Filtering Images in the Spatial Domain

Ross Whitaker
SCI Institute, School of Computing
University of Utah

Overview

- Correlation and convolution
- Linear filtering
  - Smoothing, kernels, models
  - Detection
  - Derivatives
- Nonlinear filtering
  - Median filtering
  - Bilateral filtering
  - Neighborhood statistics and nonlocal filtering

Cross Correlation

- Operation on image neighborhood and small …
  - "mask", "filter", "stencil", "kernel"
- Linear operations within a moving window

Input image

100	130	104	99	…
87	95	103	150	…
50	36	150	104	…
20	47	205	77	…
.	.	.	.	
.	.	.	.	

Filter

0.0	0.1	0.0
0.1	0.6	0.1
0.0	0.1	0.0

Output image

.	.	.	.
.	.	.	.
.	55.8	134.8	.
.	.	.	.

0.0*87 + 0.1*95 + 0.0*103
+ 0.1*50 + 0.6*36 + 0.1*150
+ 0.0*20 + 0.1*47 + 0.0*205 = 55.8 134.8

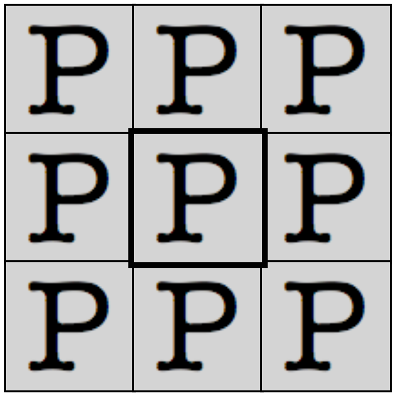
Cross Correlation

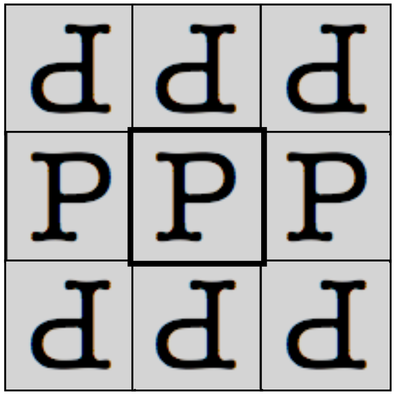
- **1D** $$g(x) = \sum_{s=-a}^{a} w(s) f(x+s)$$
- **2D** $$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s, y+t)$$

$$w(s,t) = \begin{matrix} w(-a,-b) & \cdots & & \cdots & w(a,-b) \\ \vdots & & & & \vdots \\ & \cdots & w(0,0) & \cdots & \\ \vdots & & & & \vdots \\ w(-a,b) & \cdots & & \cdots & w(a,b) \end{matrix}$$

Correlation: Technical Details

- Boundary conditions
  - Pad image with amount (a,b)
    - Constant value or repeat edge values
  - Cyclical boundary conditions
    - Wrap or mirroring





Correlation: Technical Details

- Boundaries
  - Can also modify kernel - no long correlation
- For analysis
  - Image domains infinite
  - Data compact (goes to zero far away from origin)

$$g(x,y) = \sum_{s=-\infty}^{\infty} \sum_{t=-\infty}^{\infty} w(s,t) f(x+s, y+t)$$

Correlation: Properties

- **Shift invariant**

$$g = w \circ f \qquad g(x,y) = w(x,y) \circ f(x,y)$$

$$w(x,y) \circ f(x-x_0, y-y_0) = \sum_{s=-\infty}^{\infty} \sum_{t=-\infty}^{\infty} w(s,t) f(x-x_0+s, y-y_0+t) = g(x-x_0, y-y_0)$$

- **Linear** $w \circ (\alpha e + \beta f) = \alpha w \circ e + \beta w \circ f$

Compact notation

$$C_{wf} = w \circ f$$

Filters: Considerations

- Normalize
  - Sums to one
  - Sums to zero (some cases, later)
- Symmetry
  - Left, right, up, down
  - Rotational
- Special case: auto correlation

$$C_{ff} = f \circ f$$

Examples 1

$$\begin{matrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix}$$

$$1/9 * \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

Examples 2

$$\frac{1}{9} * \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

$$\frac{1}{25} * \begin{matrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{matrix}$$

Smoothing and Noise

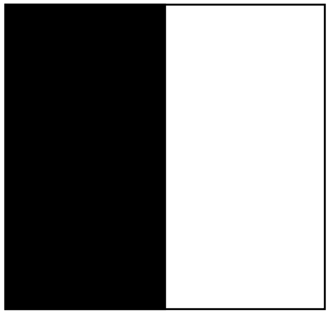
Noisy image

5x5 box filter

Noise Analysis

- Consider an a simple image I() with additive, uncorrelated, zero-mean noise of variance s
- What is the expected rms error of the corrupted image?
- If we process the image with a box filter of size 2a+1 what is the expected error of the filtered image?

$$\mathrm{RMSE} = \left(\frac{1}{|\mathcal{D}|} \sum_{(\mathrm{x},\mathrm{y}) \in \mathcal{D}} \left(\tilde{\mathrm{I}}(\mathrm{x},\mathrm{y}) - \mathrm{I}(\mathrm{x},\mathrm{y}) \right)^2 \right)^{\frac{1}{2}}$$



Cross Correlation Continuous Case

- f, w must be “integrable”
  - Must die off fast enough so that integral is finite

$$g(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} w(s,t) f(x+s, y+t)\,ds\,dt$$

- Same properties as discrete case
  - Linear
  - Shift invariant

Other Filters

- Disk
  - Circularly symmetric, jagged in discrete case
- Gaussians
  - Circularly symmetric, smooth for large enough stdev
  - Must normalize in order to sum to one
- Derivatives – discrete/finite differences
  - Operators

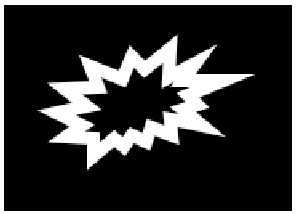
Pattern Matching/Detection

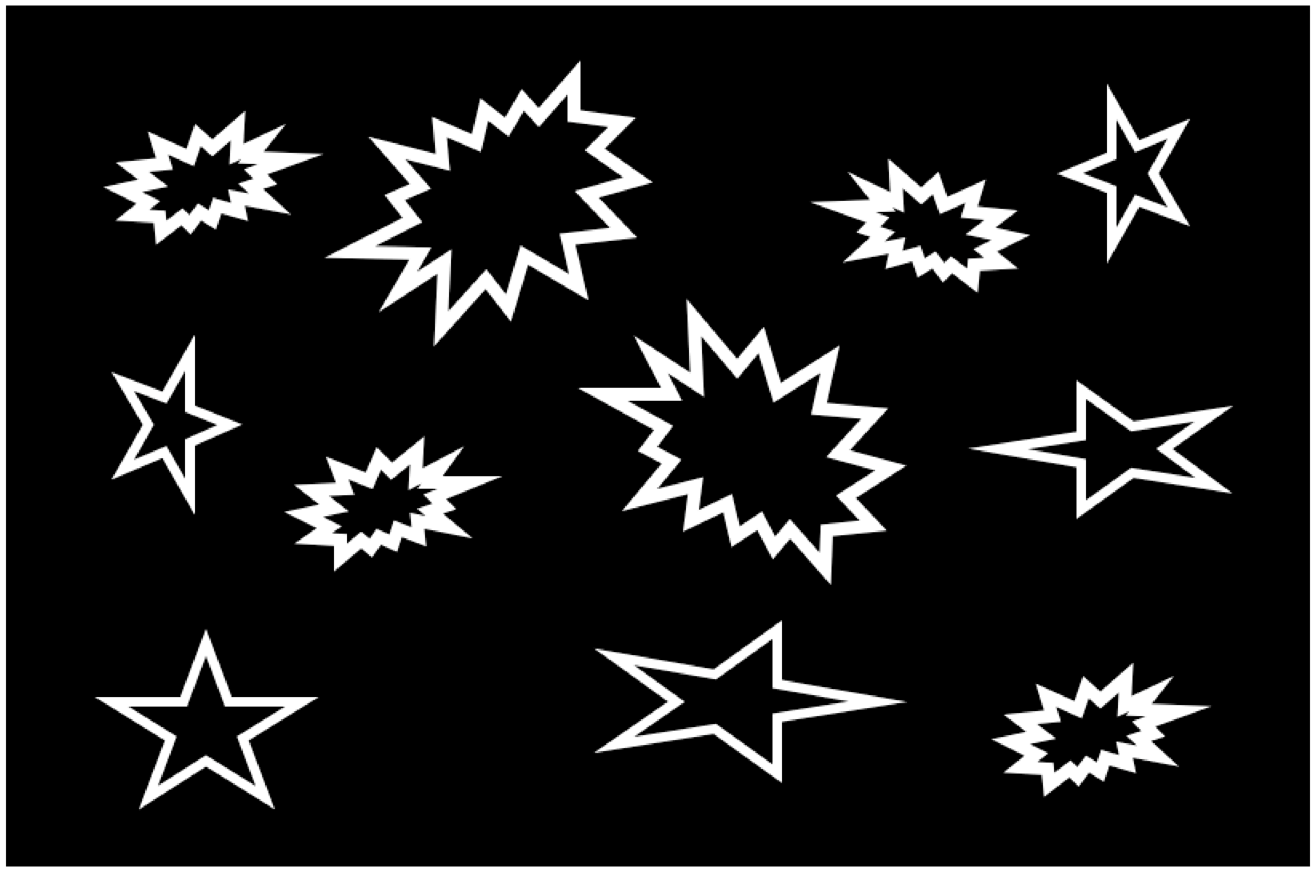
- The optimal (highest) response from a filter is the autocorrelation evaluated at position zero

$$\max_{\bar{x}} C_{ff}(\bar{x}) = C_{ff}(0) = \int f(\bar{s}) f(\bar{s}) d\bar{s}$$

- A filter responds best when it matches a pattern that looks itself
- Strategy
  - Detect objects in images by correlation with "matched" filter

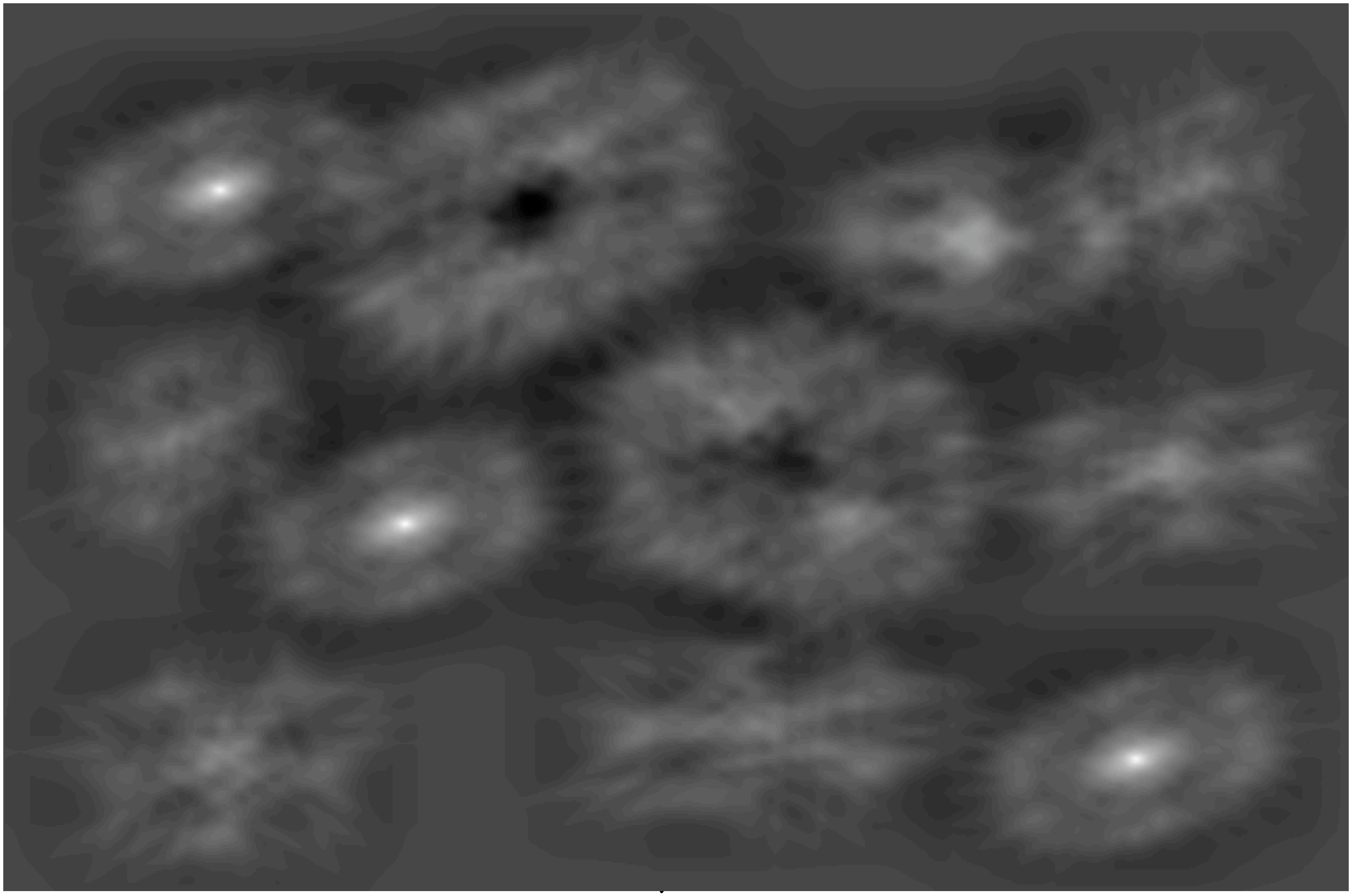
Match Filter Example



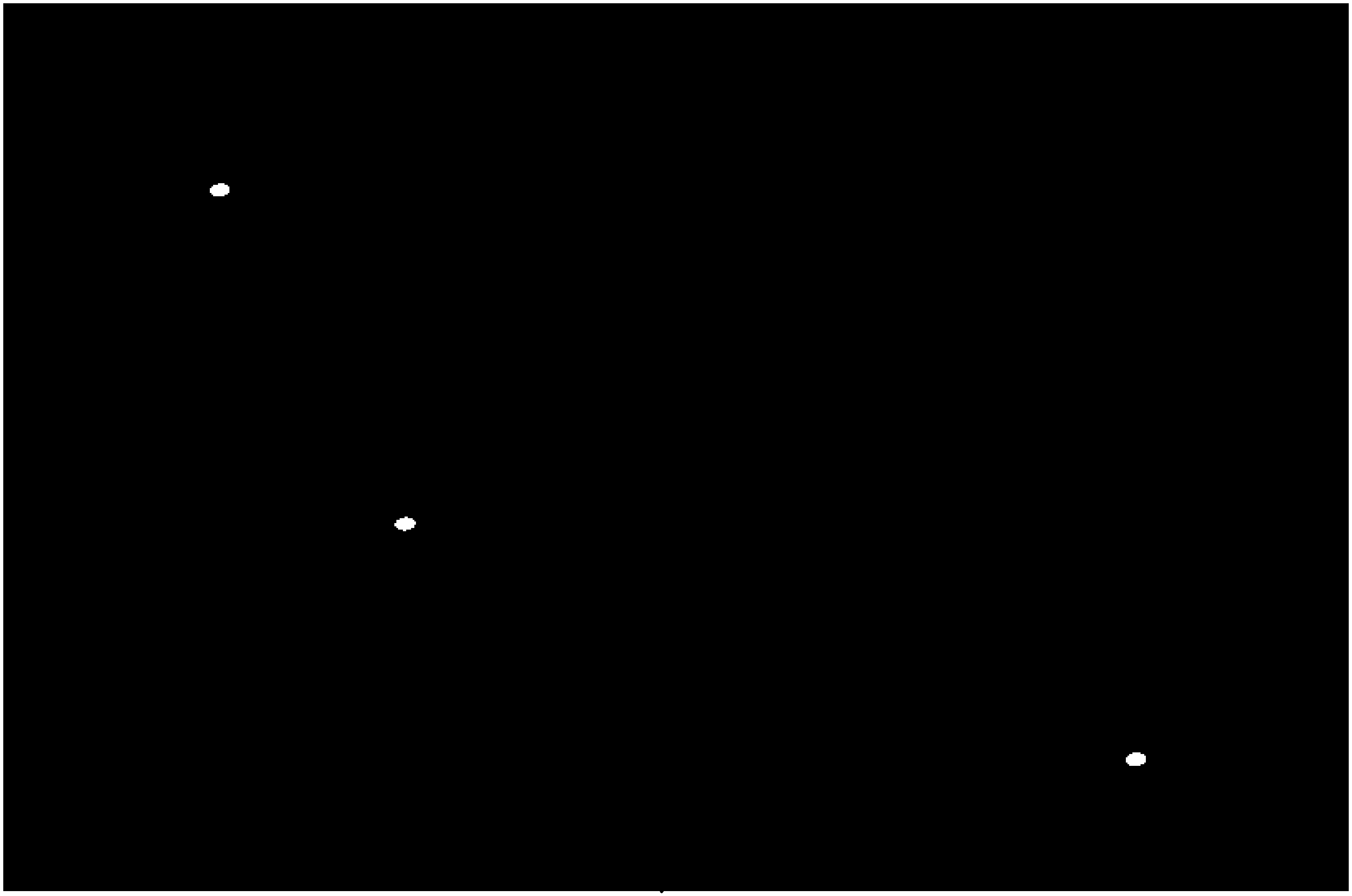


Trick: make sure kernel sums to zero

Match Filter Example



Match Filter Example



Derivatives: Finite Differences

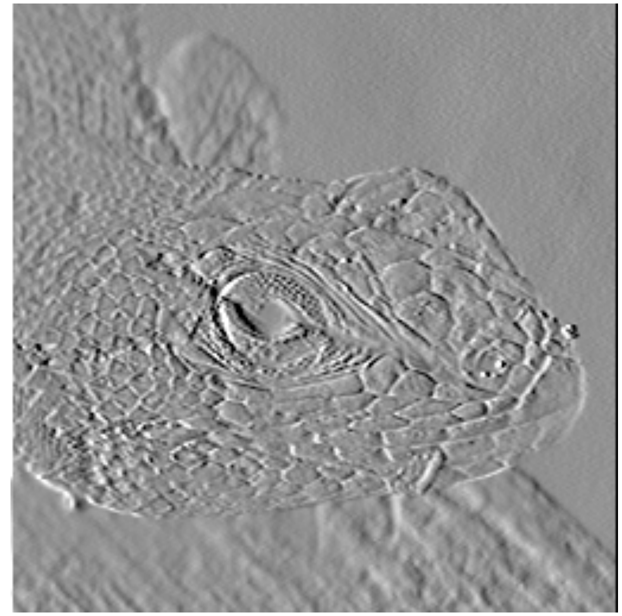
$$\frac{\partial f}{\partial x} \approx \frac{1}{2h}\left(f(x+1,y) - f(x-1,y)\right)$$

$$\frac{\partial f}{\partial x} \approx w_{dx} \circ f \qquad w_{dx} = \begin{array}{|c|c|c|}\hline -\frac{1}{2} & 0 & \frac{1}{2} \\ \hline \end{array}$$

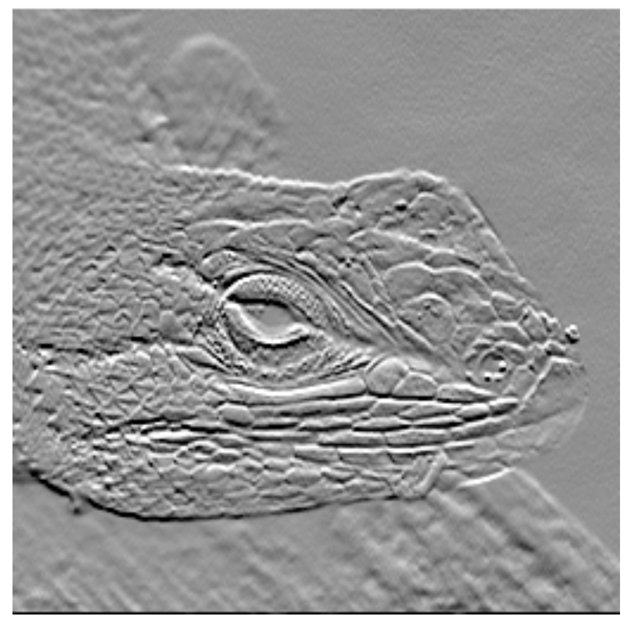
$$\frac{\partial f}{\partial y} \approx w_{dy} \circ f \qquad w_{dy} = \begin{array}{|c|}\hline -\frac{1}{2} \\ \hline 0 \\ \hline \frac{1}{2} \\ \hline \end{array}$$

Derivative Example

$$\begin{matrix} 0 & 0 & 0 \\ -1 & 0 & 1 \\ 0 & 0 & 0 \end{matrix}$$



$$\begin{matrix} 0 & -1 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{matrix}$$



Univ of Utah, CS6640 2009

Convolution

- Discrete

$$g(x,y) = w(x,y) * f(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x-s, y-t)$$

- Continuous

$$g(x,y) = w(x,y) * f(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} w(s,t) f(x-s, y-t) ds dt$$

- Same as cross correlation with kernel transposed around each axis
- The two operations (correlation and convolution) are the same if the kernel is symmetric about axes

$$g = w \circ f = w^* * f$$

w^* reflection of w

Convolution: Properties

- Shift invariant, linear
- Cummutative

$$f * g = g * f$$

- Associative

$$f * (g * h) = (f * g) * h$$

- Others (discussed later):
  - Derivatives, convolution theorem, spectrum...

Computing Convolution

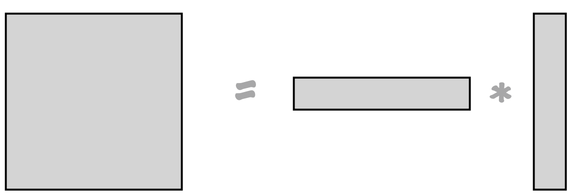
- Compute time
  - MxM mask
  - NxN image

  $O(M^2N^2)$ "for" loops are nested 4 deep

- Special case: *separable*

$$w = \overbrace{w_x * w_y}^{\text{Two 1D kernels}}$$

$$w * f = \underbrace{(w_x * w_y) * f}_{O(M^2N^2)} = \underbrace{w_x * (w_y * f)}_{O(MN^2)}$$



Separable Kernels

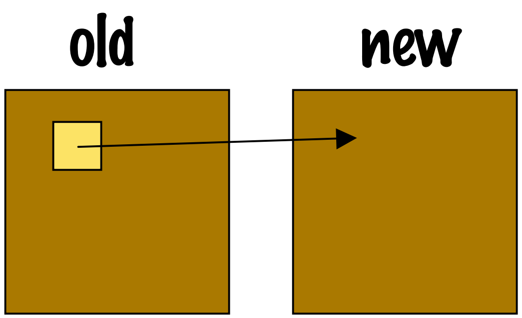
- Examples
  - Box/rectangle
  - Bilinear interpolation
  - Combinations of partial derivatives
    - $d^2f/dxdy$
  - Gaussian
    - Only filter that is both circularly symmetric and separable
- Counter examples
  - Disk
  - Cone
  - Pyramid

Nonlinear Methods For Filtering

- Median filtering
- Bilateral filtering
- Neighborhood statistics and nonlocal filtering

Median Filtering

- For each neighborhood in image
  - Sliding window
  - Usually odd size (symmetric) 5x5, 7x7,...
- Sort the greyscale values
- Set the center pixel to the median
- Important: use "Jacobi" updates
  - Separate input and output buffers
  - All statistics on the original image

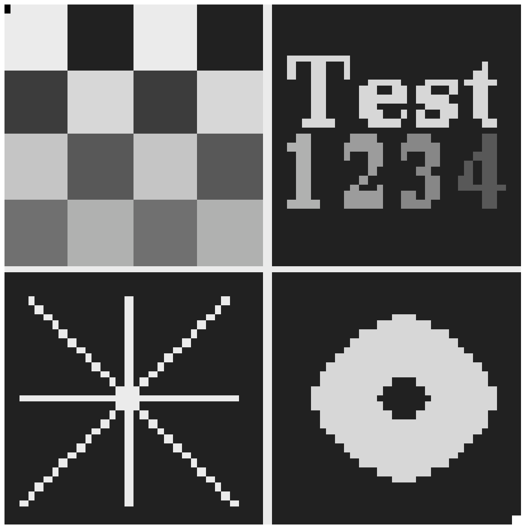


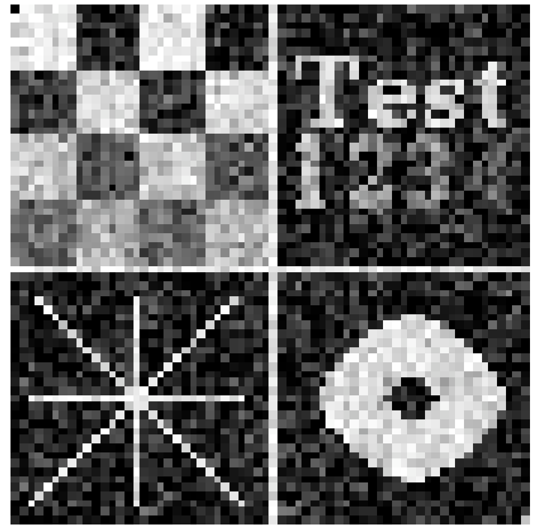
Median Filter

- Issues
  - Boundaries
    - Compute on pixels that fall within window
  - Computational efficiency
    - What is the best algorithm?
- Properties
  - Removes outliers (replacement noise – salt and pepper)
  - Window size controls size of structures
  - Preserves straight edges, but rounds corners and features

Median vs Gaussian

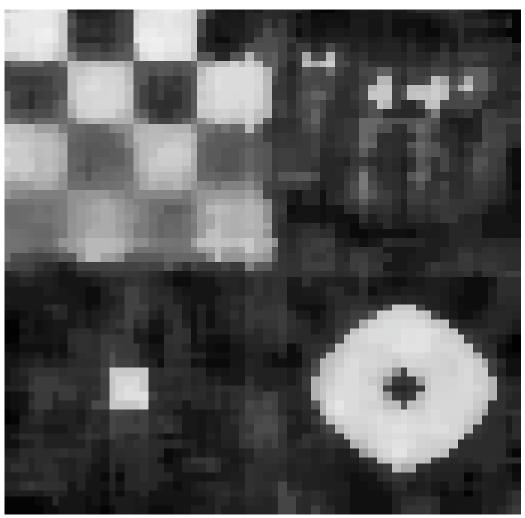
Original

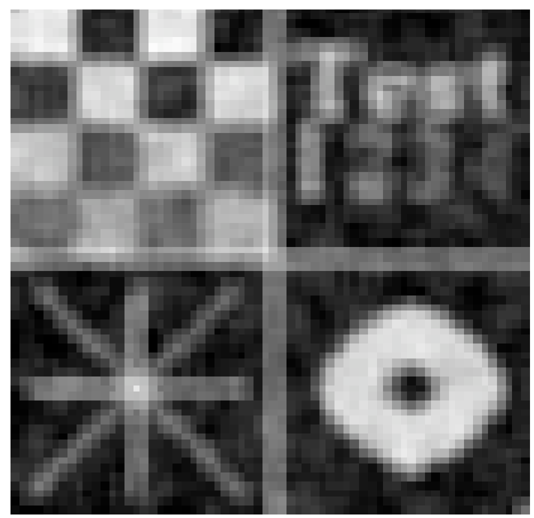




+ Gaussian Noise

3x3 Median





3x3 Box

Replacement Noise

- Also: "shot noise", "salt&pepper"
- Replace certain % of pixels with samples from pdf
- Best strategy: filter to avoid <u>outliers</u>

Smoothing of S&P Noise

- It's not zero mean (locally)
- Averaging produces local biases

Median Filtering

Median 3x3

Median 5x5

Median Filtering

Median 3x3

Median 5x5

Median Filtering

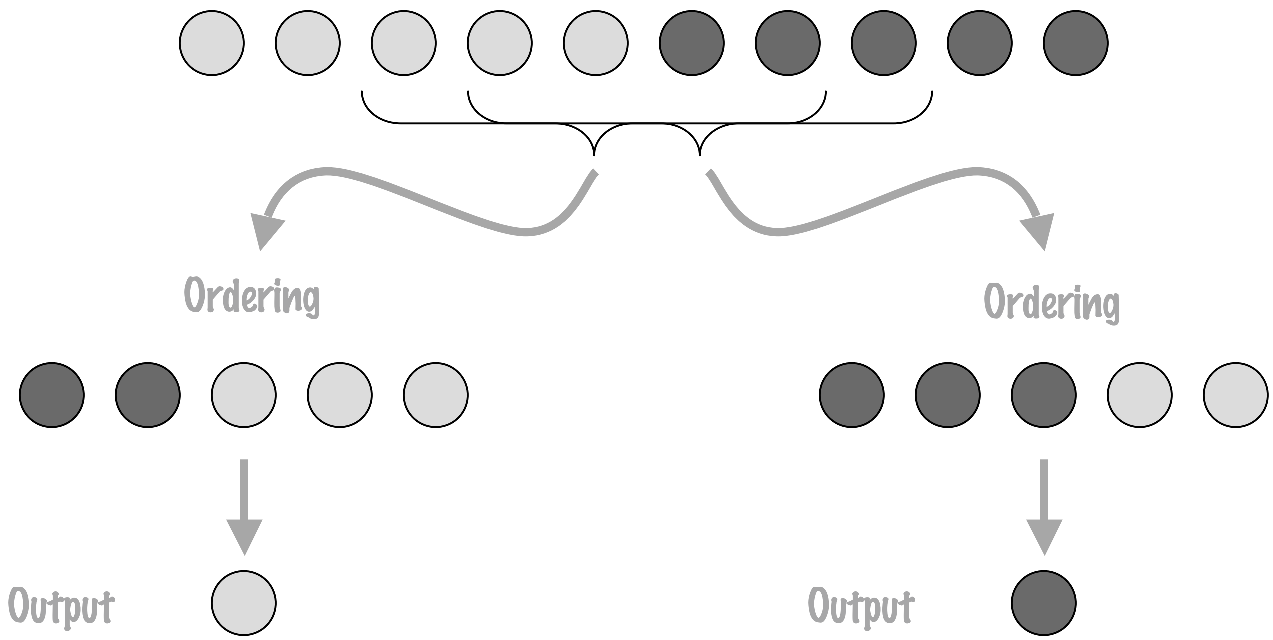
- Iterate

Median 3x3

2x Median 3x3

Median Filtering

- Image model: piecewise constant (flat)



Order Statistics

- Median is special case of order-statistics filters
- Instead of weights based on neighborhoods, weights are based on ordering of data

Neighborhood

$$X_1, X_2, \ldots, X_N$$

Ordering

$$X_{(1)} \leq X_{(2)} \leq \ldots \leq X_{(N)}$$

Filter

$$F(X_1, X_2, \ldots, X_N) = \alpha_1 X_{(1)} + \alpha_2 X_{(2)} + \ldots + \alpha_N X_{(N)}$$

Neighborhood average (box)

$$\alpha_i = 1/N$$

Median filter

$$\alpha_i = \begin{cases} 1 & i = (N+1)/2 \\ 0 & \text{otherwise} \end{cases}$$

Trimmed average (outlier removal)

$$\alpha_i = \begin{cases} 1/M & (N-M+1)/2 \leq i \leq (N+M+1)/2 \\ 0 & \text{otherwise} \end{cases}$$

Piecewise Flat Image Models

- Image piecewise flat -> average only within similar regions
- Problem: don't know region boundaries

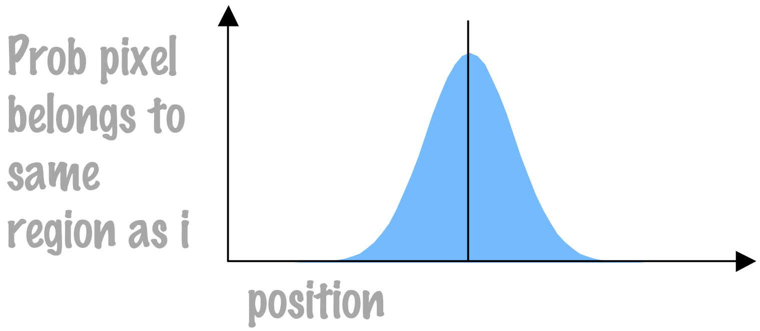
Piecewise-Flat Image Models

- Assign probabilities to other pixels in the image belonging to the same region
- Two considerations
  - Distance: far away pixels are less likely to be same region
  - Intensity: pixels with different intensities are less likely to be same region

Piecewise-Flat Images and Pixel Averaging

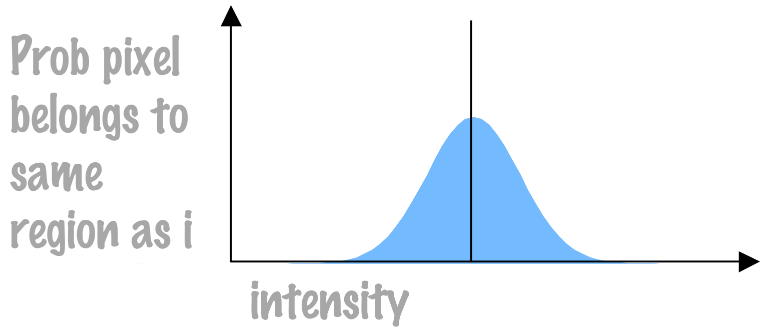
Distance (kernel/pdf)

$$G(\mathbf{x}_i - \mathbf{x}_j)$$



Distance (pdf)

$$H(f_i - f_j)$$



Bilateral Filter

- Neighborhood – sliding window
- Weight contribution of neighbors according to:

$$f_i \leftarrow k_i^{-1} \sum_{j \in N} f_j G(\mathbf{x}_i - \mathbf{x}_j) H(f_i - f_j)$$

$$k_i = \sum_{j \in N} G(\mathbf{x}_i - \mathbf{x}_j) H(f_i - f_j)$$

- G is a Gaussian (or lowpass), as is H, N is neighborhood,
  - Often use $G(r_{ij})$ where r_{ij} is distance between pixels
  - Update must be normalized for the samples used in this (particular) summation
- Spatial Gaussian with extra weighting for intensity
  - Weighted average in neighborhood with downgrading of intensity outliers

Bilateral Filtering

Gaussian Blurring

Bilateral

Bilateral Filtering


Gaussian Blurring

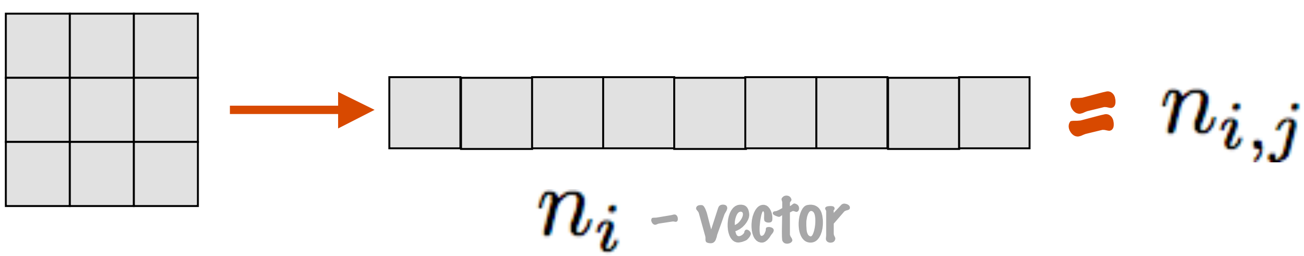

Bilateral

Nonlocal Averaging

- Recent algorithm
  - NL-means, Baudes et al., 2005
  - UINTA, Awate & Whitaker, 2005
- Different model
  - No need for piecewise-flat
  - Images consist of pixels with similar neighborhoods
    - Scattered around
      - General area of a pixel
      - All around
- Idea
  - Average pixels with similar neighborhoods

Nonlocal Averaging

- Strategy:
  - Average pixels to alleviate noise
  - Combine pixels with similar neighborhoods
- Formulation
  - $n_{i,j}$ – vector of pixels values, indexed by j, from neighborhood around pixel i



Nonlocal Averaging Formulation

- Distance between neighborhoods

$$d_{i,k} = d(n_i, n_k) = ||n_i - n_k|| = \left(\sum_{j=1}^{N} (n_{i,j} - n_{k,j})^2 \right)^{\frac{1}{2}}$$

- Kernel weights based on distances

$$w_{i,j} = K(d_{i,j}) = e^{-\frac{d_{i,j}^2}{2\sigma^2}}$$

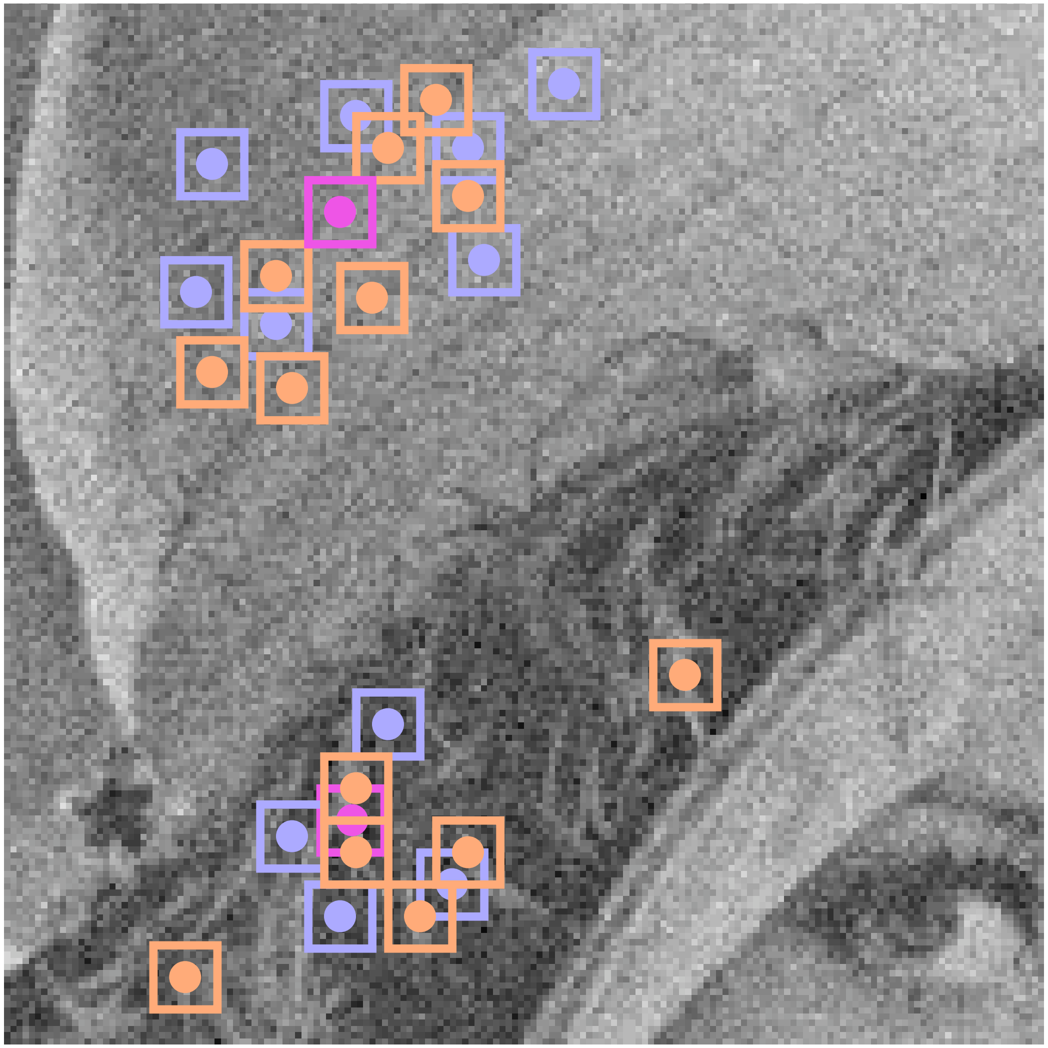
- Pixel values: f_i

Averaging Pixels Based on Weights

- For each pixel, i, choose a set of pixel locations
  - j = 1, ..., M
  - Average them together based on neighborhood weights

$$g_i \longleftarrow \frac{1}{\sum_{j=1}^{M} w_{i,j}} \sum_{j=1}^{M} w_{i,j} f_j$$

Nonlocal Averaging



Some Details

- Window sizes: good range is 5x5->11x11
- How to choose samples:
  - Random samples from around the image
    - UINTA, Awate&Whitaker
  - Block around pixel (bigger than window, e.g. 51x51)
    - NL-means
- Iterate
  - UNITA: smaller updates and iterate

NL-Means Algorithm

- For each pixel, p
  - Loop over set of pixels nearby
  - Compare the neighorhoods of those pixels to the neighborhood of p and construct a set of weights
  - Replace the value of p with a weighted combination of values of other pixels
- Repeat… but 1 iteration is pretty good

Results

Noisy image (range 0.0-1.0)

Bilateral filter (3.0, 0.1)

Results

Bilateral filter (3.0, 0.1)

NL means (7, 31, 1.0)

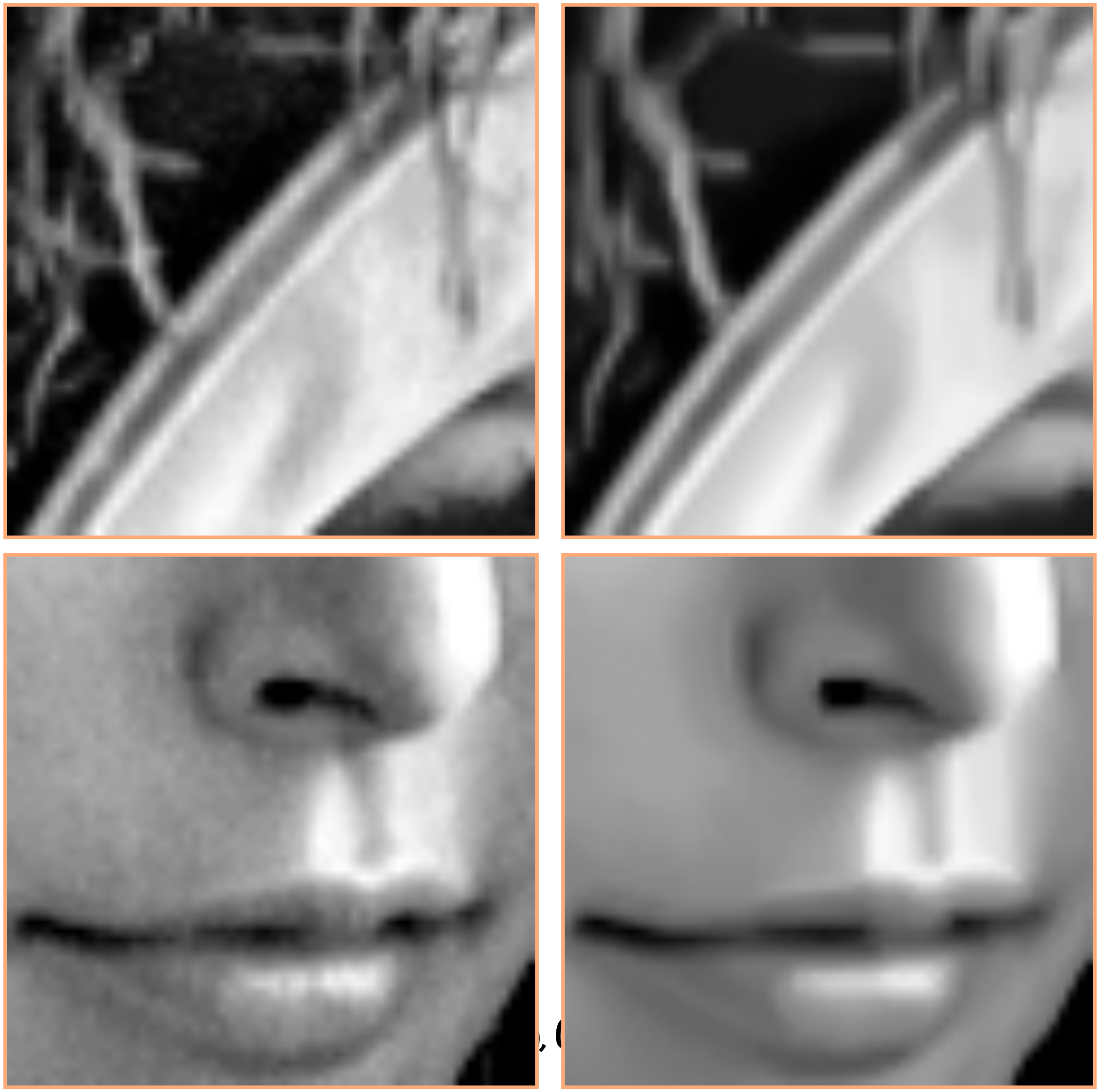
Results

Bilateral filter (3.0, 0.1)

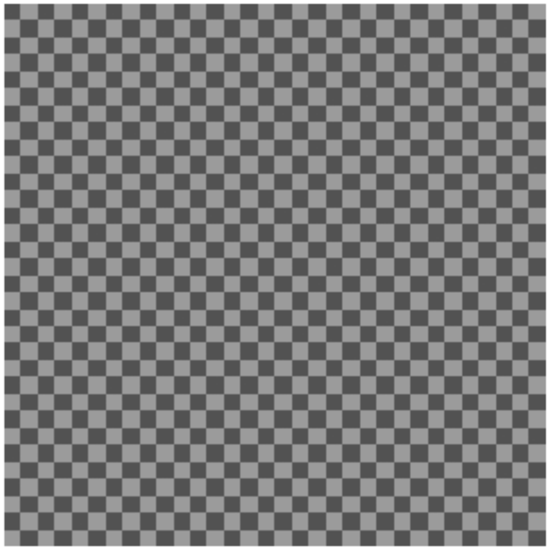
NL means (7, 31, 1.0)

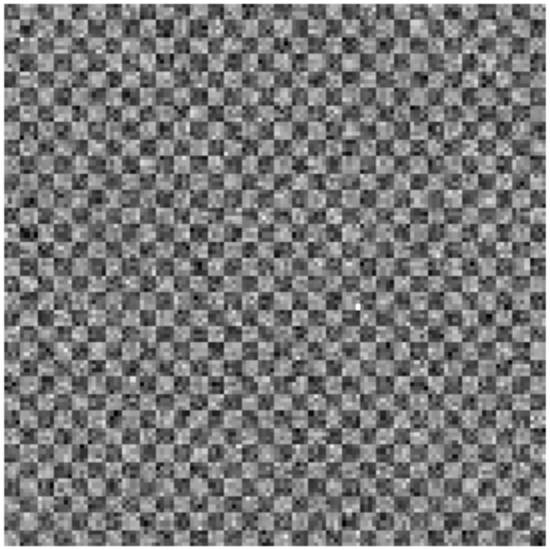
Less Noisy Example

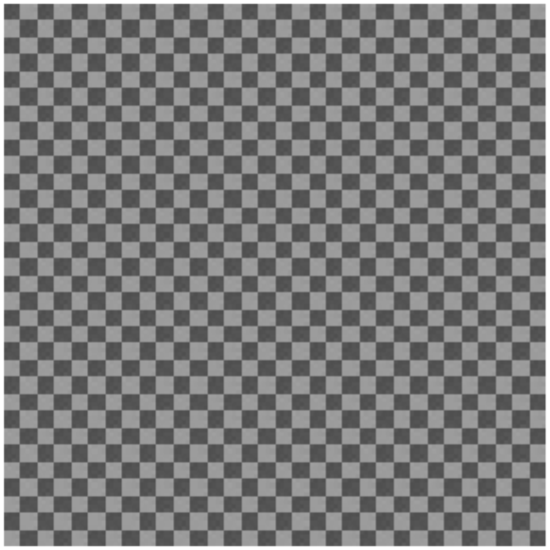

Less Noisy Example



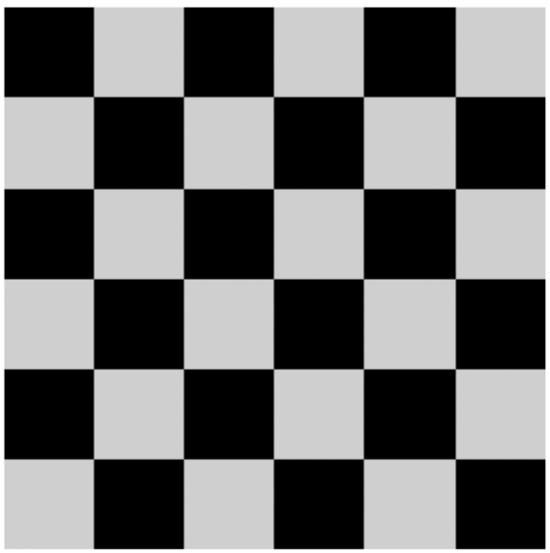
Results


Original

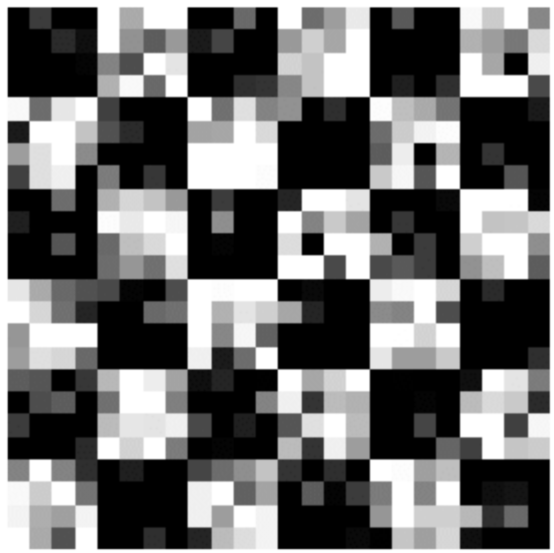

Noisy


Filtered

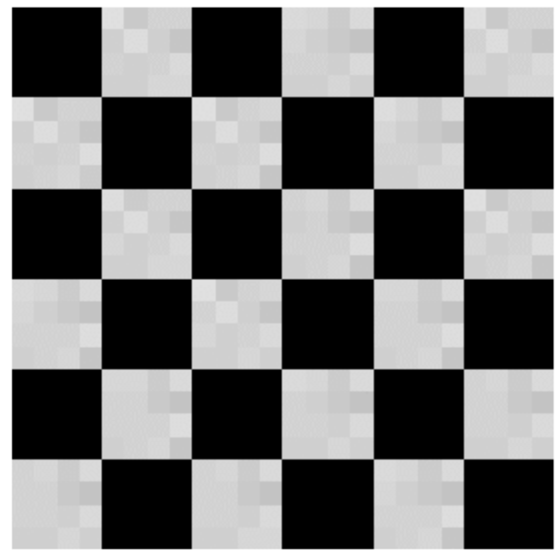
Checkerboard With Noise



Original



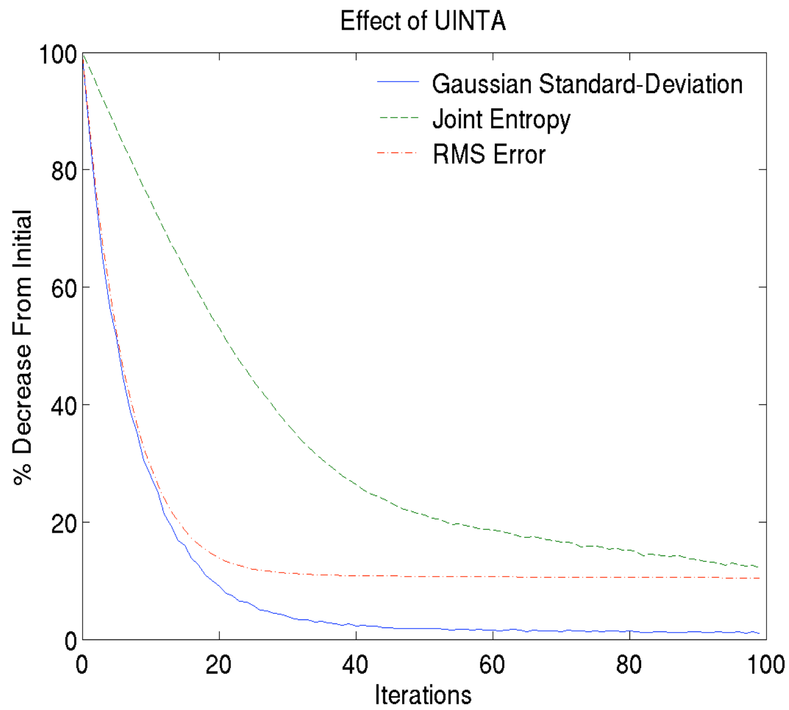
Noisy

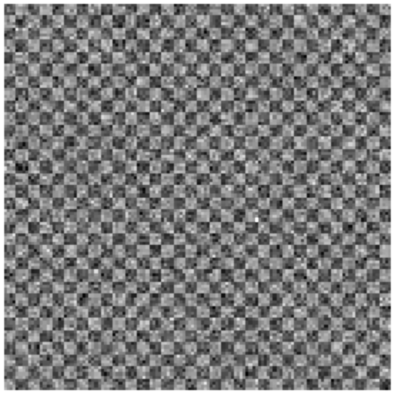


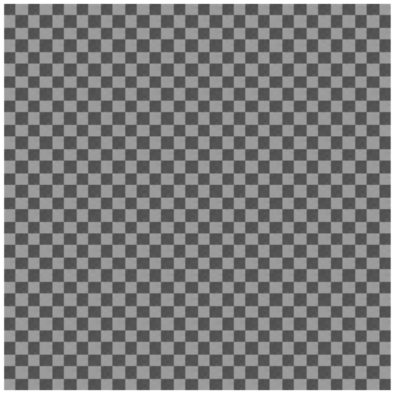
Filtered

Quality of Denoising

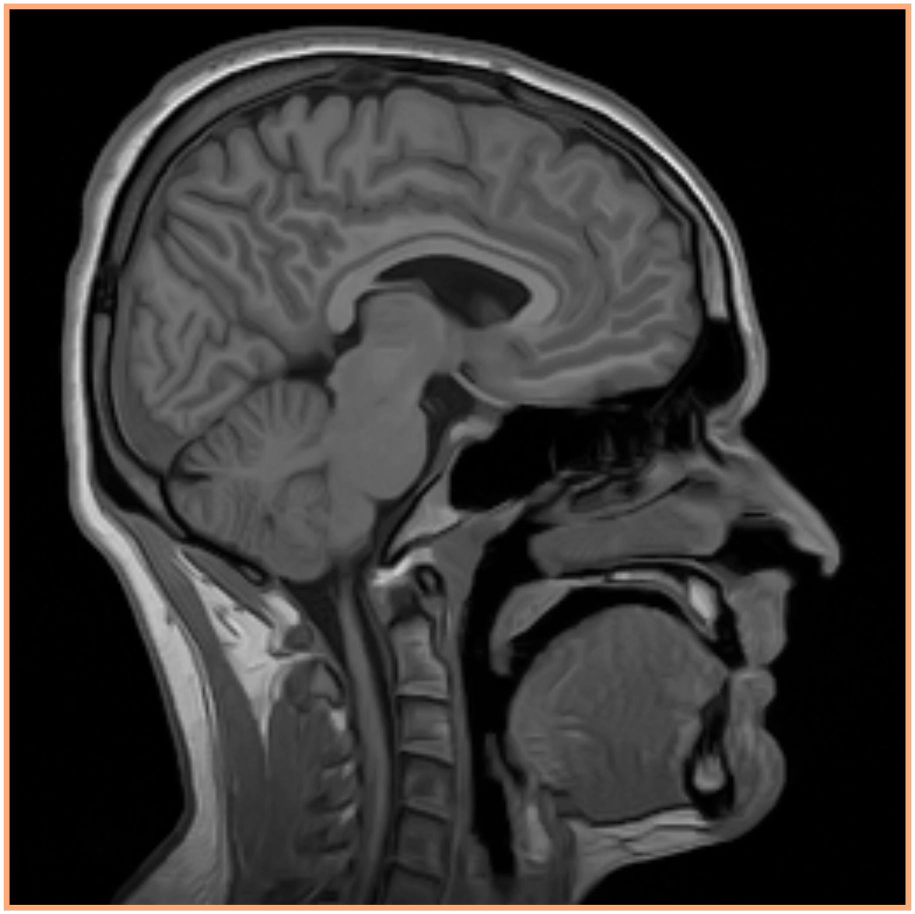
- σ, joint entropy, and RMS- error vs. number of iterations



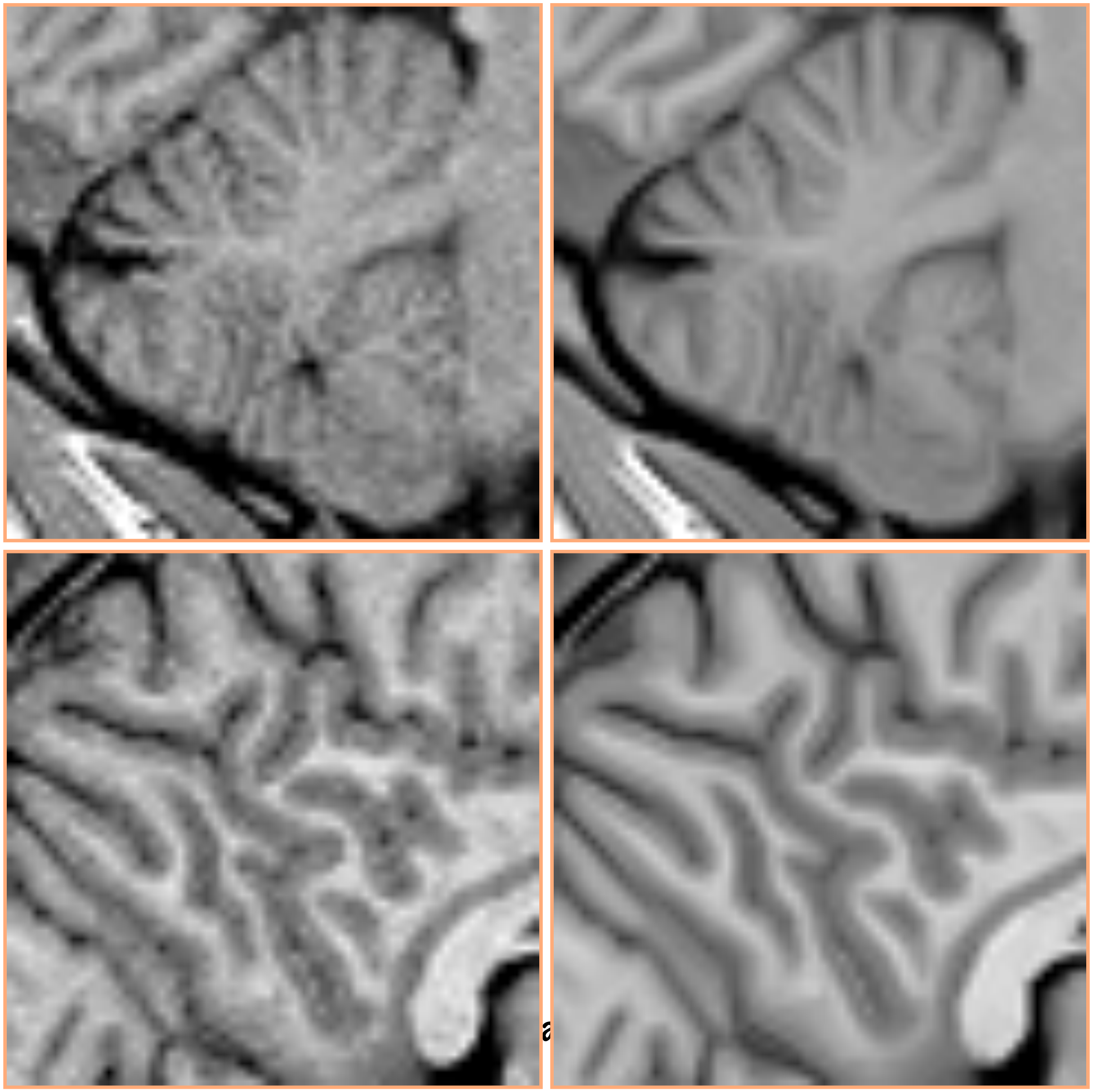




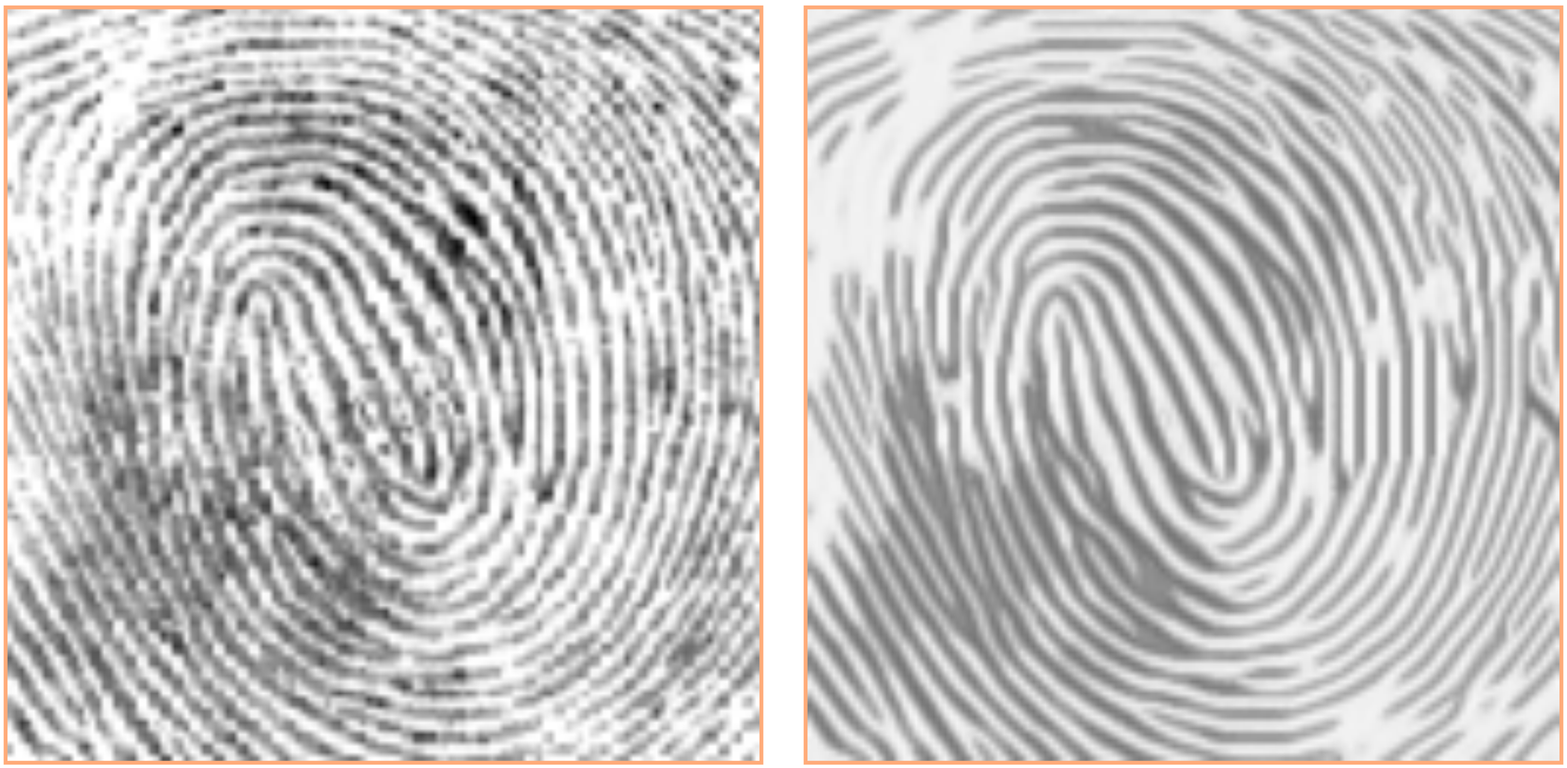
MRI Head



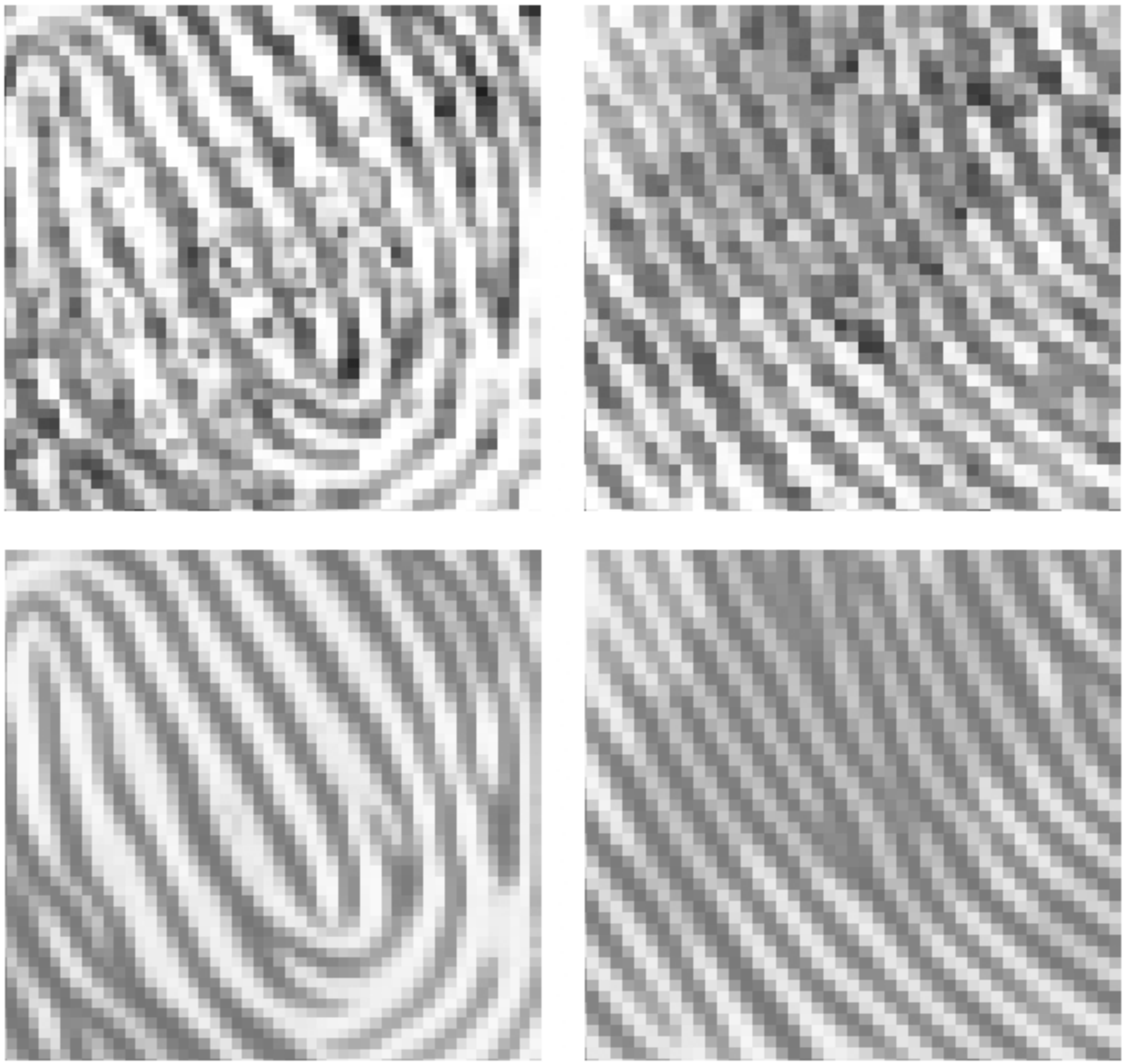
MRI Head



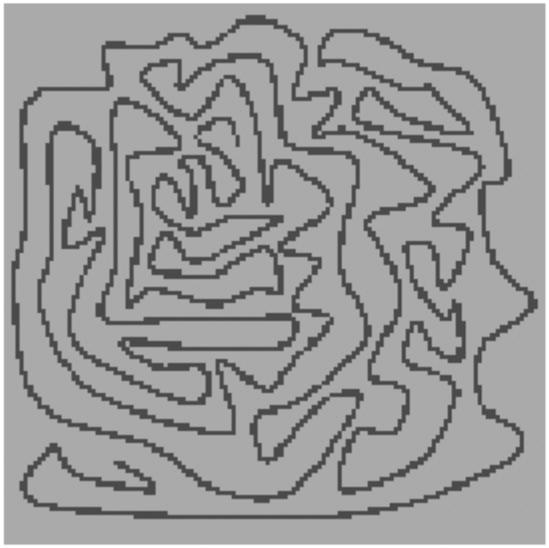
Fingerprint



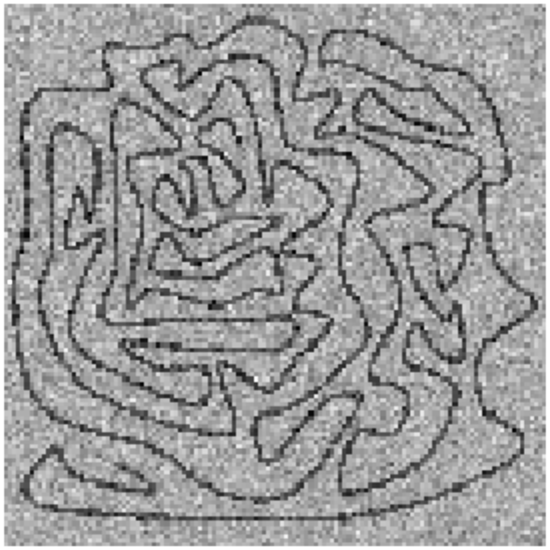
Fingerprint



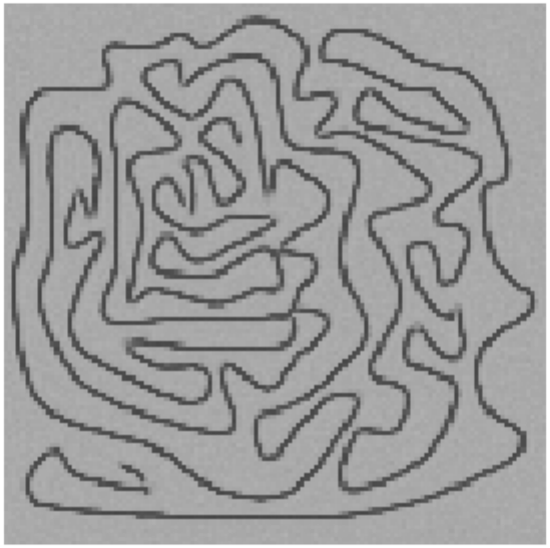
Results



Original



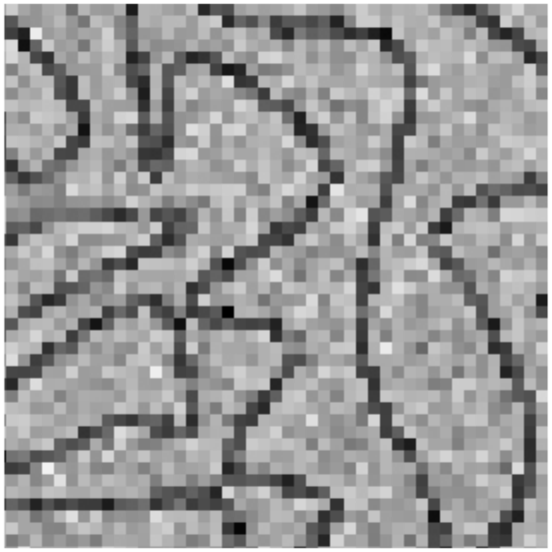
Noisy



Filtered

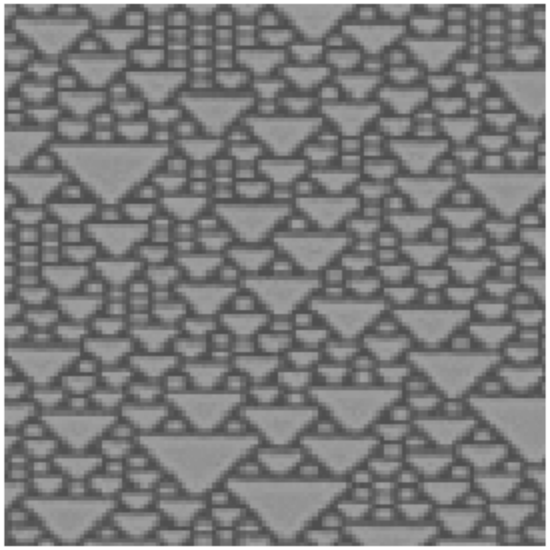
Results


Original

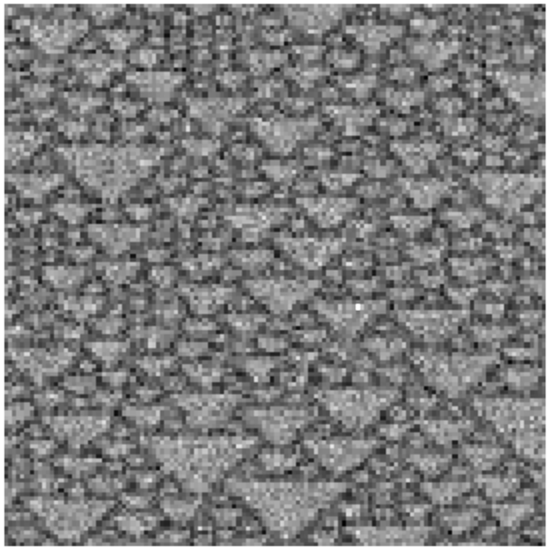

Noisy


Filtered

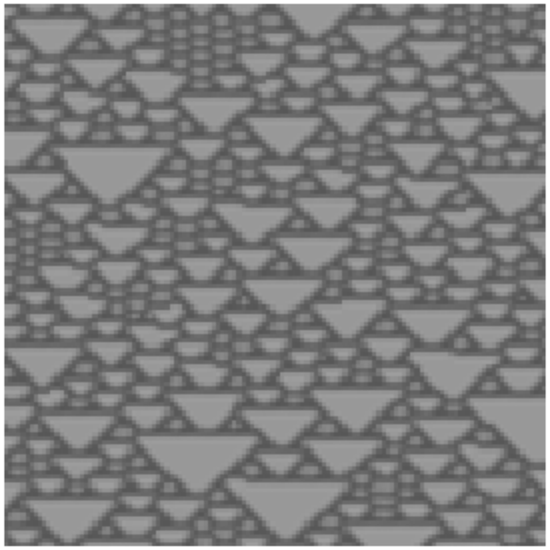
Results



Original

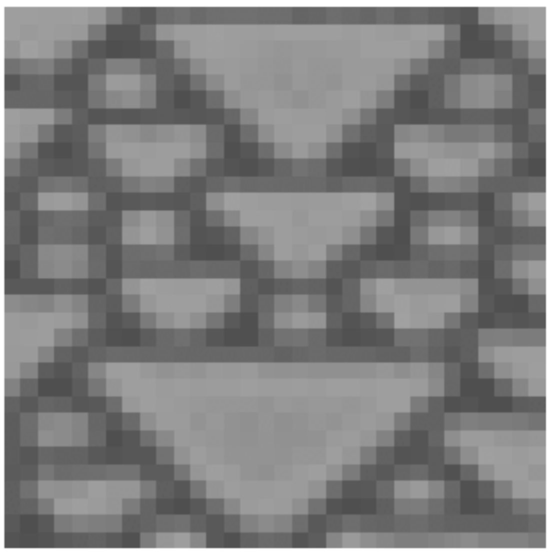


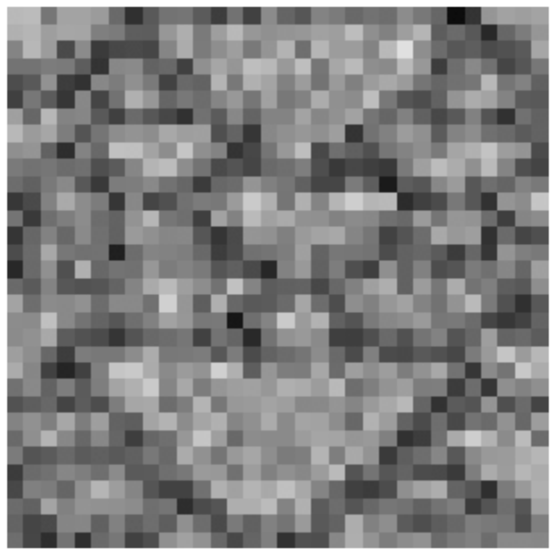
Noisy

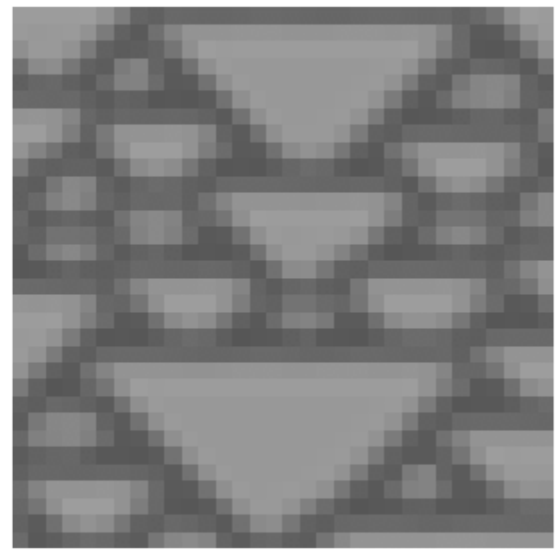


Filtered

Fractal

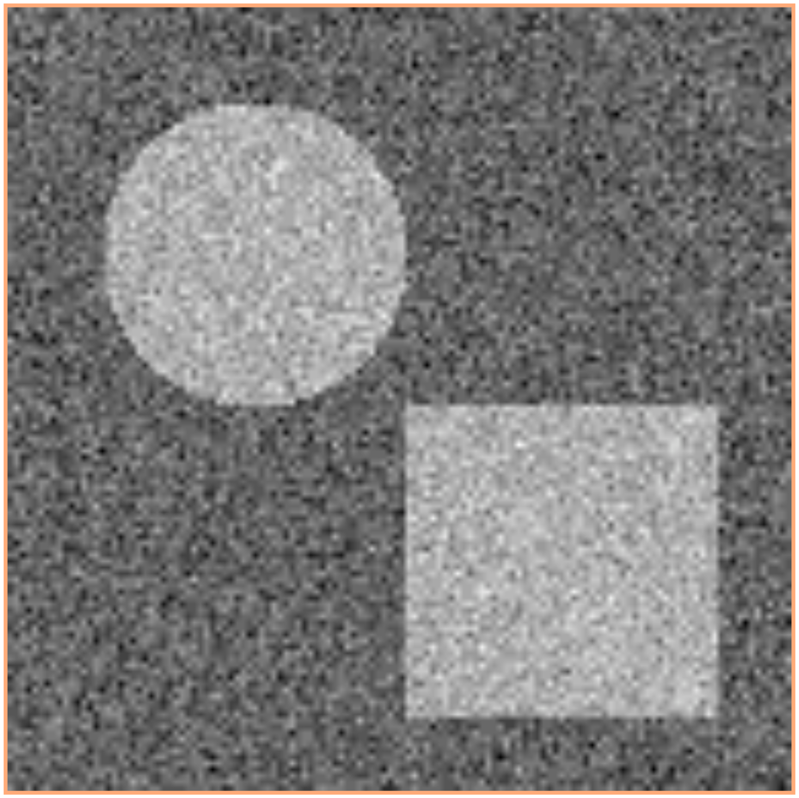

Original


Noisy


Filtered

Piecewise Constant

- Several 10s of Iterations
- Tends to obliterate rare events



Texture, Structure