

# Away from Orthonormal Basis: Sparsity Meets Redundancy

Mathematical Models and Methods for Image Processing

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# Assignment

The limitations of sparsity

# Generate a sparse 1D signal w.r.t. $D$

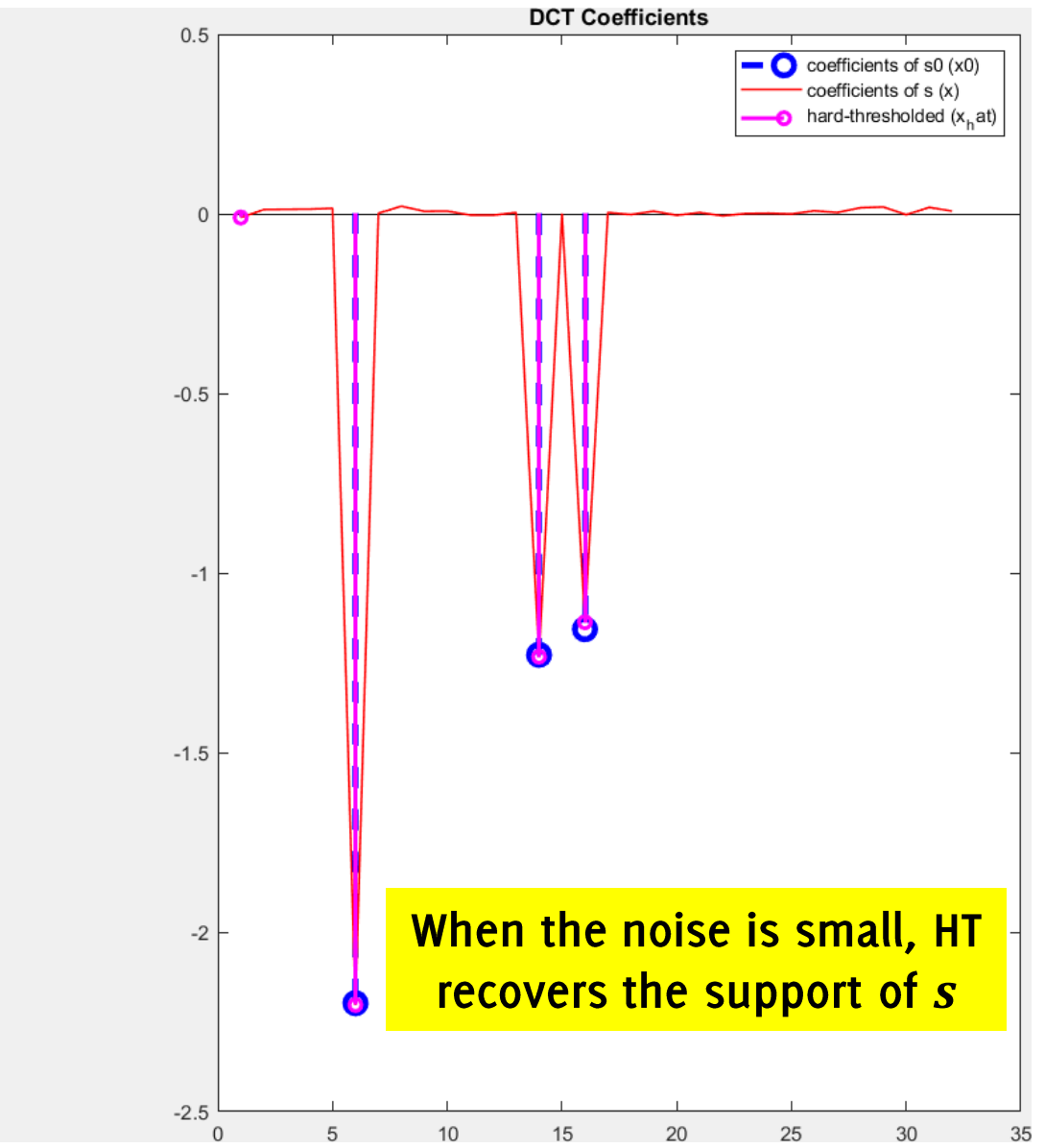
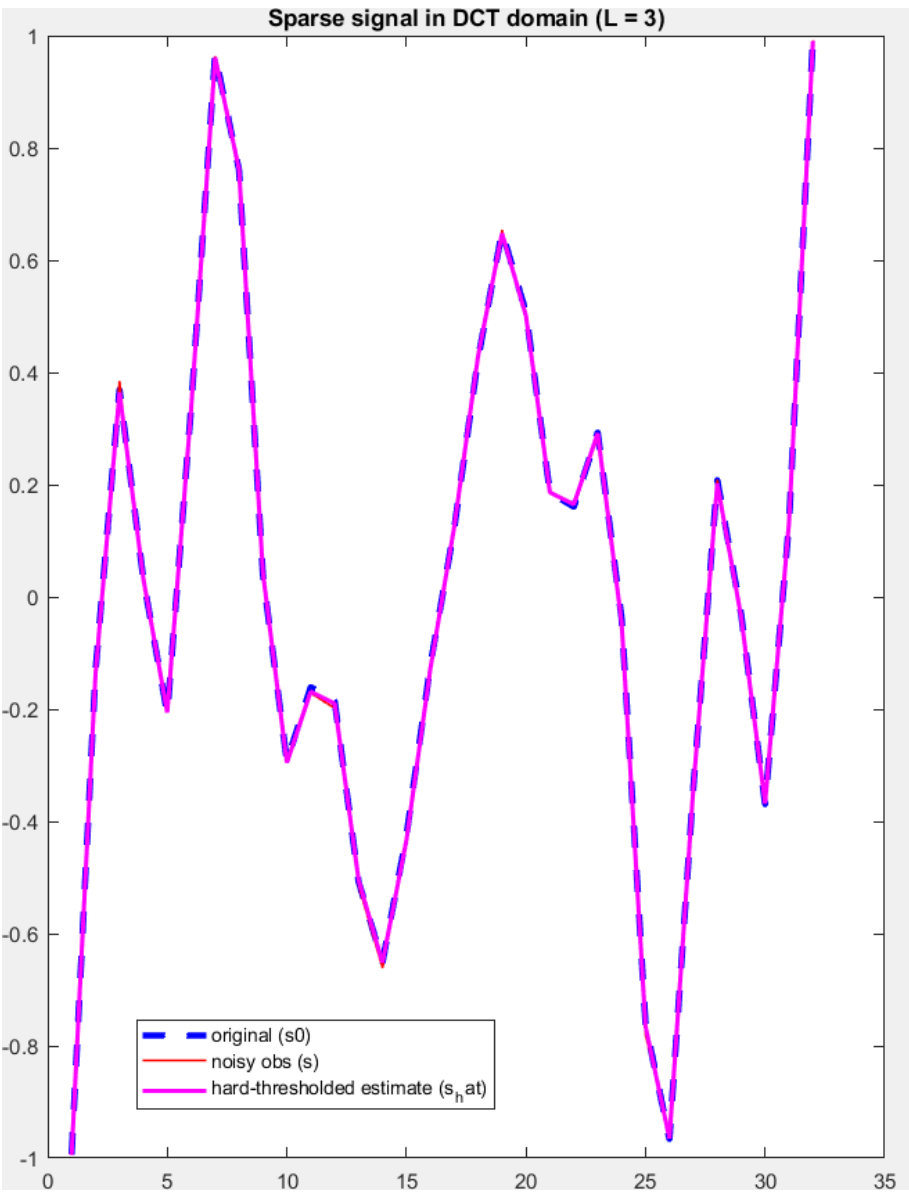
Idea:

1. Randomly define sparse coefficients  $x_0$  of size  $M$
2. Synthesis w.r.t. a DCT dictionary, i.e. compute  $s_0 = Dx_0$
3. Add white Gaussian noise  $\eta$ :  $s = s_0 + \eta$

**Rmk:**

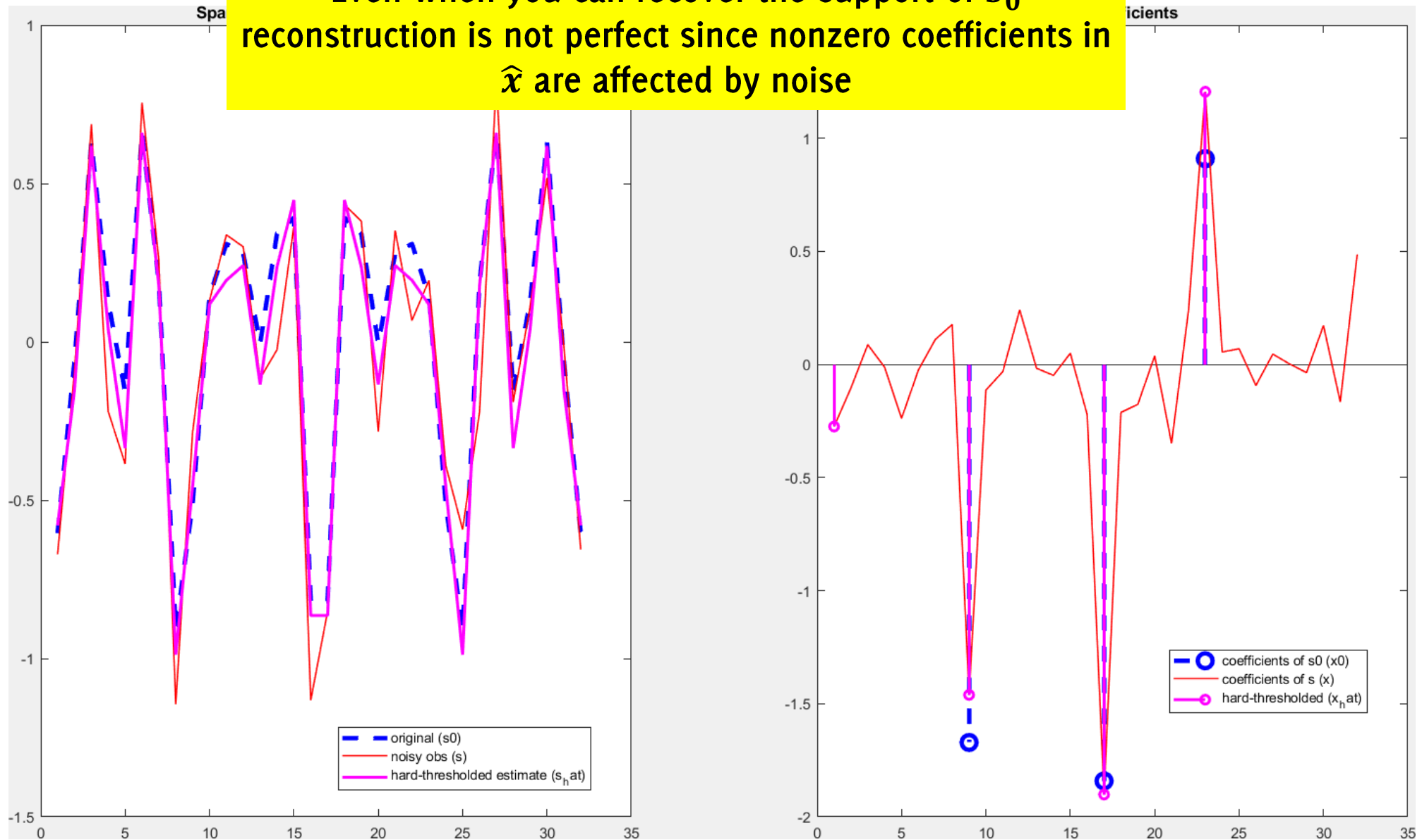
$s$  might not look very realistic, but this is truly sparse w.r.t.  $D$

# Generate a truly sparse signal w.r.t. D

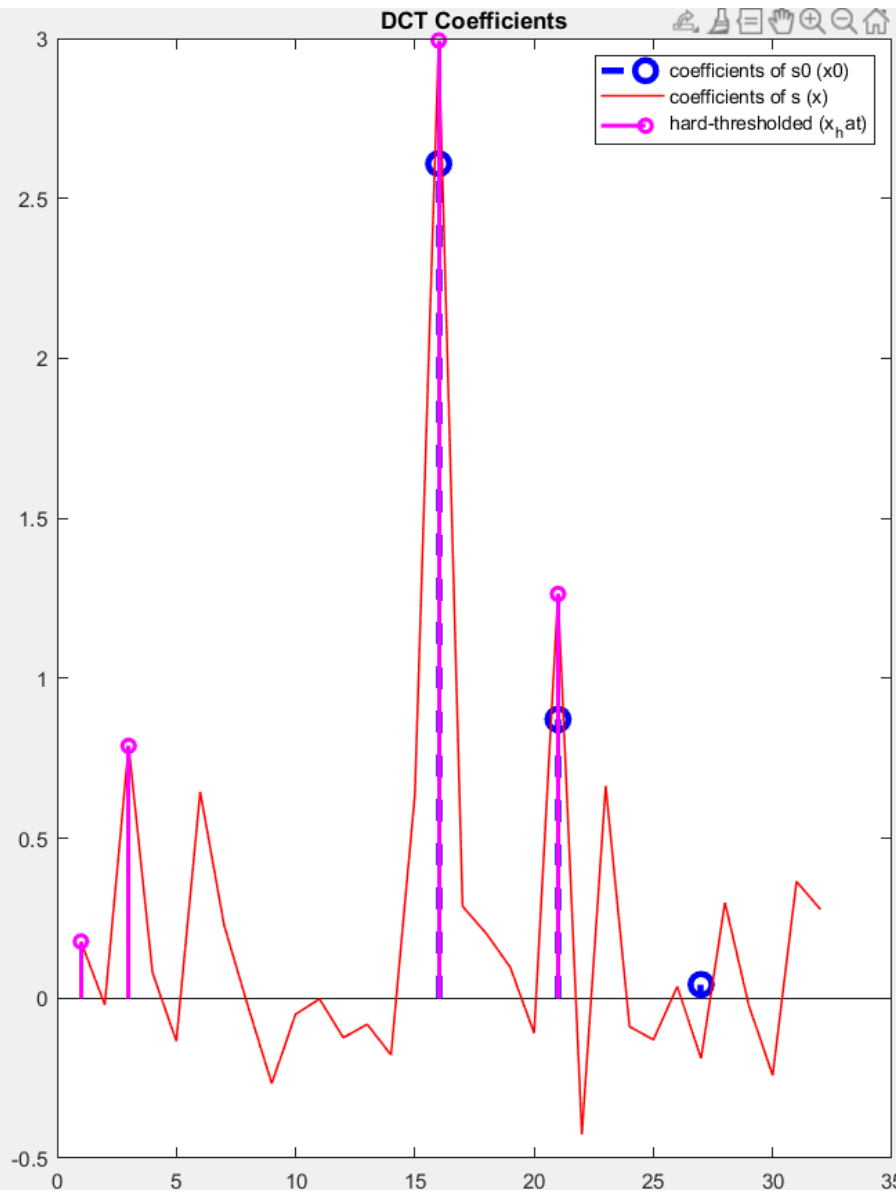
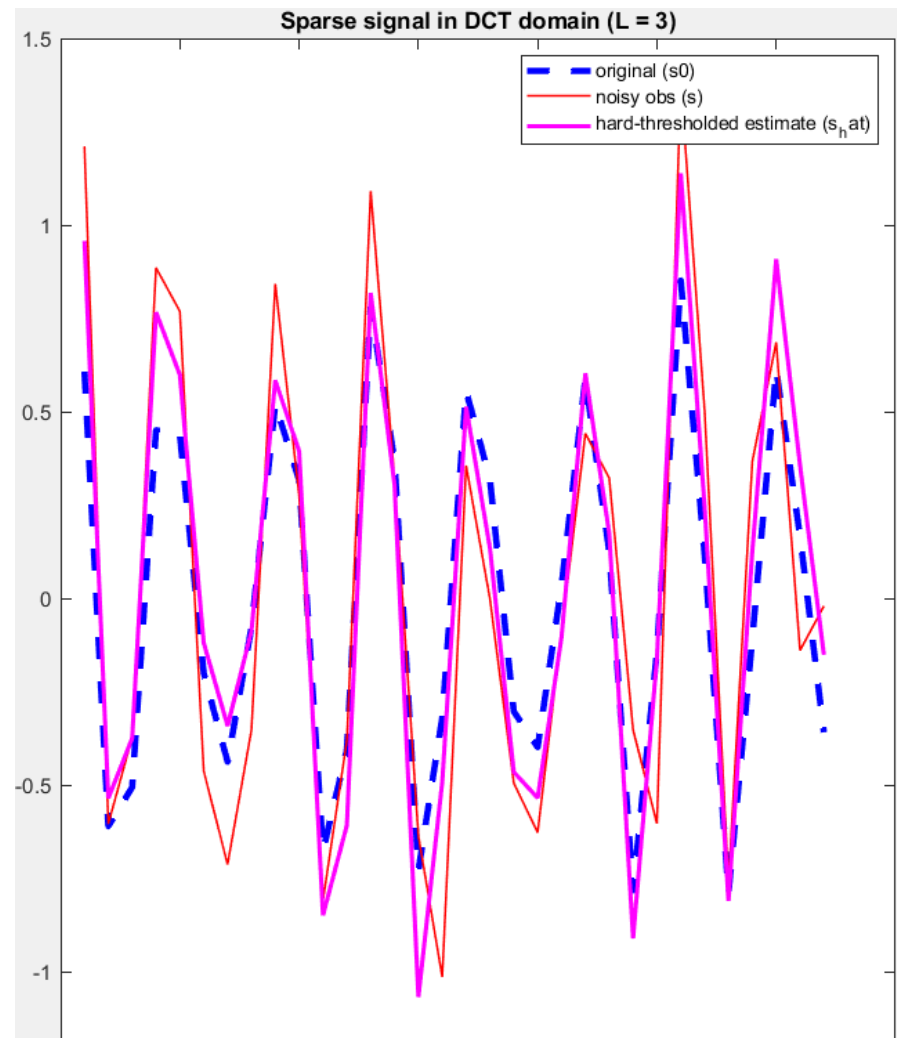


# Generate a truly sparse signal w.r.t. D

Even when you can recover the support of  $s_0$  reconstruction is not perfect since nonzero coefficients in  $\hat{x}$  are affected by noise



# Generate a truly sparse signal w.r.t. D



When the noise is large, HT might fail even at recovering the support of  $x_0$

# Now, assume your signal is sparse w.r.t. $[D, C]$

Idea:

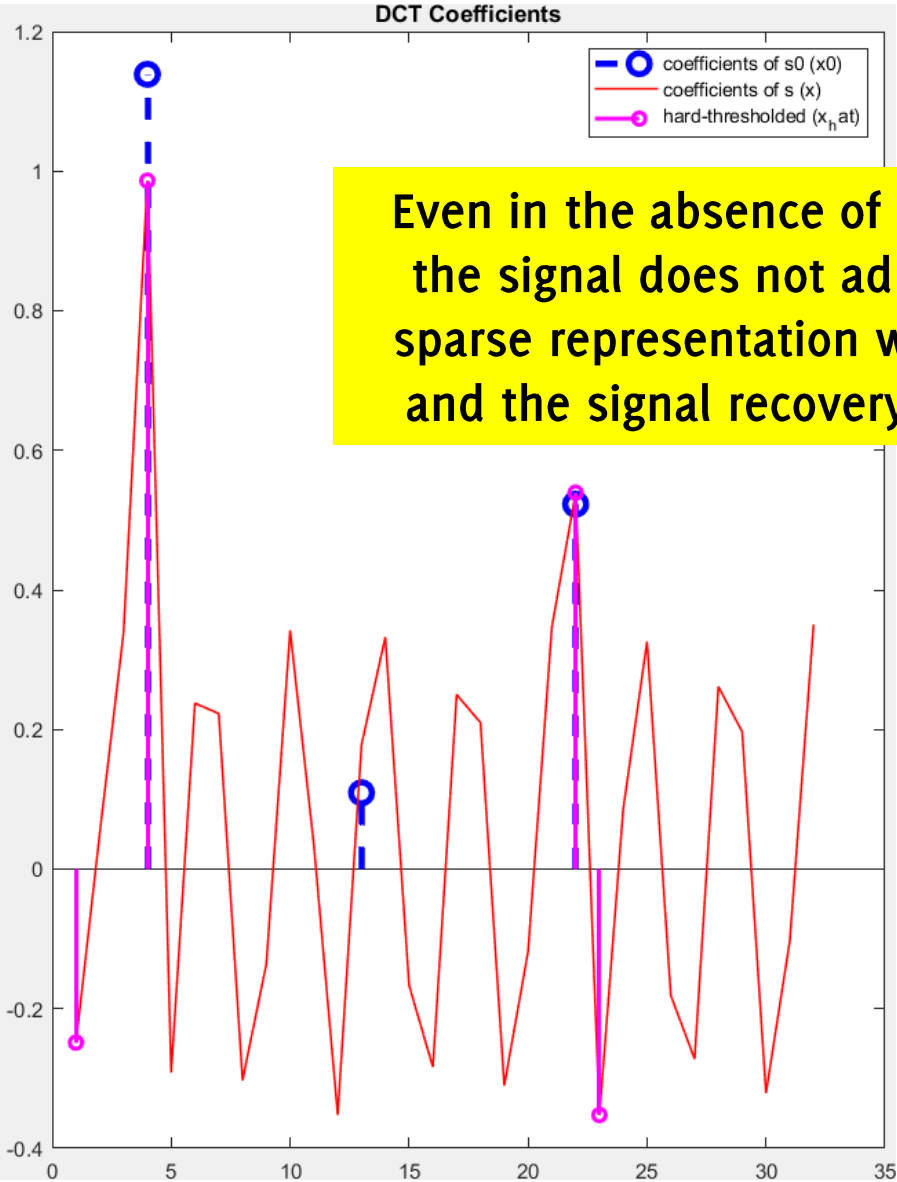
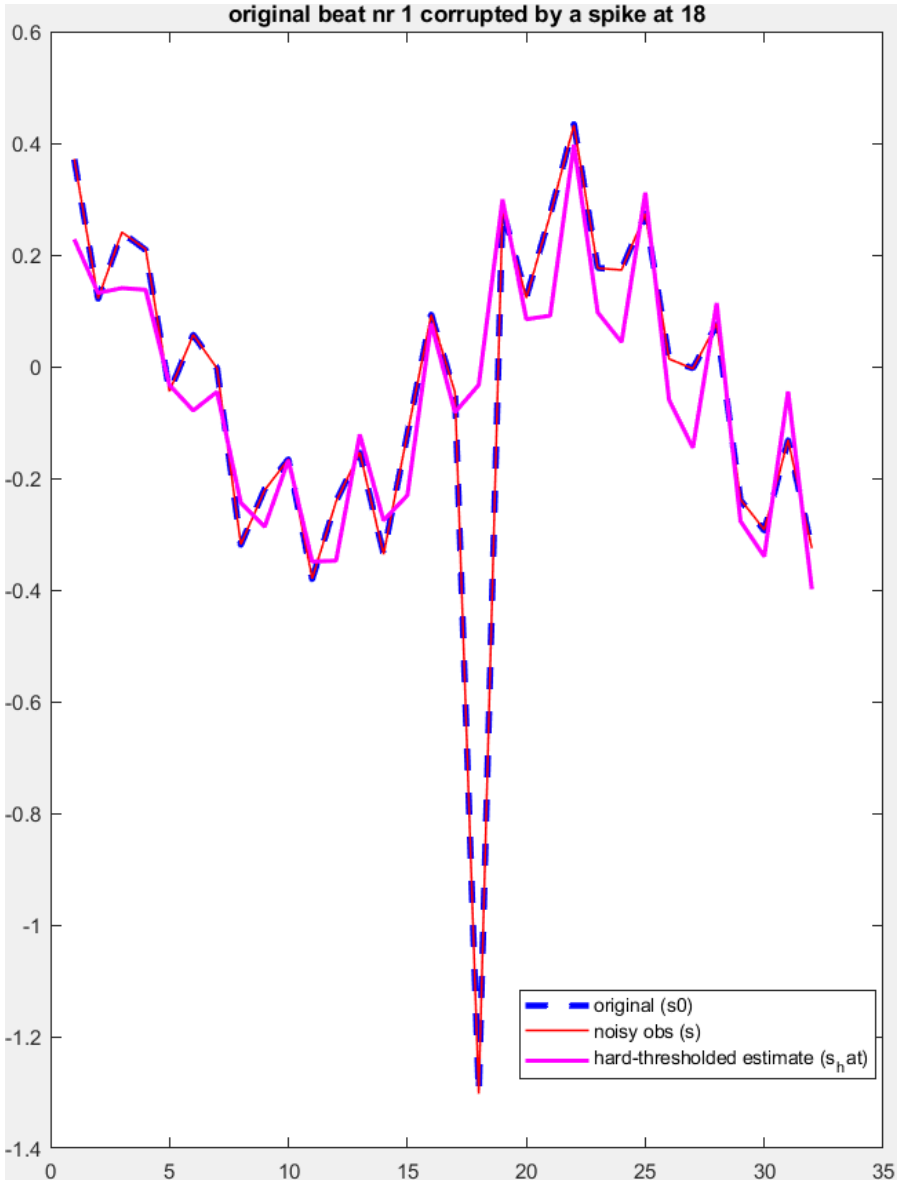
1. Randomly define sparse coefficients  $x_0$
2. Synthesis w.r.t. a DCT dictionary, i.e. compute  $s_0 = Dx_0$
3. Add a spike  $\delta_c$  at location  $c$ , which is a sparse element w.r.t.  $C$

$$s_0 = s_0 + \lambda\delta_c$$

where  $\lambda$  and  $c$  are randomly defined

4. Add noise:  $s = s_0 + \eta$

# Truly sparse signals w.r.t. $[D, C]$



Even in the absence of noise, the signal does not admit a sparse representation w.r.t.  $D$  and the signal recovery fails



# Assignment

Uniqueness of Representation

# A Simple Proof

Proof that if a set of vectors  $\{\mathbf{e}_i\}$ ,  $\mathbf{e}_i \in \mathbb{R}^M$  are linearly independent and if

$$\mathbf{v} = \sum_i x_i \mathbf{e}_i, x_i \in \mathbb{R}$$

Then the representation  $\{x_i\}$  is unique