Image Reduction

RAW IMAGE

1	67	33	45	72
8	16	54	34	38
40	35	65	68	70
36	56	49	29	37
38	39	51	38	35

REDUCED IMAGE

1	33	72
40	65	70
38	51	35

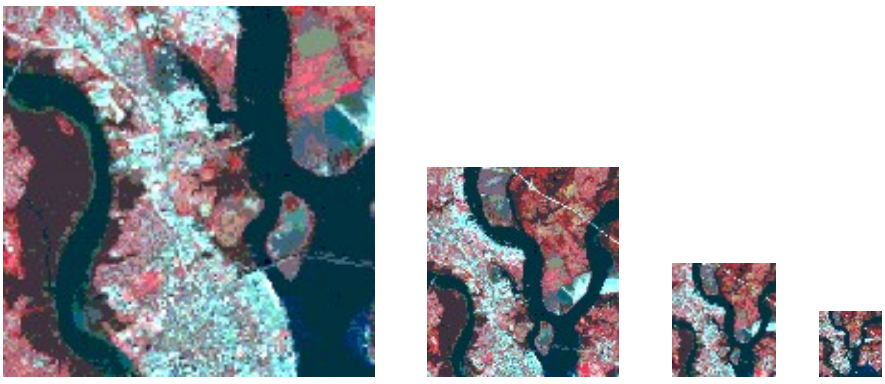
- An image sampled at a 10x reduction, i.e. every 10th row and 10th column of the image is sampled, will yield a resampled image containing only 1% of the original data and at this scale only the new image will be small enough to view the entire scene on the screen

- Because a resampled image looses many of its original pixels, it does not contain adequate data for image processing and interpretation

- Reduced images are usually used for orienting within a scene and locating the exact row and column coordinates of a specific study area

- These coordinates can then be used to extract a portion of the image for full resolution analysis

- Below Figure shows 1x, 2x, and 4x reduction of portion of a Landsat TM data



Unreduced image Reduced at 1x 2x 4x

Image Magnification

- Digital image magnification is known as zooming

- Image magnification is used for:

- Improving the scale of the image for enhanced visual interpretation
- Matching the scale of another image

- Row and column replication represent the simplest form of image magnification

- For magnifying an image by an integer factor m^2, each pixel in the original image is replaced by an mxm block of pixels which all have the equivalent brightness values as the original input pixels

- 2x magnification is shown in the below Figure.

Raw Image

42	33	45	
67	39	26	
56	18	42	

Image Magnification

42	42	33	33	45	45	
42	42	33	33	45	45	
67	67	39	39	26	26	
67	67	39	39	26	26	
56	56	18	18	42	42	
56	56	18	18	42	42	

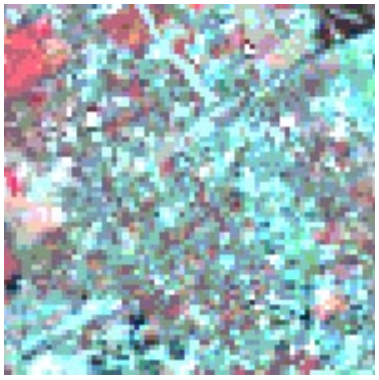
- Below Figure shows a Landsat TM data magnified 1x, 2x, 3x, 4x, and 8x.



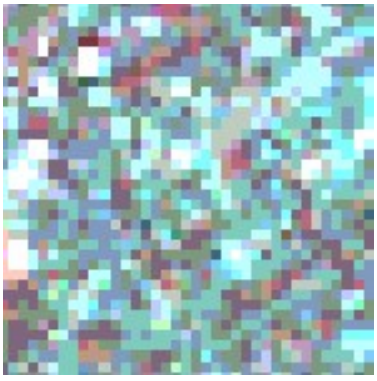
Initial TM data



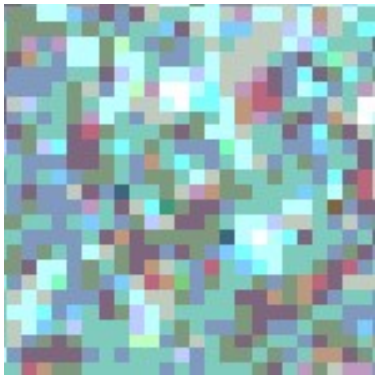
Magnified at 1x



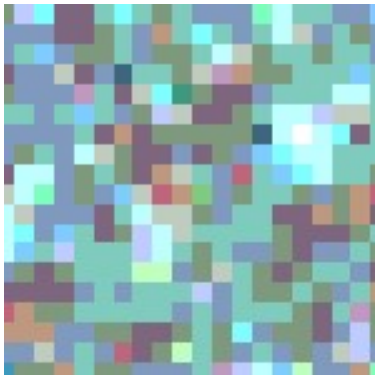
Magnified at 2x



Magnified at 3x



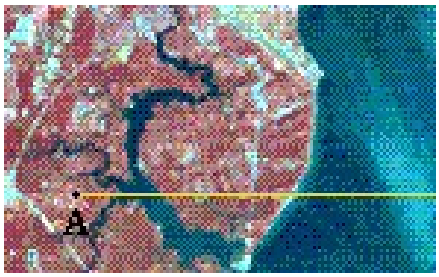
Magnified at 4x



Magnified at 8x

Transects

- Transect is a straight line between any two user-specified points within an image
- Pixels that lie on the transect can be measured and displayed to compare spectral or spatial differences



- The Brightness Profiles that occur between points A and B can be obtained for different bands
- İ.e plots where x-axis being the distance in pixels and the y-axis being the brightness values of the pixels along the transectixel value
- Each such graph contains a unique distribution per band
- Such a study is important in determining optimal bands for further analysis
- Image analysts use several transects in a single image to determine environmental trends or patterns

Contrast Enhancement

- A common problem in remote sensing is that the range of reflectance values collected by a sensor may not match the capabilities of the film or color display monitor
- Materials on the Earth's surface reflect and emit different amounts of energy
- A sensor may record a tremendous amount of energy from a one material in a certain wavelength, while another material is recorded at much less energy in the same wavelength
- Values present on an image is referred to as contrast
- Contrast enhancement is a process that makes the image features appear more clearly by making optimal use of the colors available on the display
- Contrast manipulations involve changing the range of values in an image in order to increase contrast
- E.g., an image might start with a range of values between 40 and 90. When this is stretched to a range of 0 to 255, the differences between features are emphasized

Linear Contrast Enhancement (or Contrast Stretching)

- Linear contrast enhancement linearly expands the original digital values of the remotely sensed data into a new distribution

- By expanding the original input values of the image, the total range of sensitivity of the display device can be utilized

- Linear contrast enhancement also makes subtle variations within the data more obvious

- Linear contrast enhancement is best applied to remotely sensed images with Gaussian or near-Gaussian histograms

- Gaussian histogram means all the brightness values fall within a narrow range of the histogram and only one mode is apparent

- There exists 3 methods of linear contrast enhancement:

    - Minimum-Maximum Linear Contrast Stretch

    - Percentage Linear Contrast Stretch

    - Piecewise Linear Contrast Stretch

Minimum-Maximum Linear Contrast Stretch

- When using the minimum-maximum linear contrast stretch, the original minimum and maximum values of the data are assigned to a newly specified set of values that utilize the full range of available brightness values

- Brightness After Stretch = (Brightness Before Stretch – Min. Brightness Before Stretch)/(Max. Brightness Before Stretch-Min. Brightness Before Stretch) x (Maximum Brightness Value After Stretch)

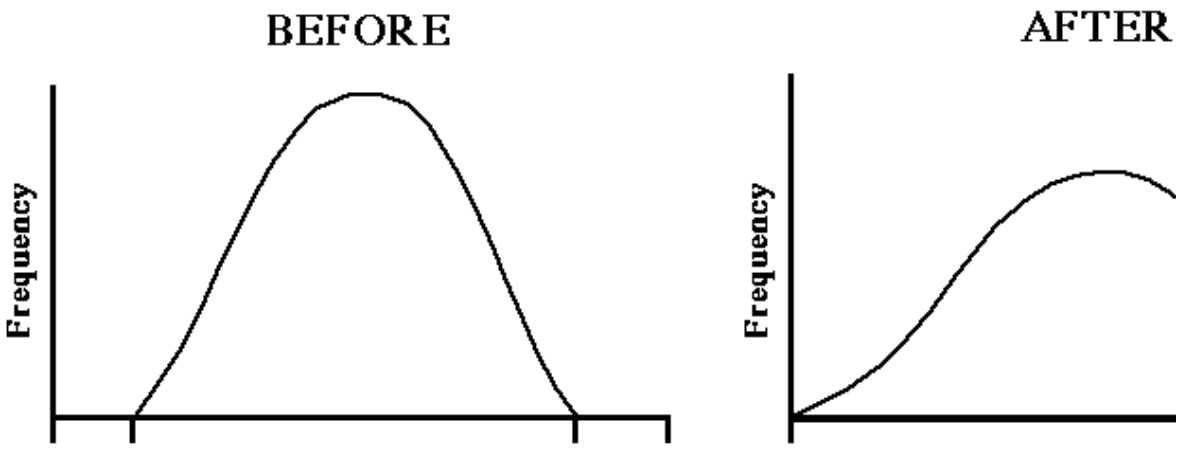
- E.g. An 8 bit resolution image (i.e. 256 Brightness Levels) image has a minimum brightness value of 45 and a maximum value of 205

- When such an image is viewed without enhancements, the values of 0 to 44 and 206 to 255 are not displayed

- Important spectral differences can be detected by stretching the minimum value of 45 to 0 and the maximum value of 206 to 255 by applying the above linear relationship

- E.g. Brightness of (45) After Stretch = (45-45)/(205-45)x255=0, Brightness of (205) After Stretch = (205-45)/(205-45)x255=255, Brightness of (145) After Stretch = (145-45)/(205-45)x255=160

- Below figure shows Minimum-Maximum Linear Contrast Stretch



- An algorithm can be used that matches the old minimum value to the new minimum value, and the old maximum value to the new maximum value

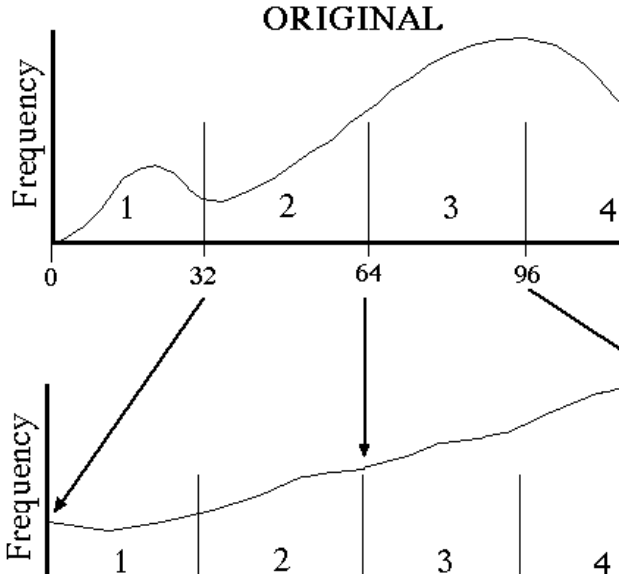
- All the old intermediate values are scaled proportionately between the new minimum and maximum values

- Many digital image processing systems have built-in capabilities that automatically expand the minimum and maximum values to optimize the full range of available brightness values

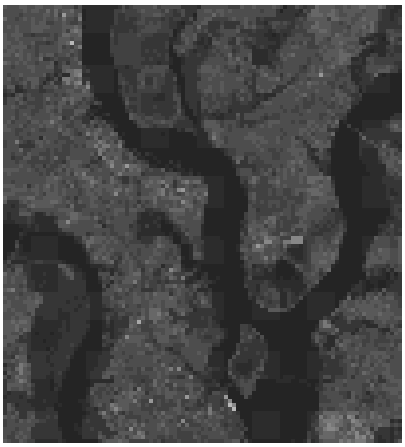
Percentage Linear Contrast Stretch

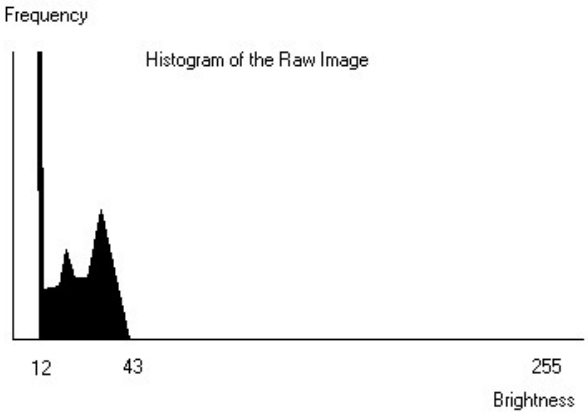
- The percentage linear contrast stretch is similar to the minimum-maximum linear contrast stretch except that the percentage linear contrast stretch method uses specified minimum and maximum values that lie in a certain percentage of pixels from the mean of the histogram

- Below Figure shows the approach used in a percentage linear contrast stretch



- Below Figures contains TM images and their associated histograms



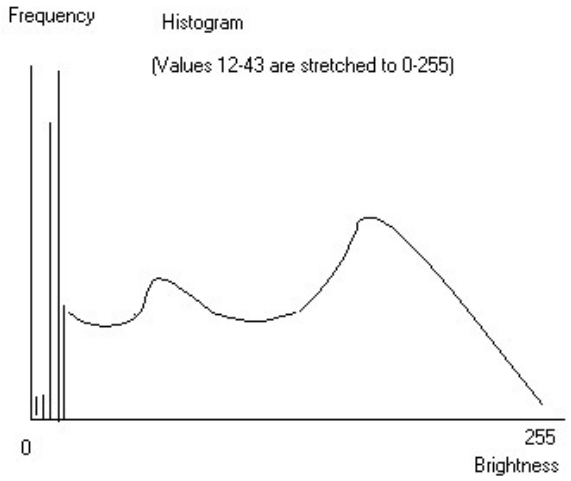


- First image below (Raw Data) displays the low-contrasting data in band 4 under normal conditions with no contrast stretch. The minimum brightness value is 12 and the maximum value 43

- Histogram shows how the data is densely clustered between these values

- In the second image (Stretch 1) below all values between 12 and 43 are linearly stretched using a minimum-maximum linear contrast stretch so that these values now lie within the range of 0 to 255





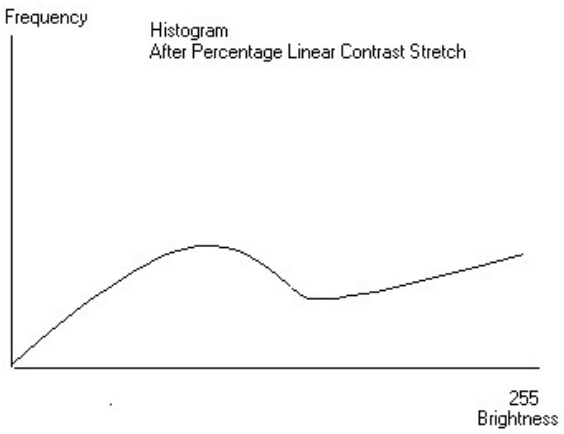
- Minimum value 12 becomes 0 and the maximum value 43 stretches to 255

- Histogram associated with this image demonstrates a wider distribution than the first histogram

- This results in a pure pixel contrast that optimizes the capabilities of the display device

- Below third image (Stretch 2) continues to stretch the data by applying percentage linear contrast stretch

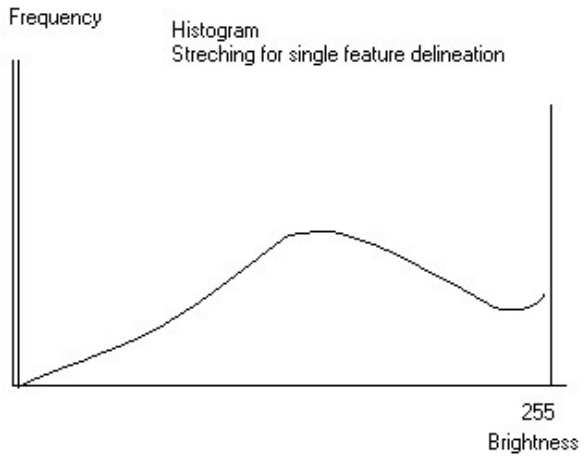




- Information content of the pixels that saturate at 0 and 255 is lost, yet a more detailed analysis of certain aspects of the image may be enhanced for better interpretation

- Below fourth image (Stretch 3) shows how an analyst would enhance an image if only interested in delineating single feature(e.g. wetlands)





- When the values between 13 and 27 are linearly stretched to 0 and 255, all values below 13 become 0 (black) and all values above 27 are set to 255 (white)

- This enhancement yields additional information on the smooth cordgrass at the expense at of the rest of the water and upland cover

- Image analysts often need to increase the contrast of an image only at specific portions of the electromagnetic spectrum

- E.g. an analyst who wants to extract detailed marine information in an image may only be interested in values between 0 and 12

- When these values are stretched to 0 and 255, subtle ocean variations can be more easily detected (see below Figure)

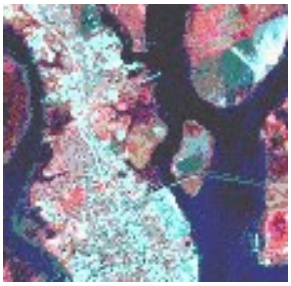
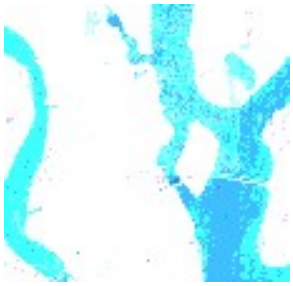
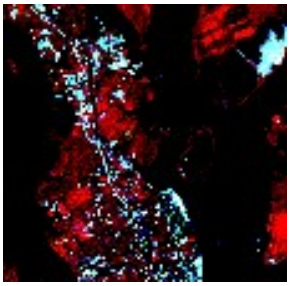


Image without Enhancements
TM Bands 4,3, and 2



Enhanced Image for Ocean Contrast
Red 0-10 Green 0-12 Blue 0-12

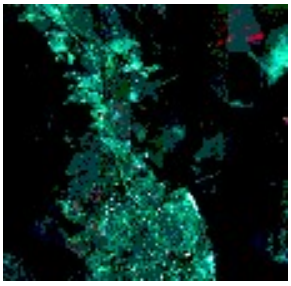
- A percentage stretch of the same image between values of 25 and 45 yields detailed vegetation information (see below Figure)



Enhanced for Vegetation Contrast
Red 25-45 Green 30-35 Blue 25-30

- This may be useful in the delineation of healthy vegetation

- If an analyst is interested in image enhancement for urban features, a percentage linear stretch between the values 40 and 70 in the red and 15 to 45 in the green and blue will increase the contrast of these features (see below Figure)



Enhanced for Urban Contrast
Red 40-70 Green 15-45 Blue 15-45

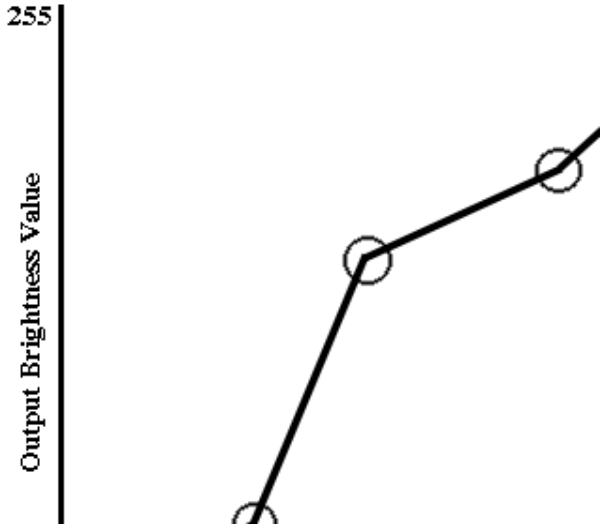
Piecewise Linear Contrast Stretch

- When the distribution of a histogram in an image is **bi or trimodal**, an analyst may stretch certain values of the histogram for increased enhancement in selected areas

- This method of contrast enhancement is called piecewise linear contrast stretch

- Piecewise linear contrast enhancement involves the identification of a number of linear enhancement steps that expands the brightness ranges in the modes of the histogram

- Below Figure shows piecewise linear contrast stretch output-input function



- In the piecewise stretch, a series of small min-max stretches are set up within a single histogram

- Piecewise linear contrast stretch is a very powerful enhancement procedure, however image interpreter must be very familar with the modes of the histogram and the features they represent in the real world

Nonlinear Contrast Enhancement

- Often involves histogram equalizations using a certain algorithm

- Nonlinear contrast stretch method has one major disadvantage that each value in the input image can have several values in the output image, so that objects in the original scene lose their correct relative brightness values

Histogram Equalization

- Histogram equalization is one of the most useful forms of nonlinear contrast enhancement

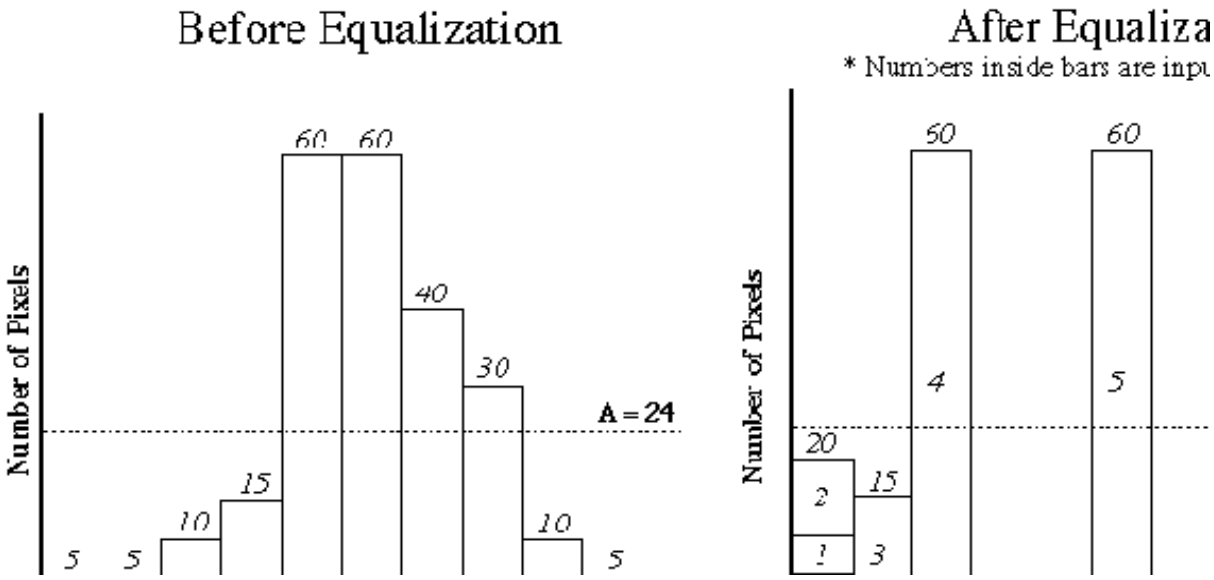
- When an image's histogram is equalized, all pixel values of the image are redistributed so there are approximately an equal number of pixels to each of the user-specified output gray-scale classes (e.g., 32, 64, and 256)

- When Histogram Equalization is applied, contrast is increased at the most populated range of brightness values of the histogram (or "peaks")

- Histogram Equalization automatically reduces the contrast in very light or dark parts of the image associated with the tails of a normally distributed histogram

- Histogram equalization can also seperate pixels into distinct groups, if there are few output values over a wide range

- Below Figure shows two histograms



- The first histogram shows values before equalization is performed

- When this histogram is compared to the equalized histogram, one can see that the enhanced image gains contrast in the most populated areas of the original histogram

- In this example, input range of 3 to 7 is stretched to the range of 1 to 8

- However, the data values at the tails of the original histogram are grouped together

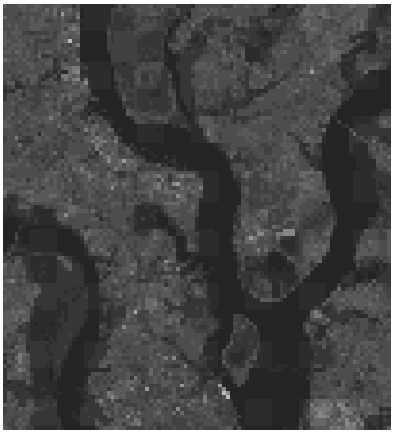
- Input values 0 through 2 all have the output values of 0

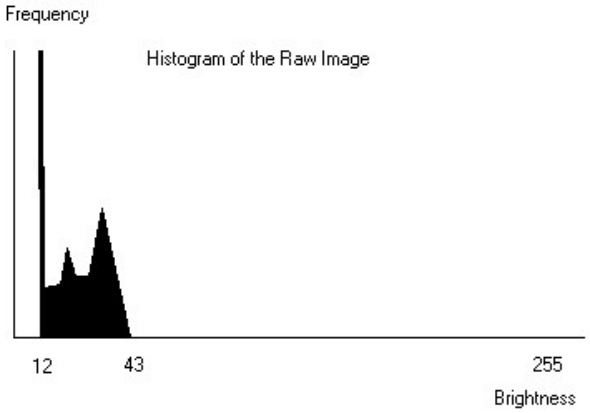
- This results in the loss of the dark and bright characteristics usually associated with the tail pixels

- Image analysts must be aware that while histogram equalization often provides an image with the most contrast of any enhancement technique, it may hide much needed information

- Histogram Equalization groups pixels that are very dark or very bright into very few gray scales

- In the below Figures notice the change in each of the histograms as values in the tails are grouped together.







Equalized Histogram

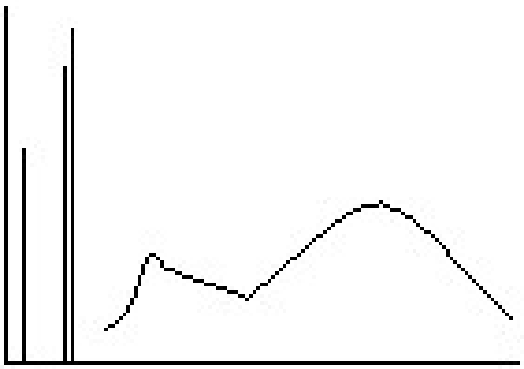


Image Enhancement - Spatial Techniques

- Spectral enhancement relies on changing the gray scale representation of pixels to give an image with more contrast for interpretation

- It applies the same spectral transformation to all pixels with a given gray scale in an image

- However, it does not take full advantage of human recognition capabilities even though it may allow better interpretation of an image by a user

- Several examples will demostrate the value of spatial characteristics in image interpretation

- Spatial enhancement is the mathematical processing of image pixel data to emphasize spatial relationships

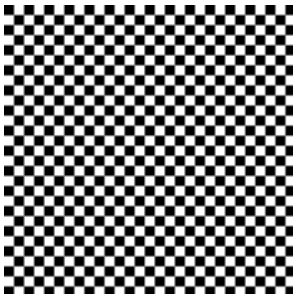
- Spatial enhancement uses the concept of spatial frequency within an image

- Spatial frequency is the manner in which gray-scale values change relative to their neighbors within an image

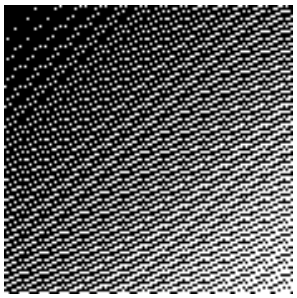
- If there is a slowly varying change in gray scale in an image from one side of the image to the other, the image is said to have a low spatial frequency

- If pixel values vary abruptly for adjacent pixels in an image, the image is said to have a high spatial frequency

- Below Figures show examples of high and low spatial frequencies:



High frequency image



Low frequency image

- Many natural and manmade features in images, such as geologic faults, edges of lakes, roads, airports have high spatial frequency

- Spatial enhancement involves the enhancement of either low or high frequency information within an image

- Algorithms that enhance low frequency image information employ a "blurring" filter (commonly called a low pass filter) that emphasizes low frequency parts of an image while de-emphasizing the high frequency components

- Enhancement of high frequency information within an image is called edge enhancement

- Edge Enhancement emphasizes edges in the image while retaining overall image quality

- There are 3 main purposes that underlie spatial enhancement techniques:

  - To improve interpretability of image data
  - To aid in automated feature extraction
  - To remove and/or reduce sensor degradation

- 2 major methods are commonly used in spatial enhancement:

  1) Convolution
  2) Fourier Transform Theory

Convolution

- Convolution involves the passing of a moving window over an image and creating a new image where each pixel in the new image is a function of the original pixel values within the moving window and the coefficients of the moving window as specified by the user

- The window, a convolution operator, may be considered as a matrix (or mask) of coefficients that are to be multiplied by image pixel values to derive a new pixel value for a resultant enhanced image

- This matrix may be of any size in pixels and does not necessarily have to be square

Example:

- Take a 3 by 3 matrix of coefficients and see the effects on an example image subset

- A set of coefficients that is used for image smoothing and noise removal is given below:

1/9 *	1	1	1
	1	1	1
	1	1	1

- If we have a sample image, given below:

3	3	4	4	5	6
2	3	3	4	4	5
1	2	2	3	3	4
1	1	2	4	4	7
1	2	4	20	20	20
2	3	6	20	20	20
2	3	4	20	20	20

- Above image normally has a low smoothly varying gray scale, except for the bottom right region, which exhibits a sharp brightness change

- We can see the effects of the convolution filter on a pixel-by-pixel basis

- Because we do not wish to consider edge effects, we will start the overlay of the moving window on the x=2, y=2 (x-being the row, y-being the column) pixel of the input image and end at the x=6, y=5 position of the original image

- First pixel of the output image p(x,y) (x=1, y=1), will have brightness value

p(1,1) = 1/9 *	(3*1 +	3*1 +	4*1+	= 23/9 = 2.56
	2*1 +	3*1 +	3*1+	
	1*1 +	2*2 +	2*1)	

- Because the output image, as well as the input image, is normally a whole number (integer) quantity, the values are rounded down to the nearest integer

- Thus p(1,1) = 2

Similarly,

p(1,2) = 1/9 *	(3*1 +	4*1 +	4*1+	= 28/9 = 3.111
	3*1 +	3*1 +	4*1+	
	2*1 +	2*1 +	3*1)	

- Thus p(1,2) = 3 and

p(1,3) = 1/9 *	(4*1 +	4*1 +	5*1 +	= 32/9 = 3.555
	3*1 +	4*1 +	4*1 +	
	2*1 +	3*1 +	3*1)	

- Thus p(1,3) = 3

- Continued application of the same window (or filter kernel) will result in an output image given by:

Convolved image

2	3	3	4
1	2	3	4
1	4	6	9
2	6	11	15
3	9	14	20

- Comparing this convolved image above with the original image below for the same pixel locations to which convolution is applied, it is seen that:

Original image

3	3	4	4
2	2	3	3
1	2	4	4
2	4	20	20
3	6	20	20

- There is sharp discontinuity in the in the original image whereas in the convolved image, sharp discontinuity is smoothed out

- İ.e. the moving window filter (convolution kernel) has a smoothing effect on the original image it is applied to

- A sample edge detection mask can be given as

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

- Then the brightness value of the convolved image p(1,1) will be

p(1,1) =	(-1*3)	+ (-1*3)	+ (-1*4)+	= 4
	(-1*2)	+ (8*3)	+ (-1*3)+	
	(-1*1)	+ (-1*2)	+ (-1*2)	

- Resulting image after application of the mask can be found as

4	-1	4	-2
1	-6	-2	-11
-7	-22	-26	-49
-4	-26	80	45
0	-28	46	0

- Since only positive values are allowed in a image file, all values are offset by the absolute value of the minimum image elements (i.e. add 49 to all the pixels)

- The resultant image is:

53	48	53	47
50	43	47	38
42	27	23	0
45	23	129	98
49	21	95	49

- Values greater than 90 are present in the output image and represent the edge of the bright region in the original image

- Alternatively, negative values can be set to 0 giving an output image of

4	0	4	0
1	0	0	0
0	0	0	0
0	0	80	45
0	0	46	0

- Above output image can be compared with the below original image

3	3	4	4
2	2	3	3
1	2	4	4

2	4	20	20
3	6	20	20

- One of the most used convolution kernels for edge enhancement of images is given by Chavez

- The kernel is specified as:

1/9 *	-1	-1	-1
	-1	17	-1
	-1	-1	-1

- Above kernel is used for enhancement of high frequency information in an image

- For a particular image pixel location and channel number, a low pass filter may be used to evaluate the average value in a 3 by 3 window

- The convolution kernel is then given by:

avg = 1/9 *	1	1	1
	1	1	1
	1	1	1

- High frequency (HF) component in any given pixel wil then be given by:

- HF = pixel - avg

- Represented in terms of a convolution kernel, HF becomes:

HF =	0	0	0	- 1/9 *	1	1	1
	0	1	0		1	1	1
	0	0	0		1	1	1

- İ.e.

HF = 1/9 *	-1	-1	-1
	-1	8	-1
	-1	-1	-1

- By adding the high frequency part, HF, back to the original pixel, a high frequency enhancement will be obtained as:

- New value = pixel value + HF

- This is given by:

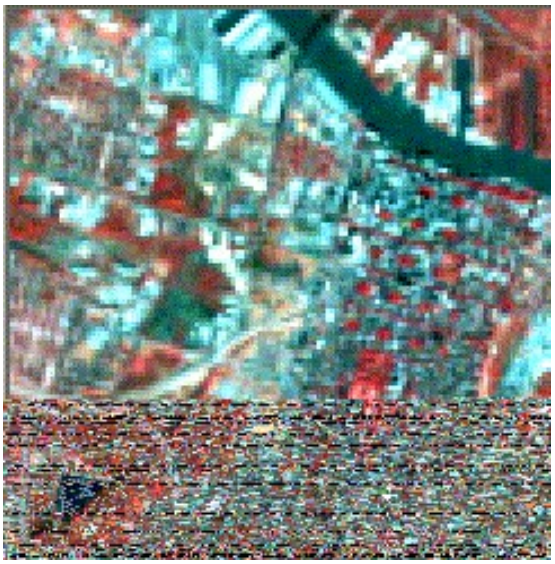
New value =	0	0	0	+ 1/9 *	-1	-1	-1
	0	1	0		-1	8	-1
	0	0	0		-1	-1	-1

or

New Value = 1/9 *	-1	-1	-1
	-1	17	-1
	-1	-1	-1

- Below Figures show Landsat Thematic Mapper (TM) images before enhancement, and after applying the above convolution kernel to the original image

Raw image (Before Enhancement)



After High Frequency Enhancement



Fourier Transform

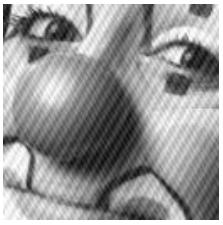
- Fourier Transform as applied to image (2-Dimensional) describes the image in terms of its spatial frequency components

- Fourier Transform is used in a wide range of applications, such as image analysis, image filtering, image reconstruction and image compression.

- Fourier Transform is used to convert images from the spatial domain into the frequency domain and vice-versa.

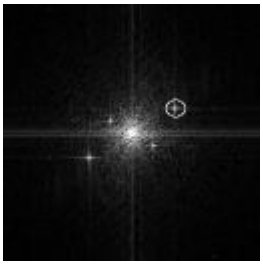
- Fourier Transform helps to visualize and solve certain issues in the spatial frequency domain, which are otherwise very difficult to solve in spatial domain

- For example the below image is covered by noise before Fast Fourier Transform (FFT) is applied

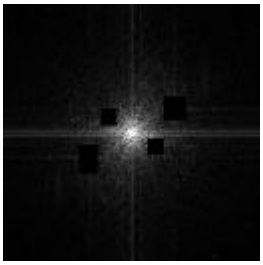


- Below FFT of the above noisy image is shown

- Due to its regularity, the noise pattern stands out as four spikes, one of which is marked



- Below is the picture in which the four noise spikes, which corresponded to the regular noise patterns, have been deleted from the FFT



- Inverse FFT is applied to the above corrected FFT and the below clean image is found



- Fourier Transform is used to decompose an image into its sine and cosine components

- Output of the transformation represents the image in the **Fourier or frequency domain**

- Assume an image **"I"**

- Spatial Frequency Domain **"SFD"** is a space in which each image value at image position F represents the amount that the intensity values in the image **"I"** vary over a specific distance related to F

- In the frequency domain, changes in image position correspond to changes in the spatial frequency (or the rate at which image intensity values are changing in the spatial domain image **"I"**)

- E.g. suppose that there is the value 20 at the point that represents the spatial frequency 0.1 (or 1 period every 10 pixels)

- This means that in the corresponding spatial domain image **"I"**, the intensity values vary from dark to light and back to dark over a distance of 10 pixels

- And also it means that the contrast between the lightest and darkest is 40 gray levels (2 times 20)

- Spatial frequency domain is required because:

  - It makes explicit periodic relationships in the spatial domain and

  - Image processing is more efficient or sometimes it is the only practical procedure when applied in the frequency domain

- Spatial frequency refers to the inverse of the periodicity with which the image intensity values change

- Image features with high spatial frequency (such as edges) are those that change greatly in intensity over short image distances in the spatial domain

- In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image

Discrete Fourier Transform (DFT)

- Only Discrete Fourier Transform (DFT) will be examined since we are interested in the digital images

- DFT is the sampled Fourier Transform and therefore does not contain all frequencies forming an image, but only a set of samples which is large enough to fully describe the spatial domain image

- The number of frequencies corresponds to the number of pixels in the spatial domain image, i.e. the image in the spatial and Fourier domain are of the same size

- For an image of size M×N, the two-dimensional DFT is given by:

$$F(k, l) = (1/MN) \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) \exp\{ - i 2 \pi [(k m / M) + (l n / N)] \}$$

where

f(m,n) is the image in the spatial domain,

exponential term is the basis function corresponding to each point F(k, l) in the Fourier space

- Above DFT equation can be interpreted as: the value of each point F(k, l) is obtained by multiplying the spatial image with the corresponding base function and summing the result

- The basis functions are sine and cosine waves with increasing frequencies

- F(0,0) represents the DC-component of the image which corresponds to the average brightness

- F(M-1,N-1) represents the highest frequency

- In a similar way, the Fourier image can be re-transformed to the spatial domain

- Inverse Discrete Fourier transform is given by:

$$f(m,n) = (1/MN) \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} F(k, l) \exp\{ i 2 \pi [(k m / M) + (l n / N)] \}$$

- To obtain the result for the above equations, a double sum has to be calculated for each image point.

- However, because the Fourier Transform is separable, it can be written as

$$F(k, l) = (1/N) \sum_{n=0}^{N-1} p(k,n) \exp\{ - i 2 \pi (l n / N) \}$$

where

$$p(k, n) = (1/M) \sum_{m=0}^{M-1} f(m,n) \exp\{ - i 2 \pi (k m / M) \}$$

- Using the above two formulas, the spatial domain image is first transformed into an intermediate image using M one-dimensional Fourier Transforms

- This intermediate image is then transformed into the final image, using *N* one-dimensional Fourier Transforms

- The Fourier Transform produces a complex number valued output image

- Fourier Transformed image can be displayed with two images, either with the **real** and **imaginary** part or with **magnitude** and **phase**

- In image processing, often only the magnitude of the Fourier Transform is displayed, as it contains most of the information of the geometric structure of the spatial domain image

- However, if it is required to re-transform the Fourier image into the correct spatial domain after some processing in the frequency domain, both magnitude and phase of the Fourier image must be preserved

- Fourier transform is used in the calculation of image convolutions

$$g(a,b) = (1/MN) \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n)\, h(a - m, b - n)$$

where

f(m,n) is the original image in spatial domain

h (a,b) is the two dimensional impulse response of the filter in the spatial domain (a,b)

g(a,b) is the image in spatial domain (a,b) at the output of the filter

- Convolution theorem is given by

  $G(u,v) = F(u,v)\, H(u,v)$

  where G(u,v), F(u,v) and H(u,v) are the Discrete Fourier Transforms of the image at the output of the filter, input image and the Transfer Function of the filter, respectively (All in the spatial frequency domain (u,v))

- Thus g(a,b) can be found by the inverse Discrete Fourier Transform of G(u,v) = F(u,v) H(u,v) as below:

$$g(a,b) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u,v)\, H(u,v) \exp\{ i\, 2\pi [(a\, u / M) + (b\, v / N)] \}$$

- Computational load of calculating convolutions reduce significantly when the above relationship is used

Use of Fourier Transform

- Fourier Transform is used if it is required to access the geometric characteristics of a spatial domain image

- Because the image in the Fourier domain is decomposed into its sinusoidal components, it is easy to examine or process certain frequencies of the image, thus influencing the geometric structure in the spatial domain

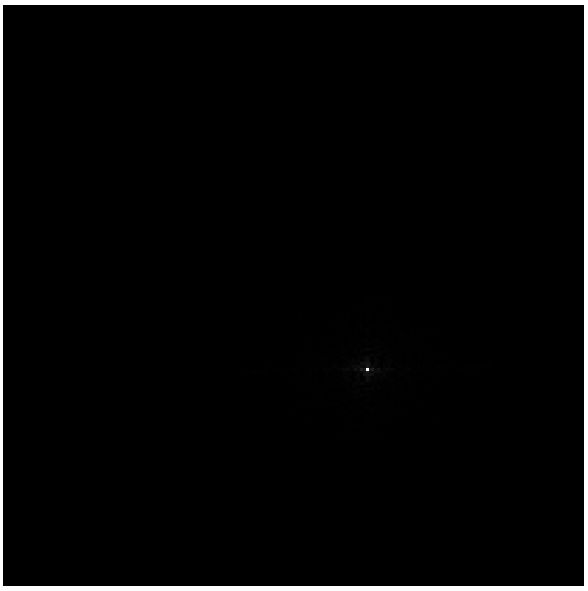
- In most implementations the Fourier image is shifted in such a way that the DC-value (i.e. the image mean) F(0,0) is displayed in the center of the image

- The further away from the center an image point is, the higher is its corresponding frequency

- Consider applying the Fourier Transform to the below image



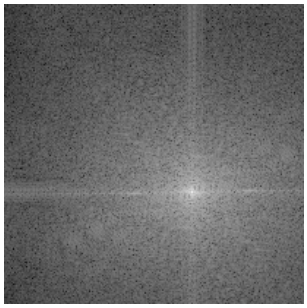
- The magnitude calculated from the complex result is shown below:



- It can be see that the DC-value is the largest component of the image

- The dynamic range of the Fourier coefficients (i.e. the intensity values in the Fourier image) is too large to be displayed on the screen, therefore all other values appear as black

- If a logarithmic transformation is applied to the image the following is obtained

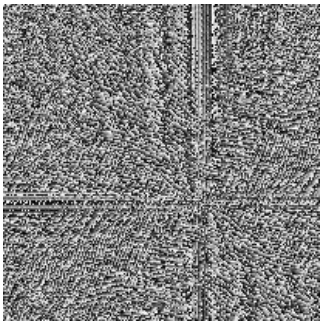


- The result shows that the image contains components of all frequencies, but that their magnitude gets smaller for higher frequencies

- Hence, low frequencies contain more image information than the higher ones

- Transformed image also shows that there are two dominating directions in the Fourier image, one passing vertically and one horizontally through the center. These originate from the regular patterns in the background of the original image

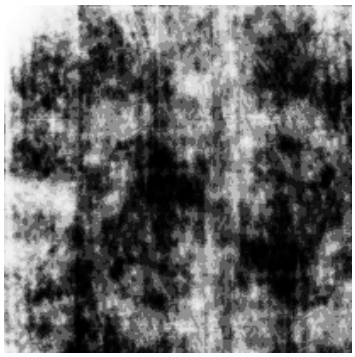
- Phase of the Fourier transform of the same image is shown below



- Value of each point determines the phase of the corresponding frequency

- As in the magnitude image, one can identify the vertical and horizontal lines corresponding to the patterns in the original image

- If inverse Fourier Transform is applied the to the above magnitude image while ignoring the phase (and then histogram equalize the output) below image is obtained



- Although the above image contains the same frequencies (and amount of frequencies) as the original input image, it is so corrupted that it can not be recognized

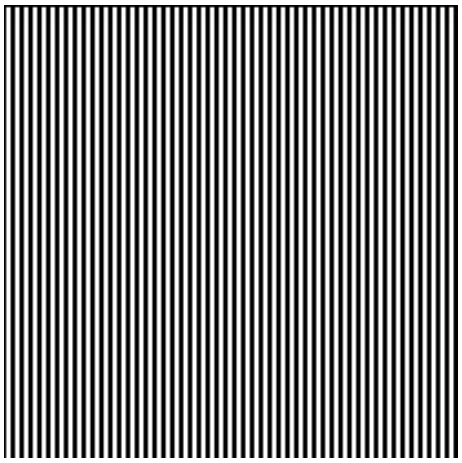
- This shows that the phase information is crucial to reconstruct the correct image in the spatial domain

- The phase image does not yield much new information about the structure of the spatial domain image so in the following examples only the magnitude of the Fourier Transform will be displayed

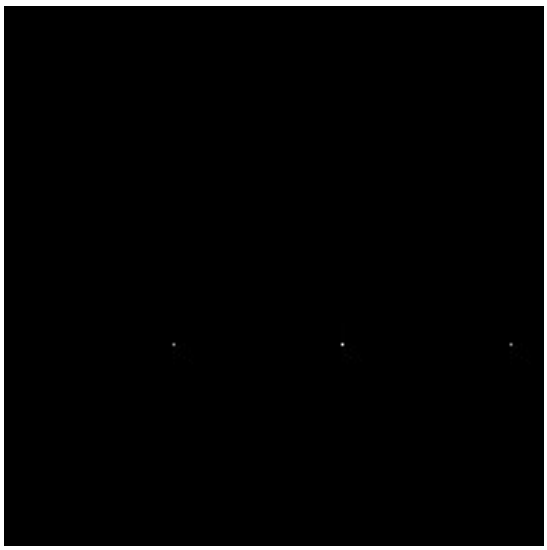
- Below some simple images will be investigated to better understand the nature of the Fourier transform

- Response of the Fourier Transform to periodic patterns in the spatial domain images can be seen in the following artificial images

- The below image shows 2 pixel wide vertical stripes



- Fourier transform of this image is shown below



- Above it can be seen that it contains 3 main values: the DC-value and since the Fourier image is symmetrical to its center, two points corresponding to the frequency of the stripes in the original image

- Note that the two points lie on a horizontal line through the image center, because the image intensity in the spatial domain changes the most if we go along it horizontally

- The distance of the points to the center can be explained as follows: the maximum frequency which can be represented in the spatial domain are one pixel wide stripes

  f_{max}= (1/1 pixel)

- Hence, the two pixel wide stripes in the above image represent

  f = (1/2 pixel) = f_{max}/2

- Thus, the points in the Fourier image are halfway between the center and the edge of the image, i.e. the represented frequency is half of the maximum

14. Feature Reduction

Feature reduction focuses on decreasing computational overhead, dropping redundant inputs, and avoiding the "curse of dimensionality" (the Hughes phenomenon) by eliminating ineffective variables or highly correlated bands.

14.1. Separability Measures

Separability measures mathematically assess how effectively different land-cover classes can be distinguished from each other within a chosen feature space. They are primary criteria used during **band selection** workflows.

- **Divergence:** Evaluates the statistical distance between two class probability distributions. Standard divergence expands quadratically with class distance, which can cause misleading calculations if a few outlier classes skew the variance.
- **Transformed Divergence (TD):** Applies an exponential saturation filter to the standard divergence calculation. It forces values onto a strict boundary scale between 0 and 2.0 (or 2000), where high values signify clear class separability.
- **Bhattacharyya Distance:** Computes the overall statistical overlap between two normal distributions. This metric assumes Gaussian class structures and checks for shifts in both mean vectors and covariance matrices.
- **Jeffries-Matusita (JM) Distance:** A non-linear logarithmic transformation applied to the Bhattacharyya distance. Like TD, the JM distance saturates asymptotically at a maximum value of 2.0, minimizing statistical distortion caused by extreme, widely separated outliers.

14.2. Feature Reduction by Data Transformation

Instead of picking out a subset of raw, unmodified bands, **feature extraction** uses linear or non-linear operators to project the entire multi-band space into a brand-new, optimized coordinate system.

- **Principal Component Analysis (PCA):** An unsupervised transformation that aligns correlated multispectral data along a fresh set of orthogonal axes (Principal Components) arranged by decreasing variance. The leading components normally contain the vast majority of useful scene information, while background noise is relegated to the tail-end components.
- **Canonical Analysis (Linear Discriminant Analysis - LDA):** A supervised feature extraction technique that maximizes the ratio of among-class variance to within-class variance. It seeks new coordinate axes that explicitly maximize the distance between pre-identified training classes.
- **Minimum Noise Fraction (MNF):** A specialized two-stage cascade PCA model frequently applied to hyperspectral files. It orders the newly generated components based on their direct Signal-to-Noise Ratio (SNR) rather than total variance alone.

15. Statistical Methods

Statistical methods establish the mathematical frame for traditional pixel-level mapping, classification, and parametric design recognition.

- **Parametric Classifiers:** Rely on a central assumption that the underlying pixel dataset follows a known, symmetric probability distribution (typically a normal Gaussian distribution).
    - **Maximum Likelihood Classifier (MLC):** Assigns an unknown pixel to whichever thematic class has the highest probability density at that exact coordinate

location. This method relies heavily on accurately calculated class mean vectors and covariance matrices.
    - **Mahalanobis Distance Classifier:** An asymmetrical distance metric that accounts for distinct class variability by utilizing the group covariance matrix. It assumes all classes exhibit uniform covariance structures.
- **Non-Parametric Classifiers:** Do not require or assume any fixed, underlying probability distribution profile. They excel when mapping multimodal, asymmetrical data envelopes.
    - **k-Nearest Neighbor (k-NN):** Classifies a given pixel vector based on a simple majority vote among its closest neighboring training samples within the multidimensional feature space.
    - **Decision Trees:** Hierarchical, branching structures that split complex datasets into distinct classes using sequential, rule-based value thresholds.

16. Knowledge-Based Image Analysis

Conventional classification routines review images pixel-by-pixel using standalone spectral values from single capture dates. **Knowledge-based image analysis** incorporates non-spectral datasets, geographical rules, and logical spatial reasoning into the data extraction pipeline.

- **Contextual Data Integration:** Combines spatial, temporal, and external thematic raster vectors (such as Digital Elevation Models, soil classification maps, or road networks managed inside a **Geographic Information System (GIS)**) directly into the classification process.
- **Integration Frameworks:**
    - **Pre-classification Stratification:** Uses cartographic boundaries (e.g., regional administrative borders or elevation zones) to break an image into discrete zones so that each region can be handled with its own custom classifier.
    - **Classifier Modification:** Injects deterministic or probabilistic rules during execution to adjust initial class weights and probabilities dynamically.
    - **Post-classification Editing:** Deploys an automated expert rule system after initial classification to identify and fix logical spatial anomalies (e.g., correcting an error where a pixel is labeled as "mangrove swamp" on an alpine mountain ridge).
- **Evidential Reasoning (Dempster-Shafer Theory):** A mathematical probability architecture designed to combine separate, sometimes conflicting evidence from independent spectral classifiers and GIS rules into a unified final decision.
- **Object-Based Image Analysis (OBIA):** Groups adjacent, similar pixels into meaningful vector objects (segments) before classification. This permits the rule engine to incorporate shape parameters, structural texture, and relative spatial topology into the model.

17. Hyperspectral Image Data

While standard multispectral satellites capture wide, disconnected sections of the spectrum, **hyperspectral sensors** systematically record electromagnetic energy across hundreds of narrow, continuous bands.

17.1. Data Volume, Redundancy, and Calibration

- **Data Volume & Multi-Collinearity:** Collecting hundreds of bands produces large data payloads. Because adjacent narrow bands match closely, hyperspectral datasets exhibit

massive spectral redundancy, leading to unstable statistical estimates during parametric modeling.
- **Calibration:** Hyperspectral routines require converting raw Digital Numbers (DN) into precise Top-of-Atmosphere (TOA) radiance, followed by surface reflectance calibration to eliminate atmospheric scattering and absorption artifacts.

17.2. Spectral Analysis

- **Spectral Signatures:** Ultra-narrow band gaps record distinct, fine-scale absorption and reflectance features that act as fingerprints for specific surface materials.
- **Spectral Matching Algorithms:**
  - **Spectral Angle Mapper (SAM):** Measures the geometric angle between an unknown pixel spectrum vector and a reference library spectrum vector across an-dimensional space. It assesses overall curve shape independent of variations in lighting and shading.
  - **Spectral Mixture Analysis (SMA) / Linear Unmixing:** Resolves sub-pixel details by modeling a pixel's total reflectance as a linear combination of distinct, pure target components called **endmembers** (e.g., fraction percentages of pure soil, deep water, and green foliage within one pixel).

17.3. Spectral Transformations

- **Derivative Spectroscopy:** Calculates the first or second-order mathematical derivatives of a continuous reflectance curve to accent fine inflection points and separate overlapping absorption bands (e.g., pinpointing the exact "red edge" shifting point in vegetation).
- **Continuum Removal:** Standardizes a complex reflectance curve by fitting a mathematical hull over the top of the spectrum, isolating local absorption pits to objectively isolate their specific width, depth, and material composition.

17.4. Compression

Due to the large data footprint of hyperspectral data cubes, compression is critical for onboard storage and downlinking.

- **Lossless Compression:** Shrinks file sizes while guaranteeing that the restored data matches the original, bit-for-bit ground truth exactly (e.g., Huffman or LZW encoding).
- **Lossy Compression:** Permanently discards imperceptible noise or redundant data variance to achieve much higher compression ratios (e.g., JPEG2000 or 3D Wavelet compression models).

18. Examples of Remote Sensing Applications

Remote sensing datasets function as active, scalable tools for global observation, environmental protection, and asset management.

- **Precision Agriculture:** Checking crop stress, predicting agricultural yields, and mapping field boundaries over time by monitoring localized vegetation index variations.
- **Urban Mapping & Development:** Automatically extracting 3D road networks, detecting buildings, and measuring shifts in municipal green space using object-based geometric analysis.

- **Geology & Mining:** Mapping surface mineral deposits and matching outcropping formations by cross-referencing narrow absorption positions with global spectral library databases.
- **Environmental Management:** Assessing ecosystem degradation, tracking regional land-use change, and running quality controls across sensitive river watersheds and forest reserves.