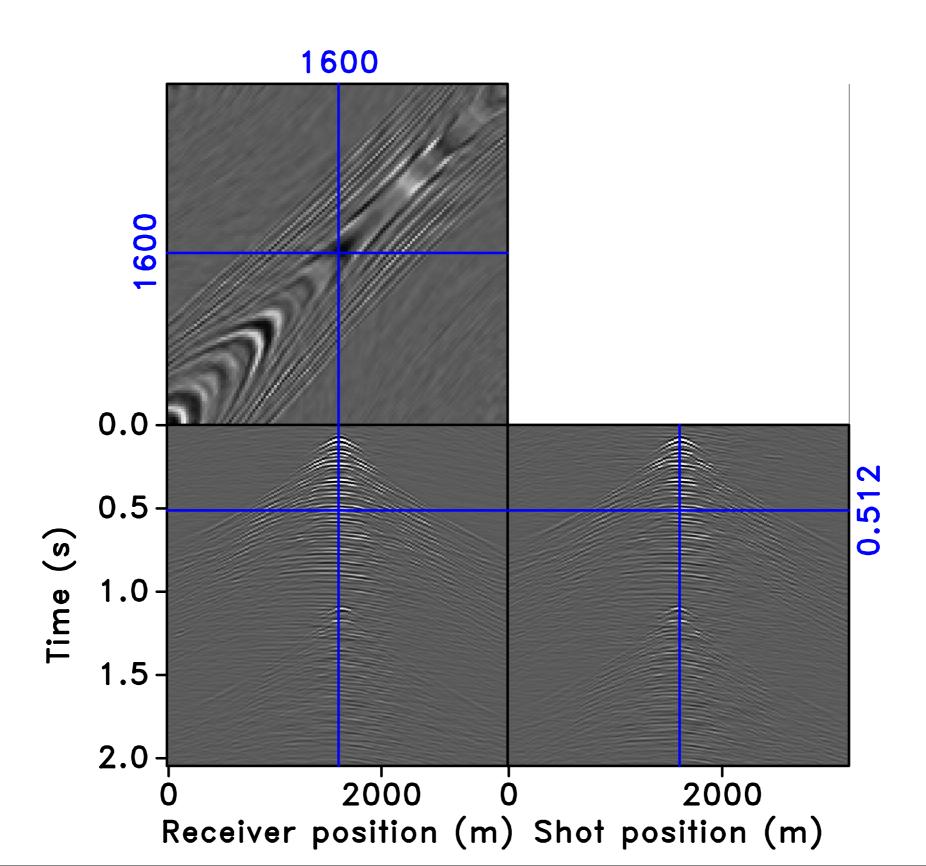
Conventional recovery: Random time-shifting SNR = 5.04 dB



Sparsity-promoting recovery: Random time-shifting SNR = 9.52 dB



Sparsity-promoting recovery: Constant time-shifting SNR = 4.80 dB





Conclusions

Simultaneous acquisition is a linear subsampling system

Critical for reconstruction quality:

- design of source subsampling schemes (i.e., acquisition scenarios)
- appropriate sparsifying transform
- sparsity-promoting solver



Future plans

- Extensions to simultaneous acquisition frameworks for towed streamer surveys
- Use different transforms for sparsitypromoting processing

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Thank you!

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