

Digital Image Processing Information Extraction

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Information Extraction

Procedures

- Principal Component Analysis
- Ratio Images
- Change Detection Analysis
- Multispectral Classification

Principal Component Analysis (PCA)

For any pixel in MSS images, DN values are commonly correlated from band to band.

Correlation shows that there is redundancy in MSS data

If this redundancy could be reduced, the amount of storage required for MSS data can be compressed.

For the two band data PC transformation defines a new axis y_1 oriented in the long dimension of the distribution and a second axis y_2 perpendicular (orthogonal) to y_1 .

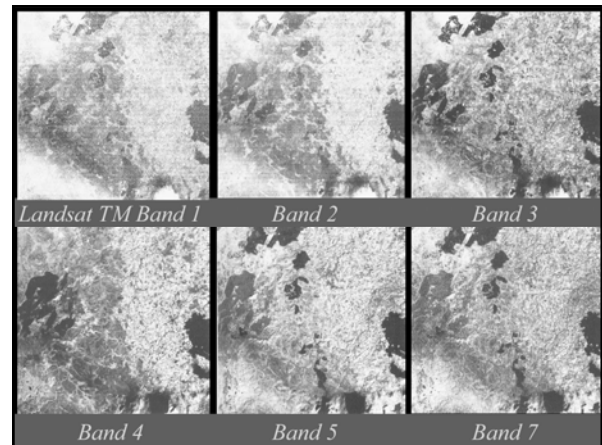
$$y_1 = \alpha_{11}x_1 + \alpha_{12}x_2$$

$$y_2 = \alpha_{21}x_1 + \alpha_{22}x_2$$

Production of principal components axes by means of a translation and rotation of the original axes.

These axes are produced using eigen values and eigenvectors.

Spread of data z is greater along the first principal component (PC1) than along either x or y .



Principal Component Analysis (PCA)

Band	Mean	Standard deviation
1	36.41	5.96
2	13.12	3.14
3	13.54	4.25
4	22.20	7.41
5	17.99	5.49
7	7.39	2.09

Variance-covariance matrix							
	1	2	3	4	5	7	
1	35.4						
2	17.4	9.9					
3	23.0	12.6	18.1				
4	21.2	15.2	18.6	55.0			
5	4.2	4.8	7.9	26.7	30.1		
7	2.0	1.8	3.1	8.1	9.7	4.4	

Principal Component Analysis (PCA)

Visualisation of the principal components is simple but to create the PC axes, it is necessary to calculate the length of the PC axes and their direction.

These are computed by determining the eigen values (length) and eigenvectors (direction) from the variance-covariance matrix.

First PC contains over 65 per cent of the variance while PC4, PC5 and PC6 combined have a little over 2 per cent. (first 3 components explain 98%)

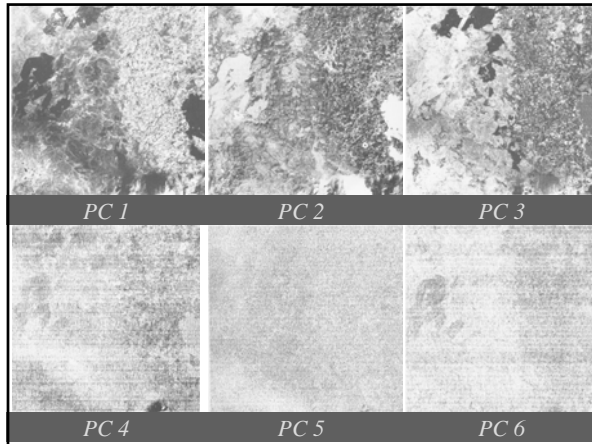
PC1 is a weighted average of all the input bands; thus a pixel with the following DN - TM 1: 12; TM 2: 8; TM3: 14; TM4:23; TM5:6; TM7: 18- has a DN of 33 in PC1 [(12 x 0.45) + (8 x 0.27) + (14x0.36) + (23 x 0.68) + (6 x 0.36) + (18 x 0.12)].

In this case, TM 4 and PC1 look similar because this band is major contributor.

Noise is relegated to Bands 4, 5 and 6.

PC1	Eigenvalue	% Variance
1	100.4	65.69
2	37.6	24.63
3	11.6	7.61
4	1.6	1.07
5	1.04	0.69
6	0.47	0.31

Eigenvectors of covariance matrix							
	PC1	PC2	PC3	PC4	PC5	PC6	
Band 1	0.45	0.62	0.18	-0.6	0.02	0.1	
Band 2	0.27	0.23	0.02	0.23	0.01	-0.9	
Band 3	0.36	0.30	0.25	0.75	-0.10	0.38	
Band 4	0.68	-0.33	-0.65	-0.01	0.05	0.08	
Band 5	0.36	-0.57	0.63	-0.16	-0.33	-0.01	
Band 7	0.12	-0.17	0.28	0.04	0.94	0.03	



Principal Component Analysis (PCA)

FCC
R - PC1
G - PC2
B - PC3

FCC
R - PC2
G - PC3
B - PC4

FCC: Red - TM4,
Green - TM3, Blue - TM5

Principal Component Analysis (PCA)

False colour image of part of the Andes, Peru produced by projecting TM 5 in red, TM 4 in green and TM 3 in blue. There is no evidence for mineralisation when this band combination is used

Principal component version of the image is considerably more colourful than the conventional FCC and the ore body is quite prominent

Ratio Image

The production of a ratio image, formed by dividing the digital number in one band by the corresponding DN of another band for every pixel, is one of the commonest arithmetic operations performed on digital remote sensing data

If an area of grassland on either side of a hill is imaged in two bands, it will not have a uniform signature on either image because the digital numbers will be consistently lower for both bands in shadow

A computer classification of this scene may correspondingly assign the sunlit and shadowed sections of the grassland to different classes

Band 1		Band 2	
180	64	142	36
98	72	80	95

Ratio image (before rescaling)

1.27	1.77
1.23	0.76

Band 1
Band 2

DN (Band 1) : 80
DN (Band 2) : 65
Ratio Band 1 : 1.23
Ratio Band 2 : 1.23

DN (Band 1) : 62
DN (Band 2) : 51
Ratio Band 1 : 1.21
Ratio Band 2 : 1.21

Illumination

Ratio Image

Ratioing effectively suppresses the 'topographic & albedo effect' but enhances gradient changes in the spectral reflectance curves of different materials.

False colour image of part of the Andes, Peru produced by projecting TM 5 in red, TM 4 in green and TM 3 in blue. There is no evidence for mineralisation when this band combination is used

A ratio image produced by projecting bands 1/2 in blue, 3/4 in green and 5/7 in red clearly defines an elliptical ore body in the northwest, shown in orange. Area approximately 15x15 km

Vegetation Indices

Intrinsic Indices

- Ratio Vegetation Index (RVI)

$$RVI = \frac{NIR}{R}$$
- Normalised Difference VI (NDVI)

$$NDVI = \frac{NIR - R}{NIR + R}$$
- Normalised Difference Wetness Index (NDWI)

$$NDWI = \frac{SWIR - MIR}{SWIR + MIR}$$
- Green Vegetation Index (GVI)

$$GVI = \frac{NIR + SWIR}{R + MIR}$$

Soil-line related Indices

- Perpendicular Vegetation Index (PVI)

$$NIR_{soil} = aR_{soil} + b$$

$$PVI = \frac{NIR - aR - b}{\sqrt{1 + a^2}}$$
- Weighted Difference VI (WDVI)

$$a = NIR_{soil} / R_{soil}$$

$$WDVI = NIR - aR$$
- Soil Adjusted VI (SAVI)

$$L = 0.5$$

$$SAVI = \frac{(1 + L)(NIR - R)}{NIR + R + L}$$

Atmospherically corrected Indices

- Atmospherically Resistant Vegetation Index (ARVI) (depends on aerosol type)

$$RB = R - \gamma(B - R)$$
- Soil Adjusted Atmospherically Resistant VI (SARVI)

$$L = 0.5$$

$$SARVI = \frac{(1 + L)(NIR - RB)}{NIR + RB + L}$$

Change Detection Analysis

Change detection has a number of applications within the environmental sphere

- Urbanisation is continually encroaching on the green belts surrounding many cities and the growth and direction of urban development may be monitored
- Land-use change may entail documenting changes in the types of crops being grown in a particular region
- The extent of deforestation in tropical rainforests can also be mapped
- One signal of increasing temperatures that can be readily monitored from space borne remote sensing systems is the retreat of valley glaciers

Two simple arithmetic procedures, subtraction and addition, are used to produce a change detection (or difference) image.

Initially two images for the same scene are obtained and co-registered to each other.

subtract the digital numbers for one image from the digital numbers for the other image and scale them

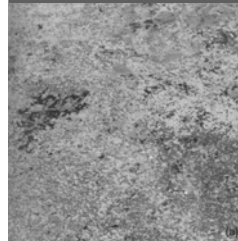
2nd date			1st date		
100	84	28	110	88	8
90	59	42	98	59	26
77	51	30	82	50	30
↓					
117	123	147	-10	-4	20
119	127	143	-8	0	16
122	128	127	-5	1	0
Difference image					

Change Detection Analysis

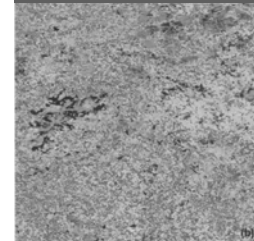
Minimum Maximum Mean Standard deviation

	Minimum	Maximum	Mean	Standard deviation
2 May 1990				
Band 1	37	255	55	7.5
Band 2	21	255	41	11
Band 4	19	255	151	44
6 May 1989				
Band 1	43	171	64	7
Band 2	27	150	45	10
Band 4	21	255	153	40

Landsat MSS FCC 6 May 1989

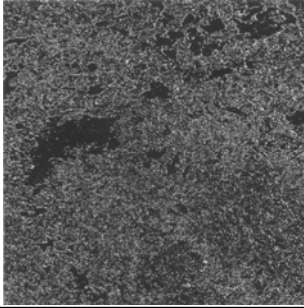


Landsat MSS FCC 2 May 1990



Change Detection Analysis

Density-sliced MSS 4 (Infrared) image produced by subtracting the MSS image obtained on 6 May 1989 from the one acquired on 2 May 1990. Width approximately 70km.



Range	Colour
More than 3 standard deviations lower	dark blue
2-3 standard deviations lower than mean	pale blue
1-2 standard deviations lower than mean	green
± 1 standard deviation	black
1-2 standard deviations higher than mean	yellow
2-3 standard deviations higher than mean	orange
More than 3 standard deviations	purple

Areas that have remained reasonably constant between the two dates are displayed as black

Different crops are being grown in the fields on a yearly rotation cycle

It is more likely that climatic conditions were different in the two years resulting in either delay in the planting of crops or retarding their growth

MSS Classification

On remotely sensed images, a range of digital numbers rather than a single value represents a single surface class such as water

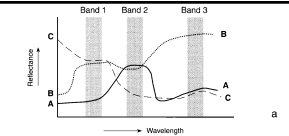
Many maps have large areas that are blank (or white), i.e. no land use or land cover has been assigned to them. Images, in contrast, provide a continuous record of land cover in these blank areas.

Classification is used to smooth out small, insignificant variations and simplify an image into a thematic map of land cover.

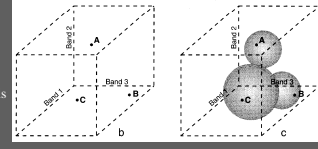
Classification is the process by which pixels which have similar spectral characteristics and which are consequently assumed to belong to the same class are identified and assigned a unique colour.

In general, a more accurate classification result is obtained if greater number of bands are used.

Increasing the number of bands to be used in classification also greatly increases the computing time (use PCA components).



	Band 1	Band 2	Band 3
A distinguished from B	Yes	No	Yes
B distinguished from C	No	Yes	Yes
A distinguished from C	Yes	Yes	No



Differentiation of surface classes A, B and C in bands 1, 2 and 3

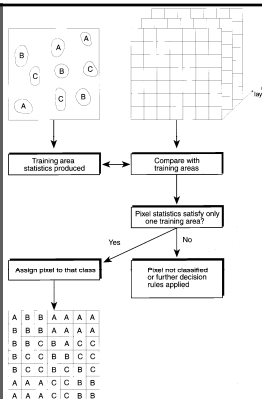
Supervised Classification

Initially the operator projects the image and outlines sample or training areas for each surface class (from ancillary data or Ground truth)

These are used to provide the classification program with typical examples of each kind of land cover for each class

Computer then generates statistical parameters from the training areas and compares the digital numbers of every pixel in the image with these statistical parameters

If the DNs for a pixel fall within a known training area, then the pixel is assumed to belong to the same surface class as the training area. (Classification algorithms) After the classification process has taken place, different colours represent different surface classes.



Generalised sequence of steps in a classification process

Supervised Classification

A sufficient number of pixels for each surface class must be delineated in order to ensure that a representative sample is obtained for each class.

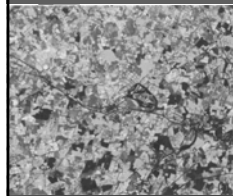
The training areas for any one class should not be concentrated in one part of the image but should encompass the entire scene. The histograms for training areas should be unimodal and conform to a normal distribution (Campbell 1996) The training areas should be as separate and uniquely representative as possible, otherwise a substantial Overlap between classes may occur and pixels will be misclassified.

Some times it may not be possible to ensure that classes are discrete because they may have similar reflectance characteristics in the bands that are being classified. In such a situation it may be preferable to merge the training sites and consider them as a single class.

It may be preferable to isolate an individual class and this is simply achieved by assigning a value of zero to all other classes.

Only three bands were used in the example though in practice more bands are usually employed.

Supervised Classification



FCC

R-TM4
G-TM5
B-TM3

Training areas for supervised classification

(background image blacked out)

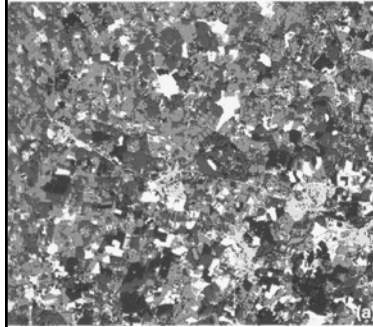
Colour	Land class	% of image
Pink	water	0.07
Pale blue	oil seed rape	0.12
Green	late crops	30.21
White	bare soil	12.4
Yellow	urban/industry	7.2
Blue	forest/early crops	8.54
Red	pasture	18.63
Black	unclassified	22.83

	Mean	Standard deviation
Training area: water		
TM 3	18.6	1.5
TM 4	13.5	4.7
TM 5	8.9	4.1
Training area: oil seed rape		
TM 3	62	7.4
TM 4	150	2.6
TM 5	67	2.7
Training area: late crops		
TM 3	24.7	1.3
TM 4	123.2	8.5
TM 5	86.3	3.9
Training area: bare soil		
TM 3	53.6	11.7
TM 4	82.3	14.2
TM 5	119.5	13.1
Training area: urban/industry		
TM 3	55.4	4.9
TM 4	58.8	11.3
TM 5	65.5	7.4
Training area: forest/early crops		
TM 3	20.4	1.5
TM 4	92.6	9.3
TM 5	47.9	7.1
Training area: pasture		
TM 3	20.7	1.1
TM 4	142	7.6
TM 5	68	6.2

Supervised Classification

Look-up Table (LUT)

Supervised classification (MLE) representation:
Density sliced classified image



Colour	Land class	% of image
Pink	water	0.07
Pale blue	oil seed rape	0.12
Green	late crops	30.21
White	bare soil	12.4
Yellow	urban/industry	7.2
Blue	forest/early crops	8.54
Red	pasture	18.63
Black	unclassified	22.83

Supervised Classification Algorithms

Minimum Distance to Mean (nearest neighbour) Classifier

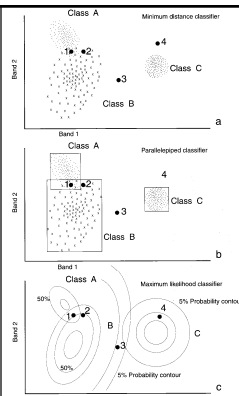
- Every pixel is assigned a class based on its distance from the mean of each class

Parallelepiped (or box) Classifier

- Size of the box is decided based on SD
- Pixels outside the box are not assigned to any class
- Pixels falling in more than one box may be left unclassified

Maximum Likelihood Classifier

- Assumes a normal distribution for the training areas
- Probability contours are created around each training area and a pixel assigned to a class depending upon the value of the probability contours that encompass it
- The maximum likelihood classifier is generally considered to be the most powerful but is also considered the most computer intensive
- Using this algorithm, pixel 1 belongs to class A, pixel 2 to class B and pixel 4 to class C. Pixel 3 has a higher probability of belonging to class B than class C.



Representation of Classification Algorithms

Unsupervised Classification

Unsupervised classification is a technique that groups the pixels into clusters based upon the distribution of the digital numbers in the image.

An unsupervised classification program, such as ISODATA clustering, requires following

- Maximum number of classes
- Maximum number of iterations
- Threshold value

An unsupervised classification operates in an iterative fashion.

Initially it assigns arbitrary means to the classes and allocates each pixel in the image to the class mean to which it is closest.

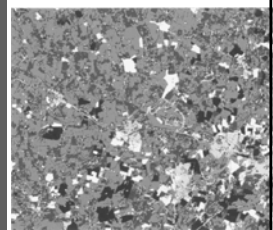
New class means are then calculated and each pixel is then again compared to the new class means.

This procedure is repeated over number of iterations.

Pixels move between clusters following each iteration until threshold is reached.

A threshold of 0.98 means that the program terminates when less than 2% of the pixels move between adjacent iterations.

The classes produced from unsupervised classification are spectral classes and may not correlate exactly with 'information classes' as determined by supervised classification.



Density sliced image using unsupervised classification process