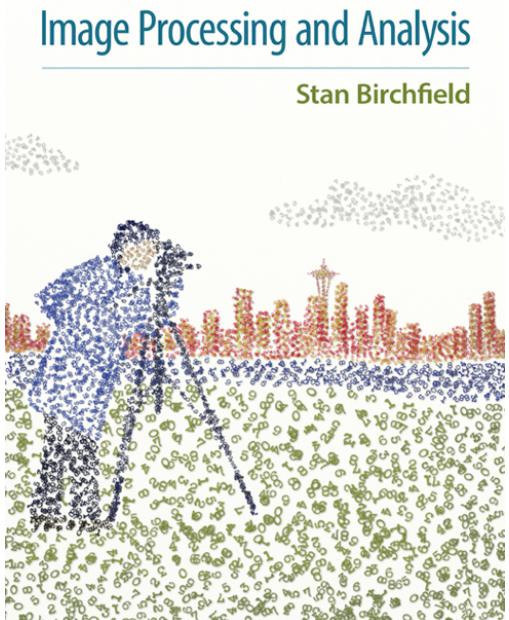


Prof. Kjersti Engan

ELE510 Image processing and computer vision

Nonlinear filtering (chap 5.5 Birchfield) 2020

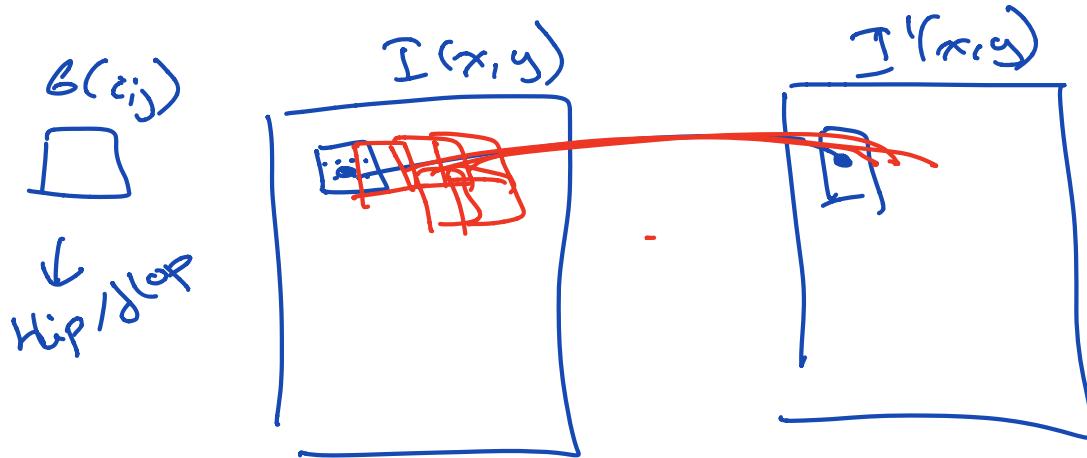


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Remember – linear shift-invariant filters

Filters so far: linear and shift-invariant filters. Convolution formula is valid. w and h are the width and height of the kernel.

$$I'(x, y) = I(x, y) \circledast G(x, y) = \sum_{i=0}^{w-1} \sum_{j=0}^{h-1} I(x + \tilde{w} - i, y + \tilde{h} - j) G(i, j)$$



Effect of mean /box filtering

$$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

3x3

5x5

7x7

Salt &
Pepper
noise



Gaussian
noise

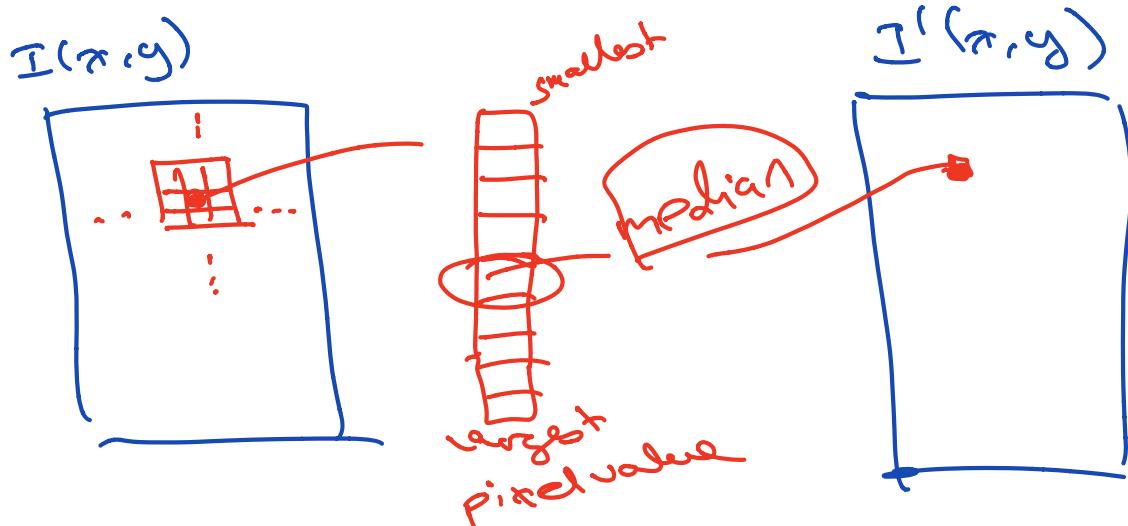


Side effect - blur



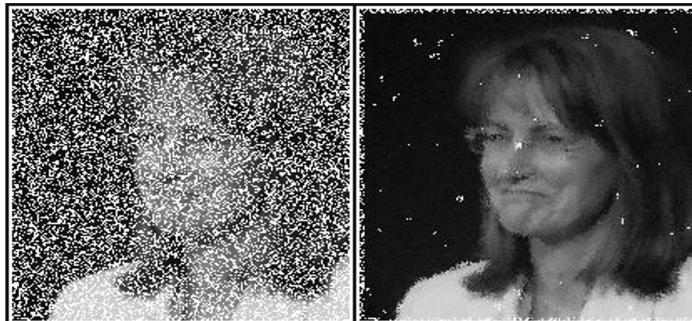
(5.5) Non-linear filtering

- filters that are not linear are called **non-linear filters**
- Common example: Median filter** - replaces each pixel with the median of all the gray levels in a local neighborhood, generally defined by a square window.



Median filter

- Different type of noise needs different filters.
- We have seen that for **salt and pepper** noise the Gaussian, or flat mean (box filters) does not work well. These are both examples of linear low pass (LP) filters.
- For salt/pepper noise a median filter is a good alternative
- A *median filter* operates over a window by selecting the median intensity in the window.



Median filter – not linear

$$T(f_1 + f_2) = T(f_1) + T(f_2)$$

linear operators

A *median filter* operates over a window by selecting the median intensity in the $T(\cdot)$ window.

Median filter is an example of non-linear filtering, and an example of rank-order filter

$$\boxed{\text{Median}(f_1(x) + f_2(x)) \neq \text{Median}(f_1(x)) + \text{Median}(f_2(x))}$$

$$1 = \text{Median} \left(\begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 1 \\ 1 & 1 & 1 \end{bmatrix} \right) = \text{Median} \left(\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \right) + \text{Median} \left(\begin{bmatrix} 0 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 0 \end{bmatrix} \right) \neq$$

$$\text{Median} \left(\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \right) + \text{Median} \left(\begin{bmatrix} 0 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 0 \end{bmatrix} \right) = 1 + 1 = 2$$

Median filter



3x3



5x5



7x7

Median filter, salt end pepper noise. Mask 3x3, 5x5, 7x7

Salt & Pepper noise

Mean



Gaussian



Median



3x3

5x5

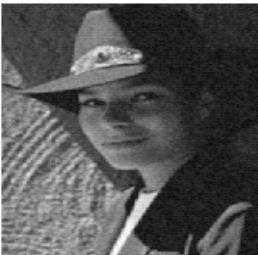
7x7



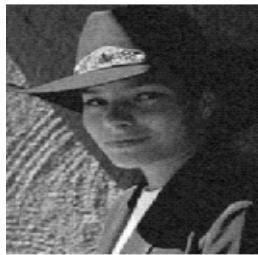
Gaussian noise

3x3

Mean



Gaussian

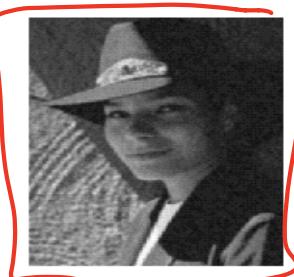


Median



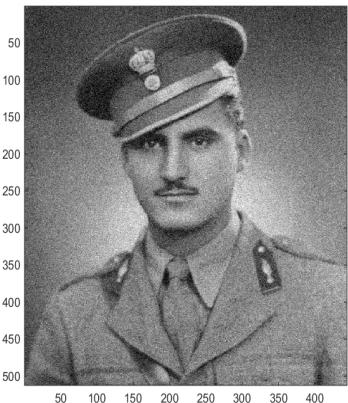
5x5

7x7



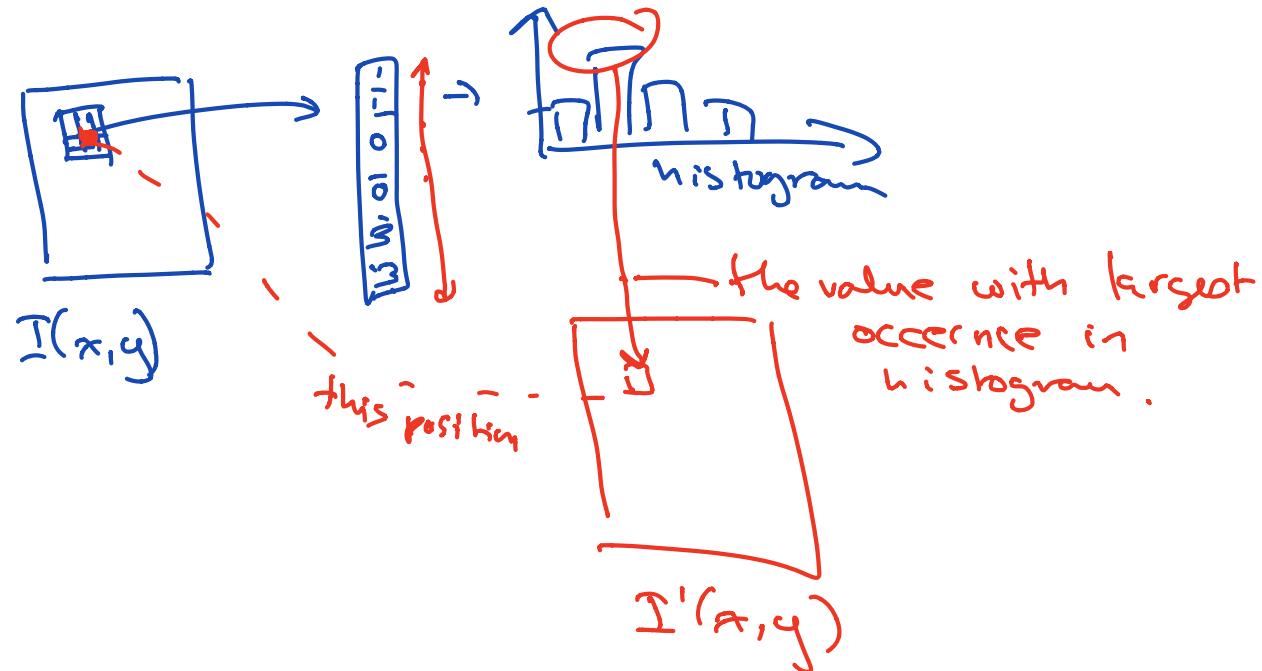


Salt and pepper noise,
median filter,
gaussian filter



Gaussian noise,
median filter,
gaussian filter

Mode filter



Example nonlinear filter - Non-local means

- **Non-local means (NLM):** a particularly effective way to reduce the effects of noise in an image by computing a weighted average over *all* pixels in the image.
- Weight based on the similarity between the regions

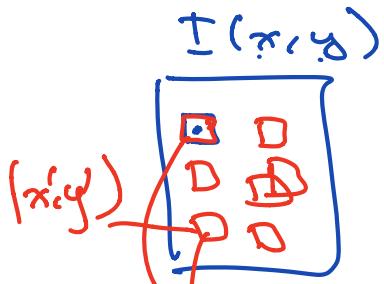
ALGORITHM 5.12 Perform non-local means filtering on an image

NONLOCALMEANS(I, w)

Input: grayscale image I , set of pixels \mathcal{W} specifying window
Output: smoothed image from applying non-local means filtering

```
1  for  $(x, y) \in I'$  do                                ➤ For each pixel in the output image (same size as input image),
2       $val \leftarrow 0$                                      initialize value to zero,
3       $norm \leftarrow 0$                                     and normalization factor to zero.
4      for  $(x', y') \in I$  do                            ➤ For each pixel in input image,
5           $d \leftarrow 0$                                      initialize distance to zero.
6          for  $(\delta_x, \delta_y) \in \mathcal{W}$  do            ➤ Compute the dissimilarity between the two windows.
7               $d \leftarrow + I(x + \delta_x, y + \delta_y) - I(x' + \delta_x, y' + \delta_y)$ 
8               $w \leftarrow \exp(-d * d / (2 * \sigma * \sigma))$     ➤ Set the weight to the similarity.
9               $val \leftarrow + w * I(x', y')$                   ➤ Update the sum of the weighted pixels,
10              $norm \leftarrow + w$                            and the normalization factor.
11              $I'(x, y) \leftarrow val/norm$                 ➤ Set the output pixel to the normalized value.
12  return  $I'$ 
```

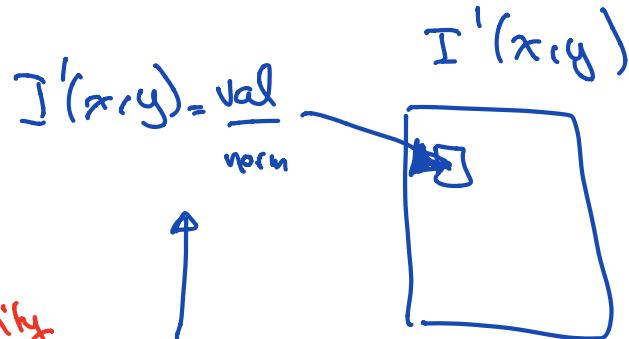
Non-local means



compare windows
find distance, dissimilarity

$$w_{(x,y)} = e^{-\frac{d^2}{2\sigma^2}}$$

weight
everywhere



$$\text{val} = \sum_{(x',y')} w_{(x',y')} \cdot I(x',y')$$

$$\text{norm.} = \sum_{(x',y')} w_{(x',y')}$$

Non-local means

OpenCV, python

From documentation; https://opencv-python-tutorials.readthedocs.io/en/latest/py_tutorials/py_photo/py_non_local_means/py_non_local_means.html#non-local-means

OpenCV provides four variations of this technique.

1. cv2.fastNIMeansDenoising() - works with a single grayscale images

2. cv2.fastNIMeansDenoisingColored() - works with a color image.

3. cv2.fastNIMeansDenoisingMulti() - works with image sequence captured in short period of time (grayscale images)

4. cv2.fastNIMeansDenoisingColoredMulti() - same as above, but for color images.

- Common arguments are:
h : parameter deciding filter strength. Higher h value removes noise better, but removes details of image also. (10 is ok)
- hForColorComponents : same as h, but for color images only. (normally same as h)
- templateWindowSize : should be odd. (recommended 7)
- searchWindowSize : should be odd. (recommended 21)

Example nonlinear filter - Bilateral filtering

- Contains two kernels, a spatial kernel and a range kernel.
- The spatial kernel g_s weights neighboring samples according to their proximity to the central sample, while the range kernel g_r weights neighboring samples according to their similarity in *value* to the central sample.

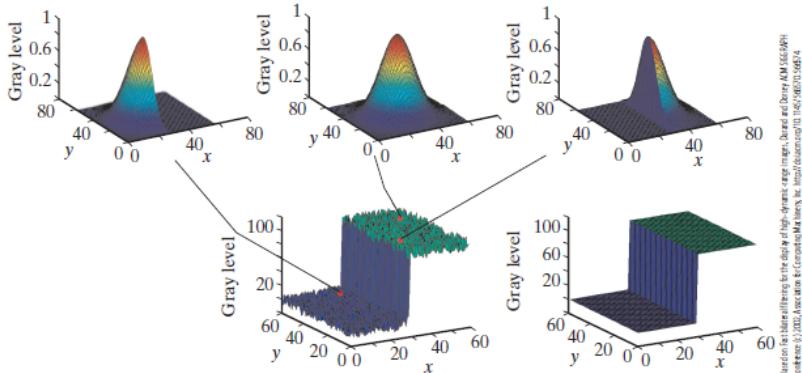
$$f'(x) = f(x) \odot \langle g_s(x), g_r(z) \rangle = \frac{1}{\eta(x)} \sum_i f(i) g_s(x - i) g_r(f(x) - f(i))$$

- Smoothing, but preserves edges
- Repeated applications gives a cartoon-like image



OpenCV, python:

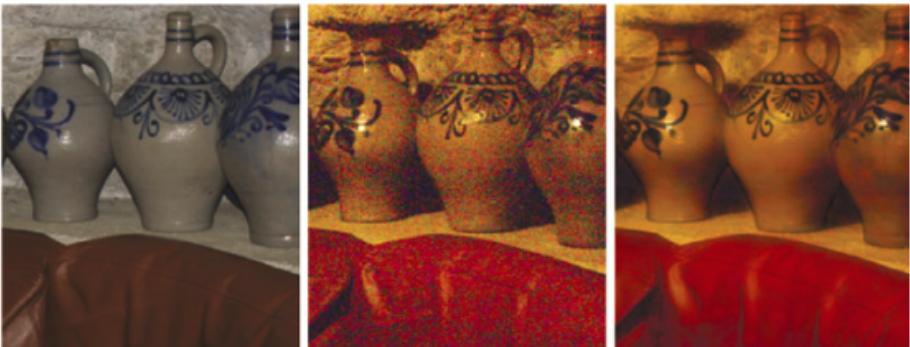
```
dst=cv2.bilateralFilter(src, d, sigmaColor, sigmaSpace[, dst[, borderType]])
```



Bilateral filtering for denoising of high dynamic range image. Deriche and Berthod. *AM'95/96/RHIC*. © 2002 Association for Computing Machinery, Inc. Reprinted by permission.

Figure 5.17 Bilateral filtering of a noisy step edge preserves the crisp edge as it smooths out the noise on either side of the edge. The top row shows the kernel at three locations: Far from the edge, the kernel approximates a Gaussian, whereas near the edge it approximates half a Gaussian.

Figure 5.21 One of the more interesting applications of the bilateral filter is to combine a flash image (left) with a no-flash image (middle) to preserve both detail and the original viewing conditions of the scene (right).



© Peshkin, R. Szeliski, M. Agrawala, M. Cohen, H. Hoppe, and K. Toyama,
“Digital photography with fast and no-flash images,” ACM SIGGRAPH 2004, 16(7), 647–652, August 2004. © 2004 Association for
Computing Machinery, Inc. Reprinted by permission.

Other non-linear filters

- Anisotropic diffusion
 - The image values are smoothed by repeatedly performing local averages, but doing so in a way that weights neighbour pixels less if they lie on an intensity edge. Blurs the images within regions, but not across boundaries.
- Adaptive smoothing
 - Find weighted averages of neighbors of pixels, with weights discouraging smoothing across boundaries. Bilateral filter is special case of adaptive smoothing.
- Gray-scale morphological operators

Other non-linear filters

- Mean-shift filter
 - Clustering both in color values and in distance. Group pixels near in color values AND distance, and recalculalte mean according to mean-shift. Iteratively replaces each pixel with the mean of the pixels in a range- r neighborhood and whose value is within a distance d until mean-shift =0.

