

INTRODUCTION TO DIGITAL IMAGES AND DIGITAL ANALYSIS TECHNIQUES:

**A Basic Course for the Appreciation of Digital
Analysis of Remotely Sensed Multispectral Data**

**INSTRUCTIONS
(EXERCISE FORMS)
(EXERCISE SOLUTIONS)**

**T. T. Alföldi
Applications Division**

**Technical Note 78-1
Printed March 1978
Reprinted October 1986
Digital Version August 1996**

**Canada Centre for Remote Sensing
Natural Resources Canada
(formerly: Energy, Mines and Resources Canada)**

Ottawa, Canada

ABSTRACT

This document provides a self-teaching mechanism for the student of digital multispectral image analysis. The detailed step-by-step instructions and the corresponding figures lead the reader through some of the basic analysis procedures used in the study of satellite images for a variety of earth resources applications. No mathematical ability is required. Using only pencil (and eraser) the reader is led through steps which mimic the actions of a computer. Once this exercise is completed, the reader should have a functional knowledge of the basic multispectral analysis methods and data presentation formats.

RÉSUMÉ

Le présent document permet au lecteur d'étudier par lui-même l'analyse numérique d'images multispectrales; des instructions détaillées et des graphiques illustrent chaque étape; le lecteur prend connaissance des procédés fondamentaux d'analyse utilisés pour l'étude des images transmises par satellite et appliquée à la détection d'une gamme de ressources terrestres. Aucune aptitude spéciale pour les mathématiques n'est requise. Le lecteur franchit uniquement à l'aide d'un crayon et d'une gomme à effacer, les étapes qui reproduisent les opérations d'un ordinateur. Une fois cet exercice terminé, le lecteur devrait posséder des connaissances fonctionnelles de la méthode fondamentale d'analyse spectrale et des modes de présentation des données.

AVAILABILITY/PERMISSION

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1. INTRODUCTION

A simulation of 'hands-on' processing of digital images has been designed to give the new user familiarity with the manipulation of digital data. Although the original intent of this exercise was to provide a self-teaching mechanism for potential users of the IMAGE-IOO at the Canada Centre for Remote Sensing (CCRS), the concepts contained herein are sufficiently general as to be applicable to most digital image processing systems. If an instructor is available, the practical exercise should be preceded by a description of the basic characteristics of digital, multispectral remotely-sensed images: spatial, temporal, spectral and radiometric.

Note:

To permit hand simulation with only paper and pencil, the following simplifications have been made:

- a) The 'picture' to be processed by the reader is reduced in size to 49 picture elements (pixels), compared to the several millions typical of digital images.
- b) A multispectral image often contains from four to 24 spectral channels or bands. For hand simulation purposes, the 'pseudo' images have been designed with only two spectral bands (or dimensions in feature space).
- c) The number of intensity levels which may be recorded by a sensor is typically 64 to 256. This is impractical to manipulate by hand, so the reader's image has merely 10 levels.

The manual techniques to be described are very similar to the tasks performed by computer. However, the computer's great speed permits it to handle much larger images with more channels and greater radiometric range.

2. DATA ARRANGEMENT AND PRESENTATION

Figure 1 shows the data from two bands of a small segment of a satellite scene, with brightness information quantified into 10 levels (from 0 to 9) for each band. One band 'A' is red-sensitive and the other band 'B' covers a portion of the reflective infrared. The format of the data in this figure is "line-interleaved". For the 7 x 7 image represented on this tape, the first seven numbers correspond to the pixel intensities in the first line of band 'A', from left to right in the picture. The next seven numbers are for the same first line but of band 'B' data. This is followed by the next seven numbers which are for line No. 2, band 'A', and so on. For the 7 x 7 picture area, there are 7 lines x 7 pixels x 2 bands = 98 numbers. It is useful to arrange the numbers in a geometrically convenient form.

INSTRUCTION No. 1:

Beginning at the 'start', mark off every seven numbers from left to right, and label the first seven for band 'A', the second seven for band 'B', the third seven for band 'A', and so on.

Figure 2 prepares the format of the digital image. Band 'A' and band 'B' represent the same area on the earth's surface, but are coded separately because they represent different portions of the electromagnetic spectrum (or colours of light).

INSTRUCTION No. 2:

Insert the numbers from the tape into their appropriate geometric position thus: The first seven numbers of band 'A' from the tape are positioned as pixels 1 - 7 of line No. 1 of the band 'A' matrix in Figure 2. The next seven numbers from the tape are for pixels 1-7 of line No. 1 of band 'B' in Figure 2. Continue in this manner until the two matrices of Figure 2 are filled.

The digital or numerical maps constructed in Figure 2 may now be converted into another format which will permit a visual appreciation of the image. A "grey map" is produced to synthesize a visual image from the numbers at hand.

The computer-produced grey maps usually present a problem, in that the number of intensity levels (64 to 256) greatly exceeds the number of available grey 'shades' which the printing device can generate. Each pixel in the 7 x 7 image is coded at a particular intensity level from 0-9 (10 levels). It is appropriate in this simple example then, to use three shades of grey, in an attempt to represent the 10-level image.

INSTRUCTION No. 3:

For each of the band 'A' and 'B' digital images (Figure 2), transform the numerical values of each pixel into a "shade" of grey according to the following conversion:

Numerical Value	0	1	2	3	4	5	6	7	8	9
Grey Level										

and sketch these 'transformed' pixels into Figure 3. Note that the smallest intensities are represented as the 'darkest'.

Note that in the completed Figure 3, there are some similar and some dissimilar patterns appearing when bands 'A' and 'B' are compared. Although some environmental spatial patterns are beginning to appear, it is obvious that the grey maps represent much less information than is inherent in the digital maps.

Following are a number of techniques which are intended to give a better understanding of the data.

An 'intensity profile' gives a one-dimensional view of a single cross-section of the data. It is a popular technique in photographic analysis as well, where a 'density profile' is constructed.

INSTRUCTION No. 4:

An intensity profile will be constructed for line number 6 of each of the band 'A' and band 'B' images. Use the graph outlines prepared in Figure No. 4. For band 'A', line No. 6, determine the intensity level for each pixel using the digital map, and plot a point to correspond to that pixel number and intensity level. When all seven points are plotted, join the points, progressing from pixel numbers 1 to 7. Repeat the same procedure for band 'B'.

The completed Figure 4 now represents the intensities of reflected light as found on the ground track which corresponds to line No. 6 of the image. These intensity profiles may be produced for any line drawn across the image (at any angle). The inherent limitations of this technique reduce its usefulness. A more informative data arrangement is described below.

A one-dimensional histogram offers a graphical representation of the data distribution for a single band. The plot (see Figure 5) shows the number of pixels which have a particular intensity level. This is an abstract, but important concept. Alternately, one may ask: 'What area of the image corresponds to a particular intensity level?'

INSTRUCTION No. 5:

For band 'A', count the number of pixels which have an intensity of zero. Use the digital image in Figure 2. Enter this number in the space provided below the left graph of Figure 5. Now count the number of times that the intensity level 1 occurs and similarly record it on Figure 5. Continue for all levels. Check that the sum of these values is 49 (= 7 x 7). Now plot these values on the graph and join the plotted points with straight lines, progressing from left to right. Similarly construct the histogram for band 'B'.

There are several observations to be made regarding the appearance of these two histograms. First, the fact that the two histograms are significantly different means that there is different information (and perhaps useful information) available from the two bands concerning the same pixel (or ground area). Second, note the various peaks of the histograms. Each peak separated from neighbouring peaks by valleys is called a 'mode' of the histogram. Often it is found that a mode corresponds to a particular feature on the ground. The presence of several of these modes (a multi-modal histogram) leads to the conclusion that several (different) environmental features have been imaged.

Next, consider the band 'B' histogram. There are two major modes in this histogram, separated by the valley at intensity level 2. Since band 'B' is a reflective infrared band, knowledge of the infrared reflection characteristics of land and water can help identify these two modes. Water strongly absorbs infrared, resulting in low reflectivity. The typically vegetation-covered land surfaces will have high reflection during the summer months. Thus, the assumption is made that the left peak or mode designates water while the large mode on the right is of the land surfaces. By counting the number of pixels in each mode, we already have an idea of the relative size of areas of land and water in the image, even though we haven't seen the image as yet!

The 'spectral signature' of any one pixel is the combination of its intensity levels in the two bands. This characteristic may be plotted in a two-dimensional (2-D) histogram. In a 2-D histogram, the two axes depict the intensity levels for the two bands (see Figure 6). What is to be plotted is the frequency of occurrence of any one combination of band 'A' and band 'B' intensities. Stated in another manner, a 2-D histogram indicates the number of pixels which have a particular combination of intensities in the two bands. As an example, refer to pixel number 6 of line 2 (using Figure 2). In band 'A' it has an intensity value of 4, and in band 'B' a value of 6. Thus in Figure No. 6 it would be plotted at the coordinates 4,6 for the band 'A' and band 'B' axes respectively. What the completed histogram will show, is the data distribution of both bands simultaneously.

INSTRUCTION No. 6:

Plot the intensity coordinates for each pixel on Figure 6. Use the digital maps of Figure 2. When the intensity coordinates for a pixel are found in Figure 6, place a tick mark in the appropriate square. These tick marks will be summed later to find the total in any one square. Only the pixels in the first three lines of Figure 2 should be plotted, since the last four lines are already plotted as may be seen in Figure 6.

INSTRUCTION No. 7:

Transfer the data of Figure 6 into Figure 7 by summing the tick marks in each square and placing the numerical value in the corresponding square of Figure 7.

Each 'square' or location in the completed 2-D histogram is called a 'cell' or sometimes a 'vector'. The number in any one cell of Figure 7 depicts the frequency of occurrence of that particular set of intensity coordinates to be found in the original 7 x 7 image. This 2-D histogram plot is also the spectral signature domain. Cells which are close to each other in this plot have near-similar spectral characteristics. A much more sophisticated analysis is possible using the two spectral axes simultaneously (2-D histogram), then separately (1-D histograms), as shown in the examples below.

3. CLASSIFICATION USING ONE BAND

Figure 8 represents a ground verification map for a particular environmental feature: 'forest'. Three sites have been positively identified on the ground as being forested terrain, and the experts who collected this data are further assured that the combination of these three sites is representative of all forest types to be found in the area covered by the remotely sensed image. The ground verification map has been geometrically registered to the image, so that the same point on the map and the image may now be referenced by 'line' and 'pixel' coordinates. By using the spectral signature of these verified 'forest' areas, one may find all other 'forest' pixels. This can be done by searching all pixels in the scene for similar spectral signatures. The first task is then to define the spectral characteristics of the given training sites.

INSTRUCTION No. 8:

Find the intensities corresponding to each of the three test sites for band 'A'. Use Figure 8 to obtain the geometric locations, and extract the intensity levels from the corresponding locations of Figure 2. Enter these values below Figure 8. The category or class, 'forest', may then be assumed to be characterized by the range of intensities found in band 'A'. The range is defined by the minimum and maximum value from these three samples. Enter these also below Figure 8. Repeat the process for band 'B'.

The actual classification process now involves searching for all pixels which have an intensity level falling within the range of intensities found in the test sites. This is done separately for each band.

INSTRUCTION No. 9:

Using the band 'A' digital image of Figure 2, scan all of the pixels in the image for intensities falling in the range defined for band 'A' in the previous instruction. For any pixel with a band 'A' intensity falling in this range (inclusive of the minimum and maximum intensities), darken the corresponding pixel in Figure No. 9A. Repeat the process using the band 'B' digital image of Figure 2, the band 'B' intensity range defined in the previous instruction, and map onto Figure 9B.

The two forest theme maps in Figure 9A and 9B represent the same environmental feature (= forest), yet are different because each map was generated using information from one band only. The procedure used to produce these theme maps is akin to a rudimentary form of intensity 'slicing'. One specific range of intensities was sliced from the total available range. A more valid or 'correct' classification may be produced if the intensities in both bands were to be considered simultaneously.

4. MULTISPECTRAL CLASSIFICATION (RECTANGULAR)

In order to classify an image in a multi-spectral (or multi-band) mode, the intensities in all bands must be considered simultaneously. In Figure 10A, the range of intensities in band 'A' representing 'forest', is represented by the shaded area from band 'A' intensity 2 to 5 inclusive. Similarly for band 'B', 'forest' is represented by the shaded area of intensities 3 to 7 inclusive. The overlap of these two individual intensity ranges in this two-dimensional diagram is a cross-hatched area representing the multispectral (rectangularly-defined) spectral signature of 'forest'. In order to produce a multispectral classification of 'forest', it is necessary to find all pixels of the image whose spectral coordinates fall inside the cross-hatched rectangular area.

INSTRUCTION No. 10:

Using the digital images of Figure 2, scan all pixels for band 'A' intensities of 2, 3, 4, or 5. When a pixel has one of these band 'A' intensities, check if its band 'B' intensity is 3, 4, 5, 6 or 7. If a pixel agrees with both of these criteria, then shade in the corresponding pixel in Figure 10B. Only the last four lines of the image need to be considered, since the first three lines are already mapped in this manner.

As a check on this classification, note that a total of 21 pixels should have been identified as 'forest'. Further, it may be noted that the forest map of Figure 10B is the logical overlap between forest maps 9A and 9B.

In review, a rectangular classification, as has been performed above, requires 'representative samples' of the environmental feature to be mapped. The intensities of these sample pixels are collected in each band. The range of intensities which correspond to the feature of interest is plotted as spectral band versus spectral band (feature space). The rectangle thus defined in two-dimensional feature space is the spectral signature of the environmental feature. When more than two dimensions are used (hundreds of bands on airborne multispectral sensors is not uncommon, then N-bands can produce an N-dimensional 'rectangular parallelepiped' spectral signature, which is analogous to the (two-dimensional) rectangle produced above.

5. MULTISPECTRAL CLASSIFICATION (VECTOR)

A further refinement of the spectral signature, as defined by rectangular multispectral classification, is possible. To illustrate this, it is appropriate to demonstrate the most basic limitation of the rectangular classification technique.

INSTRUCTION No. 11:

The forest map of Figure 10B now has been verified on the ground by visual inspection, and homogeneous stands of coniferous and deciduous forest identified. Figure 11A shows the spatial distribution of these two forest types. The task is to delineate the portions of spectral feature space which correspond to each of the two forest types. For each pixel identified in the ground verification map of Figure No. 11A, find the corresponding band 'A' and band 'B' intensities in Figure 2. Plot each such spectral coordinate in Figure 11b using symbols 'C' (coniferous) and 'D' (deciduous). Draw a rectangle to define the spectral signature of 'coniferous forest'. The two vertical sides of this rectangle are the lower and upper limits of the range of intensities for band 'A'. The top and bottom lines of the rectangle are the upper and lower limits of the range of intensities for band 'B'. Draw a similar rectangle for the spectral signature of 'deciduous forest'. Note that the two rectangles will partially overlap.

It is this overlapping of spectral signatures in feature space which is a major limiting factor to the usefulness of the rectangular classification method. If a particular pixel has spectral coordinates which fall into the overlap region, then one is at a loss whether to label this pixel as 'coniferous' or 'deciduous'.

The multispectral vector classifier looks inside any feature space rectangle to identify each spectral coordinate (also known as "cell" or 'vector') and the number of pixels which are associated with each coordinate. This defines the data density distribution in feature space.

The next task is to use a multispectral vector classification scheme to map coniferous and deciduous forests in another scene. The first scene has been used in Figure 11A and 11B to 'train' the classifier. In other words the first scene contains the test sites from which the spectral signatures of the two forest types have been defined. One may extrapolate these spectral signatures to another area (scene No. 2) to look for similar environmental features. Here, we must recognize the fact that similar spectral signatures are the only themes which a machine or an algorithm will produce. It is the analyst who must make the assumption that similar spectral signatures indicate similar environmental phenomena.

INSTRUCTION No. 12:

Figures 12A and 12B contain the digital images of band 'A' and band 'B' of the new scene (No. 2). Figure 12C is the feature space representation of the spectral signatures of coniferous (C) and deciduous (D) forests, as previously constructed. Scan the new scene pixel by pixel for the first four lines (the last three lines have been mapped already). In order to classify any one pixel as one of the two forest types, it must agree in band 'A' and band 'B' intensities with one of the cells in Figure 12C, which is marked 'C' or 'D'. It is NOT sufficient for the spectral coordinates to merely fall within the rectangular limits. It is mandatory that the spectral coordinates being considered coincide with a cell marked by 'C' or 'D'. Only in this manner will ambiguities related to the overlap region be avoided. Those pixels thus identified in Figure 12C should be marked appropriately as 'C' or 'D' on the theme map of Figure 12D.

The above procedure is sometimes called: 'N-dimensional training', to refer to the fact that the intensities of more than one band are considered simultaneously. This type of training and classification scheme is also known as 'non-parametric' in that the absolute location of spectral coordinates in feature space is the criterion for defining an environmental feature, and NOT statistical parameters such as mean and standard deviation.

6. INTERPRETATIONS (FROM SPECTRAL SIGNATURES)

Although ground verification is essential in assigning environmentally valid names to features found on an image, it is, however, apropos to make deductions concerning an unverified feature, from its spatial and spectral characteristics.

INSTRUCTION No. 13:

As has been previously described, a one-dimensional histogram of the infrared band 'B' will display a marked difference between a low intensity mode corresponding to water, and a high intensity mode corresponding to land features. This may be observed on the one-dimensional histogram of band 'B' of scene No. 2, plotted in Figure 13A. The left mode of the histogram comprising band 'B' intensities less than 2 will relate to water pixels to a high degree of certainty. (The major conflicting phenomenon would be shadow areas due to clouds or mountains which would also result in low intensities.) Find those pixels in Figure 12B which have intensities less than 2 and mark the corresponding pixels in Figure 12D as: 'W'

Figure 13B shows the data density of spectral feature space for scene No. 2. Note the cluster of three low-intensity cells which correspond to 'water'. Sum the number of pixels corresponding to these three cells and check that the number of pixels marked 'W' in Figure 12D agrees with this sum.

The portions of feature space which were previously defined as representing coniferous and deciduous forest are indicated in Figure 13B. It is reasonable to assume that the portion of feature space which lies between two specific spectral signatures, may represent a mixed environmental target. Thus, the cells lying between the areas shown as 'coniferous' and 'deciduous' may be the spectral representation of the mixture of these two forest types, namely mixedwood. Identify the pixels which are represented by these (three) cells, and mark them on Figure 12D as 'M'. Verify that the correct number of pixels have been identified as mixedwood by summing the densities of the three cells in Figure 13B.

7. UNSUPERVISED CLASSIFICATION

The previous classification schemes used a training area in the image from which a spectral signature was defined, and for which the investigator had some prior knowledge. This spectral signature was then extrapolated throughout the image, or to another image, in search of other spectrally similar areas. This is known as a variation of 'supervised classification'. An investigator may prefer to reverse the procedure. It is often useful to delineate spectrally dissimilar areas of an image, even when nothing is known about the environmental character of the resulting subdivisions or classes. These classes are then mapped and the map taken into the field to identify the classes. This procedure is known as 'unsupervised

classification' since no training sites are involved. The main advantage of using an unsupervised classification technique is that the classes are subdivided based on their statistical characteristics usually covering large geographical areas, rather than depending on a 'training sample' which may be quite unrepresentative of the class variability over the whole scene to be mapped.

There are a large number of mathematical algorithms which use various schemes to locate and separate the statistically "cohesive" clusters in feature space, which are likely to have environmental significance. Most of these algorithms rely on finding areas of high pixel density (in feature space) which are separated by regions of low density. The following task serves to illustrate this by a less sophisticated algorithm than is actually used in practice.

INSTRUCTION No. 14:

The feature space representation of scene No. 2 is reproduced in Figure 14A. Into Figure 14B, copy those cells from Figure 14A, which have a count of (density) 3 or more.

To be observed now in Figure 14B are three clusters of high density cells. These groupings of high density cells are each only the nucleus of a cluster. The next step is to define the boundaries of each whole cluster. For reference, the cluster with a nucleus of two cells will be called cluster 'A' in feature space and class 'A' when it is finally mapped geographically (by line and pixel). Identify each cell which touches the nucleus cells of cluster 'A', by marking such cells with the letter 'A'. There should be 10 such cells marked, counting even those cells which touch with a corner only.

Repeat the process for cluster 'B' (with three nucleus cells) using the letter 'B' for the neighbouring cells, and also for cluster 'C' (with one nucleus cell) and using the letter 'C'. There will be a point of ambiguity where two clusters overlap and a cell is identified as belonging to the neighbourhood of two clusters. A decision must be forced, so identify this conflict cell as belonging to the cluster with the larger nucleus.

Draw the boundary for each cluster enclosing its complete neighbourhood in Figure 14B. There should be 11 cells inside the boundary for cluster 'A', 15 cells in cluster 'B', and six cells in cluster 'C'. Transfer just the boundaries back to the original feature space in Figure 14A.

For the final representation of feature space as divided into clusters, transfer those cells in Figure 14A, which fall inside the boundary for cluster 'A' and which display a count or density of 1 or greater, into Figure 14C, and identify those cells by the letter 'A'. Repeat the procedure for clusters 'B' and 'C' using the appropriate designation.

Now that feature space has been (pseudo-) statistically subdivided into cohesive clusters, it remains to map these clusters into their

geographical locations. This will require that for each pixel of Figure 14D which is to be classified, its spectral coordinates must be obtained from the digital maps of Figures 12A and 12B. These coordinates are located in Figure 14C, and the representative symbol (A, B, or C) allocated to the pixel in Figure 14D. Only the last three lines of pixels need to be considered, since the first four lines have been mapped.

The unsupervised classification shown in Figure 14D now requires that the individual classes (A, B, C) be identified environmentally. This may be done by a variety of techniques, notably airphoto interpretation, or actually visiting the site, if practical. But it is not necessary to completely cover the scene in question. Another advantage of the unsupervised classification scheme is that it can direct fieldwork or other forms of ground verification, to convenient, small and representative locations, where environmentally valid names may be assigned to the classes. For instance, the location marked by an asterisk in Figure 14D would be a suitable location to identify classes 'A', 'B', and 'C' because of their proximity to each other. Just a few such locations need to be investigated for a large scene, in order to be able to name the classes with confidence. Sometimes this field investigation procedure is used to establish classification accuracy figures.

Also, during a ground verification exercise, it may be opportune to identify those areas which are 'unclassified' (such as pixel No. 4, line No. 6 on Figure 14D). Whereas these unclassified areas may be due to imperfections in the processing technique or a 'noisy' image, if the areas seem large and cohesive, they may be identified as a particular environmental feature.

8. FURTHER STUDY

A few examples are shown of documents which deal with similar topics and are instructional in format. They vary, however, in complexity, approach and emphasis.

Grabau, W.E., "Pixel Problems", Miscellaneous Paper M-76-9 Mobility and Environmental Systems Laboratory, U.S. Army Engineering Waterways Experiment Station, P.o. Box 631, Vicksburg, Miss. 39180. May, 1976.

Landgrebe, D.A.. "Machine Processing for Remotely Acquired Data", LARS Information Note 031573, Purdue University, West Lafayette, Indiana. 1973.

Lindenlaub, J. and J. Russell, "An Introduction to Quantitative Remote Sensing", LARS Information Note 110474, Purdue University, West Lafayette, Indiana, 1974.

Orhaug, T. and I. Akersten, "A Workshop Introduction to Digital Image Processing, FOA Report D-30053-El. Research Institute of Sweden National Defense, S-104 50 Stockholm 80, Sweden. September 1976.

Smith, J.A., L.D. Miller, and T. Ells, "Pattern Recognition Routines for Graduate Training in the Automatic Analysis of Remote Sensing Imagery -- RECOGII, Science Series No. 3A, Colorado State University, Fort Collins, Colorado. February, 1972.

Readers are reminded that the above list was compiled in 1978. Since that date, a wealth of instructional documentation has been constructed on this topic by many authors and can be found in remote sensing journals, symposia proceedings, textbooks and the World Wide Web.