Chapter 10 Image Processing - Conversion

10.1 Image Enhancement and Feature Extraction

Image enhancement can be defined as conversion of the image quality to a better and more understandable level for feature extraction or image interpretation, while radiometric correction is to reconstruct the physically calibrated value from the observed data.

On the other hand, **feature extraction** can be defined as the operation to quantify the image quality through various parameters or functions, which are applied to the original image.

These processes can be considered as conversion of the image data. Image enhancement is applied mainly for image interpretation in the form of an image output, while feature extraction is normally used for automated classification or analysis in a quantitative form (see Figure 10.1.1).

a. Image Enhancement

Typical image enhancement techniques include **gray scale conversion**, **histogram conversion, color composition, color conversion between RGB and HSI,** etc., which are usually applied to the image output for image interpretation.

b. Feature Extraction

Features involved in an image are classified as follows.

(1) Spectral features
special color or tone, gradient, spectral parameter etc.

(2) Geometric features
edge, linearment, shape, size, etc.

(3) Textural features
pattern, spatial frequency, homogeneity, etc.

Figure 10.1.2 shows three examples of spectral, geometric and textural feature extraction.

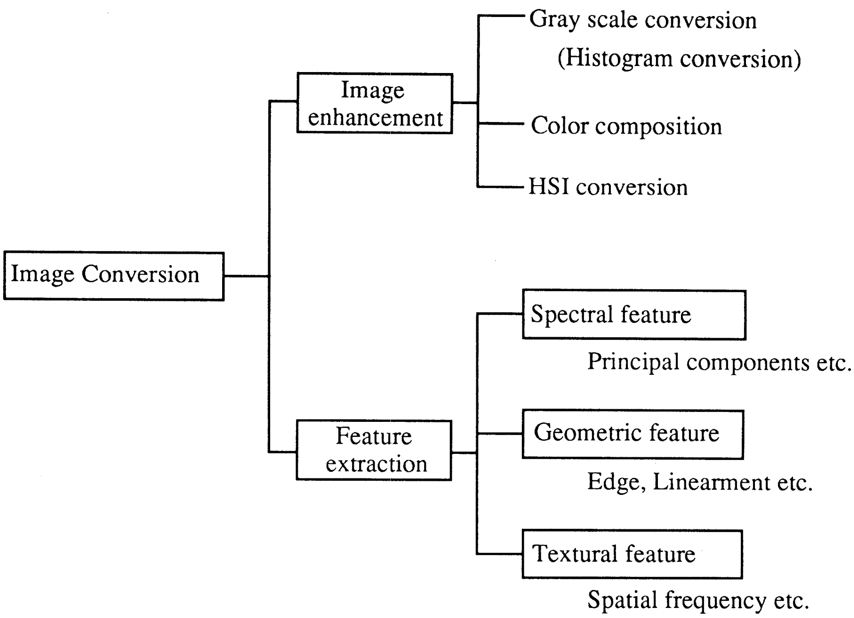
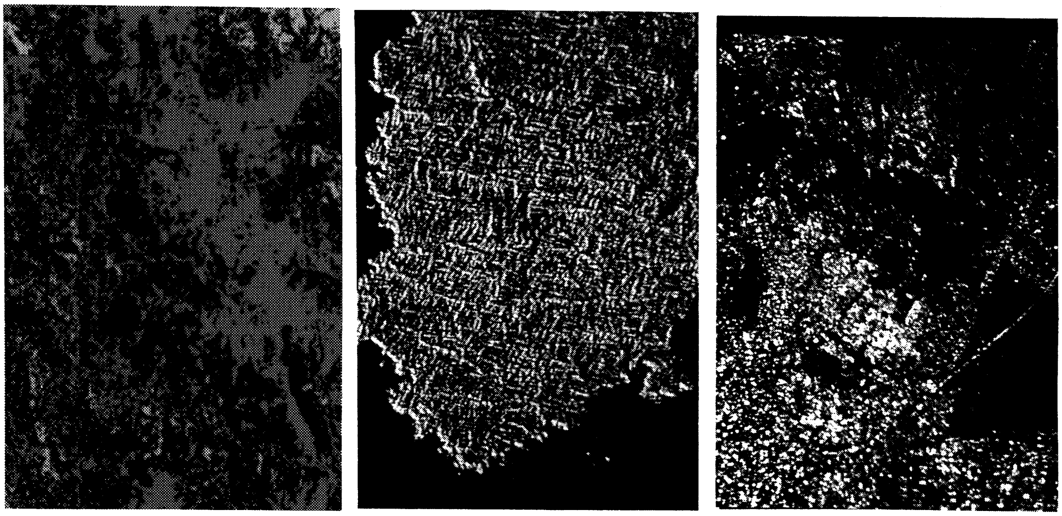


Figure 10.1.1 Image conversion



a) Spectral feature b) Geometric feature c) Textural feature

Figure 10.1.2 Samples of feature extraction

10.2 Gray Scale Conversion

Gray scale conversion is one of the simplest image enhancement techniques. Gray scale conversion can be performed using the following function.

$$y = f(x)$$

where x : original input data

y : converted output data

In this section, the following five typical types are introduced, though there are many more functions that could be used. (see Figure 10.2.1)

a. Linear conversion

$y = ax + b$ $\quad$ a : gain , $\quad$ b : offset

contrast stretch is one of linear conversion as follows.

$$Y = \frac{y_{max} - y_{min}}{x_{max} - x_{min}} (x - x_{min}) + y_{min}$$

Statistical procedures can be also applied in two ways as follows.

(1) Conversion of average and standard deviation

$$y = \frac{S_y}{S_x} (x - x_m) + y_m$$

where x_m : average of input image

S_x : standard deviation of input image

y_m : average of output image

S_y : standard deviation of output image

(2) Regression

In such cases as multi-date images for producing a mosaic or radiometric adjustment, a selected image can be related to other images using regression technique.
Line noise due to different detectors, for example Landsat MSS, can be eliminated by using the regression technique between different detectors.

Figure 10.2.2 shows various examples of gray scale conversion.

b. Fold conversion

Multiple linear curves are applied in order to enhance only a part of the gray scale.

c. Saw conversion

Where a discontinuous gray scale, occurs, drastic contrast stretch can be made.

d. Continuous function

Function such as exponential, logarithm, polynomials etc. may be applied.

e. Local gray scale conversion

Instead of the conversion being applied to the whole scene by a single formula, parameters are changed with respect to small local areas.

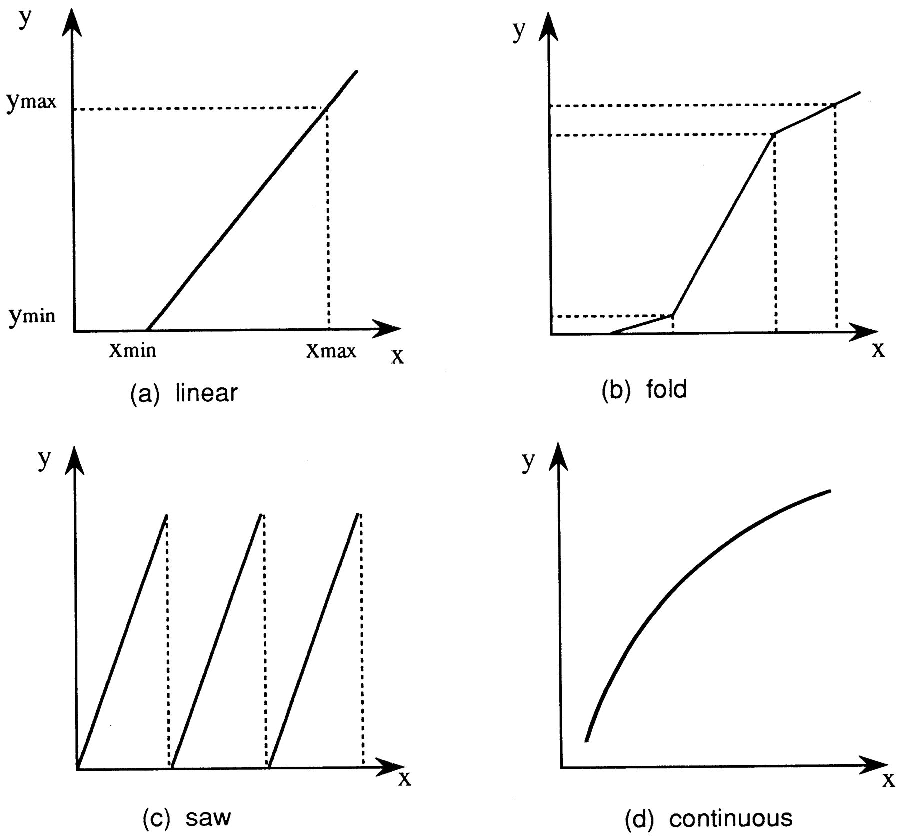
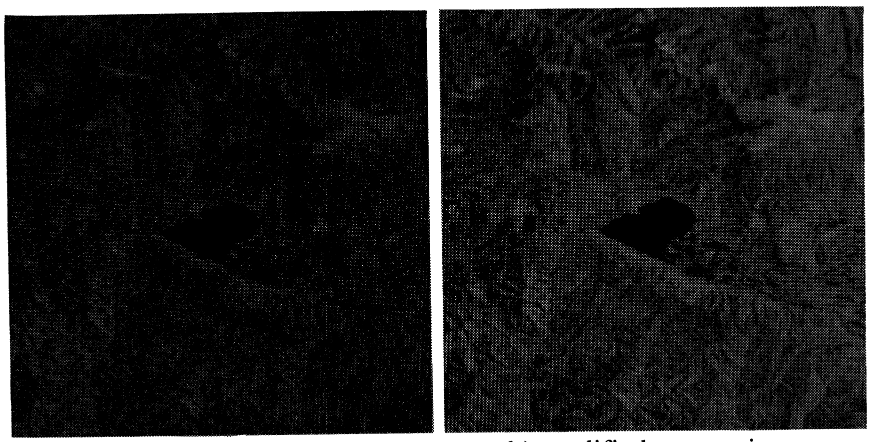


Fig 10.2.1 Typical Density Conversion



a) original Image b) modified conversion

Fig 10.2.2 Examples of gray scale conversion

10.3 Histogram Conversion

Histogram conversion is the conversion of the histogram of original image to an other histogram. Histogram conversion can be said to be a type of gray scale conversion.

There are two typical histogram conversion techniques.

a. **Histogram equalization**

Histogram equalization is to convert the histogram of an original image to equalized histogram as shown in Figure 10.3.1. As a first step, an accumulated histogram should be made. Then the accumulated histogram should be divided into a number of equal regions. Thirdly , the corresponding gray scale in each region should be assigned to a converted gray scale.

The effect of histogram equalization is that parts of the image with more frequency variation will be more enhanced, while parts of an image with less frequency will be neglected.

Figure 10.3.2 shows a comparison between the original image and the converted image, after histogram equalization.

b. **Histogram normalization**

Generally a normal distribution of the density in an image would create an image that is natural for a human observation. In this sense the histogram of the original image may be sometimes converted to the normalized histogram as shown in Figure 10.3.3. However in this conversion, pixels with same gray scale should be reallocated to other pixels with a different gray scales, in order to form a normalized histogram.

Therefore such a gray scale conversion is not a 1:1 conversion and thus enables no reverse conversion. Histogram normalization may be applied, for example, to an unfocused image of a planet with a low dynamic range, though it is not be very much popular for ordinary remote sensing data.

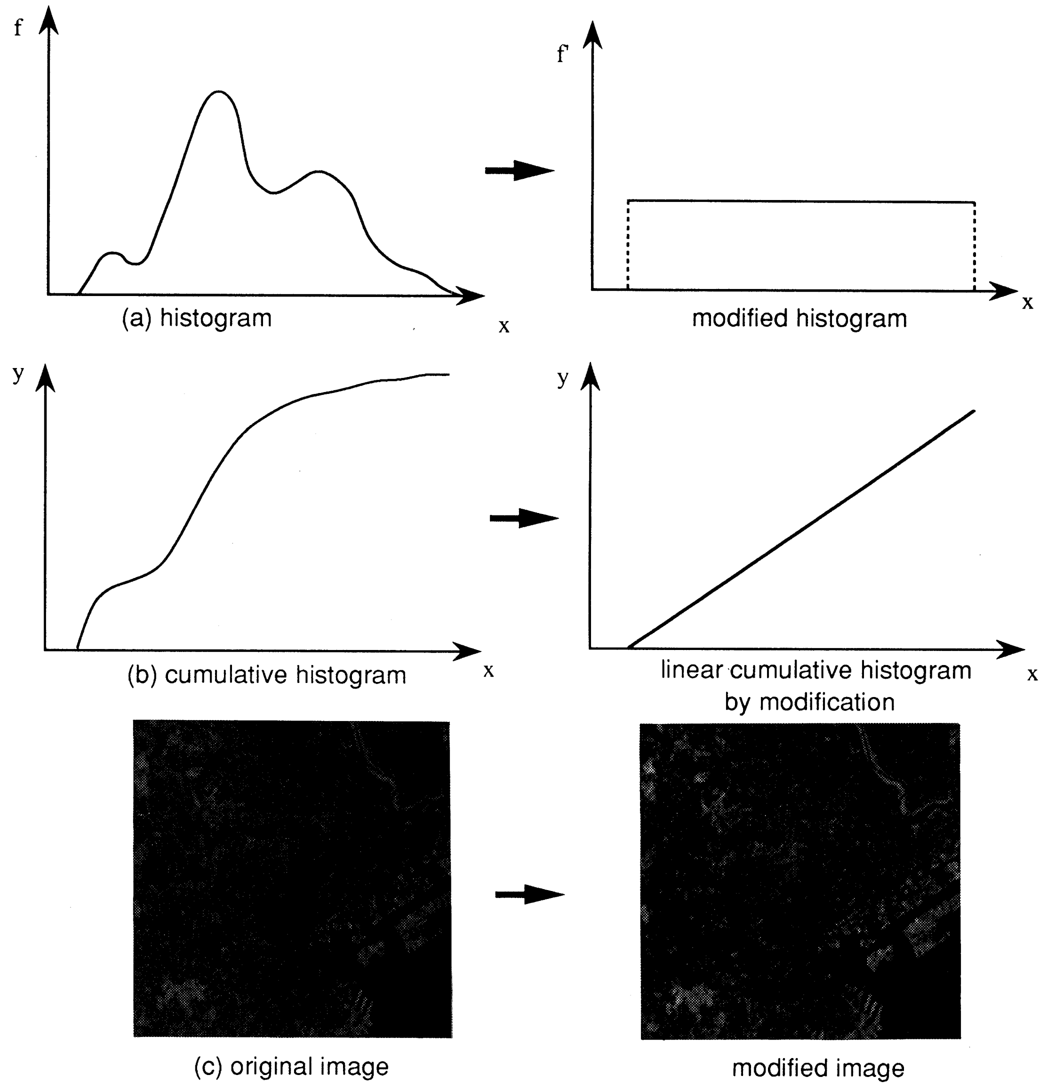


Fig.10.3.1 histogram equalization

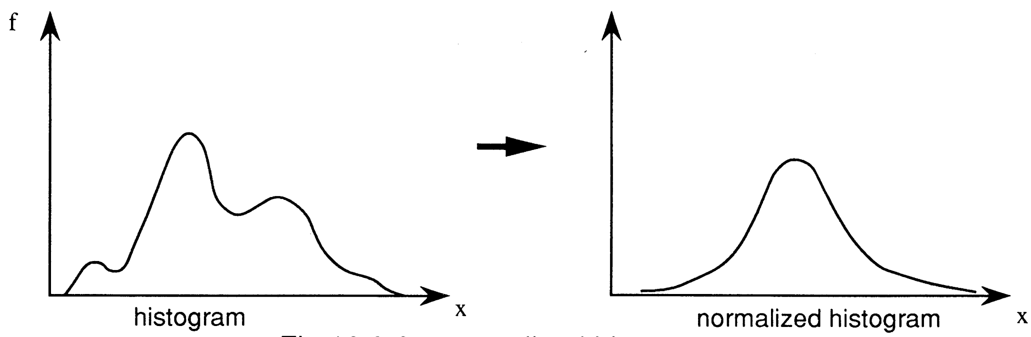


Fig.10.3.2 normalized histogram

10.4 Color Display of Image Data

Color display of remote sensing data is of importance for effective visual interpretation. There are two color display methods; color composite, to generate color with multi-band data and pseudo-color display, to assign different colors to the gray scale of a single image.

a. **Color Composite**

A color image can be generated by composing three selected multi-band images with the use of three primary colors. Different color images may be obtained depending on the selection of three band images and the assignment of the three primary colors.

There are two methods of color composite; an additive color composite and a subtractive color composite, as shown in Figure 10.4.1. Additive color composite uses three light sources of three primary colors (Blue, Green and Red) for example, in a multispectral viewer or color graphic display. The subtractive color composite, uses three pigments of three primary color (Cyan, Magenta and Yellow), for example, in color printing.

When three filters of B, G and R are assigned to the same spectral regions of blue, green and red as shown in Figure 10.4.2, almost the same color as the natural scale, can be reproduced, and is called a natural color composite.

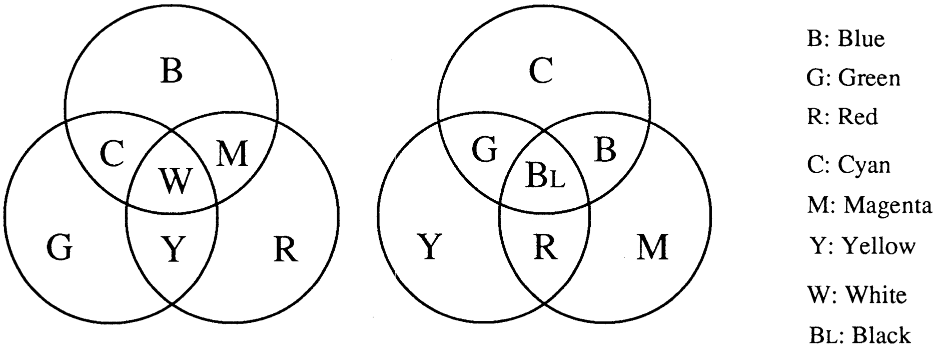
However in remote sensing multi-band images are not always divided in to the same spectral regions as the three primary color filters. In addition invisible regions, such as infrared, are often used, which are required to be displayed in color. As a color composite with an infrared band is no longer natural color, it is called a **false color composite**.

In particularly the color composite with the assignment of blue to the green band, green to the red band and red to the near infrared band is very popular, and is called an **infrared color composite,** which is the same as found in color infrared film (see Figure 10.4.2).

In the case of digital data, three values corresponding to R, G and B will make various color combinations, as listed in Table 10.4.1.

b. **Pseudo Color Display**

Different colors may be assigned to the subdivided gray scale of a single image. Such a color allocation is called pseudo-color. For example, a pseudo-color image of a thermal infrared image will give a temperature map. If one wishes to produce a continuous color tone, three different functions of three primary colors should be applied. Figure 10.4.3 is an example of a pseudo-color display with continuous color tone.



(a) additive color composite (b) subtractive color composite

Figure 10.4.1 Methods of color composite

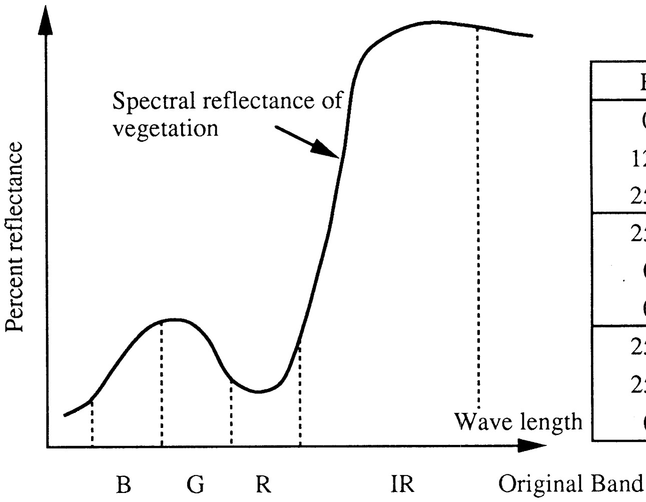


Table 10.4.1 Samples of color composite from digital data

B	G	R	Color
0	0	0	Black
127	127	127	Gray
255	255	255	White
255	0	0	Blue
0	255	0	Green
0	0	255	Red
255	255	0	Cyan
255	0	255	Magenta
0	255	255	Yellow

Assignment of three primary colors
- B G R — Natural color composite
- B G R — Infrared color composite

Figure 10.4.2 Example of color composite

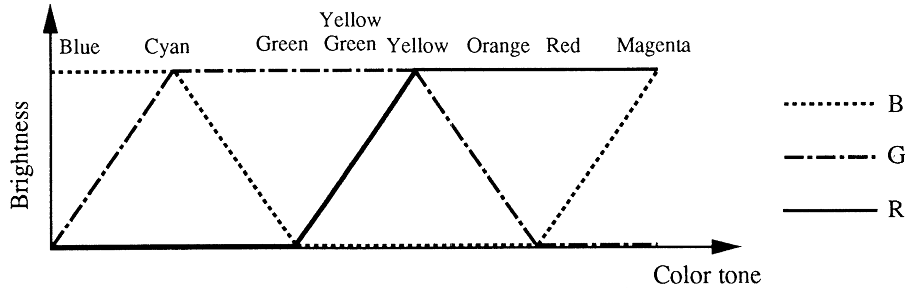


Figure 10.4.3 Example of pseudo color display

10.5 Color Representation - Color Mixing System

Light is perceived as color by the human eye, termed **color stimulus**, and corresponds to the visible region of electro-magnetic spectrum, with a specific spectral curve of radiance as shown in Figure 10.5.1.

However as the physical value such as a spectral curve, is not convenient for representing color in daily life, a psychological representation or sensitivity expression are more practical.

Color representation can be classified into two types; a color mixing system using a quantitative and physical approach, and a **color appearance system** using a qualitative approach, by color code or color sample.

The color mixing system can generate any color by mixing of the three primary colors. The **RGB color system** specified by CIE, uses three primary color stimuli; blue of 435.8 nm(B), green of 546.1 nm(G) and red of 700.0 nm(R) by which all spectral colors ranging from 380 nm to 780 nm, can be generated with the mixing combinations (termed a **color matching function** or **spectral tristimulus values**) as shown in Figure 10.5.2.

As a part of the three spectral stimuli $\bar{r}(\lambda)$,$\bar{g}(\lambda)$ and $\bar{b}(\lambda)$ includes a negative region, a coordinate transformation is applied to generate the virtual three spectral stimuli $\bar{r}(\lambda)$,$\bar{g}(\lambda)$ and $\bar{x}(\lambda)$,$\bar{y}(\lambda)$ and $z(\lambda)$ with positive values, as shown in Figure 10.5.3. This is called the **XYZ color system**. The three stimuli, X, Y and Z, can be computed as follows.

$$X=\kappa\int_{380}^{780}\bar{x}(\lambda)L(\lambda)\rho(\lambda)d\lambda$$

$$Y=\kappa\int_{380}^{780}\bar{y}(\lambda)L(\lambda)\rho(\lambda)d\lambda$$

$$Z=\kappa\int_{380}^{780}\bar{z}(\lambda)L(\lambda)\rho(\lambda)d\lambda$$

where K: constant

$L(\lambda)$: spectral irradiance of standard illumination

$\rho(\lambda)$: spectral reflectance of sample

Trichromatic coordinates (x,y) can be computed as follows.

$$x=\frac{X}{X+Y+Z}\ ,\quad y=\frac{Y}{X+Y+Z}$$

The value of Y corresponds to brightness while the coordinates of (x,y) represent hue and saturation (or chrome) that is drawn as a trichromatic chart as shown in Figure 10.5.4.

The fringe of the bell shape corresponds to the spectral color with high chrome, while the inside corresponds with a low chrome.

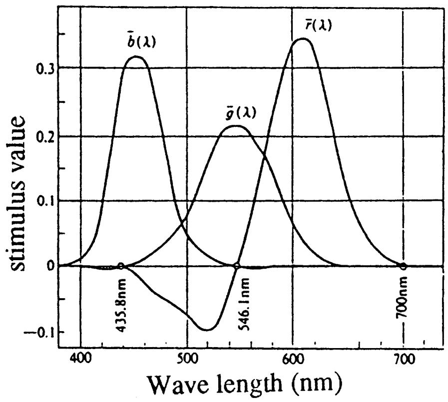


Figure 10.5.1 Color matching function of CIE1931RGB

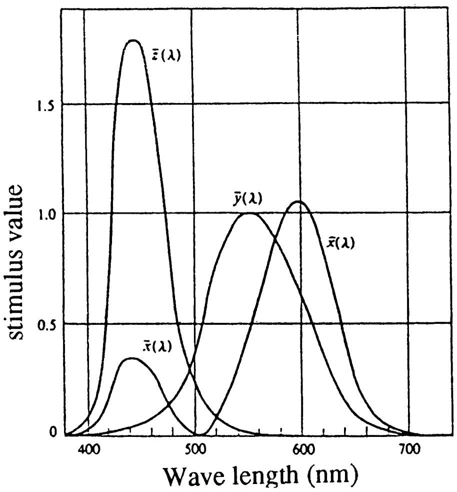


Figure 10.5.2 Color matching function of CIE1931XYZ

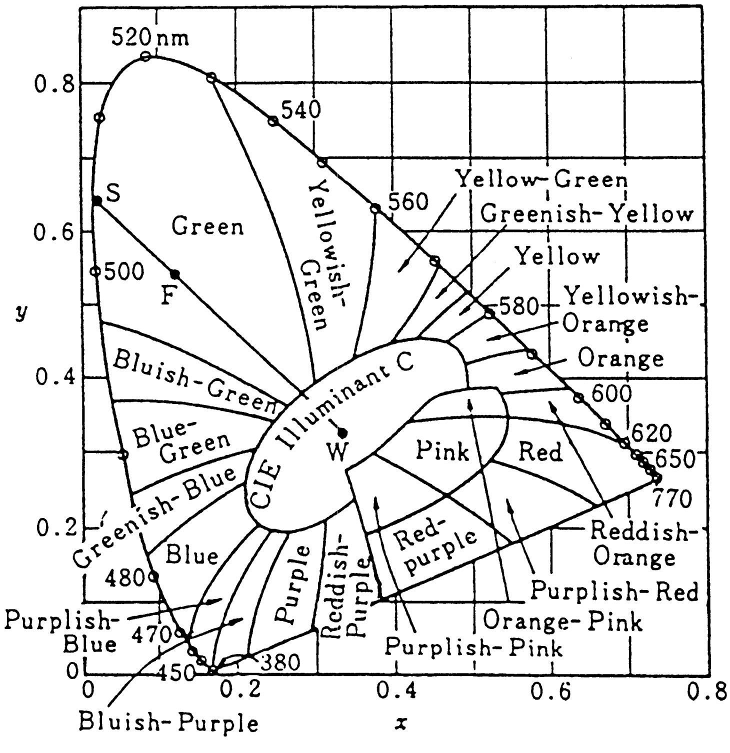


Figure 10.5.3 XYZ color system

10.6 Color Representation - Color Appearance System

The **Munsell color system** is a typical **color appearance system,** in which color is represented with hue (H), saturation(S) and intensity (I) as a psychological response. Hue is composed of the five basic color; red (R), yellow (Y), green(G), blue (B) and purple (P) which are located along a hue ring with intervals of 72 degrees as shown in Figure 10.6.1. Intermediate colors between the above five basic colors; YR, GY, BG, PB and RP are located in between each other. Finally each hue is divided into ten but actually four. For example 1R, 5R, 10R, 1YR, 5YR, 10YR, 1Y, ... are a series along the hue ring.

Intensity is an index of brightness with 11 ranks from 0 (dark) to 10 (light). Saturation is an index of pureness ranging from 0 to 16 depending on the hue and intensity. Color in the Munsell color system is identified as a combination of hue, intensity / saturation, for example 5R4 / 10, which means 5R (hue), 4 (intensity) and 10 (saturation).

Figure 10.6.2 shows a three dimensional color solid as called the Munsell's solid, with the 40 panels with color samples of intensity and saturation with respect to the hue. Munsell color samples are available in the commercial market. Any user can identity arbitrary colors by comparison with the Munsell's color samples. Psychologically defined HSI has been correlated with physically defined RGB or Yxy as mentioned in 10.5. Therefore **conversion between RGB and HSI** can be made mathematically. In the case of a color display using a digital image processing device, the RGB signal has to be input, though color control is much easier using HSI indices. Figure 10.6.3 shows the relationship between RGB space and HSI space.

The following are conversions from RGB to HSI, and from HSI to RGB. The ranges of R,G,B,S,I are [0,1] :, the range of H is $[0,2\pi]$.

(1) from RGB to HSI

$I = \text{Max.}(R,G,B)$

1) $I = 0$; $S = 0$, H= indeterminate

2) $I \neq 0$

$S = (I-i)/I$, where $i = \min.\{R, G, B\}$

Let $r = (I-R)/(I-i)$, $g = (I-G)/(I-i)$, $b = (I-B)/(I-i)$, then

if $R = I$ $H = (b-g)\pi/3$

if $G = I$ $H = (2+r-b)\pi/3$

if $B = I$ $H = (4+g-r)\pi/3$

(2) from HSI to RGB

1) $S = 0$; $R = G = B = I$ regardless of value of H

2) $S \neq 0$

$H' = 3H/\pi$ $h = \text{floor}(H')$ If $H = 2\pi$, then $H = 0$

(floor (x): the function of getting the truncated value of x)

$P = I(1-S)$, $Q = I\{1-S(H'-h)\}$, $T = I\{1-S(1-H'+h)\}$, then

h = 0	R = I, G = T, B = P
h = 1	R = Q, G = I, B = P
h = 2	R = P, G = I, B = T
h = 3	R = P, G = Q, B = I
h = 4	R = I, G = P, B = Q
h = 5	R = I, G = P, B = Q

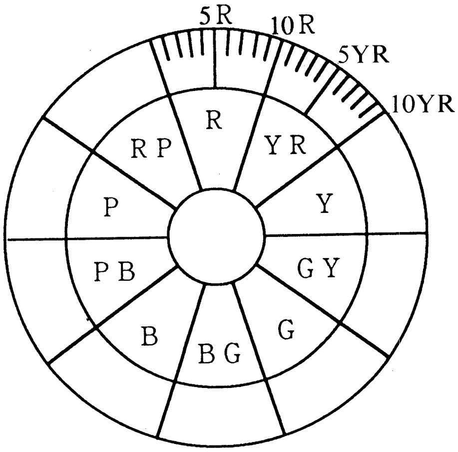


Figure 10.6.2 Three dimensional color solid (Munsell's solid)

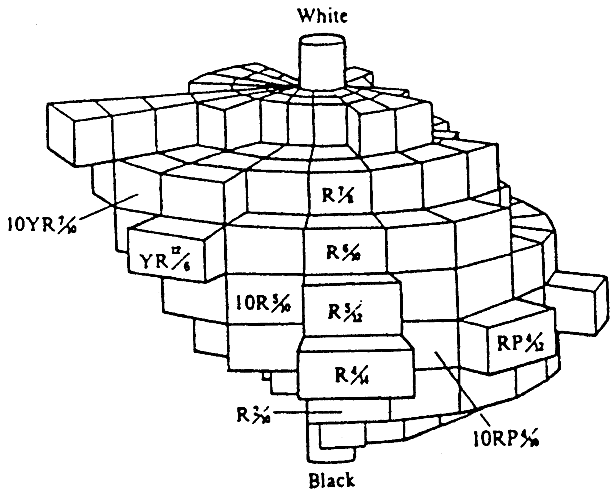


Figure 10.6.1 Munsell color system

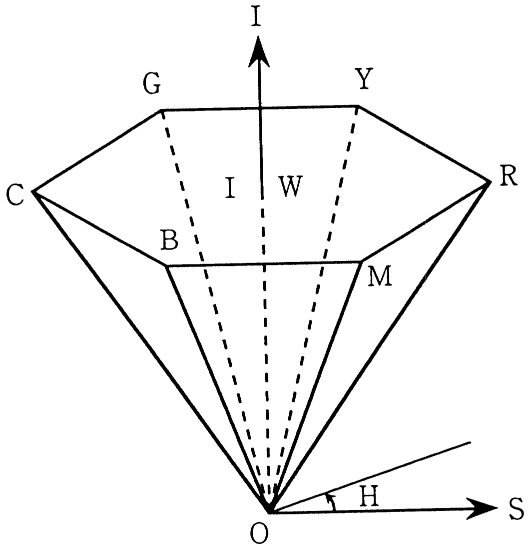


Figure 10.6.3 Relationship between RGB space and HSI space

10.7 Operations between Images

Operations between multi-spectral images or multi-date images are very useful for image enhancement and feature extraction.

Operations between images include two techniques; arithmetic operation and logical operation.

a. **Arithmetic Operations**

Addition, subtraction, multiplication, division and their combinations, can be applied for many purposes, including noise elimination. As the results of the operation can sometimes negative or small values between 0 and 1, they should be adjusted to a range, usually in eight bits or 0 to 255 for image display.

Typical operations are ratioing, for geological feature extraction, and normalized difference vegetation index, for vegetation monitoring with NOAA AVHRR data or other visible near infrared sensors.

(1) Ratioing

$$\text{Ratio} = \frac{x_i}{x_j}$$

Ratioing may be useful for geological feature extraction. Such ratioing can be applied to multi-temporal thermal infrared data for extraction of thermal inertia.

(2) **Normalized Difference Vegetation Index(NDVI)**

$$\text{NDVI} = \frac{\text{ch.2} - \text{ch.1}}{\text{ch.2} + \text{ch.1}}$$

where Ch.1 : red band
Ch.2 : infrared band

NDVI shows as a high value for denser vegetation, while the NDVI is very low in desert, or non-vegetation regions.

Figure 10.7.1 shows two examples of arithmetic operations.

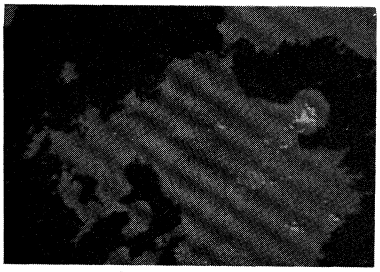
b. **Logical Operation**

Logical addition (OR set), logical multiplication (AND set), true and false operations etc. can be applied to multi-date images or a combination of remote sensing images and thematic map images.

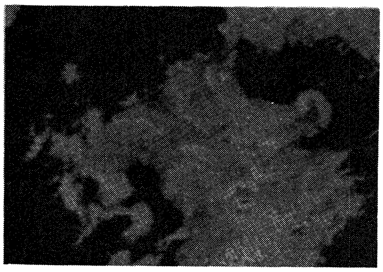
For example a remote sensing image or the classified result can be overlaid on map data, such as political boundaries.

Figure 10.7.2 shows an example of forest land change by overlaying a remote sensing image on the forest land which has been mapped from the old map. Such an overlay will be very useful for change detection.

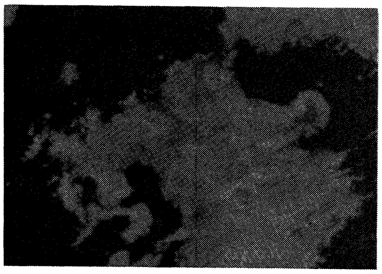
Channel No.1



Channel No.2

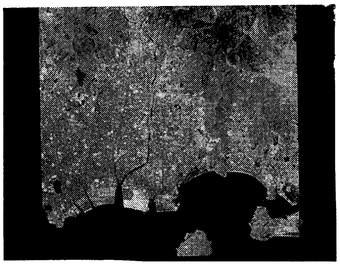


Rationing



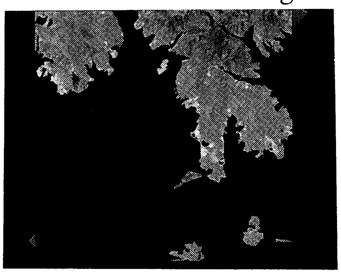
NDVI

Figure 10.7.1 Examples of arithmetic operation

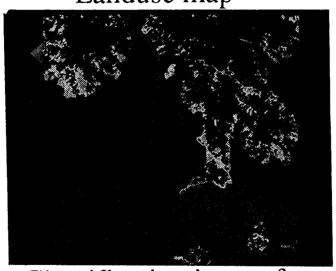


LANDSAT TM Image

Landuse map



Masked image on
the forest land



Classification image from
masked image

Figure 10.7.2 Examples of forest land change by logical operation

10.8 Principal Component Analysis

Principal component analysis is used to reduce the dimensions of measured variables (p dimension) to the representative principal components (m dimension , m<p) with a linear combination of the measured variables. Principal component analysis is applied to multi-band data or multi-temporal data in order to reduce it to two or three principal components. It should be noted that in fact p components are formed, but the higher components of order greater than m, usually contain noise and can be discarded.

Let the measured p dimensional variables be $\{x_i\}$ i = 1,p, the principal components $\{z_k\}$ k = 1, m can be expressed as the linear combination as follows.

$$z_k = a_{1k}\, x_1 + a_{2k}\, x_2 + \ldots\ldots + a_{pk}\, x_p$$

The coefficients (a_{1k} - a_{pk}) are determined under the following constrains.

(1) $\Sigma\, a_{ik}^2 = 1$

(2) Variance $\sigma_{zk}^{\ 2}$ should be maximum

(3) z_k and z_{k+1} should be independent of each other

The solution of the above problem can be obtained by determining the unique values and the unique vectors which correspond to the variance and vector of the principal components respectively.

The unique value represents the contribution ratio which indicates how much percentage the principal component represents of the total tendency of the variables. The **accumulative contribution ratio** percentage all the principal components represent of the total tendency of the variables. Using an accumulative contribution ratio of 80 - 90 percent, will indicate how many principal components should be adopted to effectively represent the major variations in the image data.

Graphically speaking, the first principal component for example in the case of two dimensional variables (see Figure 10.8.1) will be the principal axis which gives the maximum variance. The principal component analysis can be used for the following applications.

(1) Effective classification of land use with multi-band data

(2) Color representation or visual interpretation with multi-band data

(3) Change detection with multi-temporal data

In the case of multi-band data with more than four bands, all bands cannot be assigned to R, G or B at the same time. However the first three principal components can represent up to five spectral variables with little information loss.

Figure 10.8.2 show the principal components and their color composite of Landsat TM (6 bands). Generally the first principal component corresponds to the total radiance (brightness), while the second principal component represents the vegetation activity (greenness).

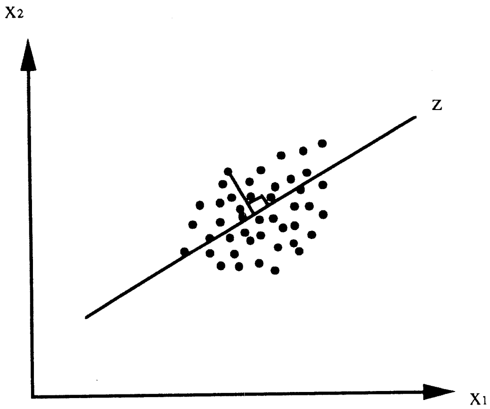


Figure 10.8.1 Example of principal component analysis

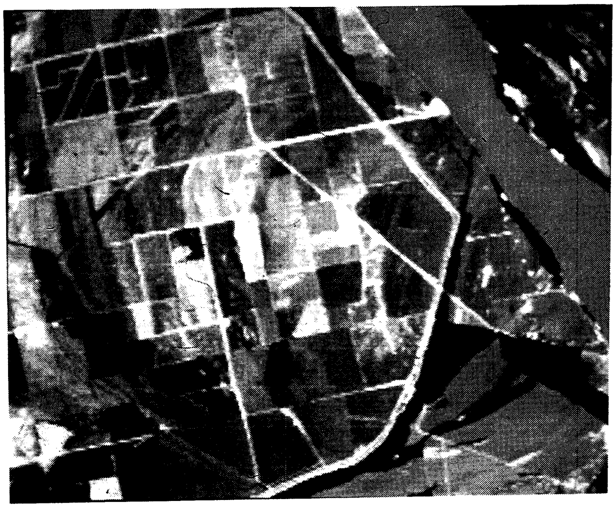


Figure 10.8.2 principal components and their color composite of LANDSAT TM

10.9 Spatial Filtering

Spatial filtering is used to obtain enhanced images or improved images by applying, filter function or filter operators in the domain of the image space (x,y) or spatial frequency (x,h). Spatial filtering in the domain of image space aims at image enhancement with so-called enhancement filters, while in the domain of spatial frequency it aims at reconstruction with so-called reconstruction filters.

a. Filtering in the Domain of Image Space

In the case of digital image data, spatial filtering in the domain of image space is usually achieved by local convolution with an n x n matrix operator as follows.

$$y(i,j) = \sum_{k=i-w}^{i+w} \sum_{l=j-w}^{j+w} f(k,l)\, h(i-k,j-l)$$

where f: input image
h: **filter function**
g: output image

The convolution is created by a series of shift-multiply-sum operators with an n x n matrix (n: odd number). Because the image data are large, n is usually selected as 3, although n is sometimes selected as 5, 7, 9 or 11.

Figure 10.9.1 shows typical 3 x 3 enhancement filters. Figure 10.9.2 shows the input image and several output images with various 3 x 3 operators.

b. Filtering in the domain of Spatial Frequency

Filtering in the domain of spatial filtering uses the Fourier transformation to convert from image space domain to spatial frequency domain as follows.

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

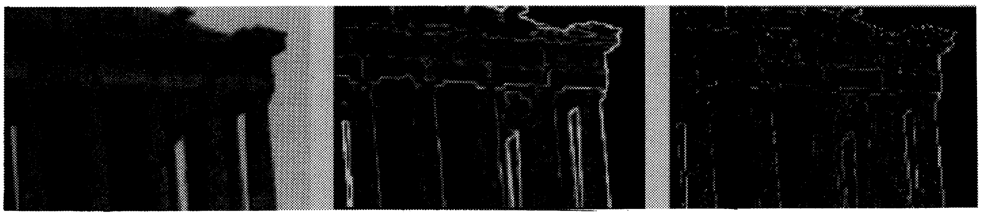
F: Fourier transformation of input image
H: filter function

An output image from filtering of spatial frequency, can be obtained by using an inverse Fourier transformation of the above formula.

Low pass filters, high pass filters, band pass filters etc., are typical filters with a criterion of frequency control. Low pass filters which out puts only lower frequency image data, less than a specified threshold, can be applied to remove high frequency, noise,while high pass filter are used for removing, for example, stripe noise of low frequency.

Fig.10.9.1 Examples of spatial filters of 3 × 3 window

SPATIAL FILTERS	3 × 3 OPERATOR	EFFECTS
Sobel	$\mid A \mid + \mid B \mid$ or $\sqrt{A^2+B^2}$ where, $A=\begin{bmatrix} -1 & 0 & -1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ $B=\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$	gradient (finite differences)
Preneit	$\mid A \mid + \mid B \mid$ or $\sqrt{A^2+B^2}$ where, $A=\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$ $B=\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$	gradient (finite differences)
Laplacian	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$ or $\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	differentia l
smoothing	$\begin{bmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{bmatrix}$ or $\begin{bmatrix} 0 & 1/5 & 0 \\ 1/5 & 1/5 & 1/5 \\ 0 & 1/5 & 0 \end{bmatrix}$	
median	Replaced with median of 3 × 3 window	smoothed image
high-pass	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$ or $\begin{bmatrix} -1/9 & -1/9 & -1/9 \\ -1/9 & 8/9 & -1/9 \\ -1/9 & -1/9 & -1/9 \end{bmatrix}$	edge-enhancement
sharpening	$\begin{bmatrix} 1/9 & -8/9 & 1/9 \\ -8/9 & 37/9 & -8/9 \\ 1/9 & -8/9 & 1/9 \end{bmatrix}$	clear image



a) original image b) Sobel c) Laplacian

d) smoothing e) median f) high pass

Figure 10.9.2 Image enhancement with use of 3x3 operators

10.10 Texture Analysis

Texture is a combination of repeated patterns with a regular frequency. In visual interpretation texture has several types, for example, smooth, fine, coarse etc., which are often used in the classification of forest types. **Texture analysis** is defined as the classification or segmentation of textural features with respect to the shape of a small element, density and direction of regularity.

Figure 10.10.1 (a) shows two different textures of density, while Figure 10.10.1 (b) shows two different textures with respect to the shape of the elements.

In the case of digital image, it is difficult to treat the texture mathematically because texture cannot be standardized quantitatively and the data volume is so huge.

However texture analysis has been made with statistical features which are combined with spectral data for improving land cover classification. Power spectrum analysis is another form of textural analysis in which direction and wavelength or frequency can be determined for regular patterns of , for example, sea waves and sand waves in the desert.

a. Use of Statistical Features

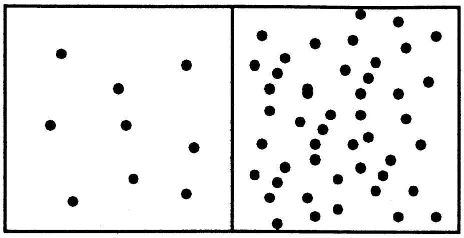
The following statistical values of an n x n window can be used as textural information

(1) Gray level histogram
(2) Variance - co-variance matrix
(3) Run-length matrix

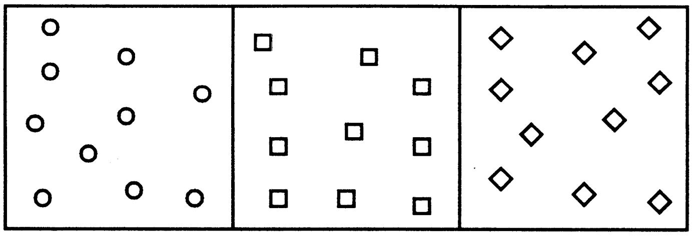
These values are used for classification together with the spectral data.Figure 10.10.2 (a) shows the land cover classification using only spectral data while Figure 10.10.2 (b) shows the result of classification with spectral data as well as textural information. The result shows a better classification for the urban area which has a higher frequency and variance of image density.

b. Analysis using Power Spectrum

Power spectrum analysis is useful for those images which have regular wave patterns with a constant interval, such as glitter image of the sea surface or wave patterns of sand dunes. Fourier transformation is applied to determine the power spectrum which gives the frequency and direction of the pattern.



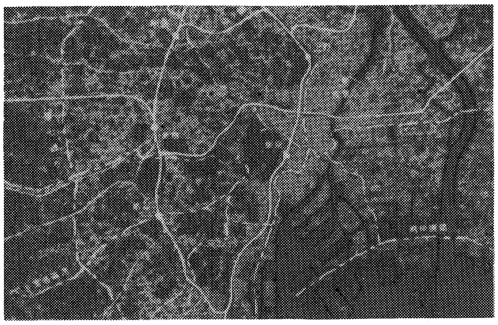
(a) different density



(b) shape of elements

Figure 10.10.1 Texture analysis

a) only with spectral data



b) with spectral data as well as textural information

Figure 10.10.2 Classification with use of texture analysis

10.11 Image Correlation

Image correlation is a technique by which the conjugate point of a slave image (right) corresponding to the master image (left) will be searched for the maximum correlation coefficient. Image correlation is applied to stereo images for DEM (digital elevation model) generation or multi-date images for automated recognition of ground control points.

As shown in Figure 10.11.1, the master window in the left image is fixed, while the slave window in the right image is moved to search for the maximum image correlation as computed from the following formula.

$$r = \frac{(\sum a_i b_i)^2}{\sum a_i^2 \sum b_i^2}$$

or

$$r = \frac{n\sum a_i b_i - \sum a_i \sum b_i}{\{n\sum a_i^2 - (\sum a_i)^2\}\{n\sum b_i^2 - (\sum b_i)^2\}}$$

where a_i : image data of the master window

b_i : image data of the slave window

n : total number of image data

Because the above two correlations show almost no difference, the first correlation is preferred to save computing time.

The size of the window should be selected depending on the image resolution and feature size. For example, 5 x 5 to 9 x 9 windows might be selected for SPOT stereo images, while 9 x 9 to 21 x 21 would be better used for digitized aerial photographs.

When the conjugate points of stereo images are determined, the corresponding digital elevation can be computed using collinearity equations based on photogrammetric theory.

Figure 10.11.2 shows the conjugate points as white dots in a pair of SPOT stereo images, which were automatically recognized by image correlation techniques.

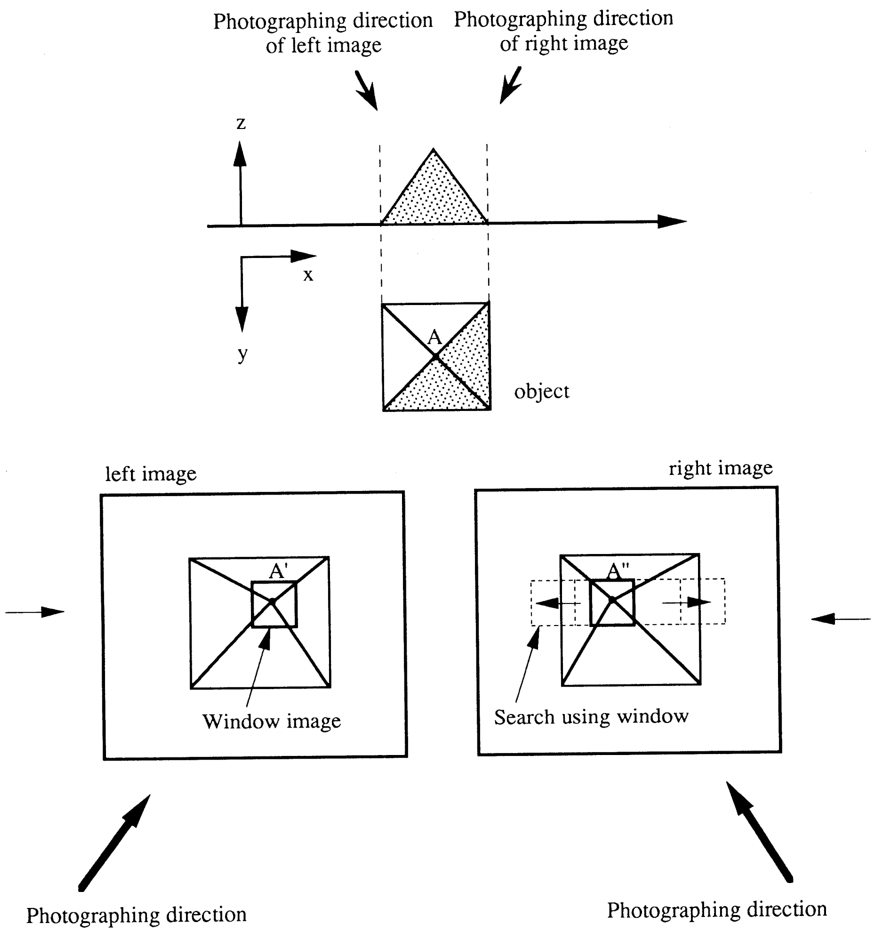


Figure 10.11.1 conjugate point Search (A' and A") on stereo image

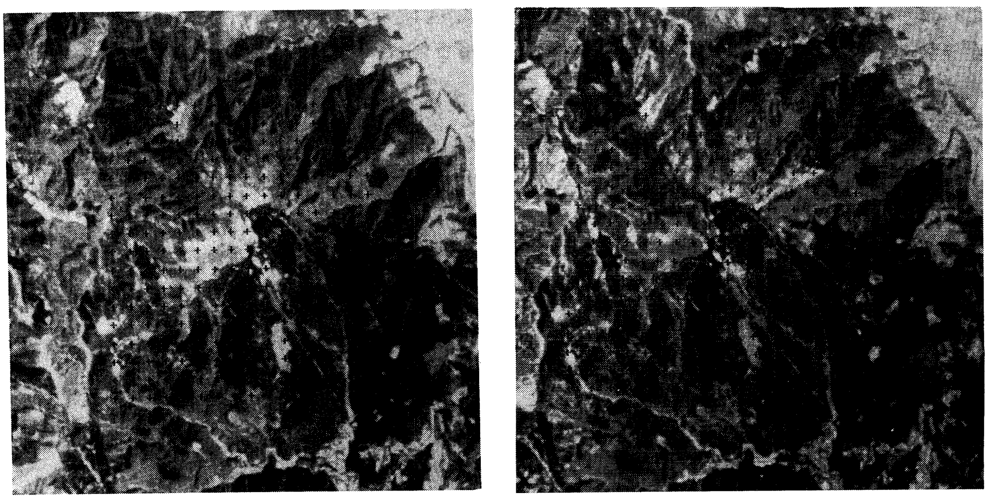


Figure 10.11.2 Automatically recognized conjugate point by image correlation technique