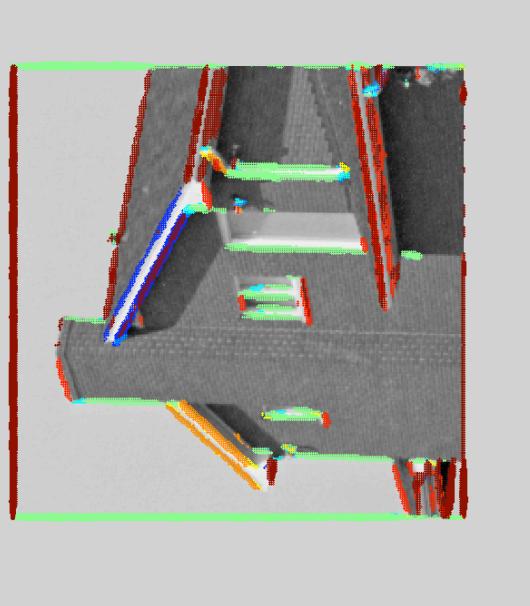




What are channels?



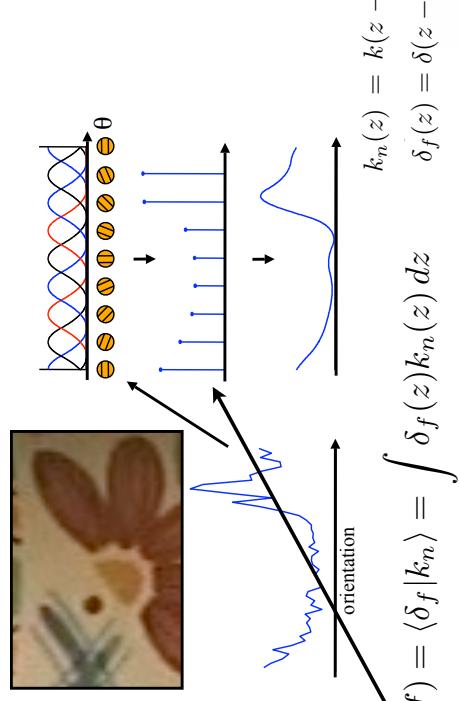
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Channel Representation



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Adaptive Filtering using Channel Representations ?

Michael Felsberg

Computer Vision Laboratory
Linköping University, Sweden

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Collaborators

- Gösta Granlund
- Per-Erik Forssen
- Björn Johansson
- Erik Jonsson
- Johan Hedborg
- Martin Berg
- Norbert Krüger, et al. (Stirling)
- Hanno Scharr (Intel)
- Remco Duits, Bart ter Haar Romeny (Eindhoven)
- Didier Stricker, Alain Paganini (Fraunhofer Darmst.)

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Relation to Density Estimation

- Adding channel representation of samples = sampled kernel density estimation

$$c_n = (\delta_f \star k)(n) = \int \delta_f(z') k(z' - z) dz' \Big|_{z=n}$$

$$E\{c_n(f)\} = (p_f \star k)(n)$$

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First Application

- Line/edge detection by approximated entropy

$$\tilde{H}(x) = - \sum_{n=1, c_n(x) \neq 0}^N c_n(x) \log c_n(x)$$

$$E\{\tilde{H}\} = H_{B2*p}$$

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B-Spline Encoding

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

$$c_n(f) = B_2(f - n) \quad n = 1 \dots N$$

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

Algorithm 1 Channel encoding algorithm.

```

Require:  $f \in [1..N - 0.5]$ 
1:  $c \leftarrow 0$ 
2: for all samples  $f$  do
3:    $i \leftarrow \text{round}(f)$ 
4:    $g \leftarrow f - i$ 
5:    $c_{i-1} \leftarrow c_{i-1} + (g - 1/2)^2 / 2$ 
6:    $c_i \leftarrow c_i + 3/4 - g^2$ 
7:    $c_{i+1} \leftarrow c_{i+1} + (g + 1/2)^2 / 2$ 
8: end for

```

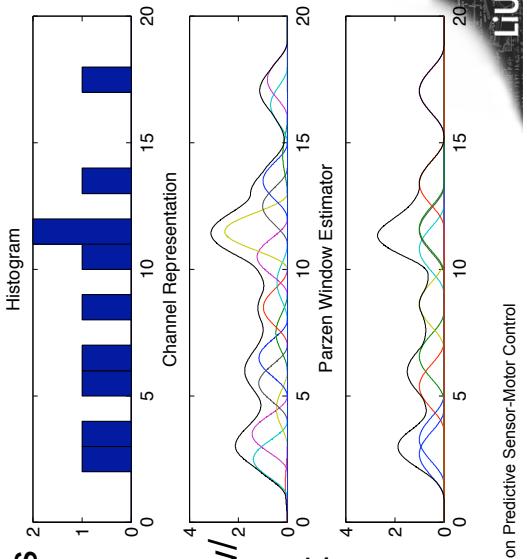
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Channels are ...

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

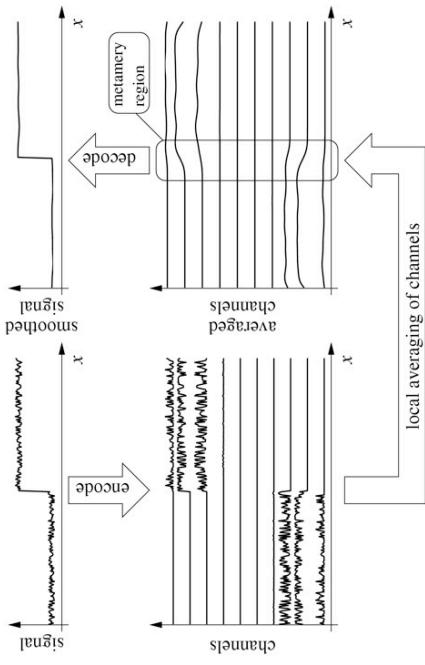


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Channel Smoothing



Decoding

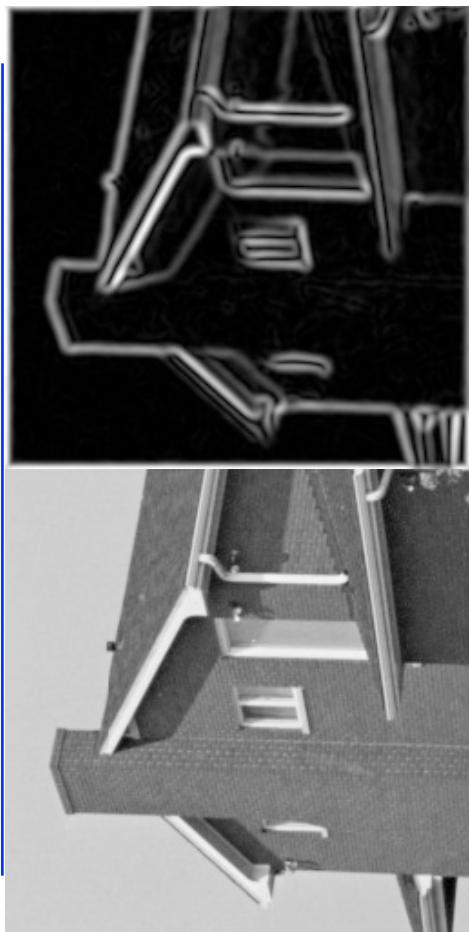
- Choose n_0 :

-Largest response of 3-box filter
 $M_n = c_{n-1} + c_n + c_{n+1}$ $n_0 = \arg \max M_n$

- Additional: local maximum
- Normalized convolution of the channel vector

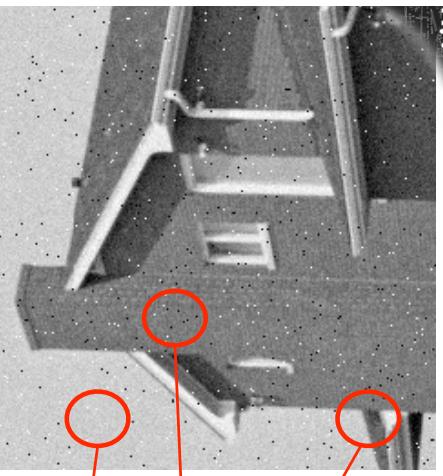
$$\hat{f} = \frac{c_{n_0+1} - c_{n_0-1}}{M_{n_0}} + n_0$$

Edge-Energy



Problem: Image Denoising

- Real data is noisy and discontinuous





Quadratic Decoding I

- Idea: detect local maximum of B-spline interpolated channel vector
- Step 1: recursive filtering to obtain interpolation coefficients:

$$\begin{aligned} c_n^+ &= c_n + hc_{n-1}^+, & c_1^+ &= c_1 \\ c_n^- &= h(c_{n+1}^- - c_n^+), & c_N^- &= \frac{h}{h^2 - 1} c_N^+ \\ c'_n &= 8c_n^- . & h &= 2\sqrt{2} - 3 \end{aligned}$$

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Quadratic Decoding II

- Step 2: detect zeros

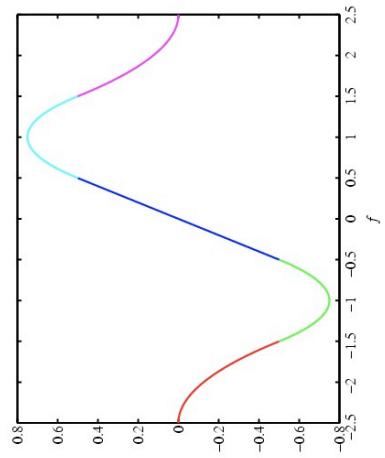
$$\begin{aligned} 0 &= \lambda \beta_n^2 + \mu \beta_n + \nu \quad \text{with} \\ \lambda &= (c'_{n-2} - 2c'_{n-1} + 2c'_{n+1} - c'_{n+2})/2 \\ \mu &= (-c'_{n-2} + 2c'_{n-1} - c'_{n+2})/2 \\ \nu &= (c'_{n-2} + 6c'_{n-1} - 6c'_{n+1} - c'_{n+2})/8 \end{aligned}$$

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Influence Function of C.R.



Obtained from linear decoding:

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

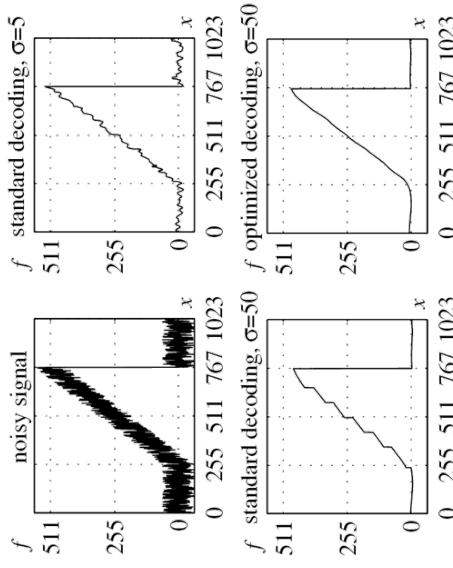
$$\hat{f} = \frac{c_{n_0+1} - c_{n_0-1}}{M_{n_0}} + n_0$$

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Quantization Effect



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Quadratic Decoding III

-Step 3: compute error

$$E(n) = \frac{23}{24} + \beta_n v + \beta_n^2 \mu / 2 + \beta_n^3 \lambda / 3$$

Rule of thumb: $\frac{24c'_{n_0-1} + 46c'_{n_0} + 24c'_{n_0-1}}{c'_{n_0-2}}$

• Few channels (e.g. 8): quadratic decoding

• Many channels (e.g. 32): linear decoding
Step 4: sort c_n according to their error

($n + \beta_n$ with least error is most probable)

-Step 5: shift and rescale to original interval

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Algorithm 2 Virtual shift decoding algorithm.

Require: \mathbf{c} is non-negative and normalized

1: if periodic domain then

2: $\mathbf{c} \Leftarrow \text{IDFT}_N(8(\text{DFT}_N([6\ 1\ 0\dots 0\ 1])_N))^{-1}\text{DFT}_N(\mathbf{c})$

3: $\mathbf{c} \Leftarrow [c_{N-1}\ c_N\ \mathbf{c}^T\ c_1\ c_2]^T$

4: else

5: $h \Leftarrow 2\sqrt{2} - 3$

6: for $n = 2$ to N do

7: $c_n \Leftarrow c_n + hc_{n-1}$

8: end for

9: $c_N \Leftarrow 8\frac{h}{h^2 - 1}c_N$

10: for $n = N-1$ to 1 do

11: $c_n \Leftarrow h(c_{n+1} - 8c_n)$

12: end for

13: end if

14: $\boldsymbol{\lambda} \Leftarrow \text{conv}(\mathbf{c}, [-\frac{1}{2}\ 1\ 0\ -1\ \frac{1}{2}])$

15: $\boldsymbol{\mu} \Leftarrow \text{conv}(\mathbf{c}, [-\frac{1}{2}\ 0\ 1\ 0\ -\frac{1}{2}])$

16: $\mathbf{v} \Leftarrow \text{conv}(\mathbf{c}, [-\frac{1}{8}\ -\frac{3}{4}\ 0\ \frac{3}{4}\ \frac{1}{8}])$

17: $\boldsymbol{\beta} \Leftarrow (-\boldsymbol{\mu}/2 + \sqrt{\boldsymbol{\mu}^2/4 - \mathbf{v} \cdot \boldsymbol{\lambda}}) / \boldsymbol{\lambda}$

18: $\boldsymbol{\gamma} \Leftarrow \text{conv}(\mathbf{c}, [\frac{1}{48}\ \frac{1}{24}\ \frac{1}{24}\ \frac{1}{48}\ \frac{1}{48}])$

19: $\mathbf{f} \Leftarrow \boldsymbol{\beta} + [1\ 2\dots N]$

20: $\mathbf{E} \Leftarrow \frac{23}{24} + (-2 < 2\boldsymbol{\beta} < 1) \cdot (\boldsymbol{\beta} \cdot \mathbf{v} + \boldsymbol{\beta}^2 \cdot \boldsymbol{\mu} / 2 + \boldsymbol{\beta}^3 \cdot \boldsymbol{\lambda} / 3 - \boldsymbol{\gamma})$

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Quadratic Decoding III

-Step 3: compute error

$$E(n) = \frac{23}{24} + \beta_n v + \beta_n^2 \mu / 2 + \beta_n^3 \lambda / 3$$

$$\beta_n = \frac{-\mu/2 + \sqrt{\mu^2/4 - v\lambda}}{\lambda}$$

-Step 4: sort $n + \beta_n$ according to their error
($n + \beta_n$ with least error is most probable)

-Step 5: shift and rescale to original interval

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Quadratic Decoding II

-Step 2: detect zeros

$$\beta_n = \frac{-\mu/2 + \sqrt{\mu^2/4 - v\lambda}}{\lambda}$$

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Quadratic Decoding II

-Step 2: detect zeros

$$\beta_n = \frac{-\mu/2 + \sqrt{\mu^2/4 - v\lambda}}{\lambda}$$

-Step 4: sort $n + \beta_n$ according to their error
($n + \beta_n$ with least error is most probable)

-Step 5: shift and rescale to original interval

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Channel Smoothing

Algorithm 3 Channel smoothing algorithm.

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

1: **for all** \mathbf{x} **do**

2: $\mathbf{c}(\mathbf{x}) \Leftarrow \text{encode}(f(\mathbf{x}))$

3: **end for**

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

5: $c_n \Leftarrow \text{conv2}(c_n, g_\sigma)$

6: **end for**

7: **for all** \mathbf{x} **do**

8: $[\mathbf{f}(\mathbf{x}) \mathbf{E}(\mathbf{x})] \Leftarrow \text{decode}(\mathbf{c}(\mathbf{x}))$

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

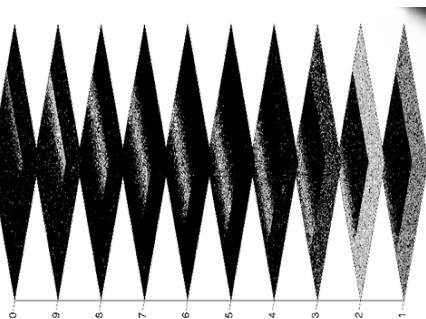
10: $[\hat{f}(\mathbf{x}) \hat{E}(\mathbf{x})] \Leftarrow [f_{i(\mathbf{x})}(\mathbf{x}) E_{i(\mathbf{x})}(\mathbf{x})]$

11: **end for**

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Channel Smoothing

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11: **end for**

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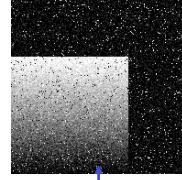
10: $[\hat{f}(\mathbf{x}) \hat{E}(\mathbf{x})] \Leftarrow [f_{i(\mathbf{x})}(\mathbf{x}) E_{i(\mathbf{x})}(\mathbf{x})]$

11: **end for**

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Algorithm 3 Channel smoothing algorithm.

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

1: **for all** \mathbf{x} **do**

2: $\mathbf{c}(\mathbf{x}) \Leftarrow \text{encode}(f(\mathbf{x}))$

3: **end for**

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

5: $c_n \Leftarrow \text{conv2}(c_n, g_\sigma)$

6: **end for**

7: **for all** \mathbf{x} **do**

8: $[\mathbf{f}(\mathbf{x}) \mathbf{E}(\mathbf{x})] \Leftarrow \text{decode}(\mathbf{c}(\mathbf{x}))$

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

11: **end for**

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Image Denoising



Channel Smoothing



Algorithm 3 Channel smoothing algorithm.

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

```

1: for all  $\mathbf{x}$  do
2:    $\mathbf{c}(\mathbf{x}) \leftarrow \text{encode}(f(\mathbf{x}))$ 
3: end for
4: for  $n = 1$  to  $N$  do
5:    $c_n \leftarrow \text{conv2}(c_n, g_\sigma)$ 
6: end for
7: for all  $\mathbf{x}$  do
8:    $[f(\mathbf{x}) E(\mathbf{x})] \leftarrow \text{decode}(\mathbf{c}(\mathbf{x}))$ 
9:    $i(\mathbf{x}) \leftarrow \arg \max_n E_n(\mathbf{x})$ 
10:   $[f_i(\mathbf{x}) \hat{E}(\mathbf{x})] \leftarrow [f_i(\mathbf{x}) E_{i(\mathbf{x})}(\mathbf{x})]$ 
11: end for
```



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Image Denoising

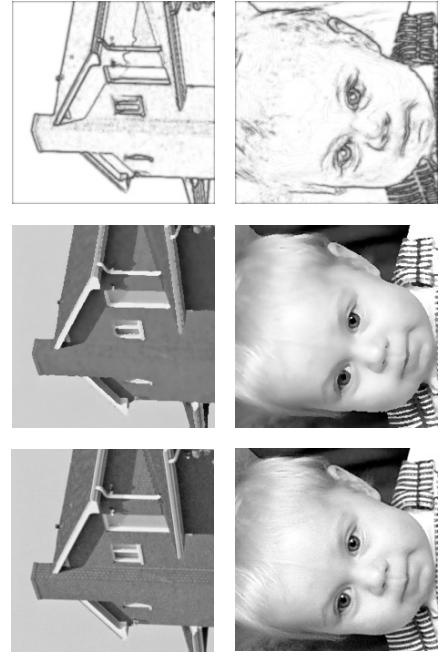


Image Denoising



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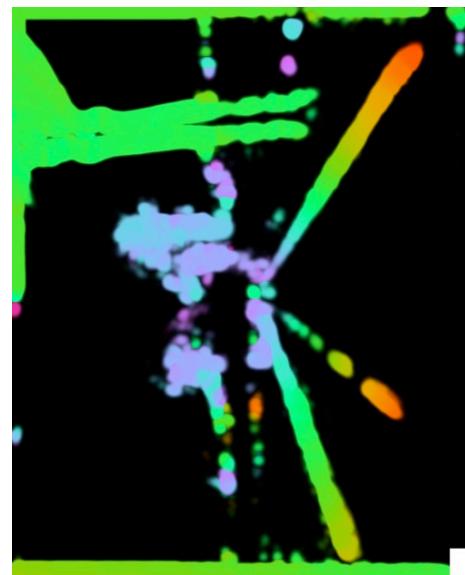
Disparity Estimation



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Disparity Estimation



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Random Sample Reconstruction

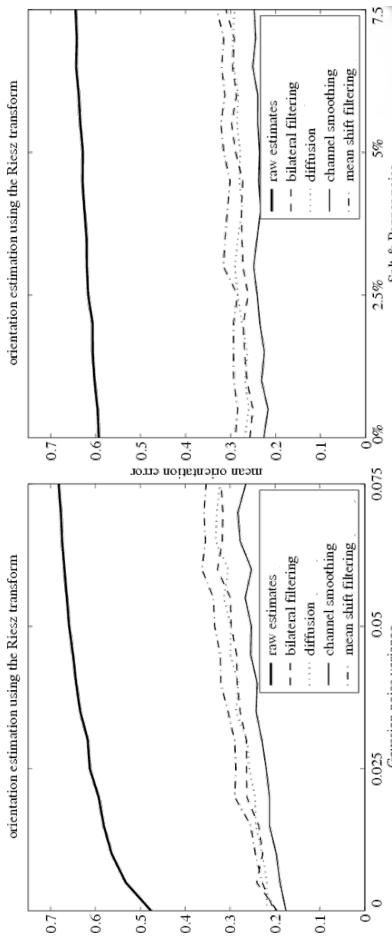
- Real data is incomplete
- Strong regularization required



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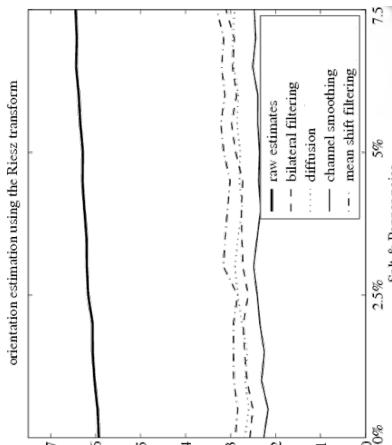
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Orientation Estimation



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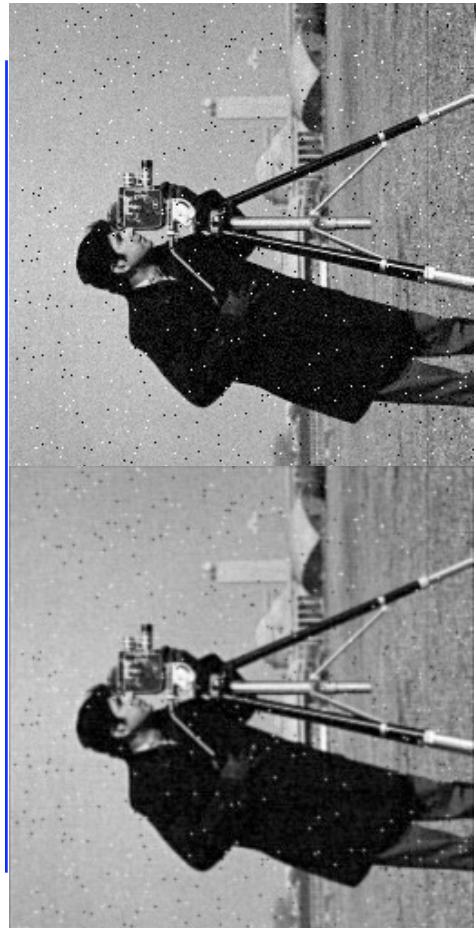


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Experiment 2



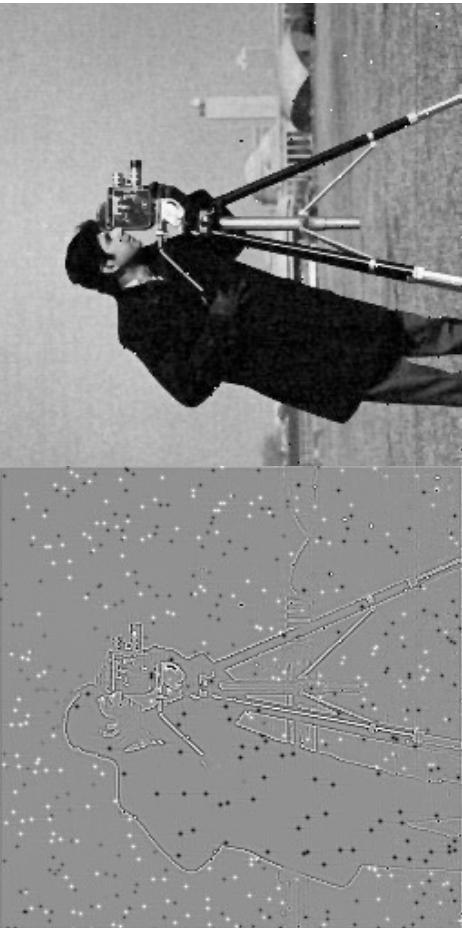
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Experiment 2



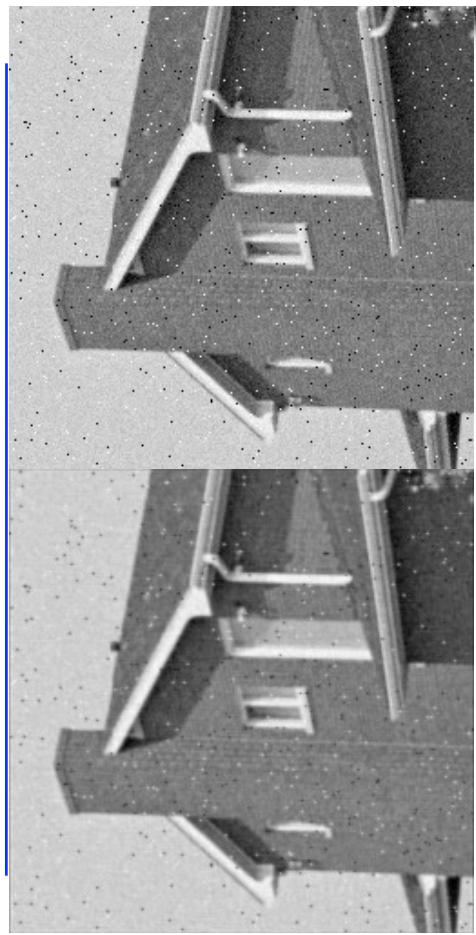
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Experiment 1



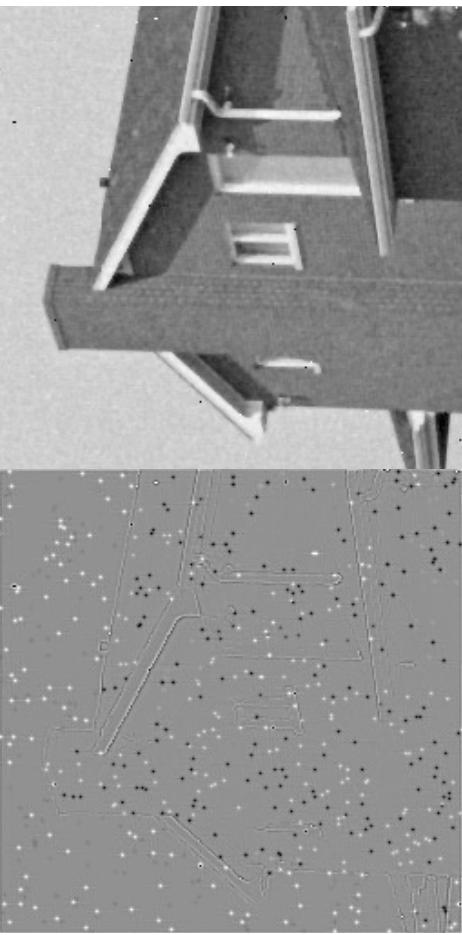
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Experiment 1



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Masked Normalized Averaging

- Normalized averaging: $\hat{f} = \frac{(a * (bf))}{(a * b)}$

Averaging filter / applicability: a

• Certainty:

$$b(\mathbf{x}) = \begin{cases} 1 & \mathbf{x} \in \Omega \\ 0 & \mathbf{x} \notin \Omega \end{cases}$$

• Mask result: $\hat{c}_n = b_n \frac{(a * (b_n c_n))}{(a * b_n)}$

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Graph-Cut Channel Smoothing

Algorithm 5 Graph-cut channel smoothing algorithm.

```

Require:  $f \in [1.5; N - 0.5]$ 
1: for all  $\mathbf{x}$  do
2:    $\mathbf{c}(\mathbf{x}) \leftarrow \text{encode}(f(\mathbf{x}))$ 
3: end for
4: for  $n = 1$  to  $N$  do
5:    $b_n \leftarrow \text{binary-graph.cut}(c_n, \mathcal{N}, \lambda, \theta)$ 
6:    $c_n \leftarrow b_n \text{conv2}(b_n c_n, g_\sigma) / \text{conv2}(b_n, g_\sigma)$ 
7: end for
8: for all  $\mathbf{x}$  do
9:    $[\mathbf{f}(\mathbf{x}), \mathbf{E}(\mathbf{x})] \leftarrow \text{decode}(\mathbf{c}(\mathbf{x}))$ 
10:   $i(\mathbf{x}) \leftarrow \arg \max_n E_n(\mathbf{x})$ 
11:   $[\hat{f}(\mathbf{x}), \hat{E}(\mathbf{x})] \leftarrow [f_{i(\mathbf{x})}(\mathbf{x}), E_{i(\mathbf{x})}(\mathbf{x})]$ 
12: end for

```

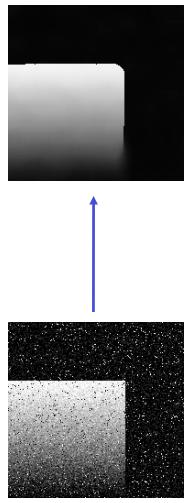
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Channel Smoothing

- Task: Reduce noise without blurring edges
 - locally linear
- Problem: No consideration of the multidimensional neighborhood structure



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Binary Graph-Cut

- Solves globally this labeling problem:

$$\hat{f} = \arg \min E(f) = \arg \min E_{\text{smooth}}(f) + E_{\text{data}}(f)$$

- where

$$E_{\text{data}}(f) = \sum_{p \in \mathcal{P}} D_p(f_p)$$

$$E_{\text{smooth}}(f) = \sum_{\{p, q\} \in \mathcal{N}} V_{p, q}(f_p, f_q)$$

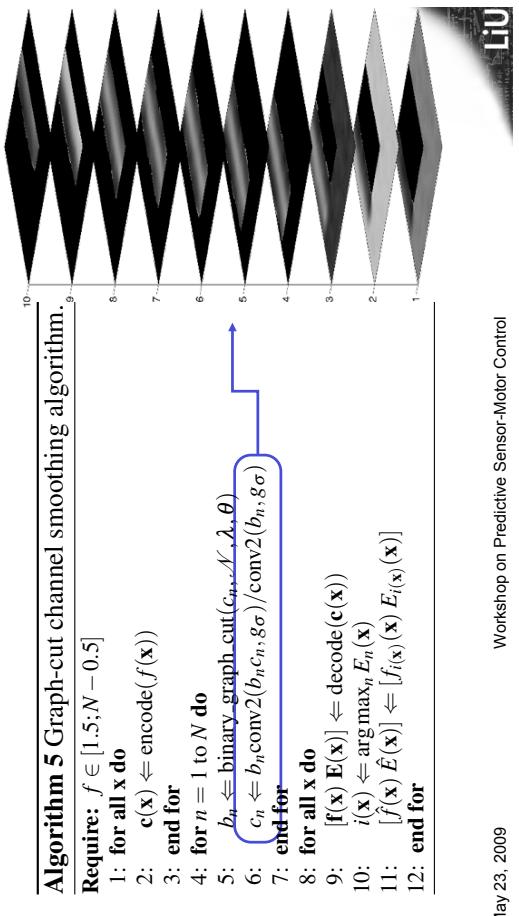
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Graph-Cut Channel Smoothing



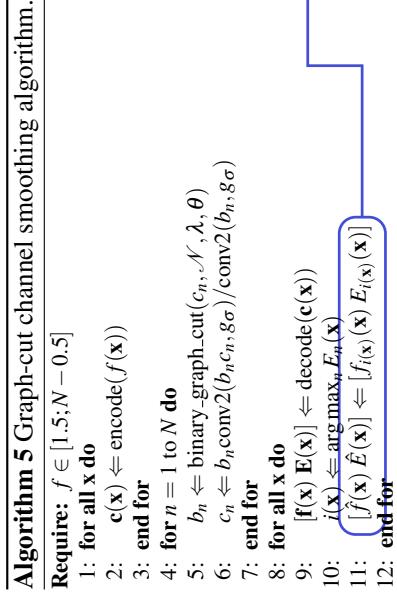
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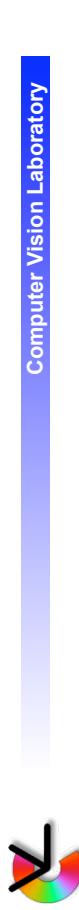
Graph-Cut Channel Smoothing



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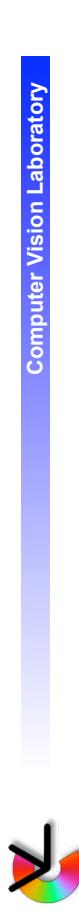
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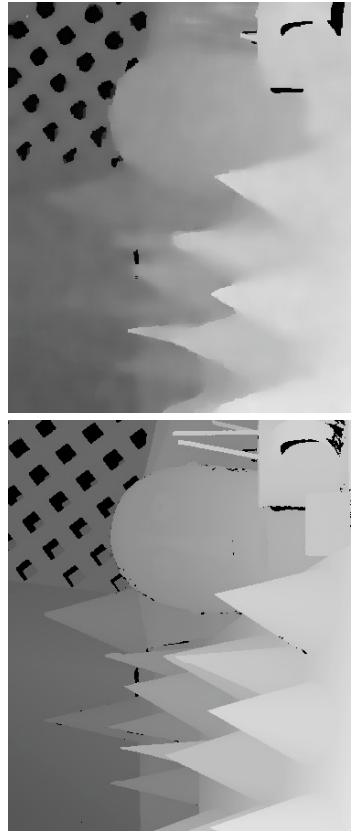


Evaluation (Middlebury)



Evaluation (Middlebury)

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Ground truth

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GC channel smoothing



Ground truth

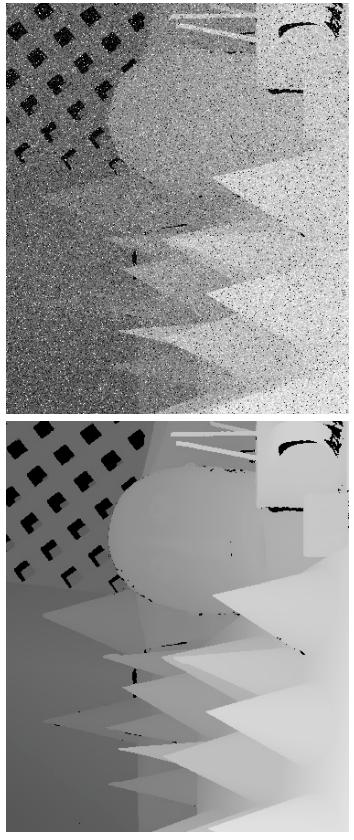
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Drawback Channel Smoothing

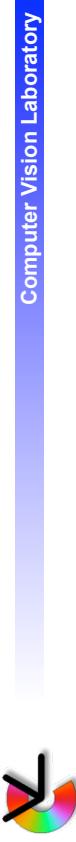
- no coherence enhancing filtering



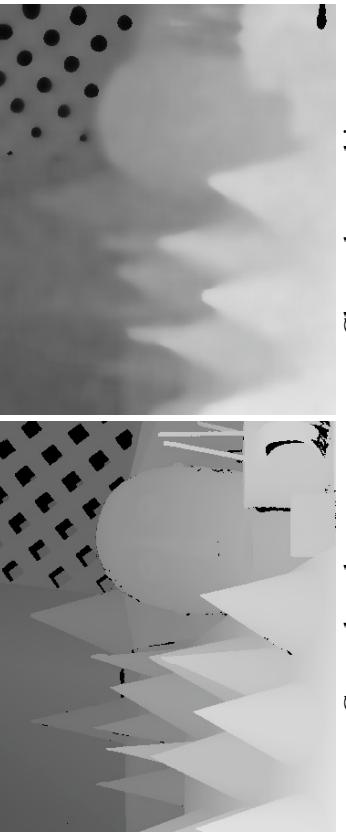
Ground truth Gaussian noise (10% std) and S&P (5%)

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Evaluation (Middlebury)



Ground truth Channel smoothing

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Experiment

original
image



coherence
enhancing diffusion



anisotropic
channel smoothing

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Experiment

original
image



coherence
enhancing diffusion

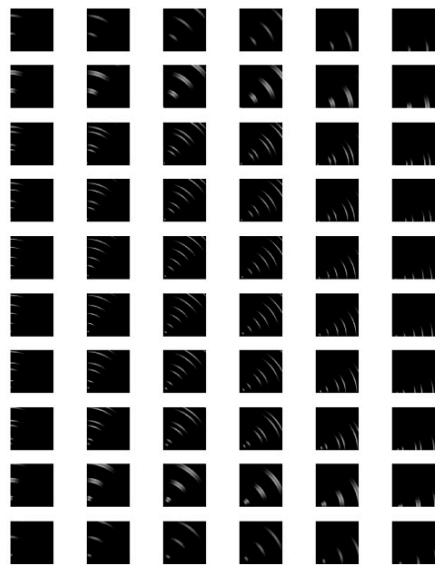


anisotropic
channel smoothing

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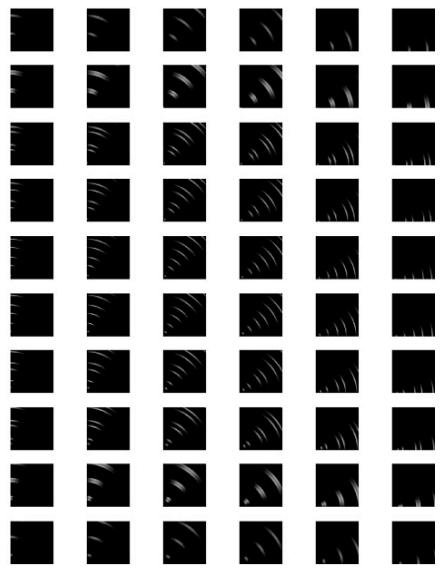
Orientation Adaptive CS



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Orientation Adaptive CS



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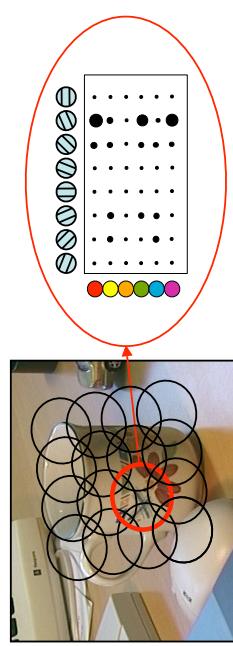
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CCFMs



Filter Adaptation

- Significant improvement by bringing in model knowledge:
 - Perpendicular orientation should not be influenced
 - Polar filter design is appropriate for orientation data
- Model fitting of “hourglass” filter



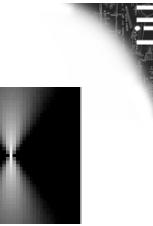
- point-wise encoding

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

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Different Formulations

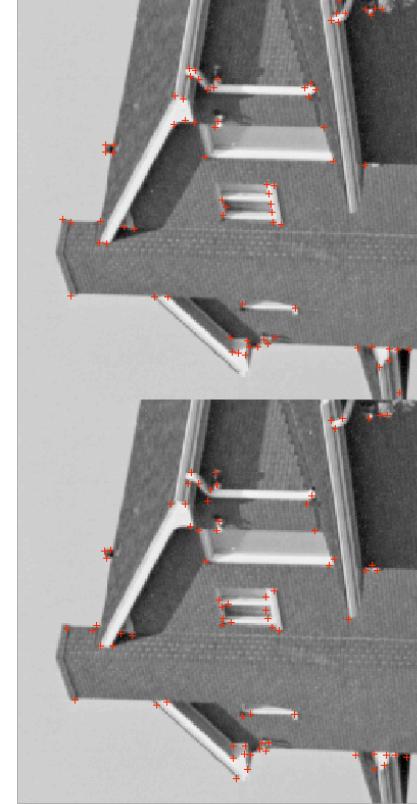
- Scalar product / correlation

$$\begin{aligned} c_{l,m,n}(f) &= \langle \delta_f | k_{f,n} k_{x,l} k_{y,m} \rangle = \iiint \delta_f(x, y, z) k_{f,n}(z) k_{x,l}(x) k_{y,m}(y) dz dy dx \\ &= (\delta_f \star (k_f k_x k_y))(n, m, l). \end{aligned}$$

- where

$$\delta_f(x, y, z) = \delta(z - f(x, y))$$

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



Corner Detection



P-Channel Conversion

- Probabilistic analysis with overlapping kernels

- Avoid high computational cost using P-channels (mono-pieces)

- Convert P-channels to linear splines

$$B_1 = \frac{h_1 + h_2}{2} + o_1 - o_2$$

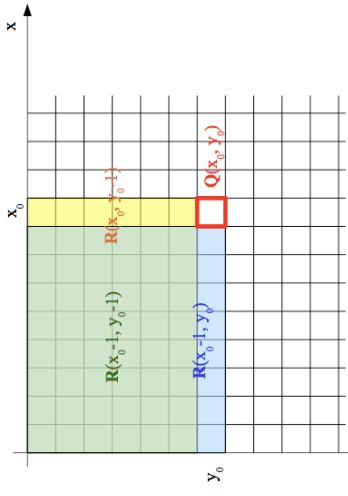
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Integral Image

- any statistical moment can be computed by integral images



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Algorithm

- direct implementation

Algorithm 6 CCFM algorithm.

```

Require:  $f \in [1.5; N - 0.5]$ 
Require:  $\mathbf{x} = (x, y)^T \in [1.5; X - 0.5] \times [1.5; Y - 0.5]$ 
1:  $C \leftarrow 0$ 
2: for all  $\mathbf{x}$  do
3:    $\mathbf{c}_f \leftarrow \text{encode}(f(\mathbf{x}))$ 
4:    $\mathbf{c}_x \leftarrow \text{encode}(x)$ 
5:    $\mathbf{c}_y \leftarrow \text{encode}(y)$ 
6:    $C \leftarrow C + \mathbf{c}_f \otimes \mathbf{c}_x \otimes \mathbf{c}_y$ 
7: end for

```

- other alternatives: "mono-pieces"

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Algorithm

- direct implementation

Algorithm 6 CCFM algorithm.

```

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

- other alternatives: "mono-pieces"

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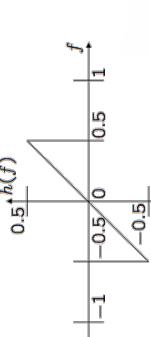


P-Channel Representation

- Simplest channel representation: Histogram
- Basis function:

• No reconstruction possible

- Second basis function:



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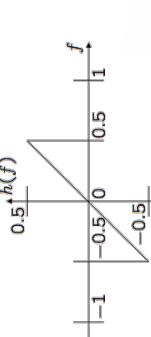


P-Channel Representation

- Simplest channel representation: Histogram
- Basis function:

• No reconstruction possible

- Second basis function:



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COLL-100 Objects

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

Method	ROC integral
KLD, θ	0.9817
SVD, θ	0.9840
KLD, RGB	0.9983
SVD, RGB	0.9998
KLD, $hs\theta$	0.9939
SVD, $hs\theta$	1.0000

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Videos

- The image contains four separate photographs illustrating cluttered environments:

 - Top Left:** A child's play area with various toys scattered on the floor. A red and green bounding box highlights a toy car and a blue toy truck.
 - Top Right:** A collection of toys and items on a light-colored surface. A red bounding box highlights a toy car.
 - Bottom Left:** A cluttered room with a large green bag in the foreground. A blue and red bounding box highlights the bag.
 - Bottom Right:** A collection of colorful, star-shaped wooden puzzle pieces scattered on a light surface. A red bounding box highlights one of the puzzle pieces.

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New Linear Scale-Space

- 3D linear scale-space

$$\delta_f(x,y) = \delta(z,x,y))$$

- Parabolic PDE?

- Just 3D Gaussian / alpha Kernel?

Comparing CCFMs

- Several alternatives tested:
 - Euclidean distance
 - relative information / Kullback-Leibler
 - least-squares mapping to index
 - chi-squared distance
 - square-root distance / Bhattacharyya
 - quadratic form distance
 - earth mover's distance

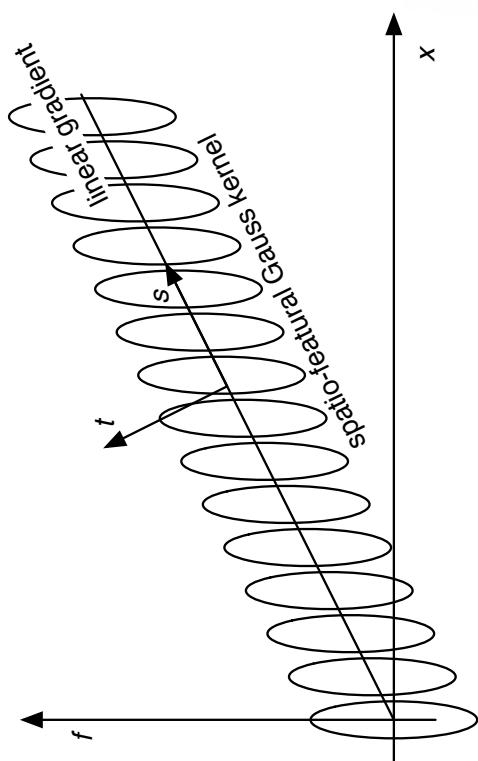
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Example

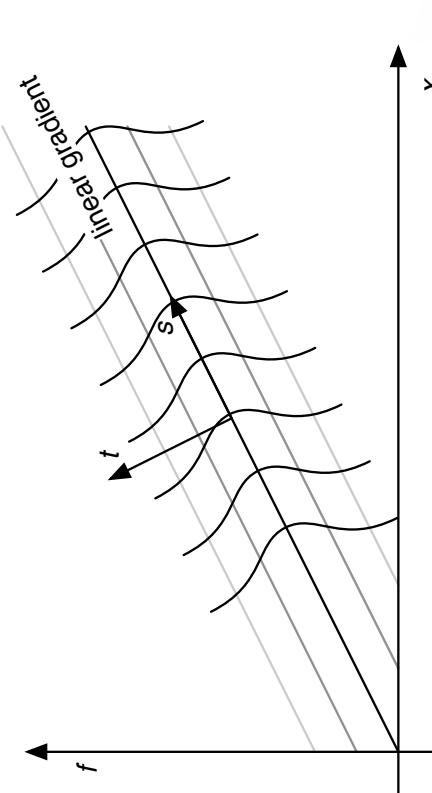


Considerations

- simultaneously increasing scale in spatial domain and feature domain is obviously wrong (consider e.g. decreasing scale)
- from a statistical point of view it makes sense to increase feature resolution with decreasing spatial resolution



Example



$$\begin{aligned}x' &= x + t_x \\f' &= f + \tan(\phi)x + t_f\end{aligned}$$

Theorem

- f-x uncertainty relation

$$\exists k > 0 : (\Delta x)(\Delta f) \geq k$$

$$k = \frac{1}{2} \sigma_f \sigma_x$$

- proof based on isotropic geometry



- Questions?
- Comments?
- Contact
mfe@isy.liu.se
- Further info:
www.cvl.isy.liu.se

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Welcome to the Computer Vision Laboratory, Linköping University, Sweden

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TEKNIKA & MÄRKAN

Computer Vision Laboratory

3D Computer Vision

We can rewrite this expression as $f = \arg\max_{f(x)} \int_{\Omega} (f(x))^2 d\Omega$ which can be further reduced to

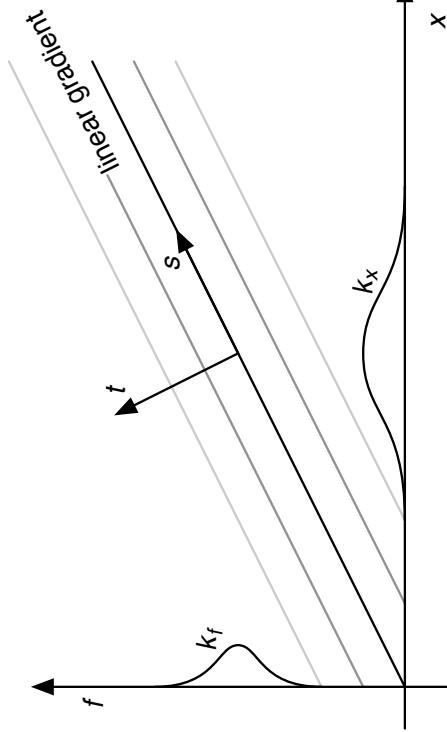
Cognitive Vision Systems

Education

Medical Imaging

Image Analysis

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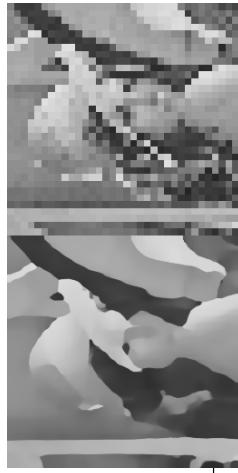
Channel Pyramid

Algorithm 7 CCFM smoothing algorithm.

```

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

```



frame#: 114
resolution: 32 x 32
channels: 20

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