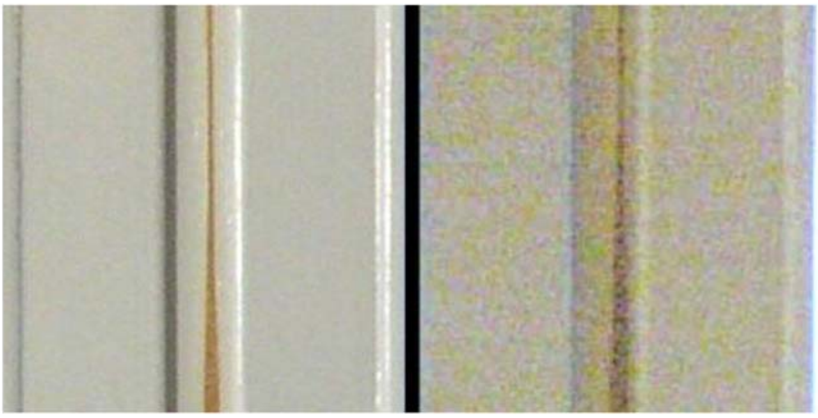
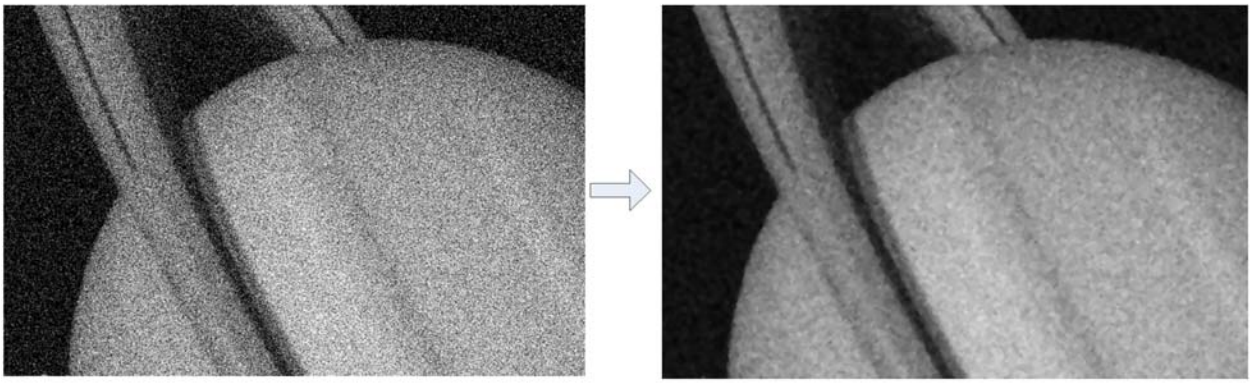
4 – NOISE REDUCTION

Image noise may be present as a result of sampling, quantization, transmission, or disturbances in the environment during image acquisition. In this chapter, we look at some techniques for reducing noise.



Comparison of “clean” and “noisy” images



Noisy image

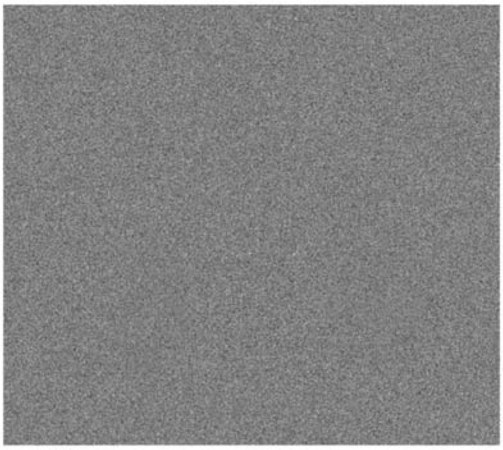
After noise reduction

Noise is classified based on the distribution of its intensity. Some common types of noise are:

- *Uniform noise*: The noise values are distributed with equal probability within a finite range of values.
- *Gaussian noise*: The intensity values follow Gaussian distribution. It is a very good model for many kinds of sensor noise.
- *Salt-and-pepper noise*: The image contains random occurrences of both black and white intensity values. Salt-and-pepper noise belongs to the family of noise called outlier noise, because the noise values that are generated deviate far beyond the values that are normally expected.
- *Impulse or salt noise*: Contains only random occurrences of white intensity values.

Original, I_0

Contaminated by Gaussian noise, I_n



$I_1 = 128 + (I_0 - I_n)$

Histogram of I_1

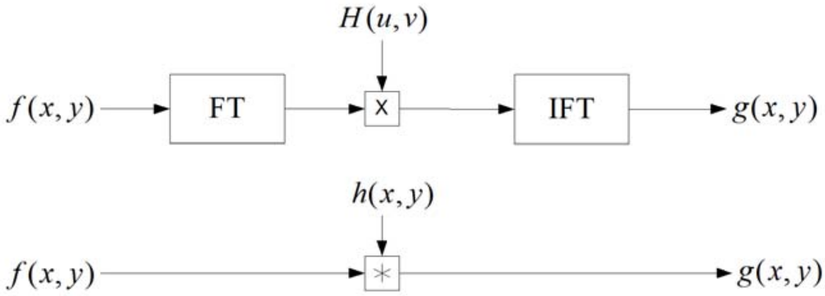
Contaminated by salt and pepper noise

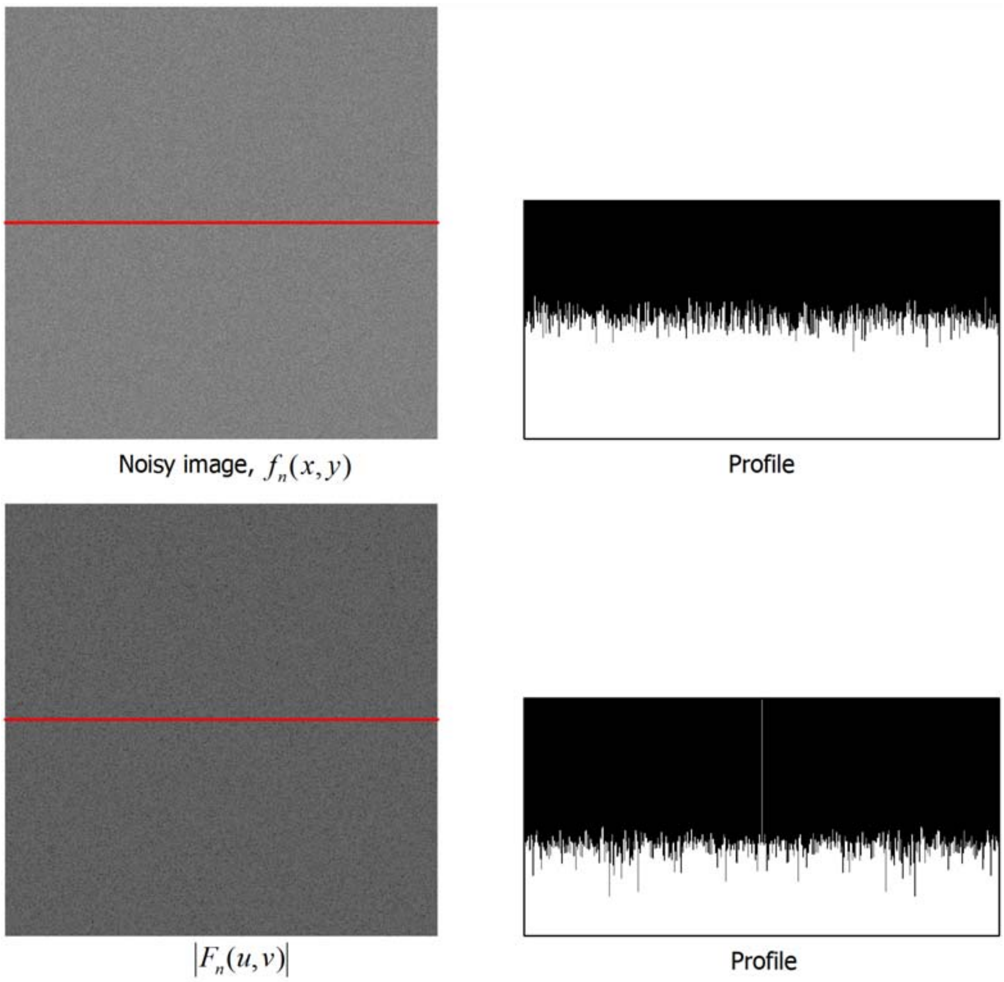
Noise reduction (also called image smoothing) may be implemented as filtering in the frequency domain or as convolution in the spatial domain.

(a) *Frequency domain approach*: FT of image is multiplied by the filter transfer function. The IFT is performed on the product.

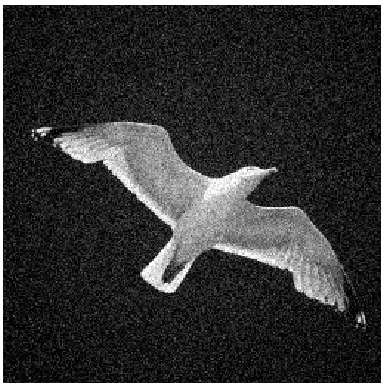
(b) *Spatial domain approach*: The image is convolved with the filter impulse response or a suitable (smaller) mask.

Noise typically has a broad-frequency spectrum, so low-pass filtering will help to reduce it.

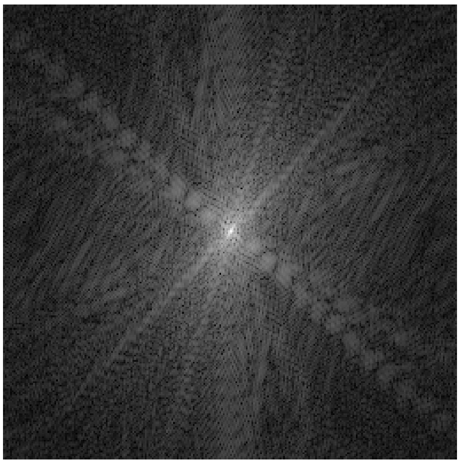




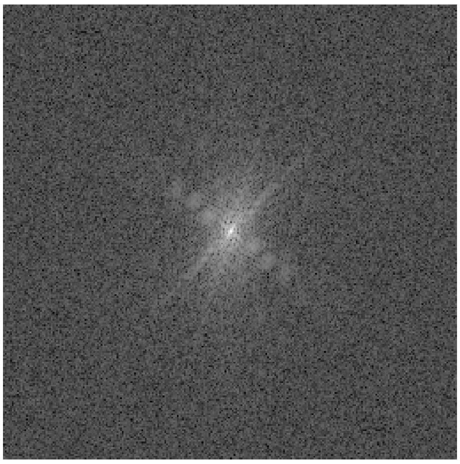
Original image



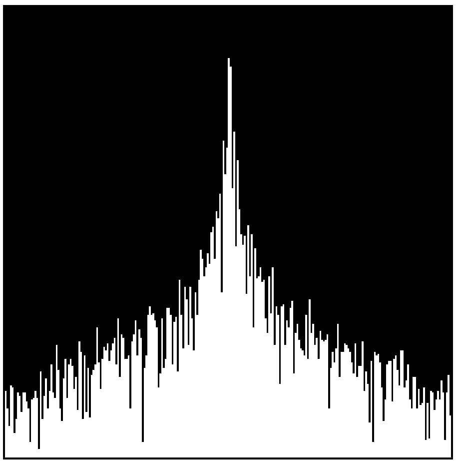
Noisy image



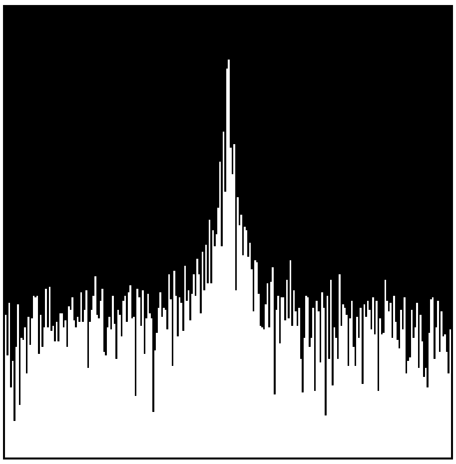
FT



FT



Profile



Profile

MEAN FILTERING

Mean filtering (or neighbourhood averaging) is achieved by using the mask

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

The filter weight of $\frac{1}{9}$ is introduced so that an intensity bias is not introduced into the processed image.

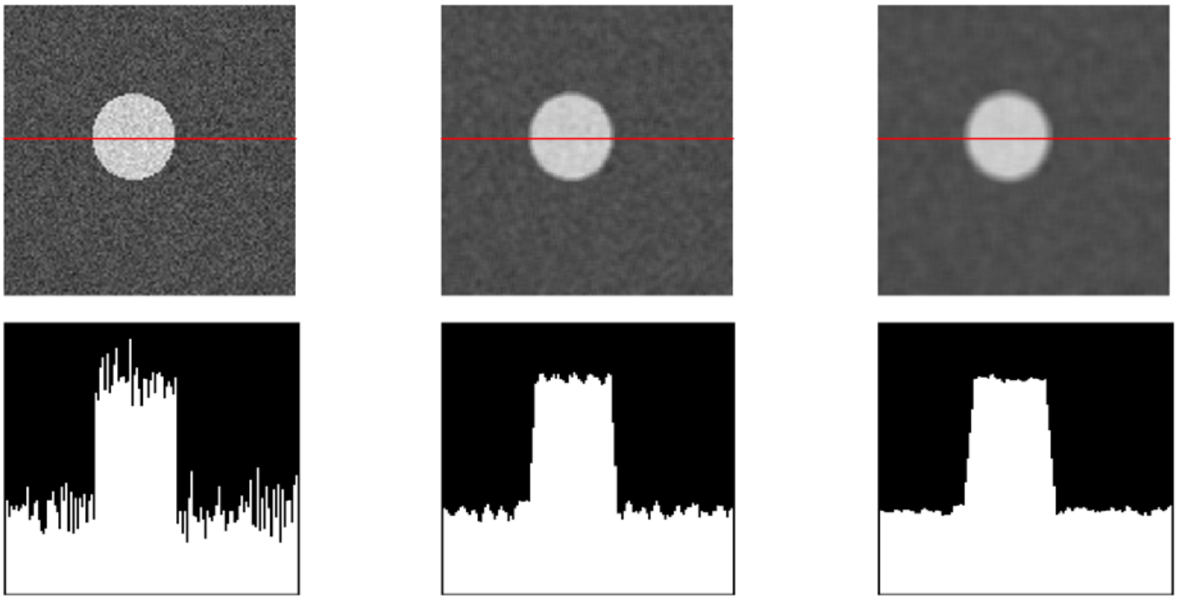
Other commonly used noise-cleaning masks are:

$$\frac{1}{10}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad \frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

Although noise is suppressed by mean filtering, the signal is also affected. This is manifested in the form of blurring.

Masks bigger than 3×3 may be used. A larger convolution mask will result in greater noise reduction and also greater loss of image detail.

Example



Noisy image — Mean filtering - 3x3 — Mean filtering - 5x5

Filtering can also be done with a Gaussian mask, in which the mask coefficients are samples from a 2D Gaussian function:

$$h(x, y) = \exp\left[-\frac{(x^2 + y^2)}{2\sigma^2}\right]$$

Example of a 5×5 Gaussian mask:

$$\frac{1}{121}\begin{bmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 7 & 11 & 7 & 2 \\ 3 & 11 & 17 & 11 & 3 \\ 2 & 7 & 11 & 7 & 2 \\ 1 & 2 & 3 & 2 & 1 \end{bmatrix}$$

MEDIAN FILTERING

To preserve edges and details, median filtering may be more appropriate than mean filtering. The gray level of each pixel is replaced by the median of the intensities in a predefined neighbourhood of this pixel. This technique is particularly useful for salt and pepper noise and impulse noise.

Given a set of N pixel intensities obtained over a local image region, R, denoted as z_i, $i = 1, 2, \ldots, N$, the ordering of these values in increasing value is $R(\mathbf{z}) = \{z_1, z_2, \ldots, z_N\}$, where $z_i \leq z_{i+1}$. The output is the median of the pixel intensities:

$$g(\mathbf{z}) = \mathrm{med}(R(\mathbf{z})). \tag{1}$$

In a 3×3 neighbourhood, the output is the 5th value in the ordered sample set.

Example

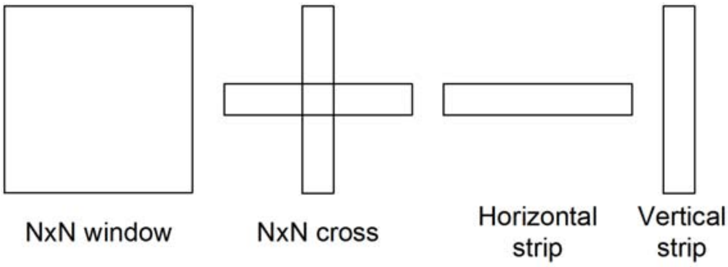
$$\begin{array}{ccc} 75 & 68 & 70 \\ 80 & 200 & 82 \\ 70 & 69 & 77 \end{array} \quad \longrightarrow \quad R(\mathbf{z}) = \{68, 69, 70, 70, 75, 77, 80, 82, 200\}$$

The median is $g(\mathbf{z}) = 75$, while the mean is 88.

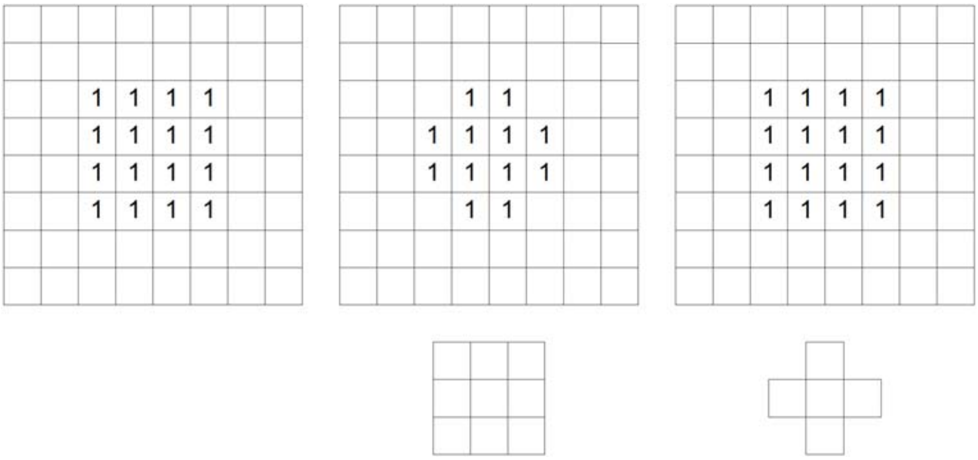
Since the median is the $(N+1)/2$ largest value (assuming N is odd), its search requires $(3(N^2 - 1)/8$ comparisons with the bubble sort algorithm. This number equals 30 for 3×3 windows and 224 for 5×5 windows. (More efficient algorithms are available.)

Properties

- Different window shapes and sizes may be used. They are chosen based on a *a priori* knowledge of the image noise characteristics.

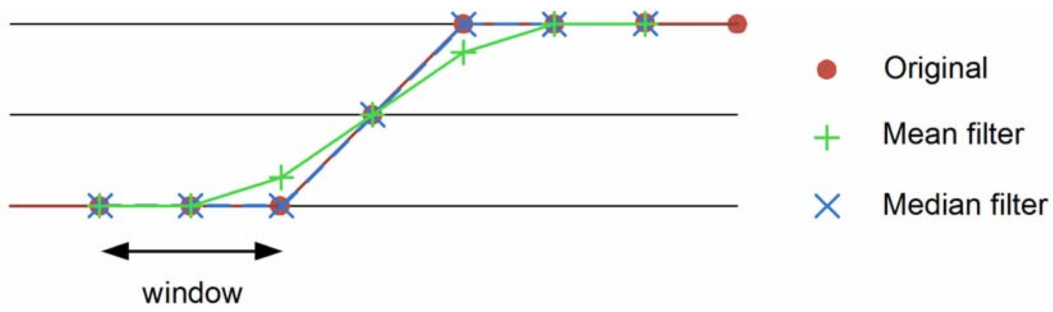


- The shape chosen for the filter may affect the processing results. A 2D $L \times L$ filter results in more noise suppression than processing with a cross-shaped filter, but also results in greater signal suppression.

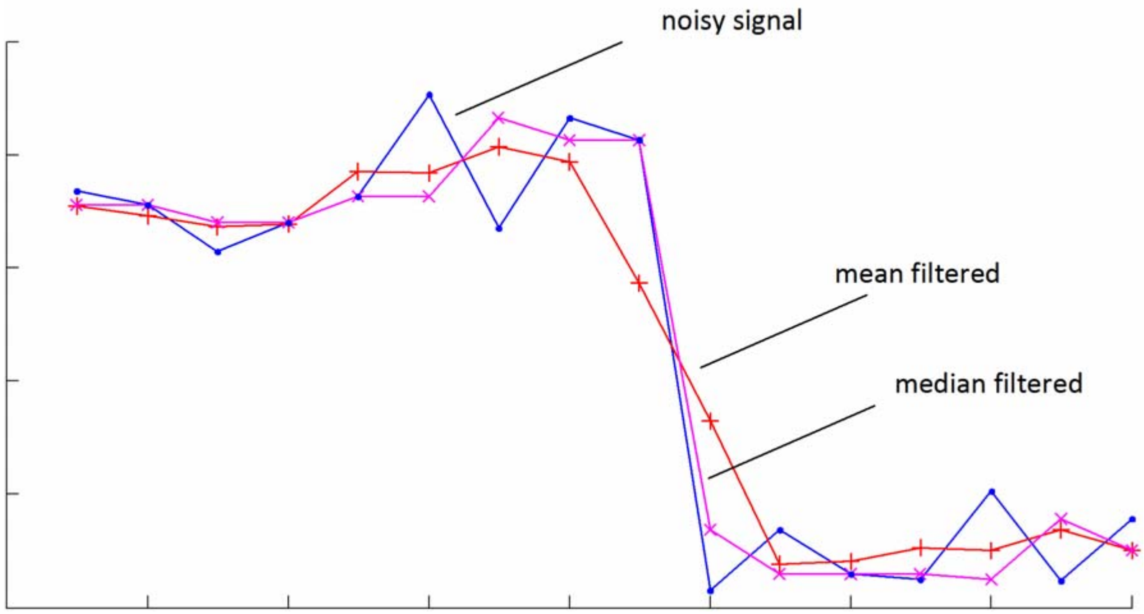


- The median filter reduces the variance of the intensities in the image.
- No new gray values are generated; binary images remain binary, the dynamic range of the filtered image cannot exceed that of the input image.
- In general, the median filter tends to preserve edges while removing noise effectively.

1D examples



Original
Mean filter
Median filter
window



noisy signal
mean filtered
median filtered

Example

With Gaussian noise

With salt & pepper noise

After mean filtering

After mean filtering

After median filtering

After median filtering

Non-linear Spatial Filtering

Non-linear filters based on order statistics require that all the pixels be first ordered from their minimum to their maximum values:

$$z_1 \leq z_2 \leq \ldots \leq z_{N-1} \leq z_N$$

The median filter is an example of such a filter; in this case the output is

$$\text{output} = z_{(N+1)/2} \qquad \text{for } N \text{ odd}$$

There are several filters in this family that have been found to be useful in noise reduction.

(a) Midpoint filter

This filter is defined as the average of the minimum and maximum gray levels of the ordered set of pixels that are included in the filter operation:

$$\text{output} = \frac{z_1 + z_N}{2}$$

The filter mask for this filter simply defines the pixels within the image that are to be included in the filter operation.

The midpoint filter should not be used with images that contain outlier noise such as salt-and-pepper noise.

(b) Maximum and minimum filters

The minimum filter is defined as the minimum gray level of all the pixels defined by the filter mask, i.e.,

$$\text{output} = z_1$$

If an image contains only salt noise, then the minimum filter removes this noise.

The maximum filter is defined as the maximum gray level of all the pixels defined by the filter mask, i.e.,

$$\text{output} = z_N$$

It is effective in smoothing an image containing only pepper noise.

Both the minimum and maximum filters are biased filters. The maximum filter increases the average brightness of the filtered image, while the minimum filter decreases it.

Image with salt noise

After mininum filtering

(c) Alpha-trimmed mean filter

This gives a mixture of the mean and median filters. It performs reasonably well in the presence of both Gaussian and outlier noise. The computation of the output requires the ordering of pixels that are defined by the filter mask. The output is

$$\text{output} = \frac{1}{N-2p} \sum_{i=p+1}^{N-p} z_i$$

where

$$p = 0, 1, 2, 3, \ldots, \frac{N-1}{2} \qquad N \text{ odd}$$

The value of p determines the type of filtering that is performed.

- For $p = 0$, the α-trimmed mean filter reduces to the mean filter.
- When p is set to its maximum value, the filter reduces to the median filter.

The filter is a mean or averaging filter that removes a selective number of pixels that are close in gray level to the maximum and minimum gray levels contained within the neighbourhood. If an image contains both outlier and Gausssian type noise, selecting p other than zero removes some of the outlier noise pixels in the calculation of the mean. For a given $p \neq 0$, there is is less blurring compared to an equivalent sized mean filter.

Examples:

Consider

20	20	8
21	19	12
19	22	10

The ordered list is $\{8, 10, 12, 19, 19, 20, 20, 21, 22\}$

For different values of p, the output is as follows:

p:	0	1	2	3	4
output:	16.8	17.3	18.0	19.3	19.0

Consider

20	20	8
21	100	12
19	22	10

The ordered list is $\{8, 10, 12, 19, 20, 20, 21, 22, 100\}$

For different values of p, the output is as follows:

p:	0	1	2	3	4
output:	25.8	17.7	18.4	19.7	20.0

Image with Gaussian and salt-and-pepper noise

Mean filter

Median filter

Alpha-trimmed mean filter ($N = 9$, $p = 2$)

Adaptive Filtering

An adaptive filter alters its basic behaviour as the image is processed according to the local image characteristics at that point. The typical criteria used to determine filter behaviour are usually measured by the local gray-level statistics.

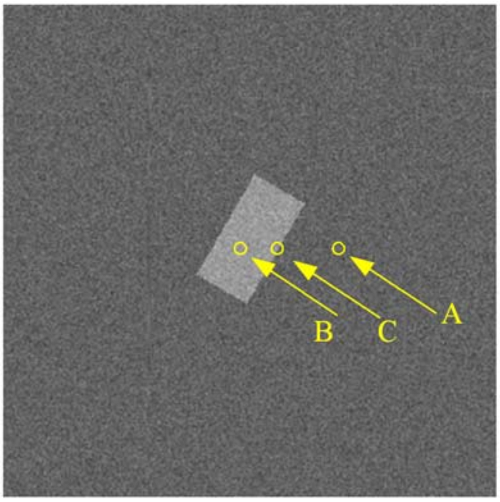
An example of an adaptive filter is the minimum mean-square error (MMSE) filter, which works best with Gaussian noise. This filter adapts itself to the local image statistics, preserving image details while removing noise.

$$\begin{aligned} g(x,y) &= f(x,y) - \frac{\sigma_\eta^2}{\sigma_l^2}[f(x,y) - m_l(x,y)] \qquad (2) \\ &= \left(1 - \frac{\sigma_\eta^2}{\sigma_l^2}\right) f(x,y) + \frac{\sigma_\eta^2}{\sigma_l^2} m_l(x,y) \qquad (3) \end{aligned}$$

σ_η^2 = noise variance (assunmed constant throughout the image)
σ_l^2 = local variance (in the window under consideration)
m_l = local mean (in the window under consideration)

- With no noise in the image, $\sigma_\eta^2 = 0$, and $g(x,y) = f(x,y)$, i.e., no filtering takes place.
- In background regions of the image, where the gray values are fairly constant in the uncorrupted image, $\sigma_\eta^2 = \sigma_l^2$, and the equation reduces to the mean filter.
- In areas of the image where the local variance is much greater than the noise variance, the filter returns a value close to the unfiltered image data. This is desired since the high local variance implies high detail (edges), and an adaptive filter tries to preserve the original image detail.

In general, the MMSE filter returns a value that consists of the unfiltered image data $f(x,y)$ with some of the original value subtracted out and some of the local mean added. The window size and noise variance to be used has to be specified by the user.



	Background (A)			Object (B)			Edge (C)	
Var(noise)	127			127			127	
Var(local)	143			114			816	
Mean(local)	100			155			140	
Input pixel	63	100	127	130	155	177	130	177
Output pixel	96	99	103	158	155	152	132	171

Image with Gaussian noise:
background ~100, object ~155

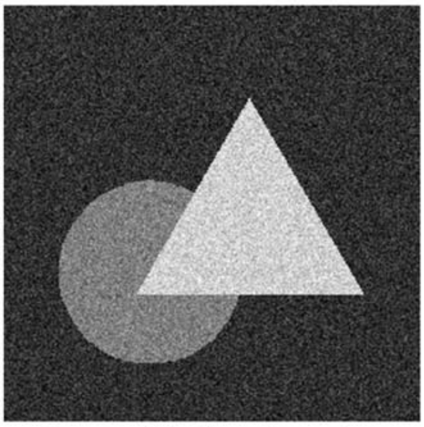
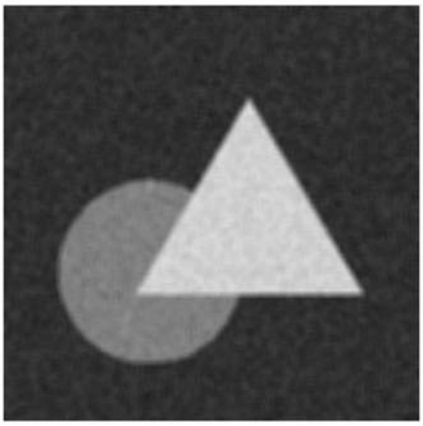
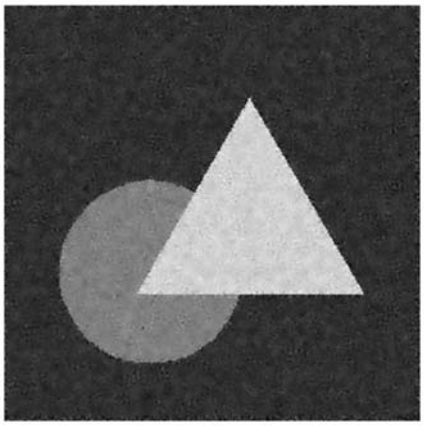


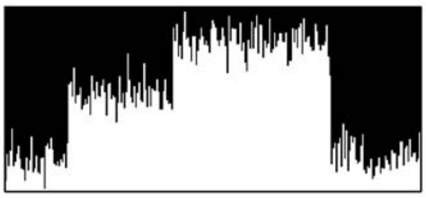
Image with Gaussian noise



Mean filter



MMSE filter



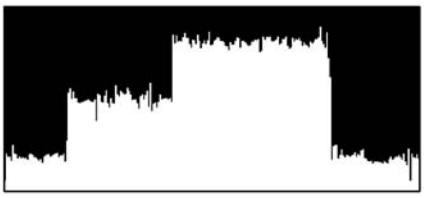


Image Averaging

Consider a noisy image $g(x, y)$ formed by the addition of noise $\eta(x, y)$ to an uncorrupted image $f(x, y)$, where the noise is uncorrelated and has zero mean:

$$g(x, y) = f(x, y) + \eta(x, y). \tag{4}$$

The image formed by averaging K different noisy images is

$$\begin{aligned}
\bar{g}(x, y) &= \frac{1}{K} \sum_{t=1}^{K} g_t(x, y) \\
&= \frac{1}{K} \sum_{t=1}^{K} f(x, y) + \frac{1}{K} \sum_{t=1}^{K} \eta_t(x, y) \\
&= f(x, y) + \frac{1}{K} \sum_{t=1}^{K} \eta_t(x, y)
\end{aligned}$$

Thus the expected value ($K \to \infty$) of $\bar{g}(x, y)$ is

$$E\{\bar{g}(x, y)\} = f(x, y). \tag{5}$$

The variance of $\bar{g}(x, y)$ is

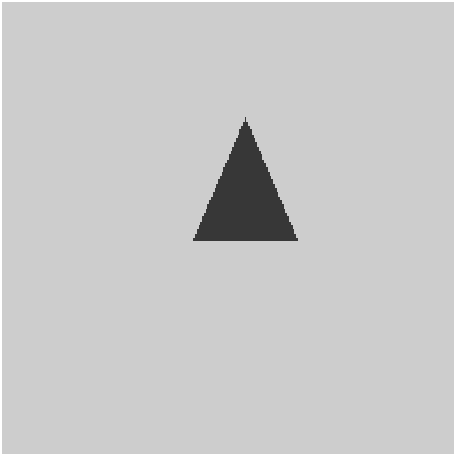
$$\sigma_{\bar{g}}^2(x, y) = \frac{1}{K} \sigma_\eta^2(x, y) \tag{6}$$

where $\sigma_\eta^2(x, y)$ is the variance of $\eta(x, y)$.

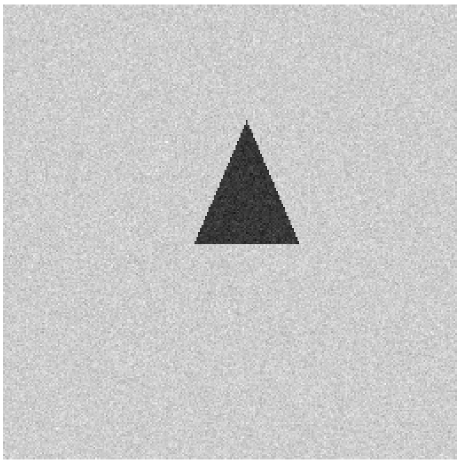
We can conclude that as K increases

1. $\bar{g}(x, y)$ approaches the uncorrupted image $f(x, y)$ – Eq. (5)
2. the variability of the pixel values decreases – Eq. (6)

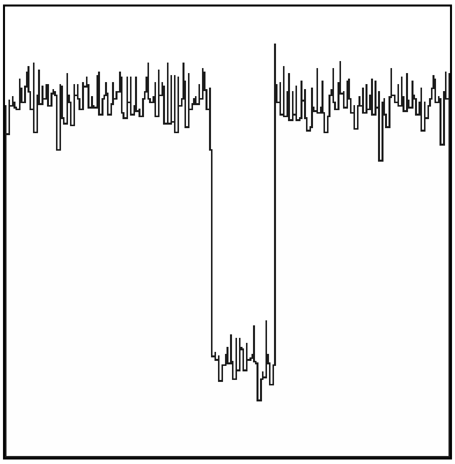
This operation is often considered an automatic image acquisition pre-processing operation. With appropriate hardware, an entire image addition can be done in one frame interval.



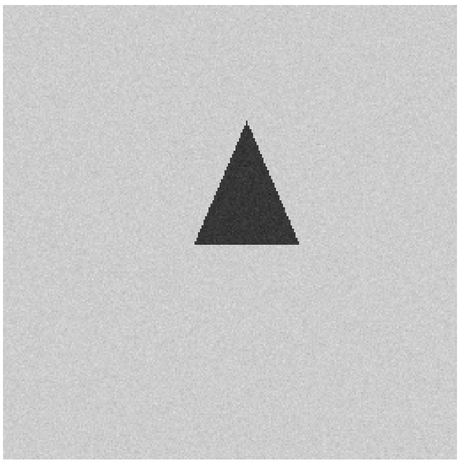
Noise-free image



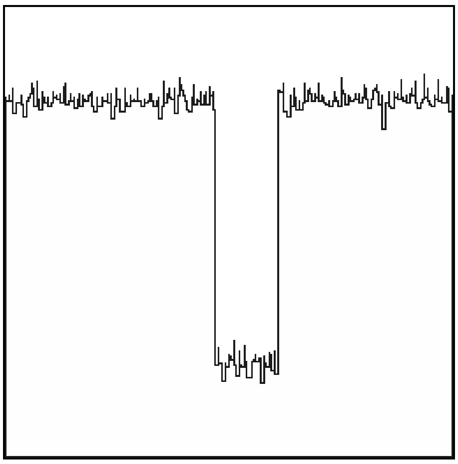
Noisy image



Profile



After averaging 4 frames



Profile