2. DIGITAL IMAGE PROCESSING
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Image Processing and Analysis can be defined as the "act of examining images for the purpose of identifying objects and judging their significance". Image analysts study the remotely sensed data and attempt through logical process in detecting, identifying, classifying, measuring, and evaluating the significance of physical and cultural objects, their patterns, and spatial relationships.

Digital Image Processing is a collection of techniques for the manipulation of digital images by computers. The raw data received from the imaging sensors on the satellite platforms contains flaws and deficiencies. To overcome these flaws and deficiencies in order to get the originality of the data, it needs to undergo several steps of processing. This will vary from image to image depending on the type of image format, initial condition of the image, and the information of interest and the composition of the image scene.

Digital Image Processing undergoes three general steps:

- Pre-processing or Image correction
- Enhancement
- Information extraction or Interpretation or image classification

**Pre-processing** consists of those operations that prepare data for subsequent analysis that attempts to correct or compensate for systematic errors. The digital imageries are subjected to several corrections such as geometric, radiometric, and atmospheric, though all this correction might not be necessarily applied in all cases. These errors are systematic and can be removed before they reach the user. The investigator should decide which pre-processing techniques are relevant on the basis of the nature of the information.
to be extracted from remotely sensed data. After pre-processing is complete, the analyst may use feature extraction to reduce the dimensionality of the data. Thus feature extraction is the process of isolating the most useful components of the data for further study while discarding the less useful aspects (errors, noise etc). Feature extraction reduces the number of variables that must be examined, thereby saving time and resources.

**Image Enhancement** operations are carried out to improve the interpretability of the image by increasing apparent contrast among various features in the scene. The enhancement techniques depend upon two factors mainly

- The digital data (i.e. with spectral bands and resolution)
- The objectives of interpretation

As an image enhancement technique often drastically alters the original numeric data, it is normally used only for visual (manual) interpretation and not for further numeric analysis. Common enhancements include image reduction, image rectification, and image magnification; transect extraction, contrast adjustments, band rationing, spatial filtering, Fourier transformations, and principal component analysis and texture transformation.

**Information Extraction** is the last step towards the final output of the image analysis. After pre-processing and image enhancement the remotely sensed data is subjected to quantitative analysis to assign individual pixels to specific classes. Classification of the image is based on the known and unknown identity to classify the remainder of the image consisting of those pixels of unknown identity. After classification is complete, it is necessary to evaluate
its accuracy by comparing the categories on the classified images with the areas of known identity on the ground. The final result of the analysis consists of maps (or images), data and a report. These three components of the result provide the user with full information concerning the source data, the method of analysis and the outcome and its reliability.

2.1 Pre-Processing of the Remotely Sensed Images

When remotely sensed data is received from the imaging sensors on the satellite platforms it contains flaws and deficiencies. Pre-processing refers to those operations that are preliminary to the main analysis. Preprocessing includes a wide range of operations from the very simple to extremes of abstractness and complexity. These are categorized as:

1. Feature Extraction
2. Radiometric Corrections
3. Geometric Corrections
4. Atmospheric Correction

The techniques involved in removal of unwanted and distracting elements such as image/system noise, atmospheric interference and sensor motion from an image data occurred due to limitations in the sensing of signal digitization, or data recording or transmission process. Removal of these effects from the digital data are said to be "restored" to their correct or original condition, although we can, of course never know what are the correct values might be and must always remember that attempts to correct data what may
themselves introduce errors. Thus image restoration includes the efforts to correct for both radiometric and geometric errors.

**Feature Extraction**

Feature Extraction does not mean geographical features visible on the image but rather "statistical" characteristics of image data like individual bands or combination of band values that carry information concerning systematic variation within the scene. Thus in a multispectral data it helps in portraying the necessity elements of the image. It also reduces the number of spectral bands that has to be analyzed. After the feature extraction is completed the analyst can work with the desired channels or bands, but in turn the individual bandwidths are more potent for information. Finally such a pre-processing increases the speed and reduces the cost of analysis.

**Radiometric Corrections**

Radiometric Corrections are carried out when an image data is recorded by the sensors they contain errors in the measured brightness values of the pixels. These errors are referred as radiometric errors and can result from the

1. Instruments used to record the data
2. From the effect of the atmosphere

Radiometric processing influences the brightness values of an image to correct for sensor malfunctions or to adjust the values to compensate for atmospheric degradation. Radiometric distortion can be of two types:
1. The relative distribution of brightness over an image in a given band can be different to that in the ground scene.

2. The relative brightness of a single pixel from band to band can be distorted compared with spectral reflectance character of the corresponding region on the ground.

The following methods define the outline for the basis of the cosmetic operations for the removal of defects:

**Line-Dropouts**
A string of adjacent pixels in a scan line contain spurious DN. This can occur when a detector malfunctions permanently or temporarily. Detectors are loaded by receiving sudden high radiance, creating a line or partial line of data with the meaningless DN. Line dropouts are usually corrected either by replacing the defective line by a duplicate of preceding or subsequent line, or taking the average of the two. If the spurious pixel, sample x, line y has a value DNx, y then the algorithms are simply:

\[
\begin{align*}
    DN_{x,y} &= DN_{x,y-1} \\
    DN_{x,y} &= (DN_{x, y-1} + DN_{x, y+1})/2
\end{align*}
\]

DN=Digital Number

**De-Striping**
Banding or striping occurs if one or more detectors go out of adjustment in a given band. The systematic horizontal banding pattern seen on images produced by electro-mechanical scanners such as Landsat's MSS and TM results in a repeated patterns of lines with consistently high or low DN. Two reasons can be thus put forward in favor of applying a 'de-striping' correction:
1. The visual appearance and interpretability of the image are thereby improved.

2. Equal pixel values in the image are more likely to represent areas of equal ground leaving radiance, other things being equal.

*The two different methods of de-striping are as follow:*  
First method entails a construction of histograms for each detector of the problem band, i.e., histograms generated from by the six detectors: these histograms are calculated for the lines 1, 7, 13, lines 2, 8, 14, etc. Then the means and standard deviation are calculated for each of the six histograms. Assuming the proportion of pixels representing different soils, water, vegetation, cloud, etc. are the same for each detector, the means and standard deviations of the 6 histograms should be the same. Stripes however are characterized by distinct histograms. De-striping then requires equalization of the means and standard deviation of the six detectors by forcing them to equal selected values - usually the mean and standard deviation for the whole image.  
The process of histogram matching is also utilized before mosaicking image data of adjacent scenes (recorded at different times) so as to accommodate differences in illumination levels, angles etc. A further application is resolution merging, in which merging with high spatial resolution image sharpens a low spatial resolution image.

Second method is a non-linear in the sense that relationship between radiance rin (received at the detector) and rout (output by the sensor) is not describable in terms of single linear segments.
Random Noise

Odd pixels that have spurious DN crop up frequently in images - if they are particularly distracting, they can be suppressed by spatial filtering. By definition, these defects can be identified by their marked differences in DN from adjacent pixels in the affected band. Noisy pixels can be replaced by substituting for an average value of the neighborhood DN. Moving windows of $3 \times 3$ or $5 \times 5$ pixels are typically used in such procedures.

Figure 2.1 Cross Track Distortion
Systematic Distortions are well-understood ands easily corrected by applying formulas derived by modeling the sources of distortions mathematically.

**Atmospheric Corrections:**
The output from the instrument on satellite depends on the intensity and spectral distribution of energy that is received at the satellite. The intensity and spectral distribution of energy/radiation has traveled some distance through the atmosphere and accordingly has suffered both attenuation and augmentation in the course of journey. The problem comes when one is not able to regenerate the correct radiation properties of the target body on the earth surface with the data generated by the remote sensing.

**Effect Of The Atmosphere on Radiation (Radioactive Transfer Theory)**
Fig 2.2 depicts the effect of the atmosphere in determining various paths for energy to illuminate a pixel and reach the sensor. The path radiation coming from the sun to the ground pixel and then being reflected to the sensor. In this on going process, absorption by atmospheric molecules takes place that converts incoming energy into heat. In particular, molecules of oxygen, carbon-di-oxide, ozone and water attenuate the radiation very strongly in certain wavelengths. Scattering by these atmospheric particles is also the dominant mechanism that leads to radiometric distortion in image data.
Figure 2.2

Effect of the atmosphere in determining various paths for energy to Ultimate a pixel and to Reach the Sensor
Radioactive Transfer theory is used to make quantitative calculations of the difference between the satellite received radiance and earth leaving radiance. Radiation traveling in a certain direction is specified by the angle \( f \) between that direction and the vertical axis \( z \) and setting a differential equation for a small horizontal element of the transmitting medium (the atmosphere) with thickness \( dz \). The resulting differential equation is called the radioactive transfer equation. The equation will therefore be different for different wavelengths of electromagnetic radiation because of the different relative importance of different physical process at different wavelength.

**Need for Atmospheric Correction:**

When an image is to be utilized, it is frequently necessary to make corrections in brightness and geometry for accuracy during interpretation and also some of the application may require correction to evaluate the image accurately. The various reason for which correction should be done:

- Derive ratios in 2 bands of multi spectral image since the effect of atmospheric scattering depends on the wavelength, the two channels will be unequally affected and the computed ratio will not accurately reflect the true ratio leaving the earth's surface.

- When land surface reflectance or sea surface temperature is to be determined.
• When two images taken at different times and needed to be compared or mosaic the images

**Correction Methods**

Rectifying the image data for the degrading effects of the atmosphere entails modeling the scattering and absorption processes that take place. There are a number of ways of correcting the image data for atmospheric correction

• Ignore the atmosphere

• Collecting the ground truth measurements of target temperature, reflectance etc and calibrating these values or quantities on the ground and the radiance values by the sensor.

• Modeling the absorption or scattering effects for the measurement of the composition and temperature profile of the atmosphere.

• Utilizing the information about the atmosphere inherent to remotely sensed data i.e. use the image to correct itself.

**Correcting For Atmospheric Scattering**

This correction is done when the two bands of image are subjected to ratio analysis. Atmospheric scattering scatters short wavelength and causes haze and reduces the contrast ratio of images. This follows two techniques for example TM bands 1 & 7, where TM 1 has the highest component of 1 and the TM7 (infrared) has the least. Both techniques are DN value dependent as TM band 7 is free from scattering effect there it has DN value either 0 or 1 (shadows).
1. In TM 7 the shadows having DN value 0 & 1. Now for each pixel the DN in TM 7 is plotted against TM 1 and a straight line is fitted through the plot using least square techniques. If there were no haze in TM 1 then the line would pass through the origin. But as there is haze the intercept is offset along the band 1. Haze has an additive effect on scene brightness. Therefore to correct the haze effect on TM 1, the value of the intercept offset is subtracted from the DN of each band 1 pixel for the entire image. (Fig 2.3)

Figure 2.3 Scattering of DN values
2. The second technique also uses the areas with DN as 0 or 1 in TM 7 which is shown in Fig 2.4. The histogram of TM 7 has pixels with 0 whereas the histogram of TM 1 lacks the pixel in the range from 0 to 20 approximately because of light scattered into the detector by atmosphere thus this abrupt increase in pixels in TM 1 is subtracted from all the DNs in band 1 to restore effects of atmospheric scattering.

Figure 2.4 Intensity variations of DN Values
The amount of atmospheric correction depends upon

- Wavelength of the bands
- Atmospheric conditions

Short wavelength cause more severe scattering. Humid, smoggy and dusty cause more scattering than clear and dry atmospheres.

2.2 IMAGE ENHANCEMENT

Image Enhancement techniques are instigated for making satellite imageries more informative and helping to achieve the goal of image interpretation. The term enhancement is used to mean the alteration of the appearance of an image in such a way that the information contained in that image is more readily interpreted visually in terms of a particular need. The most commonly applied digital enhancement techniques. Three techniques can be categorized as contrast manipulation. Spatial feature manipulation, or multi image manipulation. Within these broad categories, we treat the following:

1. **Contrast Manipulation:** Gray-level threshold, level slicing, and contrast stretching.

2. **Spatial enhancement:** Spatial filtering, edge enhancement, and Fourier analysis.

3. **Multi-image manipulation:** Multispectral band rationing and differencing, principal components, canonical components, vegetation components, intensity-hue-saturation (HIS) colors space transformations, and decorrelation stretching.
**Contrast Manipulation:**

**Density Slicing**

Density Slicing is the mapping of a range of contiguous grey levels of a single band image to a point in the RGB color cube. The DNs of a given band are "sliced" into distinct classes. For example, for band 4 of a TM 8 bit image, we might divide the 0-255 continuous ranges into discrete intervals of 0-63, 64-127, 128-191 and 192-255. These four classes are displayed as four different grey levels. This kind of density slicing is often used in displaying temperature maps.

**Contrast Stretching**

The operating or dynamic, ranges of remote sensors are often designed with a variety of eventual data applications. For example for any particular area that is being imaged it is unlikely that the full dynamic range of sensor will be used and the corresponding image is dull and lacking in contrast or over bright. Landsat TM images can end up being used to study deserts, ice sheets, oceans, forests etc., requiring relatively low gain sensors to cope with the widely varying radiances upwelling from dark, bright, hot and cold targets. Consequently, it is unlikely that the full radiometric range of brand is utilized in an image of a particular area. The result is an image lacking in contrast - but by remapping the DN distribution to the full display capabilities of an image processing system, we can recover a beautiful image. Contrast Stretching can be displayed in three categories:

**Linear Contrast Stretch**

This technique involves the translation of the image pixel values from the observed range DNmin to DNmax to the full range of the
The display device (generally 0-255, which is the range of values represent in an 8bit display devices) This technique can be applied to a single band, grey-scale image, where the image data are mapped to the display via all three colors LUTs.

It is not necessary to stretch between DNmax and DNmin - Inflection points for a linear contrast stretch from the 5th and 95th percentiles, or ±2 standard deviations from the mean (for instance) of the histogram, or to cover the class of land cover of interest (e.g. water at expense of land or vice versa). It is also straightforward to have more than two inflection points in a linear stretch, yielding a piecewise linear stretch.

**Histogram Equalization**
The underlying principle of histogram equalization is straightforward and simple; it is assumed that each level in the displayed image should contain an approximately equal number of pixel values, so that the histogram of these displayed values is almost uniform (though not all 256 classes are necessarily occupied). The objective of the histogram equalization is to spread the range of pixel values present in the input image over the full range of the display device.

**Gaussian Stretch**
This method of contrast enhancement is based upon the histogram of the pixel values is called a Gaussian stretch because it involves the fitting of the observed histogram to a normal or Gaussian histogram.
**Spatial enhancement:**

**Spatial filtering:**
*Spatial Filtering* can be described as selectively emphasizing or suppressing information at different spatial scales over an image. Filtering techniques can be implemented through the Fourier transform in the frequency domain or in the spatial domain by convolution.

**Convolution Filters**
Filtering methods exists is based upon the transformation of the image into its scale or spatial frequency components using the Fourier transform. The spatial domain filters or the convolution filters are generally classed as either high-pass (sharpening) or as low-pass (smoothing) filters.

**Low-Pass (Smoothing) Filters**
Low-pass filters reveal underlying two-dimensional waveform with a long wavelength or low frequency image contrast at the expense of higher spatial frequencies. Low-frequency information allows the identification of the background pattern, and produces an output image in which the detail has been smoothed or removed from the original.

A 2-dimensional moving-average filter is defined in terms of its dimensions, which must be odd, positive and integral but not necessarily equal, and its coefficients. The output DN is found by dividing the sum of the products of corresponding convolution kernel
and image elements often divided by the number of kernel elements.

A similar effect is given from a median filter where the convolution kernel is a description of the PSF weights. Choosing the median value from the moving window does a better job of suppressing noise and preserving edges than the mean filter.

Adaptive filters have kernel coefficients calculated for each window position based on the mean and variance of the original DN in the underlying image.

**High-Pass (Sharpening) Filters**

Simply subtracting the low-frequency image resulting from a low pass filter from the original image can enhance high spatial frequencies. High-frequency information allows us either to isolate or to amplify the local detail. If the high-frequency detail is amplified by adding back to the image some multiple of the high frequency component extracted by the filter, then the result is a sharper, de-blurred image.

High-pass convolution filters can be designed by representing a PSF with positive center weights and negative surrounding weights. A typical 3x3 Laplacian filter has a kernel with a high central value, 0 at each corner, and -1 at the center of each edge. Such filters can be biased in certain directions for enhancement of edges.

A high-pass filtering can be performed simply based on the mathematical concepts of derivatives, i.e., gradients in DN throughout the image. Since images are not continuous functions,
calculus is dispensed with and instead derivatives are estimated from the differences in the DN of adjacent pixels in the x, y or diagonal directions. Directional first differencing aims at emphasizing edges in image.

**Frequency Domain Filters**
The Fourier transform of an image, as expressed by the amplitude spectrum is a breakdown of the image into its frequency or scale components. Filtering of these components use frequency domain filters that operate on the amplitude spectrum of an image and remove, attenuate or amplify the amplitudes in specified wavebands. The frequency domain can be represented as a 2-dimensional scatter plot known as a Fourier spectrum, in which lower frequencies fall at the center and progressively higher frequencies are plotted outward.

Filtering in the frequency domain consists of 3 steps:

- Fourier transform the original image and compute the Fourier spectrum
- Select an appropriate filter transfer function (equivalent to the OTF of an optical system) and multiply by the elements of the Fourier spectrum.
- Perform an inverse Fourier transform to return to the spatial domain for display purposes.

**Multi-Spectral Enhancement Techniques**

**Image Arithmetic Operations**
The operations of addition, subtraction, multiplication and division are performed on two or more co-registered images of the same
geographical area. These techniques are applied to images from separate spectral bands from single multispectral data set or they may be individual bands from image data sets that have been collected at different dates. More complicated algebra is sometimes encountered in derivation of sea-surface temperature from multispectral thermal infrared data (so called split-window and multi channel techniques).

**Addition of images** is generally carried out to give dynamic range of image that equals the input images.

**Band Subtraction** Operation on images is sometimes carried out to co-register scenes of the same area acquired at different times for change detection.

**Multiplication of images** normally involves the use of a single 'real' image and binary image made up of ones and zeros.

**Band Rationing** or Division of images is probably the most common arithmetic operation that is most widely applied to images in geological, ecological and agricultural applications of remote sensing. Ratio Images are enhancements resulting from the division of DN values of one spectral band by corresponding DN of another band. One investigation for this is to iron out differences in scene illumination due to cloud or topographic shadow. Ratio images also bring out spectral variation in different target materials. Multiple ratio images can be used to drive red, green and blue monitor guns for color images. Interpretation of ratio images must consider that they are "intensity blind", i.e., dissimilar materials with different
absolute reflectance’s but similar relative reflectance’s in the two or more utilized bands will look the same in the output image.

**Principal Component Analysis**

Spectrally adjacent bands in a multispectral remotely sensed image are often highly correlated. Multiband visible/near-infrared images of vegetated areas will show negative correlations between the near-infrared and visible red bands and positive correlations among the visible bands because the spectral characteristics of vegetation are such that as the vigor or greenness of the vegetation increases the red reflectance diminishes and the near-infrared reflectance increases. Thus presence of correlations among the bands of a multispectral image implies that there is redundancy in the data and *Principal Component Analysis* aims at removing this redundancy.

*Principal Components Analysis* (PCA) is related to another statistical technique called factor analysis and can be used to transform a set of image bands such that the new bands (called principal components) are uncorrelated with one another and are ordered in terms of the amount of image variation they explain. The components are thus a statistical abstraction of the variability inherent in the original band set.

To transform the original data onto the new principal component axes, transformations coefficients (eigen values and eigen vectors) are obtained that are further applied in a linear fashion to the original pixel values. This linear transformation is derived from the covariance matrix of the original data set. These transformation coefficients describe the lengths and directions of the principal axes. Such transformations are generally applied either as an
enhancement operation, or prior to classification of data. In the context of PCA, information means variance or scatter about the mean. Multispectral data generally have a dimensionality that is less than the number of spectral bands. The purpose of PCA is to define the dimensionality and to fix the coefficients that specify the set of axes, which point in the directions of greatest variability. The bands of PCA are often more interpretable than the source data.

**Canonical Components**

PCA is appropriate when little prior information about the scene is available. Canonical component analysis, also referred to as multiple discriminate analyses, may be appropriate when information about particular features of interest is available. Canonical component axes are located to maximize the reparability of different user-defined feature types.

**Hue, Saturation and Intensity (HIS) Transform**

Mixing red generates hues; coordinates on the red, green and blue axes of the color cube characterize green and blue light. The hue-saturation-intensity hex cone model, where hue is the dominant wavelength of the perceived color represented by angular position around the top of a hex cone, saturation or purity is given by distance from the central, vertical axis of the hex cone and intensity or value is represented by distance above the apex of the hex cone. Hue is what we perceive as color. Saturation is the degree of purity of the color and may be considered to be the amount of white mixed in with the color. It is sometimes useful to convert from RGB color cube coordinates to HIS hex cone coordinates and vice-versa.
The hue, saturation and intensity transform is useful in two ways: first as a method of image enhancement and secondly as a means of combining co-registered images from different sources. The advantage of the HIS system is that it is a more precise representation of human color vision than the RGB system. This transformation has been quite useful for geological applications.

**Fourier Transformation**

The Fourier Transform operates on a single-band image. Its purpose is to break down the image into its scale components, which are defined to be sinusoidal waves with varying amplitudes, frequencies and directions. The coordinates of two-dimensional space are expressed in terms of frequency (cycles per basic interval). The function of Fourier Transform is to convert a single-band image from its spatial domain representation to the equivalent frequency-domain representation and vice-versa.

The idea underlying the Fourier Transform is that the grey-scale values forming a single-band image can be viewed as a three-dimensional intensity surface, with the rows and columns defining two axes and the grey-level value at each pixel giving the third (z) dimension. The Fourier Transform thus provides details of

- The frequency of each of the scale components of the image
- The proportion of information associated with each frequency component.
2.3 Image Interpretations or Classification

Image Classification has formed an important part of the fields of Remote Sensing, Image Analysis and Pattern Recognition. In some instances, the classification itself may form the object of the analysis. Digital Image Classification is the process of sorting all the pixels in an image into a finite number of individual classes. The classification process is based on following assumptions:

- Patterns of their DN, usually in multi channel data (Spectral Classification).
- Spatial relationship with neighboring pixels
- Relationships between the data acquired on different dates.

Pattern Recognition, Spectral Classification, Textural Analysis and Change Detection are different forms of classification that are focused on 3 main objectives:

1. Detection of different kinds of features in an image.
2. Discrimination of distinctive shapes and spatial patterns
3. Identification of temporal changes in image

Fundamentally spectral classification forms the bases to map objectively the areas of the image that have similar spectral reflectance/emissive characteristics. Depending on the type of information required, spectral classes may be associated with identified features in the image (supervised classification) or may be chosen statistically (unsupervised classification). Classification has also seen as a means to compressing image data by reducing the large range of DN in several spectral bands to a few classes in a single image. Classification reduces this large spectral space into
relatively a few regions and obviously results in loss of numerical information from the original image. There is no theoretical limit to the dimensionality used for the classification, though obviously the more bands involved, the more computationally intensive the process becomes. It is often wise to remove redundant bands before classification.

Classification generally comprises four steps:

- **Pre-processing**, e.g., atmospheric correction, noise suppression, band rationing, Principal Component Analysis, etc.

- **Training** - selection of the particular features which best describe the pattern

- **Decision** - choice of suitable method for comparing the image patterns with the target patterns.

- **Assessing the accuracy** of the classification

The informational data are classified into systems:

- Supervised
- Unsupervised

**Supervised Classification**

In this system each pixel is supervised for the categorization of the data by specifying to the computer algorithm, numerical descriptors of various class types. There are three basic steps involved in typical supervised classification.

**Training Stage**

The analyst identifies the training area and develops a numerical description of the spectral attributes of the class or land cover type.
During the training stage the location, size, shape and orientation of each pixel type for each class.

**Classification Stage**

Each pixel is categorized into land cover class to which it closely resembles. If the pixel is not similar to the training data, then it is labeled as unknown. Numerical mathematical approaches to the spectral pattern recognition have been classified into various categories.

1. Measurement son Scatter Diagram: Each pixel value is plotted on the graph as the scatter diagram indicating the category of the class. In this case the 2-dimensional digital values attributed to each pixel is plotted on the graph.

2. Minimum Distance to Mean Classifier/Centroid Classifier: This is a simple classification strategy. First the mean vector for each category is determined from the average DN in each band for each class. Computing the distance from its spectral position to each of the means and assigning it to the class with the closest mean can then classify an unknown pixel. One limitation of this technique is that it overlooks the different degrees of variation.

3. Parallelepiped Classifier: For each class the estimate of the maximum and minimum DN in each band is determined. Then Parallelepiped are constructed o as to enclose the scatter in each theme. Then each pixel is tested to see if it falls inside any of the parallelepiped and has limitation.
4. A pixel may fall outside the parallelepiped and remained unclassified.

5. Theme data are so strongly corrected such that a pixel vector that plots at some distance from the theme scatter may yet fall within the decision box and be classified erroneously.

6. Sometimes parallel piped may overlap in which case the decision becomes more complicated then boundary are slipped.

7. Gaussian Maximum Likelihood Classifier: This method determines the variance and covariance of each theme providing the probability function. This is then used to classify an unknown pixel by calculating for each class, the probability that it lies in that class. The pixel is then assigned to the most likely class or if its probability value fail to reach any close defined threshold in any of the class, be labeled as unclassified. Reducing data dimensionally before hand is a one approach to speeding the process up.

**Unsupervised Classification**

This system of classification does not utilize training data as the basis of classification. This classifier involves algorithms that examine the unknown pixels in the image and aggregate them into a number of classes based on the natural groupings or cluster present in the image. The classes that result from this type of classification are spectral classes. Unsupervised classification is the identification, labeling and mapping of these natural classes. This method is usually used when there is less information about the data before classification.
There are several mathematical strategies to represent the clusters of data in spectral space.

1. **Sequential Clustering**
   In this method the pixels are analyzed one at a time pixel-by-pixel and line-by-line. The spectral distance between each analyzed pixel and previously defined cluster means are calculated. If the distance is greater than some threshold value, the pixel begins a new cluster otherwise it contributes to the nearest existing clusters in which case cluster mean is recalculated. Clusters are merged if too many of them are formed by adjusting the threshold value of the cluster means.

2. **Statistical Clustering**
   It overlooks the spatial relationship between adjacent pixels. The algorithm uses 3x3 windows in which all pixels have similar vector in space. The process has two steps
   - Testing for homogeneity within the window of pixels under consideration.
   - Cluster merging and deletion

Here the windows are moved one at time through the image avoiding the overlap. The mean and standard derivation is calculated for each band of the window. The smaller the standard deviation for a given band the greater the homogeneity of the window. These values are then compared by the user specified parameter for delineating the upper and lower limit of the standard deviation. If the window passes the homogeneity test it forms cluster. Clusters are created until the number exceeds the user
defined maximum number of clusters at which point some are merged or deleted according to their weighting and spectral distances.

3. **Iso Data Clustering (Iterative Self Organizing Data Analysis Techniques)**
   Its repeatedly performs an entire classification and recalculates the statistics. The procedure begins with a set of arbitrarily defined cluster means, usually located evenly through the spectral space. After each iteration new means are calculated and the process is repeated until there is some difference between iterations. This method produces good result for the data that are not normally distributed and is also not biased by any section of the image.

4. **RGB Clustering**
   It is a quick method for 3 band, 8 bit data. The algorithm plots all pixels in spectral space and then divides this space into 32 x 32 x 32 clusters. A cluster is required to have minimum number of pixels to become a class. RGB Clustering is not biased to any part of the data.