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Enhancing Sonar resolution through smart signal processing

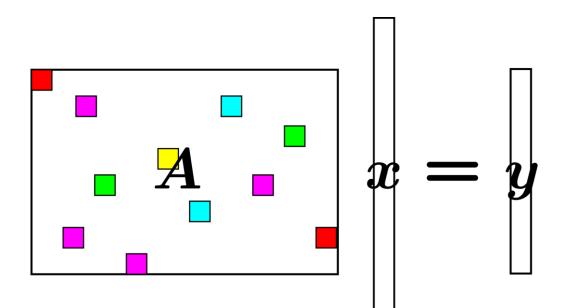
UDT 2019 Sthlm

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Outline

- Compressive Sensing
 - The Inverse Problem
 - l_1 -norm
 - Propagators
 - Model
- Examples
 - High Resolution from 1 ping measurement
 - Scatterer point representation
 - Multiple pings
- Summary



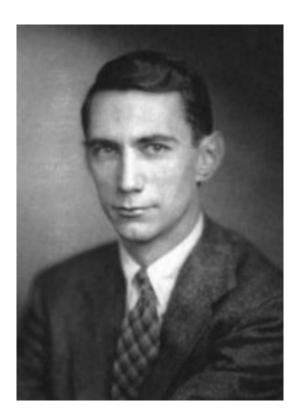


H. Nyquist (1889-1976) and C. Shannon(1916-2001)

Nyquist-Shannon Sampling Theorem

"If a function contains no frequencies higher than B Hertz, it is completely determined by giving its ordinates to a series of points spaced 1/(2B) seconds apart." (Wikipedia)







Data compression



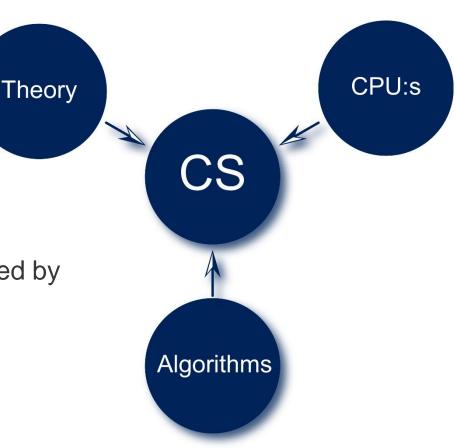


- Example: JPEG compression from 487 to 71 kB (16%)
- Typical compression rate with a factor of 10
- To much data is collected
- Idea: Reduce data collection and compensate with signal processing



Compressive Sensing

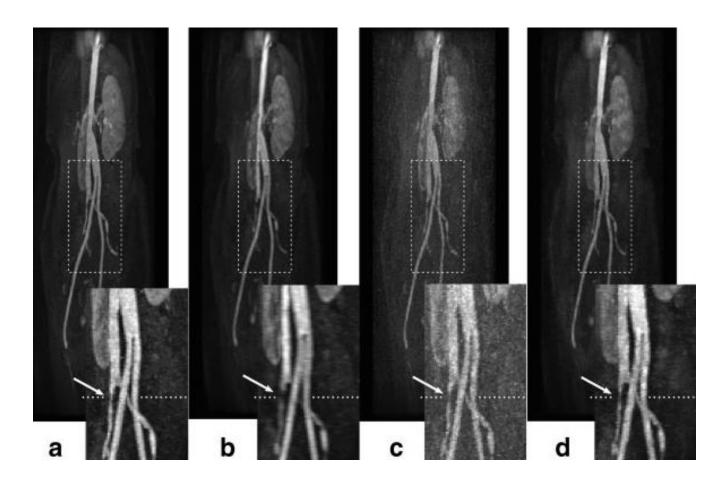
- Developments of theory for Compressive Sensing (CS)
- Faster algorithms
- Faster computers (flops/cpu)
- Enabling practical use of Compressive Sensing (CS)
- Pioneered by: Emmanuel Candés, David Donoho, Justin Romberg and Terence Tao (2004)
- CS means that less data is collected which is compensated by using postprocessing





Compressive sensing – early application MRI

- Magnetic resonance imaging (MRI)
- Picture a shows an MRIimage using complete data set and conventional data processing
- Picture d shows an image using 20% of data set (from a) and CS



M. Lustig, D. Donoho, and J. M. Pauly. "Sparse MRI: The application of compressed sensing for rapid MR imaging." Magnetic resonance in medicine 58, no. 6 (2007): 1182-1195.



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Inverse problems

• Linear set of equations:

$$Ax = y \begin{cases} x \in \mathbb{C}^N \\ A \in \mathbb{C}^{m \times N} \\ y \in \mathbb{C}^m \end{cases}$$

- y is an observation/measurement, and we are trying to find x (parameter)
- Normally this set of equations are undetermined (m<<N) =>infinitely many solutions (provided that there exists at least one)
- Sonar: The reflected signal is used to determine position, speed, target class..., i.e. parameters.



Inverse problems

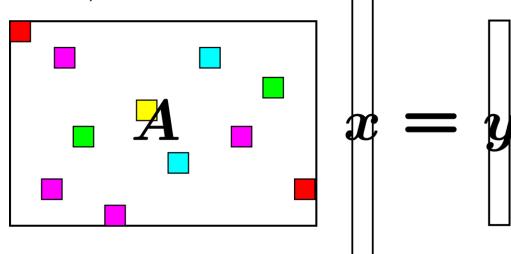
• Underdetermined linear set of equations:

Ax = y

- Possible to reconstruct signals under assumption of sparsity! (A vector/matrix is sparse if most of its components are zero)
- Efficient algorithms exists, in this work: Quadratically constrained I1-minimization problem:

 $\min \|x\|_1 \ subj. \ to \ \|Ax - y\|_2 \le \sigma$ $\sigma \ related \ to \ SNR$

(other variants exist: LASSO, Dantzig selector, ...)

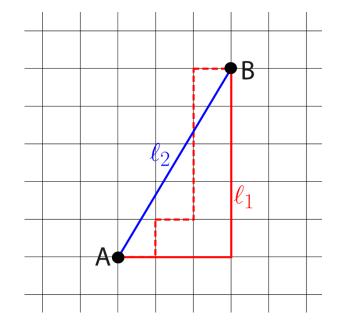




$$l_0$$
-, l_1 - and l_2 -norms

- Norm: total size or length
- l_2 : "straight-line" Euclidian distance $||x||_2 = \sqrt{\sum_i x_i^2}$
- *l*₀: Sparsity ||*x*|||₁ = #(*i*|*x_i* ≠ 0) (total number of non-zero elements in a vector. Useful for finding the sparsest solution. However: minimization is regarded as NP-hard.
- $l_1: ||x||_1 = \sum_i |x_i|$
- l_1 relaxed l_0 :used in Compressive sensing. Not as smooth as l_2 , but this problem is better and more unique than the l_2 -optimization.

The optimization road is convex optimization.





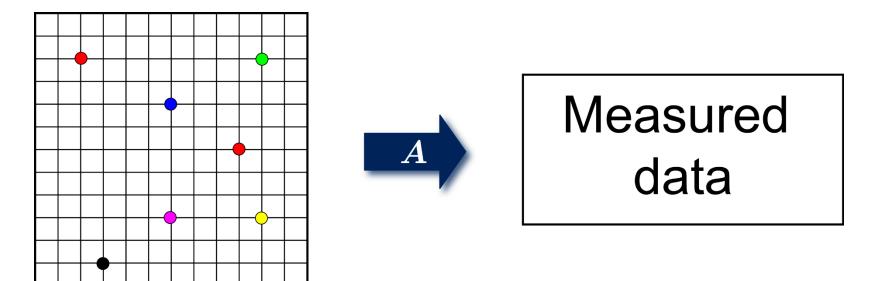
Compressive sensing

- Sonar
 - Point scatter model
 - Back-propagator
 - Forward-propagator



Model (Point scatterer)

- Isotropic, frequency independent point scatterer as model.
- Ax = y
- A: signal generator (from point scatterer to element signals)



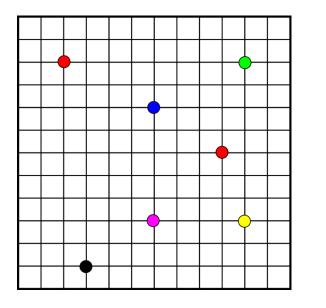


Back-propagator

• Classical Delay-And-Sum:

$$\hat{\gamma}(r) = \frac{1}{N} \sum_{n=1}^{N} A_n s_n(t_n(r))$$

A



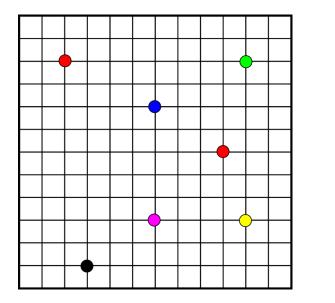




Forward-propagator

Signal observed at time t and position r emitted from a point scatterer at r':

$$s(t,r) = \frac{A\left(t - \frac{|r - r'|}{c}\right)}{|r - r'|^2} e^{i\omega t \left(t - \frac{|r - r'|}{c}\right)}$$









Outline

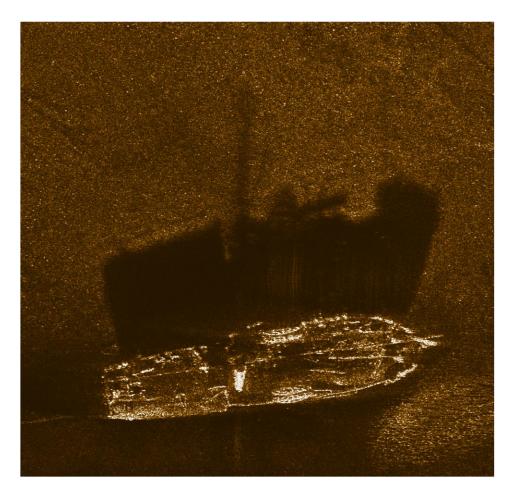
- Synthetic Aperture Sonar
- Compressive Sensing
- Examples
 - High Resolution from 1 ping measurments
 - Robustness
 - Modell from different pings
 - Autofocus position based
 - Autofocus phase based
- Summary



Measurement setup

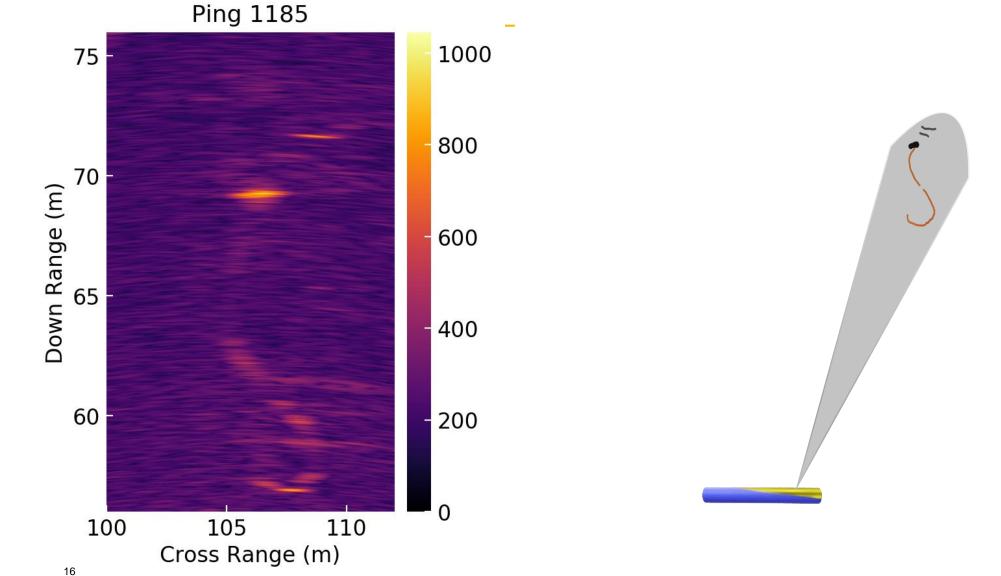
- Sapphires
- SAS resolution <4x4 cm
- Fresh water lake: Vättern





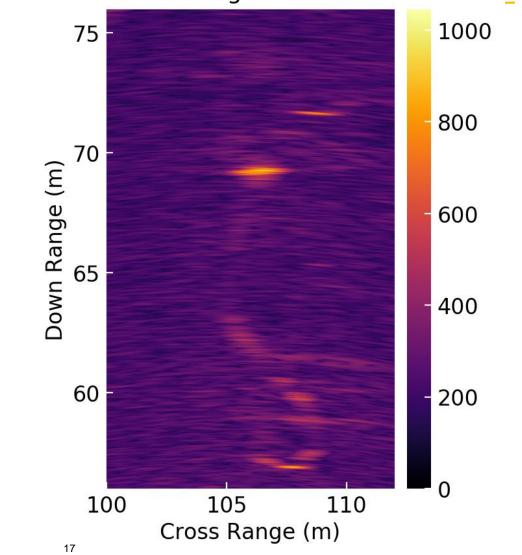


Normal resolution from 1 ping measurement

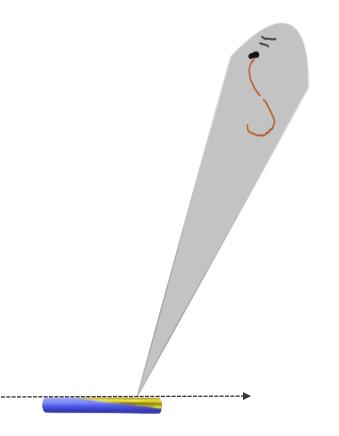




Normal Resolution from 1 ping measurment



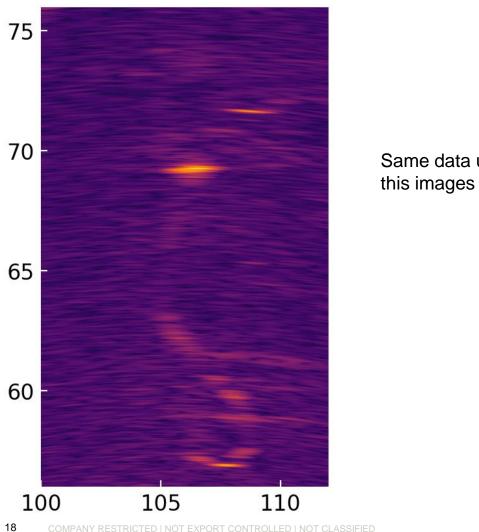
 $\min \|x\|_1 \ subj. \ to \ \|Ax - y\|_2 \le \sigma$ Visualize with longer array



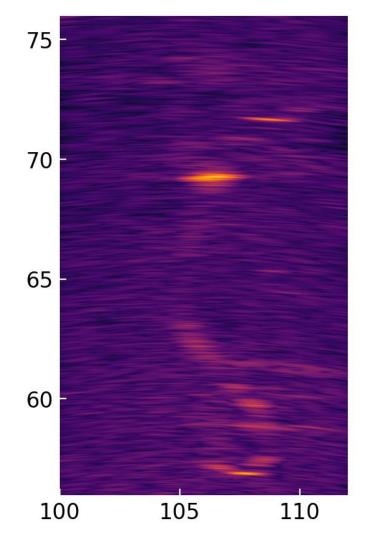


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Same data used for both



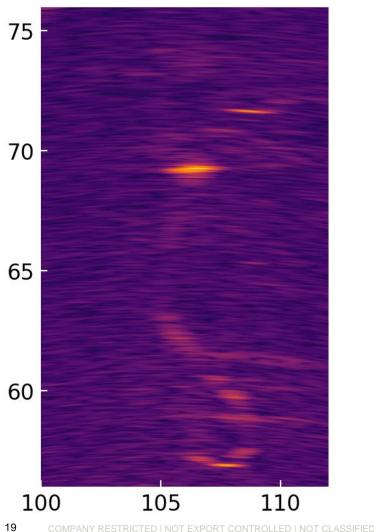
18 COMPANY RESTRICTED | NOT EXPORT CONTROLLED | NOT CLASSIFIED Andreas Gällström | Document Identification | Issue 1 $\min \|x\|_1 \operatorname{subj.to} \|Ax - y\|_2 \le \sigma \text{ same resolution}$



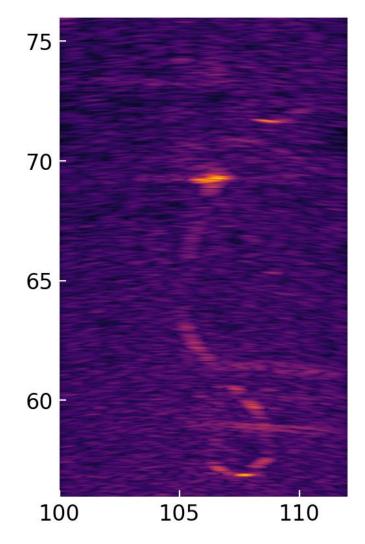


Same data used for both

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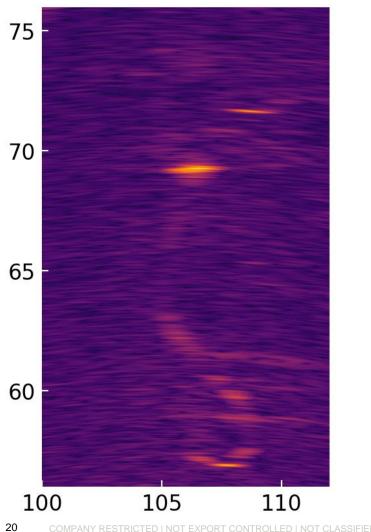
COMPANY RESTRICTED | NOT EXPORT CONTROLLED | NOT CLASSIFIED Andreas Gällström | Document Identification | Issue 1 $\min \|x\|_1 \operatorname{subj.to} \|Ax - y\|_2 \le \sigma \operatorname{res:} x2$



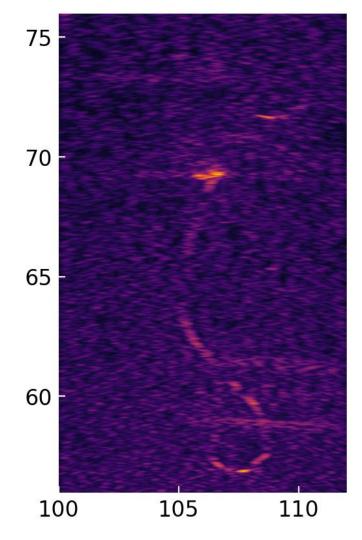


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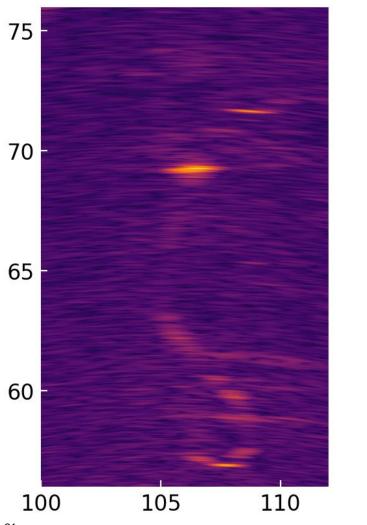
COMPANY RESTRICTED | NOT EXPORT CONTROLLED | NOT CLASSIFIED Andreas Gällström | Document Identification | Issue 1 $\min \|x\|_1 \ subj. \ to \ \|Ax - y\|_2 \le \sigma \ res: \ x4$



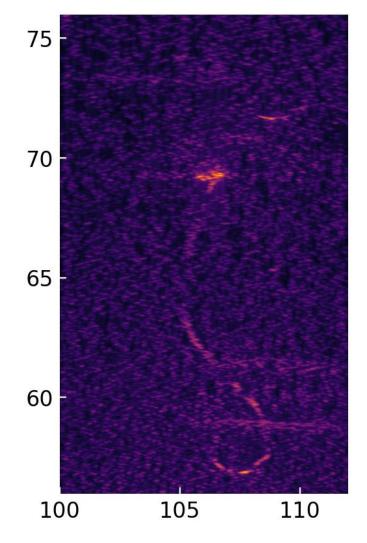


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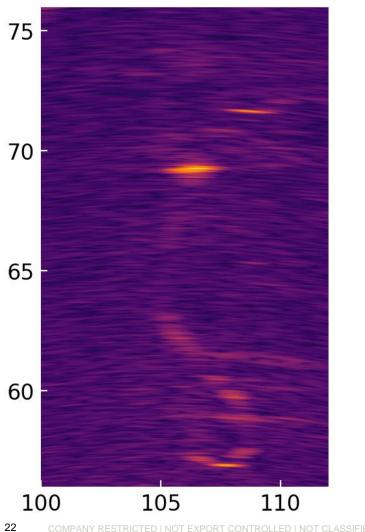
21 COMPANY RESTRICTED | NOT EXPORT CONTROLLED | NOT CLASSIFIED Andreas Gällström | Document Identification | Issue 1 $\min \|x\|_1 \operatorname{subj.to} \|Ax - y\|_2 \le \sigma \operatorname{res:} x8$



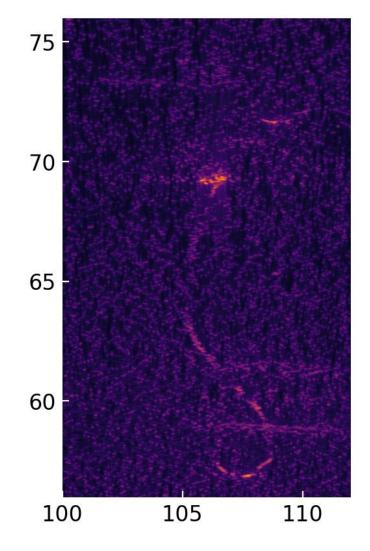


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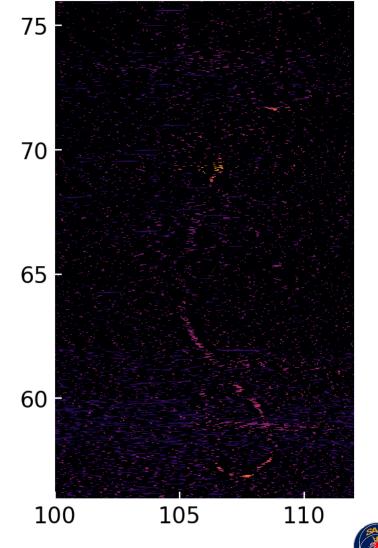
2 COMPANY RESTRICTED | NOT EXPORT CONTROLLED | NOT CLASSIFIED Andreas Gällström | Document Identification | Issue 1 $\min \|x\|_1 \operatorname{subj.to} \|Ax - y\|_2 \le \sigma \operatorname{res:} x16$



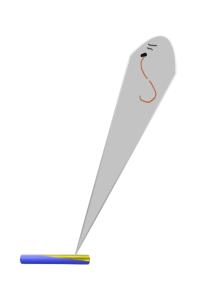


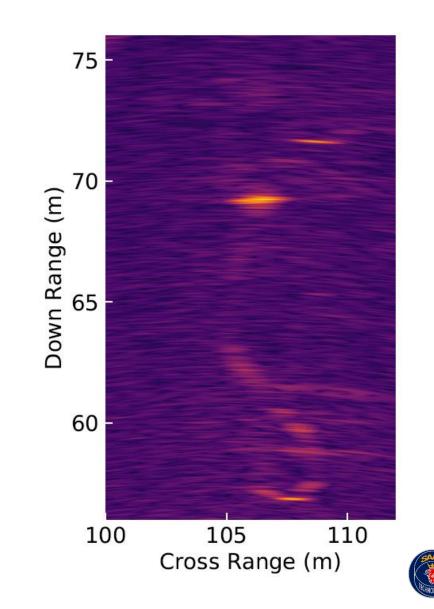
Modell

- Visualization of point scatterers based on one ping
- Sparsivity: ~10%



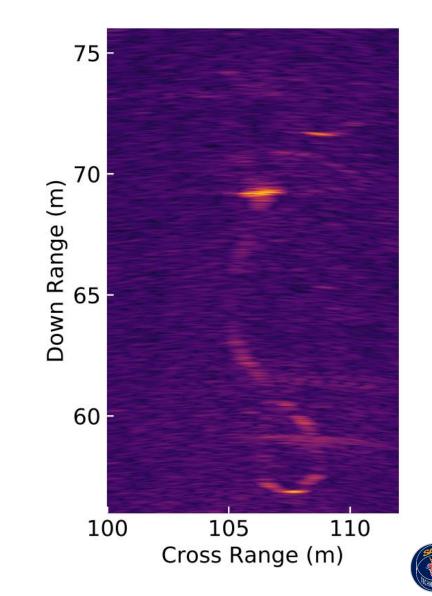
1 ping





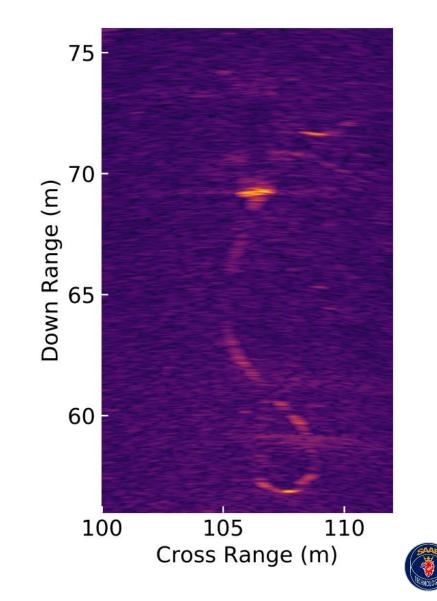
2 pings



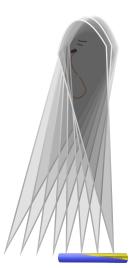


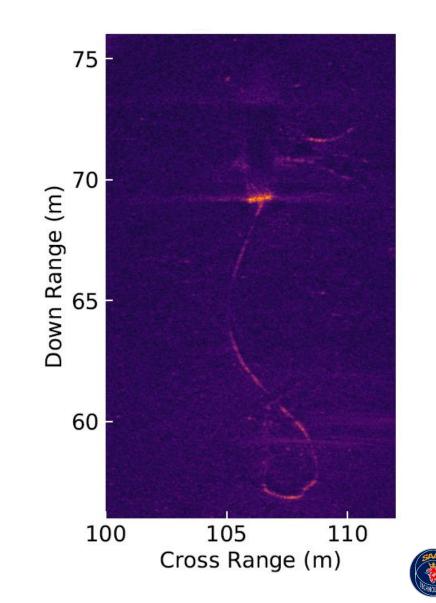
3 pings





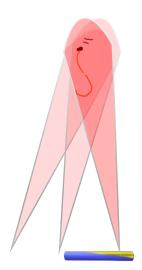
~30 pings

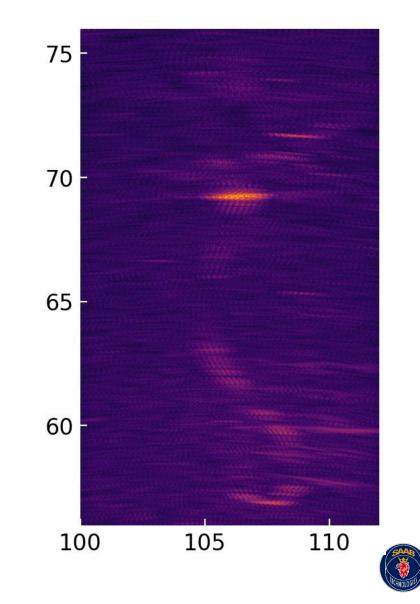




Several pings

Three pings used, with no overlap (and no autofocus), *coherently* added

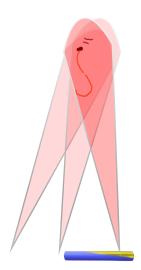


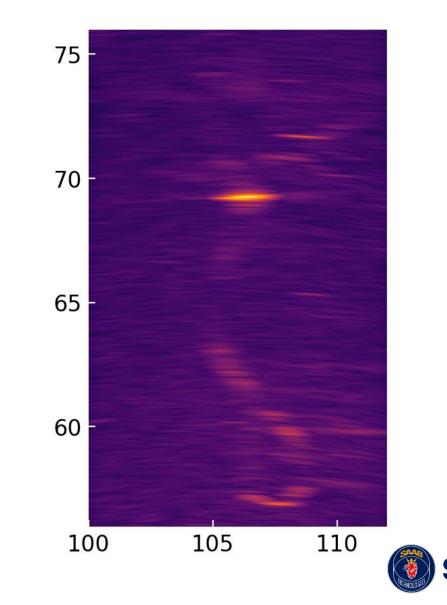


B

Several pings

Three pings used, with no overlap (and no autofocus), *incoherently* added

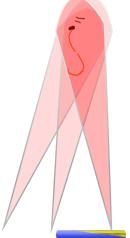


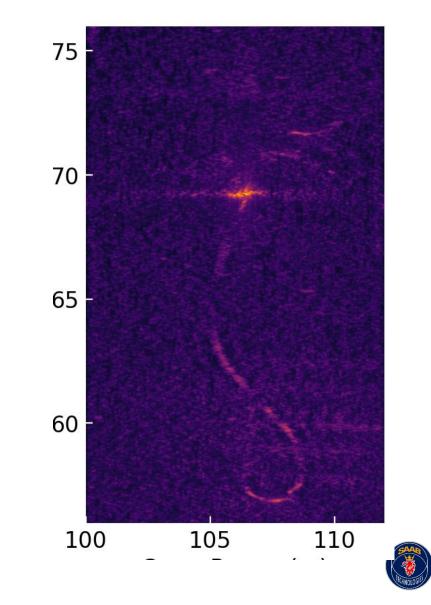


B

Several pings

Three pings used, with no overlap (and no autofocus), *processed* using CS and incoherently added





Same data from 3 non-overlapping pings without autofocus

75

70

65

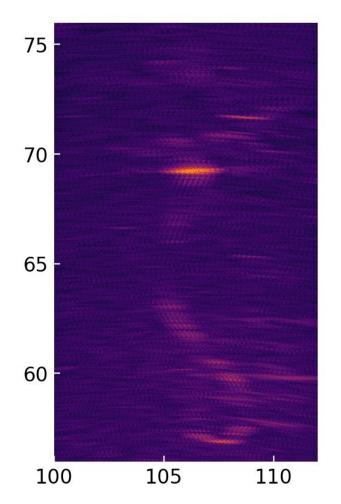
60

100

105

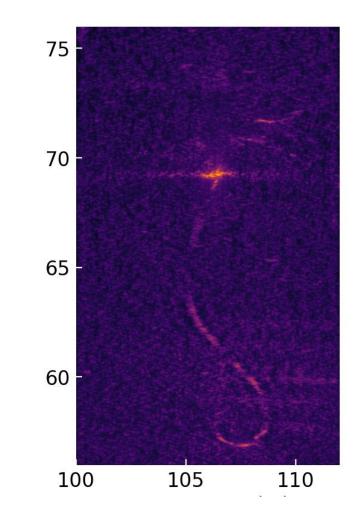
110

Coherently added



Incoherently added

CS and *incoherently* added





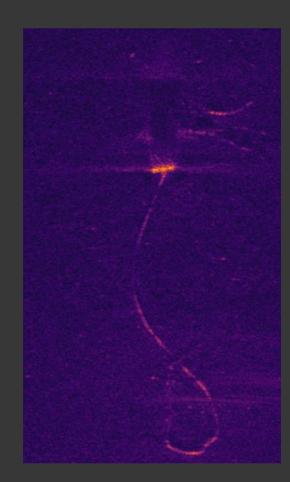
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- Compressive sensing utilizing the sparsity in sonar data is an interesting and promising tool
- Examples:
 - Enhancing resolution in one-ping images
 - Combining multiple pings



Thank you





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