Tutorial on Channel Representations

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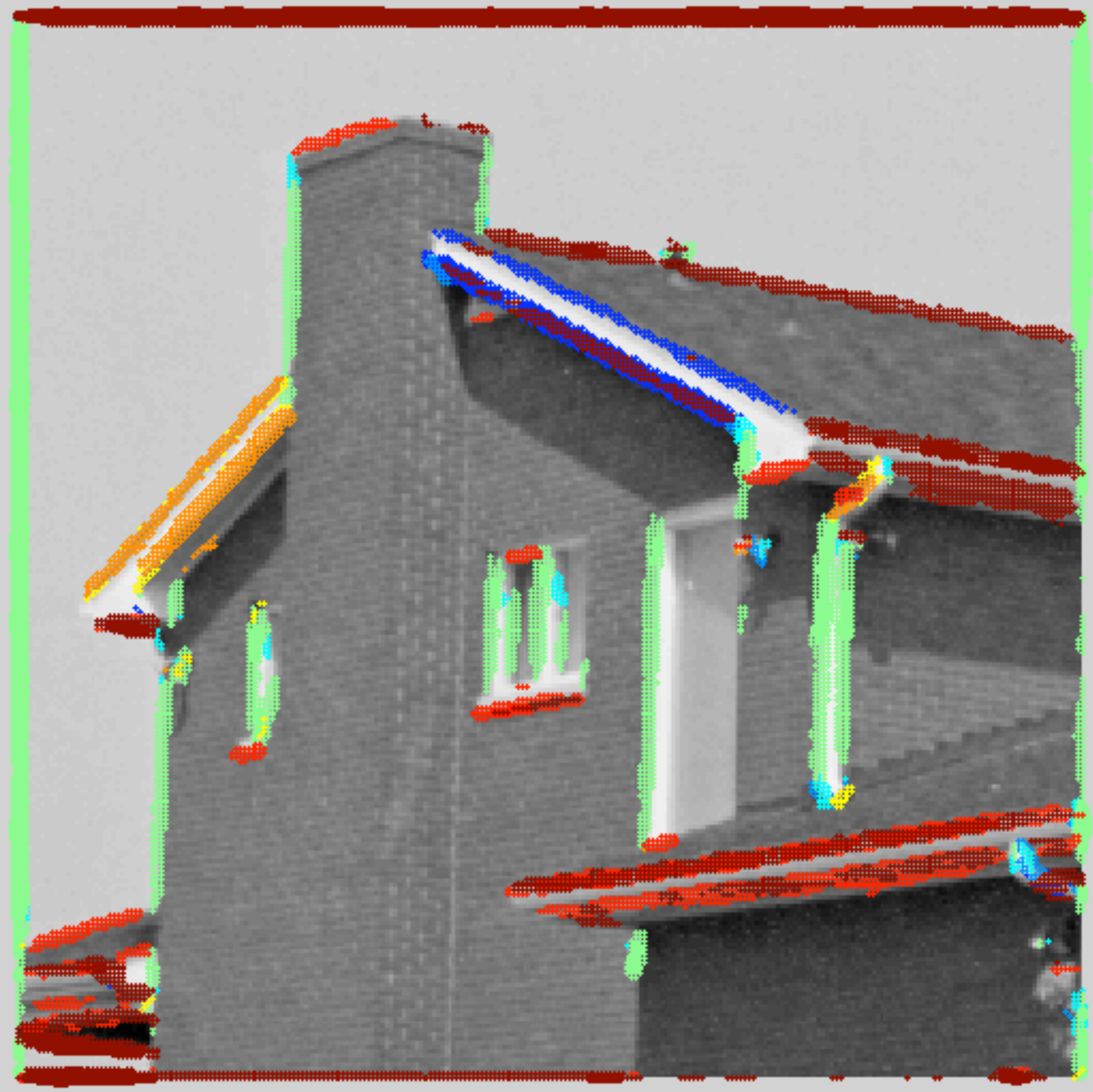
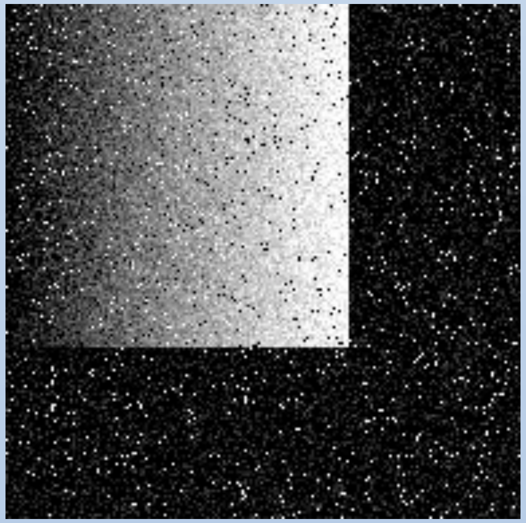
What are channels?



Channel Representation

- *distribution functions* (Granlund, 1973)
- *channel coding* (Snippe/Koenderink, 1992)
- *bandpass channels* (Howard/Rogers, 1995)
- *population coding* (Zemel et al., 1998)
- *channel representation* (Granlund, 2000)
- *channel filtering* (Felsberg/Granlund, 2003)
- *channel smoothing* (Felsberg et al., 2006)
- *"bilateral filtering"* (Paris/Durand, 2006)
- *orientation scores* (Duits et al., 2007)
- *channel coded feature maps* (Jonsson/ Felsberg, 2007)
- *distribution fields* (Sevilla-Lara/Learned-Miller, 2012)



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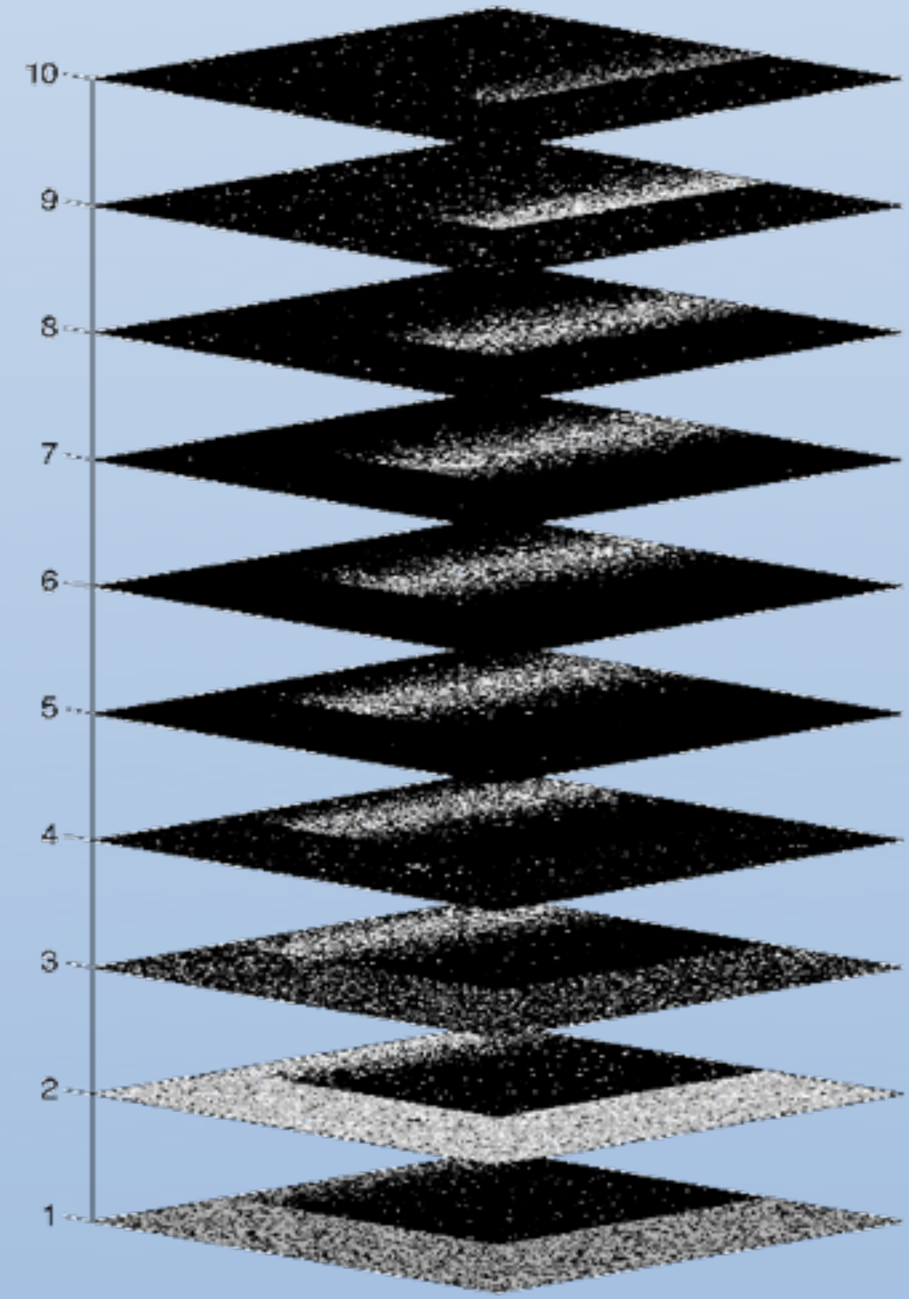

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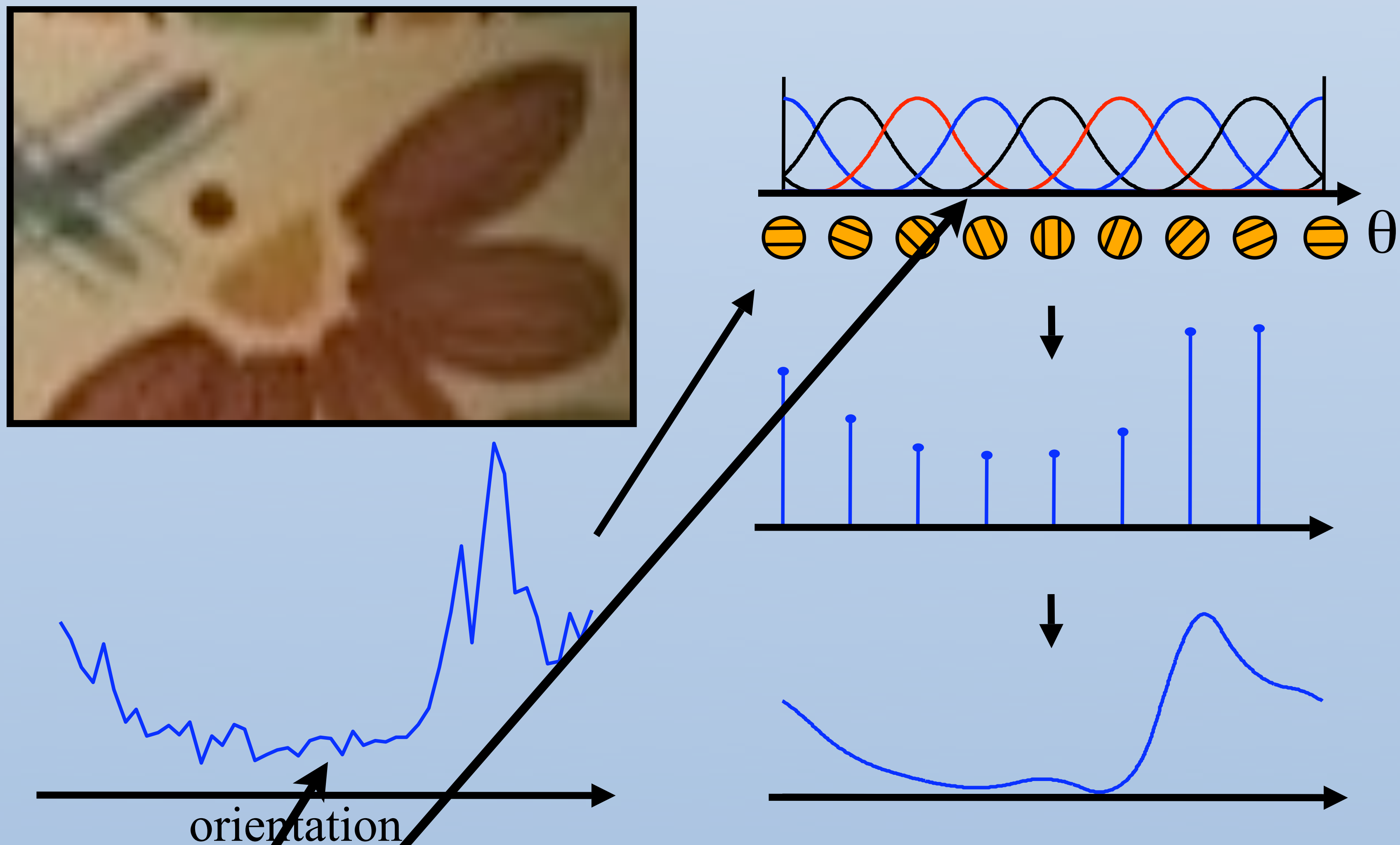
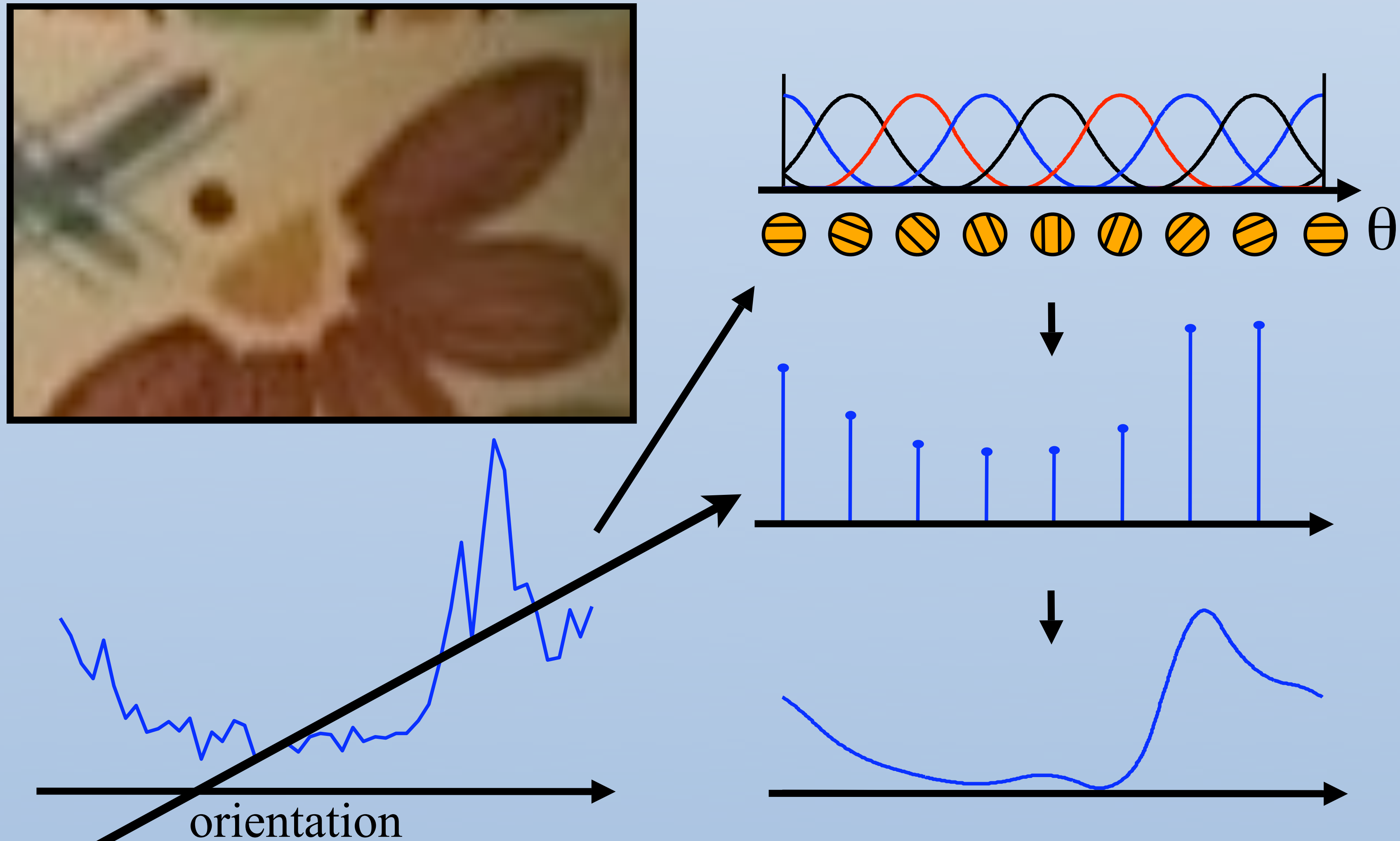


$$c_n(f) = \langle \delta_f | k_n \rangle = \int \delta_f(z) k_n(z)\, dz$$

$$k_n(z) = k(z-n)$$

$$\delta_f(z) = \delta(z-f)$$

Channel Representation

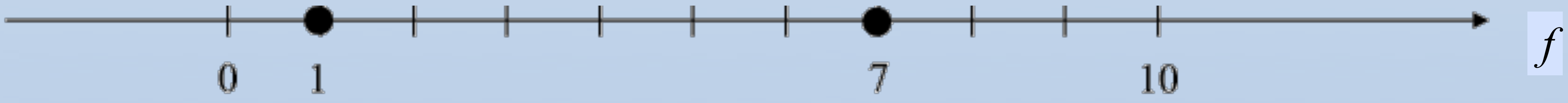


$$k_n(z) = k(z-n)$$

$$\delta_f(z) = \delta(z-f)$$

$$c_n(f) = \langle \delta_f | k_n \rangle = \int \delta_f(z) k_n(z)\, dz$$

Channel Representation

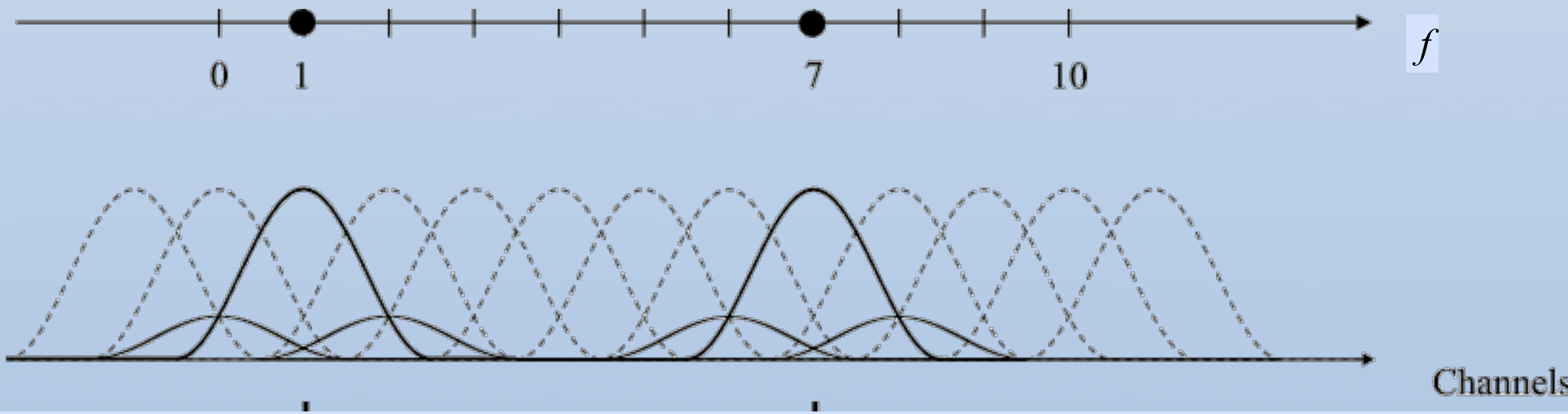


Encode values in K-D channel vector

$$x_k = F_k(f) \qquad k = 1,\ldots, K$$

Motivated from population coding, sparse coding

Channel Representation



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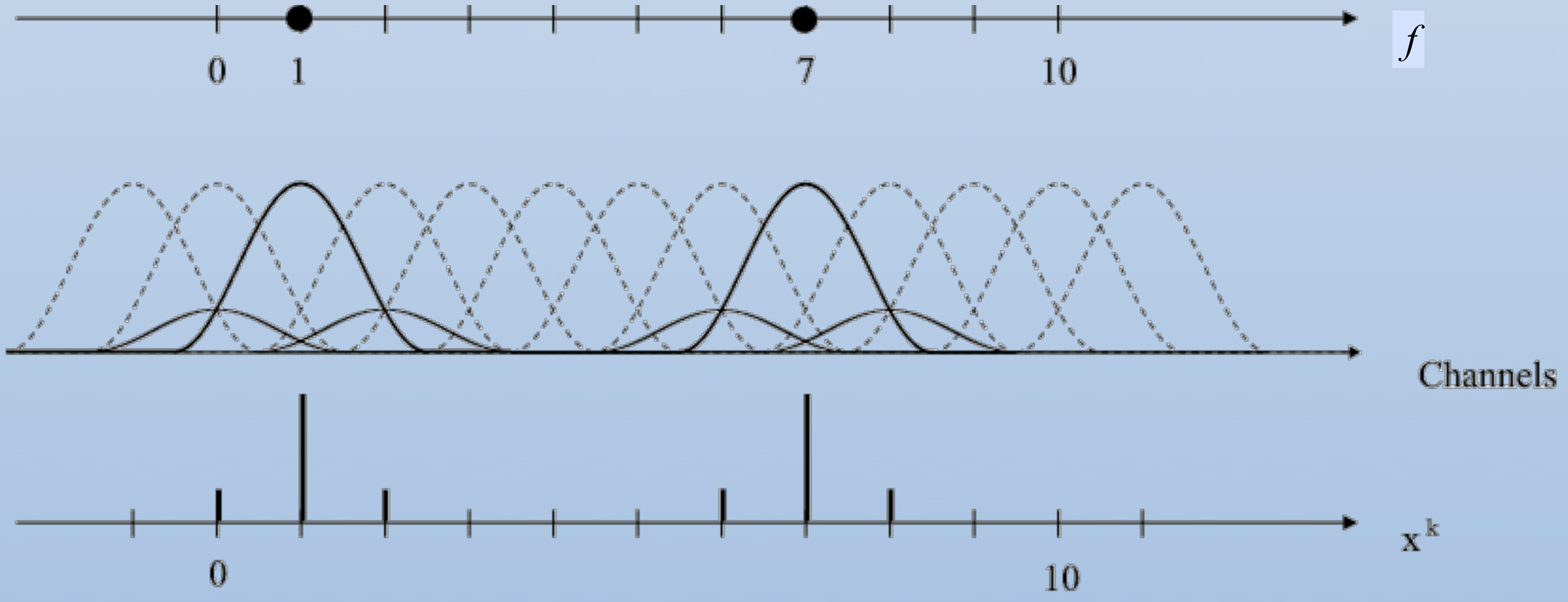

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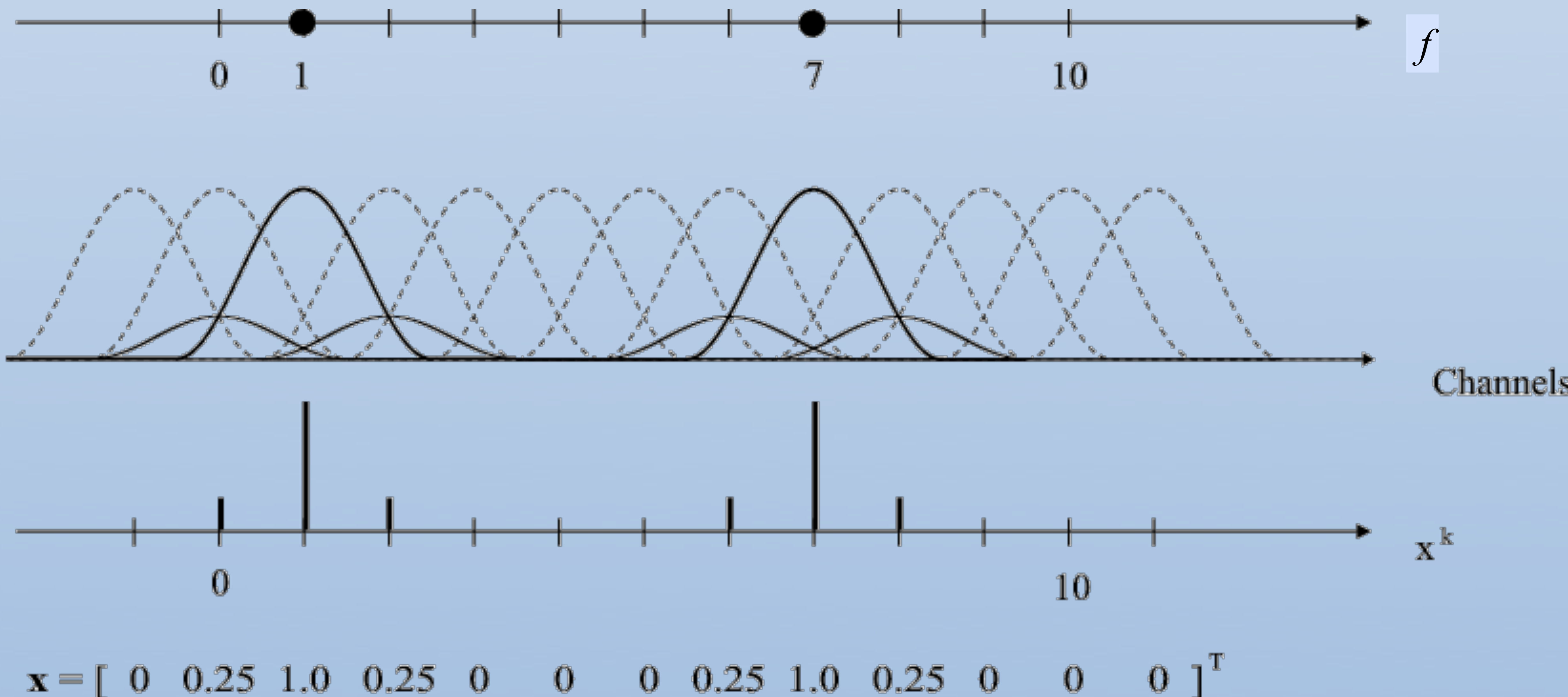
Channel Representation

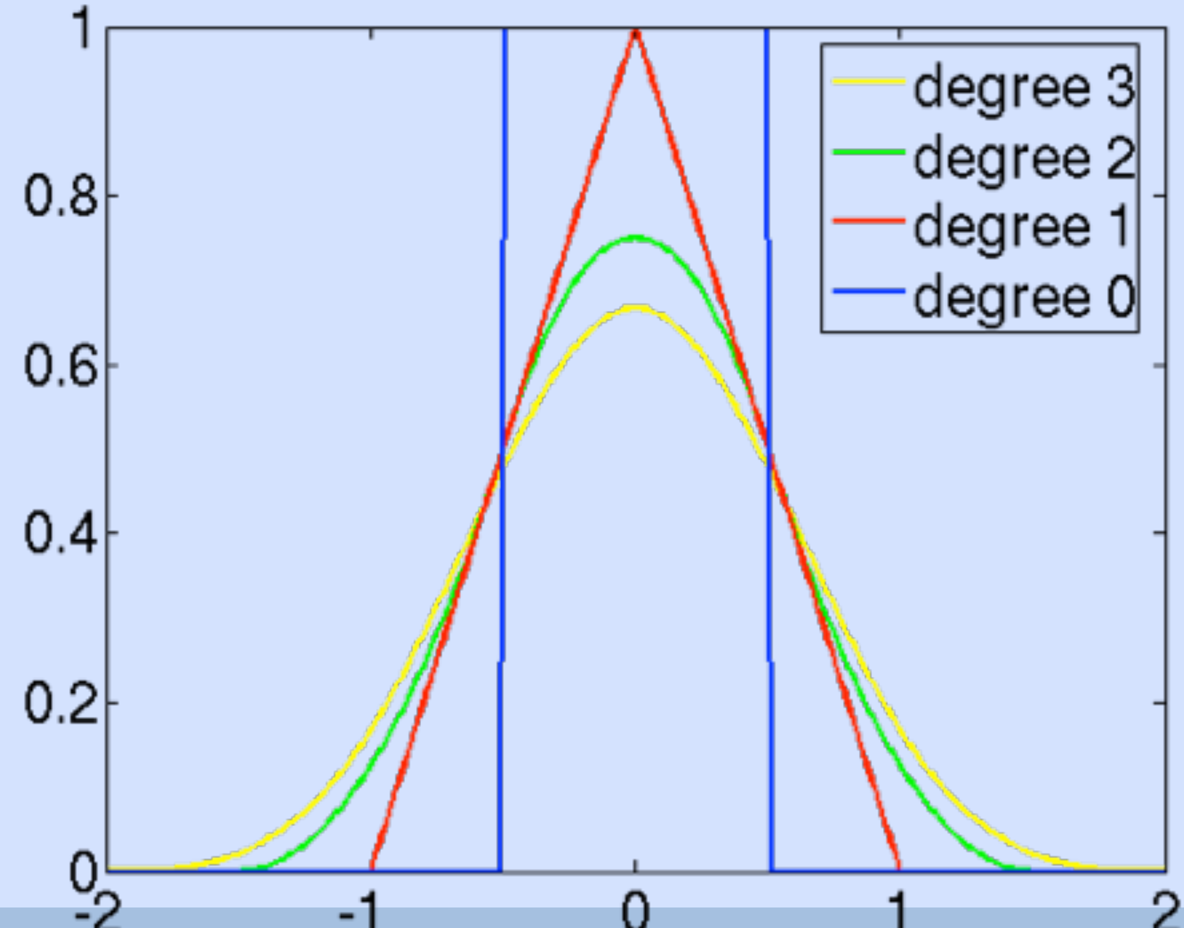


B-Spline Encoding

- The value of the k-th channel is obtained by

  $$x_k(f) = B_2(f - k) \qquad k = 1\ldots K$$

  (f is shifted and rescaled such that the channels are at integer positions)



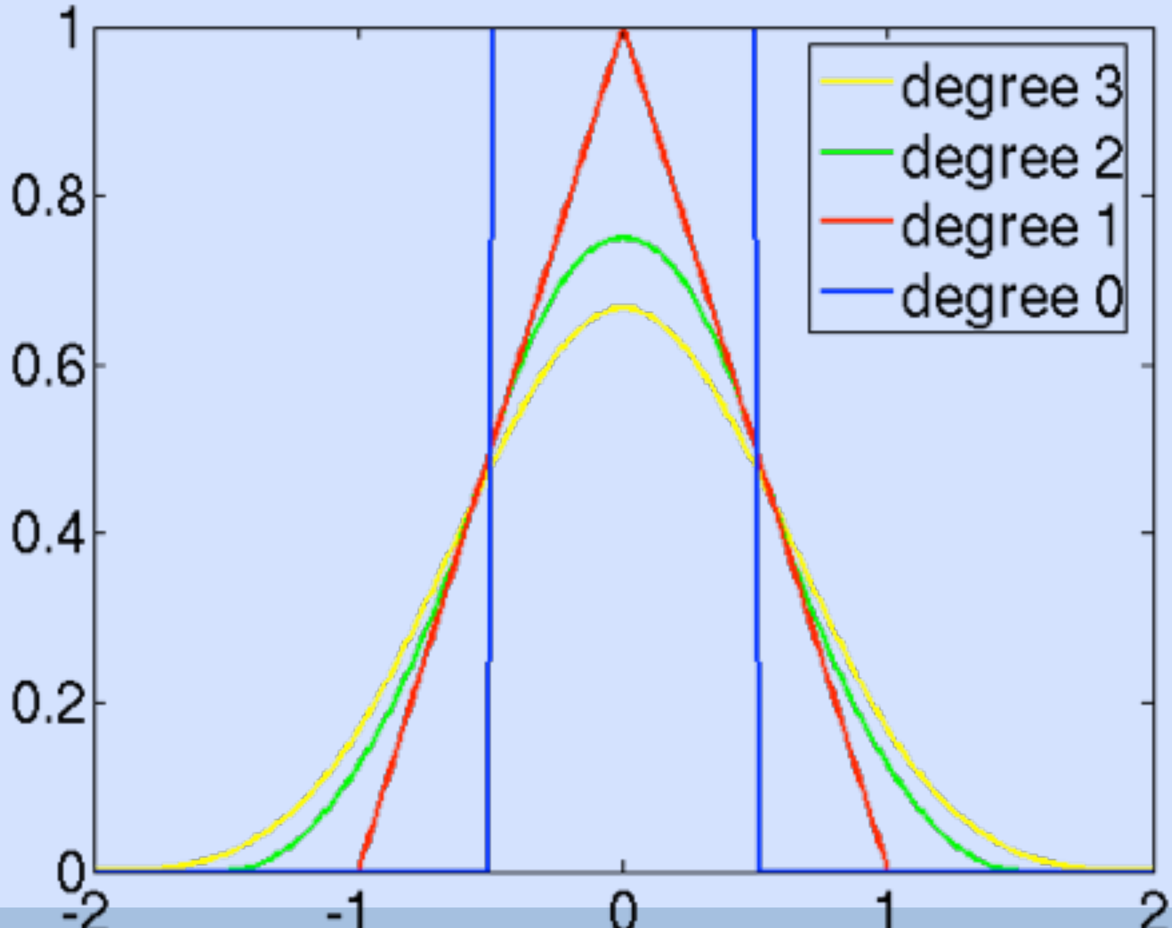
B-Spline Encoding

- The value of the k-th channel is obtained by

$$x_k(f) = B_2(f - k) \qquad k = 1\ldots K$$

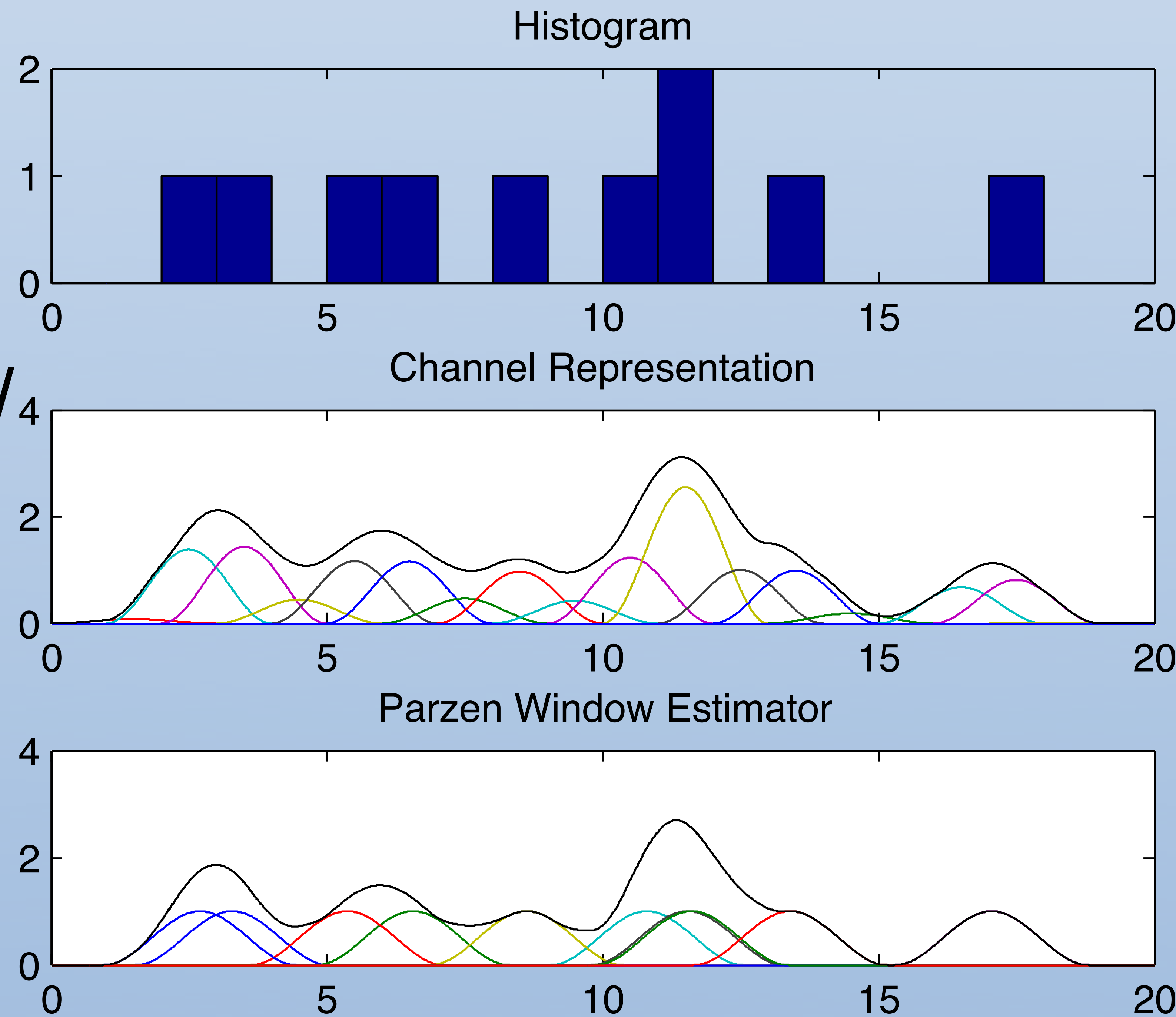
(f is shifted and rescaled such that the channels are at integer positions)

$k = \mathrm{round}(f)$
$x[k\text{-}1] = (f\text{-}k\text{-}0.5)^2/2$
$x[k] = 0.75\text{-}(f\text{-}k)^2$
$x[k\text{+}1] = (k\text{-}f\text{-}0.5)^2/2$
$x[1\ldots k\text{-}2] = x[k\text{+}2\ldots K] = 0$



Channels are ...

- soft histograms
- frame vector projections
- different from Parzen window/ kernel density estimators (not located at samples)



Kernel Density Estimation

- Estimate pdf from samples by convolving with a kernel function

$$\tilde{p}(f) = \frac{1}{N} \sum_{n=1}^{N} k(f - f_n)$$

- Expectation of estimate:

$$\mathrm{E}\{\tilde{p}(f)\} = \int k(f - f')p(f')\,df' = (k * p)(f)$$

Relation to Channels

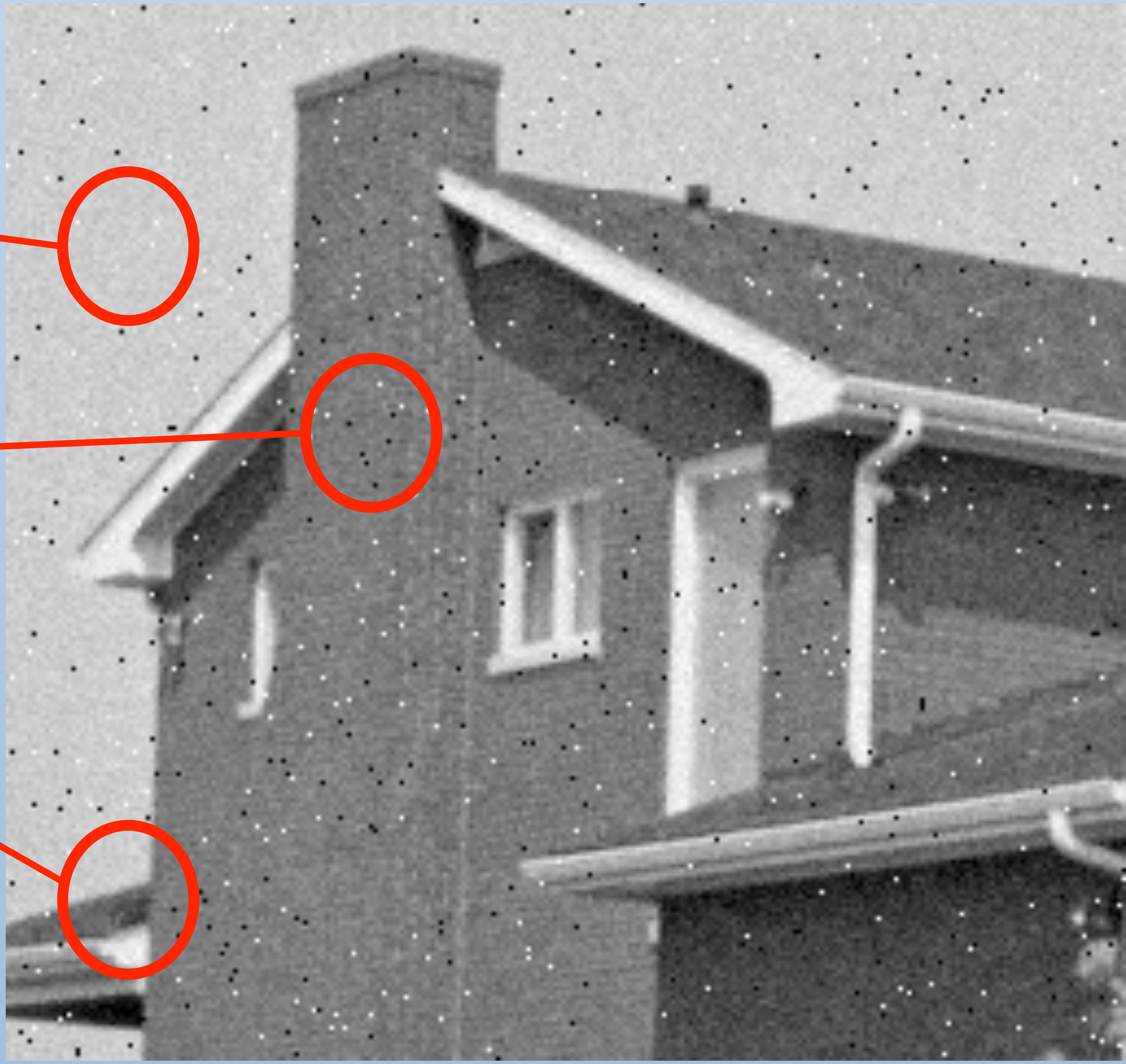
- Adding channel representation of samples = sampled kernel density estimation

$$\mathrm{E}\left\{\frac{1}{N}\sum_{n=1}^{N} u_k\left(f_n\right)\right\} = \mathrm{E}\left\{\tilde{p}\left(f\right)\right\}\Big|_{f=k}$$

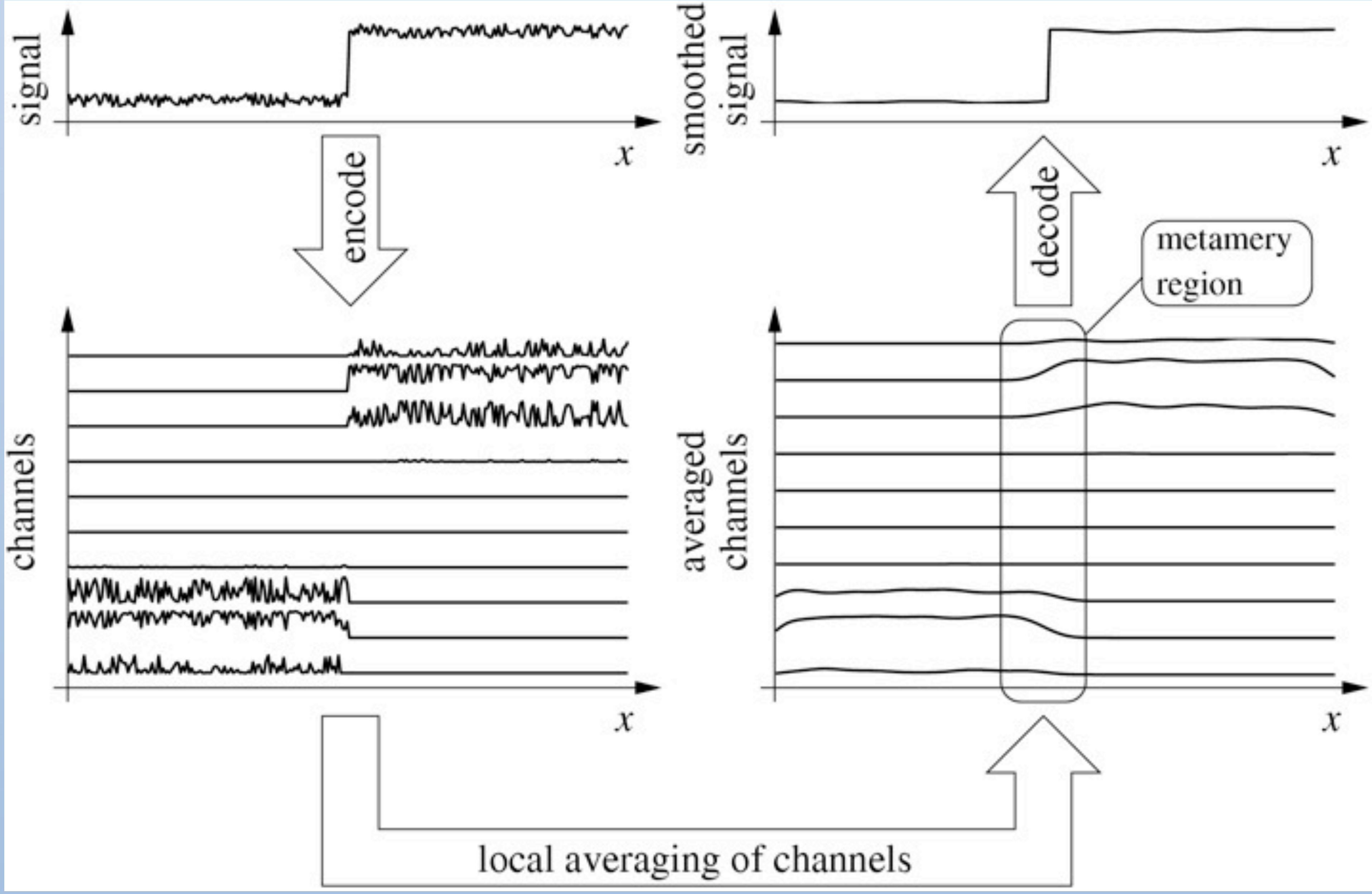
$$= \left(B_2 * p\right)\left(f\right)\Big|_{f=k} \qquad k = 1 \ldots K$$

Problem: Image Denoising

- Real data is noisy and discontinuous
  - Inlier noise
  - Salt&Pepper noise
  - Image discontinuities



Channel Smoothing



Decoding

- Normalized convolution of the channel vector

$$f_{k_0} = \frac{u_{k_0+1}(f) - u_{k_0-1}(f)}{u_{k_0-1}(f) + u_{k_0}(f) + u_{k_0+1}(f)} + k_0$$

- Choice of k_0:
  - –Largest denominator (3-box filter)
  - –Additional: local maximum

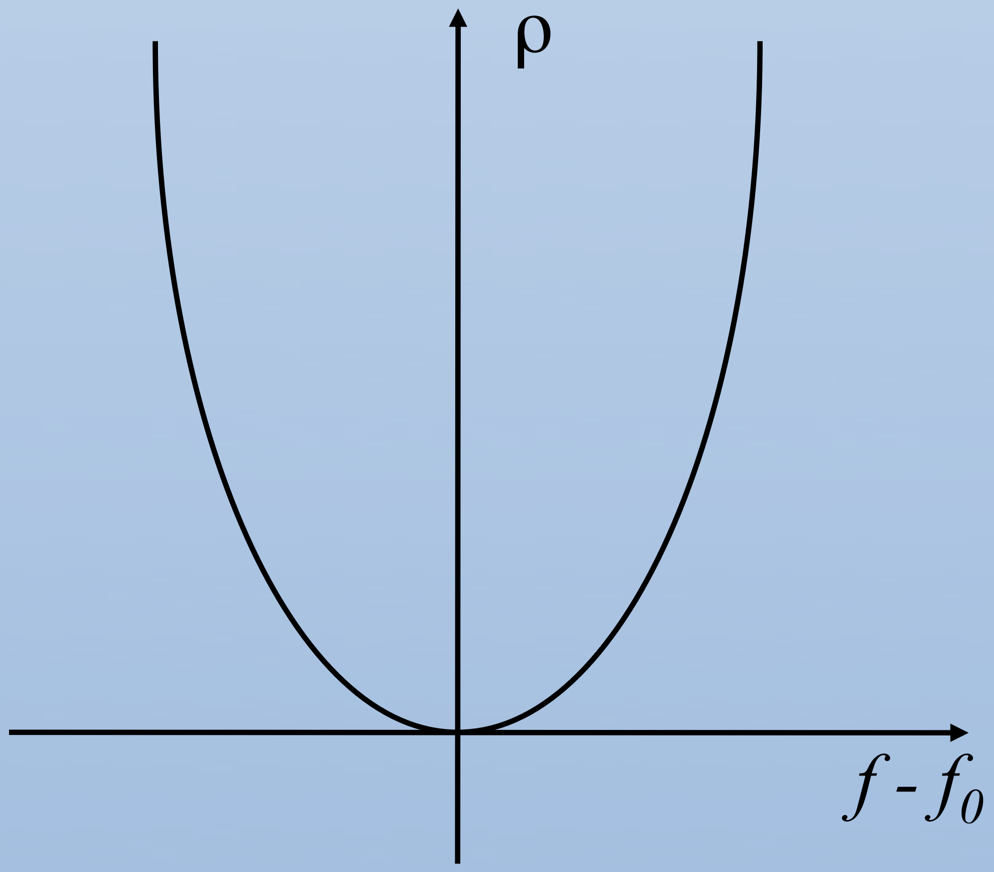
LS & Robust Optimization

- Minimize error functional:

$$E(f_0) = \int (f - f_0)^2 \, p(f) \, df$$

$$f_0 = \arg\min E(f_0)$$

- Idea of robust error norm:
  - –saturated for outliers
  - –quadratic near the origin
- in Bayesian sense



LS & Robust Optimization

- Minimize error functional:

$$E(f_0) = \int \boxed{\rho(f - f_0)} p(f)\, df$$

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Robust error norm

- Idea of robust error norm:
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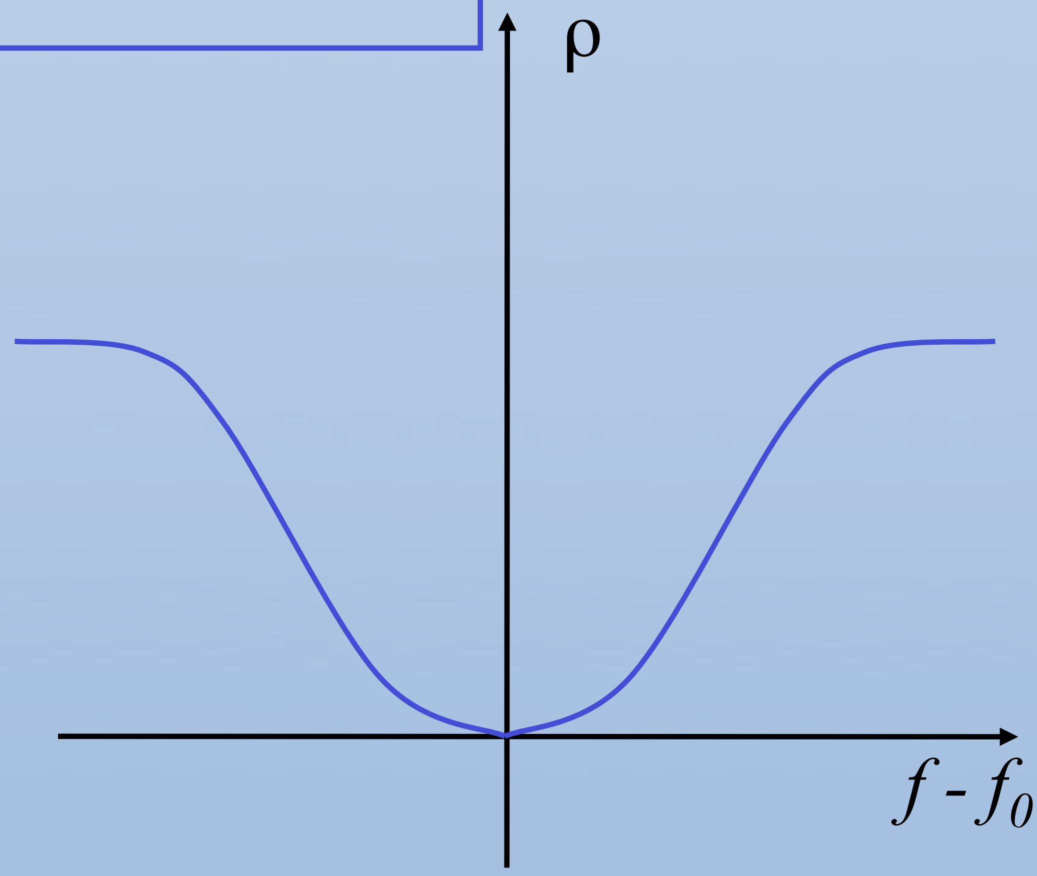


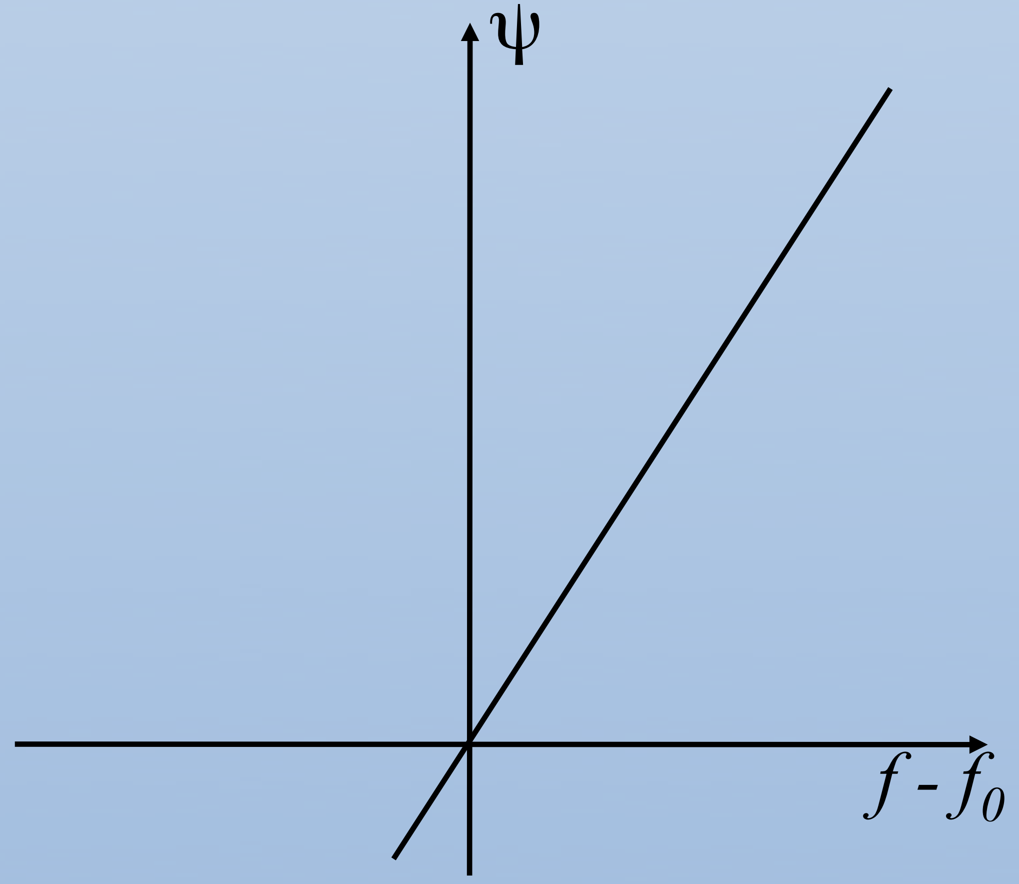
LS & Robust Optimization

- Necessary condition:

$$0 = \int \left(f - f_0\right) \; p\left(f\right) df$$

$$f_0 = \int f \; p\left(f\right) df$$

- Robust influence:
  - –zero for outliers
  - –no direct solution



LS & Robust Optimization

- Necessary condition:

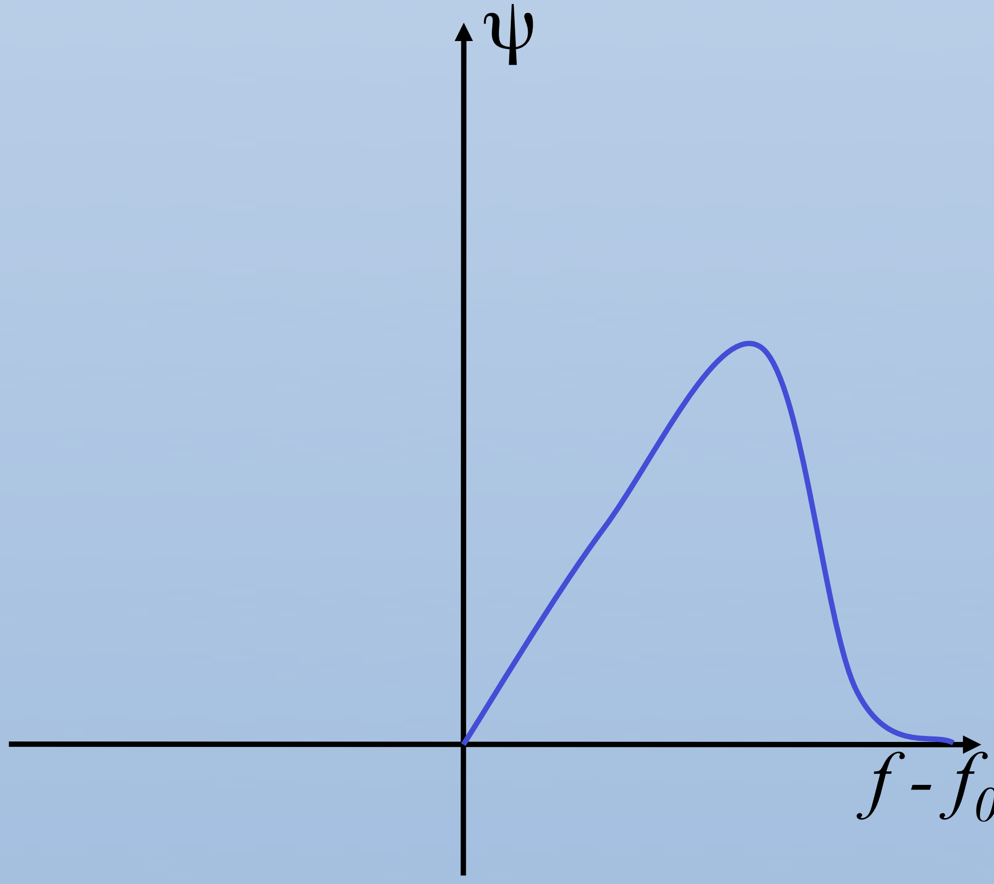
$$0 = \int \psi(f - f_0) p(f)\, df$$

$$\boxed{\psi = \rho'}$$

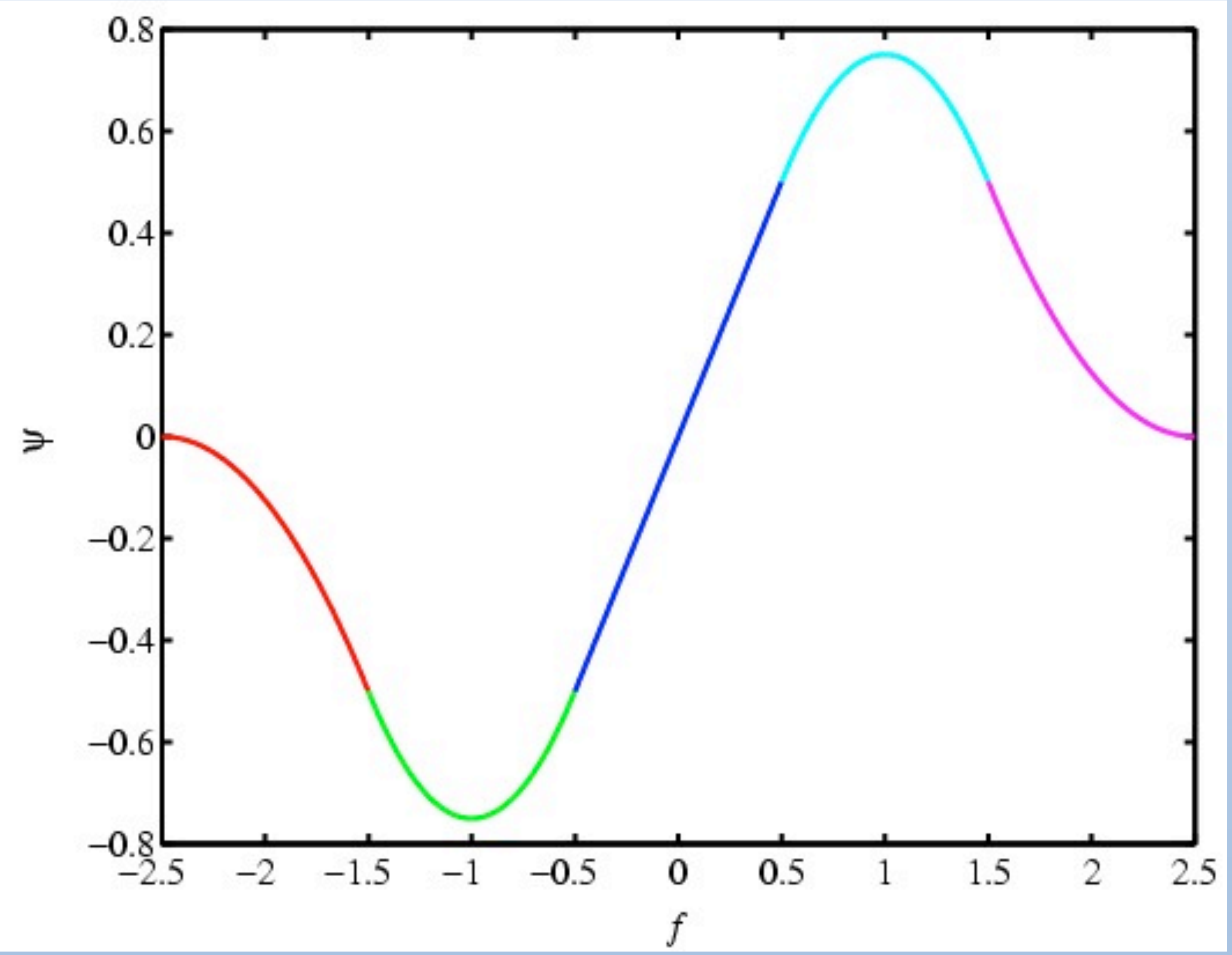
Influence function

- Robust influence:
  - –zero for outliers
  - –no direct solution

Efficient methods required!



Influence Function of C.R.



Obtained from linear decoding:

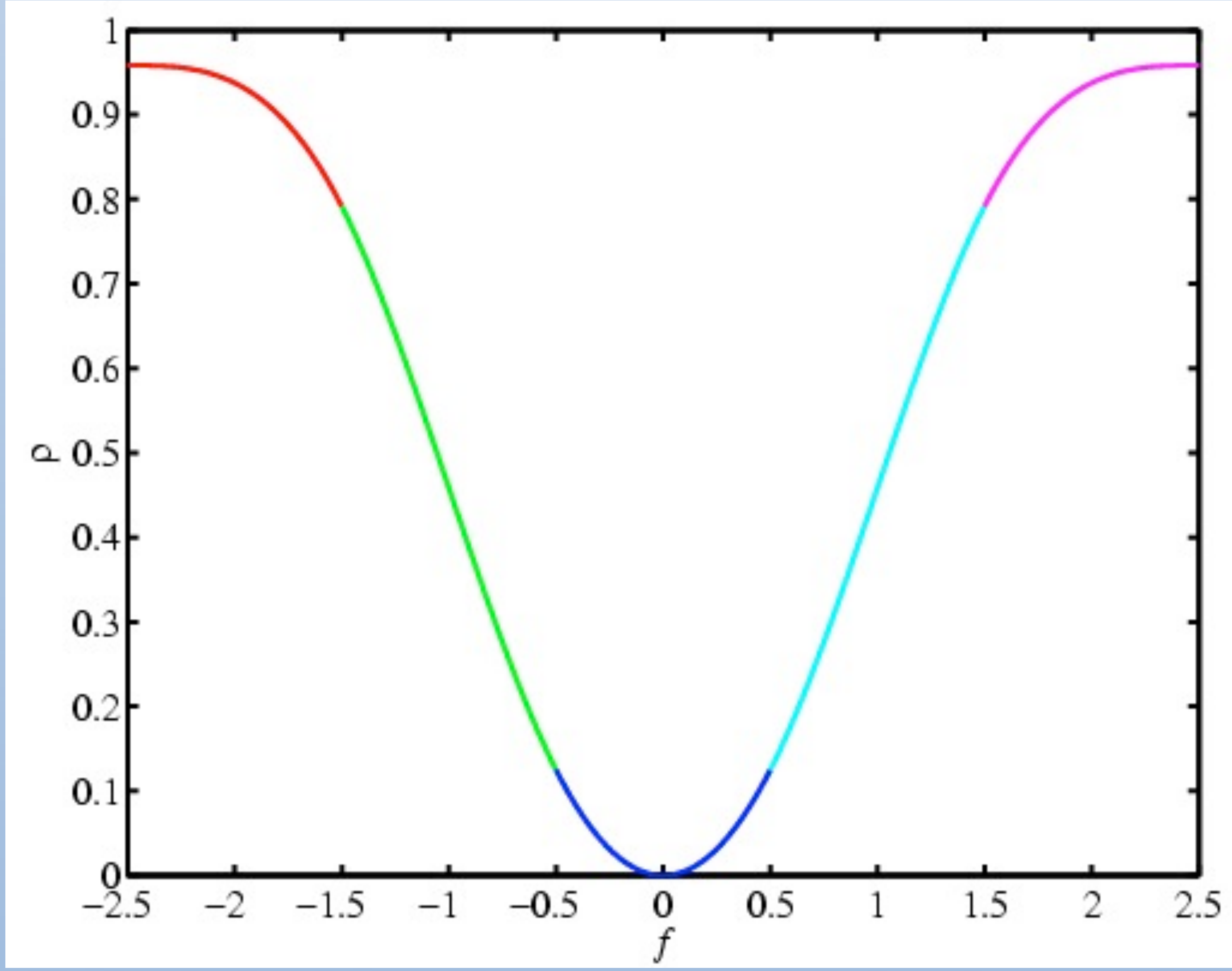
$$\psi(f) = B_2(f-1) - B_2(f+1)$$

$$f_{k_0} = \frac{u_{k_0+1}(f) - u_{k_0-1}(f)}{u_{k_0-1}(f) + u_{k_0}(f) + u_{k_0+1}(f)} + k_0$$

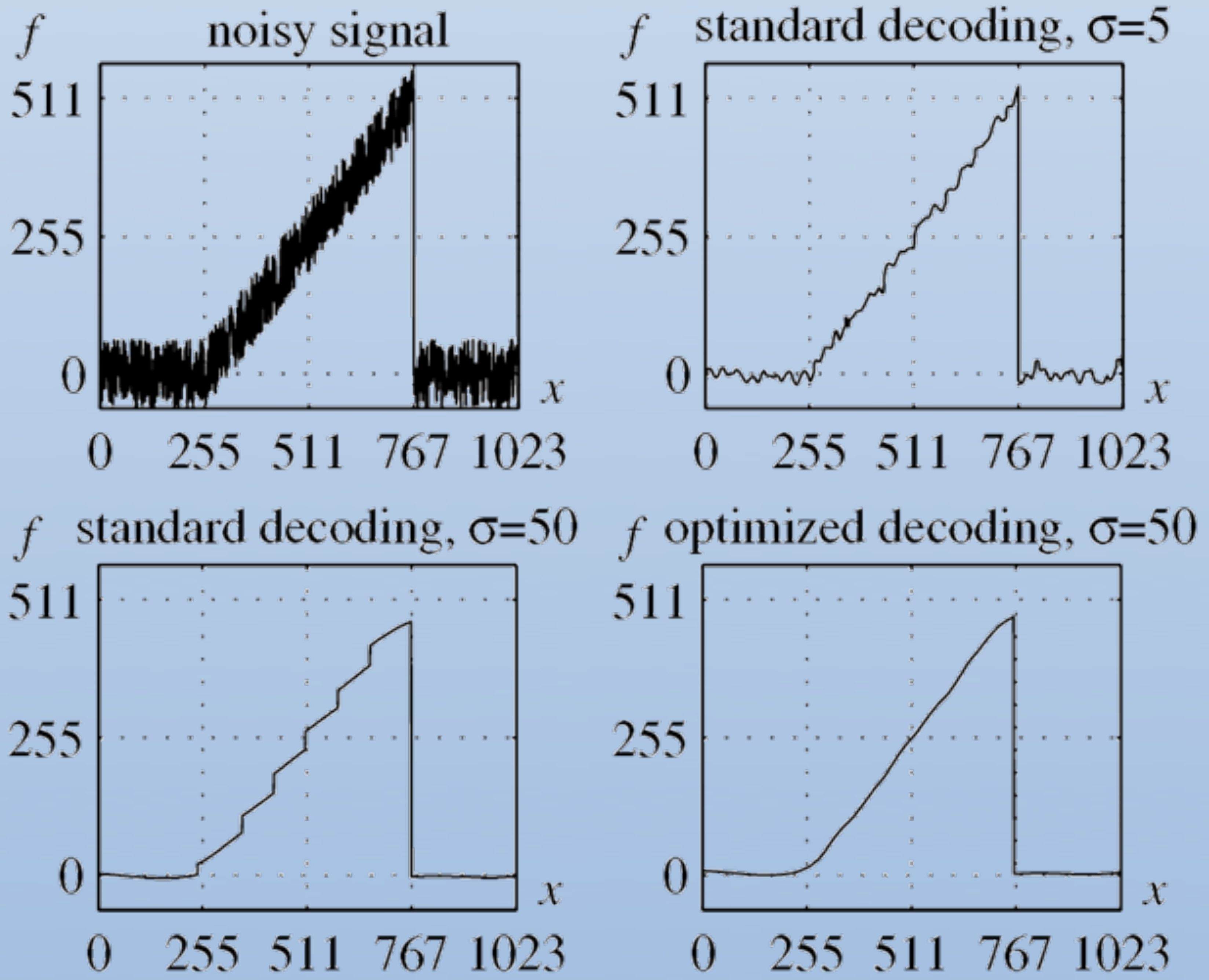
Error Norm of C.R.

Obtained by integrating the influence function:

$$\rho(f) = 2B_3\left(\frac{1}{2}\right) - B_3\left(f + \frac{1}{2}\right) - B_3\left(f - \frac{1}{2}\right)$$



Quantization Effect



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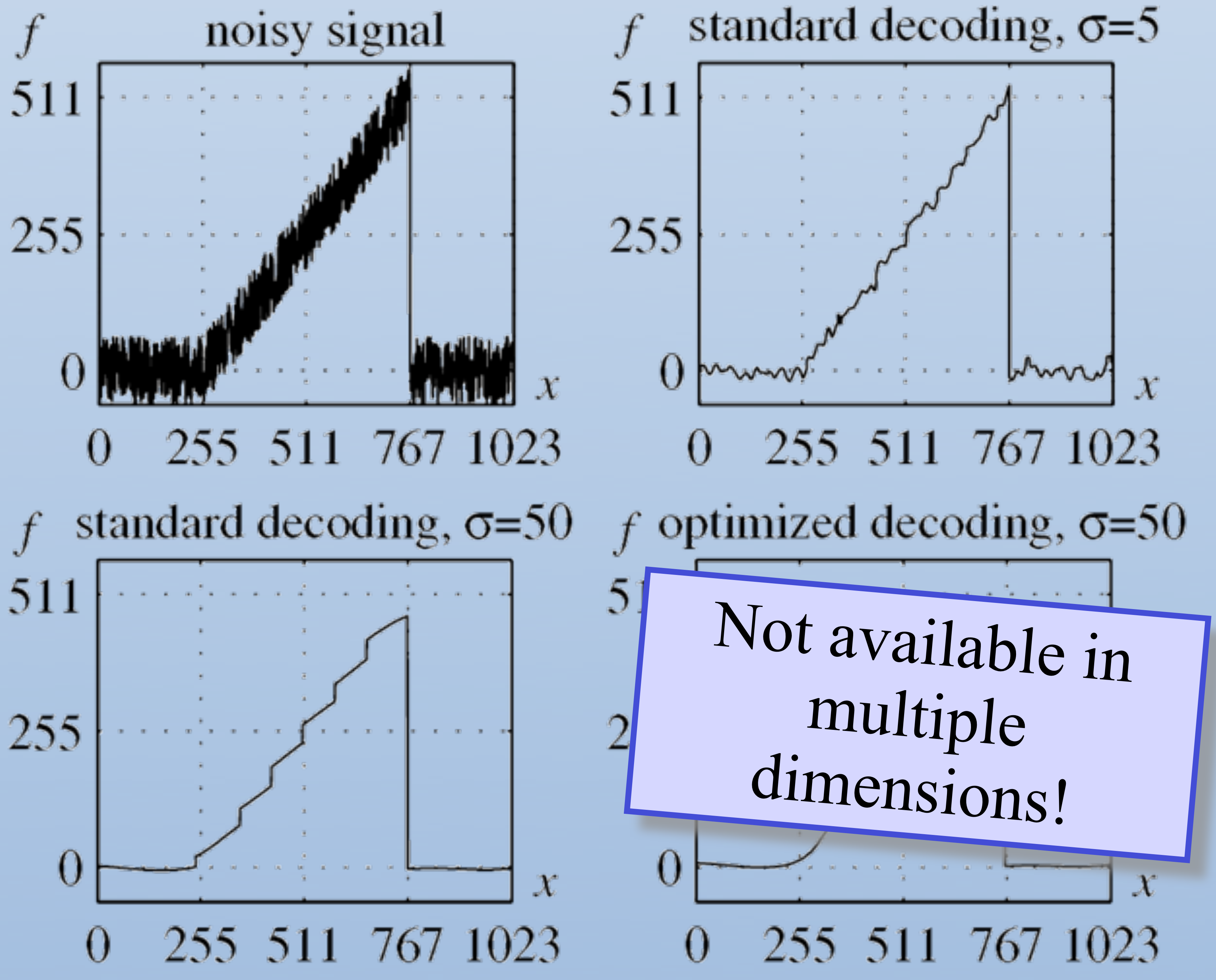


Channel Smoothing

Algorithm 1 Channel smoothing algorithm.

Require: $\boxed{f \in [1.5; N - 0.5]}$

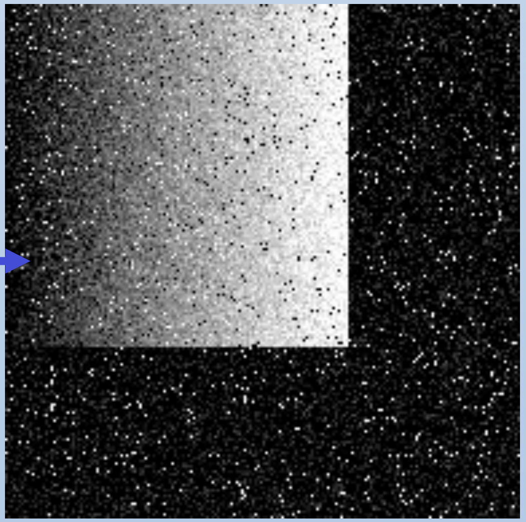
for $n = 1$ to N **do**

$\quad c_n \Leftarrow B_2(f - n)$

$\quad c_n \Leftarrow g_\sigma * c_n$

end for

$[\hat{f}, \hat{\rho}] \Leftarrow \mathrm{decode}(\mathbf{c})$



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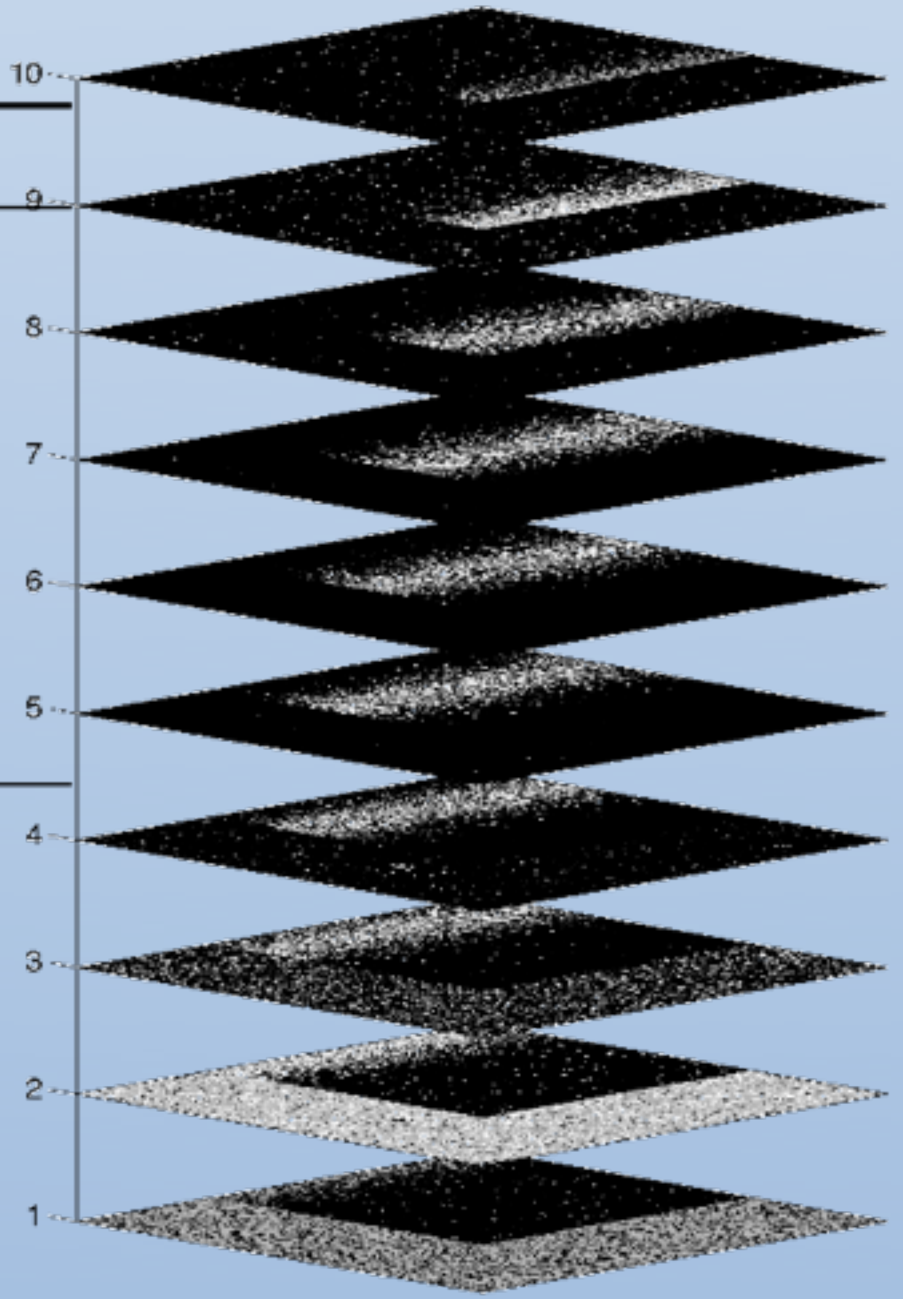

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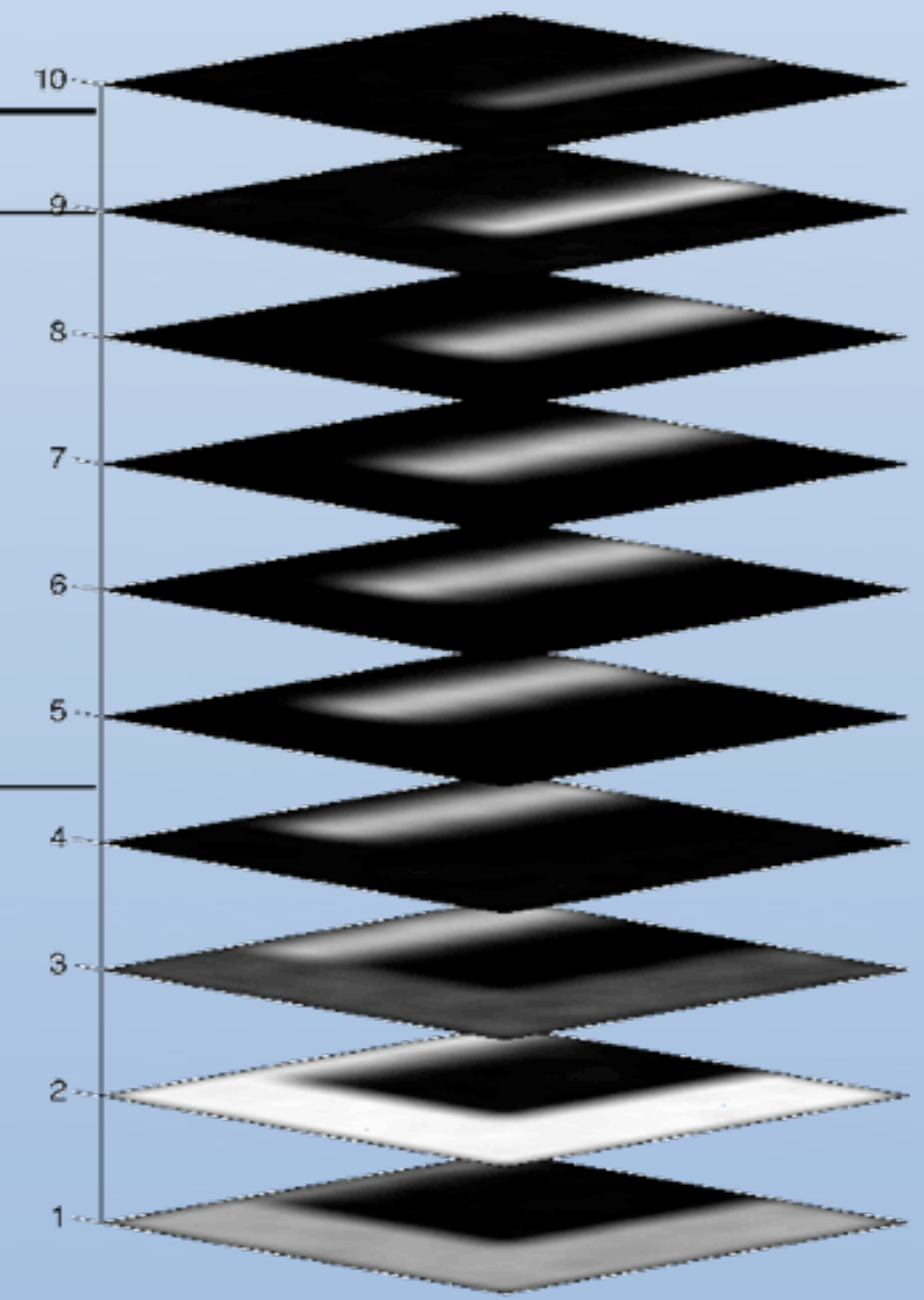

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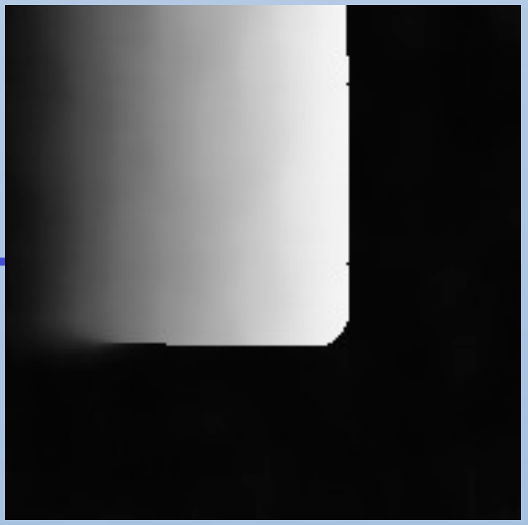
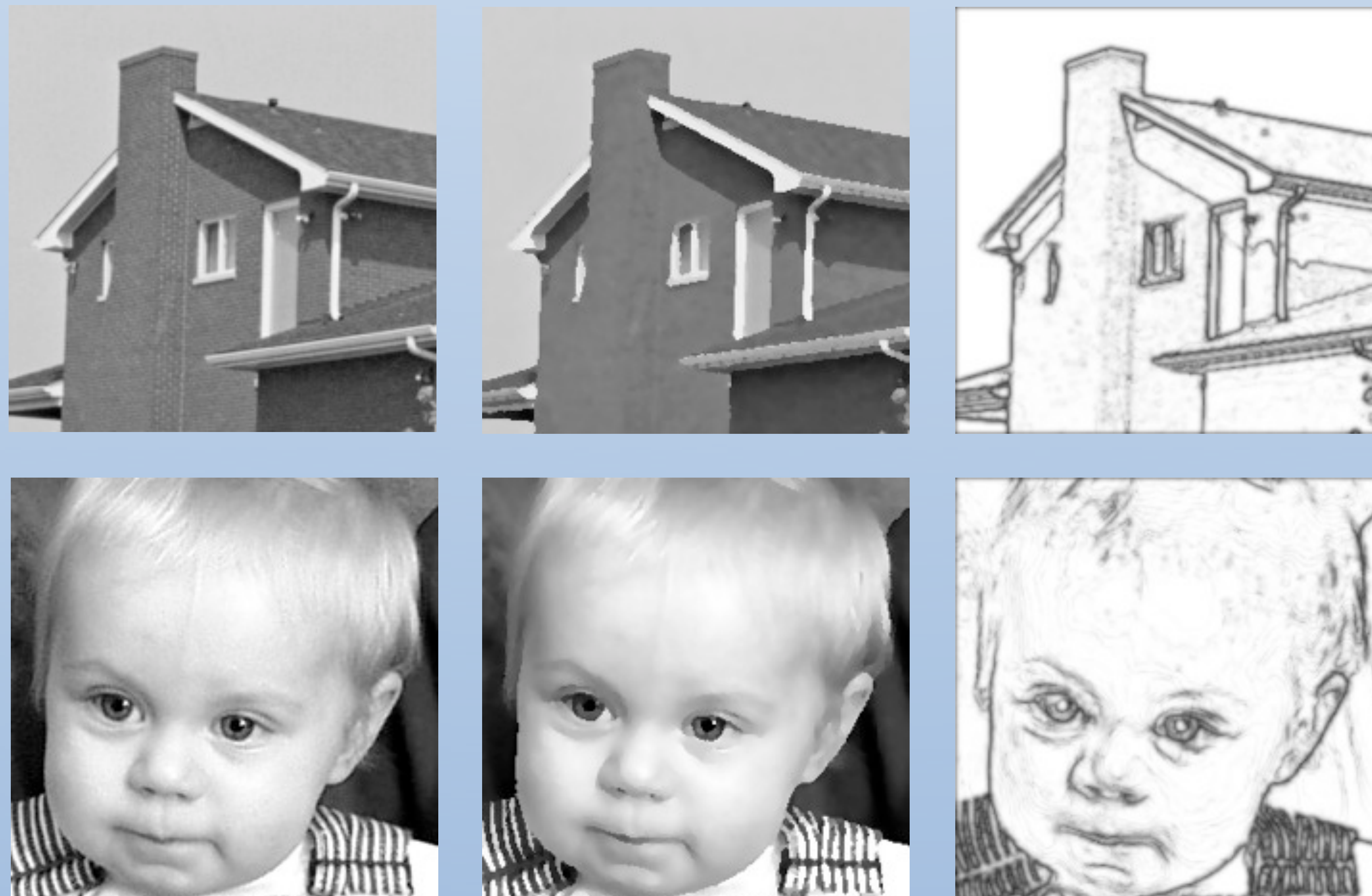
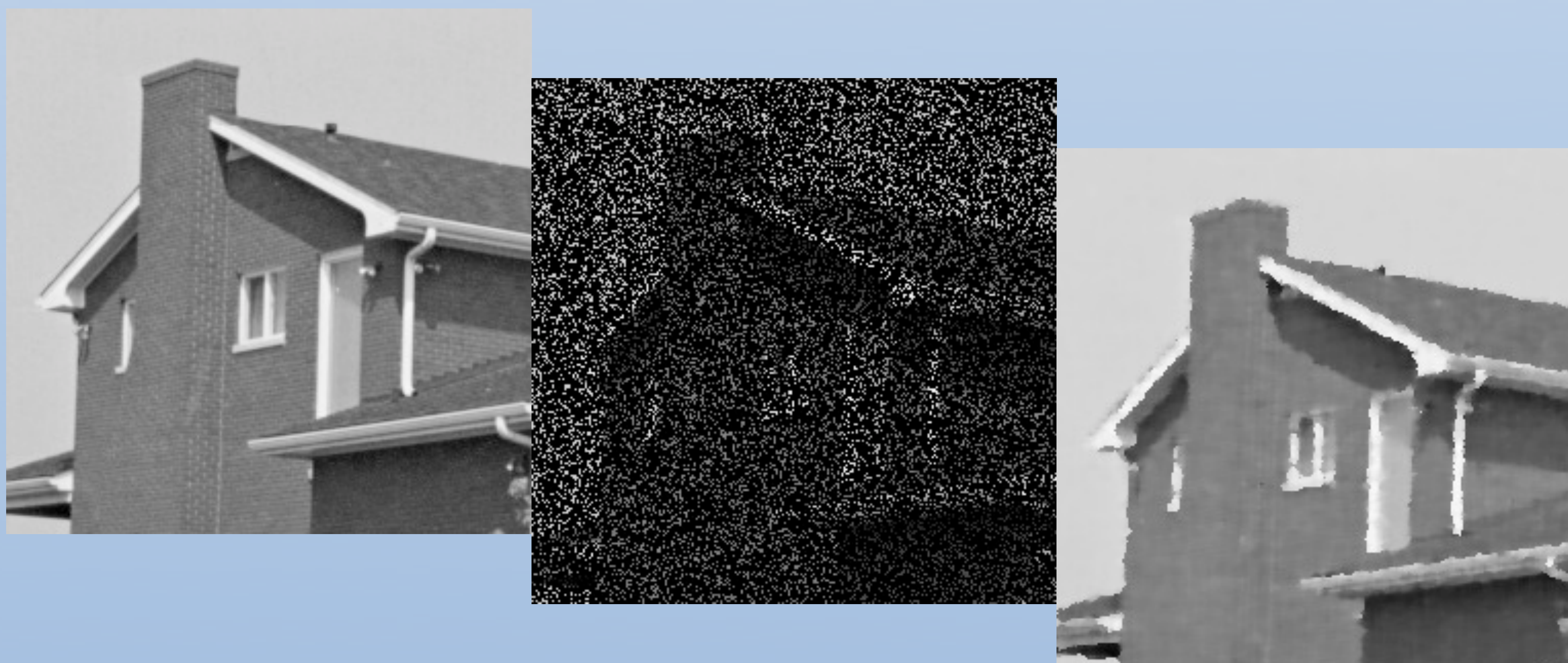


Image Denoising

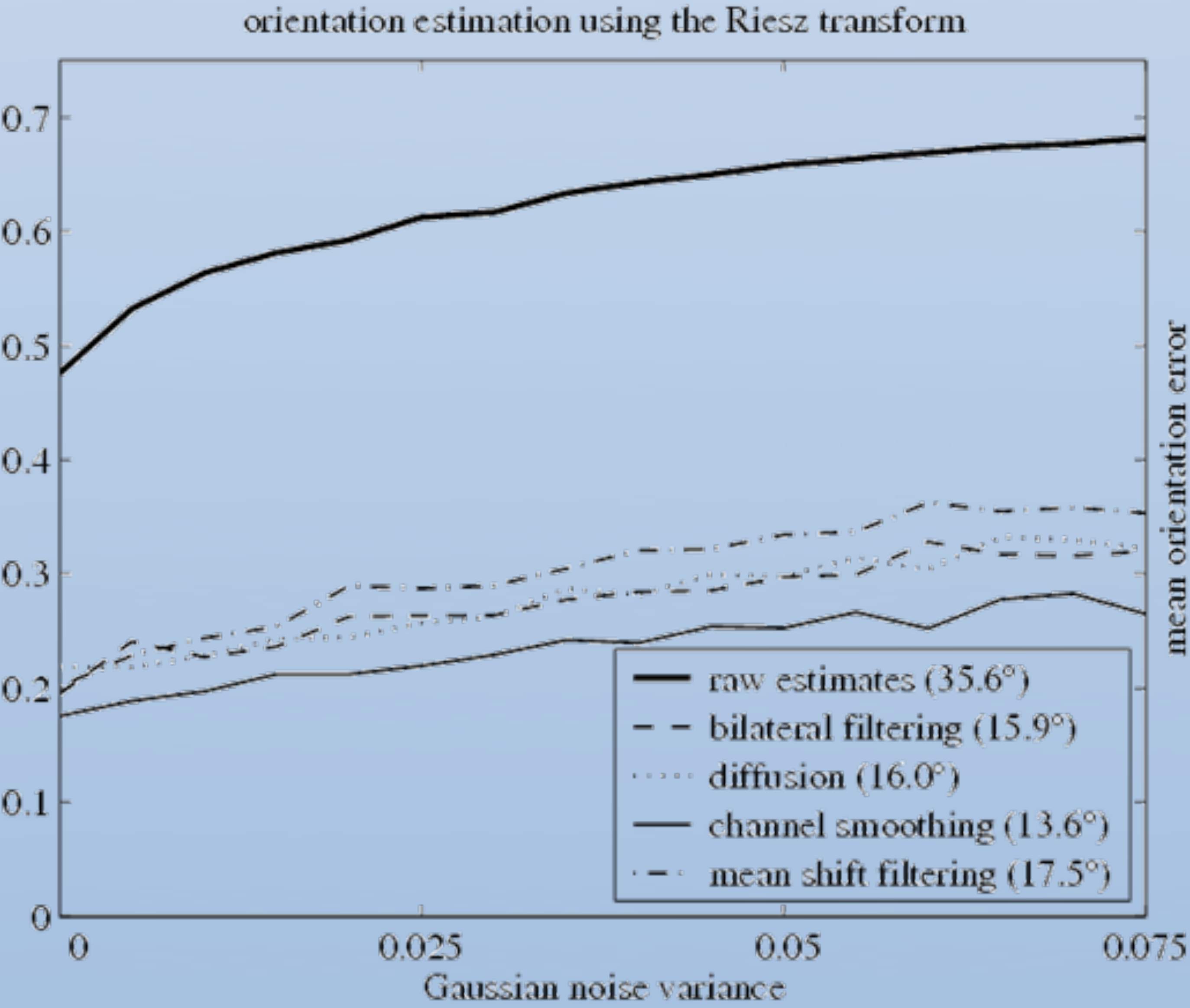


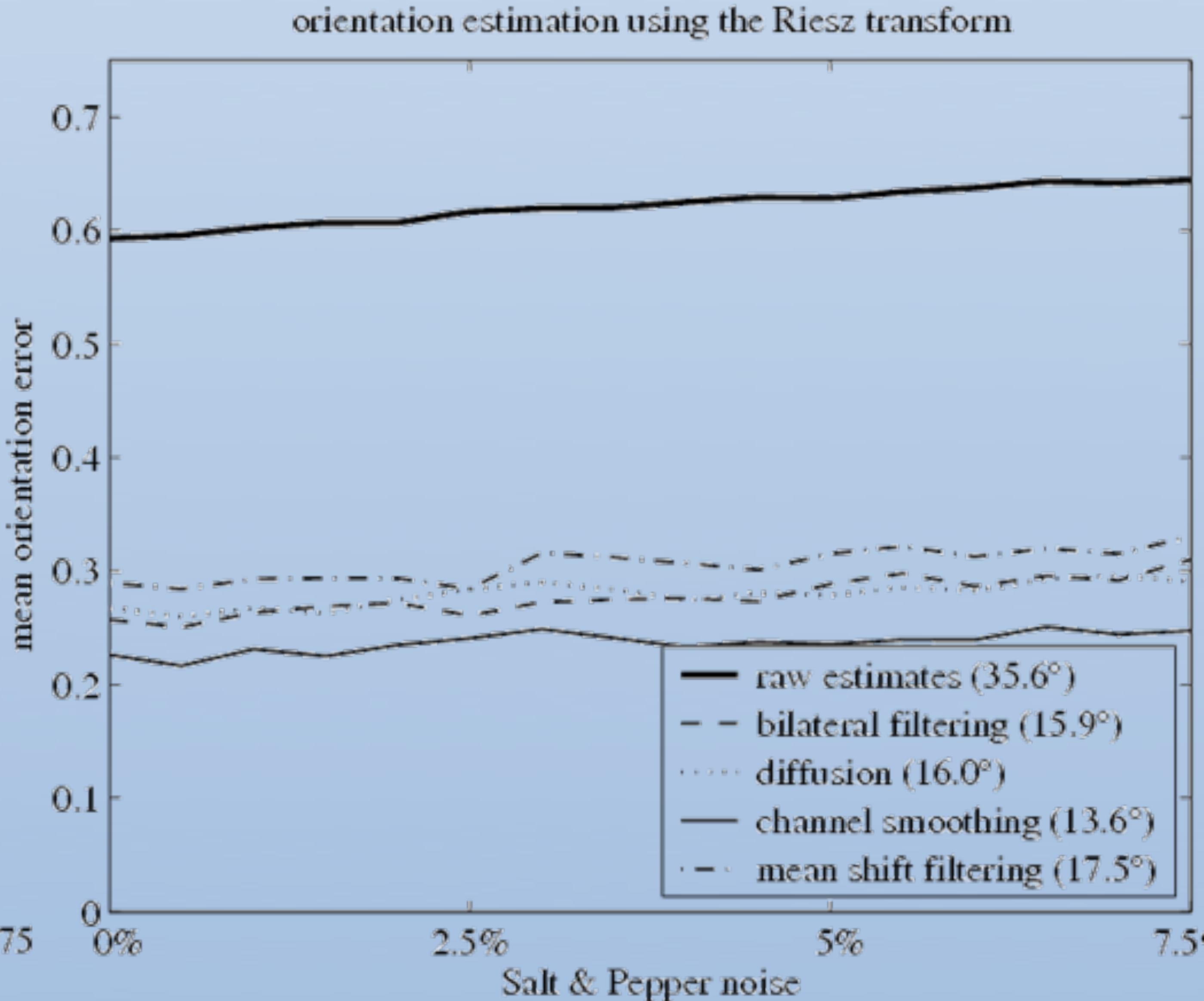
Random Sample

- Real data is incomplete



Orientation Estimation





Disparity Estimation

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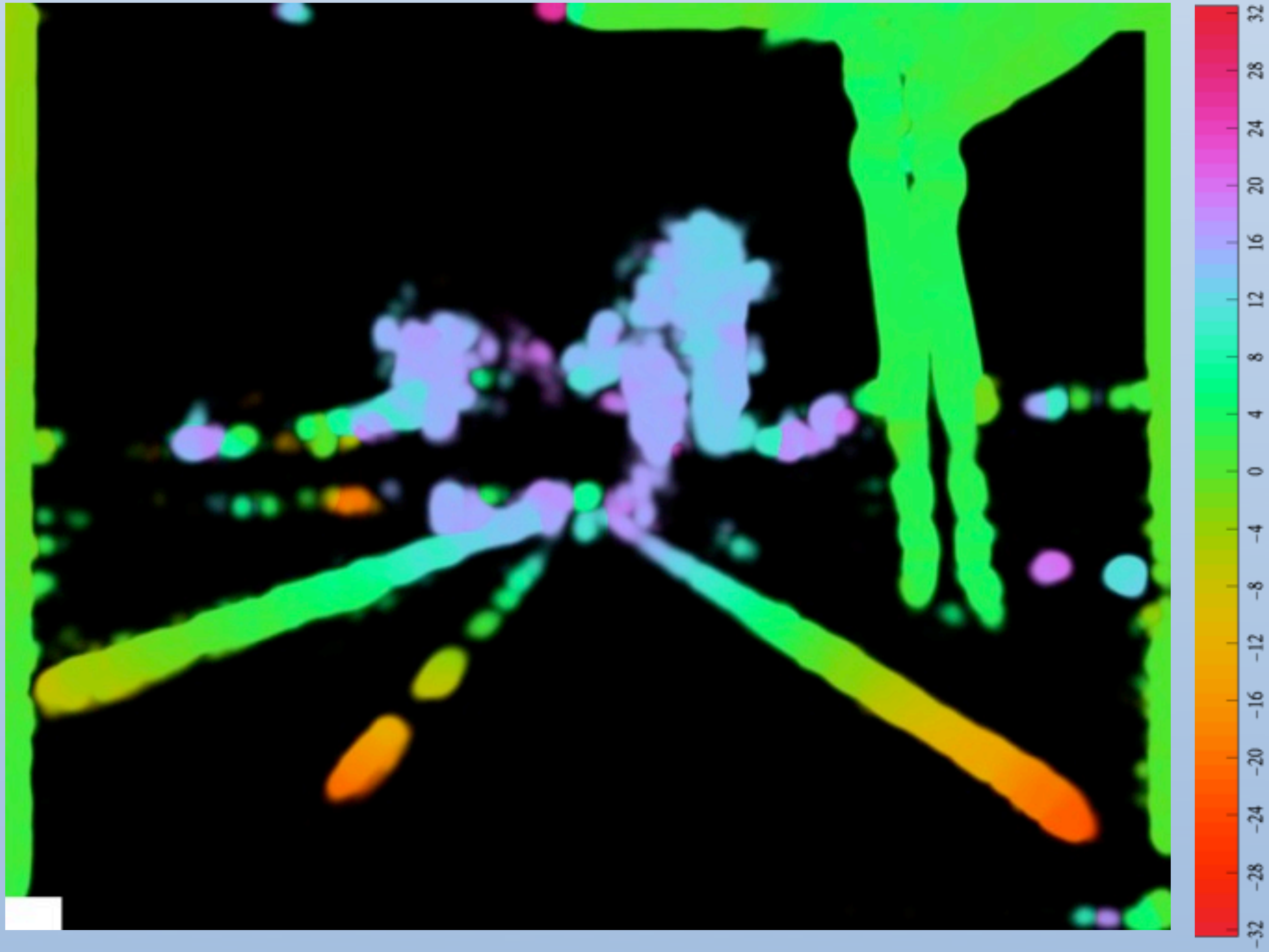
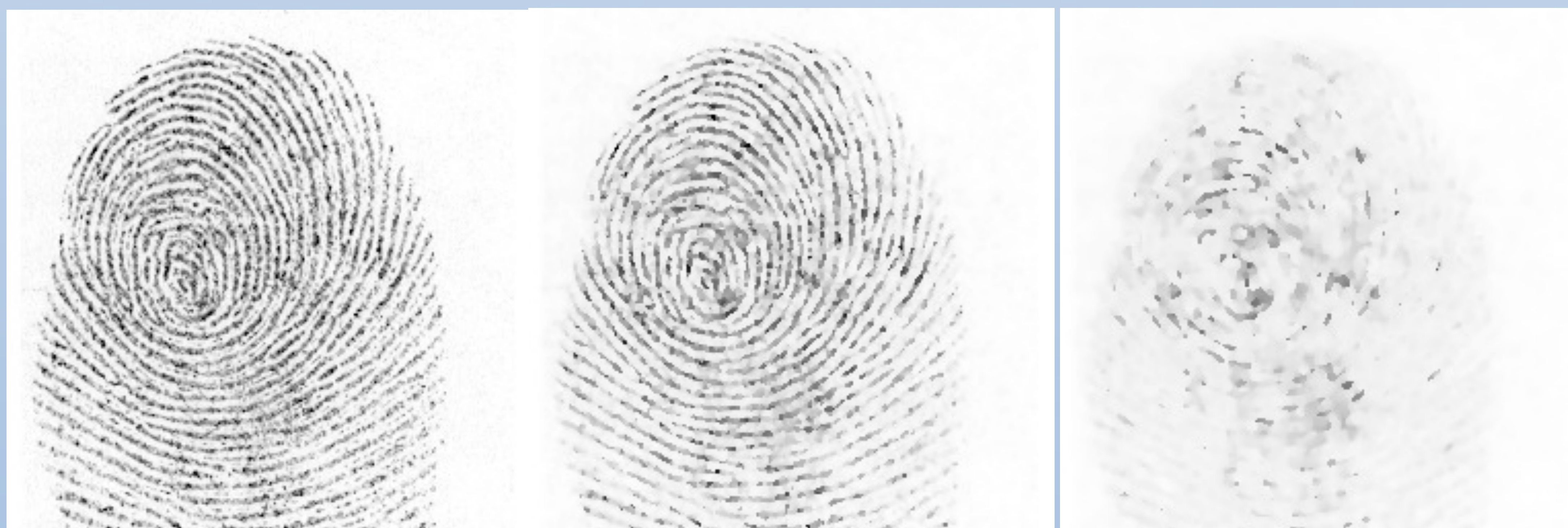
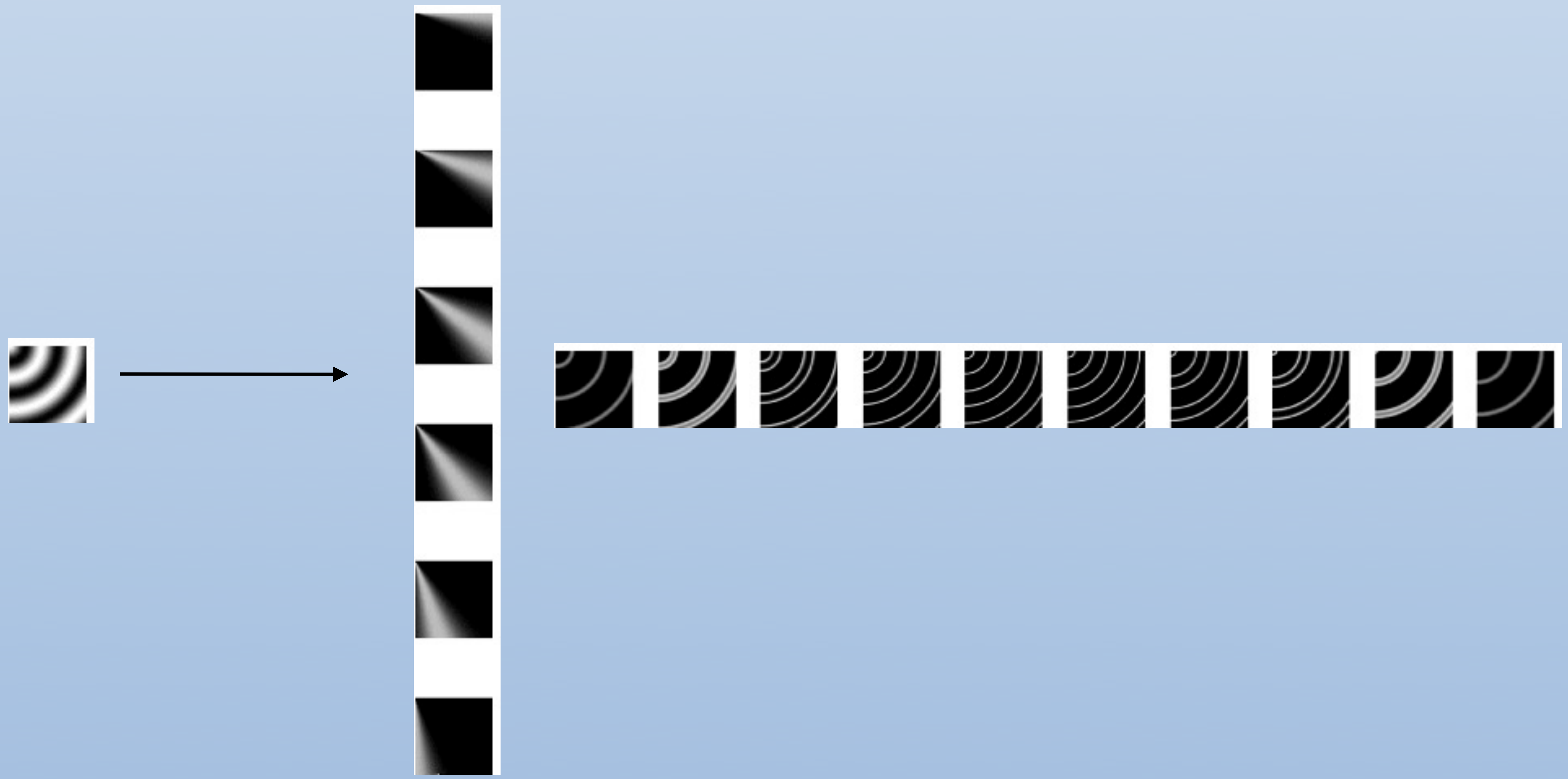


Drawback

- no coherence enhancing filtering possible



Channel Matrix



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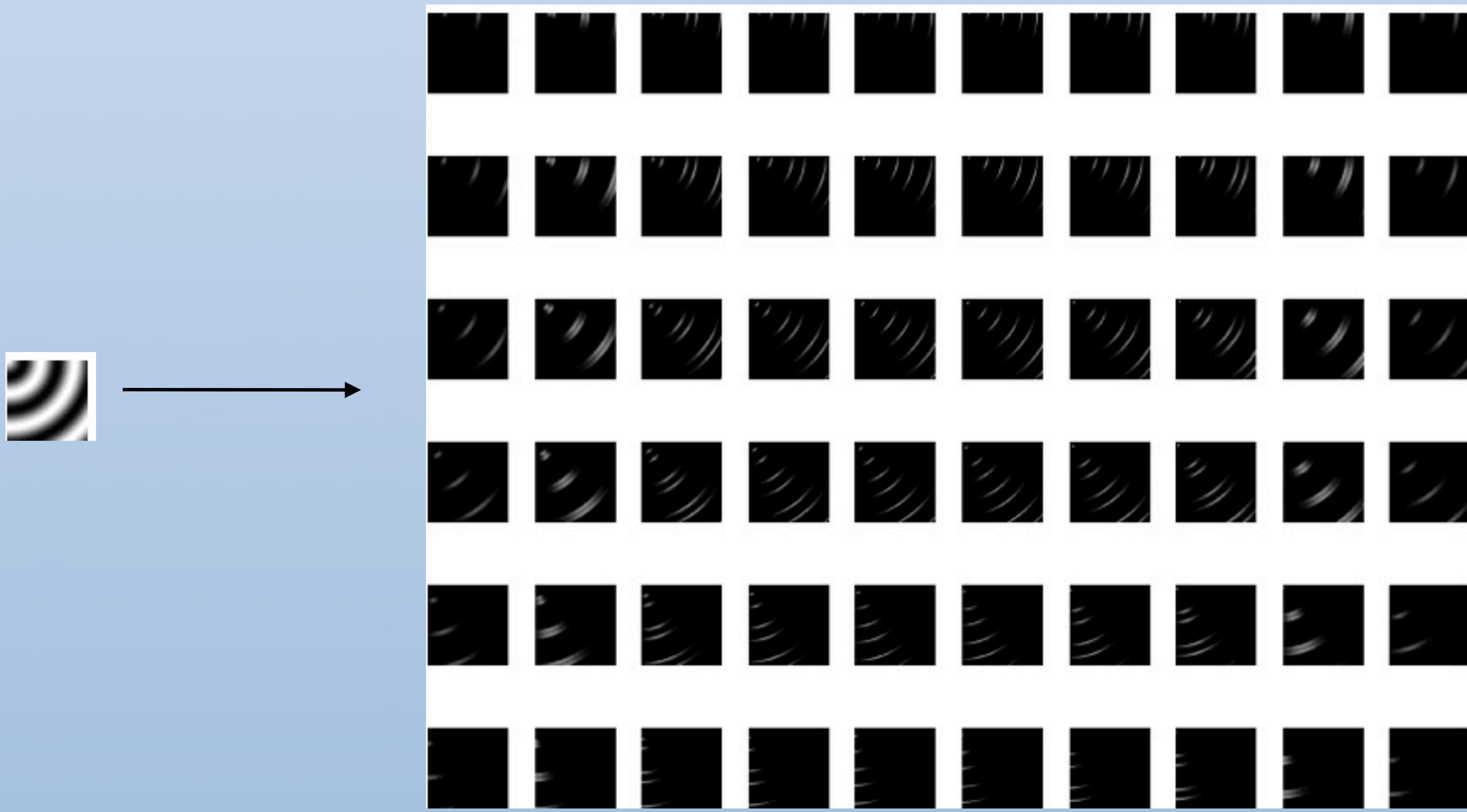

Experiment

original image

coherence enhancing diffusion

anisotropic channel smoothing

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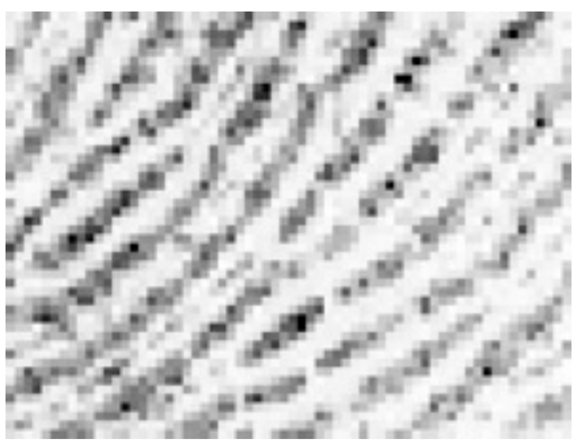
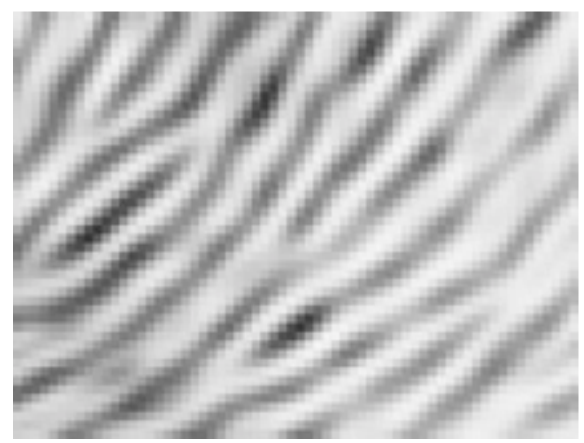
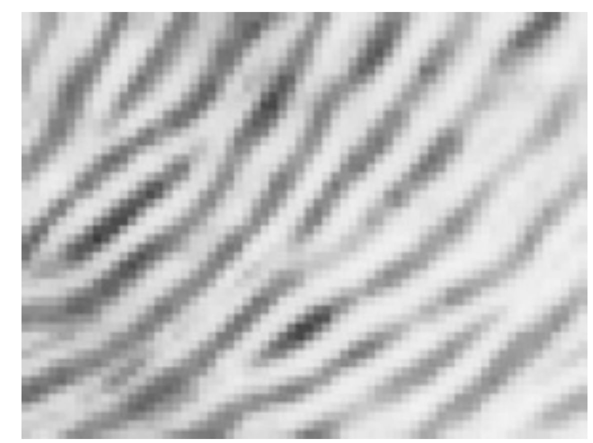


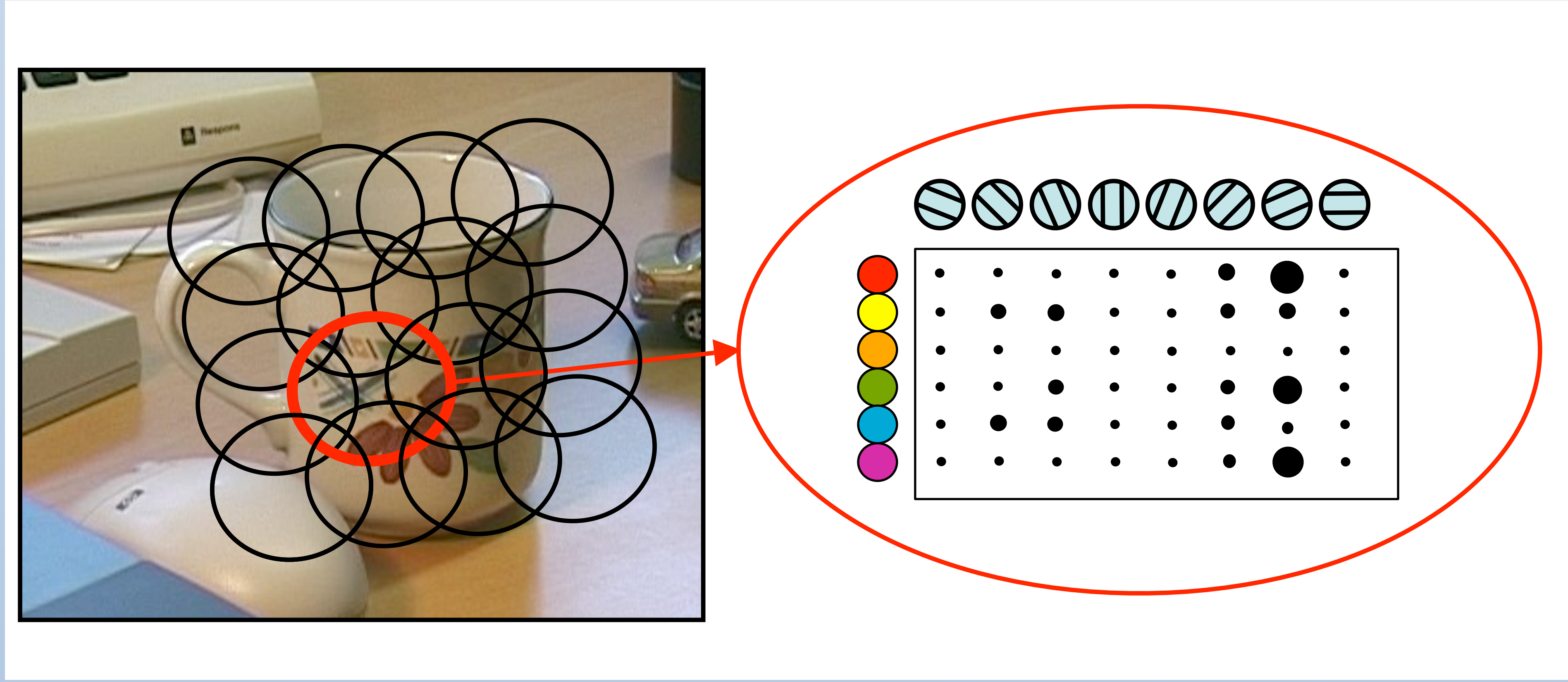




Corner Detection

Motivation CCFM

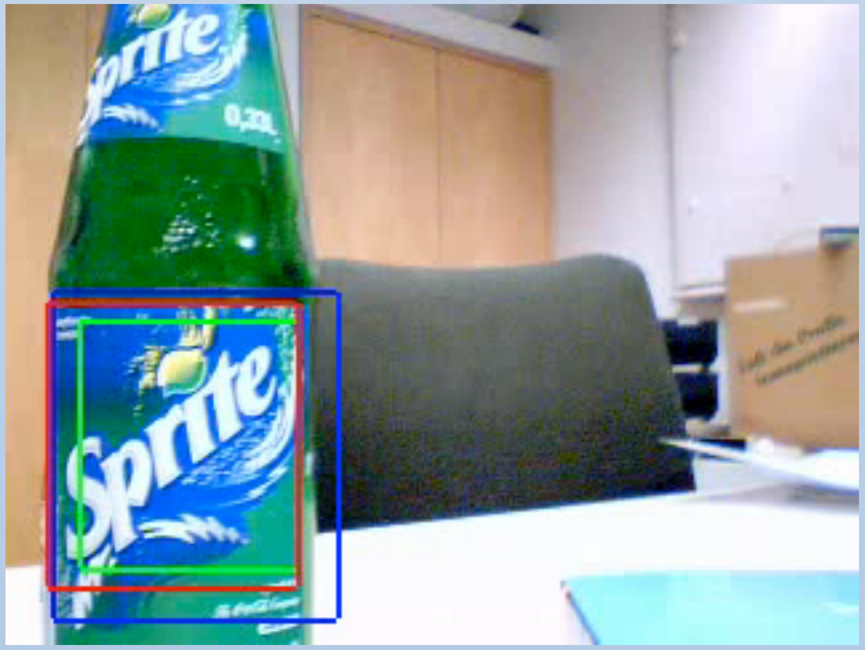
CCFMs



- point-wise encoding

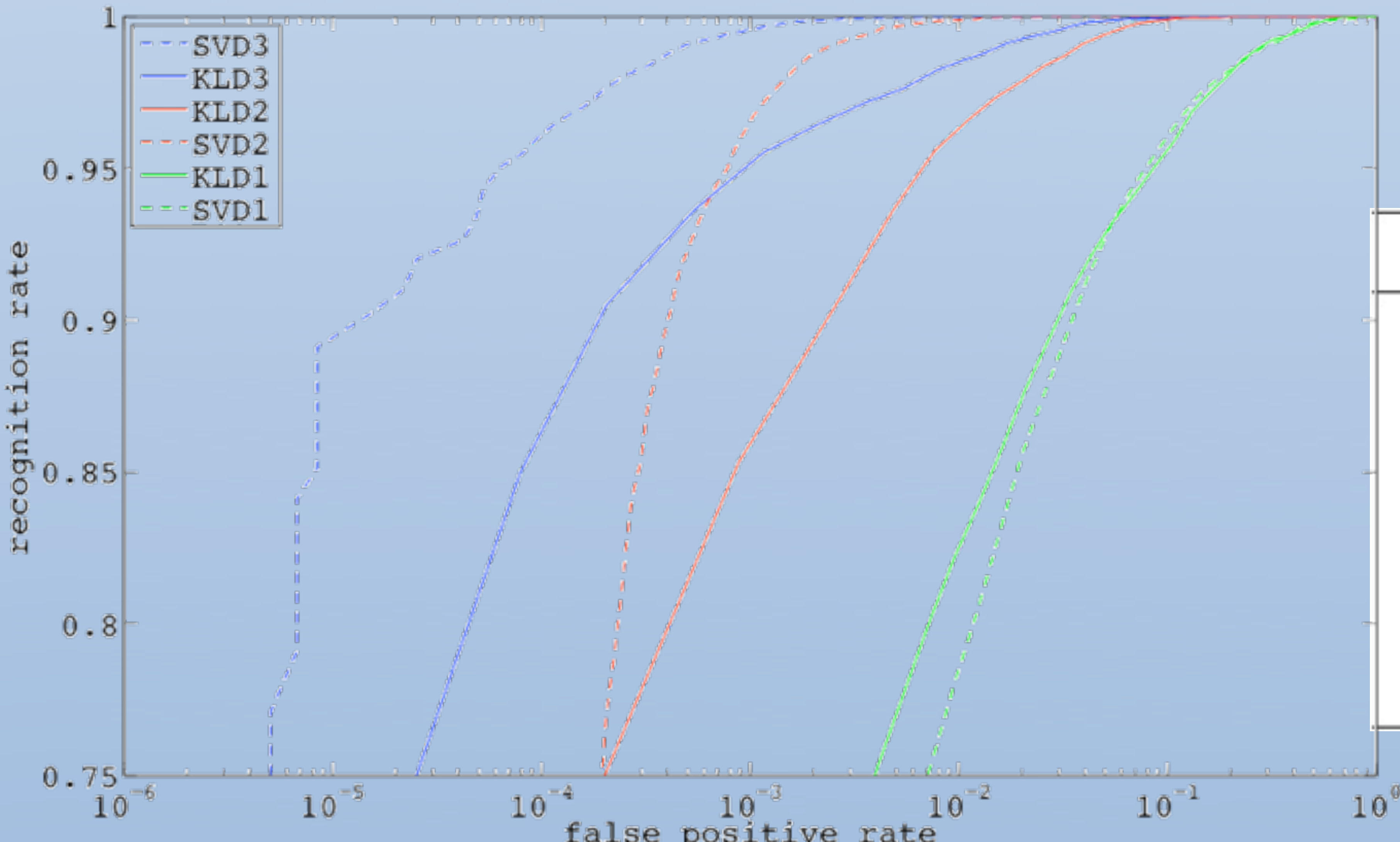
$$c_{l,m,n}(f(x,y)) = k_f(f(x,y)-n)k_x(x-l)k_y(y-m)$$

Object Recognition



COIL-100 Objects

- All 100 objects
- 12 / 60 view for training / evaluation

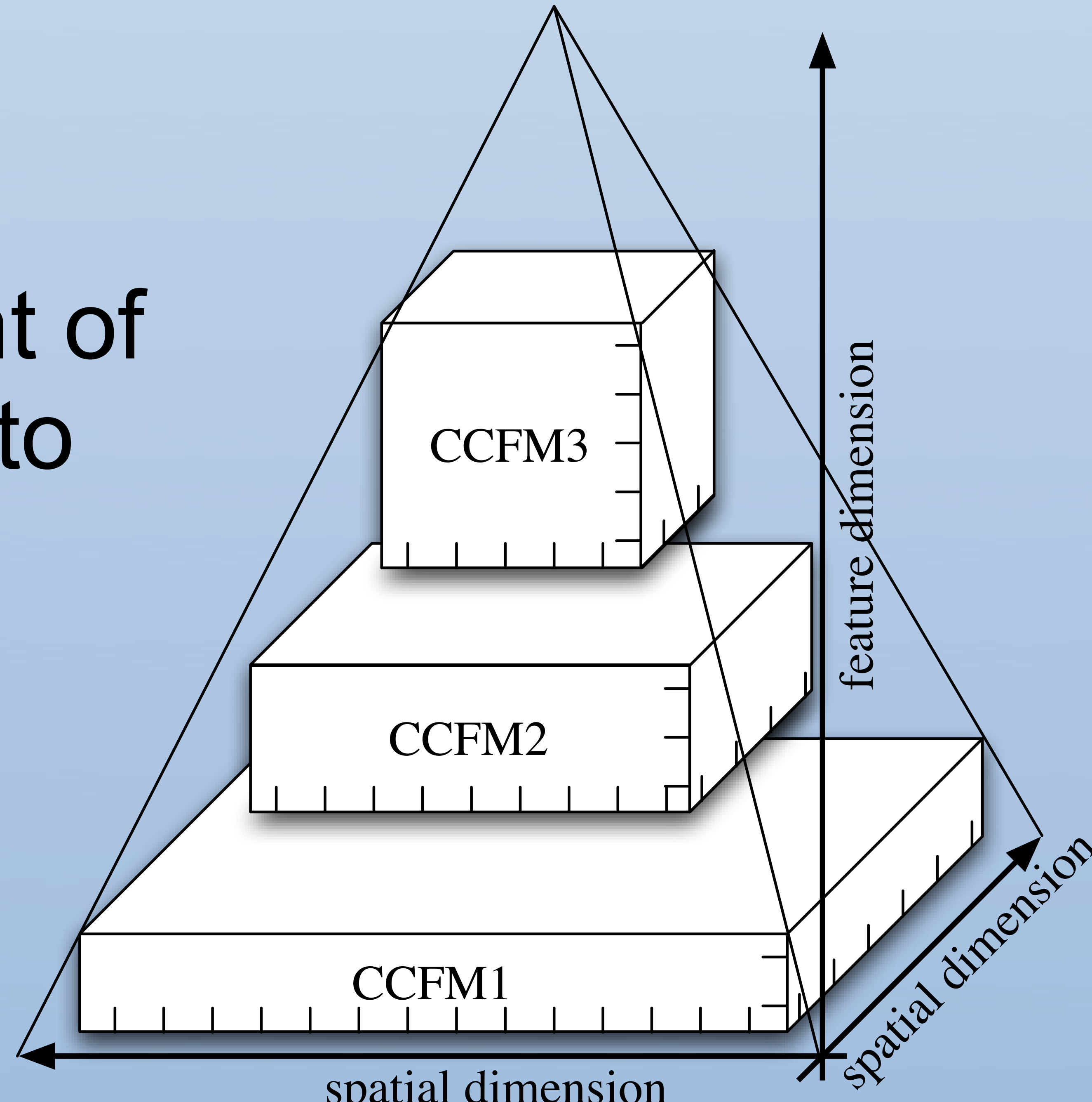


Method	ROC int
KLD, θ	0.9817
SVD, θ	0.9840
KLD, RGB	0.9983
SVD, RGB	0.9998
KLD, hsθ	0.9939
SVD, hsθ	1.0000

New Linear Scale-Space

- simultaneously increasing scale in spatial domain and feature domain is obviously wrong

- from a statistical point of view it makes sense to increase feature resolution with decreasing spatial resolution



CCFM Smoothing

Algorithm 7 CCFM smoothing algorithm.

Require: $f \in [1.5; N - 0.5]$

Require: $\mathbf{x} = (x,y)^T \in [1.5; X - 0.5] \times [1.5; Y - 0.5]$

$\mathbf{C} \Leftarrow \mathrm{CCFM}(x,y,f)$

for all x do

$\quad \mathbf{c}_f \Leftarrow \mathrm{interpolate}(\mathbf{C},\mathbf{x})$

$\quad [\mathbf{f}(\mathbf{x})\ \mathbf{E}(\mathbf{x})] \Leftarrow \mathrm{decode}(\mathbf{c}_f)$

$\quad i(\mathbf{x}) \Leftarrow \arg\max_n E_n(\mathbf{x})$

$\quad [\hat{f}(\mathbf{x})\ \hat{E}(\mathbf{x})] \Leftarrow [f_{i(\mathbf{x})}(\mathbf{x})\ E_{i(\mathbf{x})}(\mathbf{x})]$

end for

CCFM Smoothing

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Require: $f \in [1.5; N - 0.5]$
Require: $\mathbf{x} = (x, y)^T \in [1.5; X - 0.5] \times [1.5; Y - 0.5]$
1: $\mathbf{C} \Leftarrow \mathrm{CCFM}(x, y, f)$
2: **for all x do**
3: $\quad \mathbf{c}_f \Leftarrow \mathrm{interpolate}(\mathbf{C}, \mathbf{x})$
4: $\quad [\mathbf{f}(\mathbf{x})\ \mathbf{E}(\mathbf{x})] \Leftarrow \mathrm{decode}(\mathbf{c}_f)$
5: $\quad i(\mathbf{x}) \Leftarrow \arg\max_n E_n(\mathbf{x})$
6: $\quad [\hat{f}(\mathbf{x})\ \hat{E}(\mathbf{x})] \Leftarrow [f_{i(\mathbf{x})}(\mathbf{x})\ E_{i(\mathbf{x})}(\mathbf{x})]$
7: **end for**