# Compressive sensing in medical ultrasound (Invited paper)

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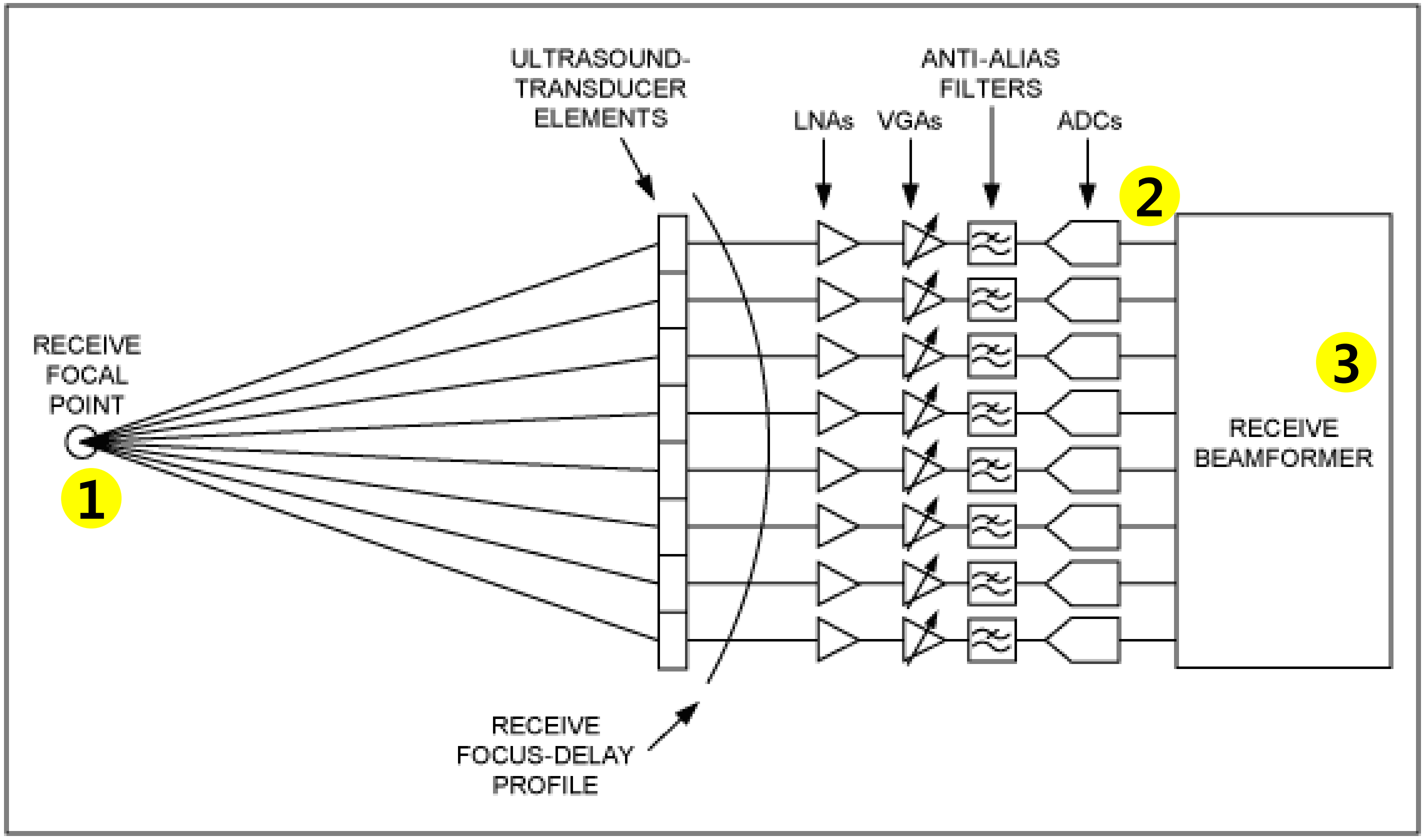
# Introduction

- Compressed sensing can be applied for two main purposes:
  - *i*) it can lower the amount of data needed and thus allows to speed up acquisition.
  - An example in the field of medical imaging of such application is dynamic MRI [4].
  - *ii*) it can improve the reconstruction of signals/images in fields where constraints or the physical acquisition set up yields very sparse data sets.
  - A typical example is seismic data recovery in geophysics [5].
- The objective of this paper is
  - to give the reader an overview of the different attempts to show the feasibility of CS in medical ultrasound.
- The classification of the studies is done according to the data that are considered to be sparse.
  - the scatterer distribution itself, the pre-beamforming channel data, the beamformed RF signal and even Dopple data.

# Introduction

- The way that how to be sparse in some domains is a key idea to apply the inverse problem to the CS problem.
- In this paper, they show several schemes that expand data into sparse signals.



# Application to Ultrasound Imaging

- A central concern in CS is that the data under consideration should have sparse expansion in some dictionaries.
  - Fourier basis, wavelet basis, dictionary learned from data, etc...
  - i.e., the number of non-zero coefficients of the image or signal in this representation basis should be as small as possible.
- One of the main features of the existing studies is the type of signal/image to be reconstructed and the choice of the representation where the US data are assumed to be sparse.
- We overview the following models in the sparse domains
  - Sparse diffusion map
  - Sparse Raw RF
  - Sparse assumption of the RF images Fourier transform
  - Doppler imaging

# Sparse diffusion map

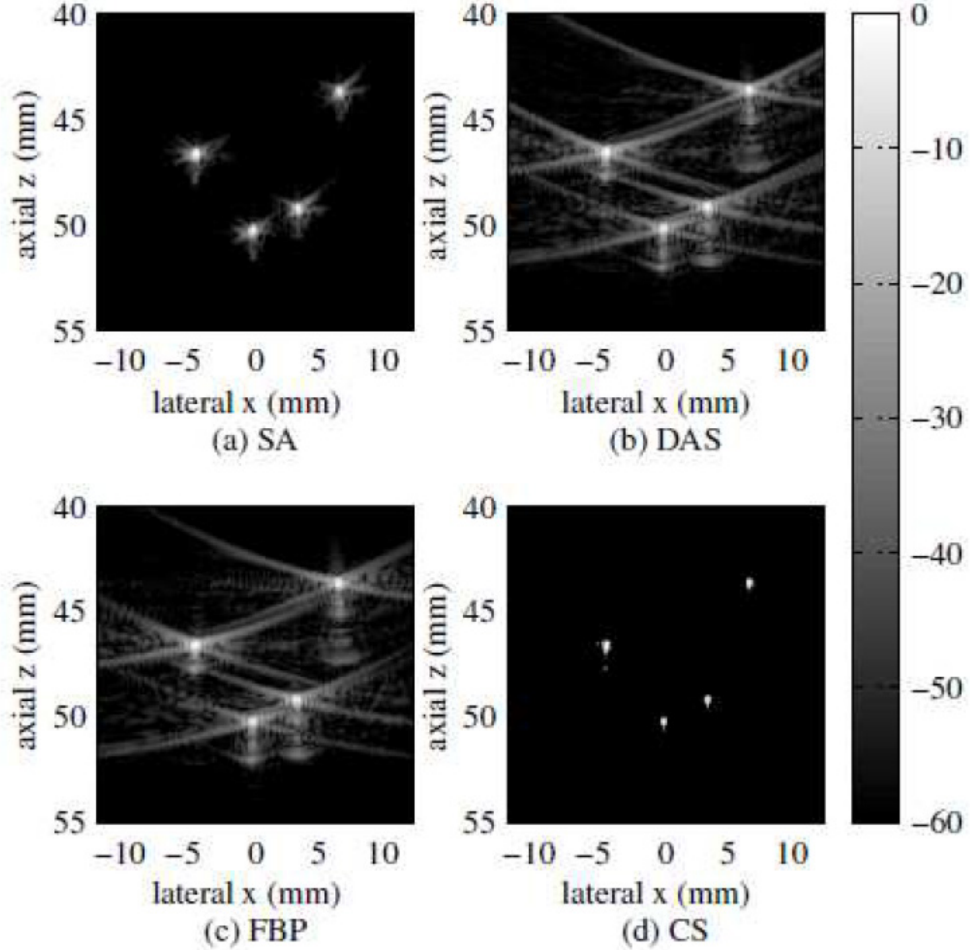
- Several groups of authors [12-18] have chosen to model the medium under investigation itself as a sparse distribution of scatters.
- However, considering that most of the scatters have an echogenecity close to zero is more unusual.
- The basic idea [12-13] is to write the direct scattering problem and solve the inverse problem under the constraint that the scatter distribution is sparse.

$$\boldsymbol{p}^{sc}\left(e_\theta\right)=\boldsymbol{G}\left(e_\theta\right)\gamma_K$$

  - With $\boldsymbol{p}^{sc}\left(e_\theta\right)$ the scattered pressure received by the transducer elements after transmission of a plane wave in direction $\theta$, $\boldsymbol{G}\left(e_\theta\right)$ represents propagation and interaction with the scatters and $\gamma_K$ is the scatter distribution lying on a regular grid.
- If $\gamma_K$ is assumed to be sparse, this problem is equivalent to the CS problem.

# Sparse diffusion map

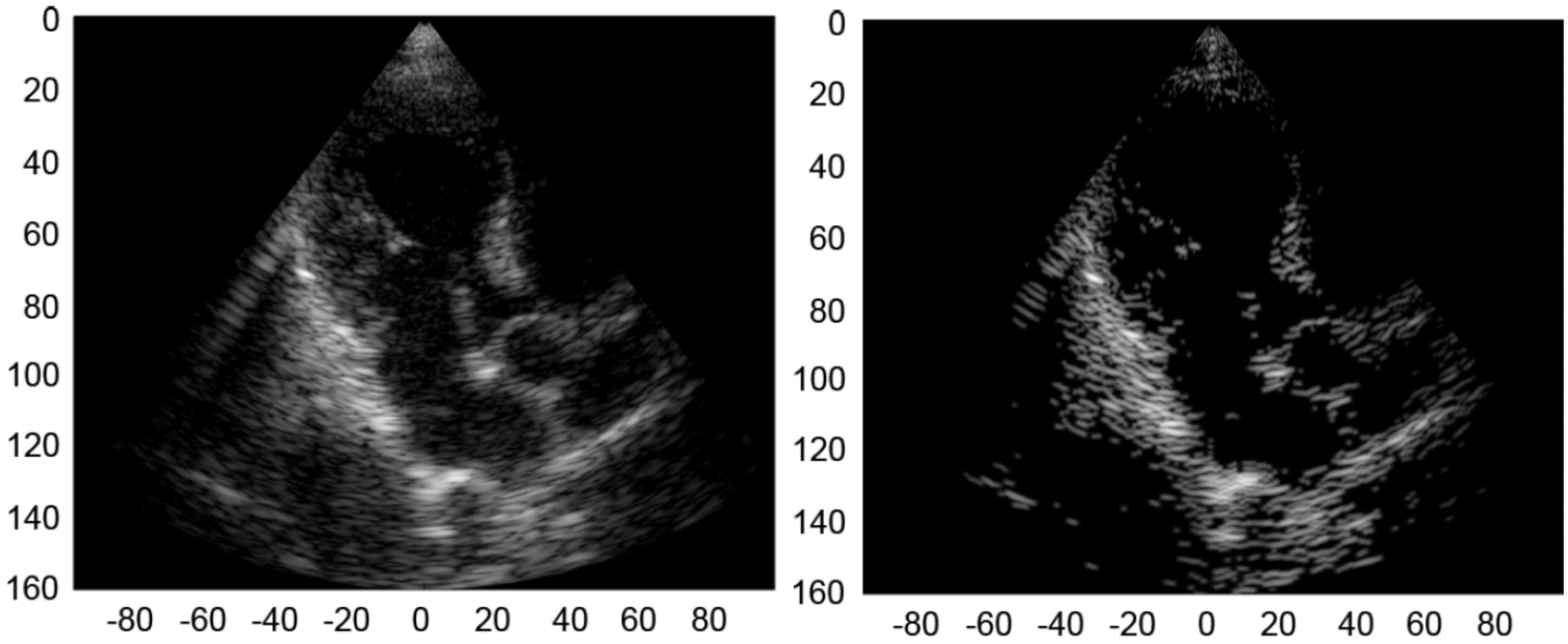
- Figure shows a result from a simple phantom consisting in four isolated scatters obtained with this approach.




- The CS result (d) is compared with synthetic aperture (a), delay and sum (b) and Fourier propagation (c).

# Sparse diffusion map

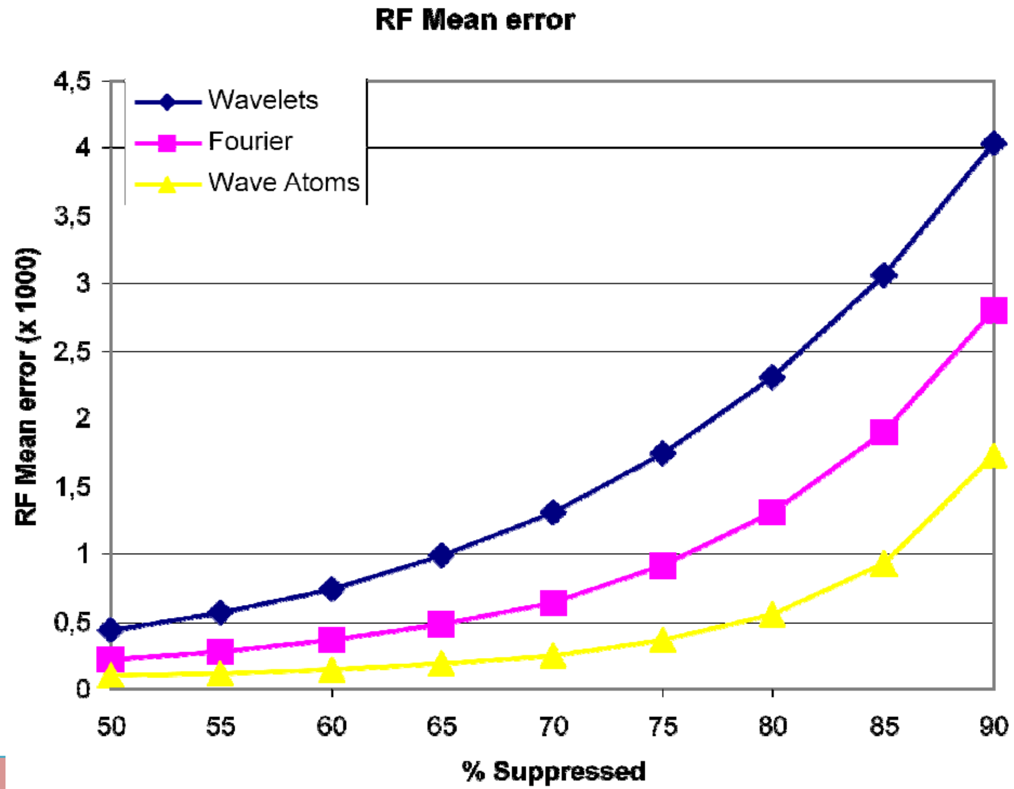
- With the same assumption [14, 15] proposed another approach based on finite rate of innovation and Xampling.




- The edges are well reconstructed but the speckle is close to be completely lost in some parts of the images.
- This is consistent assumption of scatter map sparsity.

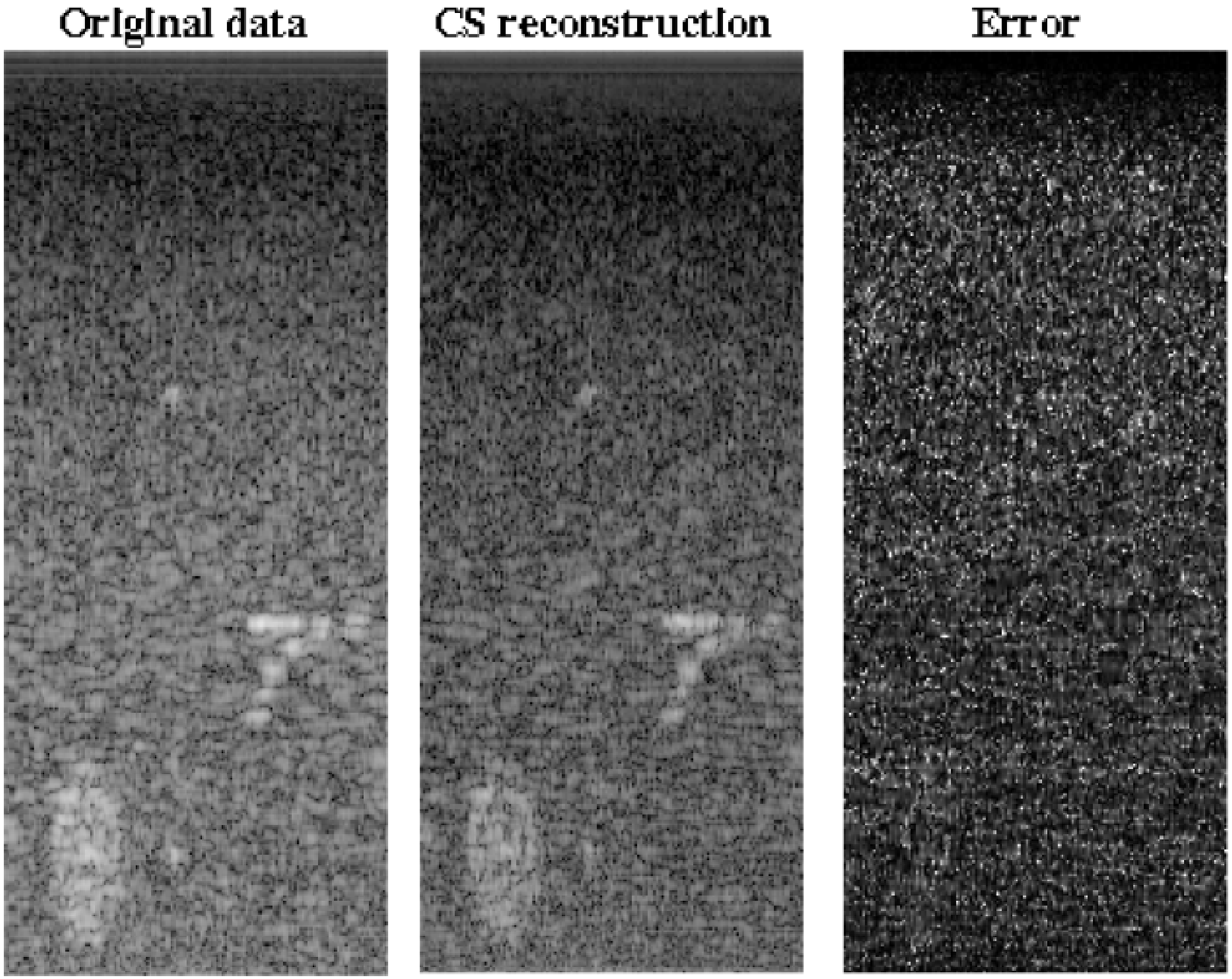
# Sparse Raw RF

- Another group of authors [21-24] consider that the raw channel data gathered at each transducer element during receive have a sparse decomposition in some basis.
- The objective of such an approach is to reduce the quantity of pre-beamformed data acquired and evaluate the ability of this approach to reconstruct B-mode images of good quality.



# Sparse Raw RF

- Figure shows experimental results obtained from only 20% of the original data using CS and wave atoms.



# Sparse assumption of the RF images Fourier transform

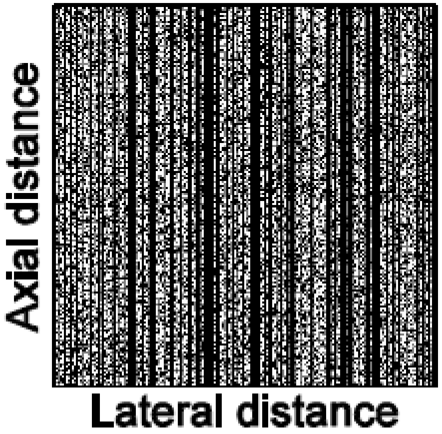
- The reconstruction of post-beamforming 2D RF images via CS technique is addressed.
- The sparsity assumption is related to the assumption of bandlimited RF signal acquisition.
- The 2D Fourier transform of RF images is assumed to be sparse.

$$y = \Phi \Psi x$$

  – $\Phi$ denotes the sampling mask, $\Psi$ is the 2D Fourier Transform.

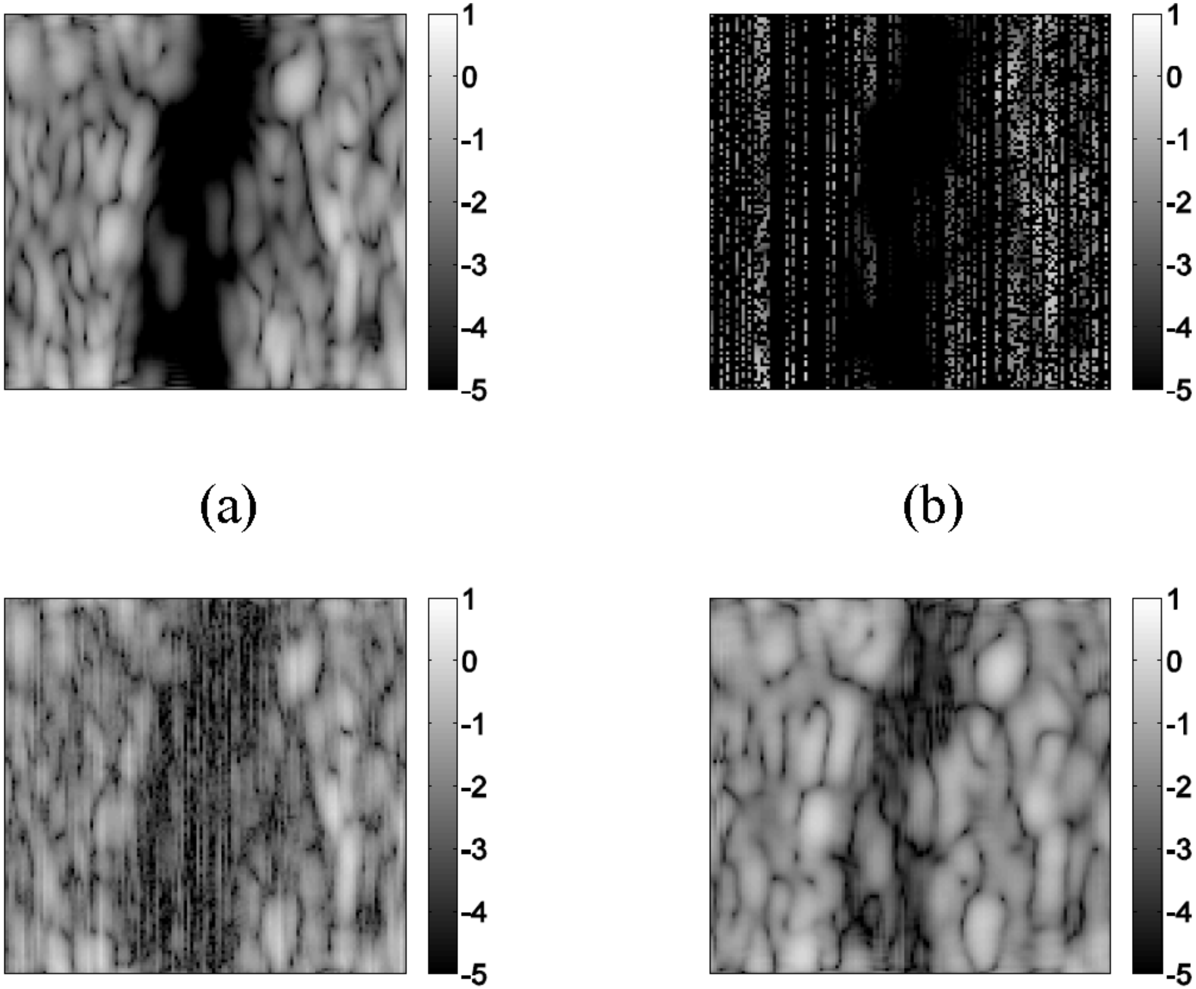
Random post-beamforming

RF sampling mask



# Sparse assumption of the RF images

- (a) original simulated RF image, (b) RF samples used for reconstruction, (c) reconstructed RF image using a reweighted conjugate gradient optimization, (d) reconstructed RF image using the Bayesian framework proposed in [20].

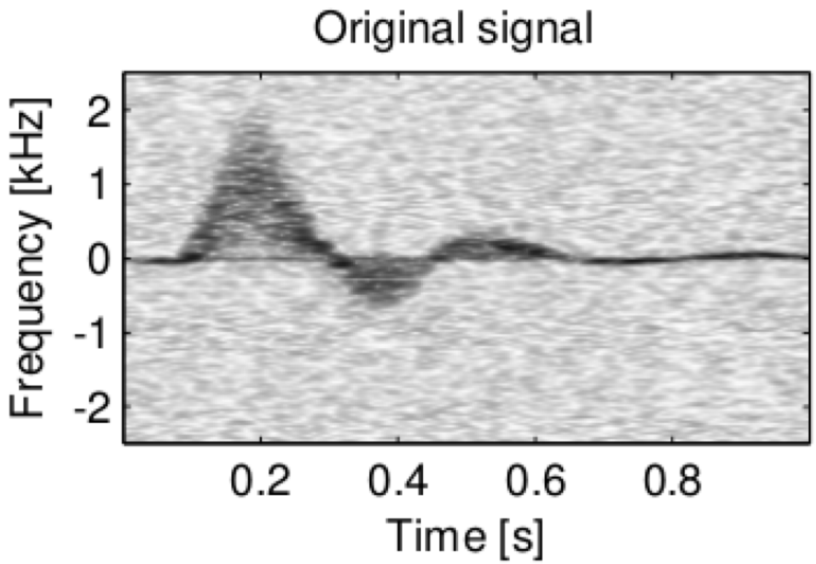



(a) (b)

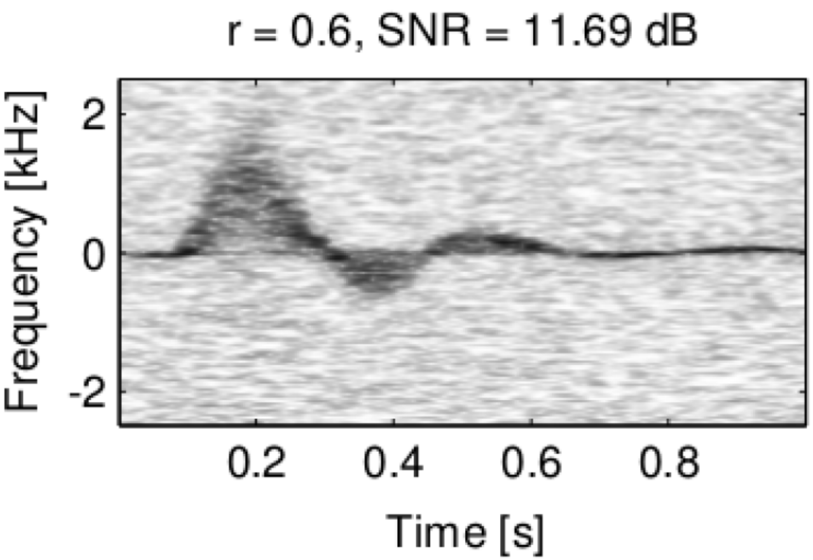
(c) (d)

# Doppler imaging

- CS has also been proposed for Doppler imaging [32, 33].
- The authors [32] made the assumption that the Fourier transform of the Doppler signal is sparse.



(a)



(b)

- In vivo Doopler result from a femoral artery. (a) real sonogram; (b) reconstructed sonogram based on CS, where r is the ratio of the number of Doppler samples to the total number of samples.

# Conclusion

- Compressed sensing medical ultrasound is a very recent field of research that can lead to drastic modifications in the way ultrasound scanners are developed.
- The technique is feasible but far from its technological applicability.
- The key points for CS to work are
  - A sparsifying basis
  - A measure basis in coherent with the sparsifying basis
  - Dedicated acquisition material
  - Fast and robust reconstruction algorithms
- Improvements are necessary for all of these concerns.
- Efforts should be made in order to maintain the real-time characteristic of medical ultrasound.

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