

# Fast Multidimensional Signal Processing with Shearlab.jl

Héctor Andrade Loarca

TU Berlin, BMS

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# What is a signal?

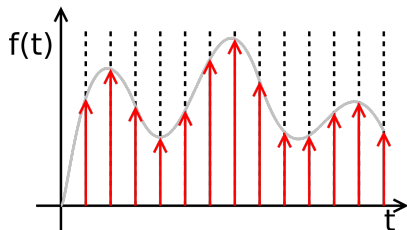
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Function (or something that can be represented as) that contains information about the behavior or attributes of some phenomenon. It can be digital (discrete) or analog (continuous).

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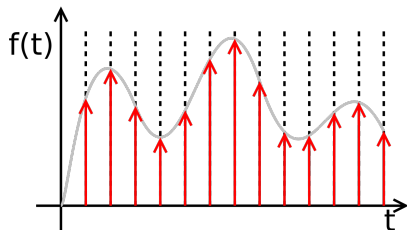


Figure: Digital and continuous one-dimensional signals

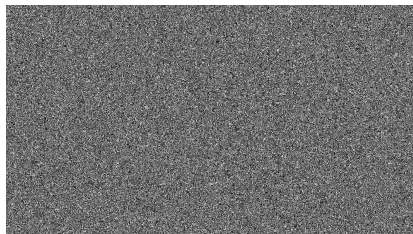


Figure: White noise, not a signal

# Sparse representations of signals

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- ▶ Goal: Find the right dictionary to represent optimally our data.

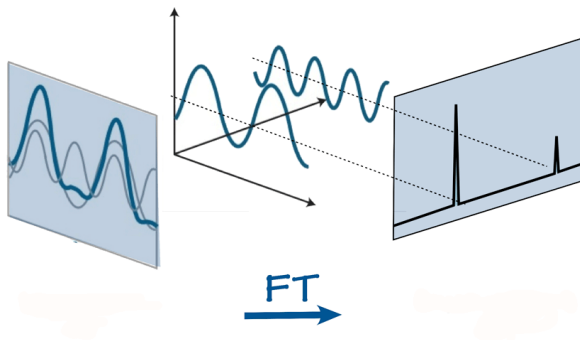
The diagram illustrates the equation  $x = D \hat{\alpha}$ . On the left, a vertical blue bar represents the signal  $x$ . This is equal to a matrix multiplication. The matrix is the 'Sparse Dictionary  $D$ ', composed of several vertical bars of different colors (red, blue, yellow, and green) and vertical ellipses indicating more columns. To the right of the dictionary is a vertical vector of 'Sparse Coefficients  $\hat{\alpha}$ '. This vector contains several small boxes, some of which are highlighted with colored borders (red, blue, yellow, and green) to show that only a few coefficients are non-zero, representing sparsity.

# Fourier Transform (Fourier, 1822)

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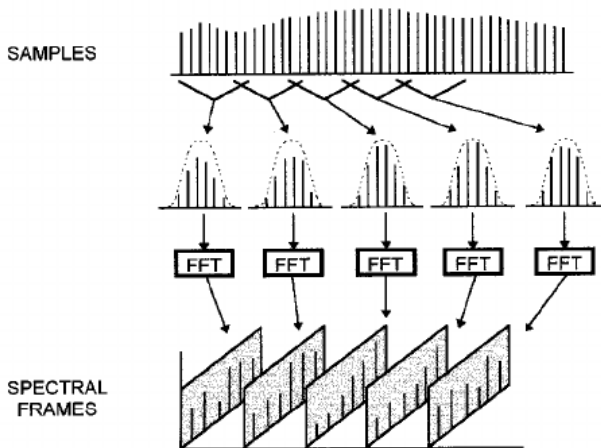


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$$\begin{aligned}\mathcal{W}_\psi f(a, b) &= \int_{\mathbb{R}} f(t) a^{-\frac{1}{2}} \overline{\psi\left(\frac{t-b}{a}\right)} dt \\ &= (f * D_a \bar{\psi}^*)(b), \quad (a, b) \in \mathbb{R}^+ \times \mathbb{R}\end{aligned}$$

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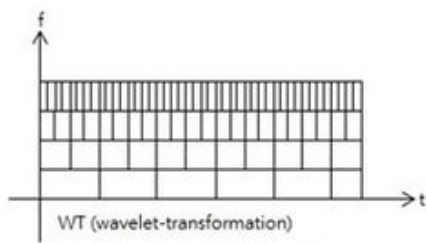
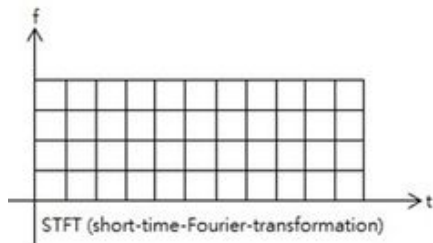
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# Cartoon-like functions

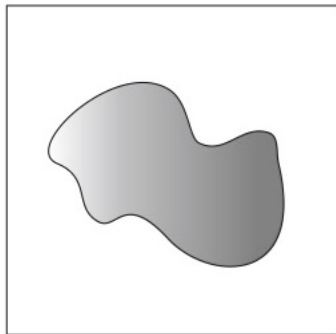
## Definition

Let  $f : \mathbb{R}^2 \rightarrow \mathbb{C}$ ,  $f \in \mathcal{E}^2(\mathbb{R}^2)$  if  $f = f_0 + \chi_B f_1$ , with  $B \subset [0, 1]^2$ ,  $\partial B \in C^2$  and with bounded curvature. Moreover,  $f_i \in C^2(\mathbb{R}^2)$  with  $\|f_i\|_{C^2} \leq 1$  and  $\text{supp} f_i \subset [0, 1]^2$  for  $i = 0, 1$ .

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# Optimal error for 2D signals

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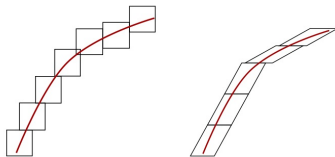
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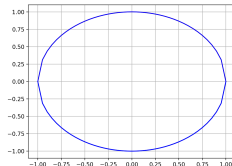
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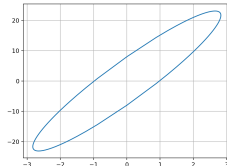
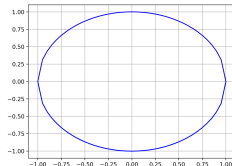
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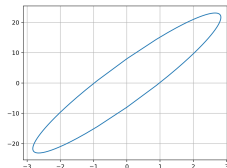
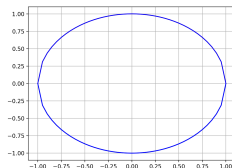
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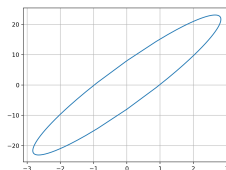
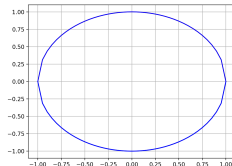
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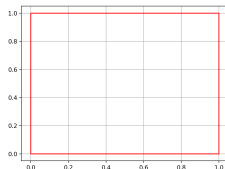
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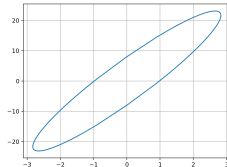
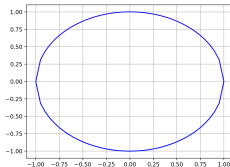
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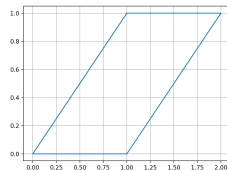
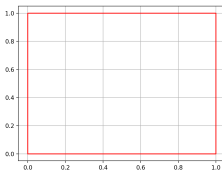
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$$\mathcal{SH}(\psi) = \{\psi_{j,k,m}(x) = 2^{3j/4} \psi(S_k A_j x - m) : (j, k) \in \mathbb{Z}^2, m \in \mathbb{Z}^2\}$$

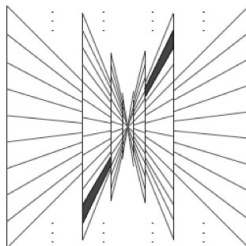
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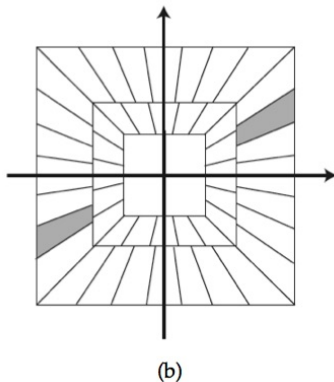
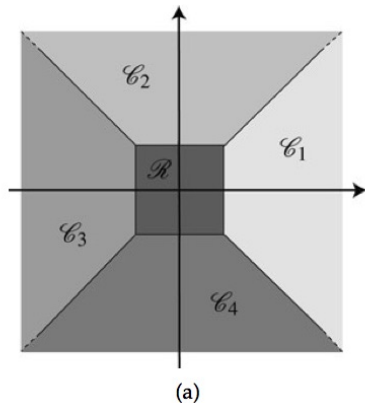


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$$\mathcal{SH}(\phi, \psi, \tilde{\psi}, c) := \mathcal{P}_{\mathcal{R}}\Phi(\phi, c1) \cup \mathcal{P}_{\mathcal{C}_1}\Psi(\psi, c) \cup \mathcal{P}_{\mathcal{C}_2}\tilde{\Psi}(\tilde{\psi}, c)$$

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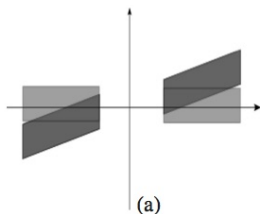
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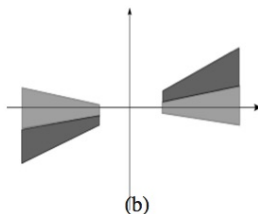
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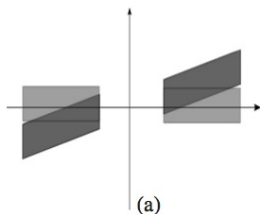
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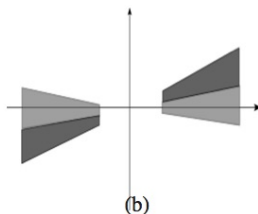
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## ► Best $N$ -term approximation error

$$\sigma_N(f, \{\psi_{j,k,m}\}_{j,k,m}) \sim N^{-1}(\log(N))^{3/2}$$



## ► Matlab

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- 2D/3D Shearlet Toolbox (D. Labate, University of Houston)  
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## ▶ Julia

- ▶ **Shearlab.jl** (H. Andrade, TU Berlin)  
<https://github.com/arsenal9971/Shearlab.jl>

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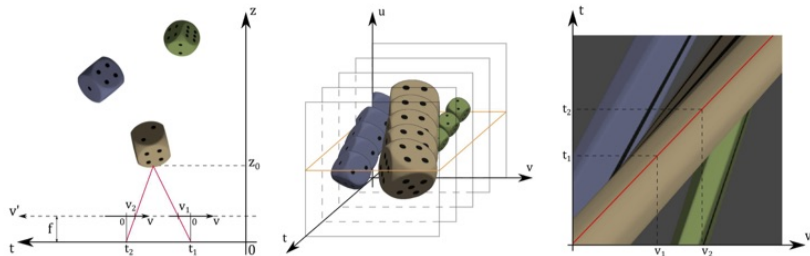
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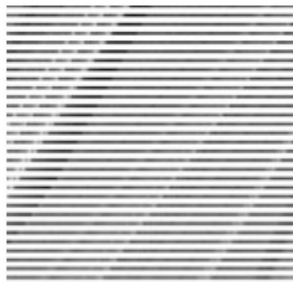
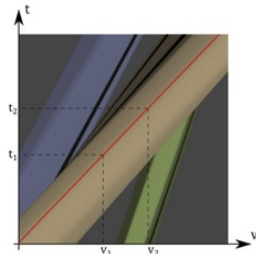
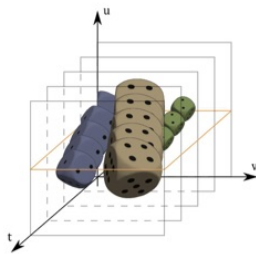
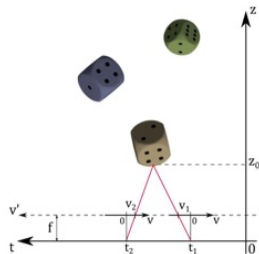
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- ▶ Support of multithreading and painless GPU processing with `ArrayFire.jl` .

# Current application: Light Field Recovery

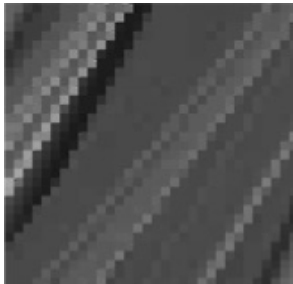
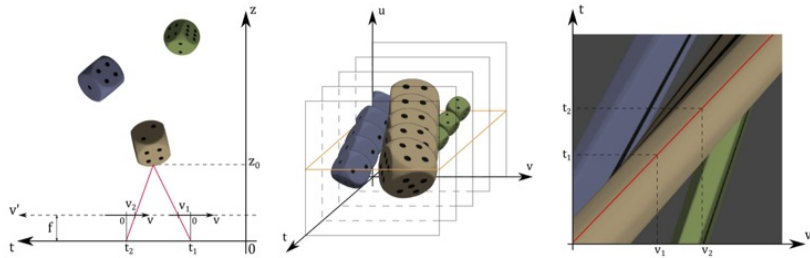




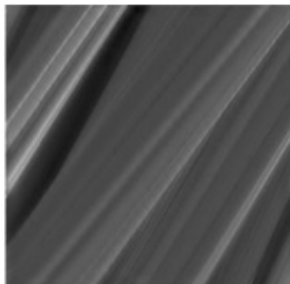
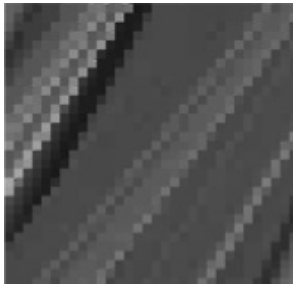
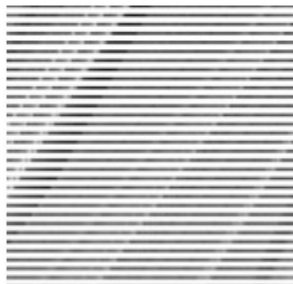
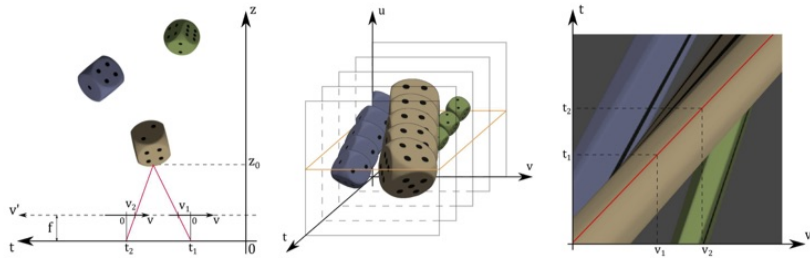
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# Thanks!

## Questions?

