MODULE – 5 LECTURE NOTES – 4

IMAGE TRANSFORMATION

1. Introduction

Image transformation is the technique used to re-express the information content within several remotely sensed images, captured in different bands/wavelengths. Multitemporal or multidate satellite imageries can be subjected to image transformation procedures. The transformed images provide a different perspective of looking at satellite imagery. Such a transformed image is bound to display properties suitable for particular applications, over and above the information content that is present within the original image. Operations performed include image addition, subtraction, multiplication and division. The operation chosen will essentially depend on the application intended. For example, two images captured by the same sensor on different dates shed light on the amount of change that has occurred between the two dates, which is extremely important in disaster management studies in flood aftermath etc. Another example is the wide usage of image ratioing techniques. For example, the ratio of images captured in near infrared and red bands on a single date is used as a vegetation index to measure hydrological variables like leaf area index (LAI), vegetation moisture content, mapping biomass, vegetation health etc. Some popular vegetation indices are Perpendicular Vegetation Index (PVI), Normalised Difference Vegetation Index (NDVI) etc. In this context, it is essential to discuss the widely used technique of principal component analysis, which also aims at re-expressing the information content of a set of images in terms of various principal components that are extracted according to the order of their decreasing variance. Image transformation operations also include expressing images within a frequency domain like using wavelets that decompose the input signal in terms of wavelength (1D) or space (2D) and scale simultaneously. With the increased availability of hyperspectral imageries, image transformation techniques to extract details using the shape of spectral reflectance curves have also equally advanced. All these topics are vast in their own way; therefore this module will focus on the simpler image transformation techniques using arithmetic operators followed by change detection.

2. Arithmetic Operations

Arithmetic operations are performed on two or more georeferenced imageries (referenced to the same coordinate system) depicting the same area that are captured using separate spectral bands on a single date or on multiple dates. Each of the operations are discussed in detail below:

2.1 Image Addition

Image addition essentially implies a form of image averaging which is mainly employed as a means to reduce the overall noise contribution. It is usually carried out in a pixel by pixel manner. In mathematical terms, assume that a single image captured at a certain day and time be expressed in the form of:

$$I(x, y) = F(x, y) + N(x, y)$$

where $I(x, y)$ is the recorded image, $F(x, y)$ is the true image and the random noise component is given by $N(x, y)$. The true image value will generally be constant whereas the noise component is usually assumed to be normally distributed with a mean of zero. The noise component can either be positive or negative in nature. Hence, adding two images of the same area taken at the same time will cause the error term at a particular pixel position to get cancelled. Another point to note is the image display system. Suppose both the images which are to be added posses an 8 bit display system whose values vary from 0-255. Addition of these two images will cause the resulting image to have a dynamic range of 0-510 which is not advisable. Hence, this condition is averted by dividing the sum of two images with a factor of 2 in order to express in the dynamic range of 0-255. Image enhancement techniques such as contrast stretching always tend to alter the dynamic range of an image. Therefore, performing image addition in such contrast stretched images might not lead to meaningful results. Hence, always it is advisable to carry on arithmetic operations on images before these are subjected to any kind of enhancement techniques.

2.2 Image Subtraction

Similar to image addition, the operation of image subtraction is also performed on a pair of images of the same area, which are co-registered but are taken during different times. Unlike the operation of addition, image subtraction is essentially used to perform change detection studies between the dates of imaging. This operation is also performed on a pixel by pixel basis. Assume 2 images with an 8 bit display system showing their respective digital numbers in a dynamic range of 0-255. The maximum positive and negative differences that can be encountered with image subtraction will be +255 and -255. This implies that the resulting subtracted image will need to be rescaled onto a 0-255 range. This can be done by adding 255 to the obtained difference which will automatically shift the dynamic range to 0-510. Now, dividing this range with 2 will display the resulting subtracted image in 0-255 range.

Typically, a difference image will have a histogram either Gaussian or normal in shape with peak at a value of 127 indicating pixels that have not changed much and tails falling in either directions. Difference images can be very well represented using density slicing technique or pseudocolor transform wherein selected parts of the dynamic range are assigned to a particular color or shade of grey. To perform this simple technique, suitable thresholds need to be selected, however these can also be chosen arbitrarily or by trial and error approaches. This is similar to assigning a numerical value to represent a particular land cover type while performing image classification technique. More details on change detection can be found in the book by Lunetta and Elvridge (1998) wherein various methods detailing the detection and measurement of change is explained using remotely sensed images.

2.3 Image Multiplication

Image multiplication is usually employed when an image consists of two or more distinctive regions wherein an end user is just interested to view one of these regions. The best example is masking operation which is generally used to separate regions of land from water using information captured in the near infrared band as reflection from water bodies in the near infrared band is very low and those from vegetated land regions is very high. A suitable threshold can be chosen by visually inspecting the image histogram of the near infrared pixel values. With this threshold, a binary mask can be generated wherein all the pixels having values below the chosen threshold are labeled as '1' and those having pixel values above the chosen threshold are labeled as '0'. This immediately results in a black and white image which can then be used to multiply with the original image to extract the required regions.

2.4 Image Ratio and Vegetation Indices

Collecting accurate information regarding the world's food crops is important to address various applications but collecting using in situ techniques is not only expensive, time consuming but also near to impossible. Alternate method is to measure the vegetation amount using spectral measurements from remotely sensed imagery. The aim is to effectively extract information using multiple bands of satellite imagery in order to predict the canopy characteristics such as biomass, leaf area index (LAI) etc. Generation of ratio images is one of the most commonly used transformations applied to remotely sensed images. Image ratioing consists of dividing the pixel values of one image by the corresponding pixel values in a second image. This has many advantages like reduction of the undesirable effects on radiance values which may result either owing to variable illumination or due to varying topography. Also, different aspects of spectral reflectance curves of different earth surface cover types can be brought out by this technique of image ratioing. These two main properties of ratio images (i.e., reduction of topographic effect and correlation between ratio values and shape of spectral reflectance curves between two given wavebands) enable the widespread usage of spectral ratios in geology. The most common use of image ratioing is to study the vegetation status. Vegetation tends to reflect strongly in the near infrared band and absorb radiation in the red wavelength band which results in a grayscale image. This can be subjected to low pass filtering and density sliced to create an image that shows variation in biomass and in green leaf area index. It should be noted that the concepts of low pass filtering have been introduced in module 4. Ratio images tend to display the spectral or color characteristics of image features irrespective of the scene illumination. Consider a hypothetical situation wherein the digital numbers observed for each land cover type are tabulated below:

Land Cover/ Illumination	**Band 1**	**Band 2**	**Ratio (Band 1/Band 2)**
Deciduous			
Sunlit	48	50	0.96
Shadow	18	19	0.95
Coniferous			
Sunlit	31	45	0.69

Shadow	11	16	0.69

It can be observed that the ratio values of both the bands give same values irrespective of the scene illumination. This is because ratio images are capable of displaying the variations in the slopes of the spectral reflectance curves between the two bands involved irrespective of the absolute reflectance values observed in these two bands. The ratio of near infrared band to red band is very high for healthy vegetation whereas it tends to be comparatively lower for stressed vegetation. The resulting vegetation indices have been extensively employed to quantify relative vegetation greenness and biomass values. Some of the popular vegetation indices are discussed below:

a) Normalized Difference Vegetation Index (NDVI)

Rouse et al (1973) came up with this vegetation index based on a comparison of normalized difference of brightness values from MSS7 and MSS5 which was named as normalized different vegetation index hereinafter referred as NDVI. This vegetation index essentially used the sum and differences of bands rather than the absolute values which makes it more suitable for use in studies wherein change detection over a particular area is involved. This is owing to the fact that NDVI might be affected by varying atmospheric conditions, illumination and viewing angles, soil background reflectance etc. If images be captured in the near infrared (NIR) and red (R) bands, then the index of NDVI can be defined as:

$$NDVI = \frac{NIR - R}{NIR + R}$$

Vegetation indices based on NDVI have extensively found use to measure vegetation amount on a worldwide basis. Maximum of 10 day NDVI images can be corrected for cloud cover and used for crop forecasts as proposed by Groten (1963).

b) Transformed Vegetation Index (TVI)

Deering et al (1975) added 0.5 to NDVI and taking the square root which resulted in the transformed vegetation index or the TVI. The TVI is expressed as:

$$TVI = \left[\left(\frac{NIR - R}{NIR + R}\right) + 0.5\right]^{\frac{1}{2}} * 100$$

This index aids in ranch management decisions wherein TVI data correlates with the estimated forage level present in pastures contained in remotely sensed satellite imagery. Different versions of TVI have come up, proposed by several scientists.

c) Soil Adjusted Vegetation Index (SAVI)

In order to overcome the limitations of PVI index, Huete (1988) proposed the soil adjusted vegetation index (SAVI). He transformed the NIR and red reflectance axes in order to minimize the error owing to soil brightness variation. For this purpose, addition of two parameters (L_1 and L_2) was proposed which when added to NIR and red reflectance bands was found to either remove to reduce the variation caused by soil brightness. The expression is given as:

$$SAVI = \frac{NIR + L_1}{R + L_2}$$

A number of indices have been developed which correspond to this class. Several modifications have also been proposed along the years. Steven (1998) proposed the optimized soil adjusted vegetation index (OSAVI) which is given by the expression:

$$OSAVI = \frac{NIR - R}{NIR + R + 0.16}$$

This index minimizes soil effects. More information regarding this can be obtained from Baret and Guyot (1991), Sellers (1989) etc.

d) Perpendicular Vegetation index (PVI)

Developed by Richarson and Wiegand (1977), this index indicates the plant development by relying on a plot showing radiance values obtained in the visible red band against those obtained in the near infrared band. In the figure, bare soil pixels with no vegetation will essentially lie along the line (45^0 straight line). Pixels depicting vegetation will lie below and to the right of the soil line. Richardson and Wiegand (1977) proposed that the perpendicular distance to the soil line can be used as a measure that can be correlated with leaf area index and biomass. The expression of PVI using bands of Landsat Multispectral Scanner (MSS) is given as:

$$PVI7 = \sqrt{(0.355MSS7 - 0.149MSS5)^2 + (0.355MSS5 - 0.852MSS7)^2}$$
$$PVI6 = \sqrt{(0.498MSS6 - 0.487MSS5 - 2.507)^2 + (2.734 + 0.498MSS5 - 0.543MSS6)^2}$$

In 1984, Perry and Lautenschlager modified the PVI indices finding them to be computationally ineffective and incapable of distinguishing the water from green vegetation. They proposed a new perpendicular vegetation index which considered these factors. PVI has been extensively used to take into account the background variation in soil conditions which effect soil reflectance properties. But this index gets easily effected by rainfall when the vegetation cover is incomplete. For wet soil conditions, PVI will essentially underestimate leaf area index as canopy cover increases. Hence, PVI was considered to moderately perform well but less efficient to detect plant stress. It should be noted that this index is not widely used presently. It has been described to explain the concept of 'soil line'. The Tasseled cap transformation is a better alternative which is discussed in the next section.

e) Tasseled Cap Transformation

Developed by Kauth and Thomas (1976), the tasseled cap transformation produces an orthogonal transformation of the original four channel Multi Spectral Scanner (MSS) data into a four dimensional space. This technique has found extensive usage in agricultural research as it resulted in four new indices namely, the soil brightness index (SBI), the green vegetation index (GVI), the yellow stuff index (YVI) and a non such index (NSI) that is associated with atmospheric effects. The soil line and the vegetation region are represented in a better manner using this transformation. In this new, rotated coordinate system, there exists four axes of '*brightness*', '*greenness*', '*yellowness*' and '*nonesuch*'. The '*brightness'* axis represents variations in soil background reflectance whereas the '*greenness'* axis displays the vigour of green vegetation. The '*yellowness*' axis represents the yellowing associated with senescent vegetation and the '*nonesuch*' axis is related to atmospheric conditions. The point to note is that all these four axes are statistically uncorrelated and hence can be represented in a four dimensional space defined by the four Landsat MSS bands.

This technique essentially provides a physically based coordinate system for interpreting images of agricultural area captured during different growth stages of the crop. As the new sets of axes are defined a priori, they will not be affected by variations in growth stages of crop or variations from image to image captured over a period of time. This technique can be very well compared with the principal component analysis wherein the new set of axes (principal components) can be computed using statistical relationships between individual bands of the image being analysed. As a direct consequence, in principal component analysis, the correlations among various bands will differ based upon the statistics of pixel values in each band which in turn will vary over a period of time (different for growing season and for end of growing season of crops). Kauth et al (1979) and Thompson and Wehmanen (1980) had come up with coefficients for the four vegetation indices based on Landsat 2 MSS data.

$$SBI = 0.332MSS4 + 0.603MSS5 + 0.675MSS6 + 0.262MSS7$$
$$GVI = -0.283MSS4 - 0.660MSS5 + 0.577MSS6 + 0.388MSS7$$
$$YVI = -0.899MSS4 + 0.428MSS5 + 0.076MSS6 - 0.041MSS7$$
$$NSI = -0.016MSS4 + 0.131MSS5 - 0.452MSS6 + 0.882MSS7$$

Similar to the principal component analysis, the tasseled cap transform relies on empirical information for estimating the coefficients of the brightness axis.