La Physique Au Canada
PP. 145-151

See CCRS slides
3003126-3140

IMAGE ANALYSIS TECHNIQUES IN REMOTE SENSING

W.M. Strome

Dept. of Energy, Mines and Resources

Canada Centre for Remote Sensing

Ottawa, Ontario, Canada

IMAGE ANALYSIS TECHNIQUES IN REMOTE SENSING

W.M. Strome

Dept. of Energy, Mines and Resources

Canada Centre for Remote Sensing

Ottawa, Ontario, Canada

ABSTRACT

Remote sensing techniques often provide a representation of the earth's surface as a set of images. The brightness of each point in an image represents the intensity of reflected or emitted electromagnetic energy from a corresponding point on the earth as measured by some sensing device carried aboard a platform such as an aircraft, a balloon, or a satellite. In some instances, simple visual inspection of the images permits positive identification of features of interest. For many applications, however, sophisticated digital analysis techniques are required to extract the desired information concerning earth resources and the environment.

INTRODUCTION

In order to effectively monitor and manage earth resources and the environment, it is necessary to know what is present in an area of interest on or near the earth's surface. Traditional methods of determining the status of forests, agricultural areas, urban features, snow cover, drainage patterns, location of man-made structures, water quality, ice, etc., involve ground surveys and sampling schemes. Ground observations have the advantage of making it usually possible to determine the features present at any given time and location with a specific degree of precision. However, ground sampling is slow, tedious and expensive in both monetary and human resources. Thus, in any practical ground sampling program, only a relatively few sample points can be obtained in any reasonably short period of time.

The most important features of interest as well as their characteristics, can often be determined or inferred by observations made at some distance, such as from an aircraft or satellite. These observations depend upon the measurement of reflected or radiated electromagnetic energy in some specific region or regions of the spectrum. The simplest such form of observation is visual - an observer is carried by an aircraft or helicopter over the region of interest. He may note the characteristics he is looking for by sketching their locations on a map. This technique is commonly applied while searching for open water, or leads, in the Arctic ice pack and is used also in spotting forest fires. To obtain a more accurate localization of features of interest, aerial photographs may be taken, using black-and-white, colour or false-colour infrared film. These photographs may be analyzed later by a trained photointerpreter to determine the location and condition of features.

In many instances, neither visual observation nor photography are effective in reliably detecting subtle differences among the objects of interest, or even where differences can be seen, or unambiguously identifying these features. These techniques provide only relative measurements of reflected radiation from objects on the ground. Where more absolute measurements are needed, where differences occur only in narrow regions of the spectrum, the investigator must resort to the use of electronic sensors in order to acquire the data.

Generally, there are two classes of electronic remote sensing instruments commonly employed: profiling and imaging. A profiling device measures reflected or emitted radiation from a point directly below the aircraft or satellite. As the platform moves, successive measurements build up a profile of the parameters measured along the flight path. A typical imaging sensor makes a large number of measurements along a line perpendicular to the flight path. Each such set of measurements is called a scan, and successive scans produced by the moving platform can be used to build up a two-dimensional array of data for each parameter measured. The data array can then be displayed as an image by recording the measured value at each point as an intensity on a television screen or on photographic film.

Since the dwell time, or time period during which a parameter is measured, is much longer with a profiling sensor, better signal-to-noise ratios can be obtained than with imaging sensors. In addition, the overall data rate for each measured parameter is much lower, since data are collected only along a line and not over a wide area. For these reasons, it is practical to construct a profiling sensor with much greater sensitivity and/or much finer spectral resolution. However, by the very nature of a profiling device, the data acquired form only a sample, and values must be interpolated between successive flight lines. A practical imaging sensor tends to be limited to fairly wide spectral band passes, limited sensitivity and relatively few parameters. Nevertheless, complete aerial coverage of a region can be obtained using imaging or scanning techniques.

Four imaging type sensors are commonly used for remote sensing of the near surface environment from aircraft and satellites. These are: multispectral scanners operating in the ultraviolet, visible and near-infrared regions; thermal infrared scanners operating in the 2-4 and/or 10-12 μm region; both real and synthetic aperture side-looking radars operating at X, L or C band (9.5 GHz, 1.3 GHz and 5.3 GHz); and passive microwave scanners operating at similar frequencies. It is possible that scanning laser flourosensors may be developed in the future. In all of these devices, electromagnetic radiation from a series of points to one or both sides of the platform is spectrally filtered and converted to electrical signals, which are then recorded on magnetic tape or photographic film, either on-board the platform or after transmission to the ground. The signals on magnetic tape may be either recorded directly in analogue form, or may be converted to digital form before recording.

Often, the two-dimensional data acquired by imaging sensors are simply recorded on photographic film and interpreted visually. However, for many applications it is necessary to apply sophisticated digital image analysis techniques to extract the desired information from the data. The image analysis techniques described here have all been implemented on the Canada Centre for Remote Sensing (CCRS) Image Analysis System (CIAS) which has been described by Goodenough (1977).

DATA CORRECTION

Before remotely sensed data may be properly analyzed, they must be corrected for various errors or artifacts. In the case of a multispectral scanner, calibration data must be used to correct for variations in sensor sensitivity (Strome *et al*, 1975; Ahern and Murphy, 1978). In some cases, it is necessary to correct for variations in sun-angle, viewing angle and slope and aspect of the target. Corrections to radar are much more complex, including the effects of the antenna radiation pattern and loss in received power with range. The atmosphere can significantly alter the intensity of the radiation received from the target through scattering and absorption. Some atmospheric effects are simple, depending only on the path length, hence viewing angle, while others are dependent upon the aerosol and water vapour content of the atmosphere between the sun and target and between the target and sensor. In the near visible region, algorithms have been developed (Strome *et al*, 1978) to correct for some of these effects. A fundamental difference between Synthetic Aperture Radar and most other imaging sensors is coherent speckle or fading which arises due to the coherent nature of the illuminating radiation and the method of coherent detection, causing rapid variability in the image intensity from one picture element (pixel) to the next. Even with a perfectly noiseless radar and a field of uniform reflectance, the image from a coherent system will show statistical variations where the variance is of nearly the same value as the mean. Thus, before the reflectance of an area under study can be determined to any accuracy, a number of returns must be averaged. There is a complex affiliation between radar intensity resolution that is related to the statistics of the scatterers in the scene and to the detection and processing schemes used in the radar and processor to generate the image.

In addition to radiometric corrections, there are many geometric distortions to be corrected. Typical aircraft scanners use a rotating mirror to image successive points on the ground onto the sensor. Since the data sampling rate is usually linear in time, each sample corresponds to an area of different size on the ground. In the case of a satellite, significant geometric distortions are caused by effects of earth curvature, panoramic distortion and non-uniform mirror velocity. In both instances, the geometry of the image data is affected by the attitude, altitude and velocity of the platform. The image analysis process usually involves extracting information concerning the ground cover and assigning the information to specific locations on a map. To do so accurately, the data must be geometrically corrected. Furthermore, data sets from different dates, or even different sensors, must be registered to each other prior to analysis. The most factual method of registration and/or geometric correction involves locating Ground Control Points (GCP's) whose actual positions are accurately known on the image data. The positions of a number of these points are then used to define a geometric "rubber sheet stretching" transformation of the image data. A new set of data samples is created using various interpolation techniques in which the values at the new grid points are determined (Shlien, 1978) as illustrated in Figure 1. These new grid points might correspond to the sample points in a reference image, or to a regularly spaced grid on a standard topographic map.

Most SAR data analyzed by CCRS are obtained using the dual frequency, dual polarization system of the Environmental Research Institute of Michigan (Rawson, R., Smith, F. and Larson, R., 1975). The four radar channels, although recorded simultaneously, are optically processed separately and thus must be digitally registered after image generation. The high variance to mean ratio for these data makes digital registration more difficult for radar data than for multispectral or multitemporal scanner data. CCRS scanner imagery, for example, is of sufficient quality that common points (GCP's) between a reference image and a corresponding source image of the same area may be identified automatically by correlation. SAR imagery, on the other hand, has too much "speckle" for automatic selection of GCP's and must therefore be selected manually. Once the necessary number of GCP's are selected, a rubber-sheet polynomial transformation of the source image is performed together with an approximation to (sin x/x) interpolation. The resulting corrected image is thus matched to the reference channel or image. This process is repeated for each remaining channel of the radar data set. The new four-channel set may now be treated as a four-feature image for subsequent analysis, after the data are spatially smoothed.

IMAGE ENHANCEMENT

For some applications, the best approach to image analysis is to simply provide an enhancement for later visual analysis by a trained photo-interpreter. A number of such enhancements are commonly employed. Perhaps the most basic is a simple contrast stretch. Figure 2a shows a histogram of the data for a single channel of a typical imaging sensor. If this were data from a visible sensor aboard a satellite, the first narrow peak might correspond to water, the central one to land and the third to clouds. Notice that the maximum observed value is just slightly over one-half full scale. Better use of the dynamic range at the display medium, either photographic film or CRT, can be obtained if the observed values are simply multiplied by some factor, stretching the histogram as shown in Figure 2b. If cloud and water detail are of no interest, scaling can be applied to stretch the observed values over land areas to fill the dynamic range, forcing the water and cloud data into saturation at the top and bottom end of the scale as shown in Figure 2c. Such contrast stretching can be performed on several channels of data, and three of these can be combined to form a colour composite.

A more complex radiometric enhancement has been developed by Taylor, M.M., (1973). Only three channels of image information may be displayed in registered form simultaneously by means of a colour composite image using the three primary colours, red, green and blue. If the image data consists of more than three channels, one may normally display any three of these channels at a time. Typically, the data contained in the various channels exhibit some degree of correlation. The eigenvectors can be determined by computing the covariance matrix for the data in all channels. A coordinate rotation can then be performed on the data to produce the same number of channels with features represented by intensities along the eigenvectors. By selecting those three channels with maximum variation in the rotated space, a new colour image may be produced containing the maximum amount of information available. Normally, each of the new data channels would be contrast stretched. The result is an image which produces even greater discrimination between objects with different spectral characteristics than that obtainable through simple contrast stretching alone. This is illustrated by Figure 3. Two parameters x_1 and x_2 have been measured for a number of objects of class x and class o. If a black and white image was produced using either x_1 or x_2 data alone, it would not be possible to separate the classes x and o. However, in a rotated coordinate system, the data points may be projected onto an axis where there is complete separation of the two classes as shown.

Many features in an image which define the boundaries between objects of interest, or the objects themselves, are spatial in nature. Often, these features can be made more visible through edge enhancement techniques. These are merely high frequency filters. The simplest of these is a variation of the box-car filter. The average of a number of picture elements (pixels) surrounding the one of interest are averaged. A fraction of this average is then subtracted from the value of pixel of interest to form a new value. The result is an image in which changes between adjacent pixels are accentuated. This technique is particularly interesting to geologists who are able to glean information about the geological structure from the accentuated linear features.

MACHINE CLASSIFICATION

The Multispectral Scanner System (MSS) carried aboard the U.S. National Aeronautics and Space Administration Landsats 1, 2 and 3 (NASA, 1976) has provided Canada with more digital image data than all other sensors combined. A single four-channel scene, acquired in only 25 seconds, contains 180 million bits of data. The analysis techniques described here may be adapted to any multichannel image data, but have been most widely used for extracting information from Landsat data.

The data from Landsat consist of a two dimensional array of measured incident radiation values in four spectral bands:

0.5 - 0.6 μm (green)

0.6 - 0.7 μm (red)

0.7 - 0.8 μm (near IR)

0.8 - 1.1 μm (near IR)

Figure 4 shows spectral reflectance curves in the region covered by the MSS for various materials commonly observed by remote sensing techniques. It is important to note that rather large variations in absolute reflectance are common, especially in the case of plants. However, the general shape of the spectral response tends to be similar from sample to sample. The sensors usually do not measure reflectance, but incident radiation which is affected by many factors other than the reflectance as illustrated in Figure 6, the most important of these being the sun angle, viewing angle, slope and aspect, and atmospheric absorption and scattering. Ideally, corrections should be made for all of these effects before further analysis is attempted. However, in the case of a single Landsat MSS scene, the sun angle is constant, many areas are relatively flat, the viewing angle varies by only a few degrees and the atmospheric scattering and absorption can be treated as a constant. Therefore, if there is no attempt to carry analysis from one scene to the next, most of the corrections can be ignored for many applications.

The objective of the classification of image data is to identify the various objects contained within a scene and relate these to objects on the ground. Where differences among the objects are too subtle for resolution by manual photointerpretive methods, the computer techniques developed for general pattern recognition studies can often be optimized for use in the analysis of the large volumes of data encountered with images. Two approaches are normally used: supervised and unsupervised classification.

The supervised methods rely upon a user to pick typical training sites in which he knows the nature of the object. For example, if he wishes to locate all the water in an image, he may select an area where he knows water occurs. The computer calculates the statistics of this training site and identifies all other areas with similar statistics as being of the same class. Normally, the user will select many training sites for each of a number of classes. Decision boundaries are determined in the feature space so that each point in the image is then assigned to one of the classes. Various algorithms are available for defining these decision rules. A non-parametric method permits the user to interactively form the decision boundaries by the construction of multidimensional hypercubes in the feature space which surround all the data points corresponding to the various training samples. Alternatively, assumptions may be made about the probability density functions of the classes and then use maximum likelihood decision rules to distinguish among these.

Consider one common statistical decision rule for assigning measured parameters to a given class. Assume that a set of measured parameters $\underline{x} = (x_1, x_2 \cdots x_n)$ is obtained for every observed position, and that there is a set of classes $w = (w_1, w_2 \cdots w_m)$ of interest. Assuming that the probability density function for the parameters set $\underline{x}$ is known for each class member w_i, and is denoted by $P(\underline{x} \mid w_k) \geq P(\underline{x} \mid w_j)$ $i = 1, 2 \cdots m$, and the region of $\underline{x}$ for which all objects are assigned to class w_k is denoted R_k. This is illustrated for a one dimensional case in Figure 7.

Unfortunately, the probability density functions, $p(\underline{x} \mid w_j)$ are rarely known. In many classification systems, a parametric approach is adopted. Essentially, it is assumed that $P(\underline{x} \mid w_j)$ has a known parametric form, usually

$$p(\underline{x} \mid w_j) = N(\underline{\mu}_j, \underline{\Sigma}_j) \tag{1}$$

where $\underline{\mu}_j$ is the mean and $\underline{\Sigma}_j$ is the covariance matrix for a multivariate normal distribution. The maximum likelihood estimates for $\underline{\mu}_j$ and $\underline{\Sigma}_j$ from a training set, that is from data samples from areas known to be representative of object w_j, are given by:

$$\underline{\hat{\mu}} = \frac{1}{q} \sum_{R=1}^{q} \underline{x}_k \tag{2}$$

$$\underline{\hat{\Sigma}} = \frac{1}{q} \sum_{R=1}^{q} (\underline{x}_k - \underline{\hat{\mu}})(\underline{x}_k - \underline{\hat{\mu}})^T \tag{3}$$

These estimates, given by equations (2) and (3), when substituted made into equation (1) provide probability density functions from which decision boundaries can be determined.

The problem with parametric classification is that there is little evidence radiometric measurement of objects commonly observed using remote sensing techniques actually exhibit a normal distribution. Figure 8 illustrates a number of two-dimensional distributions, all of which have the same mean and covariance.

There are several non-parametric classification procedures. Perhaps the simplest is the application of the nearest neighbour rule as illustrated in Figure 9 in two dimensions. Assume that two training sites are selected for classes A and B for which sample values of x_1 and x_2 are plotted at the a's and b's respectively. The parameters labelled x are for unknown objects. They are assigned to the class of their nearest neighbour in the training set. The type of errors in assignment that are possible with this decision rule are clearly illustrated in Figure 9.

A non-parametric classification method used extensively at CCRS is illustrated in Figure 10. Essentially, it involves the construction of a set of arbitrarily shaped decision boundaries in feature space which are composed of sets of parallelpipeds added to or subtracted from the space through a sequence of interactive training sets. For each training site, a parallelepiped is computed which contains all values for that training site. In the case of the CIAS, all areas whose values are contained in that parallelepiped are then displayed so that the operator can immediately spot other areas which have been falsely classified, or which have been missed. Through careful selection of other training sites, the operator can build up an arbitrarily complex decision boundary as illustrated in Figure 10 where three different training sites for each class o and w have been used to build the decision boundaries through a succession of six steps.

The unsupervised classification approach may be used in cases where the user is not certain

interest, or if he does not know which classes are truly distinct. By these methods, the computer examines the statistics of the data for the whole scene. Using one of a variety of algorithms, the data points are formed into distinguishable "clusters". That is, data points tend to be grouped together, with gaps between these groupings, each of which is defined arbitrarily as a class. This is illustrated in Figure 11. Of course, user interaction is required with these unsupervised methods in order to define what each of the classes represent. The most efficient clustering algorithm in use by CCRS for four channel data is one which searches for the isolated peaks in the four-dimensional histogram. Each of these peaks is identified as a centre for a class or cluster. The method of determining these peaks is analagous to flooding a mountainous area with water. When the water level rises, the peaks are identified as islands surrounded by water, illustrated in Figure 12, (Shlien and Smith, 1975).

A second commonly used clustering algorithm is the basic isodata or migrating means procedure (Duda and Hart, 1973). Starting locations are assigned for n cluster centres in feature space, $\underline{\mu}_1$, $\underline{\mu}_2$ ... μ_n. Each sample value $\underline{x}_j$ is assigned to the class w_i whose mean $\underline{\mu}_i$ is closest, usually in Euclidean distance. When all the $\underline{x}_j$ have been assigned to classes, new means, $\underline{\mu}_i$, are computed as an average of the samples now contained in each class w_i. If any of the $\underline{\mu}_i$ change position, the procedure is repeated. Figure 12 shows the trajectory of $\underline{\mu}_1$ and $\underline{\mu}_2$ for different starting values of a data set containing samples from two, two-dimensional normal distributions. The rate of convergence depends upon proper selection of the number of natural clusters occurring in the data, their separation and the initial values of the $\underline{\mu}_i$. In fact, convergence is not guaranteed at all with this procedure.

Another non-parametric clustering algorithm employed in image analysis is the valley seeking (Koontz and Fukunaga, 1972) which defines the clusters by connecting local minimum in the histogram as illustrated in Figure 13. Still another approach is graph theoretic clustering (Koontz, Narendra and Fukunaga, 1976). In this technique, sample points in the feature space are connected to their nearest neighbours to form a set of tree structures to define the clusters, as shown in Figure 14. Decision rules to determine to which tree a point belongs near a boundary ensure that these boundaries actually follow the valleys between peaks in the histogram.

A major difficulty with all machine classification systems is that they become unwieldy and very time-consuming as the dimensionality in feature space increases, i.e. as more channels of data become available. Thus, for multichannel or multitemporal data, it often becomes necessary to reduce the number of effective channels. Two methods are commonly employed. In the first, the correlations between data in each channel are computed on a pair-wise basis. Those channels with the least correlation between any other channels are then selected. This method is relatively fast and requires no further preprocessing of the original data, it is simply a method for choosing the original channels containing the data least correlated with the others. The second method of dimensionality reduction is that of principal components analysis (or Karhunen-Loére transforms), which was discussed as an image enhancement technique. For general dimensionality reduction, the n channels in rotated space containing the most information are retained.

SPATIAL ANALYSIS

Much of the information in a remote sensing image is spatial, contextual and/or textural. Visual photointerpreters tend to make greater use of these spatial cues rather than the specific radiometric values of each point, whereas in the computer techniques just described, each point is considered in isolation, and only the values assigned to it are considered.

Perhaps the simplest step toward spatial analysis is the post-classification filter (Goldberg and Goodenough, 1976). After classification has been performed using any of the methods described, the neighbours of each point can be examined and a decision made as to the probability that the point was misclassified. For example, a single point classified as corn completely surrounded by wheat is probably an error. A matrix of probabilities of misclassification is used to drive the algorithm.

Another attempt to use spatial information in the classification is that of image segmentation (Narendra and Goldberg, 1976), followed by classification. With this method, an attempt is made to define homogeneous regions which probably contain the same material. The advantage with this approach is that the resulting regions can be classified utilizing so called "field classifiers" which use their overall statistics of a region instead of examining each data element as an isolated point. The problem is finding the boundaries between homogeneous regions, especially in the presence of noise. Figure 15 illustrates a gradient technique for detection of edges using a one-dimensional example. In the two-dimensional case, a two-dimensional differentiation operation is performed, the result rectified and inverted and various valley detection schemes applied to define the boundaries. Simple thresholding can be used, although this is often rather ineffective because edges might be thick, and the height of the edges is not constant around a segment. Any valley seeking algorithms, including the graph theoretic clustering method outlined previously, may be used.

The next stage in sophistication of spatial analysis involves the definition of spatial or textural features which may be assigned to each point (Haralick and Johnson, 1974; Haralick *et al*, 1976). A typical, yet simple textural feature is the deviation of one pixel from its neighbours. For example, if i denotes the x coordinate and j the y coordinate of a parameter set $\underline{x}_i$, j, a measure of the deviation of the overall radiance at one point from its neighbours is

$$\Delta_{ij} = \sqrt{\frac{1}{9} + \sum_{l=-1}^{1} + \sum_{K=-1}^{1} \left| \underline{x}_{i}, j - \underline{x}_{i} + k, j + l \right|} \qquad (4)$$

More complex textural features can be defined.

Some spatial analysis of remotely sensed data has been performed using two-dimensional Fourier Transform. (Gramenopoulos, 1973), to detect changes over time and to classify features such as farms, mountains, desert and urban. Until recently, it has been impractical to perform Fourier Transforms over significant portions of a Landsat image, and as a result, the technique has not been fully explored. As more powerful array processors become embedded into image analysis systems, more work in spatial analysis is likely.

SUMMARY

Many rather sophisticated techniques have been adapted from the general field of pattern recognition to problems of image analysis of remotely sensed data. In some instances, new techniques have been developed to increase the efficiency of classification or enhancement of the large volumes of data which are routinely acquired by remote sensing instruments. New methods must be developed to extract spatial information barely used in machine analysis today. New sensors being developed for the early 1980's will acquire data at a rate which is an order of magnitude greater than those in use today. The challenge for the future lies in developing systems and algorithms to deal with these data, to convert them into useable information and to integrate information from remote sensing with that from other sensors in a form which can be readily used operationally to more effectively manage our resources and environment.

REFERENCES

Ahern, F.J. and Murphy, J., "Radiometric Calibration and Correction of Landsat 1, 2 and 3 MSS Data", EMR/CCRS Research Report 78-4, November, 1978.

Duda, R.O. and Hart, P.E., "Pattern Classification and Scene Analysis", John Wiley and Sons, New York, 1973, pp. 405-424.

Goldberg, M. and Goodenough, D.G., "Analysis of a Spatial Filter for Landsat Imagery", SPSE Conference Proceedings, July 19-23, 1976, Toronto, Canada, pp. 276-282.

Goodenough, D.G., "The Canada Centre for Remote Sensing's Image Analysis System (CIAS)", presented to the 4th Canadian Symposium on Remote Sensing, Quebec City, May, 1977, pp. 227-244.

Gramenopoulos, N., "Automated Thematic Mapping and Change Detection of ERTS-1 Images", Proceedings: Fourth Annual Conference on Remote Sensing in Arid Lands, Tucson, Arizona, 1973, pp. 82-96.

Haralick, R.M. *et al*, "Automatic Remote Sensor Image Processing", Topics in Applied Physics, Digital Picture Analysis, Springer-Verlag, Berlin, Heidelberg, New York, pp. 5-66.

Haralick, R.M. and Johnson, D., "Kansas Digital Image Data System (Kandidats)", June, 1974.

Koontz, W.L.G. and Fukunaga, K., "A Nonparametric Valley-Seeking Technique for Cluster Analysis", IEEE Transactions on Computers, No. 2, Volume C-21, February, 1972.

Koontz, W.L.G. and Fukunaga, K., "Asymptotic Analysis of a Nonparametric Clustering Technique", IEEE Trans. on Computers, Vol. C-21, No. 9, pp. 967-974, September, 1972.

Koontz, W.L.G., Narendra, P.M. and Fukunaga, K., "A Graph Theoretic Approach to Nonparametric Cluster Analysis", IEEE Trans. on Computers, September, 1976.

Narendra, P.M. and Goldberg, M., "A Graph-Theoretic Approach to Image Segmentation", 1976.

NASA/GSFC, "LANDSAT Data Users Handbook", Document No. 76SDS4258, September 2, 1976, Greenbelt, Maryland, 20771, U.S.A.

Rawson, R., Smith, F. and Larson, R., "The ERIM Simultaneous X- and L-Band Dual Polarization Radar", IEEE International Radar Conference, April 21-23, 1975, Arlington, Virginia, IEEE Publication 75 CHO 938-1 AES, pp. 505-510.

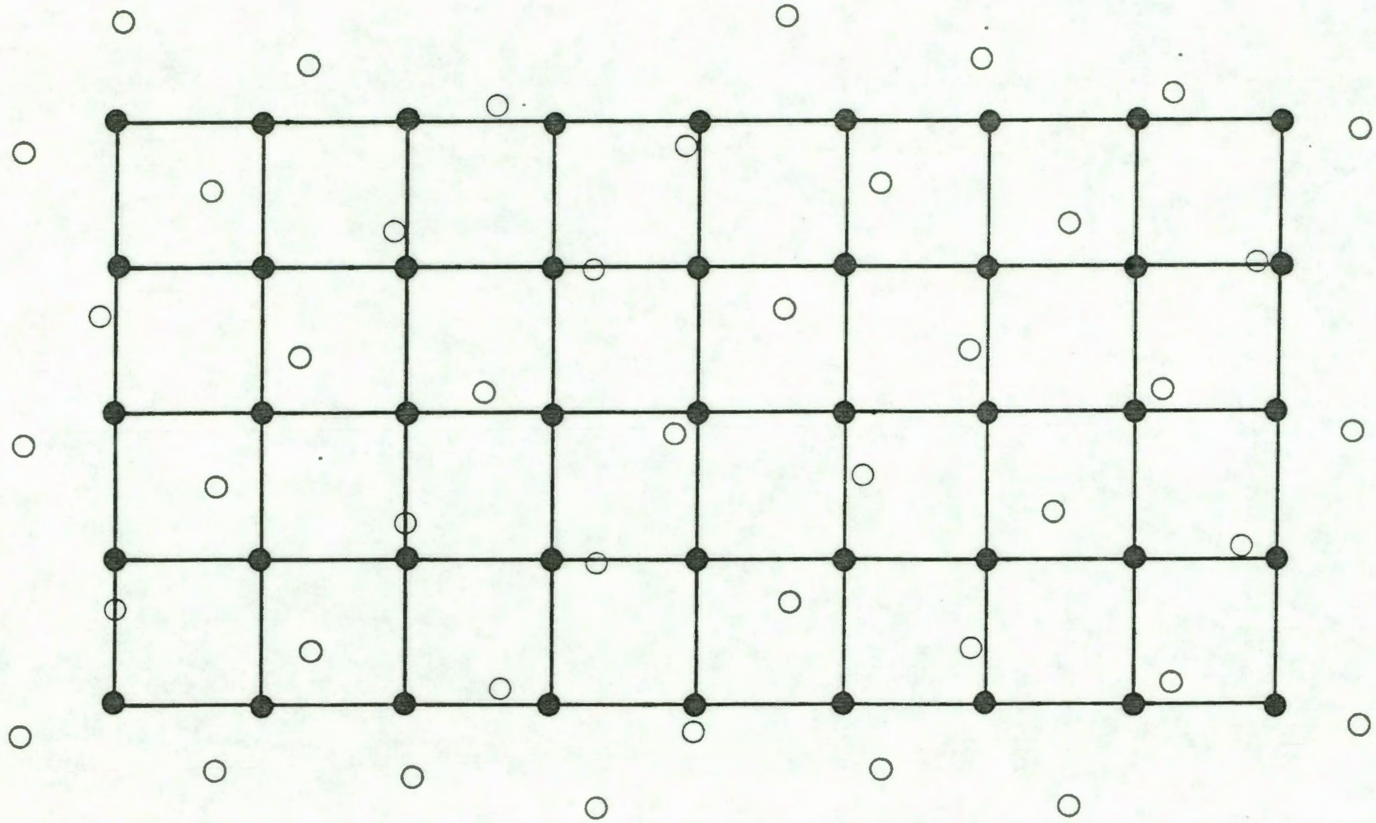
Shlien, S. and Smith, A., "A Rapid Method to Generate Spectral Theme Classification of LANDSAT Imagery", Remote Sensing of Environment 4, 67-77. (1975).

Shlien, S., "Geometric Correction, Registration, and Resampling of LANDSAT Imagery", 1978.

Strome, W.M., Vishnubhatla, S.S., and Guertin, F.E., "Format Specifications for Canadian LANDSAT MSS System Correction Computer Compatible Tape", EMR/CCRS Research Report 75-3, July, 1975.

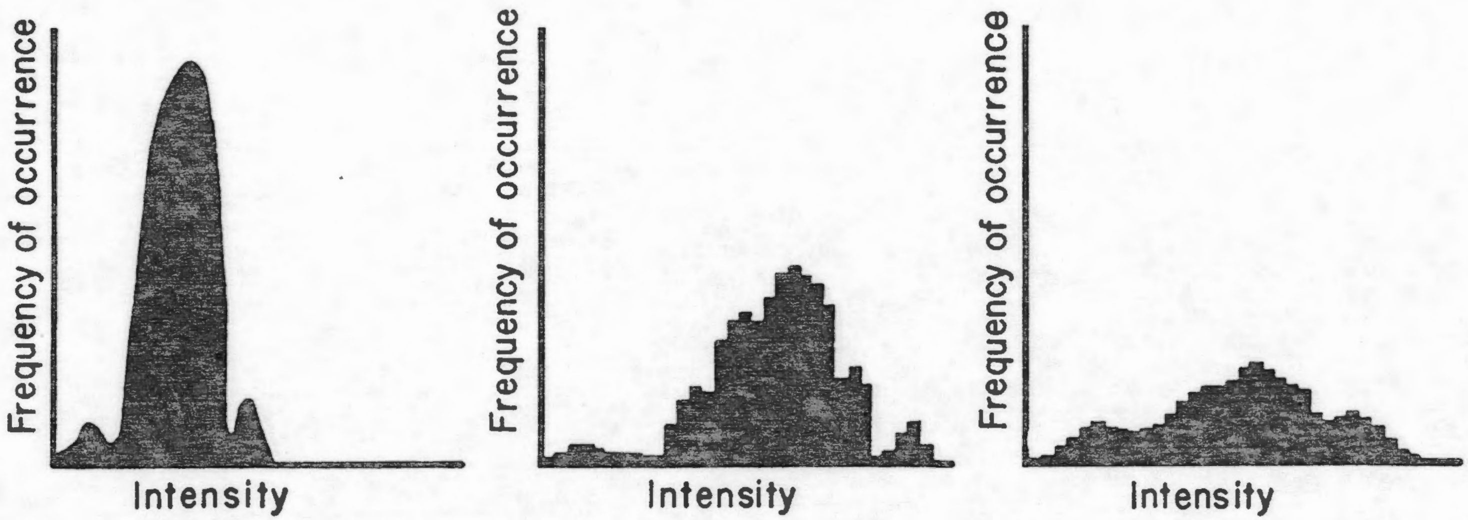
Strome, W.M., Goodenough, D.G., Ahern, F.J., Gray, L., Shlien, S. and Lowry, R., "Digital Analysis of Remotely Sensed Data at CCRS", Proceedings of CIPS Session '78, Canadian Computer Conference, Edmonton, Alberta, 23-25 May, 1978, pp. 413-420.

Taylor, M.M., "Principal Components Colour Display of ERTS Imagery", 3rd ERTS Symposium, Vol. 1, Sec. B., December 10-14, 1973, Washington, D.C., pp. 1877-1897.



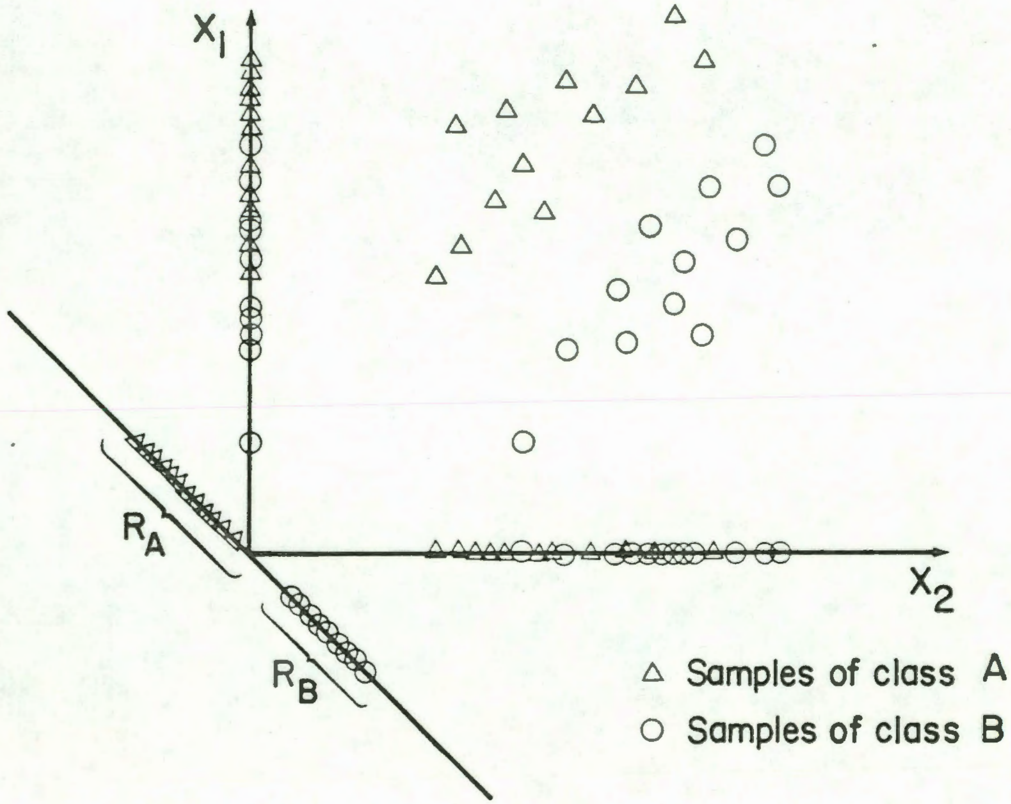
○ Original data points ● Resampled data points

J.M. Strome
Image Analysis Techniques in Remote Sensing
Figure 1 (reduce 3x)

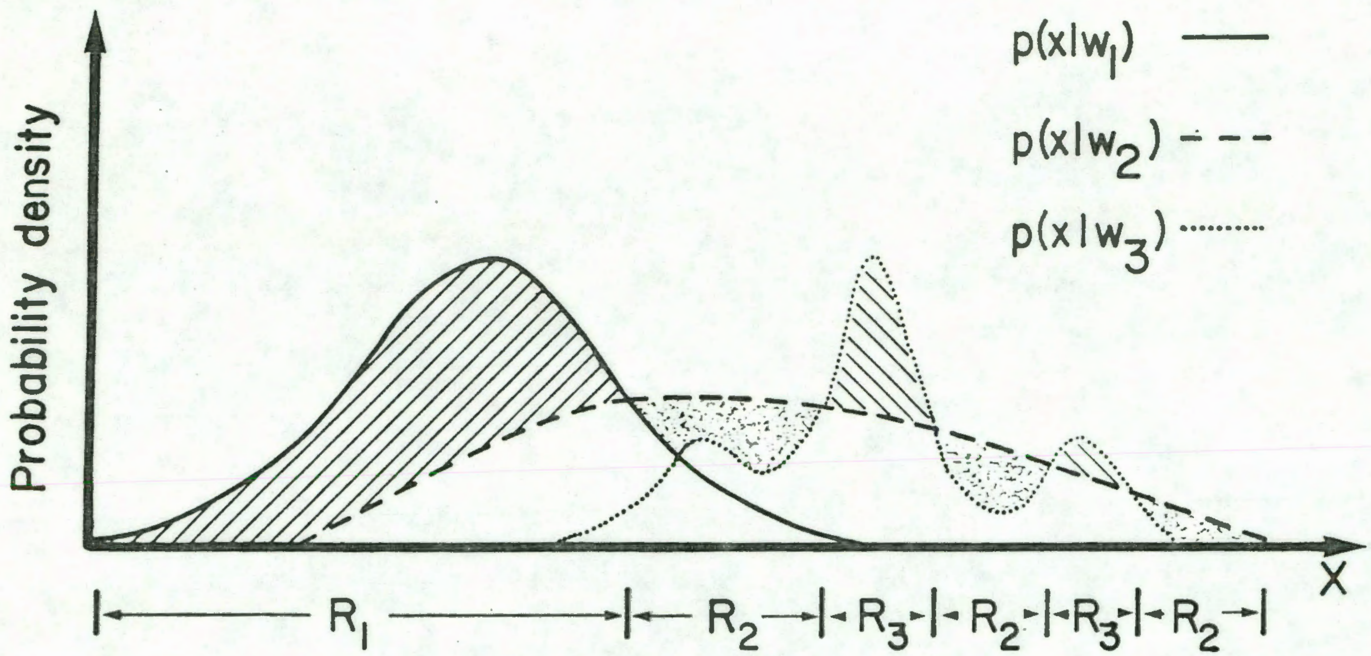


a. Original b. Linear stretch c. Saturation

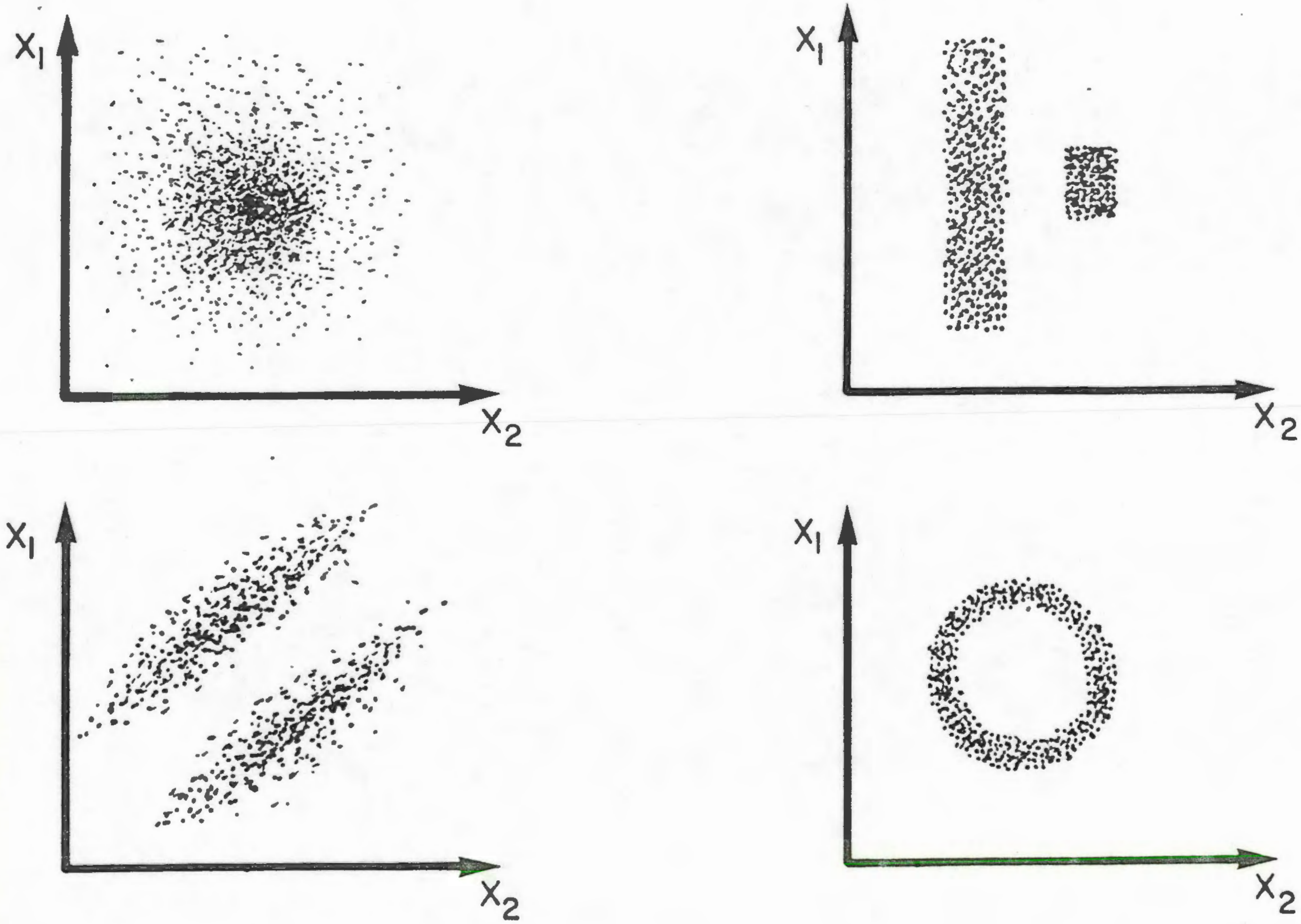
W M Strome
Image Analysis Techniques in Remote Sensing
Figure 2 (reduce 3x)



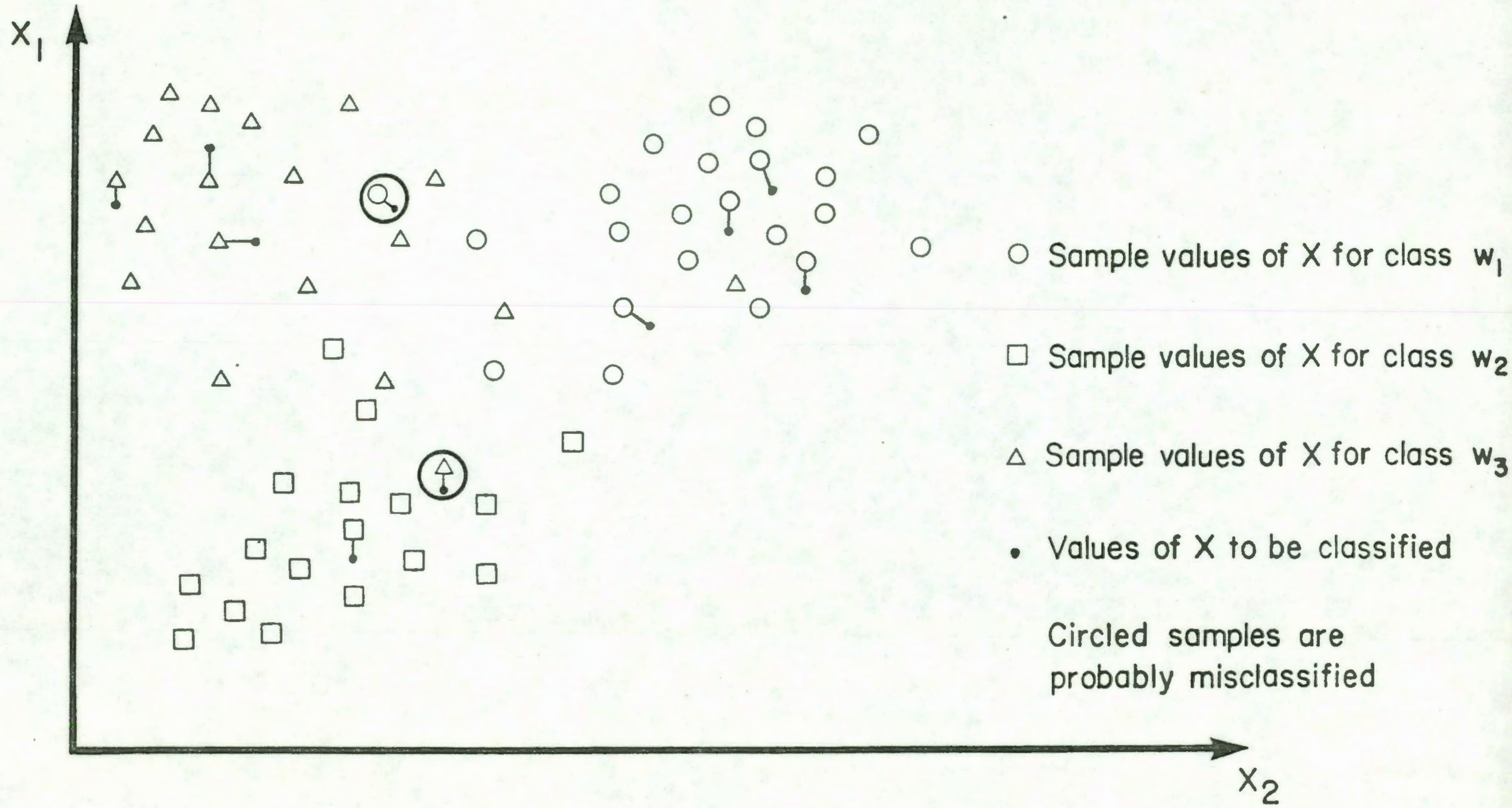
to M Shrone
Image Analysis Techniques in Remote Sensing
Figure 3 (reduce 3x)



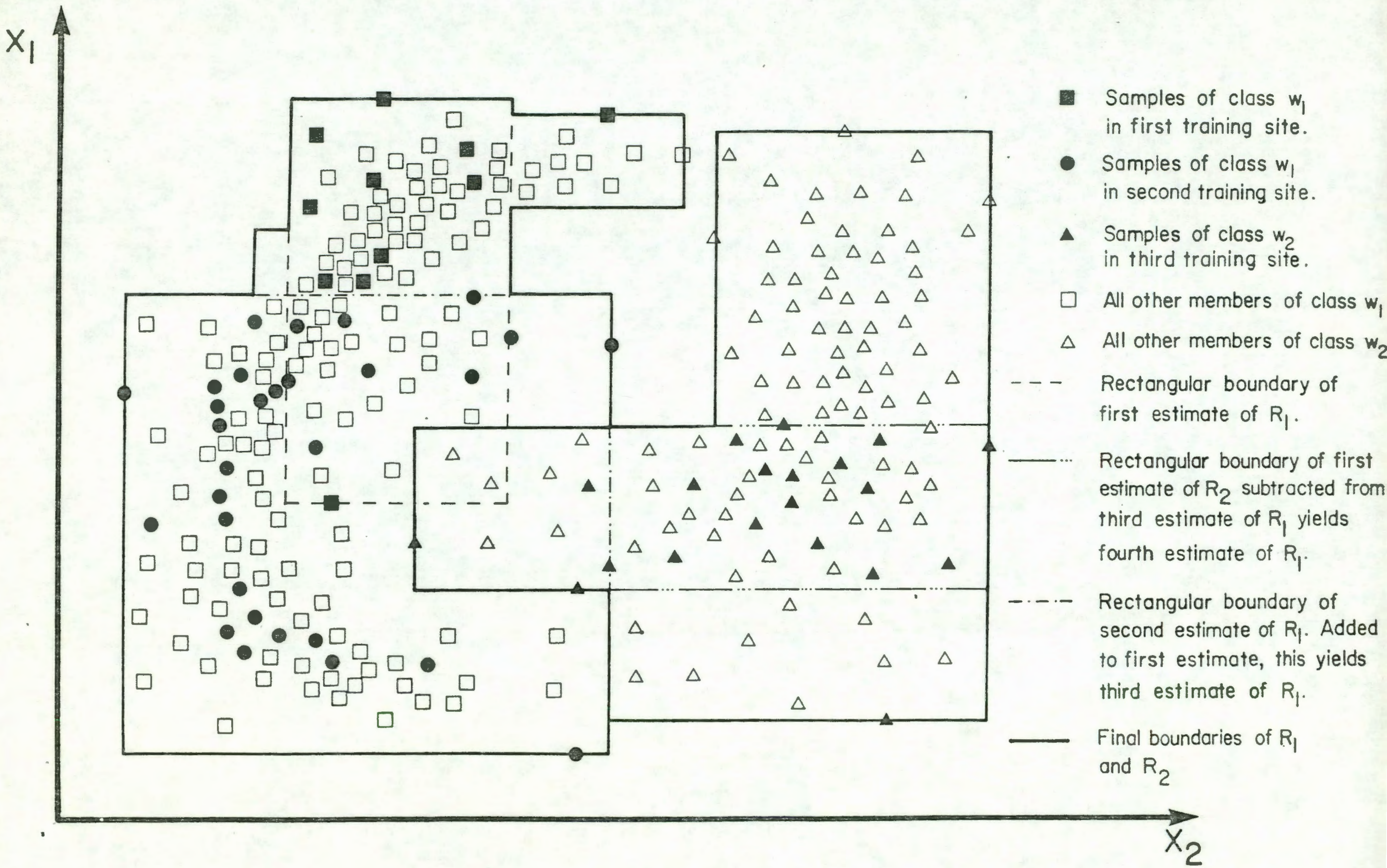
...Ston
...age Analysis Techniques in Remote Sensing
Figure 6 (Reduce 3x)

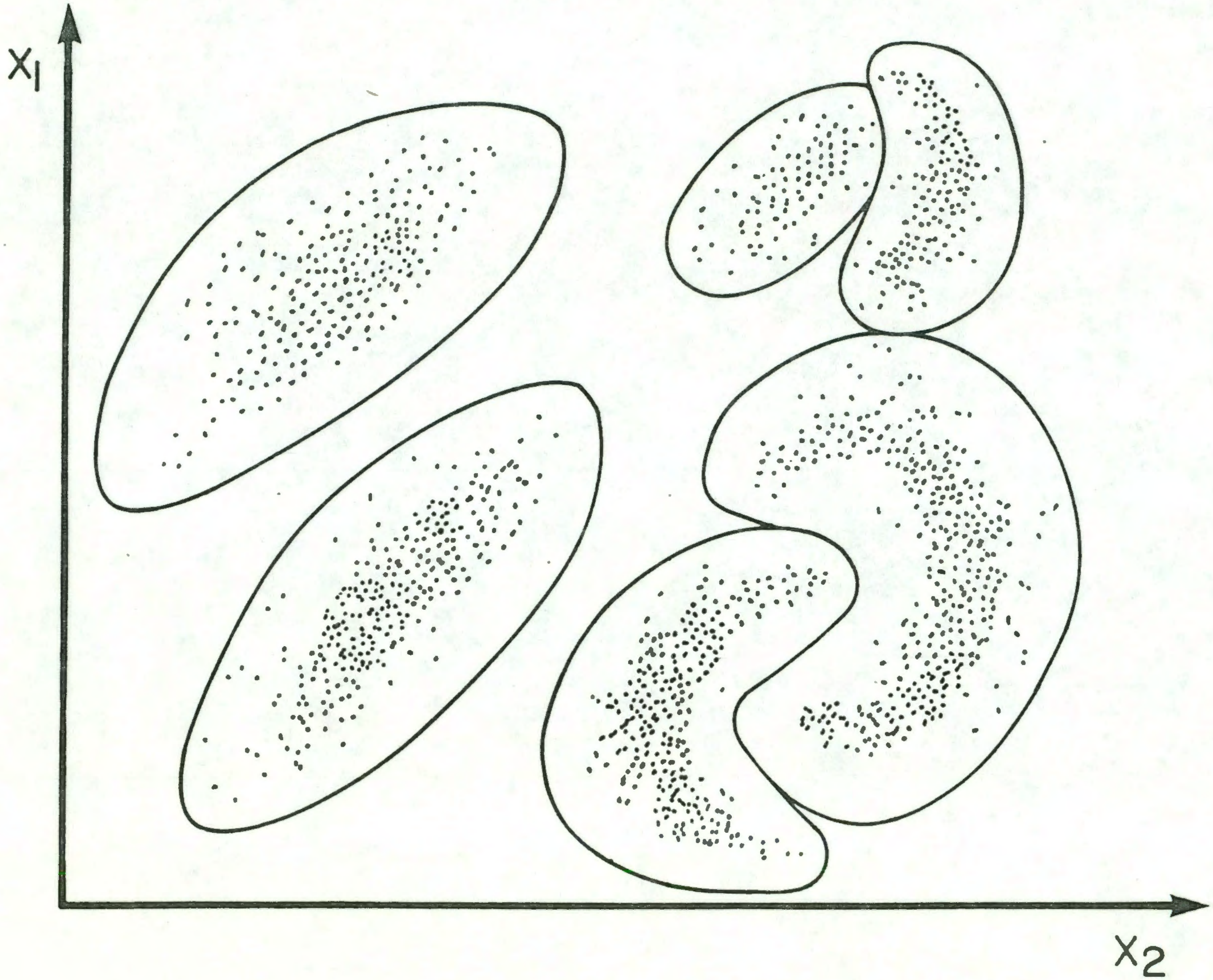


Cluster Analysis Techniques in Remote Sensing
Figure 7 (reduce 3x)

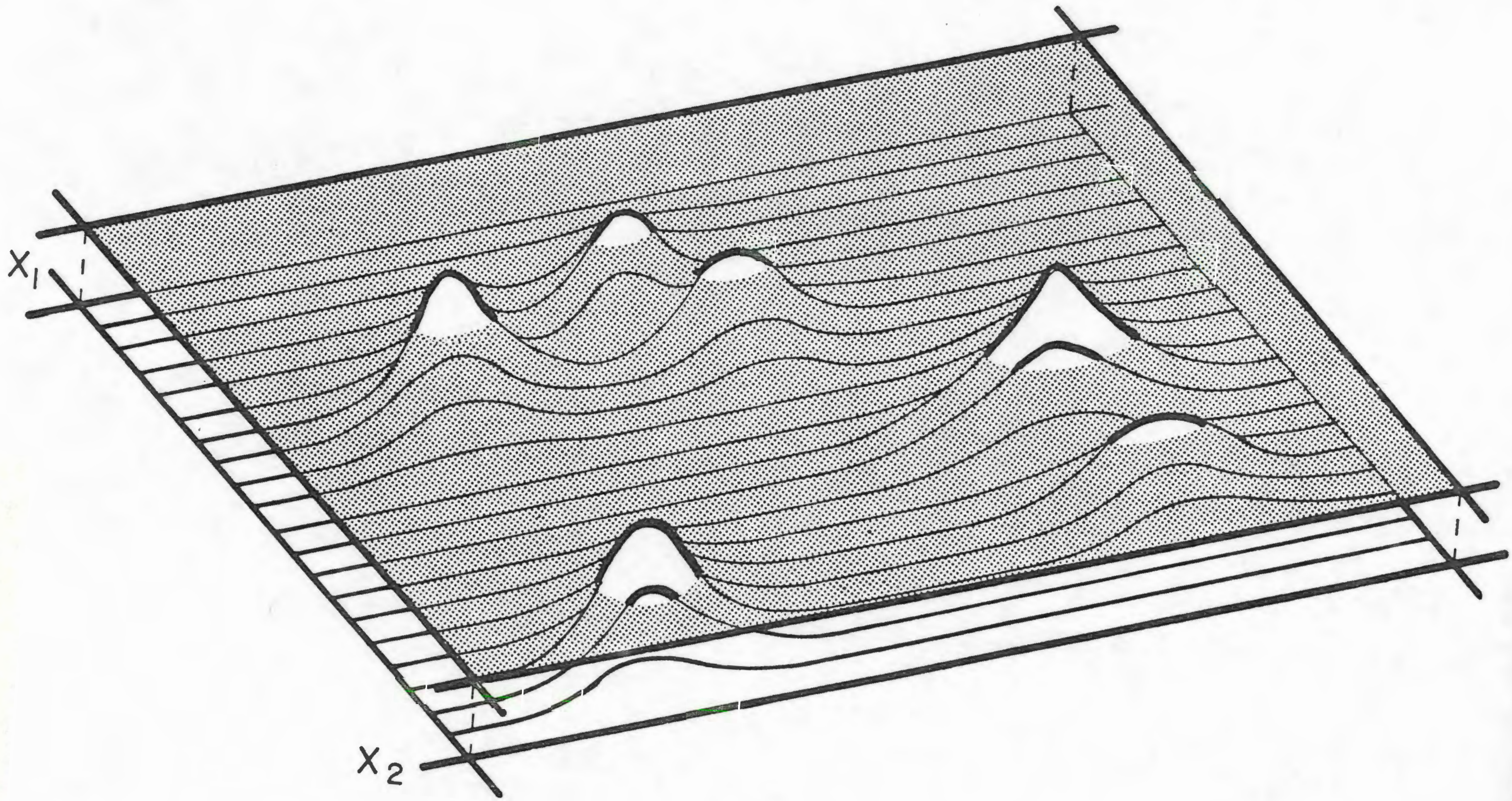


[illegible]
Image Analysis Techniques in Forest Survey
Figure 7 (Reduce 1x)

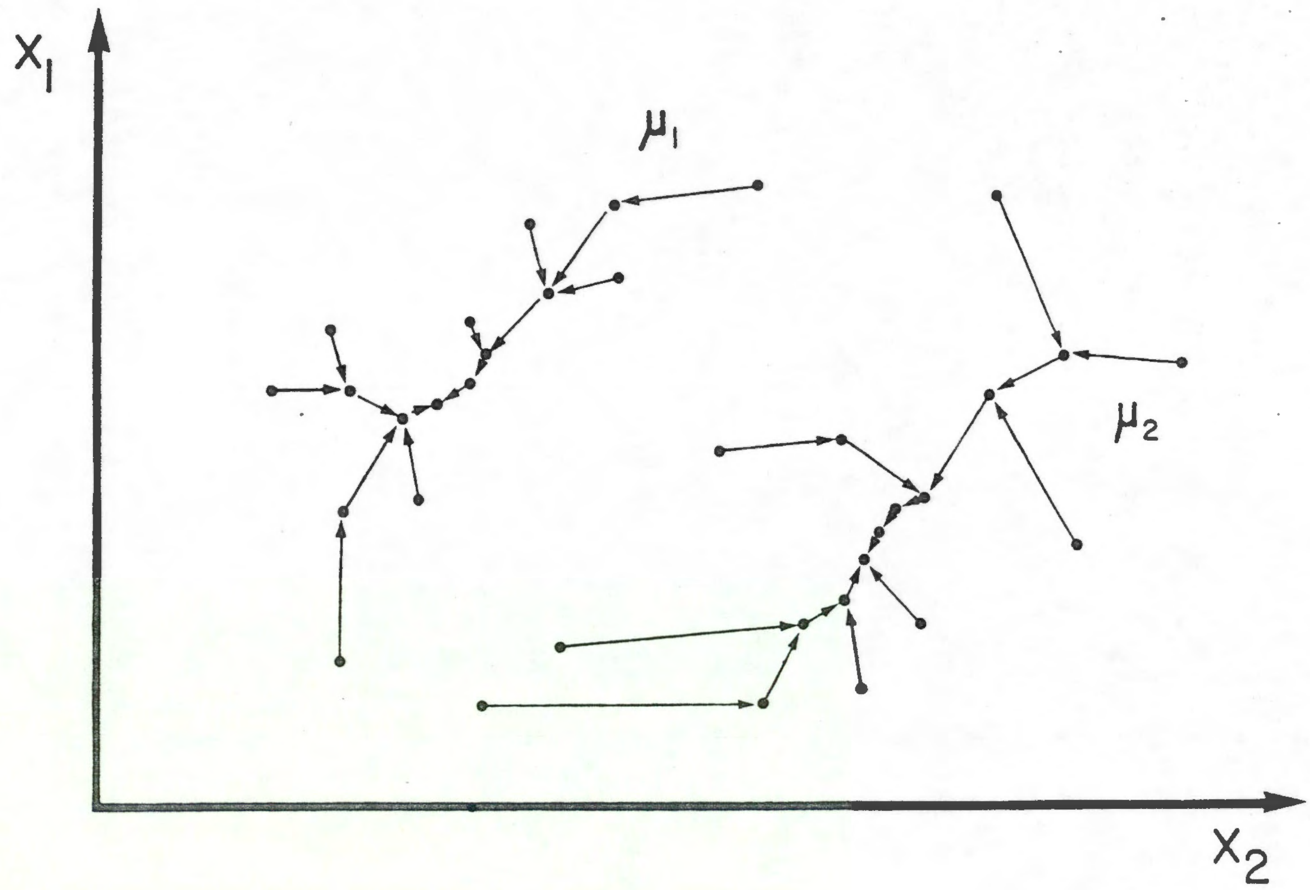

X_1
X_2
Samples of class w_1 in first training site.
Samples of class w_1 in second training site.
Samples of class w_2 in third training site.
All other members of class w_1
All other members of class w_2
Rectangular boundary of first estimate of R_1.
Rectangular boundary of first estimate of R_2 subtracted from third estimate of R_1 yields fourth estimate of R_1.
Rectangular boundary of second estimate of R_1. Added to first estimate, this yields third estimate of R_1.
Final boundaries of R_1 and R_2



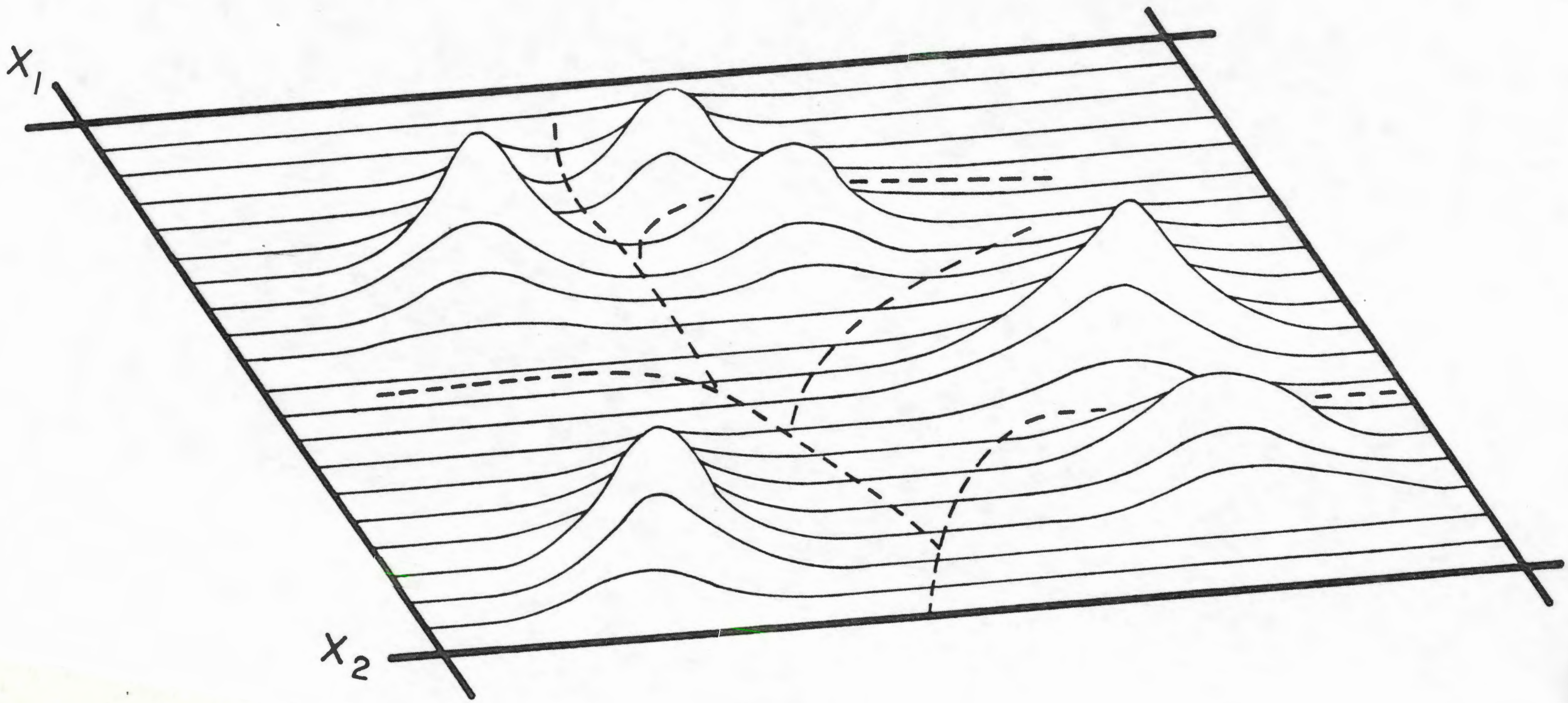
[illegible] analysis Techniques in Remote Sensing
Figure [illegible]



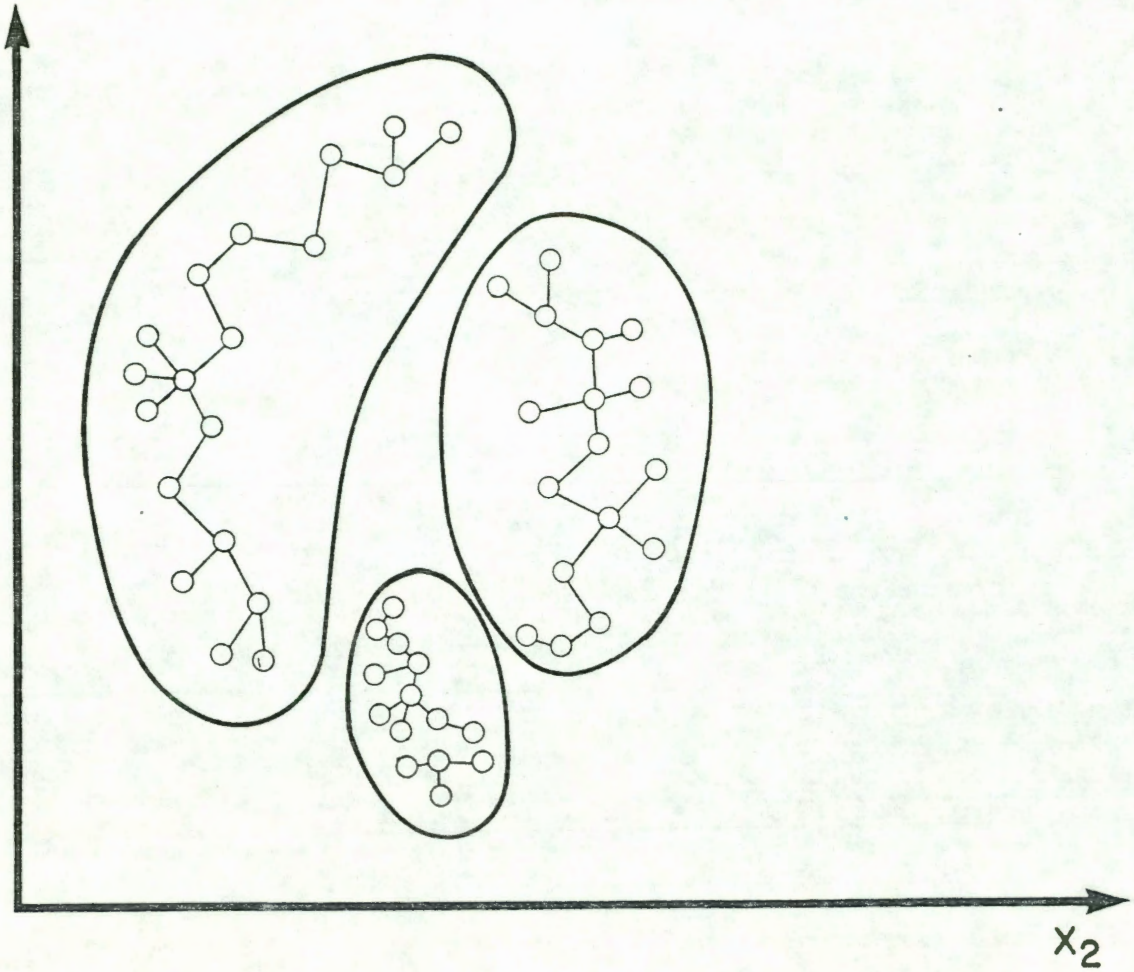
X_1
X_2



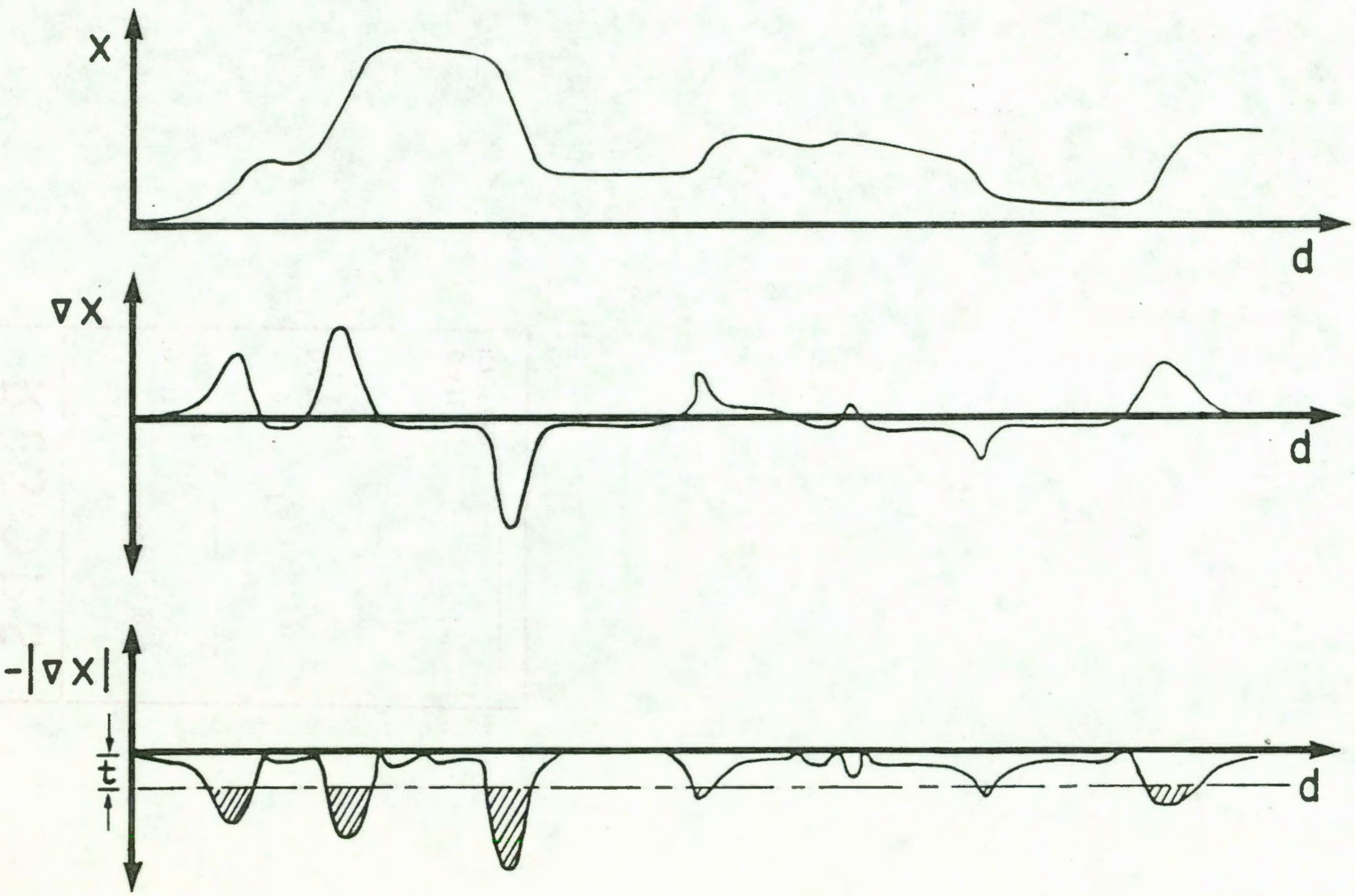
O.M. Stevens
Image Analysis Techniques in Remote Sensing
Figure 12 (reduce 3x)



Stone
Image Analysis Techniques in Point Sources
Figure 12 (Reduce 2×)


X1
X2

[illegible]



[illegible]
[Im]age Analysis Techniques in Remote Sensing
Figure 15 (Reduce 2x)