IMAGE ENHANCEMENT TECHNIQUES

INTRODUCTION

Image enhancement techniques improve the quality of an image as perceived by a human. These techniques are most useful because many satellite images when examined on a colour display give inadequate information for image interpretation. There is no conscious effort to improve the fidelity of the image with regard to some ideal form of the image. There exists a wide variety of techniques for improving image quality. The contrast stretch, density slicing, edge enhancement, and spatial filtering are the more commonly used techniques. Image enhancement is attempted after the image is corrected for geometric and radiometric distortions. Image enhancement methods are applied separately to each band of a multispectral image. Digital techniques have been found to be most satisfactory than the photographic technique for image enhancement, because of the precision and wide variety of digital processes.

Contrast

Contrast generally refers to the difference in luminance or grey level values in an image and is an important characteristic. It can be defined as the ratio of the maximum intensity to the minimum intensity over an image.

$$C = \frac{I_{max}}{I_{min}}$$

Contrast ratio has a strong bearing on the resolving power and detectability of an image. Larger this ratio, more easy it is to interpret the image.

Reasons for low contrast of image data

Most of the satellite images lack adequate contrast and require contrast improvement. Low contrast may result from the following causes:

I. The individual objects and background that make up the terrain may have a nearly uniform electromagnetic response at the wavelength band of energy that is recorded by the remote sensing system. In other words, the scene itself has a low contrast ratio.

II. Scattering of electromagnetic energy by the atmosphere can reduce the contrast of a scene. This effect is most pronounced in the shorter wavelength portions.

III. The remote sensing system may lack sufficient sensitivity to detect and record the contrast of the terrain. Also, incorrect recording techniques can result in low contrast imagery although the scene has a high-contrast ratio.

Images with low contrast ratio are commonly referred to as `Washed out', with nearly uniform tones of gray.

Detectors on the satellite are designed to record a wide range of scene brightness values without getting saturated. They must encompass a range of brightness from black basalt outcrops to white sea ice. However, only a few individual scenes have a brightness range that utilizes the full sensitivity range of remote sensor detectors. The limited range of brightness values in most scenes does not provide adequate contrast for detecting image features. Saturation may also occur when the sensitivity range of a detectors is insufficient to record the full brightness range of a scene. In the case of saturation, the light and dark extremes of brightness on a scene appear as saturated white or black tones on the image.

CONTRAST ENHANCEMENT

Contrast enhancement techniques expand the range of brightness values in an image so that the image can be efficiently displayed in a manner desired by the analyst. The density values in a scene are literally pulled farther apart, that is, expanded over a greater range. The effect is to increase the visual contrast between two areas of different uniform densities. This enables the analyst to discriminate easily between areas initially having a small difference in density.

Contrast enhancement can be effected by a linear or non linear transformation.

Linear Contrast Stretch:

This is the simplest contrast stretch algorithm. The grey values in the original image and the modified image follow a linear relation in this algorithm. A density number in the low range of the original histogram is assigned to extremely black, and a value at the high end is assigned to extremely white. The remaining pixel values are distributed linearly between these extremes. The features or details that were obscure on the original image will be clear in the contrast stretched image.

In exchange for the greatly enhanced contrast of most original brightness values, there is a trade off in the loss of contrast at the extreme high and low density number values. However, when compared to the overall contrast improvement, the contrast losses at the brightness extremes are acceptable trade off, unless one were specifically interested in these elements of the scene.

The equation $Y = ax+b$ performs the linear transformation in a linear contrast stretch method. The values of 'a' and 'b' are computed from the equations.

$$a = (Y_{max} - Y_{min})/X_{max} - X_{min}$$
$$b = (X_{max}\, Y_{min} - X_{min}\, Y_{max})/X_{max} - Y_{min}$$

where,

X = Input pixel value
Y = Output pixel value

X_{max}, X_{min} are the maximum and minimum in the input data values. Y_{max}, Y_{min} are the maximum and minimum values in the output data values. X_{min}, X_{max} values can be obtained from the scene histogram. Histograms are commonly used to display the frequency of occurrence of brightness values. Y_{min} and Y_{max} are usually fixed at 0 and 255 respectively.

When Y_{min} and Y_{max} take the values 0 and 255, the above equation reduces to

$$Y = \frac{X - X_{min}}{X_{max} - X_{min}} \cdot 255$$

Linear contrast stretch operation can be represented graphically as shown in fig 1

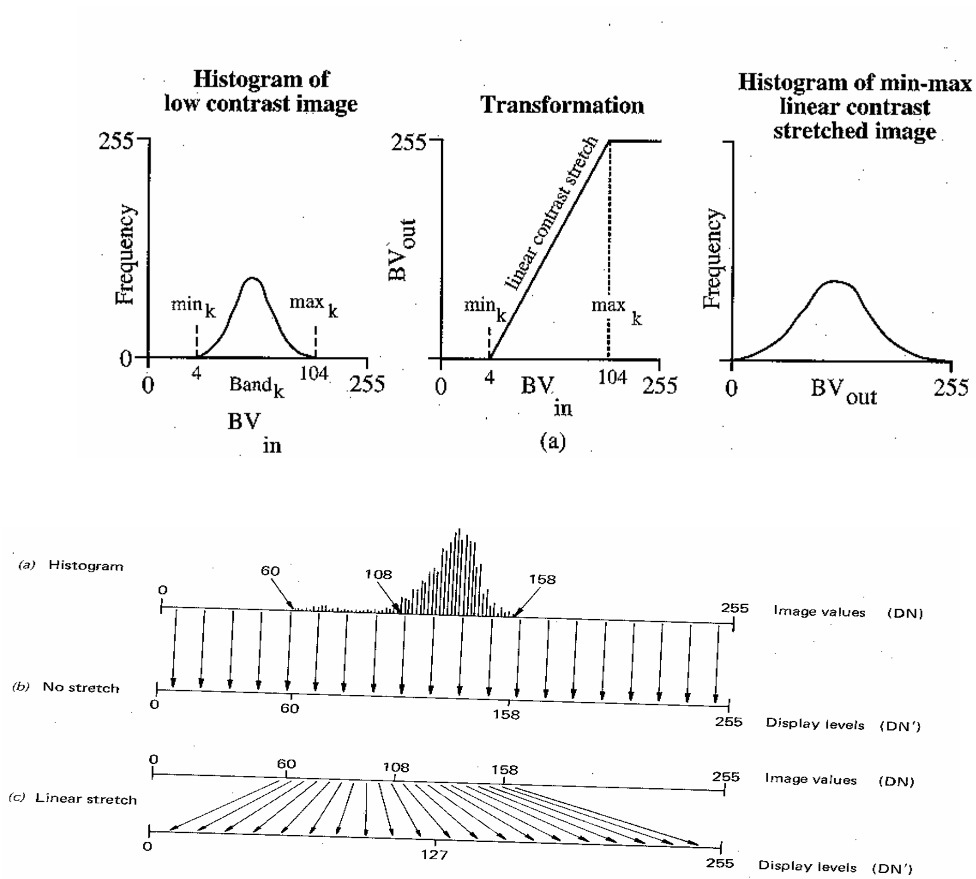


Figure 1 Linear Contrast Transformation Function and Stretch

To provide optimal contrast and colour variation in colour composites the small range of grey values in each band is stretched to the full brightness range of the output or display unit.

Non-Linear Contrast Enhancement:

In these methods, the input and output data values follow a non-linear transformation. The general form of the non-linear contrast enhancement is defined by y = f (x), where x is the input data value and y is the output data value.The non-linear contrast enhancement techniques have been found to be useful for enhancing the colour contrast between the nearly classes and subclasses of a main class.

Though there are several non-linear contrast enhancement algorithms available in literature, the use of non-linear contrast enhancement is restricted by the type of application. Good judgment by the analyst and several iterations through the computer are usually required to produce the desired results.

A type of non linear contrast stretch involves scaling the input data logarithmically . This enhancement has greatest impact on the brightness values found in the darker part of histogram. It could be reversed to enhance values in brighter part of histogram by scaling the input data using an inverse log function.(Refer figure 2).

HISTOGRAM EQUALIZATION

This is another non-linear contrast enhancement technique. In this technique, histogram of the original image is redistributed to produce a uniform population density. This is obtained by grouping certain adjacent grey values. Thus the number of grey levels in the enhanced image is less than the number of grey levels in the original image.

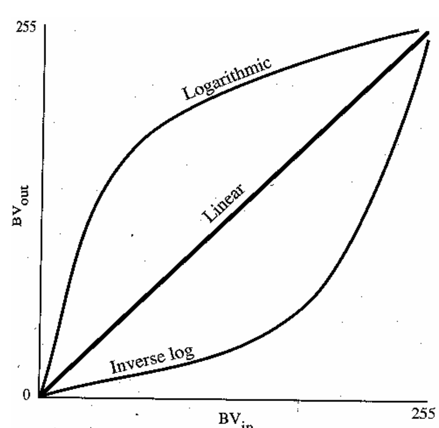


Figure 2 Logic of a Non Linear Logarithmic and Inverse Log Contrast Stretch Algorithms

The redistribution of the histogram results in greatest contrast being applied to the most populated range of brightness values in the original image. In this process the light and dark tails of the original histogram are compressed, thereby resulting in some loss of detail in those regions. This method gives large improvement in image quality when the histogram is highly peaked.

REVIEW OF HISTOGRAM EQUALIZATION USING A HYPOTHETICAL DATA SET

Consider an image that is composed of 64 rows and 64 columns (4096 pixels) with the range of brighter values from 0-7. The frequency of occurrence of individual brightness value is as summarized in Table1 .

Table 1 : Example of Histogram equations of a hypothetical Image

Fre-quency $f(BV_i)$	Original Brightness Value (BV_i)	L_i=Bright-ness Value/n	Cumulative frequency transformation $K_i = \sum_{i=o} \frac{f(BV_i}{n}$	Assign Original BV_i to the new class it is closest to in value
790	0	0	790/4096 =0.19	1
1023	1	0.14	1812/4096=0.44	3
850	2	0.28	2663/4096=0.65	5
656	3	0.42	3319/4096=0.81	6
329	4	0.57	3648/4096=0.89	6
245	5	0.71	3893/4096=0.95	7
122	6	0.85	4015/4096=0.98	7
81	7	1.0	4096/4096=1	7

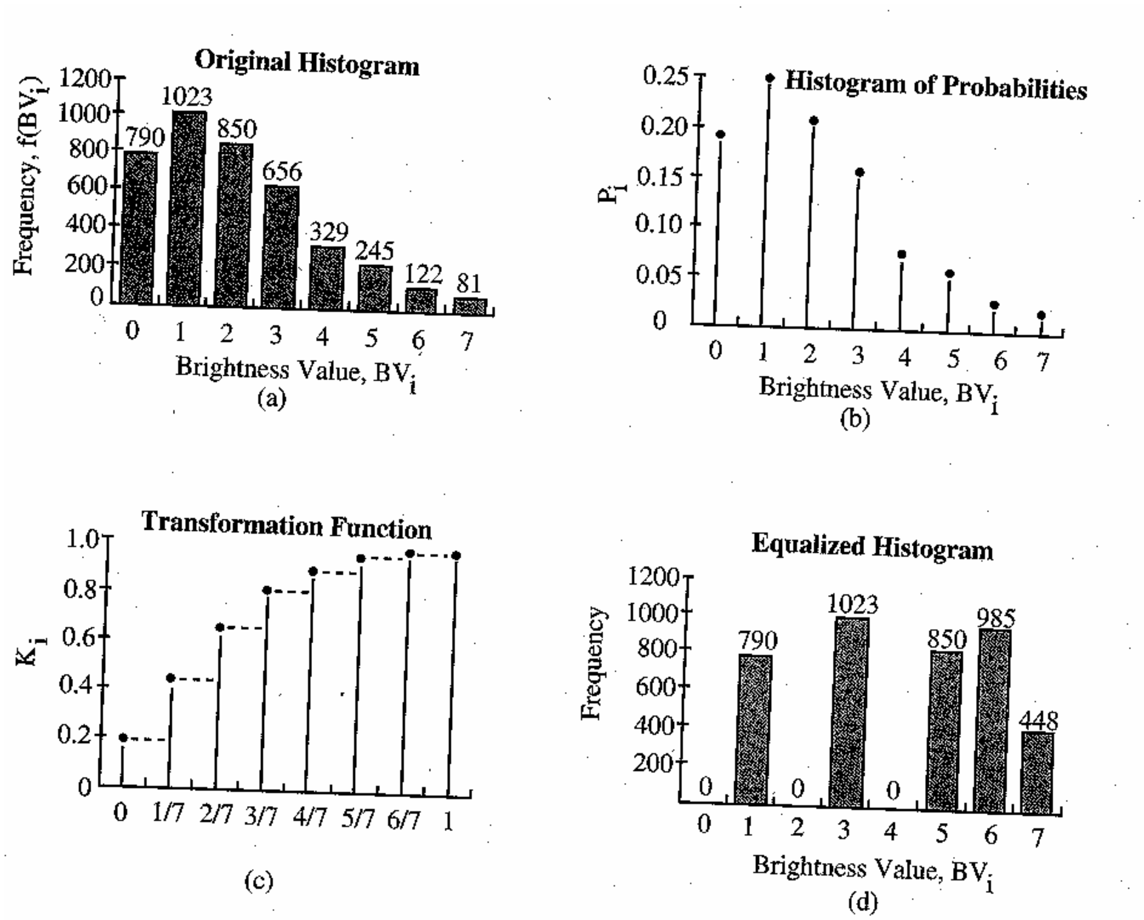


Figure3 Histogram Equalisation process applied to hypothetical data (a) Original Histogram showing the frequency of pixels in each brightness value (b) Original histogram expressed in probabilities (c) The Transformation Function (d) The Equalised Histogram showing frequency of pixels in each brightness value

In the first step, we compute the probability of the Brightness value by dividing each of the frequencies by total number of pixels in the scene. The next step is to compute a transformation function for each individual Brightness Value. For each BV, a new cumulative frequency (K_i) is calculated mechanically given as

$$K_i = \sum_{i=o}^{7} \frac{f(BV_i)}{n}$$

where
- n - total number of pixels (4096)
- $f(BV_i)$ frequency of occurrence of the individual brightness value
- Σ - Summation operator

The histogram equalization procedure iteratively compares the transformation function (K_i) with original normalized Brighter Value (Normalized BV lies between 0-1). The closest match is rearranged to the appropriate BV. (Refer Table 1 & figure 8).

DISCUSSION

The contrast algorithm to be used in an application depends on the subset of data which is of interest to the analyst. Histograms of pixel values help the analyst in identifying the regions of interest. If the analyst recognizes that the most interesting or significant information in an image is contained in the bright regions, he might increase its contrast at the expense of contrast in darker, less important regions.

To maximize the display of information for each component of an entire scene requires more sophisticated contrast stretching. For example, scene that contains land, snow and water has a trinodal histogram. Simple linear stretching would only increase contrast in the centre of the distribution, and would force the high and low peaks further towards saturation. When the three modes in the original data do not overlap, the relative photographic tones of each region are preserved. But, when the modes overlap, the overlap regions will be included in the wrong mode and incorrectly stretched.

With any type of contrast enhancement, the relative tone of different materials is modified. Simple linear stretching has the least effect on relative tones, and brightness differences can still be related to the differences in reflectivity. In other cases, the relative tone can no longer be meaningfully related to the reflectance of materials. An analyst must therefore be fully cognizant of the processing techniques that have been applied to the data.

DENSITY SLICING:

Digital images have high radiometric resolution. Images in some wavelength bands contain 128 distinct grey levels. But, a human interpreter can reliably detect and consistently differentiate between 15 and 25 shades of gray only. However, human eye is more sensitive to colour than the different shades between black and white. Density slicing is a technique that converts the continuous grey tone of an image into a series of density intervals, or slices, each corresponding to a specified digital range. Each slice is displayed in a separate colour, line printer symbol or bounded by contour lines. This technique is applied on each band separately and emphasizes subtle gray scale differences that are imperceptible to the viewer.

The images obtained after density slicing operation must be interpreted with care. This is because of the variations in reflectance's due to the specular angles, variations in atmosphere and incident light results in changes in energy flux. At the sensor, factors such as lens flare, vignetting, and film processing may introduce density variations independent of the scene reflectance. All these factors should be weighed when attempting any enhancement. In general, it is not appropriate to classify a scene by density slicing. The technique is, however, often useful in highlighting variations in low contrast scenes, such as thermal imagery and water bodies.

SPATIAL FILTERING

A characteristic of remotely sensed images is a parameter called spatial frequency defined as number of changes in Brightness Value per unit distance for any particular part of an image. If there are very few changes in Brightness Value once a given area in an image, this is referred to as low frequency area. Conversely, if the Brightness Value change dramatically over short distances, this is an area of high frequency.

Spatial filtering is the process of dividing the image into its constituent spatial frequencies, and selectively altering certain spatial frequencies to emphasize some image features. This technique increases the analyst's ability to discriminate detail. The three types of spatial filters used in remote sensor data processing are : Low pass filters, Band pass filters and High pass filters.

Spatial Convolution Filtering

A linear spatial filter is a filter for which the brightness value ($BV_{i,j}$) at location i, j in the output image is a function of some weighted average (linear combination) of brightness values located in a particular spatial pattern around the i, j location in the input image. This process of evaluating the weighted neighbouring pixel values is called two-dimensional convolution filtering. The procedure is often used to enhance the spatial frequency characteristics of an image. For example, a linear spatial filter that emphasizes high spatial frequencies may sharpen the edges within an image. A linear spatial filter that emphasizes low spatial frequencies may be used to reduce noise within an image.

Low-frequency filtering in the spatial domain

Image enhancement that de-emphasize or block the high spatial frequency detail are low-frequency or low-pass filters. The simplest low-frequency filter (LFF) evaluates a particular input pixel brightness value, BV_{in}, and the pixels surrounding the input pixel, and outputs a new brightness value, BV_{out} , that is the mean of this convolution. The size of the neighbourhood convolution mask or kernel (n) is usually 3x3, 5x5, 7x7, or 9x9. We will constrain this discussion primarily to 3x3 convolution masks with nine coefficients, c_i , defined at the following locations :

$$\text{Mask template} = \begin{array}{ccc} c_1 & c_2 & c_3 \\ c_4 & c_5 & c_6 \\ c_7 & c_8 & c_9 \end{array}$$

For example, the coefficients in a low-frequency convolution mask might all be set equal to 1:

$$\text{Mask A} = \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

The coefficients, c_i , in the mask are multiplied by the following individual brightness value (BV_i) in the input image :

$$\text{Mask template} = \begin{matrix} c_1 \times BV_1 & c_2 \times BV_2 & c_3 \times BV_3 \\ c_4 \times BV_4 & c_5 \times BV_5 & c_6 \times BV_6 \\ c_7 \times BV_7 & c_8 \times BV_8 & c_9 \times BV_9 \end{matrix}$$

where

$BV_1 = BV_{i-1, j-1}$ $\quad$ $BV_6 = BV_{i, j+1}$

$BV_2 = BV_{i-1, j}$ $\quad$ $BV_7 = BV_{i+1, j-1}$

$BV_3 = BV_{i-1, j+1}$ $\quad$ $BV_8 = BV_{i+1, j}$

$BV_4 = BV_{i, j-1}$ $\quad$ $BV_9 = BV_{i+1, j+1}$

$BV_5 = BV_{i, j}$

The primary input pixel under investigation at any one time is $BV_5 = BV_{i,j}$. The convolution of mask A (with all coefficients equal to 1) and the original data will result in a low-frequency image, where

$$LEF_{5,out} = \text{Int} \frac{\sum_{i=1}^{n=9} c_i \times BV_i}{n}$$

$$= \text{Int} \left(\frac{BV_1 + BV_2 + BV_3 + \ldots + BV_9}{9} \right)$$

The spatial moving average then shifts to the next pixel, where the average of all nine brightness values if computed. This operation is repeated for every pixel in the input image. such image smoothing is useful for removing periodic "salt and pepper" noise recorded by electronic remote sensing systems.

The simple smoothing operation will, however, blur the image, especially at the edges of objects. Blurring becomes more severe as the size of the kernel increases.

Using a 3x3 kernel can result in the low-pass image being two lines and two columns smaller than the original image. Techniques that can be applied to deal with this problem include (1) artificially extending the original image beyond its border by repeating the original border pixel brightness values or (2) replicating the averaged brightness values near the borders, based on the image behavior within a view pixels of the border.

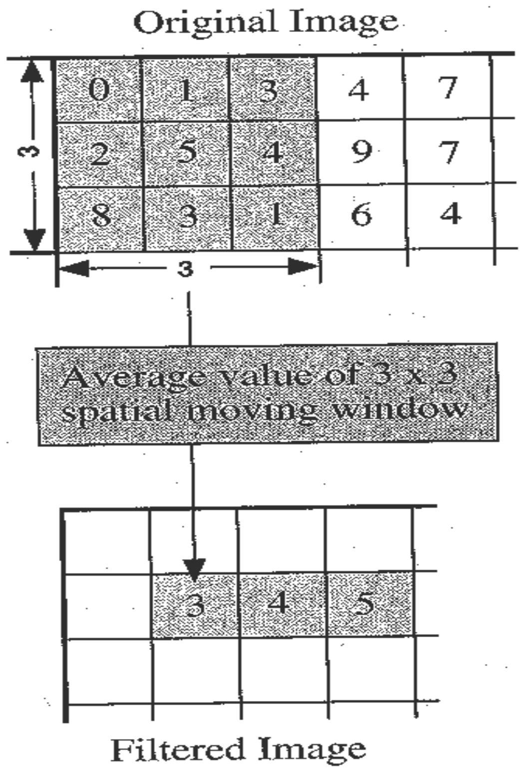


Figure 4 Diagram representing the logic of applying a low pass average filter to an image.

The neighborhood ranking median filter is useful for removing noise in an image, especially shot noise by which individual pixels are corrupted or missing. Instead of computing the average (mean) of the nine pixels in 3x3 convolution, the median filter ranks the pixels in the neighborhood from lowest to highest and selects the median value, which is then placed in the central value of the mask.

A median filter has certain advantages when compared with weighted convolution filters, including (1) it does not shift boundaries, and (2) the minimal degradation to edges allows the median filter to be applied repeatedly, which allows fine detail to be erased and large regions to take on the same brightness value.

A mode filter is used for removing random noise present in the imagery. In the mode filter, the central pixel value is the window make is replaced by the most frequently occurring value. This is a post classification filter.

HIGH-FREQUENCY FILTERING IN THE SPATIAL DOMAIN

High-pass filtering is applied to imagery to remove the slowly varying components and enhance the high-frequency local variations. One high-frequency filter ($HFF_{5,out}$) is computed by subtracting the output of the low-frequency filter ($LFF_{5,out}$) from twice the value of the original central pixel value, BV_5 :

$$HFF_{5,out} = (2 \times BV_5) - (LFF_{5,out})$$

Brightness values tend to be highly correlated in a nine-element window. Thus, the high-frequency filtered image will have a relatively narrow intensity histogram. This suggests that the output from most high-frequency filtered images must be contrast stretched prior to visual analysis.

EDGE ENHANCEMENT IN THE SPATIAL DOMAIN

For many remote sensing earth science applications, the most valuable information that may be derived from an image is contained in the edges surrounding various objects of interest. Edge enhancement delineates these edges and makes the shape and details comprising the image more conspicuous and perhaps easier to analyze. Generally, what the eyes see as pictorial edges are simply sharp changes in brightness value between two adjacent pixels. The edges may be enhanced using either linear or nonlinear edge enhancement techniques.

Linear Edge Enhancement. A straightforward method of extracting edges in remotely sensed imagery is the application of a directional first-difference algorithm and approximates the first derivative between two adjacent pixels. The algorithm produces the first difference of the image input in the horizontal, vertical, and diagonal directions. The algorithms for enhancing horizontal, vertical, and diagonal edges are, respectively;

Vertical	$BV_{i,j} = BV_{i,j} - BV_{i,j+1} + K$
Horizontal	$BV_{i,j} = BV_{i,j} - BV_{i-1,j} + K$
NE Diagonal	$BV_{i,j} = BV_{i,j} - BV_{i+1,j+1} + K$
SE Diagonal	$BV_{i,j} = BV_{i,j} - BV_{i-1,j+1} + K$

The result of the subtraction can be either negative or positive. Therefore, a constant K (usually 127) is added to make all values positive and centered between 0 and 255. This causes adjacent pixels with very little difference in brightness value to obtain a brightness value of around 127 and any dramatic change between adjacent pixels to migrate away from 127 in either direction. The resultant image is normally min-max contrast stretched to enhance the edges even more. It is best to make the minimum and maximum values in the contrast stretch a uniform distance from the midrange value (127). This causes the uniform areas to appear in shades of gray, while the important edges become black or white.

Compass gradient masks may be used to perform two-dimensional, discrete differentiation directional edges enhancement

		1	1	1
North	=	1	-2	1
		-1	-1	-1
		1	1	1
NE	=	-1	-2	1
		-1	-1	1
		-1	1	1
East	=	-1	-2	1
		-1	1	1
		-1	-1	1
SE	=	-1	-2	1
		1	1	1
		-1	-1	-1
South	=	1	-2	1
		1	1	1
		1	-1	-1
SW	=	1	-2	-1
		1	1	1
		1	1	-1
West	=	1	-2	-1
		1	1	-1
		1	1	1
NW	=	1	-2	-1
		1	-1	-1

The compass names suggest the slope direction of maximum response. For example, the east gradient mask produces a maximum output for horizontal brightness value changes from west to east. The gradient masks have zero weighting (i.e., the sum of the mask coefficients is zero) . This results in no output response over regions with constant brightness values (i.e., no edges are present).

Laplacian convolution masks may be applied to imagery to perform edge enhancement. The Laplacian is a second derivative (as opposed to the gradient, which is a first derivative) and is invariant to rotation, meaning that it is insensitive to the direction in which the discontinuities (points, line, and edges) run. Several 3 x 3 Laplacian filters are shown below.

0	-1	0
-1	4	-1
0	-1	0

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

1	-2	1
-2	4	-2
1	-2	1

The Laplacian operator generally highlights point, lines, and edges in the image and suppresses uniform and smoothly varying regions. Human vision physiological research suggests that we see objects in much the same way. Hence, the use of this operation has a more natural look than many of the other edge-enhanced images.

By itself, the Laplacian image may be difficult to interpret. Therefore, a Laplacian edge enhancement may be added back to the original image using the following mask

0	-1	0
-1	5	-1
0	-1	0

Numerous coefficients can be placed in the convolution masks. Usually, the analyst works interactively with the remotely sensed data, trying different coefficients and selecting those that produce the most effective results. It is also possible to use combinations of operation for edge detection. For example, a combination of gradient and Laplacian edge operation may be superior to using either edge enhancement alone.

Nonlinear Edge Enhancement. Nonlinear edge enhancements are performed using nonlinear combinations of pixels. Many algorithms are applied using either 2x2 or 3x3 kernels. The Sobel edge detector is based on the notation of the 3x3 window previously described and is computed according to the relationship:

$$Sobel_{5,out} = \sqrt{X^2 + Y^2}$$

where

$$X = (BV_3 = 2BV_6 + BV_9) - (BV_1 + 2BV_4 + BV_7)$$

and

$$Y = (BV_1 = 2BV_2 + BV_3) - (BV_7 + 2BV_8 + BV_9)$$

The Sobel operator may also be computed by simultaneously applying the following 3x3 templates across the image.

$$X = \begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix}, \qquad Y = \begin{matrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{matrix}$$

The Robert's edge detector is based on the use of only four elements of a 3x3 mask. The new pixel value at pixel location $BV_{5,out}$ is computed according to the equation

$$Roberts_{5,out} = X + Y$$

where

$$X = |BV_5 - BV_9| \quad \& \quad Y = |BV_6 - BV_8|$$

The Robert's operator also may be computed by simultaneously applying the following templates across the image :

$$X = \begin{matrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{matrix}, \qquad Y = \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & -1 & 0 \end{matrix}$$

The Kirsch nonlinear edge enhancement calculates the gradient at pixel $BV_{i,r}$. To apply this operator, however, it is first necessary to designate a different 3 x 3 window numbering scheme than used in previous discussions :

Window numbering for Kirsch =

$$\begin{matrix} BV_0 & BV_1 & BV_2 \\ BV_7 & BV_{I,J} & BV_3 \\ BV_6 & BV_5 & BV_4 \end{matrix}$$

The algorithm applied is

$$BV_{i,j} = \max \{1, \max_{i=0}^{7} [Abs(5S_i - T_i)]\}$$

where

$$S_i = BV_1 + BV_2 + BV_3$$

and

$$T_i = BV_4 + BV_5 + BV_6 + BV_{i+6} + BV_{i+7}$$

The subscripts of BV are evaluated modulo 8, meaning that the computation moves around the perimeter of the mask in eight steps. The window numbering moves in the next iteration in the following manner.

Window Numbering after Ist iteration

$$\begin{array}{ccc} BV_7 & BV_0 & BV_1 \\ BV_6 & BV_{I,J} & BV_2 \\ BV_5 & BV_4 & BV_3 \end{array}$$

The arrow directions indicate the movement of window numbering in consecutive steps. The edge enhancement computes the maximal compass gradient magnitude about input image point $BV_{i,j.}$ The value of S_i equals the sum of three adjacent pixels, while T_i equals the sum of the remaining four adjacent pixels. The input pixel value at $BV_{i,j}$ is never used in the computation.

BAND RATIOING

Sometimes differences in brightness values from identical surface materials are caused by topographic slope and aspect, shadows, or seasonal changes in sunlight illumination angle and intensity. These conditions may hamper the ability of an interpreter or classification algorithm to identify correctly surface materials or land use in a remotely sensed image. Fortunately, ratio transformations of the remotely sensed data can, in certain instances, be applied to reduce the effects of such environmental conditions. In addition to minimizing the effects of environmental factors, ratios may also provide unique information not available in any single band that is useful for discriminating between soils and vegetation.

The mathematical expression of the ratio function is

$$BV_{i,j,r} = BV_{i,j,k}/BV_{i,j,l}$$

where $BV_{i,j,r}$ is the output ratio value for the pixel at rwo, i, column j; $BV_{i,j,k}$ is the brightness value at the same location in band k, and $BV_{i,j,l}$ is the brightness value in band L. Unfortunately, the computation is not always simple since $BV_{i,j} = 0$ is possible. However, there are alternatives. For example, the mathematical domain of the function is 1/255 to 255 (i.e., the range of the ratio function includes all values beginning at 1/255, passing through 0 and ending at 255). The way to overcome this problem is simply to give any $BV_{i,j}$ with a value of 0 the value of 1. Alternatively, some like to add a small value (e.g.0.1) to the denominator if it equals zero.

To represent the range of the function in a linear fashion and to encode the ratio values in a standard 8-bit format (values from 0 to 255), normalizing functions are applied . Using this normalizing function, the ratio value 1 is assigned the brightness value 128. Ratio values within the range 1/255 to 1 are assigned values between 1 and 128 by the function

$BV_{i,j,n} = \mathrm{Int}\ [(BV_{i,j,r} \times 127) + 1]$

Ratio values from 1 to 255 are assigned values within the range 128 to 255 by the function

$$BV_{i,j,n} = \mathrm{Int}\ \left(128 + \frac{BV_{i,j,r}}{2}\right)$$

Band ratioing negate the effect of any extraneous factors in sensor data that act equally in all bands of analysis. Although the single band reflectance values are influenced by the extraneous factors, the ratios of the apparent reflectance's are not.

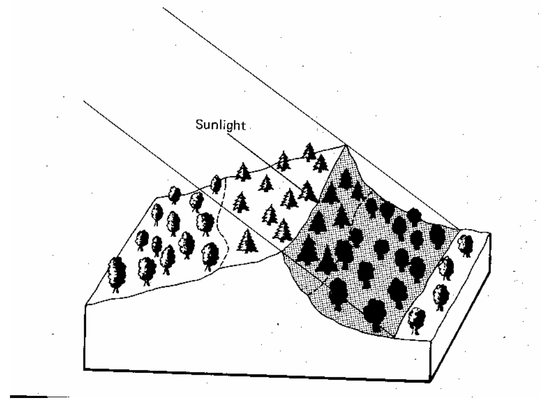
The simple ratios between band, only negate multiplicative extraneous effects. When additive effects are present, we must ratio between band differences. ratio techniques compensate only for those factors that act equally on the various bands under analysis.

Ratio images can be meaningfully interpreted because they can be directly related to the spectral properties of materials. Ratioing can be thought of as a method of enhancing minor differences between materials by defining the slope of spectral curve between two bands. We must understand that dissimilar materials having similar spectral slopes but different albedos, which are easily separable on a standard image, may become inseparable on ratio images.

Figure 5 shows a situation where Deciduous and Coniferous Vegetation crops out on both the sunlit and shadowed sides of a ridge.

In the individual bands the reflectance values are lower in the shadowed area and it would be difficult to match this outcrop with the sunlit outcrop. The ratio values, however, are nearly identical in the shadowed and sunlit areas and the sandstone outcrops would have similar signatures on ratio images. This removal of illumination differences also eliminates the dependence of topography on ratio images.

The potential advantage of band ratioing is that greater contrast between or within classes might be obtained for certain patterns of spectral signatures. Ratioing is a non-linear operation and has the property of canceling or minimizing positively correlated variations in the data while emphasizing negatively correlated variations. In other words, a ratio image will enhance contrast for a pair of variables, which exhibit negative correlation between them.



Landcover/ Illumination	Digital Number		Ratio
	Band A	Band B	
Decidous			
Sunlit	48	50	.96
Shadow	18	19	.95
Coniferous			
Sunlit	31	45	.69
Shadow	11	16	.69

Figure 5 Reduction of Scene Illumination effect through spectral ratioing

Ratio images can be meaningfully interpreted because they can be directly related to the spectral properties of materials. Increased information can be obtained when the analyst uses those ratios that maximize the differences in the spectral slopes of materials in the scene. For example, an understanding of the spectral properties of vegetation, soils, and rocks suggest that a ratio of Landsat multispectral scanner bands 5 (0.6 to 0.7 μm) and 6 (0.7 to 0.8 μm) should be sensitive to vegetation density, and in some cases, to the species differences. The concept used for mapping vegetation density with this Landsat 5/6 ratio is that as the vegetation density increases there will be a corresponding decrease in the radiance of Landsat band 5 due to the chlorophyll absorption near 0.68 μm and an increase in Landsat band 6 due to the very high reflectance of vegetation in the near infrared. Therefore, the ratio is inversely proportional to vegetation density.

Apart form the simple ratio of the form A/B, other ratios like A/(A+B), (A-B)/(A+B), (A+B)/(A-B) are also used in some investigations. But a systematic study of their use for different applications is not available in the literature.

It is important that the analyst be cognizant of the general types of materials found in the scene and their spectral properties in order to select the best ratio images for interpretation. Ratio images have been successfully used in many geological investigations to recognize and map areas of mineral alteration and for lithologic mapping.

Colour ratio composite images

We can combine several ratio images to form a colour ratio composite image. Colour ratio composite images are most effective for discriminating between the altered and unaltered sedimentary rocks, and in some cases, for distinguishing subtle differences among the altered and unaltered rocks. In some studies, it had been noticed that the ratios 4/5, 5/6 and 6/7 composite provides the greatest amount of information for discriminating between hypothermally altered and unaltered rocks, as well as separating various types of igneous rocks.

Density slicing can also be used after band ratioing to enhance subtle tonal differences.

PRINCIPAL COMPONENT ANALYSIS

The multispectral image data is usually strongly correlated from one band to the other. The level of a given picture element on one band can to some extent be predicted from the level of that same pixel in another band.

Principal component analysis is a pre-processing transformation that creates new images with the uncorrelated values of different images. This is accomplished by a linear transformation of variables that corresponds to a rotation and translation of the original coordinate system.

This transformation is conceptualized graphically by considering the two-dimensional distribution of pixel values obtained in two bands, which are labeled simply X_1 and X_2. A scatterplot of all the brightness values associated with each pixel in each band is shown in Figure 6, along with the location of the respective means,μ_1 μ_2. The spread or variance of the distribution of points is an indication of the correlation and quality of information associated with both bands. If all the data points clustered in an extremely tight zone in the two-dimensional space, these data would probably provide very little information as they are highly correlated.

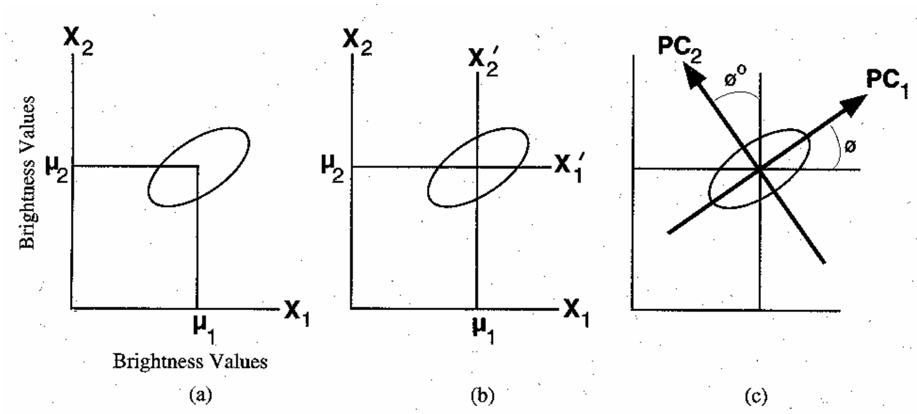


Figure 6 Diagram representing relationship between two principal components.

The initial measurement coordinate axes (X_1 and X_2) may not be the best arrangement in multispectral feature space to analyze the remote sensor data associated with these two bands. The goal is to use principal components analysis to translate and/or rotate the original axes so that the original brightness values on axes X_1 and X_2 are redistributed (reprojected) onto a new set of axes or dimensions, X'_1 and X'_2. For example, the best translation for the original data points from X_1 to X'_1 and from X_2 to X'_2 coordinate systems might be the simple relationship $X'_1 = X_1 - \mu_1$ and $X'_2 = X - \mu_2$. Thus, the origin of the new coordinate system (X'_1 and X'_2) now lies at the location of both means in the original scatter of points.

The X' coordinate system might then be rotated about its new origin (μ_1, μ_2) in the new coordinate system some ϕ degree so that the axis X'_1 is associated with the maximum amount of variance in the scatter of points . This new axis is called the first principal component ($PC_1 = \lambda_1$). The second principal component ($PC_2 = \lambda_2$) is perpendicular (Orthogonal) to PC_1. Thus, the major and minor axes of the ellipsoid of points in bands X_1 and X_2 are called the principal components. The third, fourth, fifth, and so on, components contain decreasing amounts of the variance found in the data set.

To transform (reproject) the original data on the X_1 and X_2 axes onto the PC_1 and PC_2 axes, we must obtain certain transformation coefficients that we can apply in a linear fashion to the original pixel values. The linear transformation required is derived from the covariance matrix of the original data set. Thus, this is a data-dependent process with each new data set yielding different transformation coefficients.

The transformation is mathematically computed from original spectral statistics as

Step 1. The n x n covariance matrix, (cov) of the n dimensional remote sensing data set to be transformed is computed.

Step 2. The eigen values, $E = (\lambda_1, \lambda_{2,...} \lambda_{n,n}]$ and eigen vectors EV = [$a_{kp..}$ for k = 1 to n bands, and p = 1 to n components] of covariance matrix are computed using the transformation equation

$$[cov - EI]. EV^* = 0$$

where
cov - covariance matrix
E - Eigen value matrix
EV - Transform of Eigen Vector matrix
I - Identity matrix

E is a diagonal covariance matrix whose elements λ_{ii}, called as eigen values, are the variances of the p^{th} principal components where p = l - n components. The non diagonal eigen values, $\lambda_{i,j}$ are equal to zero and can therefore be ignored.

Step 3. This appropriate transformation is applied to the data and the new Brightness values for each principal component p is computed according to the formula

$$\text{new } BV_{i,j,p} = \sum_{K=1}^{n} a_{kp}\, BV_{i,j,k}$$

where
a_{kp} = eigenvectors
$BV_{i,j,k}$ = brightness value in Band K for pixel at row i & col j &
n = no. of bands

The eigenvalues contain important information. For example, it is possible to determine the percent of total variance explained by each of the principal components, %p using the equation

$$\%p = \frac{\text{eigenvalue } \lambda_p \times 100}{\text{eigenvalue } \lambda_p}$$

But what do these new components represent ? For example, wheat does component 1 stand for? By computing the correlation of each band k with each component p, it is possible to determine how each band "loads" or is associated with each principal component. The equation is

$$R_{kp} = \frac{a_{kp} \times \sqrt{\lambda_p}}{\sqrt{Var_k}}$$

where
a_{kp} = eigenvector for band k and component p

λ_p = p^{th} eigenvalue
Var_k = variance of band k in the covariance matrix

This computation results in a new n x n matrix filled with factor loadings.

This procedure takes place for every pixel in the original image data to produce the principal component 1 image dataset. then p is incremented by 1 and principal component 2 is created pixel by pixel. If desired, any two or three of the principal components can be placed in the blue, green, and/or red image planes to create a principal component color composite. These displays often depict more subtle differences in color shading and distribution than traditional color-infrared color composite images.

Components 1, 2 and 3 account for most of the variance in the dataset. Any operation can be performed using just these three principal component images. This greatly reduces the amount of data to be analyzed and completely bypasses the expensive and time-consuming process of feature selection so often necessary when classifying remotely sensed data.

Principal component analysis operates on all bands together. Thus, it alleviates the difficulty of selecting appropriate bands associated with the band ratioing operation. Principal components describe the data more efficiently than the original band reflectance values. The first principal component accounts for a maximum portion of the variance in the data set, often as high as 98%. Subsequent principal components account for successively smaller portions of the remaining variance.

Principal component transformations are used for spectral pattern recognition as well as image enhancement. When used before pattern recognition, the least important principal components are dropped altogether. This permits us to omit the insignificant portion of our data set and thus avoids the additional computer time. The transformation functions are determined during the training stage.

Principal component images may be analysed as separate black and white images, or any three component images may be colour coded to form a colour composite.

Principal component enhancement techniques are particularly appropriate in areas where little priori information concerning the region is available.

INTENSITY -HUE SATURATION TRANSFORMATION.

Digital Images are typically displayed as additive color composites using the three color primaries :red, green and blue. Figure 7 illustrates a RGB Color cube, which is defined by the brightness levels of each of the three primary colors. For a display with 8-bit -per pixel encoding , the range of possible values for each colour component is 0 to 255 . Hence there are 256 x 256 x 256 (16,777,216) possible combinations of red, green and blue. Every pixel in a composite display may be represented by a three dimensional coordinate position within the colour cube.

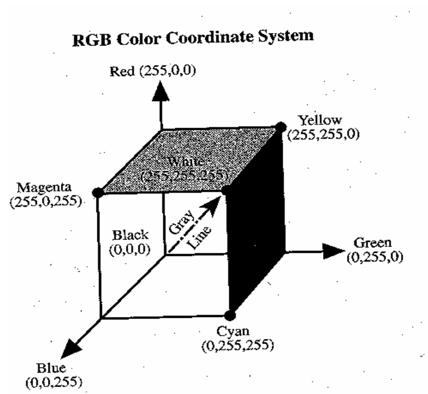


Figure 7 RGB Colour Cube

An alternative to describing colors by their RGB components is the use of Intensity, hue and saturation system. Intensity relates to the total brightness of a color. Hue refers to the dominant wavelength of the light contributing to a colour. Saturation specifies the purity of color relative to gray. Transformation of RGB components into IHS components provide more control over color enhancements and can also be used as a technique of data fusion.

Hexcone model for transforming RGB to IHS components.

This involves the projection of the RGB color cube onto a plane that is perpendicular to the gray line and tangent to the cube at the corner farthest from the origin (refer figure 8).The resulting projection is a hexagon. If the plane of the projection is moved from white to black along the gray line, successively smaller color subcubes are projected and a series of hexagons of decreasing size results. The hexacone at white is the largest and the hexagon at black degenerates to a point. The series of hexagons developed in this manner define a solid called the hexcone(figure 9a).

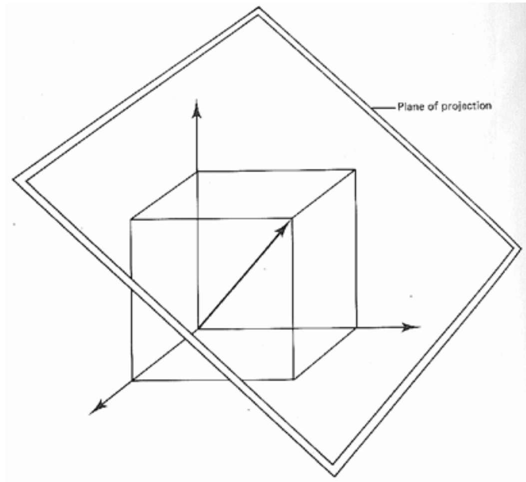


Figure 8 Planar Projection of the RGB colour cube

In the hexcone model , intensity is defined by the distance along the gray line from black to any given hexagonal projection. Hue and Saturation are defined at a given intensity, within appropriate hexagon(figure 22b). Hue is expressed by the angle around the hexagon and saturation is defined by the distance from the gray point at the center of the hexagon. The farther a point lies away from the gray point , the more saturated is the colour.

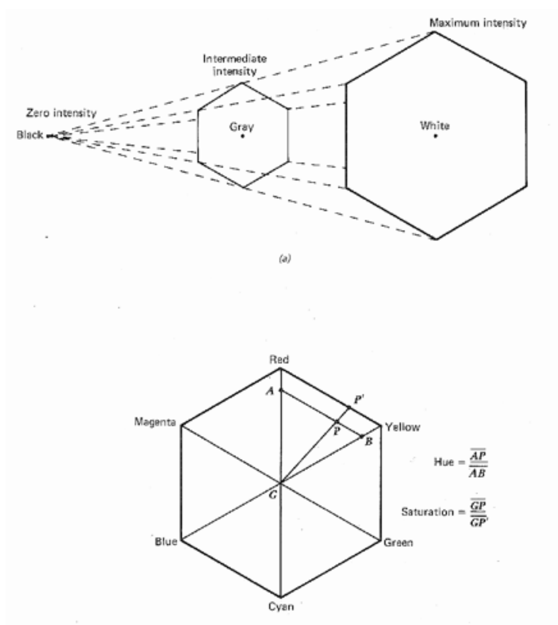


Figure 9 Hexcone colour model a) Generation of the hexcone b) definition of hue and saturation components for a pixel value P having a non zero intensity.

DATA FUSION

Different types of multispectral remote sensor data having different spatial and spectral resolutions can be merged. For example , IRS-1C PAN (panchromatic data at 5.8m resolution) and LISS -III (multispectral data with 23.5 m spatial resolution) can be merged to derive the advantage of high spatial and spectral resolution.

Merging remotely sensed data obtained using different remote sensors must be performed carefully. First all data sets o be merged must be accurately registered to one another and resample to the same pixel size. Then several alternatives exist for merging the data sets including

(1) Simple band substitution
(2) Color space transformation and substitution
(3) Principal Components

SIMPLE BAND SUBSTITUTION.

The data sets to merged are geometrically rectified to a same projection and resample to a spatial resolution using nearest neighbour or bilinear interpolation. The panchromatic data, which is a record of components of green and red energy, can be substituted directly for the green or the red bands in the display of multispectral data. The result is that the display contains the spatial detail of panchromatic data and the spectral detail of the multispectral data. This method has the advantage of not changing the radiometric quality of any of the data.

COLOR SPACE TRANSFORMATION AND SUBSTITUTION.

Any RGB multispectral dataset consisting of three bands may be transformed into IHS transformation. The IHS transformation is most popular method to merge multiple types of remote sensor data.

It involves four steps

(1) RGB to IHS transformation: three bands of lower spatial resolution data in RGB color space are transformed to IHS color space
(2) Contrast manipluation: the high spatial resolution image is contrast stretched so that it has approximately the same variance and the mean as the intensity (I) image.
(3) Substitution : The stretched , high spatial resolution image is subsituted for the intensity image. The justification for replacing the intensity (I) component with the stretched higher spatail resolution image is that the two images have approximately the same spectral characteristics.
(4) IHS to RGB : The modified IHS dataset is transformed back into RGB color space using an inverse IHS transformation.