# NON-LINEAR FILTERS

# Rank filter

Convolution is not the only way of carrying out spatial filtering. There also exist non-linear techniques some of which are referred to as order statistics filters or rank filters.

The idea is to compile an ordered (ascending) list of the gray values in a neighborhood of a pixel and then select a value from a particular position in this list to be used as output value for the new pixel.

# Median filter

Selects the median value in a (mostly square shaped) neighborhood.

As compared to the mean filter, the median is good at removing impulse noise (salt-and-peppar or shot noise) while still preserving edges.

However, a drawback is that the median erodes the corners of rectangular objects.

# Minimum filter

Selects the minimum value in a neighborhood.

Causes darker regions in an image to swell.

Contributes to non-linear blurring.

# Maximum filter

Selects the minimum value in a neighborhood.

Causes brighter regions in an image to swell.

Contributes to non-linear blurring.

# Range filter

Computes the difference between the maximum and minimum gray levels in a neighborhood.

Acts as a omnidirectional, non-linear edge detector.

# Adaptive filter

Many common filters are isotropic, that is they perform in the same way regardless of where in the image they operate.

The idea with adaptive (or non-isotropic) filtering is to change the behaviour of the filter in response to local image intensity variations.

# Adaptive filter

One example is the minimal mean square error filter. This filter computes the output as:

$$g(x,y) = f(x,y) - \frac{\sigma_n^2}{\sigma^2(x,y)}\left[f(x,y) - \bar{f}(x,y)\right] \qquad (1)$$

where $\sigma_n^2$ is an estimate of noise variance, $\sigma^2(x,y)$ is the gray-level variance computed for the neighbourhood centred on (x,y) and $\bar{f}(x,y)$ is the mean gray-level in that neighbourhood.

# Adaptive filter

In supposedly homogeneous regions of an image, noise will be the sole cause of variations in grey-levels. Thus, $\sigma^2(x, y) = \sigma_n^2$ and equ. (1) reduces to:

$$g(x, y) = \overline{f}(x, y)$$

In the vinicity of edges, we expect $\sigma^2(x, y)$ to dominate local noise variance, resulting in a small ratio of variances and a value for g(x,y) that is close to the original value at that pixel, f(x,y).