UNIT III

IMAGE ENHANCEMENT AND RESTORATION

- Spatial domain method – point operation – Histogram modeling
- Spatial operations – directional smoothening,
- median filtering, image sharpening, masking, edge crispening, interpolation
- Transform operation
- linear filtering, root filtering
- Homomorphic filtering
- Degradation model – diagonalization – Constrained and Unconstrained restoration
- Inverse filtering – Wiener filter
- Generalised inverse, SVD and iterative methods.

IMAGE ENHANCEMENT

- Improving the interpretability or perception of information in images for human viewers
- The objective of enhancement technique is to process an image so that the result is more suitable than the original image for a particular application.
- Providing `better' input for other automated image processing techniques

  - Spatial domain methods:

- operate directly on pixels

  - Frequency domain methods:

- operate on the Fourier transform of an image

SPATIAL DOMAIN METHODS

* Suppose we have a digital image which can be represented by a two dimensional random field *f* (*x*, *y*) **.**

* An image processing operator in the spatial domain may be expressed as a mathematical function *T*□□□ applied to the image *f* (*x*, *y*) to produce a new image *g*(*x*, *y*) □*T*□ *f* (*x*, *y*)□ as follows.

g(*x*, *y*) □*T*□ *f* (*x*, *y*)□

The operator *T* applied on *f* (*x*, *y*) may be defined over:

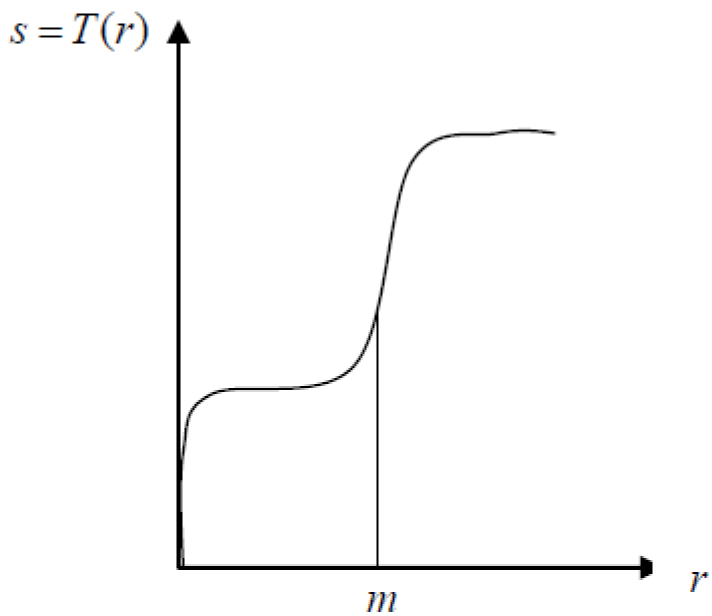
(i) A single pixel (*x*, *y*) . In this case *T* is a grey level transformation (or mapping) function.

(ii) Some neighbourhood of (*x*, *y*) .

(iii) *T* may operate to a set of input images instead of a single image

The result of the transformation shown in the figure below is to produce an image of higher contrast than the original, by darkening the levels below m and brightening the levels above m in the original image. This technique is known as **contrast stretching**.

Contrast stretching reduces an image of higher contrast than the original by darkening the levels below m and brightening the levels above m in the image.



BASIC GRAY LEVEL TRANSFORMATIONS

* We begin the study of image enhancement techniques by discussing gray-level transformation functions. These are among the simplest of all image enhancement techniques. * The values of pixels, before and after processing, will be denoted by *r* and *s*, respectively. As indicated in the previous section, these values are related by an expression of the form s=T(r), where T is a transformation that maps a pixel value *r* into a pixel value *s*. * Since we are dealing with digital quantities, values of the transformation function typically are stored in a one-dimensional a r r a y and the mappings from *r* to *s* are implemented v i a table lookups. For an 8-bit environment, a lookup table containing the values of *T* will have 256 entries. * As an introduction to gray-level transformations, consider Fig. which shows three basic types of functions used frequently for image enhancement: linear (negative and identity transformations),

logarithmic (log and inverse-log transformations), and power-law (*n*th power and *n*th root transformations). * The identity funct ion is the trivial case in which output int ens i t ie s are identical to input intensities. It is included in the graph only for completeness.

POINT PROCESSING

- The simplest kind of range transformations are these independent of position *x,y*:

  $$g = T(f)$$

- This is called point processing.
- **Important:** every pixel for himself – spatial information completely lost!

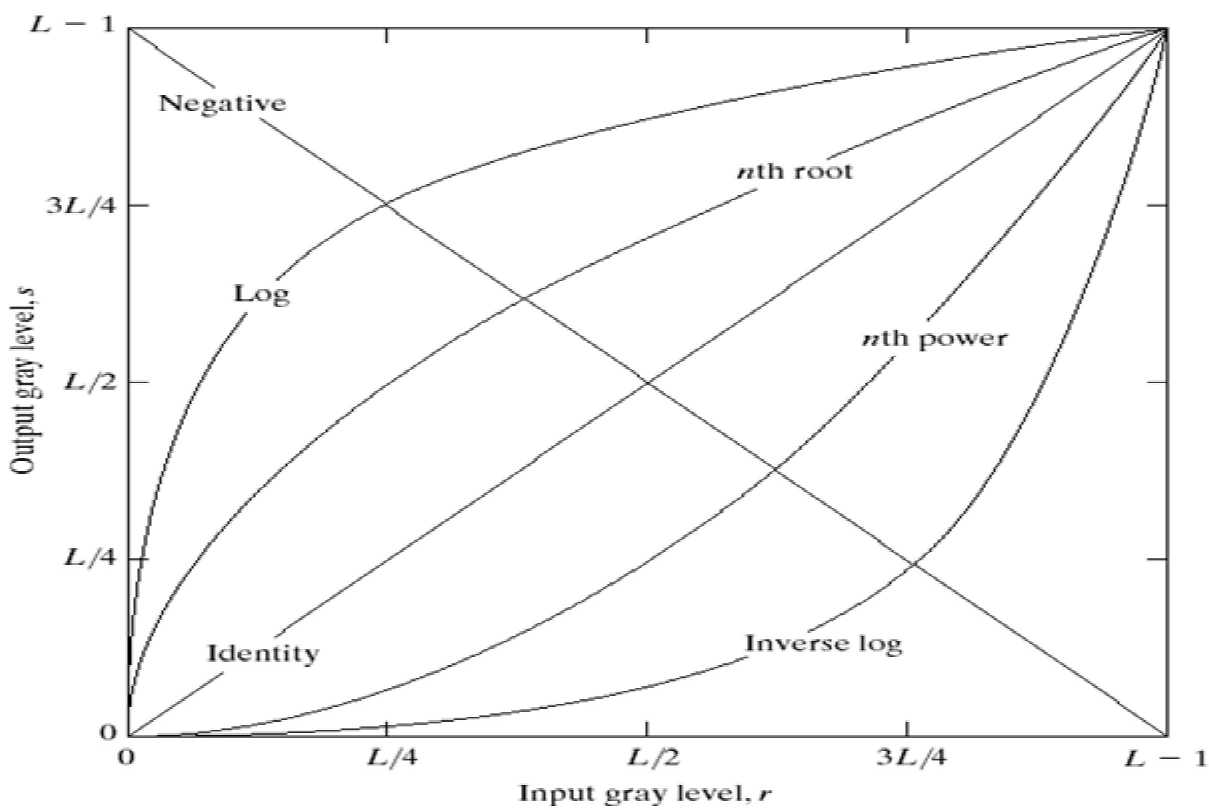
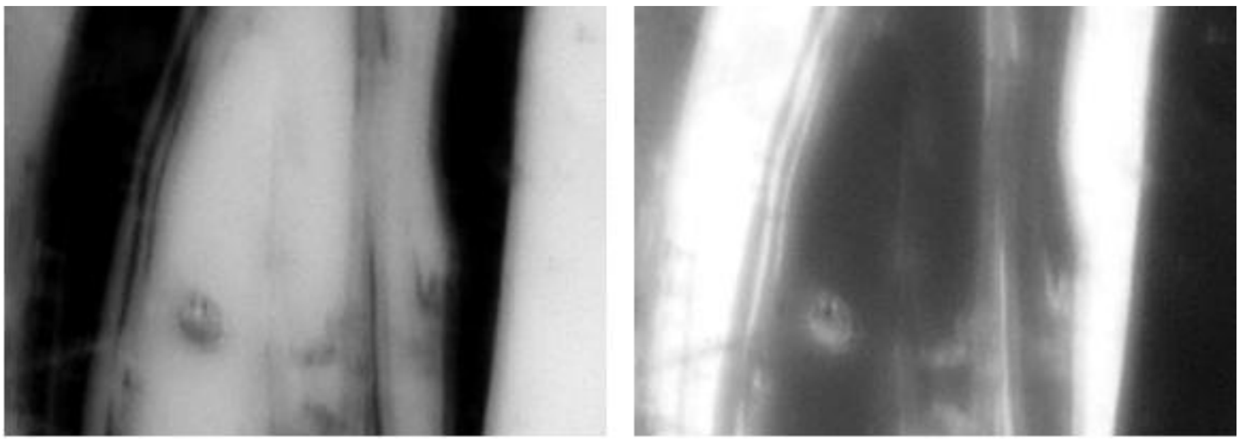


Image Negative

The negative of an image with gray levels in the range [0, L-1] is obtained by using the negative transformation shown in Fig. Reversing the intensity levels of an image in this manner produces the equivalent of a photographic negative. This type of processing is particularly suited for enhancing white or gray detail embedded in dark regions of an image, especially when the black areas are dominant in size.



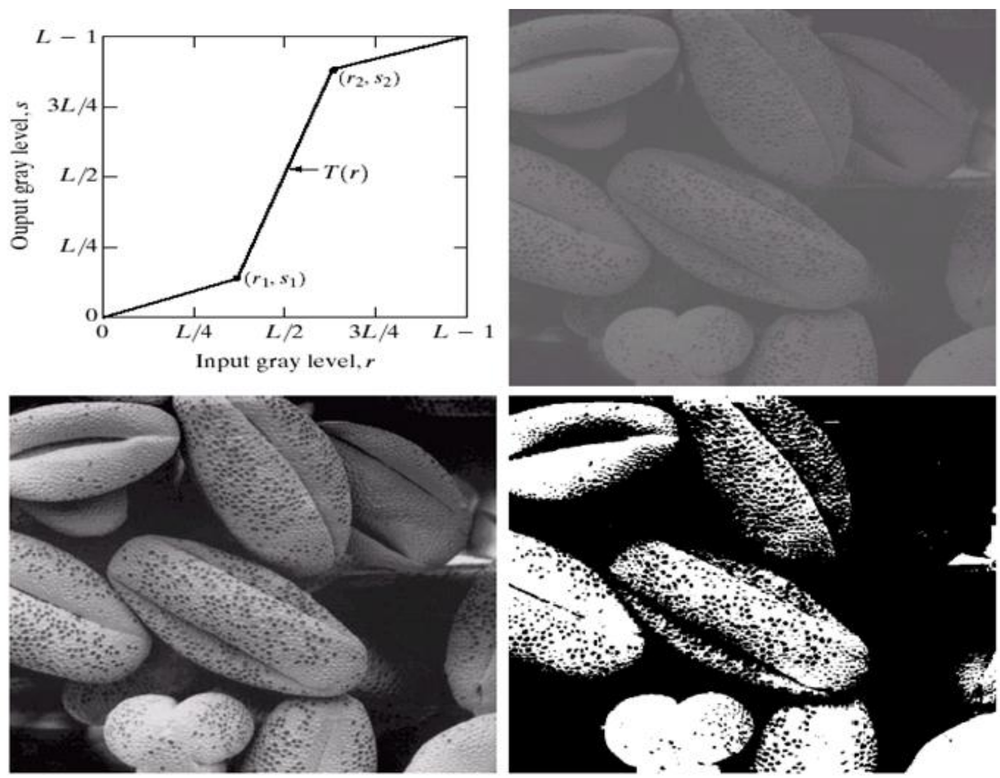
Log Transformations

The general form of the log transformation shown in Fig. 3.3 is $s = c \log (1 + r)$ where *c* is a constant, and it is assumed that r 0.

- The shape of the log curve in Fig. 3.3 shows that this transformation maps a narrow range of low gray-level values in the input image into a wider range of output levels.
- The opposite is true of higher values of input levels. We would use a transformation of this type to expand the values of dark pixels in an image while compressing the higher-level values. The opposite is true of the inverse log transformation

Contrast Stretching

Low contrast images occur often due to poor or non uniform lighting conditions, or due to nonlinearity, or small dynamic range of the imaging sensor. In the figure of Example 1 above you have seen a typical contrast stretching transformation.
Contrast stretching reduces an image of higher contrast than the original by darkening the levels below m and brightening the levels above m in the image.



a b
c d

FIGURE Contrast stretching. (a) Form of transformation function. (b) A low-contrast image. (c) Result of contrast stretching. (d) Result of thresholding. (Original image courtesy of Dr. Roger Heady, Research School of Biological Sciences, Australian National University, Canberra, Australia.)

Histogram processing

- Measure frequency of occurrence of each grey/colour value

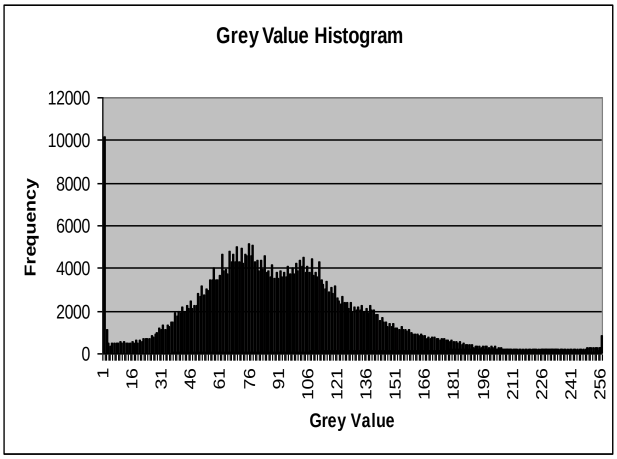
The histogram of a digital image with gray levels in the range [0, L-1] is a discrete function h(rk)=nk. rk-kth gray level nk-number of pixels in the image having gray level rk.

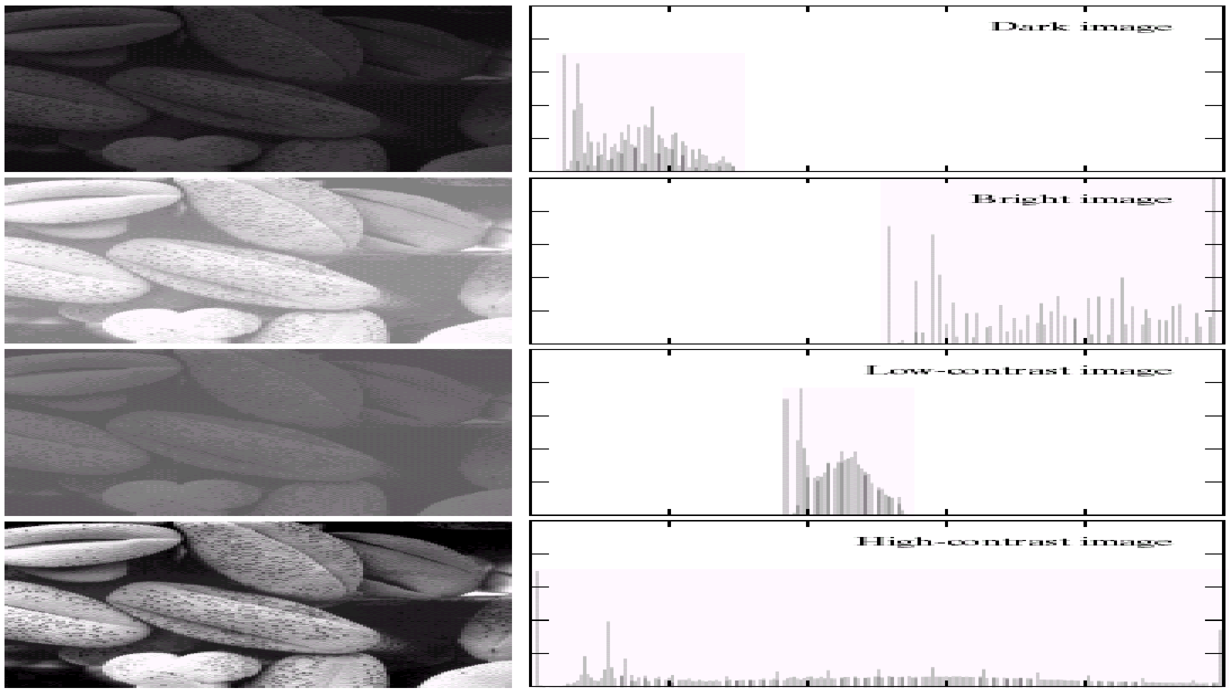
By processing (modifying) the histogram of an image we can create a new image with specific desired properties. Suppose we have a digital image of size NXN with grey levels in the range [0,L-1] . The histogram of the image is defined as the following discrete function:

$$p(r_k) = \frac{n_k}{N^2}$$

r_k is the kth grey level, $k = 0,1,\ldots,L-1$
n_k is the number of pixels in the image with grey level r_k
N^2 is the total number of pixels in the image

The histogram represents the frequency of occurrence of the various grey levels in the image. A plot of this function for all values of provides a global description of the appearance of the image.





Directional smoothing

To protect the edges from blurring while smoothing, a directional averaging filter can be useful. Spatial averages $g(x, y : \theta)$ are calculated in several selected directions (for example could be horizontal, vertical, main diagonals

$$g(x, y : \theta) = \frac{1}{N_\theta} \sum_{(k,l)} \sum_{\in W_\theta} f(x-k, y-l)$$

and a direction θ^* is found such that $\left| f(x, y) - g(x, y : \theta^*) \right|$ is minimum. (Note that W_θ is the neighbourhood along the direction θ and N_θ is the number of pixels within this neighbourhood).

Then by replacing $g(x, y : \theta)$ with $g(x, y : \theta^*)$ we get the desired result.

Median filtering

The median m of a set of values is the value that possesses the property that half the values in the set are less than and half are greater than m . Median filtering is the operation that replaces each pixel by the median of the grey level in the neighborhood of that pixel. Median filters are non linear filters because for two sequences x(n) and y(n)

$$\text{median}\{x(n) + y(n)\} \neq \text{median}\{x(n)\} + \text{median}\{y(n)\}$$

Median filters are useful for removing isolated lines or points (pixels) while preserving spatial resolutions. They perform very well on images containing binary (**salt and pepper**) noise but perform poorly when the noise is Gaussian. Their performance is also poor when the number of noise pixels in the window is greater than or half the number of pixels in the window

$$\frac{1}{273} \times \begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$

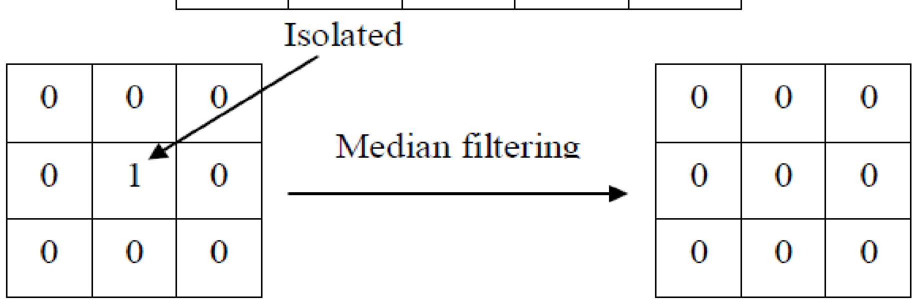


Image Enhancement

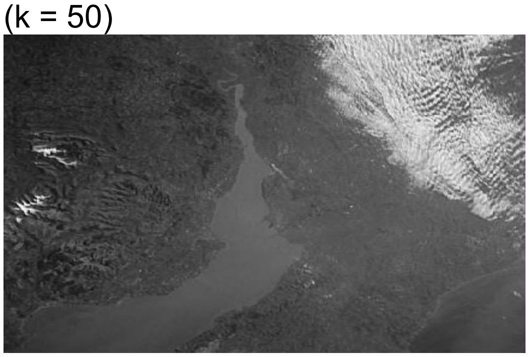
(a) Aerial image (b)-(d) results of of applying the transformation with c=1and Ỵ=3,4 and 5 respectively

Brightness Adjustment

Add a constant to all values

g' = g + k

(k = 50)

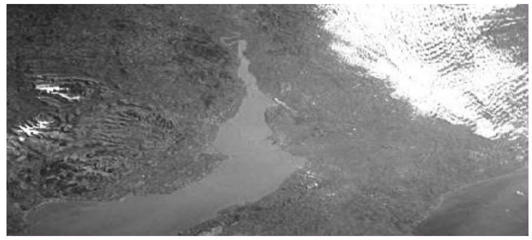


Contrast Adjustment

Scale all values by a constant

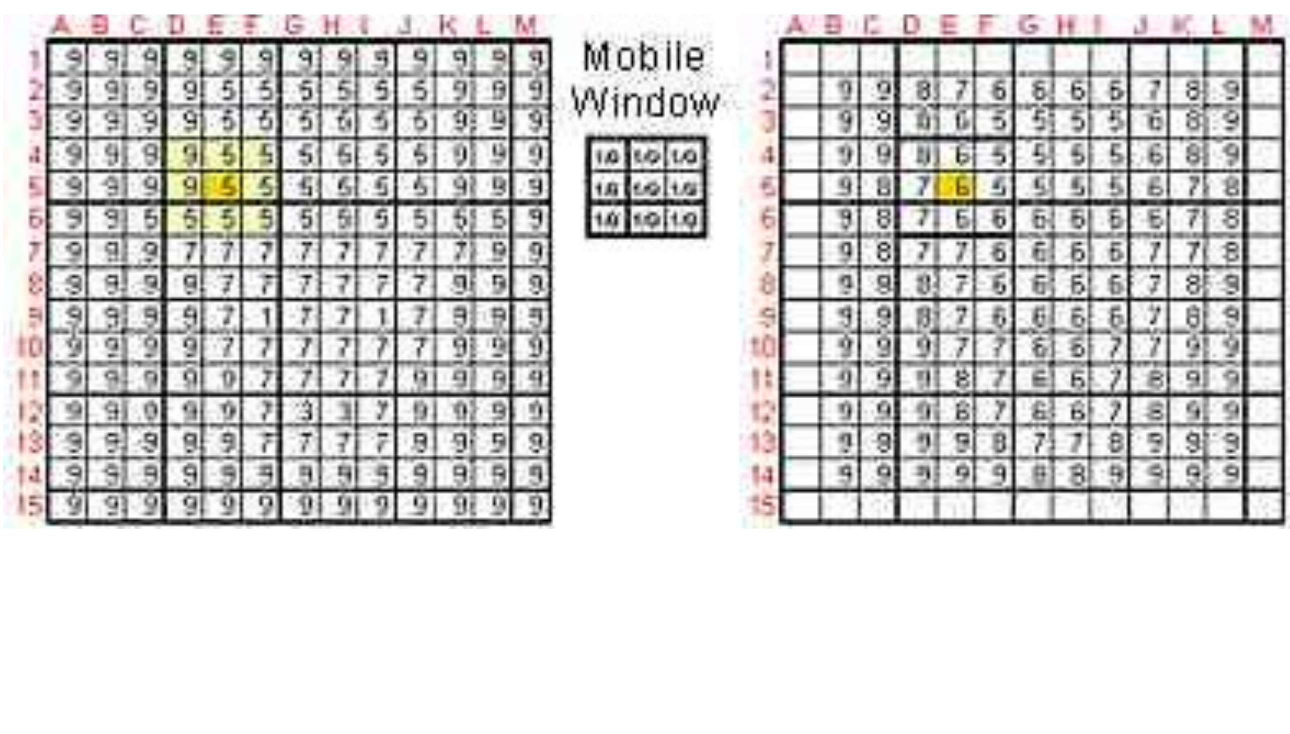
g' = g*k

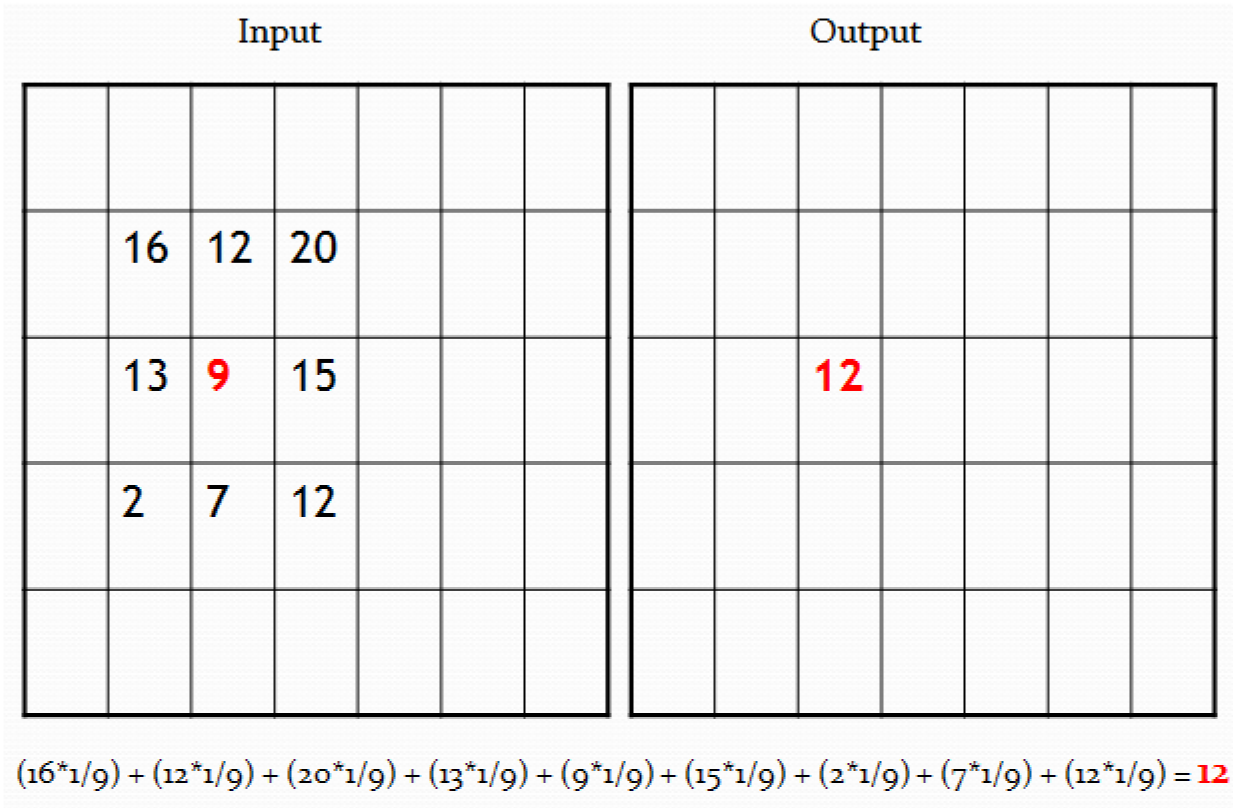
(k = 1.5)



Spatial Filtering

- Filters are commonly **used for** such things as edge **enhancement, noise removal, and the smoothing** of high frequency data
- The **principle** of the various filters is to **modify the numerical value of each pixel as a function of the neighboring pixels' values**.
- **For example**, if the value of each pixel is replaced by the average of its value and those of its eight neighbors the image is smoothed, that is to say, the finer details disappear and the image appears fuzzier.
- For example, the filtered value of the pixel located at E5 is (9*1/9) + (5*1/9) + (5*1/9) + (9*1/9) + (5*1/9) + (5*1/9) + (5*1/9) + (5*1/9) + (5*1/9) = 5.89, rounded up to 6.





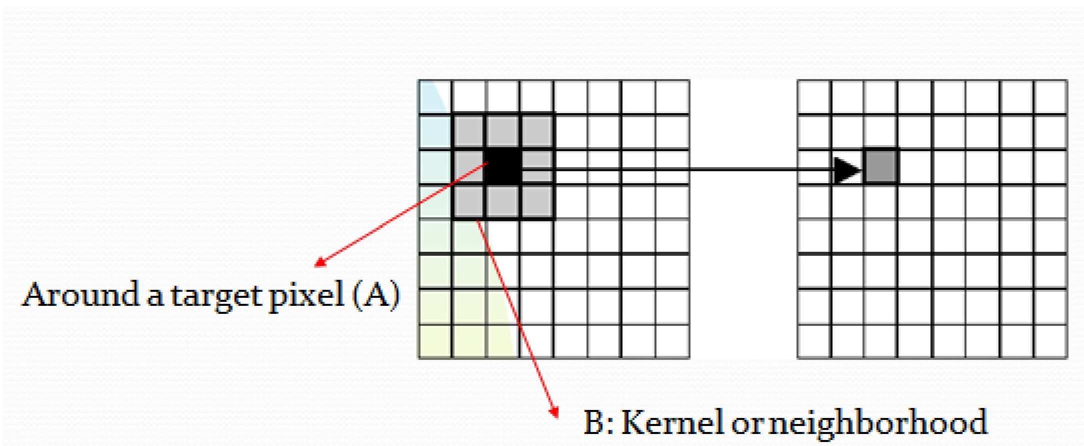
Spatial Feature Manipulation

- Spatial filters pass (emphasize) or suppress (de-emphasize) image data of various spatial frequencies
- Spatial frequency refers to the number of changes in brightness value, per unit distance, for any area within a scene
- Spatial frequency corresponds to image elements (both important details and noise) of certain size
- High spatial frequency → rough areas
    - High frequency corresponds to image elements of smallest size
    - An area with high spatial frequency will have rapid change in digital values with distance (i.e. dense urban areas and street networks)
  - Low spatial frequency → smooth areas

- Low frequency corresponds to image elements of (relatively) large size.
- An object with a low spatial frequency only changes slightly over many pixels and will have gradual transitions in digital values (i.e. a lake or a smooth water surface).

The Neighbourhood

A **resampling technique** that **calculates the brightness value of a pixel** in a corrected image from the brightness value of the pixel nearest the location of the pixel in the input image



Numerical Filters-Low Pass Filters

- Extract low frequency information (long wavelength)
- Suppress high frequency information (short wavelength)
- Low pass filter contains the same weights in each kernel element,
- Replacing the center pixel value with an average of the surrounding values
- Low pass filters are useful in smoothing an image, and reduce "salt and pepper" (speckle) noise from SAR images.

1	1	1
1	1	1
1	1	1

Numerical Filters-High Pass Filters

- Are used for removing , for example, stripe noise of low frequency (low energy, long short wavelengths)
- Filters that pass high frequencies (short wavelength)
- high pass filter uses a 3 x 3 kernel with a value of 8 for the center pixel and values of -1 for the exterior pixels
- It can be used to enhance edges between different regions as well as to sharpen an image

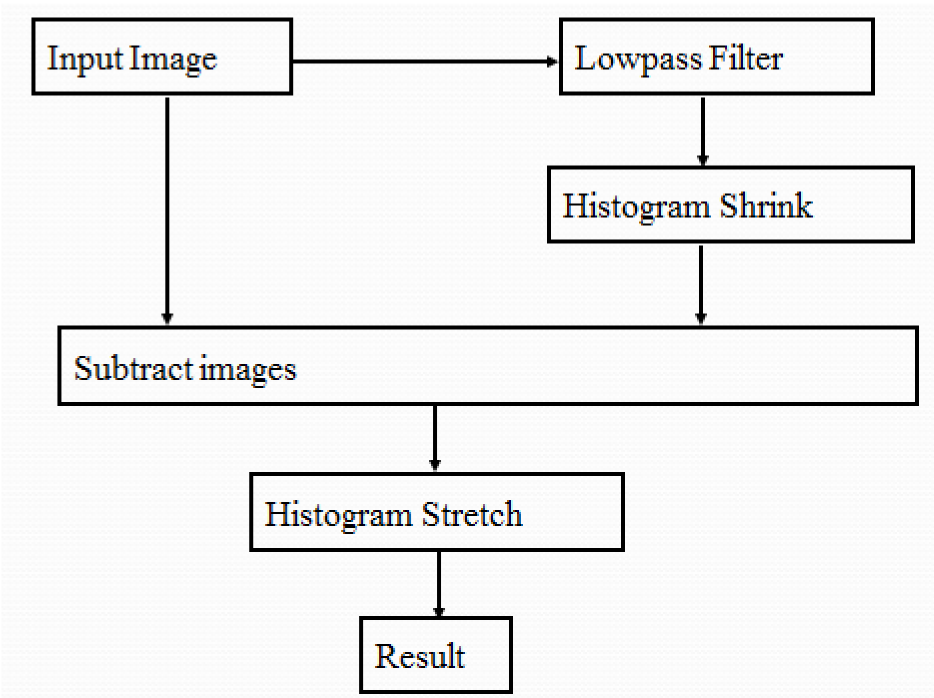
-1	-1	-1
-1	8	-1
-1	-1	-1

Masking

Mask is the small 2-D array in which the values of mask co-efficient determine the nature of process. The enhancement technique based on this type of approach is referred to as mask processing.

Unsharp Masking

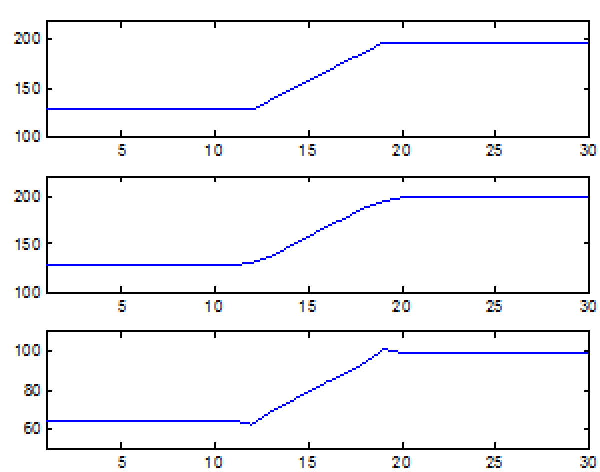
1. Originally a photographic sharpening technique
2. Superimpose a fraction of the blurred negative
3. Edge enhancement amplifies noise
4. Tradeoff between edge enhancement and noise enhancement
5. Equivalent to adding on a fraction of Laplacian



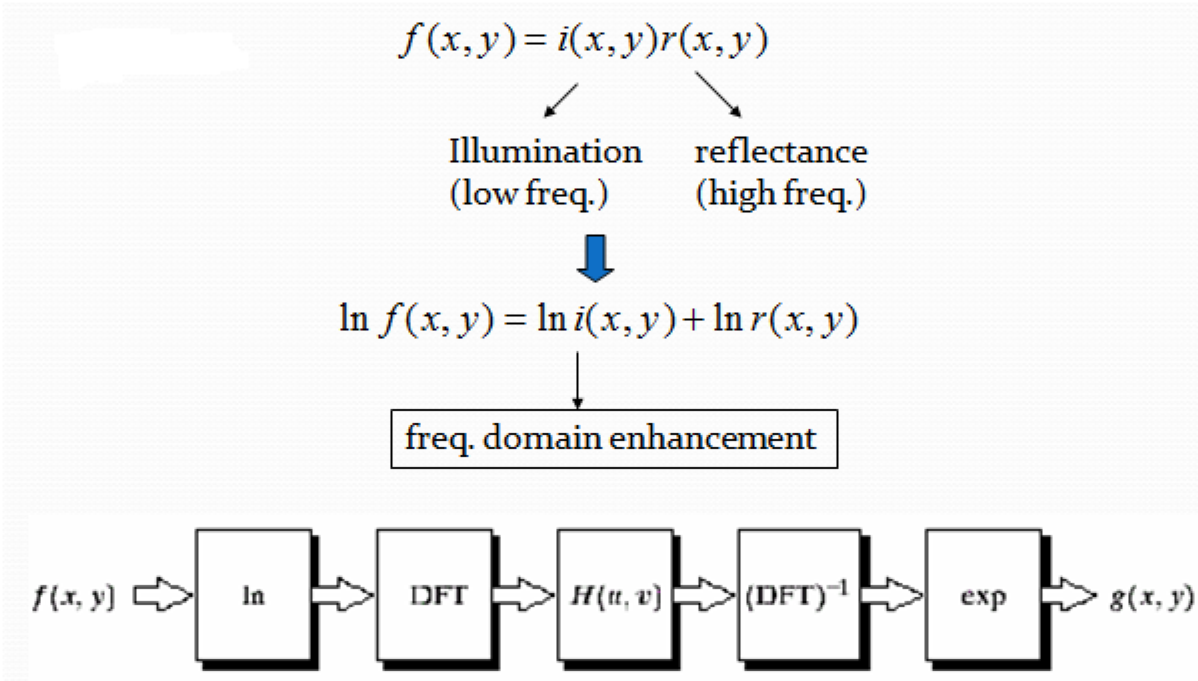
$$A(x)$$

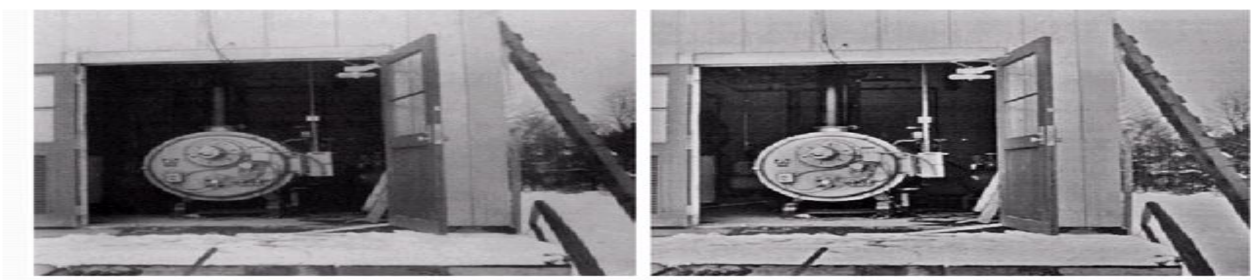
$$A(x)*B(x)$$

$$(1+k)\times A(x)-k\times A(x)*B(x)$$



Homomorphic filtering





before after

Image Restoration

Image Restoration refers to a class of methods that aim to remove or reduce the degradations that have occurred while the digital image was being obtained. All natural images when displayed have gone through some sort of degradation:

- ✓ during display mode
- ✓ during acquisition mode, or
- ✓ during processing mode

The degradations may be due to

- ➢ sensor noise
- ➢ blur due to camera misfocus
- ➢ relative object-camera motion
- ➢ random atmospheric turbulence
- ➢ others

In most of the existing image restoration methods we assume that the degradation process can be described using a mathematical model.

Objective of image restoration to recover a distorted image to the original form based on idealized models. The distortion is due to

- Image degradation in sensing environment e.g. random atmospheric turbulence
- Noisy degradation from sensor noise.
- Blurring degradation due to sensors e.g. camera motion or out-of-focus
- Geometric distortion e.g. earth photos taken by a camera in a satellite

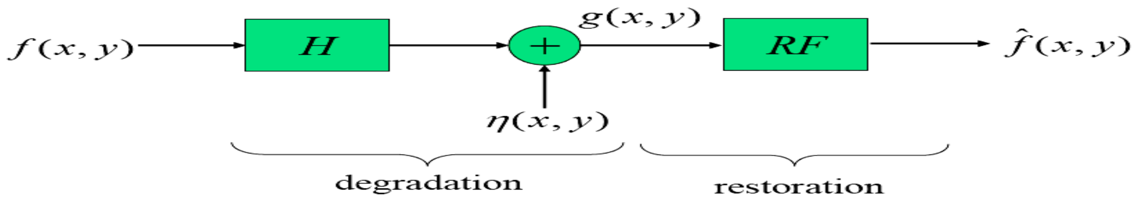
Comparison of enhancement and restoration

Image restoration differs from image enhancement in that the latter is concerned more with accentuation or extraction of image features rather than restoration of degradations.

Image restoration problems can be quantified precisely, whereas enhancement criteria are difficult to represent mathematically.

Enhancement	Restoration
Concerning the extraction of image features	Concerning the restoration of degradation
Difficult to quantify performance	Performance can be quantified
Subjective; making an image “look better”	Objective; recovering the original image

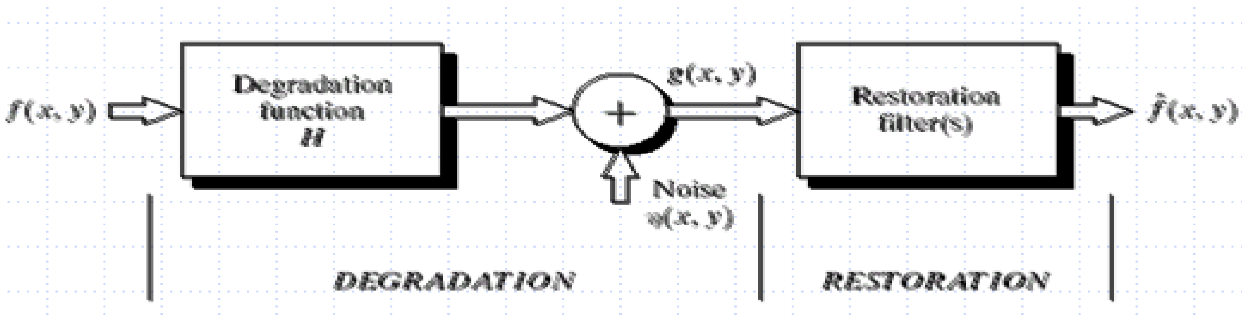
Image degradation / restoration model



- **When H is a LSI system**

$$g(x,y) = h(x,y) * f(x,y) + \eta(x,y)$$

$$G(u,v) = H(u,v)F(u,v) + N(u,v)$$



A general model of a simplified digital image degradation process

A simplified version for the image restoration process model is

$y(i, j) = H[f(i, j)] + n(i, j)$

where

$y(i, j)$ the degraded image

$f(i, j)$ the original image

H an operator that represents the degradation process

$n(i, j)$ the external noise which is assumed to be image-independent

Restoration methods could be classified as follows:

- **deterministic:** we work with sample by sample processing of the observed (degraded) image
- **stochastic:** we work with the statistics of the images involved in the process
- **non-blind:** the degradation process is known
- **blind:** the degradation process is unknown

- **semi-blind:** the degradation process could be considered partly known

Why the restoration is called as unconstrained restoration?

In the absence of any knowledge about the noise ‘n‘, a meaningful criterion function is to seek an f^ such that H f^ approximates of in a least square sense by assuming the noise term is as small as possible.

Where H = system operator.

f^ = estimated input image.

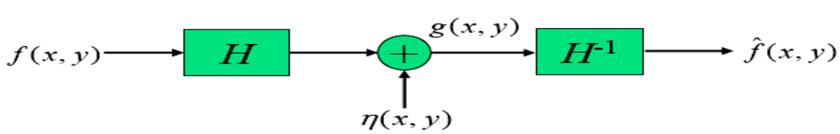
g = degraded image.

INVERSE FILTERING

- **When $H(u,v)$ is known, the simplest approach to restoration is direct inverse filtering**

$$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)}$$

$$\hat{F}(u,v) = F(u,v) + \frac{N(u,v)}{H(u,v)}$$



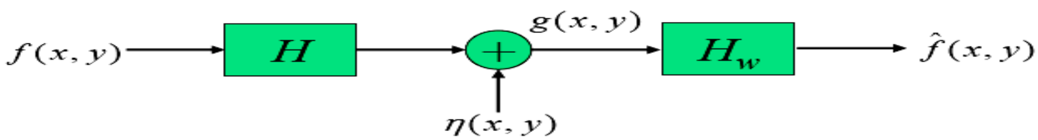
- **However, even if H is known completely, the undegraded image cannot be recovered exactly due to noise N**

$$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)} = F(u,v) + \frac{N(u,v)}{H(u,v)}$$

- **Even worse when H has zero or very small values, N/H would dominate the estimated image**
- **One way to get around this problem is to limit the filter frequencies to values near the origin where H is large in general**

WIENER FILTERING

- **Main limitation of inverse filtering**
  - Very sensitive to noise
- **Wiener filtering (minimum mean square error filtering)**
  - Use **statistic information** about signal and noise to improve the restoration
  - Consider images and noise as **random processes**
  - Objective: $e^2 = E\{(f - \hat{f})^2\} \Rightarrow \min$



CONSTRAINED LEAST SQUARES (CLS) RESTORATION

It refers to a very large number of restoration algorithms. The problem can be formulated as follows. Minimize

$$J(\mathbf{f}) = \|\mathbf{n}(\mathbf{f})\|^2 = \|\mathbf{y} - \mathbf{H}\mathbf{f}\|^2$$

subject to

$$\|\mathbf{C}\mathbf{f}\|^2 < \varepsilon$$

where Cf is a high pass filtered version of the image. **The idea behind the above constraint is that the highpass version of the image contains a considerably large amount of noise!** Algorithms of the above type can be handled using optimization techniques. Constrained least squares (CLS) restoration can be formulated by choosing an f to minimize the Lagrangian

$$\min\left(\|\mathbf{y} - \mathbf{H}\mathbf{f}\|^2 + \alpha\|\mathbf{C}\mathbf{f}\|^2\right)$$

Typical choice for is the 2-D Laplacian operator given by C

$$\mathbf{C} = \begin{bmatrix} 0.00 & -0.25 & 0.00 \\ -0.25 & 1.00 & -0.25 \\ 0.00 & -0.25 & 0.00 \end{bmatrix}$$

α represents either a Lagrange multiplier or a fixed parameter known as **regularisation parameter** and it controls the relative contribution between the term $\|\mathbf{y} - \mathbf{H}\mathbf{f}\|^2$ and the term $\|\mathbf{C}\,\mathbf{f}\|^2$. The minimization of the above leads to the following estimate for the original image

$$\mathbf{f} = \left(\mathbf{H}^{\mathbf{T}}\mathbf{H} + \alpha\mathbf{C}^{\mathbf{T}}\mathbf{C}\right)^{-1}\mathbf{H}^{\mathbf{T}}\mathbf{y}$$

ITERATIVE DETERMINISTIC APPROACHES TO RESTORATION

They refer to a large class of methods that have been investigated extensively over the last decades. They possess the following advantages.

- There is no need to explicitly implement the inverse of an operator. The restoration process is monitored as it progresses. Termination of the algorithm may take place before convergence.
- The effects of noise can be controlled in each iteration.
- The algorithms used can be spatially adaptive.
- The problem specifications are very flexible with respect to the type of degradation.

Iterative techniques can be applied in cases of spatially varying or nonlinear degradations or in cases where the type of degradation is completely unknown (blind restoration). In general, iterative restoration refers to any technique that attempts to minimize a function of the form M(f) using an updating rule for the partially restored image.

IMPORTANT QUESTIONS

TWO MARKS QUESTIONS

1. What is meant by Image Enhancement?
2. What is meant by Image Restoration?
3. Compare image enhancement and restoration.
4. Write notes on point operation.
5. Why the restoration is called as unconstrained restoration?
6. Briefly explain histogram modeling.
7. Write notes on root filtering.
8. What is meant by masking?
9. Write notes on interpolation.
10. Write notes on directional smoothening.

12 MARKS QUESTIONS

1. Explain the spatial domain Image Enhancement?
2. Briefly explain (a) median filtering (b) Homomorphic filtering
3. Explain about image restoration and degradation model.
4. Explain linear filtering and root filtering
5. Explain Inverse filtering and Wiener filter