LARS Information Note 050575

A Case Study Using LARSYS for Analysis of LANDSAT Data

BY

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John C. Lindenlaub

The Laboratory for Applications of Remote Sensing

Purdue University, West Lafayette, Indiana

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PREFACE TO THE STUDENT

Prerequisites

This Case Study is the last component of the LARSYS Educational Package. The presentation of material is based on the assumption that you have mastered the instructional objectives of the first five units of the sequence.

Instructional Objectives

The analysis of a set of multispectral scanner data can be broken down into a sequence of steps. By the time you have finished studying this volume and the recommended references, and you have carried out a detailed analysis yourself, you should be able to list the steps of the analysis sequence in the proper order. Furthermore, for each step in the analysis you should be able to do three things:

1) give a brief explanation of the significance of the analysis step with respect to the whole analysis sequence,

2) name and briefly describe any software tools available to carry out the analysis step, and

3) apply the analysis principles to a specific problem by writing control cards, running programs, and interpreting the results of the LARSYS functions used in the analysis sequence.

References

Throughout this case study references will be made to other written materials. The two most commonly referenced sources are considered part of this unit of instruction: LARSYS User's Manual, edited by T. L. Phillips, and Pattern Recognition: A Basis for Remote Sensing Data Analysis, by P. H. Swain (LARS Information Note 111572). These references should be in your site library. Be sure you have them available before you begin the case study. See your instructor if you need help locating them.

Student-Instructor Interaction

While this case study attempts to summarize the experiences of a great many multispectral data analysts, there is no real substitute for talking to someone who is already familiar with the use of the LARSYS programs. This is especially true when you begin carrying out the case study analysis. You are encouraged to discuss your progress periodically with your instructor.

Format

Each section of the case study follows this format: the instructional objectives are stated in italics, followed by a discussion of the purpose, philosophy, and analysis techniques associated with that step in the data analysis sequence; then there is an example showing control cards, computer output, and an interpretation of the results; exercises are provided to test your mastery of the section's instructional objectives; information and directions are provided to guide in the case study analysis.

The material is presented in this format so that a person wishing to become adept in the analysis of multispectral data (in particular, LANDSAT data) using LARSYS can proceed through this case study and learn what the analysis steps are, why each step is important, how each step is carried out, and gain practice in using these analysis techniques.

INTRODUCTION

Launch of the first Earth Resources Technology Satellite (ERTS), now called LANDSAT, in July, 1972 provided a new perspective for remote sensing research. Scientists interested in computer-aided analysis of multispectral scanner data had to devise new techniques appropriate to the new data characteristics and analysis problems.

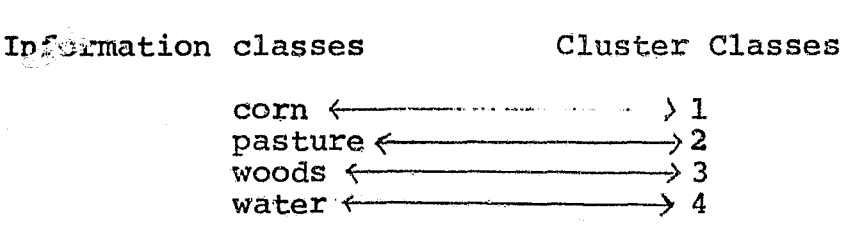
The techniques described in this manual make use of the LARSYS data processing system. LARSYS has been used for a number of years as a tool in the analysis of multispectral scanner data collected from aircraft altitudes. Analysts experienced with LARSYS in that context have brought their experience to bear on the development of techniques suitable for LANDSAT data.

The procedures used for analysis of multispectral data fall into two categories: "supervised" approaches and "unsupervised" approaches. In a "supervised" approach, data points known to contain specific cover types are used to "train" the classification algorithm. If the cover types of interest (call them information classes) are spectrally distinct (have significantly different reflectance characteristics), the classifier will perform well. If the information classes are spectrally similar, the classifier will have difficulty distinguishing between them. For more information about a "supervised" approach, see Guide to Multispectral Data Analysis Using LARSYS by J. C. Lindenlaub.

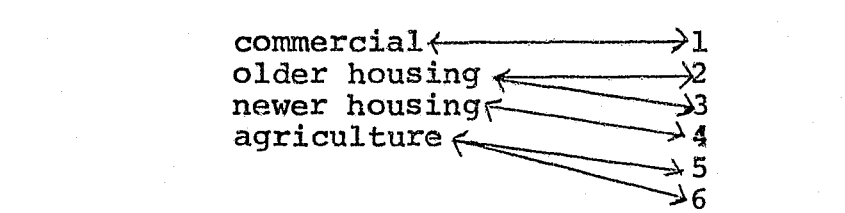
On the other hand, in an "unsupervised" approach, spectrally distinct classes are determined without reference to the cover types present on the ground. The spectrally distinct classes are found by a clustering algorithm and are called cluster classes. The cluster classes are then used to train the classification algorithm. After the data has been classified, the analyst tries to associate the cluster classes with cover types of interest. If the relationship between cluster classes and information classes is one-to-one (Figure 1a), or if several cluster classes are associated with the same information class (Figure 1b), the procedure will be considered successful. If one cluster class is associated with two or more cover types of interest (Figure 1c), it is likely that these cover types are spectrally similar and cannot be differentiated using this data set.

The procedure described in this manual combines some techniques from both the supervised and unsupervised approaches. First, the analyst chooses the geographic area to be analyzed and determines the cover types he wishes to classify. Data from areas known to contain these cover types are input to the clustering algorithm.

a)



b)



c)

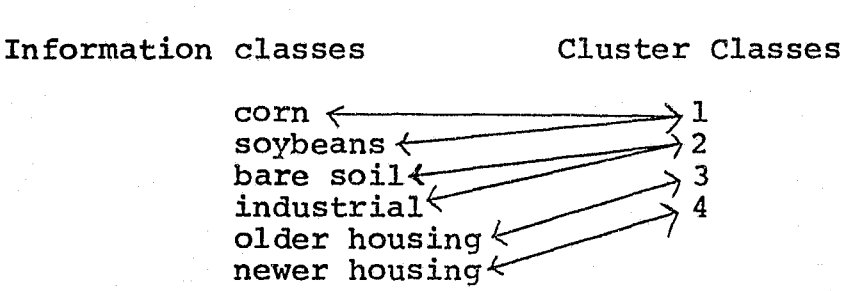


Figure 1. Examples of relationships between information classes and cluster classes.

As is the case in the unsupervised approach, cluster classes are formed, but, in this modified procedure, the cluster classes are then immediately associated with information classes (cover types of interest) before classification. The spectral similarity of the cluster classes is calculated in preparation for the next step, in which spectrally similar cluster classes belonging to the same information class are combined and labelled with their information class identification. At this point this approach resembles a supervised approach in its usage of the data points known to contain specific cover types for "training" the classifier.

This discussion of kinds of approaches points up the fact that the procedure to be described here is presented as an approach, not necessarily the approach.

For any of these procedures, the same LARSYS processors are used, although they may be used in different sequences or for somewhat different purposes in the various approaches. The way in which an analyst uses a processor depends on the characteristics of the data being analyzed, the analysis objectives, the analyst's understanding of the processor, and his experience and ingenuity.

The following steps comprise the procedure to be described in this manual:

examination of data quality

coordination of multispectral scanner data with available reference data

selection of candidate training areas

refinement of training set

calculation of statistical characteristics of training classes

classification, results display, and evaluation

information extraction and interpretation

At any step in the sequence, interpretation of the results of that step can lead you to conclude that you need to go back to a previous step and revise a decision made there. That is, the procedure is not strictly sequential, but rather tends to be iterative with feedback at various steps causing an analyst to loop back and repeat a previous step. A flow chart of the analysis sequence with dashed lines showing potential iteration loops is shown in Figure 2.

ANALYSIS FLOWCHART

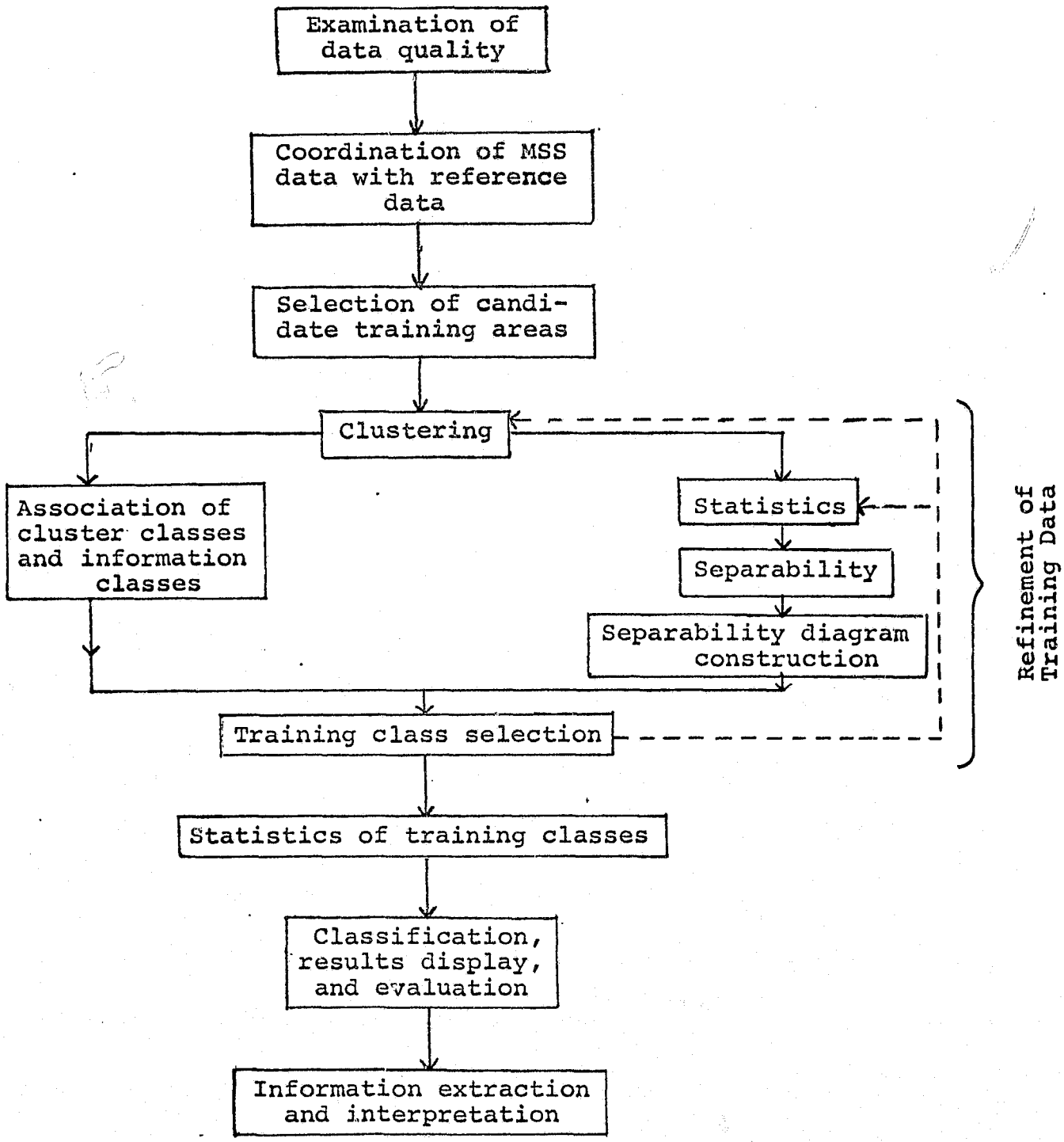


Figure 2. Flow chart indicating the sequence of steps undertaken in the analysis procedure described in this manual.

Section 1. EXAMINATION OF DATA QUALITY

The instructional objectives for each section will be printed in italics at the beginning of the section.

State at least one reason why the quality of the data set being considered for analysis must be evaluated.

Name at least two sources of data quality information.

Name at least three data idiosyncrasies which might hinder analysis.

Use LARSYS processing functions to obtain identification information about a run and to obtain gray scale printouts of multispectral data.

Formulation of a problem or a hypothesis always precedes any analysis undertaking. To carry out the analysis, two components of the problem statement must be clearly specified: the geographic area of interest, and the particular cover types of interest. These two factors identify precisely what the analysis is supposed to accomplish, that is, the analysis objectives. An example of an analysis objective is "classify Fayette County, Illinois into corn, soybeans, and other cover types." Another example is "determine the percent of the San Juan National Forest in each of these cover types: ponderosa pine, spruce-fir, aspen, and other."

After the analysis objectives are stated, a data set must be selected. LANDSAT satellites with eighteen day cycles provide a wealth of data over any area. From this data, an analyst will choose a set at the time of year suitable for the cover types of interest. In many cases, data sets with much cloud cover or snow cover will not be as desirable as cloud-free or snow-free data sets.

A preliminary evaluation of data can be made by inspecting photographic imagery created from the digital data. This kind of imagery can be obtained from the data distribution centers

which supply digital data tapes. Gross data characteristics, including cloud cover and snow cover, will be apparent in these products. Figure 1-1 shows an example of this kind of imagery, with cloud cover on the right side of the scene.

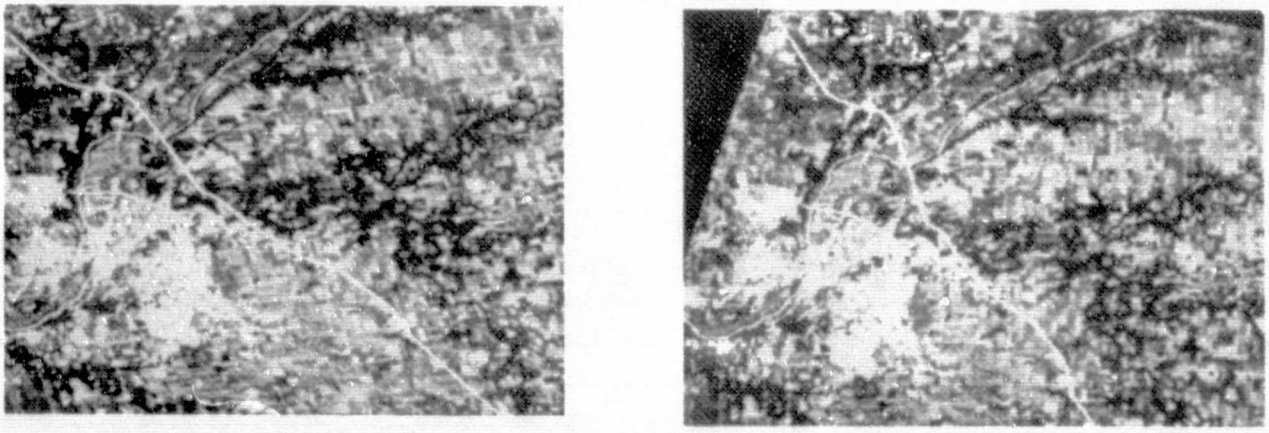
Figure 1-1. Scene number 1070-16041 over Chicago and the surrounding area has clouds obscuring the east side of the scene.

After a data set is selected, the analyst requests that the data preprocessing and reformatting group at LARS convert the LANDSAT data tapes into Multispectral Image Storage Tapes, the format required by LARSYS programs. When the data is reformatted, data log sheets are generated. A master file of these log sheets is maintained in the LARS Computer Center, and a copy is sent to the individual who requested that the data be reformatted. These log sheets are another source of information about data quality. An example is shown in Figure 1-2. Note that the section at the bottom of the form for comments includes the information that there are some bad data lines in that run.

Further examination of data quality can be done by use of LARSYS processors. Examples of various kinds of idiosyncrasies found in LANDSAT data will be given. The LARSYS run number for each data set is included, so that you can obtain gray scale printouts to observe these characteristics firsthand.

The examples were generated by use of the IMAGEDISPLAY processing function, which creates an image on a television screen by the same process PICTUREPRINT uses to create gray scale printouts.

The data in Figure 1-3 shows a phenomenon which appears in LANDSAT data due to the earth's rotation. A rectangular image on the ground appears as a skewed parallelogram, the top edge of the image being shifted to the right with respect to the bottom edge by approximately 5% of the height of the image. In addition the LANDSAT orbit is not oriented exactly over the north pole. This results in a rotation of the imagery which varies with latitude (this rotation is about 12° at 40° north latitude). Figure 1-3a shows non-rectangular fields in LANDSAT data, while Figure 1-3b shows the same data after it has been processed to remove these effects. The run number for Figure 1-3a is 72053602 and for Figure 1-3b is 72053609.



a) uncorrected b) geometrically corrected

Figure 1-3. LANDSAT data before and after processing to remove effects of the earth's rotation.

LARS FORM - 17

DATA STORAGE TAPE FILE

RUN NUMBER..... 73052002
DATE TAPE GENERATED..... MAR 16,1974
TAPE NUMBER..... 1353
FILE NUMBER..... 19
LINES OF DATA..... 536
SECONDS OF DATA..... 6.56
MILES OF DATA..... 23.41
LINE RATE..... 81.68 LINES/SEC

FLIGHTLINE ID..... 134116111 ILL
DATE DATA TAKEN..... 6/29/73
TIME DATA TAKEN..... 1011 HOURS
PLATFORM ALTITUDE..... 306200 FEET
GROUND HEADING..... 190 DEGREES
FIELD OF VIEW..... 0.027 RADIANS
DATA SAMPLES PER CHANNEL PER LINE 328
SAMPLE RATE..... 0.09 MILLIRADIANS

SPECTRAL BANDWIDTH IN MICROMETERS..

CHAN	LOWER	UPPER	CHAN	LOWER	UPPER	CHAN	LOWER	UPPER
(1)	0.50	0.60	(2)	0.60	0.70	(3)	0.70	0.80
(4)	0.80	1.10	(5)			(6)		
(7)			(8)			(9)		
(10)			(11)			(12)		
(13)			(14)			(15)		
(16)			(17)			(18)		
(19)			(20)			(21)		
(22)			(23)			(24)		
(25)			(26)			(27)		
(28)			(29)			(30)		

DATA RUN CONDITIONS..

DATA TAPE COMMENTS..

GEOMETRIC CORRECTION OF FAYETTE COUNTY, ILLINOIS - CITARS TIME II.
THIS RUN IS A GEOMETRIC CORRECTION OF RUN 73052001 (6/29/73) AND IS REGISTERED TO THE COORDINATES OF RUN 73039101 (6/11/73).
CORRECTED TO LINEPRINTER ASPECT RATIO.
CHANNELS 1,3,AND 4 HAVE 1,7, AND 11 BAD LINES RESPECTIVELY.

Figure 1-2. Data Log Sheet for LANDSAT Data.

While the "uncorrected" data is adequate for some analysis tasks, "corrected" data simplifies the analyst's job of locating features, since it can more easily be compared with reference data (maps, aerial photography).

As previously mentioned, clouds can significantly decrease the usefulness of a data set. The example shown in Figure 1-4 is from run 72033000. A more subtle situation is the presence of haze. Figure 1-5 shows data collected on September 12 and 13, 1972, over southern Indiana.*

On the 12th a thin haze was present, but on the 13th the sky was clear. Images from two spectral bands on each date are shown. Notice that the channel two image (.6-.7 μm) on the 12th shows the haze, while the channel four image (.8-1.1 μm) from the same date does not. This is due to the fact that there is less scattering of the longer wavelengths.

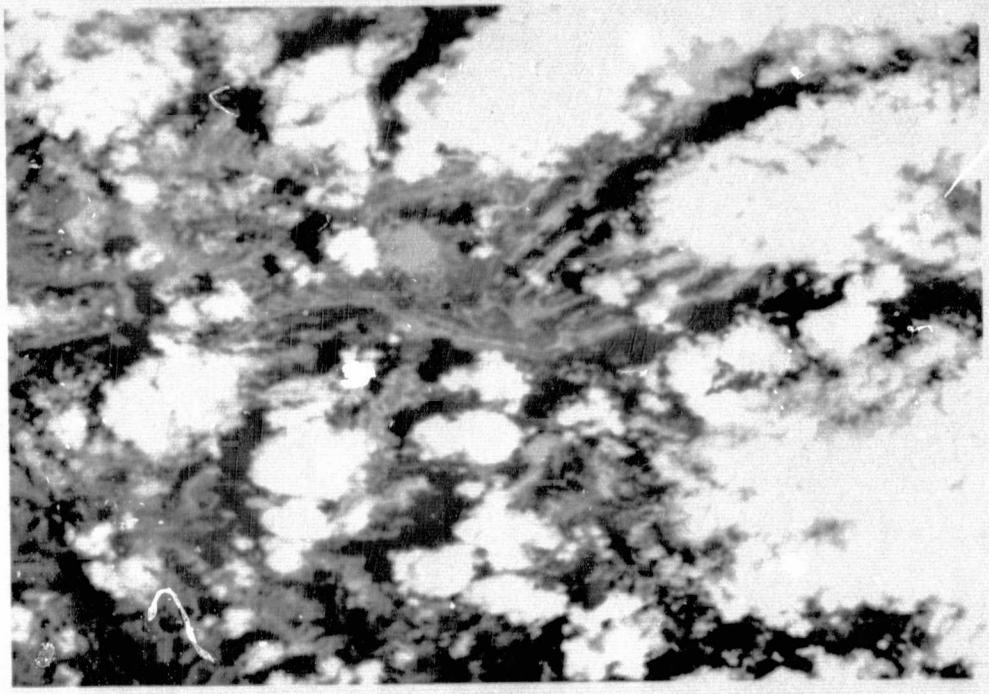
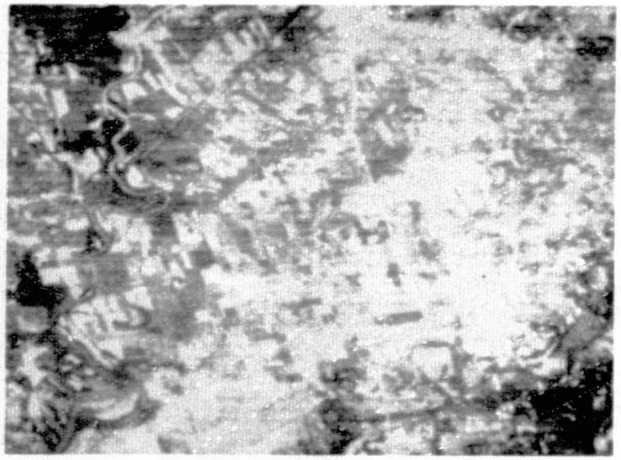
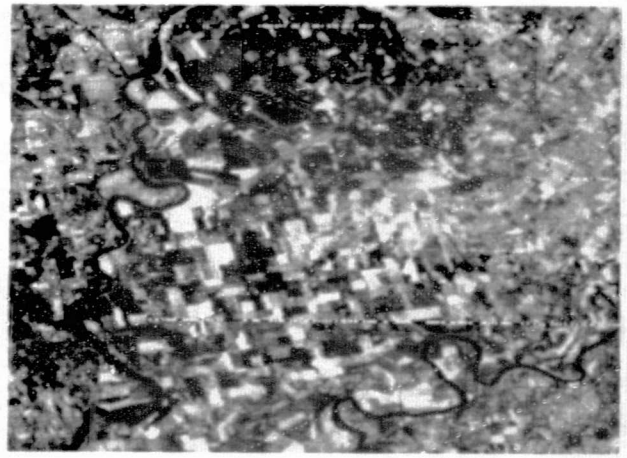


Figure 1-4. An example of clouds and their shadows.

*The coverage pattern provides sidelap on succeeding passes ranging from 14% at the equator to more than 85% at the poles. The sidelap is approximately 30% for southern Indiana.

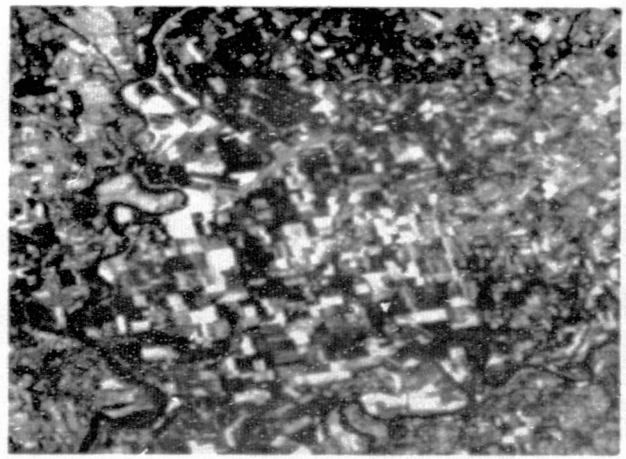


a) September 12, channel 2



b) September 12, channel 4

c) September 13, channel 2



d) September 13, channel 4

Figure 1-5. Haze was present on September 12, but September 13 was clear.

The presence of snow can be a limitation in data analysis if the cover types of interest are the vegetative cover types under the snow. The data shown in Figure 1-6, run 73034300, has quite a bit of snow cover. If the purpose of the analysis is to determine the areal extent of snow cover, the presence of snow would be desirable, but the presence of both clouds and snow in the same data set would be undesirable, since they are spectrally similar. An example of such a situation is shown in Figure 1-7, from run 72051400. Of course, if the purpose of the analysis is to compare the responses of clouds and snow, this data set would be quite useful. This example points up the necessity of clearly formulating analysis objectives and keeping the objectives in mind.

Another idiosycrasy which can occur in LANDSAT data appears as stripes in the image. In the LANDSAT scanner system, six scan lines are swept out in each wavelength band each time the mirror oscillates. A separate set of detectors is used for each of these scan lines. If these detectors and their associated electronics are not properly matched or calibrated, a striping effect may be noticeable in the imagery. A dramatic example can be seen in Figure 1-8, channel 1 of run 72044401, a LANDSAT scene which includes Lafayette, Indiana. The STATISTICS processing function was used to obtain quantitative information about this

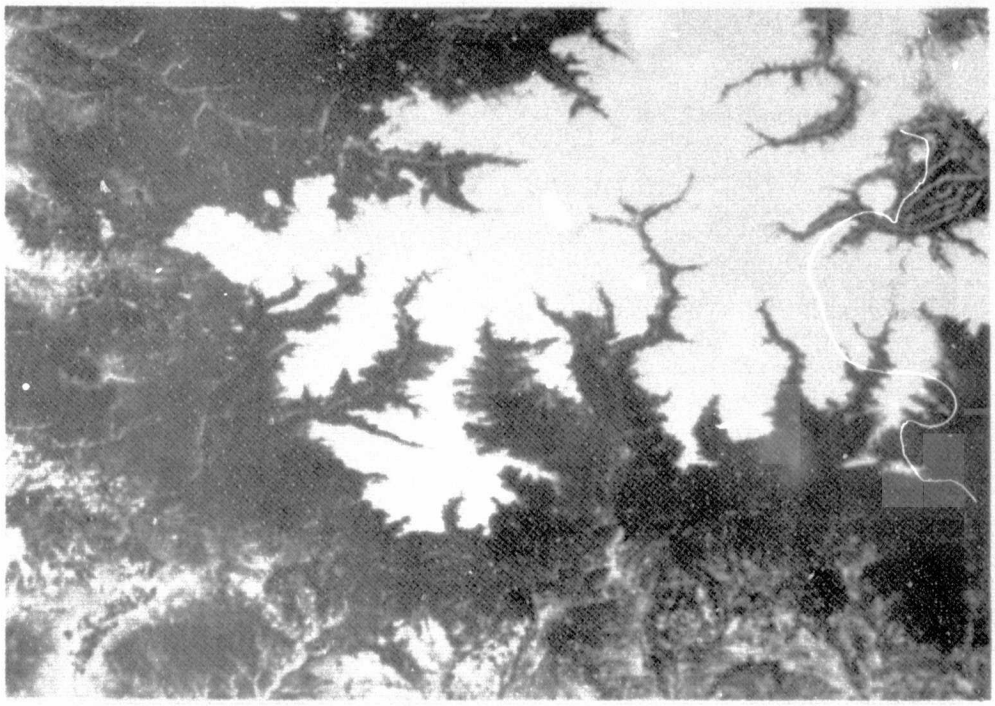


Figure 1-6. Snow covers the higher elevations in the mountains of Colorado.

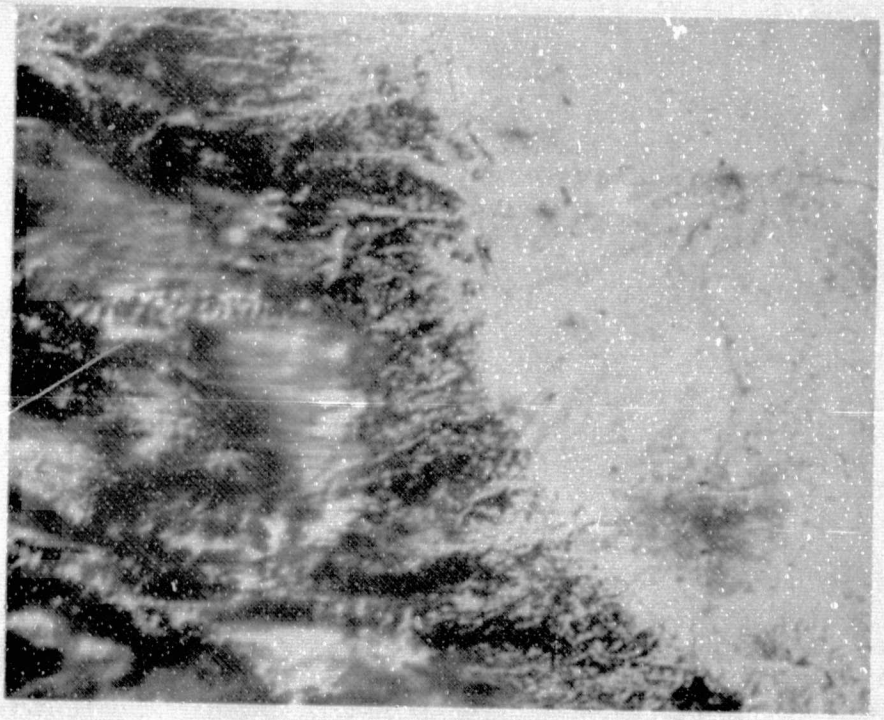


Figure 1-7. The Rocky Mountains are on the left and the Great Plains on the right. There is snow on the plains and haze over the mountains.

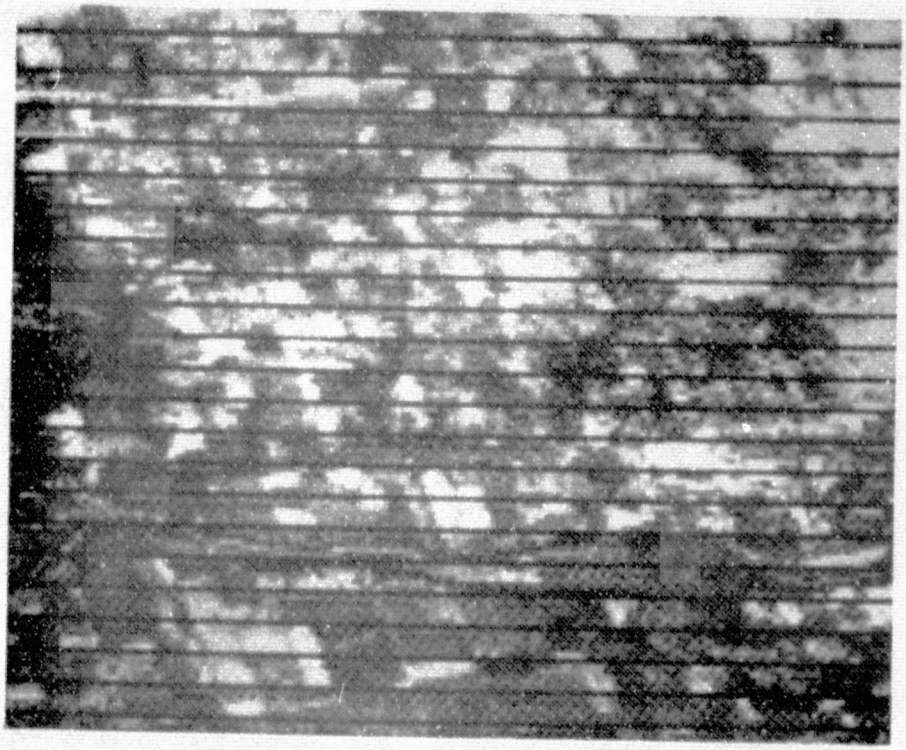


Figure 1-8. Striping effect in imagery.

striping. The table below shows the mean and standard deviation for the output of each of the channel 1 detectors over the whole frame. To obtain this information from the STATISTICS processor, a line interval of six was used, with successive starting lines of 1, 2, 3, 4, 5, and 6.

Detector	Mean	Standard Deviation
1	21.9	3.21
2	21.8	3.07
3	7.0	1.52
4	21.5	3.13
5	20.9	3.11
6	21.9	3.03

Notice that the mean value for detector 3 is very low compared to that of the other detectors. Apparently a malfunction occurred in the detector electronics, resulting in the striping illustrated in Figure 1-8.

Another data idiosyncrasy which is sometimes present in LANDSAT data is called a bad data line. In Figure 1-5, the example of haze, look at the channel four image from September 12th. In the top half of the picture there is one bad data line all the way across, and near the middle of the picture one bad data line goes about two thirds of the way across.

The material presented in this section has indicated that analysis objectives include specification of geographic area and cover types. After these are determined, a data set is chosen. Next, the quality of the data must be examined to determine whether it will be adequate for meeting the analysis objectives.

Several kinds of data characteristics were discussed and illustrated, including cloud cover, snow cover, haze, striping, and bad data lines.

The example and case study that follow will give you an opportunity to use LARSYS processing functions to examine data quality. In preparation for the material presented there, you should read the following material in the LARSYS User's Manual:

a) Section 4 (Volume 1) of the LARSYS User's Manual, pages 4-1 to 4-3, gives a general description of LARSYS Control Commands. The remaining pages in Section 4 describe the individual Control Commands in detail. In particular, review the REFERENCE RUNTABLE Control Command.

b) Section 6 (Volume 2), pages 6-1 to 6-3, gives a general description of LARSYS Processing Functions. The remaining pages in Section 6 describe the individual Processing Functions in detail. Review the DUPLICATERUN, IDPRINT, and PICTUREPRINT Processing Functions at this time. In particular note the last paragraph on page PIC-7, concerning the BLOCK control card.

The examples given in conjunction with each step of the analysis include representative control card listings, computer printouts, and interpretations drawn from an analysis of LANDSAT data from the Kenosha Pass area of Colorado, run 73057902.*

The objectives of the Kenosha Pass analysis were the following:

1) to classify and inventory the area into these cover types: snow, grassland, deciduous forest, coniferous forest, barren (bare rock and bare soil);

2) to produce a classification map of these cover types;

3) to evaluate the classification accuracy.

In order to determine if the run was in the system runtable, the analyst typed in the following information at the terminal:

```
reference runtable 73057902
```

and the computer indicated that the run was in the system runtable by responding:

RUN NO.	TAPE	FILE	LINES	CHAN	SAMP	FLIGHTLINE ID
73057902	1087	3	1535	4	2200	138817134 COL

To obtain more information about the run, the analyst used the IDPRINT processing function. The following control card deck was set up:

```
*IDPRINT
PRINT RUN (73057902)
END
```

The output is shown in Figure 1-9. Note the wavelength bands of the LANDSAT scanner system. The first two bands are in the visible portion of the spectrum, and the last two are in the near infrared.

The next step was to make a working copy of the run. The DUPLICATERUN processing function was used. A working copy can serve several purposes, as you read on page DUP-1 in Section 6 of the LARSYS User's Manual. The analyst set up the following control cards to copy the data:

```
-COMMENT COPY OF RUN 73057902 FROM 1087 TO 253
*DUPLICATERUN
FROM RUN(73057902)
TO TAPE(253), FILE (1)
END
```

*The original analysis of this data was done for the U.S. Forest Service under USDA Contract 21-292.

TECTRA
WILSSN

LABORATORY FOR APPLICATIONS OF REMOTE SENSING
PURDUE UNIVERSITY

MAY 7,1975
1C 35 14 AM
LARSYS VERSION 3

TAPE NUMBER..... 1087
CONTINUATION CODE..... 0
FLIGHT LINE.. 138817134 COL
PLATFORM ALTITUDE.3062000 FEET

FILE NUMBER..... 3
NUMBER OF DATA CHANNELS.... 4
DATE DATA TAKEN..... 8/15/73
GROUND HEADING.... 180 DEGREES
NUMBER OF LINES..... 1535

RUN NUMBER..... 73C57902
NUMBER OF DATA SAMPLES... 2200
TIME DATA TAKEN.... 0913 HOURS
REFORMATTING DATE.APR 8,1974

	SPECTRAL BAND		CALIBRATION PULSE VALUES		
CHANNEL	LOWER	UPPER	C0	C1	C2
1	0.50	0.60	0.0	2.480	0.0
2	0.60	0.70	0.0	2.000	0.0
3	0.70	0.80	0.0	1.760	0.0
4	0.80	1.10	0.0	4.600	0.0

Figure 1-9. Output from the IDPRINT processing function.

For the remainder of the analysis, the analyst used a personal runtable so that he gained access to run 73057902 in the first file of tape 253.

The analyst then wanted to combine the task of investigating data quality with the tasks of (1) locating the line and column coordinates of the area of interest, and (2) producing gray scale printouts of the area of interest to use for selection of training areas.

From experience combined with knowledge of how Earth surface features interact with the sun's electromagnetic energy, the analyst knew that one of the two channels from the visible portion of the electromagnetic spectrum together with one of the two channels from the near infrared portion would provide sufficient information for locating areas. He therefore chose channels 1 and 3 for the task of locating the line and column coordinates of the area of interest. To generate the desired gray scale printouts, the following cards were used:

```
-COMMENT GRAY SCALE FOR LOCATION OF KENOSHA PASS COORDINATES
-RUNTABLE
DATA
RUN(73057902), TAPE(253), FILE(1)
END
*PICTUREPRINT
DISPLAY RUN (73057902), LINE (1, 1535, 4), COLUMN (1, 2194,4)
CHANNELS 1, 3
END
```

The analyst used a comment card so that the output would be readily identifiable. Using these printouts in conjunction with reference data, the analyst located the coordinates of the area of interest. To look at the area in more detail (with line interval of one and column interval of one) for subsequent steps in the analysis, the analyst used the following cards:

```
-COMMENT PICTUREPRINT-KENOSHA PASS TRAINING AREA SELECTION
-RUNTABLE
DATA
TAPE(235), FILE(1)
END
*PICTUREPRINT
DISPLAY RUN (73057902), LINE (197, 531, 1), COL (401, 803, 1)
CHANNELS 2, 4
BLOCK RUN (73057902), LINE (197, 531, 2), COL (401, 803, 2)
END
```

Two points should be noted in this control card setup. First, note that different channels were used than for the previous job. The analyst has now looked at all four channels to investigate data quality. Second, note the use of the BLOCK card. In the first PICTUREPRINT, no block card was used because the entire run was to be displayed, and histogramming every tenth line and column of the run (the default parameters) seemed reasonable. In this

second PICTUREPRINT, a subset of the run was being displayed, and the analyst chose a line and column interval of two because he wanted his histogram to be based on more data points than the default interval of ten would provide. (See page PIC-7 in Volume 2 of the LARSYS User's Manual for an explanation of the block card.)

The analyst observed a couple of clouds and their shadows, but judged the overall data quality to be adequate.

EXERCISES

1. Explain in your own words why examination of data quality should precede any extensive analysis.

2. Name at least two ways in which the analyst of remote sensing can examine data quality.

3. Name at least three types of data idiosyncrasies an analyst might find in LANDSAT data.

CASE STUDY

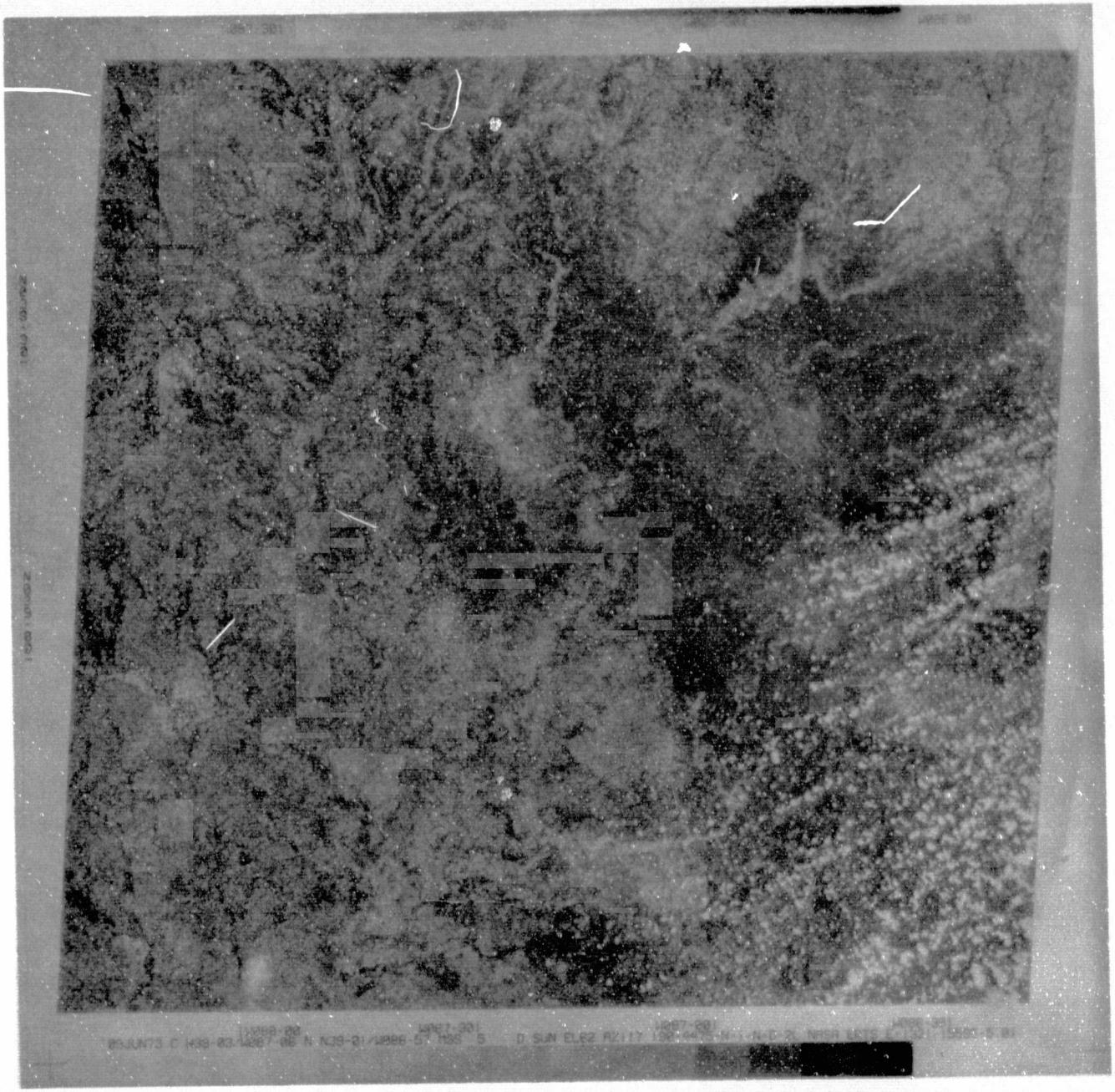
As you progress through this guide, you will be asked to carry out an analysis of a portion of LANDSAT scene 1321 - 15595, collected June 9, 1973. (Figure 1-10). The run number is 73033802*. The scene is in southern Indiana. Take time now to look at Figure 1-10 and state analysis objectives you would like to pursue. Discuss them with your instructor.

Students who have analyzed this data set have used these objectives: a) classify the area into cover type classes of urban, forest, agriculture, and water; b) produce a cover type map of these four classes; c) assess the accuracy of the classification.

The data set you will be working with has been processed for geometric correction, and it has a scale of 1:24,000, which matches the scale of the U.S. Geological Survey 7.5 minute topographic series.

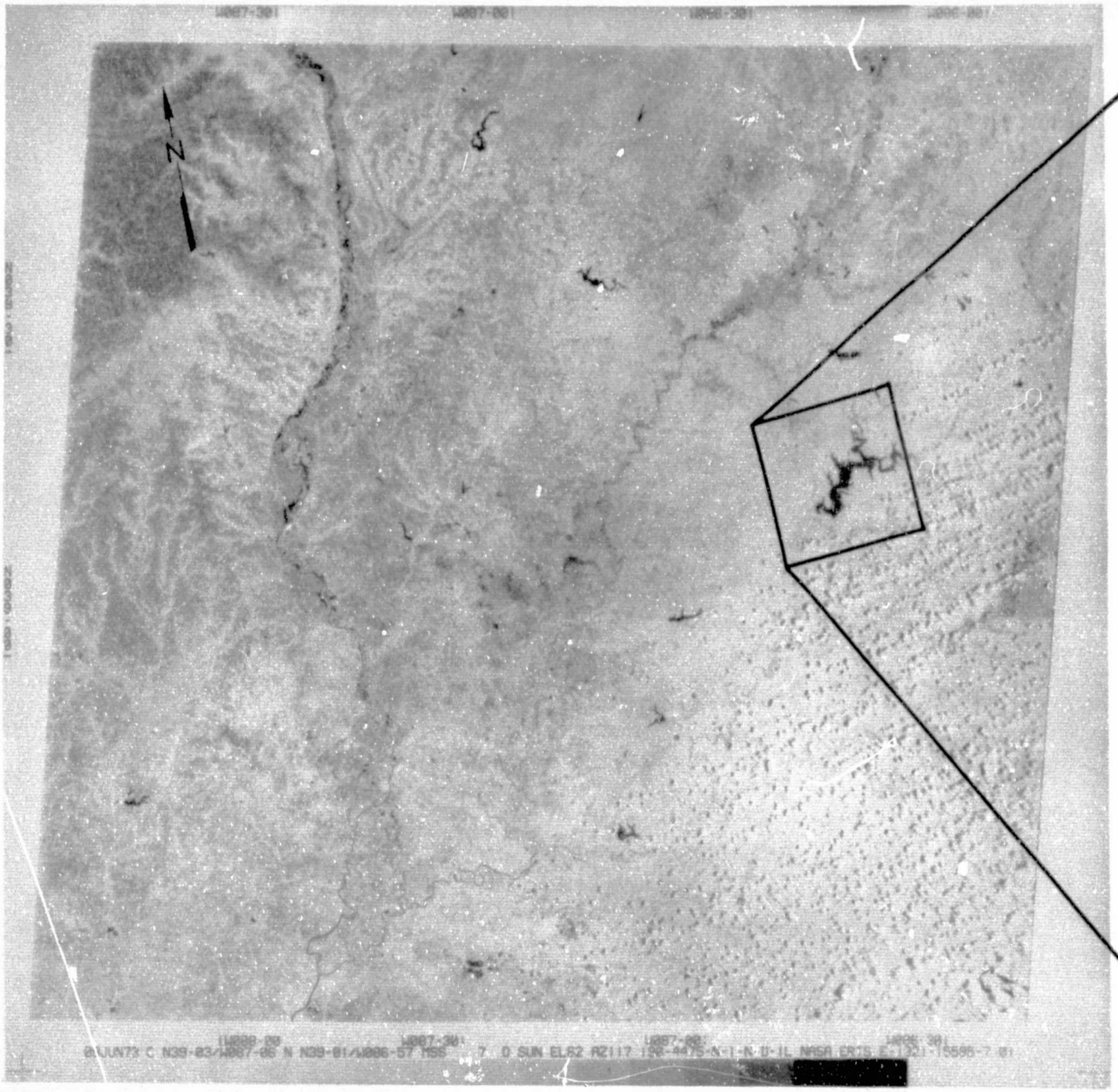
Obtain gray scale printouts for the channels corresponding to the .6 - .7 μm and .7 - .8 μm wavelength bands, for lines 30 to 430 and columns 112 to 333. These printouts will be used in the next step of the analysis.

*The DUPLICATERUN processing function has been used to make a copy of this run for your terminal site. Consult your instructor for the proper tape and file number.



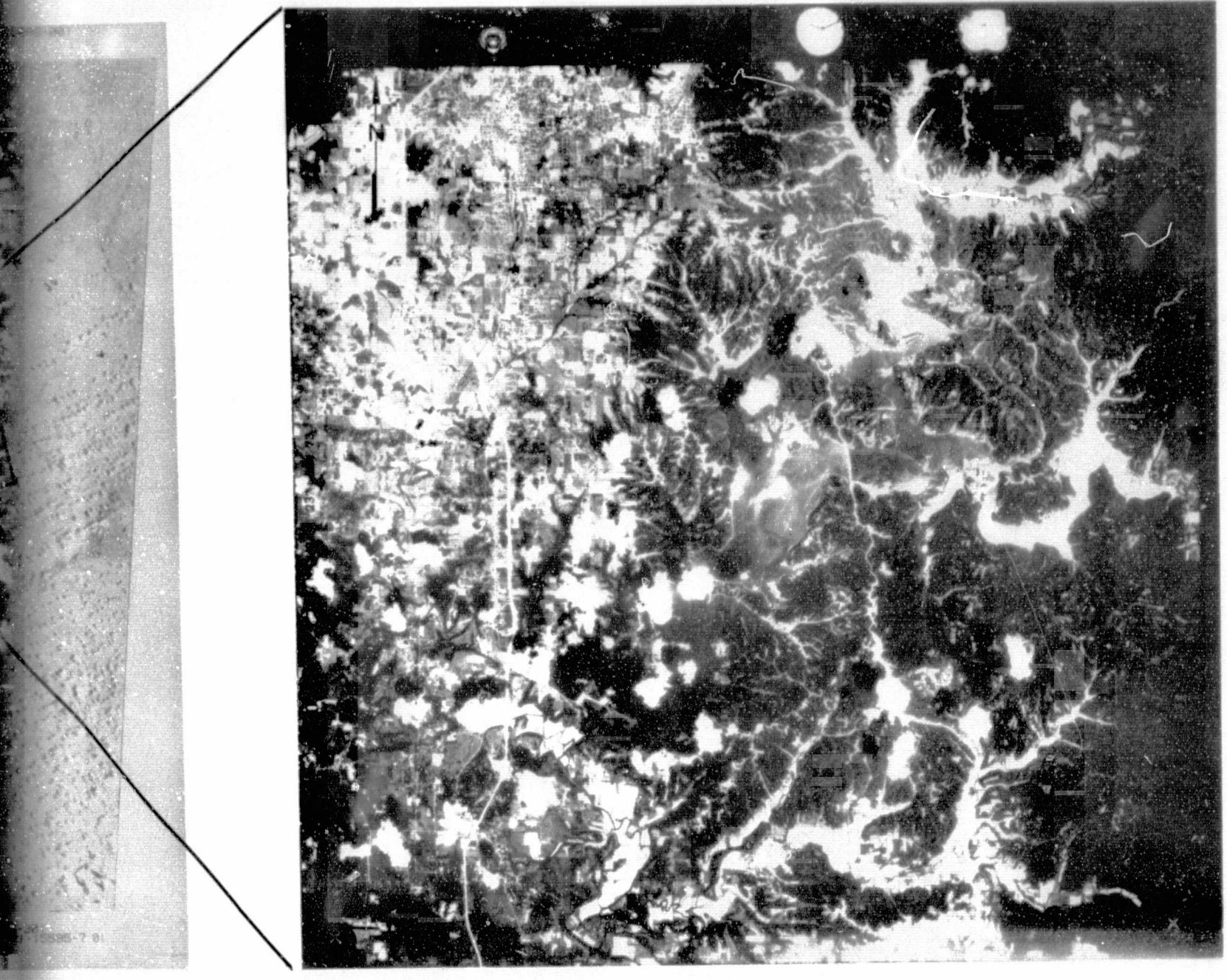
This is a print of ERTS scene 1321-15595, channel 5 (.6-.7μm), collected June 9, 1973 at 9:59 a.m. Note that north is displaced 13° from vertical.

Figure 1-10



This print shows channel 7 (.8-1.1μm) of the same ERTS scene. The area outlined corresponds to the frame of aerial photography on the next page. This area includes Monroe Reservoir and Bloomington, Indiana.

FOLDOUT FRAME



This print was made from a 9 x 9 color infrared photograph collected at an altitude of 60,000 feet at 11:40 a.m. the same day.

OUT FRAME

FOLDOUT FRAME

Section 2. COORDINATION OF MULTISPECTRAL SCANNER DATA WITH AVAILABLE REFERENCE DATA

Upon completion of this section, you should be able to do the following:

State one reason for the necessity of reference data.

State one reason for correlating multispectral scanner data with reference data.

List at least four kinds of reference data.

Correlate the location of ground features apparent on multispectral scanner data with the location of those features on an aerial photograph.

Coordination of multispectral scanner imagery with known features on the ground is necessary in order to determine the line and column coordinates of candidate training areas. The importance of accurate information about the actual ground scene is discussed in detail in LARS Information Note 120371, The Importance of "Ground Truth" Data in Remote Sensing, by Roger M. Hoffer. You should read this information note at this time.

What can an analyst use to obtain information about the ground scene? Aerial photography can be a source of information. Photography can be collected at various altitudes, resulting in reference data over a range of scales. In general, as a plane flies higher, each photograph will cover a larger area, but less detail will be discernible.

Another variable in aerial photography besides altitude is film type. Black and white film, color film, and color infrared film can all record various kinds of information about a ground scene, and serve as reference data for an analyst who understands how to interpret photographic film.

Aircraft multispectral scanner data can also serve as reference data for an analyst working with satellite data, by providing more

detailed information about the spectral characteristics of portions of a scene.

Maps (county highway maps or U.S. Geological Survey maps, for example) and historical records (past crop yields or weather patterns, for instance) can be useful to an analyst by helping him visualize an area and its characteristics.

Another source of information includes observations "at the scene" by the analyst, or other personnel. These observations can provide the key to successfully relating the spectral responses in the data to the cover types on the ground.

As a part of the case study, you will see examples of some of these kinds of reference data.

EXAMPLE

In the example analysis of the Kenosha Pass area of Colorado, the analyst had small-scale (high altitude) photography available for reference data. By looking at the photography and gray scale printouts of the data, the analyst was able to correlate the location of ground features in the two images.

EXERCISES

1. State one reason for obtaining reference data.

2. State one reason for correlating multispectral scanner data with reference data.

3. List at least four kinds of reference data.

CASE STUDY

Obtain the following materials from your instructor: U.S. Geological Survey 7.5 minute topographic quadrangle sheets for six quads,* a 35 mm slide of a color-infrared aerial photograph, and a Monroe County map. Using these materials and Figure 1-10 in conjunction with the printouts generated during the previous analysis step, mark on the printouts with a felt tip pen the boundaries of as many features as possible (Lake Monroe, Highway 37, Bloomington, for example). Note that some features are more apparent on one printout than the other.

*Oolitic, Bartlettsville, Clear Creek, Allen's Creek, Bloomington and Unionville, Indiana.

Section 3. SELECTION OF CANDIDATE TRAINING AREAS

Upon completion of this section, you should be able to do the following:

State in your own words why training areas must be selected.

Name at least two considerations that should go into the selection of candidate training areas.

Select candidate training areas, and specify their coordinates by means of Field Description Cards.

The next step in the analysis of multispectral scanner data is the selection of candidate training areas. This section will begin with a discussion of what training samples are and why they are needed, followed by a discussion of how candidate training areas are chosen.

To explain what training samples are and why they are needed, some pattern recognition concepts should be introduced. Pattern recognition provides the theoretical framework for LARSYS (Swain, 1972). The pattern recognition algorithms require that examples of typical data from each class of interest be supplied to the computer programs. These data, called training samples, are used to set certain parameters for the pattern recognition algorithms, in effect "training" the computer to recognize the training classes. When the classification operation is being carried out by the pattern recognition algorithms, each data point is "compared" to the training sample for each class, and the point is assigned to the "most likely" or most similar class. Further discussion of these concepts can be found in LARS Information Note 110474, An Introduction to Quantitative Remote Sensing by John Lindenlaub and James Russell, and in LARS Information Note 111572, Pattern Recognition: A Basis for Remote Sensing Data Analysis by Philip H. Swain. As you increase your understanding of the material presented in those readings, you will bring more insight to the interpretation of your analysis results.

To obtain training samples for this procedure, the first step is selection of candidate training areas. Experience gained during the development and evolution of this step in the analysis has indicated that a good starting point is to select candidate training areas from 40 to 100 lines by 40 to 100 columns in size, and containing from three to five cover types.

To select these candidate training areas, an analyst begins by reviewing the analysis objectives. In stating the objectives, the cover types of interest are listed. These cover types are called information classes. Candidate training areas are selected in such a way that every information class is represented in at least one of the areas. When possible, each information class is included in more than one candidate training area. This increases the likelihood that the training data will be representative of all of the variations in cover types in the scene being analyzed. When representative training data is available to the classifier, assignment of a data point to the most likely training class has a higher probability of being a correct assignment.

A common procedure for selecting the candidate training areas is to identify in the available reference data some general areas that contain the information classes. These areas are also located on gray scale printouts of the multispectral scanner data. From these areas, candidate training areas are selected, following the guidelines indicated previously: each area is from 40 to 100 lines by 40 to 100 columns, each area includes more than one cover type, and every cover type is included in at least one (preferably two or more) candidate training area. To help assure obtaining representative training data, the candidate training areas should be distributed uniformly throughout the area to be classified, but this may not be possible if adequate reference data is not available. Usually, representative training data for all information classes can be obtained by selecting from four to eight candidate training areas.

After the candidate training areas are selected, their coordinates must be specified in terms of lines and columns, so that the areas can be submitted to LARSYS processing functions in subsequent analysis steps. The formats of the Field Description Cards used to accomplish this are described in Volume 1 of the LARSYS User's Manual, pages 2 - 27 and 2 - 28. A coding sheet set up for the format is shown in Figure 3-1.

EXAMPLE

In the Kenosha Pass example, the analyst used his available reference data - color infrared aerial photography - to select candidate training areas. Since the photography was available only for a limited area, he restricted his choice of candidate training areas to fall within regions covered by photography. Review of the analysis objectives indicated that the cover types of interest were snow, grassland, deciduous forest, coniferous forest, and barren (bare rock and bare soil). With these cover

FIELD DESCRIPTION CARD CODING SHEET Page____of____

Run Number (1-8)	Field Designation (11-18)	First Line (21-25)	Last Line (26-30)	Line Interval (31-35)	First Column (36-40)	Last Column (41-45)	Column Interval (46-50)	Field Type (51-58)	Additional Information (59-72)

Figure 3-1. Field Description Card format.

types in mind, the analyst selected four candidate training areas. Each of the areas contained more than one cover type. Figure 3-2 shows a gray-level image (.6 - .7 μm band) of the Kenosha Pass area with the four candidate training areas outlined.

In terms of number of lines by number of columns, the four candidate training areas were of the following size: 89x73, 97x70, 44x103, and 56x66. Notice how these areas compare to the guideline of 40 to 100 lines by 40 to 100 columns.

By interpretation of his reference data, the analyst selected the areas so that one area included grassland, coniferous forest, and deciduous forest; a second area included those three cover types again and also included water; a third area included bare soil in addition to grassland, coniferous forest, and deciduous forest; and the fourth area included snow, grassland, bare rock, and conifers.

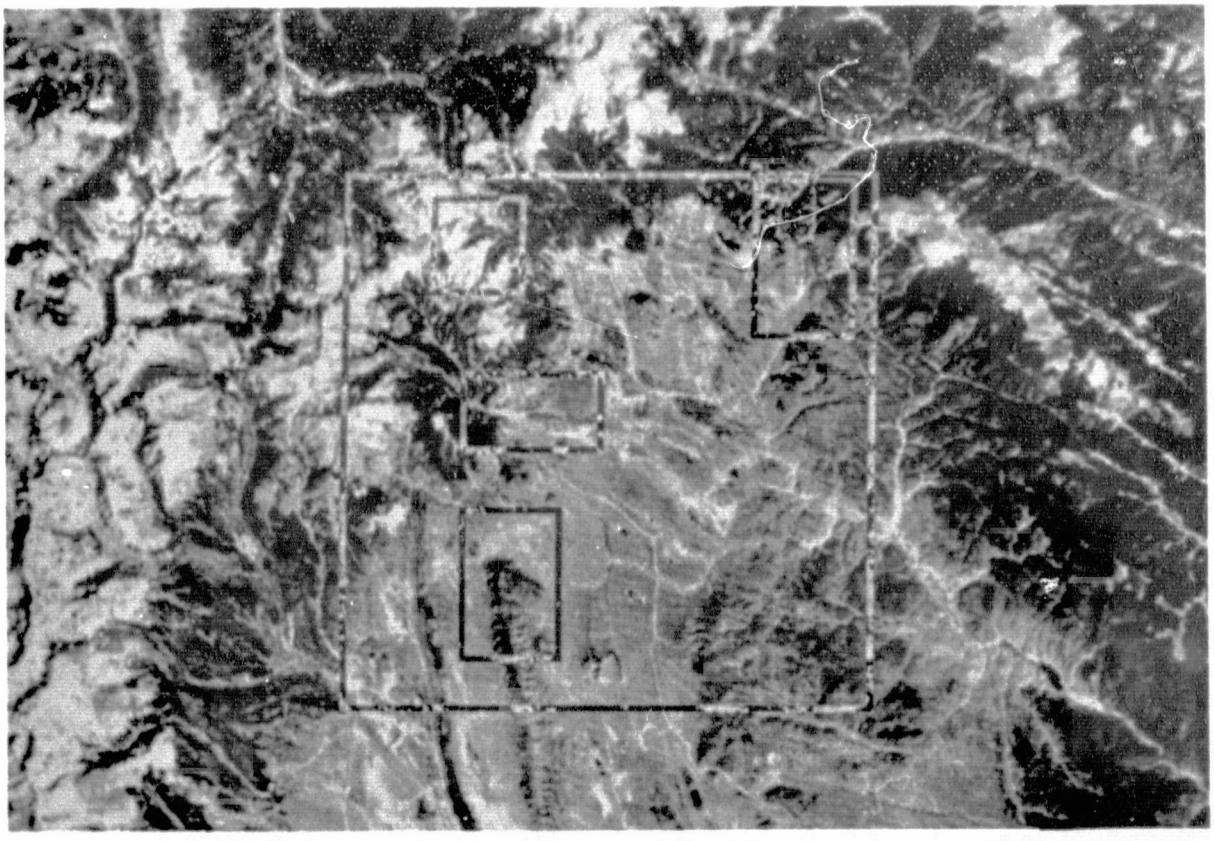


Figure 3-2. Kenosha Pass area and the four candidate training areas outlined.

Then the analyst completed this step of the analysis by specifying the coordinates on Field Description Cards.

73057902	411	499	1	493	565	1
73057902	199	295	1	719	788	1
73057902	324	367	1	494	596	1
73057902	212	267	1	468	533	1

One point which should be discussed is the percent of total area used for training. In the Kenosha Pass analysis, the areas covered slightly more than 15% of the area. However, this is a larger proportion than usual. As the size of the area to be classified increases, the percent of the area used for training generally decreases. This trend is an expression of another idea: the amount of reference data available is an upper limit on the amount of training data that can be used, and as the area being considered increases in size, the logistics and expense of collecting reference data will limit the amount collected.

Where there has been a scarcity of reference data over a large area, an analyst has used as little as one tenth of one percent of the area for training. A more common proportion ranges from 1% to 10%.

EXERCISES

1. State why training areas must be selected.

2. Name two considerations that should go into the selection of candidate training areas.

CASE STUDY

Using the available reference data and the gray scale printouts, select candidate training areas. Make sure that every cover type specified in your analysis objective is included in at least one of the candidate training areas. Specify your candidate training areas on Field Description Cards. Discuss the areas you selected with your instructor.

Section 4. CLUSTERING CANDIDATE TRAINING AREAS

Upon completion of this section, you should be able to do the following:

Describe at least two tasks the CLUSTER processing function can accomplish for you.

State the rule-of-thumb used to determine the number of clusters to request, and the reason behind it.

Given punched and printed output from the CLUSTER processor, explain the effect of choosing different MINPOINTS values.

Use the CLUSTER processing function to find spectrally distinct classes, given Field Description Cards of the areas to be clustered.

In the previous section, the concept of "training samples" was discussed, and candidate training areas were chosen. The process of getting from candidate training areas to training samples is a complex process as well as a crucial one. This section and the next five sections will all deal with aspects of this refinement process. Although the material is written in a linear or "straight-through" fashion, the process is somewhat circuitous, as indicated in Figure 4-1.

The portion of the refinement process to be discussed in this section involves use of the CLUSTER processor. LARS Information Note 111572, Pattern Recognition: A Basis for Remote Sensing Data Analysis by Philip H. Swain contains a section on clustering. Pages 27 through 36 are recommended for your reading.

The CLUSTER processor uses information from more than one channel or wavelength band (four channels in the Case Study) to produce a single image. Since more information is used, boundaries of ground features or cover types tend to be more distinct on cluster maps than on a single-channel gray scale printout. Thus, one task the CLUSTER processing function can accomplish is boundary enhancement.

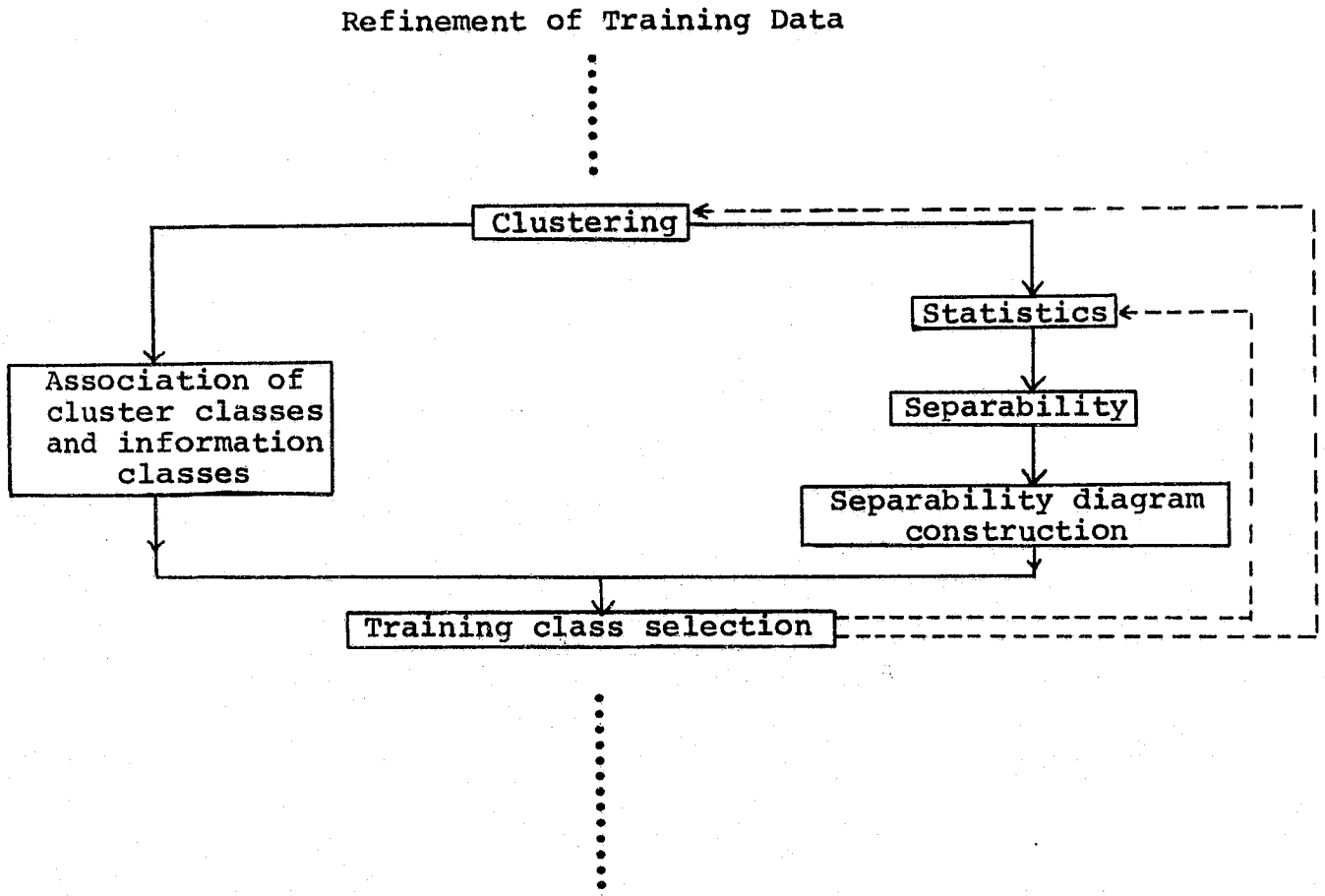


Figure 4-1. Flow chart indicating the steps involved in refinement of candidate training areas. Dashed lines indicate potential iteration loops. This is a portion of the flow chart shown in the Introduction, Figure 2.

The clustering algorithm is called an unsupervised classifier, because it finds natural groupings in multispectral scanner (MSS) data strictly on the basis of inherent properties within the data. These natural groupings in the data are called cluster classes. Thus, another task the CLUSTER processing function can accomplish is to determine cluster classes within a data set.

When data from a natural scene is clustered there is a tendency for the data points within each cluster class to be distributed in a Gaussian fashion.

Figure 4-2a shows a typical Gaussian function in one dimension -- commonly called a "normal curve." Figure 4-2b shows a two-dimensional Gaussian density function. The fact that clusters in remotely sensed data tend to be Gaussian is important because the classification algorithm to be used is based upon a Gaussian assumption, i.e., that the data to be classified can be approximated by a set of Gaussian density functions.

The distribution of the data associated with an information class is likely to be non-Gaussian such as that shown in Figure 4-3a. As an example, an agricultural crop might exhibit a multimodal distribution (more than one peak) due to different soils, moisture content, planting dates, crop density, seed varieties, or a combination of these factors. The multimodal non-Gaussian density function in Figure 4-3a could be decomposed into two Gaussian components by clustering, as shown in Figure 4-3b. These components are commonly referred to as subclasses. The subclass concept is an important one as it allows the analyst to use a classification algorithm based upon a Gaussian assumption even though the information class distributions may be non-Gaussian.

In this step of the analysis the CLUSTER processing function is used to determine cluster classes in the training areas. The enhanced boundaries on the cluster maps will be used in Section 5 to help establish associations between the cluster classes and information classes.

The clustering algorithm implemented in LARSYS requires that the analyst specify the number of clusters to be found. Experience has indicated that most cover types have multimodal distributions, and a rule-of-thumb is to request twice the number of expected information classes, except in areas of great topographic relief (such as the Kenosha Pass example), where three times the number of expected information classes seems to be a better guideline.

If an analyst requests an insufficient number of clusters, some of the clusters will be multimodal, and further clustering will still be necessary. If "too many" clusters are requested, they can be grouped back together without much trouble.

A good understanding of the interactions between solar energy and matter will help you know how many cluster classes a

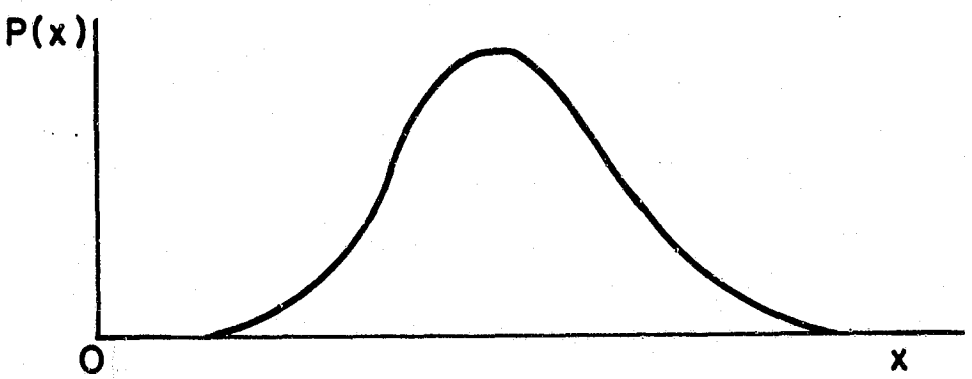


Figure 4-2a. Gaussian density function in one dimension.

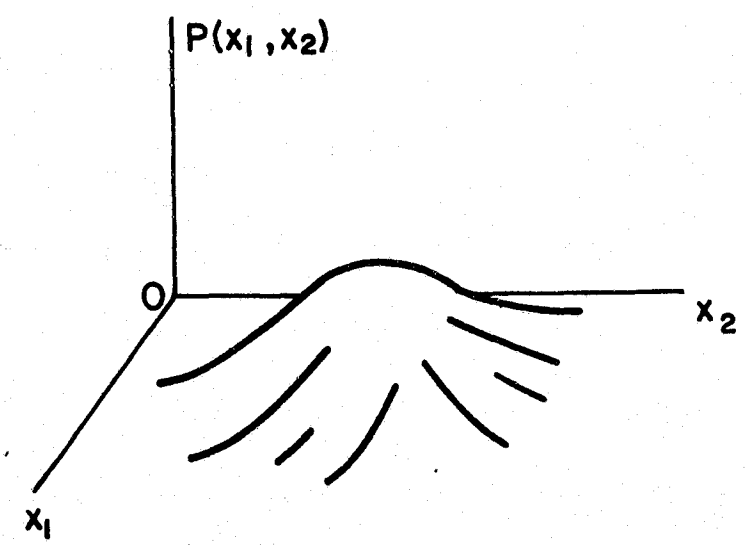


Figure 4-2b. Gaussian density function in two dimensions.

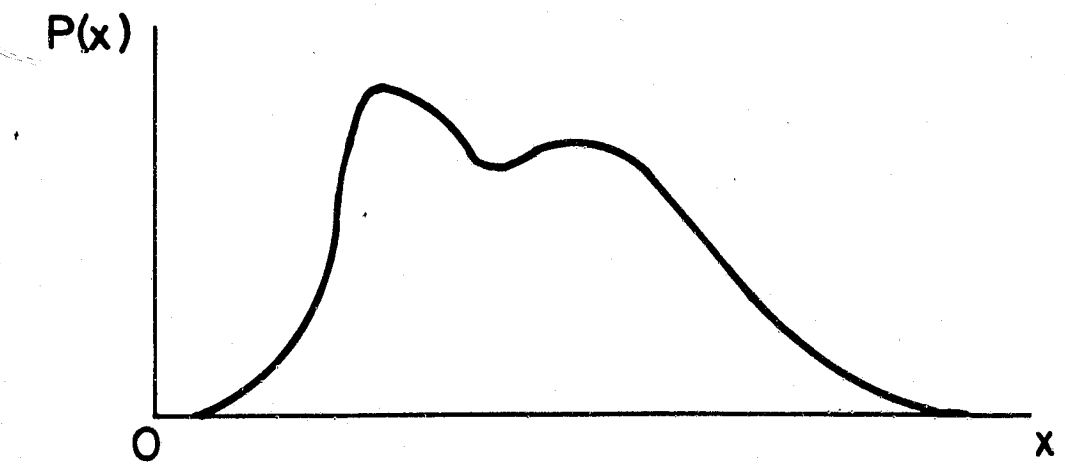


Figure 4-3a. Multimodal non-Gaussian density function.

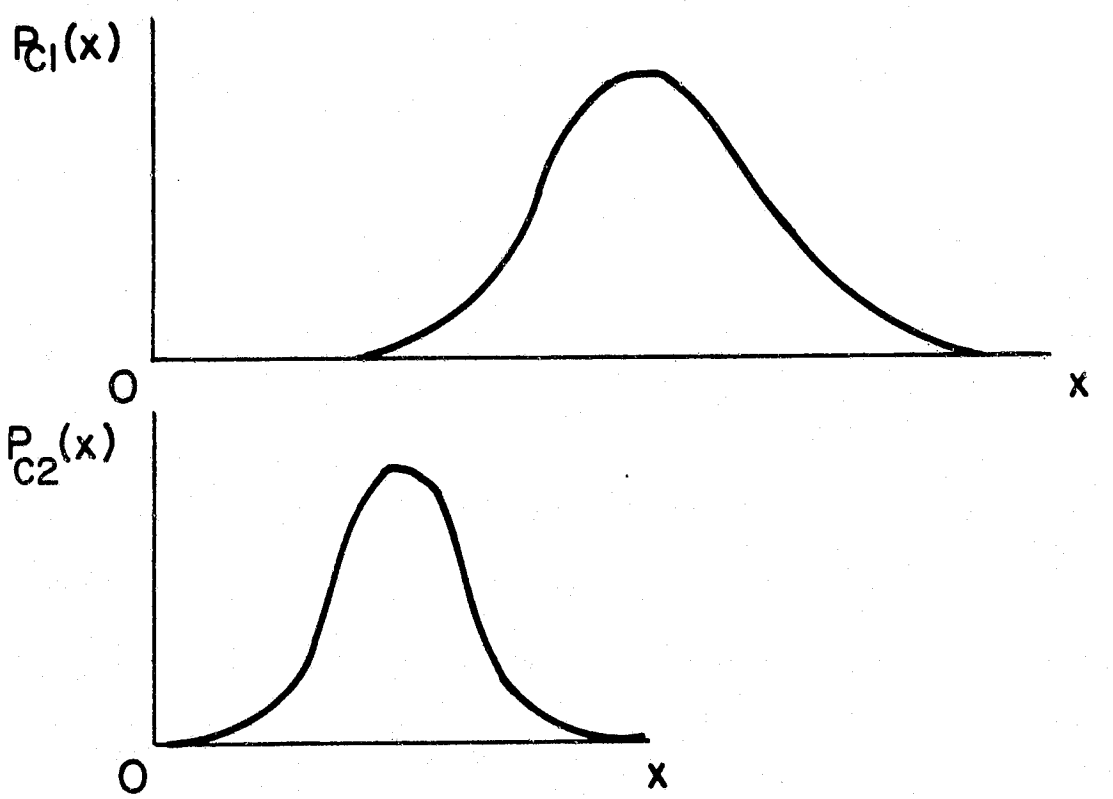


Figure 4-3b. Multimodal function decomposed into two Gaussian components.

given scene could be expected to have. Basic information of interest to the analyst of MSS data would be the reflectance properties of bare soil, green vegetation, and water, shown in Figure 4-4. For more specific information, refer to LARS Information Note 011069, Ecological Potentials in Spectral Signature Analysis, by R. M. Hoffer and C. J. Johannsen, and also LARS Information Note 072473, Emission and Reflectance from Natural Targets, by R. Kumar and L. Silva.

EXAMPLE

The analyst wanted to cluster each of his candidate training areas into distinct cluster classes, so he set up his deck in the following way:

```
-COMMENT KENOSHA PASS CANDIDATE TRAINING AREA 1
-RUNTABLE
DATA
RUN (73057902), TAPE (253), FILE (1)
END
*CLUSTER
OPTIONS MAXCLAS (15)
PUNCH FIELD, MINPOINTS (3)
CHANNELS 1, 2, 3, 4
DATA
73057902            411  499  1    494  565  1
END
-COMMENT KENOSHA PASS CANDIDATE TRAINING AREA 2
*CLUSTER
OPTIONS MAXCLAS (15)
PUNCH FIELD, MINPOINTS (3)
CHANNELS 1, 2, 3, 4
DATA
73057902            199  295  1    719  788  1
END
-COMMENT KENOSHA PASS CANDIDATE TRAINING AREA 3
*CLUSTER
OPTIONS MAXCLAS (15)
PUNCH FIELD, MINPOINTS (3)
CHANNELS 1, 2, 3, 4
DATA
73057902            212  267  1    468  533  1
END
```

Why did the analyst choose a MAXCLAS of 15? The Kenosha Pass study area includes some very rugged terrain. The analyst was looking for five cover types - snow, grassland, deciduous forest, coniferous forest, and barren. He expected an average of three subclasses per cover type due to the complexity of topographic relief. If he had wanted to, the analyst could have chosen a different MAXCLAS parameter for each area clustered.

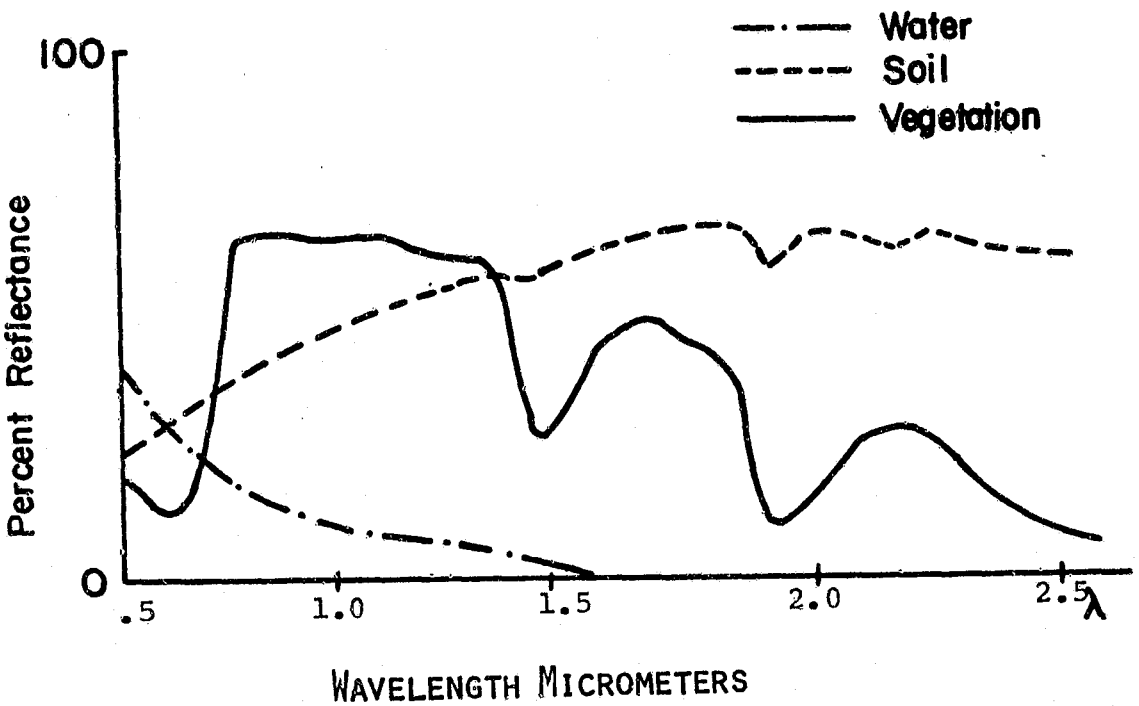


Figure 4-4. Typical reflectance properties of bare soil, green vegetation and water.

Each of these CLUSTER jobs produced a punched deck of Field Description Cards to be used in a later step in the refinement of candidate training areas (Section 6).

EXERCISES

1. Describe two tasks the CLUSTER processing function can accomplish for you.

2. State the rule-of-thumb used to determine the number of cluster classes to request, and the reason behind it.

3. The following control cards were used to generate the cluster map in Figure 4-5 and the punched output listed in Figure 4-6:

```
-COMMENT CLUSTER EXAMPLE, MINPOINTS EXERCISE
*CLUSTER
OPTIONS MAXCLAS (6)
PUNCH FIELD, MINPOINTS (2)
CHANNELS 1, 2, 3, 4
DATA
RUN (72072302), LINE (500, 515, 1), COL (445, 465, 1)
END
```

The format of the punched cards should be familiar to you from Figure 3-1. Look at the first punched card, find its coordinates on the cluster map, and mark the map with a colored pencil or felt tip marker. Follow the same procedure for all the punched cards describing cluster class 1.

Now, prepare the control cards shown above, BUT use a MINPOINTS parameter of 3. Then, looking at your cluster map, which should be the same as the one in Figure 4-5, and a listing of your punched output, again locate the data points corresponding to the Field Description Cards for the first cluster class. Observe the differences in the two punched decks. Discuss with your instructor the factors you should keep in mind when choosing a MINPOINTS parameter.

CASE STUDY

Set up the control cards to cluster separately each of the candidate training areas you chose in the last section. Remember, you can ask for a different number of cluster classes from each candidate training area if you have reason to do so.

The printed cluster maps will be used in the next section, Section 5, and your punched deck will be used in Section 6.

SBLARSYS
RUSSELL/TKC

LABORATORY FOR APPLICATIONS OF REMOTE SENSING
PURDUE UNIVERSITY

CLUSTER EXAMPLE, MINPOINTS EXERCISE

FIELD INFORMATION

FIELD
RUN NO. 72072302
OTHER INFORMATION

TYPE
NO. OF SAMPLES 336

LINES 500- 515
COLUMNS 445- 465

```
                4444444444444444444
                4444455555555566666
                5678901234567890123456789

500             XXSS SSSSSS SNNXMNMXX
501             XS   SS    SS SXXNMNXXX
502             XS   SSS      XXNXXXXXX
503             XS S   S     XNM)XNXNXX
504             SXS      S SXMN)XXXXXX
505             SSSS     S SNN)))XNXNN
506              SS    S)  S SNM))NXXNX
507              S     S)SSSNMMX))XXNN
508                    SSSXMMX)XNNNNN
509                 SSS XXNMNNNNXNNN
510               SSSS SXXXMNNXXXNSS
511             SSSSS  MNXXMMNNNNSSSX
512             SS  NSMMNXNXMNXNXXXSN
513               SMMMMNXXNNMMNNNSSSN
514             SSMXMMMMMMMNNNNNNSNM
515             SNX)))))XNMNXXNNNNNMM
```

NUMBER OF POINTS PER CLUSTER

CLUSTER	1	2	3	4	5	6
SYMBOL		)	S	X	N	M
POINTS	67	17	75	70	70	37

Figure 4-5. An example of a printed cluster map.

```
CLASS NS- 1/ 6
72072302          3   501   501    1   447   448     INS- 1/ 6
72072302          4   501   501    1   451   453     INS- 1/ 6
72072302          6   502   502    1   447   448     INS- 1/ 6
72072302          7   502   502    1   452   456     INS- 1/ 6
72072302          9   503   503    1   449   450     INS- 1/ 6
72072302         10   503   503    1   452   455     INS- 1/ 6
72072302         11   504   504    1   448   452     INS- 1/ 6
72072302         13   505   505    1   449   452     INS- 1/ 6
72072302         16   506   506    1   448   450     INS- 1/ 6
72072302         20   507   507    1   447   450     INS- 1/ 6
72072302         21   508   508    1   445   451     INS- 1/ 6
72072302         22   509   509    1   445   449     INS- 1/ 6
72072302         24   510   510    1   445   447     INS- 1/ 6
72072302         26   511   511    1   450   451     INS- 1/ 6
72072302         27   512   512    1   447   448     INS- 1/ 6
72072302         28   513   513    1   445   446     INS- 1/ 6
CLASS NS- 2/ 6
72072302          3   505   505    1   458   460     INS- 2/ 6
72072302          5   506   506    1   459   460     INS- 2/ 6
72072302          7   507   507    1   460   461     INS- 2/ 6
72072302          9   515   515    1   448   452     INS- 2/ 6
CLASS NS- 3/ 6
72072302          1   500   500    1   447   448     INS- 3/ 6
72072302          2   500   500    1   450   455     INS- 3/ 6
72072302          5   501   501    1   449   450     INS- 3/ 6
72072302          6   501   501    1   454   455     INS- 3/ 6
72072302          9   502   502    1   449   451     INS- 3/ 6
72072302         17   505   505    1   445   448     INS- 3/ 6
72072302         20   506   506    1   446   447     INS- 3/ 6
72072302         26   507   507    1   453   455     INS- 3/ 6
72072302         27   508   508    1   452   454     INS- 3/ 6
72072302         28   509   509    1   450   452     INS- 3/ 6
72072302         29   510   510    1   448   451     INS- 3/ 6
72072302         31   510   510    1   464   465     INS- 3/ 6
72072302         32   511   511    1   445   449     INS- 3/ 6
72072302         33   511   511    1   462   464     INS- 3/ 6
72072302         34   512   512    1   445   446     INS- 3/ 6
72072302         38   513   513    1   462   464     INS- 3/ 6
72072302         39   514   514    1   445   446     INS- 3/ 6
CLASS NS- 4/ 6
72072302          1   500   500    1   445   446     INS- 4/ 6
72072302          3   500   500    1   464   465     INS- 4/ 6
72072302          5   501   501    1   458   459     INS- 4/ 6
72072302          6   501   501    1   463   465     INS- 4/ 6
72072302          8   502   502    1   457   458     INS- 4/ 6
72072302          9   502   502    1   460   465     INS- 4/ 6
72072302         14   503   503    1   464   465     INS- 4/ 6
72072302         17   504   504    1   460   465     INS- 4/ 6
72072302         20   506   506    1   462   463     INS- 4/ 6
72072302         23   507   507    1   462   463     INS- 4/ 6
72072302         27   509   509    1   454   455     INS- 4/ 6
72072302         29   510   510    1   454   456     INS- 4/ 6
72072302         30   510   510    1   460   462     INS- 4/ 6
72072302         31   511   511    1   454   455     INS- 4/ 6
72072302         36   512   512    1   461   463     INS- 4/ 6
72072302         37   513   513    1   453   454     INS- 4/ 6
72072302         41   515   515    1   457   458     INS- 4/ 6
CLASS NS- 5/ 6
72072302          1   500   500    1   458   459     INS- 5/ 6
72072302         10   505   505    1   456   457     INS- 5/ 6
72072302         12   505   505    1   464   465     INS- 5/ 6
72072302         17   507   507    1   464   465     INS- 5/ 6
72072302         18   508   508    1   461   465     INS- 5/ 6
72072302         20   509   509    1   458   461     INS- 5/ 6
72072302         21   509   509    1   463   465     INS- 5/ 6
72072302         22   510   510    1   458   459     INS- 5/ 6
72072302         25   511   511    1   458   461     INS- 5/ 6
72072302         33   513   513    1   455   456     INS- 5/ 6
72072302         34   513   513    1   459   461     INS- 5/ 6
72072302         36   514   514    1   457   462     INS- 5/ 6
72072302         41   515   515    1   459   463     INS- 5/ 6
CLASS NS- 6/ 6
72072302          7   507   507    1   457   458     INS- 6/ 6
72072302          8   508   508    1   456   457     INS- 6/ 6
72072302         12   511   511    1   456   457     INS- 6/ 6
72072302         13   512   512    1   451   452     INS- 6/ 6
72072302         15   513   513    1   448   451     INS- 6/ 6
72072302         16   513   513    1   457   458     INS- 6/ 6
72072302         18   514   514    1   449   456     INS- 6/ 6
72072302         21   515   515    1   464   465     INS- 6/ 6
```


Figure 4-6. Listing of punched Field Description Cards generated by CLUSTER.

Warning! You'll get a punched deck for each cluster area. Be sure to label the cards and keep them in order.

Since clustering is both complex, and crucial to the success of your analysis, be sure to ask your instructor any questions that come up.

Section 5. ASSOCIATION OF CLUSTER CLASSES AND INFORMATION CLASSES

Upon completion of this section, you should be able to do the following:

Describe why cluster classes are associated with information classes.

Given printed cluster maps and available reference data, associate cluster classes with information classes.

Up to this point in the process of meeting analysis objectives, the LANDSAT imagery has been examined for data quality, the imagery has been correlated with reference data, candidate training areas have been selected and the data within each candidate training area has been clustered. Previous sections have introduced the concepts of information classes and cluster classes. Recall that information classes were defined during the process of stating the analysis objectives. Cluster classes for each candidate training area were determined by means of the CLUSTER processing function. The objective of this step of the analysis is to associate each cluster class with one of the information classes in order to obtain information class (or subclass) training data.

To carry out this step of the analysis, maximum use is made of all available reference data, so that the cluster classes can be reliably identified. If errors occur in this step of the analysis the training data supplied to the classifier will not be representative of the information classes. The association of cluster classes and information classes is difficult and time consuming, but this step is most important for insuring that the classifier is correctly trained.

EXAMPLE

The reference data available for the Kenosha Pass area included color infrared 9" x 9" transparencies. The analyst used

an overhead projector to superimpose the photography on the printed cluster maps. By varying the projector-to-wall distance, he was able to project the transparency to the scale of the printout, and since the data had been geometrically corrected, a good match could be obtained.

U.S. Geological Survey quadrangle sheets of the area were useful for general location, and for indicating which areas would fall in topographic shadow at the time of the satellite overpass.

The analyst identified the cover types as accurately as he could, making use of his knowledge of the area and his skill as a photointerpreter. The results of his efforts at identification are shown in Table 5-1.

There are several points to observe about Table 5-1. One point is that if the analyst felt a single cluster corresponded to more than one cover type, then he identified it that way. For example, cluster 13 in candidate training area 1 is associated with both deciduous and coniferous cover types.

Another point to observe is that the list includes grassland 1, grassland 2, and 3 and 4. There were four distinctly different kinds of grassland that the analyst could distinguish in the color infrared photography: dry grass, mountain bunch grass, wet meadows, and tundra. Since they were clearly distinct in the photography, the analyst wanted to keep that information available. Grassland 1 is dry grass. Grassland 2 is mountain bunch grass. Grassland 3 is wet meadow, and grassland 4 is tundra.

Another point to observe is that cluster class numbers from different training areas do not necessarily correspond to the same information classes. For instance, cluster 12 in candidate training area 1 was deciduous, in area 2 it was coniferous, in area 3 it was grassland 3, and in area 4 it was again coniferous. This occurred because each candidate training area was clustered separately, and the results of clustering always depend on the data being clustered. In this example, each candidate training area contained different information classes.

EXERCISES

1. State why cluster classes are associated with information classes.

CASE STUDY

To carry out the next step in your case study analysis, assemble the following materials: the printed maps you got from clustering your candidate training areas, the 35 mm slide, the Monroe County map, and the topographic maps. Then identify as completely as possible each cluster class in every candidate

Table 5-1. Kenosha Pass cluster identification

Cluster Number	Candidate Training Area 1	2	3	4
1	grassland 1	grassland 2	bare soil	snow
2	grassland 2	grassland 3	grassland 2	snow and edge
3	grassland 2	grassland 2	grassland 3	grassland 4
4	grassland 2	grassland 3	grassland 3	grassland 4
5	grassland 2	grassland 3	grassland 2	bare rock
6	grassland 2	grassland 3	grassland 3	grassland 4
7	grassland 2	grassland 3	grassland 3	bare rock?
8	grassland 3	deciduous and grassland 3	grassland 3	coniferous and grassland
9	grassland 3	edge	grassland 3	?
10	coniferous	deciduous	deciduous	bare rock
11	deciduous	water +	grassland 3	coniferous and grassland
12	deciduous	coniferous	grassland 3	coniferous
13	deciduous and coniferous	coniferous	deciduous	bare rock in shadow
14	deciduous	coniferous	coniferous	coniferous
15	coniferous	coniferous and water	coniferous	coniferous

training area. Since the topographic maps are the same scale as the MSS data, you will probably want to start with them. They will be most useful in the vicinity of the reservoir. The Monroe County map shows the Highway 37 By-Pass well.*

The 35mm slide will be helpful for making more detailed identifications, such as distinguishing fields of bare soil from green vegetation in agricultural areas or shopping centers from residential neighborhoods in the urban area.

One way to use the 35mm slide is to use a regular slide projector, and instead of projecting the slide onto a screen, project it onto the cluster map (taped to a wall). The first time you do this, the scale of the slide image will probably not match the scale of the cluster map. If the slide image is bigger than the corresponding part of the cluster map, move the projector closer and re-focus. This procedure is somewhat tedious, but it does work.

After you have identified each cluster class in every candidate training area, make a table of your results. This information will be used in Section 9.

*If you have access to a zoom transfer scope, you could use it to match the Monroe County map and the cluster maps to the same scale.

Section 6. CALCULATION OF STATISTICAL CHARACTERISTICS OF CLUSTER CLASSES

Upon completion of this section, you should be able to do the following:

Name the two statistical parameters which define a Gaussian distribution.

Use the LARSYS processing function to obtain statistics for classes described by a set of Field Description Cards.

This section describes another step in the process of getting from candidate training areas to training samples. So far, candidate training areas have been selected to contain representative data from every information class, the candidate training areas have been clustered, and the cluster classes have been associated with specific information classes.

In this section the STATISTICS processing function will be run, and the resulting statistics file will be punched out on cards for use in the next analysis step.

Input to the STATISTICS processing function includes a deck of Field Description Cards. In this step, the input will be all of the cards punched out by CLUSTER in the step described in Section 4. From the data points specified on the Field Description Cards, the STATISTICS processing function will calculate the mean vector and covariance matrix for each cluster class. The mean vector is the average of all the data vectors in the class, and the covariance matrix is a measure of the "spread" of the data.

These two statistical parameters define a Gaussian probability density function. A Gaussian distribution is assumed in processing functions to be used later (Sections 7 and 11).

In addition to the mean vectors and covariance matrices, the STATISTICS processing function can produce several kinds of printed output. The input and output are described in Volume 2 of the

LARSYS User's Manual, pages STA-1 through STA-22. Examples of printed output are shown. Take time now to read these pages.

EXAMPLE

After clustering his candidate training areas, and associating each cluster class with a ground cover type, the analyst was ready to obtain the statistical characteristics of all the cluster classes. In order to have the statistics available for the next step, he requested a punched statistics deck.

The control card deck listed below was used.

```
-COMMENT STATISTICS OF 60 CLUSTER CLASSES
-RUNTABLE
DATA
RUN(73057902), TAPE(253), FILE(1)
END
*STATISTICS
PUNCH
CHANNELS 1,2,3,4
SCALE SPCINT (1)
DATA
 .
 .
 all field description cards punched out by CLUSTER for
  cluster area 1
 .
 .
 all field description cards punched out by CLUSTER for
  cluster area 2
 .
 .
 all field description cards punched out by CLUSTER for
  cluster area 3
 .
 .
 all field description cards punched out by CLUSTER for
  cluster area 4
 .
 .
END
```

Notice that the analyst did not request histograms. When the Field Description Cards used as input for STATISTICS come from CLUSTER, individual *fields* generally have so few points that histograms of fields are not meaningful. The analyst could have requested histograms of *classes*, but they would have added considerable bulk to the printed output. Since the STATISTICS processor will be run again at a later stage in the refinement process (with a smaller number of classes), the analyst chose to wait until then to look at histograms.

Why was the SCALE control card used? One of the printed outputs from STATISTICS is a coincident spectral plot. The analyst had learned in his first few analyses of LANDSAT data

that data values range up to 128 in the first three channels, and to 64 in the fourth channel, so using an interval of 1 (rather than the default interval of three) would show more detail in the plot while still fitting on the page.

The analyst inspected the coincident spectral plot to gain insight into relationships between his various classes. He kept the Field Description Cards for use at a later stage in the analysis, and he kept the punched statistics deck for use in the next step.

EXERCISES

1. Name the two statistical parameters which define a Gaussian distribution.

2. Explain why statistics are needed at this point in the analysis.

CASE STUDY

Set up the control cards for the STATISTICS processing function. Use the punched output from CLUSTER as your input data. Request a punched statistics deck so that you will have the mean vectors and covariance matrices of each cluster available for the next analysis step.

Section 7. CALCULATION OF DISTANCES BETWEEN CLUSTER CLASSES

Upon completion of this section, you should be able to do the following:

Given two pairs of one-dimensional density functions, identify the pair which is separated by the larger statistical distance.

Name two measures of statistical distance calculated in LARSYS.

Name the two characteristics of Gaussian probability density functions which determine the statistical distance between the density functions.

Set up the control cards and run the SEPARABILITY processing function when given a punched statistics deck.

At this point in the analysis sequence, candidate training areas have been chosen and clustered, the cluster classes have been associated with information classes, and the statistical characteristics of the cluster classes have been calculated. It would be possible at this point to use all of these cluster classes to train the classifier, but that is usually not done for a couple of reasons. First, the number of clusters available at this point is normally greater than the number of classes needed to adequately train the classifier. For instance, one of the cluster classes in area 1 identified as forest may be spectrally similar to a cluster class of forest in area 3. An analyst would like to reduce the number of training classes in such cases, because a smaller number of classes saves computer time and simplifies interpretation of results. Also, some of the clusters may have too few data points to get good estimates of the mean vector and covariance matrix. By combining spectrally similar clusters, the number of data points used to calculate the mean vector and covariance matrix for a training class will be greater, and this will generally lead to a better representation of the cover type.

The second major reason a classification is not performed at this point is that the analyst would like to have some indication of the probability of correct classification in advance of doing the classification. If there appears to be confusion between classes, an analyst can do more clustering on the areas already used, asking for a different number of clusters, or perhaps the analyst would choose to go back and select additional candidate training areas in an effort to get good distinction between classes.

The SEPARABILITY processing function in LARSYS can help an analyst determine which cluster classes are similar, and it can serve as an indicator of probability of correct classification.

To explain how this can be accomplished, the concept of statistical distance must first be discussed. Figure 7-1 shows two cases of one-dimensional density functions. Intuitively you know that the "distance" between the density functions is greater in case b than in case a. There are a number of ways of measuring *statistical distance*. (Section 2.4 of LARS Information Note 100771, The Minimum Distance Approach to Classification, by Wacker and Landgrebe). The distance measure implemented in SEPARABILITY, transformed divergence, assumes that the density functions are Gaussian. The distance between two Gaussian probability density functions depends not only on the ordinary (Euclidean) distance between the mean values but also on the "spread" of the data. Figure 7-2 illustrates this point. The Euclidean distances between the mean values are equal in both of the cases shown, but the smaller variances (smaller "spread") in part b result in a larger statistical distance between the two density function.

At this point another distance measure, the one that is calculated in CLUSTER, will be discussed. The Swain-Fu distance is printed out in the column labelled QUOT on the page showing separability information for the clusters. Figure 7-3 shows an example of this information. The Swain-Fu distance is discussed in detail on pages 30 to 33 of Pattern Recognition: A Basis for Remote Sensing Data Analysis by Philip H. Swain. Analysts have observed that if the Swain-Fu distance for two clusters is less than .75, the two clusters can probably be combined back into a single class without creating a multimodal distribution. From this experience, an algorithm has been programmed that indicates which pairs of clusters could be combined together on the basis of having a distance less than .75 (or some user-specified threshold). An example of a grouping table output from CLUSTER is shown in Figure 7-4. A detailed explanation of the algorithm used to get the suggested groupings can be found on page CLU-20 of the LARSYS User's Manual.

Now, a natural question to ask is "Why don't we just use the Swain-Fu distance and the suggested grouping table?" There are two reasons why transformed divergence, calculated by SEPARABILITY, is used instead.

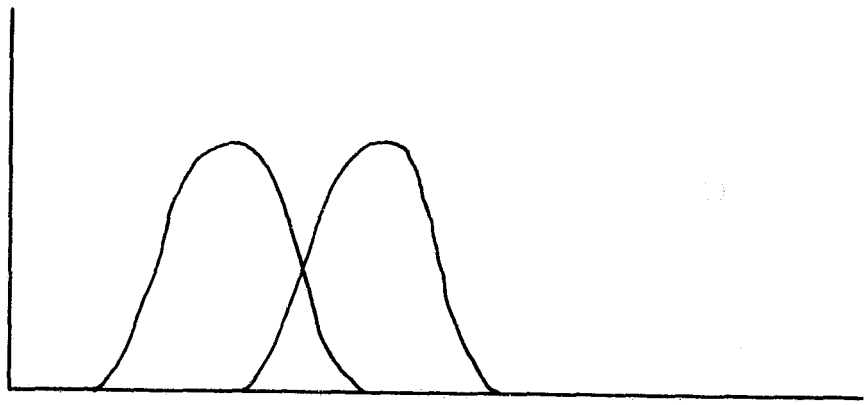


Figure 7-1a

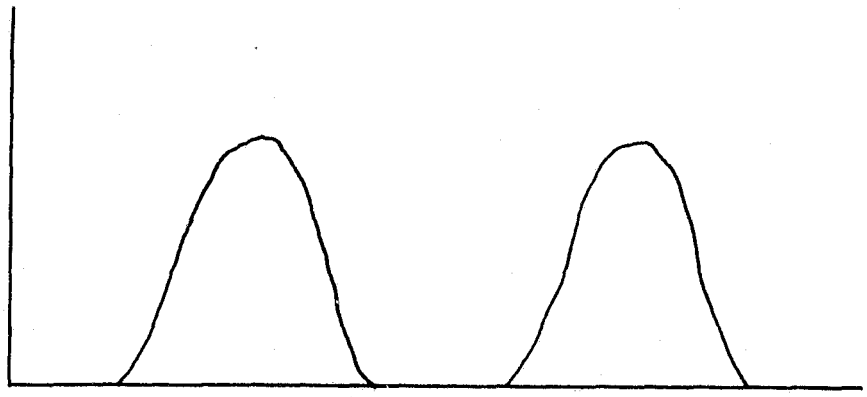


Figure 7-1b

Figure 7-1. Two pairs of one-dimensional density functions. The statistical distance between the density functions in part b is greater than in part a.

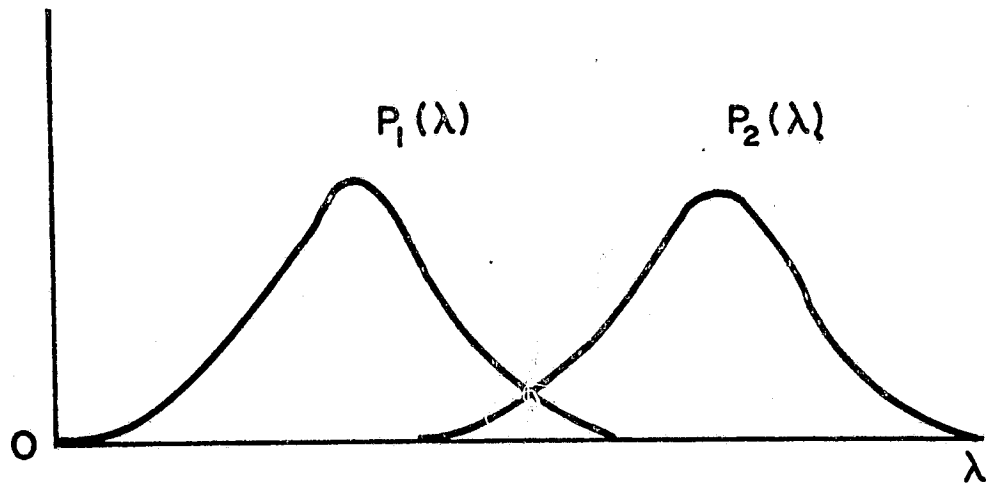


Figure 7-2a

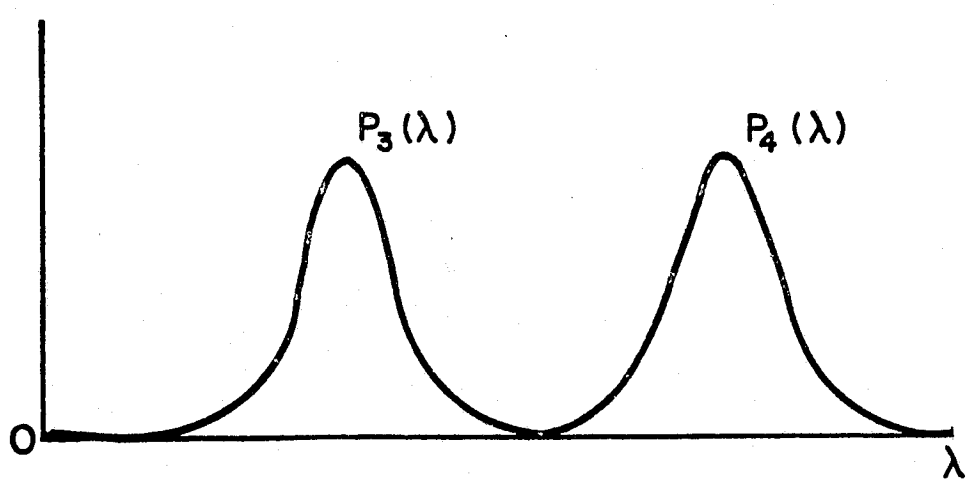


Figure 7-2b

Figure 7-2. Each pair of distribution functions shown above has equidistant means, but the smaller variance in $P_3(\lambda)$ and $P_4(\lambda)$ cause them to have a larger statistical distance.

SEPARABILITY INFORMATION

I	J	D(I,J)	D(I)	D(J)	D(I)+D(J)	QUOT
1	2	21.467	9.426	5.219	14.645	1.466
1	3	9.860	8.931	6.479	15.409	0.640
1	4	19.002	9.232	5.754	14.986	1.268
1	5	19.568	9.054	6.094	15.148	1.292
1	6	25.497	8.797	5.934	14.730	1.731
2	3	16.691	6.335	7.020	13.354	1.250
2	4	11.819	7.060	5.290	12.350	0.957
2	5	17.396	7.436	4.510	11.946	1.456
2	6	25.314	7.246	4.351	11.597	2.183
3	4	9.860	6.087	5.817	11.904	0.828
3	5	9.716	6.476	6.092	12.568	0.773
3	6	16.247	7.155	5.726	12.881	1.261
4	5	5.621	5.423	4.473	9.895	0.568
4	6	13.542	5.230	4.419	9.649	1.403
5	6	8.255	4.662	4.655	9.317	0.886

AVERAGE QUOTIENT 1.197

Figure 7-3. Separability information calculated in CLUSTER.

RESULTS OF CLUSTER GROUPING

THRESHOLD = 0.750

GROUP	CLUSTERS	NO. PTS.
1	1	67
	3	75
2	2	17
3	4	70
	5	70
4	6	37

Figure 7-4. A CLUSTER grouping table.

First, in order to have a Swain-Fu distance calculated between all the cluster pairs in all of the candidate training areas, all of the areas would have to be clustered together in one job. This would increase the computer time significantly (a factor of 7 was observed in one example).

The second reason transformed divergence is used is that transformed divergence seems to correlate better with probability of correct classification than Swain-Fu distance does.

How does transformed divergence relate to probability of correct classification? You might expect that a greater statistical distance between density functions would be accompanied by greater classification accuracy. In general, that does happen, although the relationship is not linear.

For a detailed discussion of the relationship between statistical distance and probability of correct classification, see LARS Information Note 042673, Two Effective Feature Selection Criteria for Multispectral Remote Sensing, by Swain and King. In particular, experimental results of plotting probability of correct classification versus transformed divergence for training data are shown in the graph in Figure 7-5. A transformed divergence value of 1.5 on that graph corresponds to a value of 1500 in SEPARABILITY output. See Figure 7-6 for an example of SEPARABILITY output. Notice that the distances are given for *pairs* of classes, and that the largest value appearing in the table is 2000.

Before proceeding to the exercises and case study you will want to familiarize yourself with the material on the SEPARABILITY processing function in Section 6 (Volume 2) of the LARSYS User's Manual.

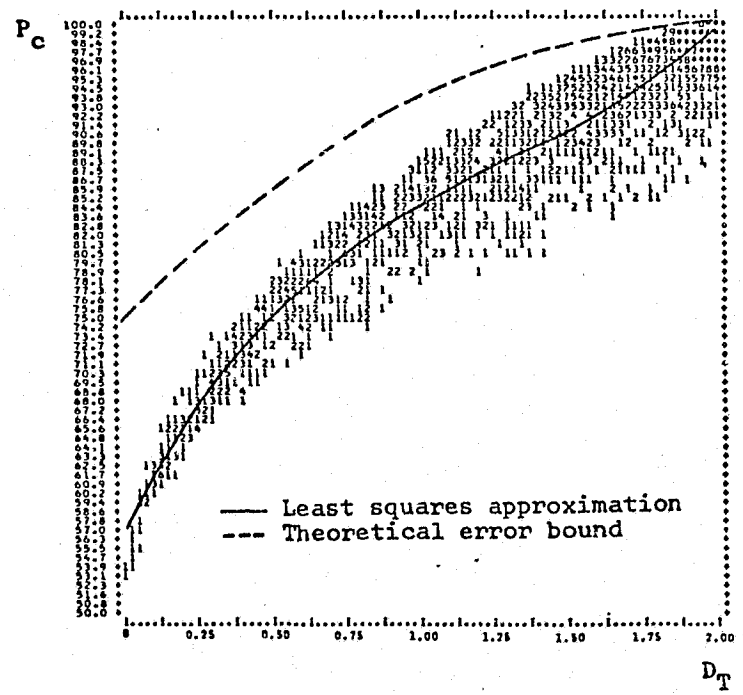


Figure 7-5. Observed values of probability of correct classification versus transformed divergence. To get transformed divergence values as they are printed by SEPARABILITY, multiply the x-axis by 1000.

RETENTION LEVEL .. 1 MAXIMUM 30000
MINIMUM ..... 0 DIVERGENCE **WITH** SATURATING TRAN:

	CHANNELS	DIJ(MIN)	D(AVE)	WEIGHTED INTERCLASS DIVERGENCE					
				AB (10)	AC (10)	AD (10)	AE (10)	AF (10)	AG (10)
1.	1 2 3 4	1253.	1976.	1626	1632	1986	2000	1948	2000

	CHANNELS	WEIGHTED INTERCLASS DIVERGENCE (DIJ)										
		AL (10)	AM (10)	AN (10)	AO (10)	AP (10)	AQ (10)	AR (10)	AS (10)	BC (10)	BD (10)	BE (10)
1.	1 2 3 4	2000	2000	2000	1994	2000	2000	2000	2000	1994	2000	2000

	CHANNELS	WEIGHTED INTERCLASS DIVERGENCE (DIJ)										
		BJ (10)	BK (10)	BL (10)	BM (10)	BN (10)	BO (10)	BP (10)	BQ (10)	BR (10)	BS (10)	CD (10)
1.	1 2 3 4	2000	2000	2000	2000	2000	1899	2000	2000	2000	2000	1688

	CHANNELS	WEIGHTED INTERCLASS DIVERGENCE (DIJ)										
		CI (10)	CJ (10)	CK (10)	CL (10)	CM (10)	CN (10)	CO (10)	CP (10)	CQ (10)	CR (10)	CS (10)
1.	1 2 3 4	1998	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

	CHANNELS	WEIGHTED INTERCLASS DIVERGENCE (DIJ)										
		DI (10)	DJ (10)	DK (10)	DL (10)	DM (10)	DN (10)	DO (10)	DP (10)	DQ (10)	DR (10)	DS (10)
1.	1 2 3 4	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Figure 7-6. Output from the SEPARABILITY processing function.

The analyst working on the Kenosha Pass area ran SEPARABILITY to determine which clusters could be combined. To do this, he used the following control cards:

```
-COMMENT SEPARABILITY FOR 60 CLUSTER CLASSES
-RUNTABLE
DATA
RUN(73057902), TAPE(253), FILE(1)
END
*SEPARABILITY
COMBINATIONS 4
SYMBOLS A,B,C,D,E,F,G,H,I,J,K,L,M,N,O,P,Q,R,S,T
SYMBOLS U,V,W,X,Y,Z,$,+,=,/,A,B,C,D,E,F,G,H,I,J
SYMBOLS K,L,M,N,O,P,Q,R,S,T,U,V,W,X,Y,Z,$,+,=,/
CARDS READSTATS
PRINT DIV(1000)
DATA
   .
   .
   .
  Punched statistics deck from previous STATISTICS
  run - 60 classes, 4 channels
   .
   .
   .
END
```

Since the analyst intends to use all four of the available channels (rather than selecting a subset of features), he used the parameter 4 on the required COMBINATIONS card. A (one-character) symbol had to be assigned to every class. The DIV(1000) on the PRINT card caused a summary listing of all class pairs whose pairwise distance was less than or equal to 1000 to be printed out. The analyst knew that this condensed listing would be useful when he constructed his "separability diagram" (Section 8), because he had chosen 1000 as his first threshold for combining classes. This part of the procedure frequently involves two or more iterations, depending on how simple or complex the analysis problem is, and the threshold may change from one iteration to the next. 1000 has been a useful starting value for combining clusters in many problems.

Notice in Figure 7-7 the legend accompanying the SEPARABILITY output. Since there were more classes than printer symbols, the analyst had to use symbols twice, requiring extra care in interpreting the results.

Figure 7-8 shows the condensed list at the end of the printout that resulted from the PRINT DIV(1000) card. The analyst annotated the list as shown in Figure 7-9 to eliminate any confusion due to duplicate symbols.

CLASSES CONSIDERED

SYMBOL	CLASS
A	NS- 1/15
B	NS- 2/15
C	NS- 3/15
D	NS- 4/15
E	NS- 5/15
F	NS- 6/15
G	NS- 7/15
H	NS- 8/15
I	NS- 9/15
J	NS-10/15
K	NS-11/15
L	NS-12/15
M	NS-13/15
N	NS-14/15
O	NS-15/15
P	NS- 1/15
Q	NS- 2/15
R	NS- 3/15
S	NS- 4/15
T	NS- 5/15
U	NS- 6/15
V	NS- 7/15
W	NS- 8/15
X	NS- 9/15
Y	NS-10/15
Z	NS-11/15
$	NS-12/15
+	NS-13/15
=	NS-14/15
/	NS-15/15
A	NS- 1/15
B	NS- 2/15
C	NS- 3/15
D	NS- 4/15
E	NS- 5/15
F	NS- 6/15
G	NS- 7/15
H	NS- 8/15
I	NS- 9/15
J	NS-10/15
K	NS-11/15
L	NS-12/15
M	NS-13/15
N	NS-14/15
O	NS-15/15
P	NS- 1/15
Q	NS- 2/15
R	NS- 3/15
S	NS- 4/15
T	NS- 5/15
U	NS- 6/15
V	NS- 7/15
W	NS- 8/15
X	NS- 9/15
Y	NS-10/15
Z	NS-11/15
$	NS-12/15
+	NS-13/15
=	NS-14/15
/	NS-15/15

Figure 7-7. The legend accompanying SEPARABILITY output for the Kenosha Pass analysis.

BB	945.	PB	152.
BU	838.	QD	599.
FQ	950.	QY	413.
FD	489.	RD	996.
FY	740.	RE	814.
GR	284.	SG	754.
GE	874.	SZ	931.
HQ	932.	TH	847.
HC	394.	TX	340.
HW	887.	UI	493.
IS	671.	UJ	873.
IY	988.	VF	468.
JE	634.	V$	658.
J$	797.	YM	597.
KU	690.	Z=	421.
KX	995.	$N	271.
KJ	541.	$/	959.
KZ	544.	+/	507.
LV	343.	=O	203.
LF	462.	BU	850.
MZ	518.	DY	238.
M=	834.	F$	957.
NY	866.	F=	753.
NM	593.	HX	581.
O+	473.	N/	646.
OO	704.	O/	666.
O/	397.		

Figure 7-8. SEPARABILITY output resulting from the PRINT DIV(1000) card.

BB	945.	B1-B2	PB	152.	P1-B2
BU	838.	B1-U2	QD	599.	Q1-D2
FQ	950.	F1-Q1	QY	413.	Q1-Y2
FD	489.	F1-D2	RD	996.	R1-D2
FY	740.	F1-Y2	RE	814.	R1-E2
GR	284.	G1-R1	SG	754.	S1-G2
GE	874.	G1-E2	SZ	931.	S1-Z2
HQ	932.	H1-Q1	TH	847.	T1-H2
HC	394.	H1-C2	TX	340.	T1-X2
HW	887.	H1-W2	UI	493.	U1-I2
IS	671.	I1-S1	UJ	873.	U1-J2
IY	988.	I1-Y2	VF	468.	V1-F2
JE	634.	J1-E2	V$	658.	V1-$2
J$	797.	J1-$2	YM	597.	Y1-M2
KU	690.	K1-U1	Z=	421.	Z1-=2
KX	995.	K1-X1	$N	271.	$1-N2
KJ	541.	K1-J2	$/	959.	$1-/2
KZ	544.	K1-Z2	+/	507.	+1-/2
LV	343.	L1-V1	=O	203.	=1-O2
LF	462.	L1-F2	BU	850.	B2-U2
MZ	518.	M1-Z1	DY	238.	D2-Y2
M=	834.	M1-=2	F$	957.	F2-$2
NY	866.	N1-Y1	F=	753.	F2-=2
NM	593.	N1-M2	HX	581.	H2-X2
O+	473.	O1-+1	N/	646.	N2-/2
OO	704.	O1-O2	O/	666.	O2-/2
O/	397.	O1-/2			

Figure 7-9. List of class pairs from Figure 7-8 annotated to eliminate confusion due to duplicate symbols.

EXERCISES

1. Look at the two pairs of one-dimensional density functions shown in Figure 7-10. For which pair is the statistical distance between density functions the largest?

2. Name two statistical distance measures calculated in LARSYS.

3. Name the two characteristics of Gaussian probability density functions which determine the statistical distance between the density functions.

CASE STUDY

Set up the control cards to run the SEPARABILITY processing function. Use the statistics deck you punched out in the previous step as input data. You should note that when you ran the STATISTICS processing function, you put the punched decks from CLUSTER in a certain order, and the punched STATISTICS deck kept the classes in the same order. When the punched statistics deck is used as input to SEPARABILITY, the same class order is still preserved. You may want to make use of the PRINT control card as the analyst did in the example.

Figure 7-10a

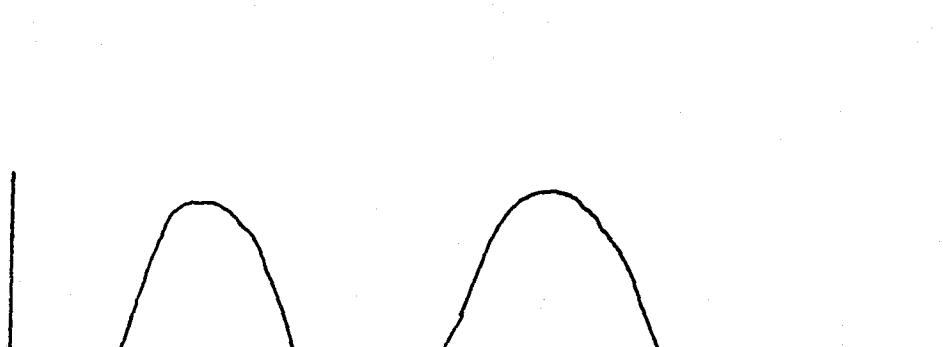


Figure 7-10b

Figure 7-10. Two pairs of one-dimensional density functions.

Section 8. CONSTRUCTION OF SEPARABILITY DIAGRAM

Upon completion of this section, you should be able to construct a "separability diagram," when given SEPARABILITY output.

The SEPARABILITY processing function was run to determine how to combine cluster classes from different cluster areas to form training samples for information classes. In this section, a technique for graphically portraying the information from SEPARABILITY will be demonstrated. In Section 9, this separability diagram will be interpreted in conjunction with the information on cluster class identification obtained in Section 5. Review the analysis flow chart, Figure 2 in the Introduction, to see how these steps fit into the analysis sequence.

There are several ways in which the information can be diagramed. Two of the possibilities are demonstrated here.

To work with a fairly simple case first, consider this example: two areas were clustered, and in each case eight clusters were requested. Statistics were calculated, and SEPARABILITY was run with the option to print out class pairs whose interclass divergence was less than 1000. The sixteen classes were assigned the symbols A,B,C,D,E,F,G,H,1,2,3,4,5,6,7, and 8. The following list was printed out:

A1	815.
C2	823.
C3	760.
D4	70.
E6	382.
F8	732.
G7	194.

One way to approach the diagram construction would be to set

all 16 symbols down in a circle, as shown in Figure 8-1. Then start at the top of the printed list with the pair A1 and draw a line connecting A and 1. Along the line, write the divergence value, 815, as shown in Figure 8-2. Then proceed to draw in lines indicating the remaining class pairs, as shown in Figure 8-3.

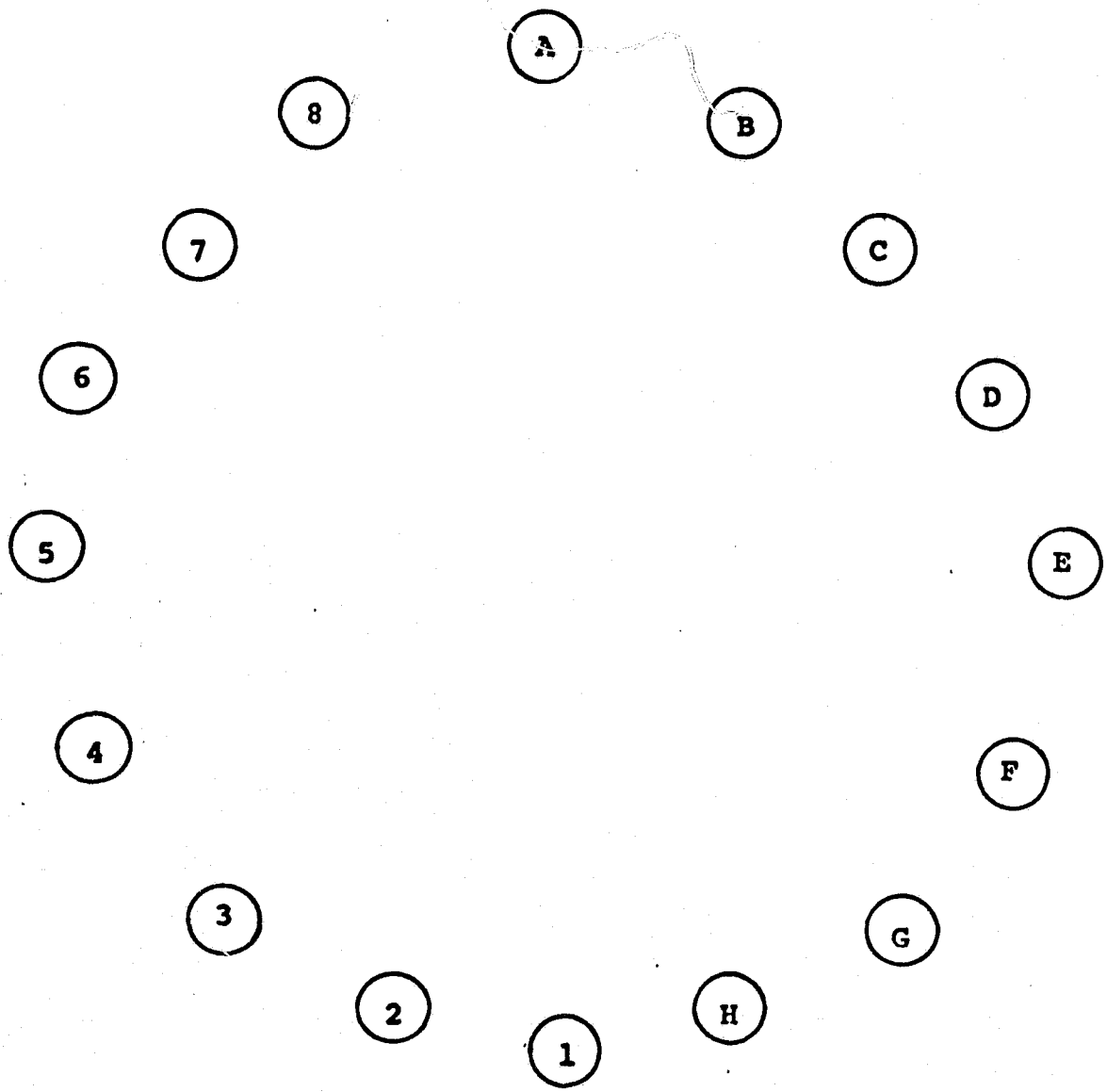


Figure 8-1. First step in one method of constructing a separability diagram.

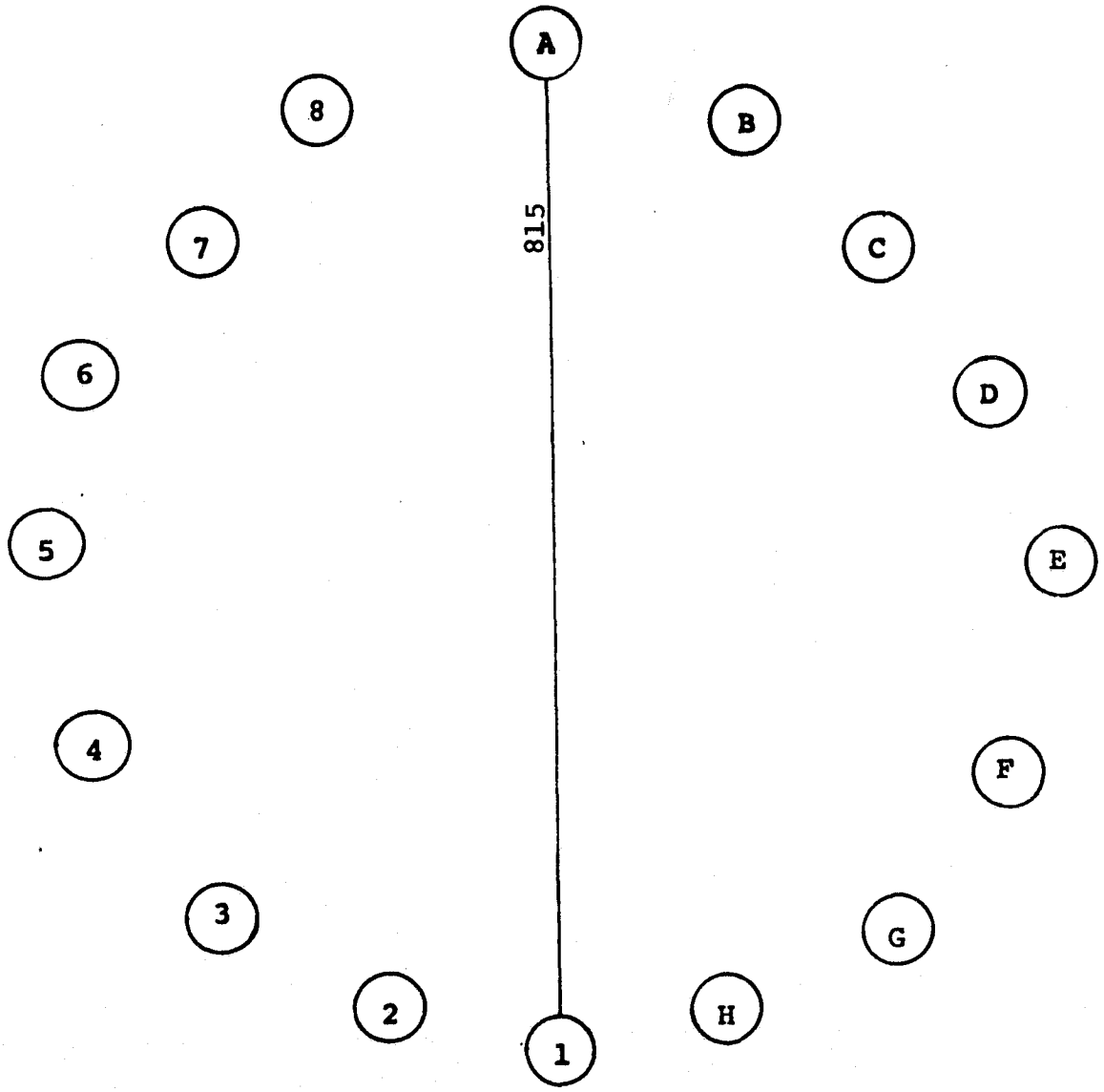


Figure 8-2. Second step in one method of constructing a separability diagram.

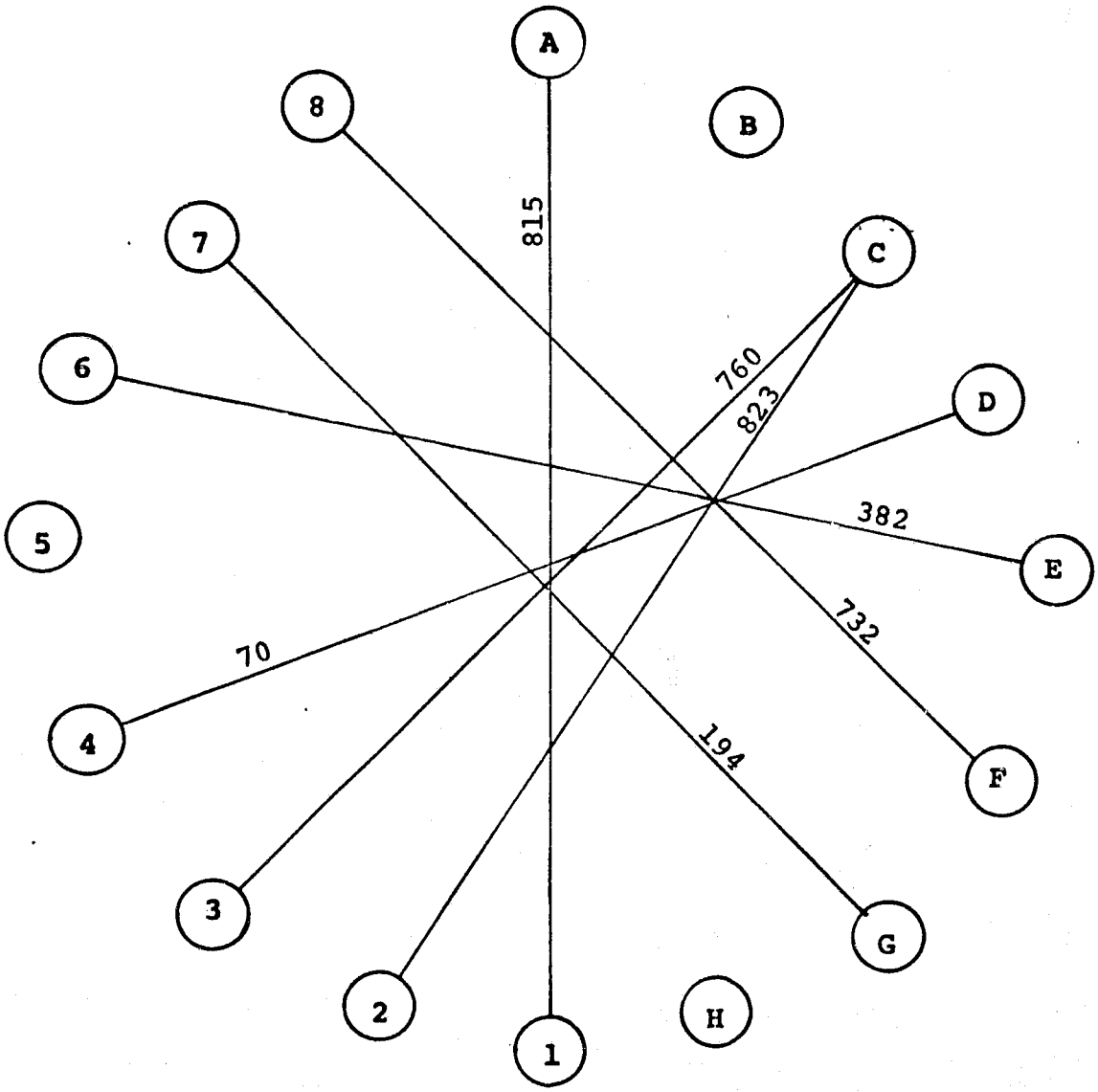


Figure 8-3. A completed separability diagram.

An alternative approach is to start at the top of the list of pairs and draw the pair relationships. First, make a list of all of the class symbols. Then, noting that the first pair is A1, draw the A, the 1, cross them off the symbol list, and draw the connecting line, as shown in Figure 8-4. The second pair is C2, and neither C nor 2 is represented yet, so draw the C, the 2, cross them off the symbol list, and draw the connecting line as shown in Figure 8-5. The next pair is C3. A check of the symbol list shows that the C has already been drawn, so draw the 3 only, cross it off the symbol list, and connect C3, as shown in Figure 8-6.

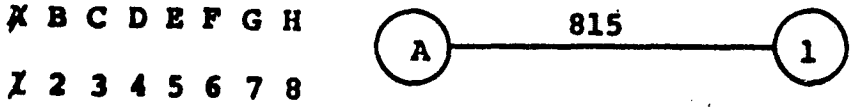


Figure 8-4. Step one of a separability diagram.

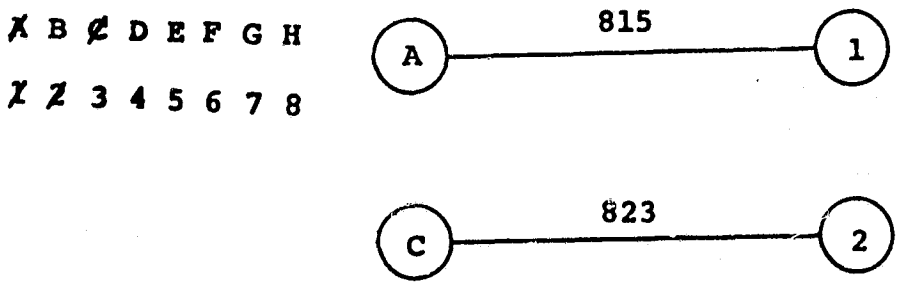


Figure 8-5. Step two.

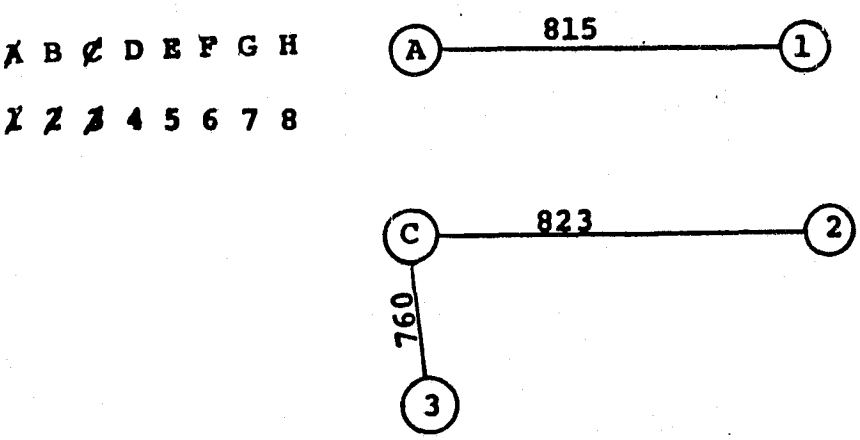


Figure 8-6. Third step.

When the list of class pairs has been exhausted, the diagram shown in Figure 8-7 results. Note that the symbol list shows that 3 classes (B, H, and 5) had a statistical distance greater than 1000 from every other class.

Figures 8-3 and 8-7 contain the same information, and you could come up with still other diagrams equivalent to these two. When carrying out this step of the analysis you will have to choose some way of representing the separability information so that the class relationships are apparent to you.

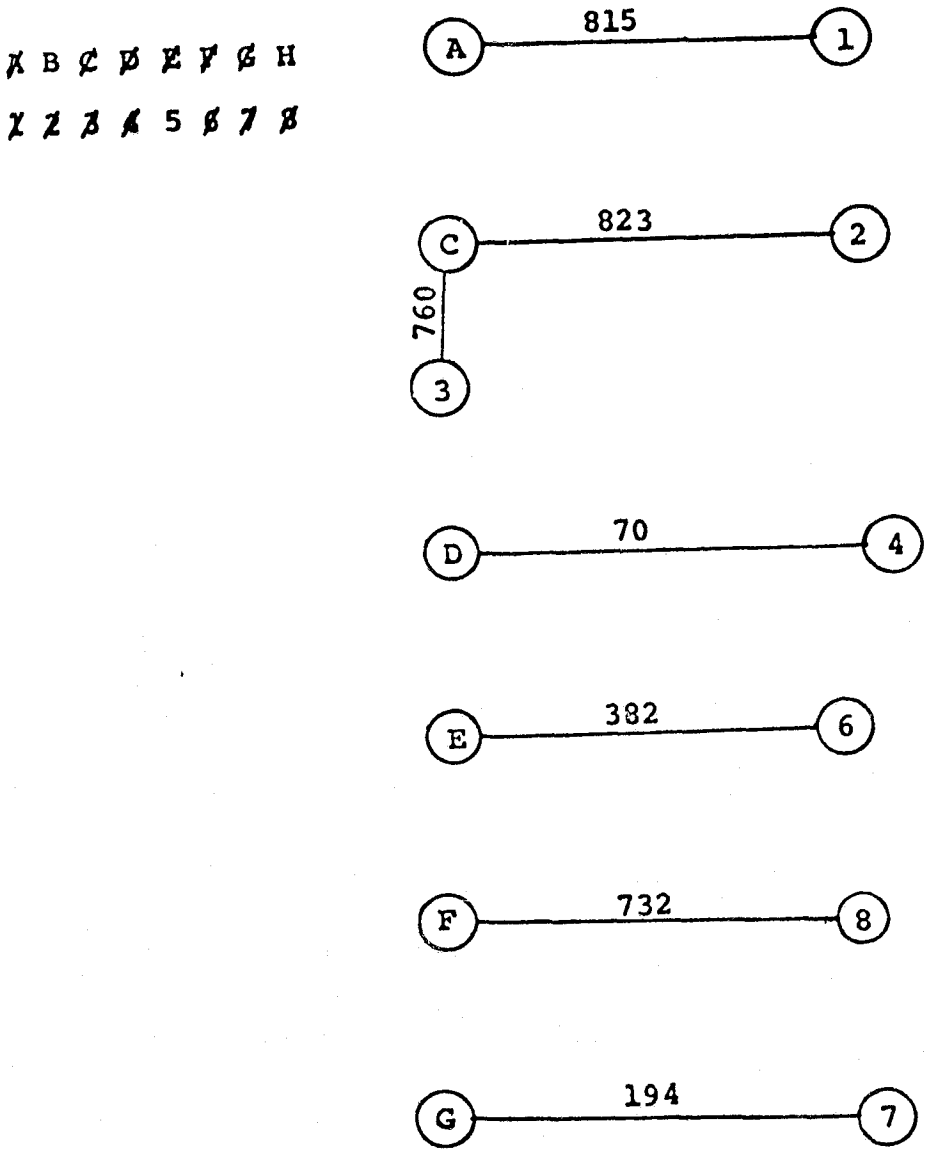


Figure 8-7. A completed separability diagram.

In the next section, you will use the separability diagram constructed here along with the cluster class identification you found in Section 5 to select training samples for the information classes you wish to classify.

EXAMPLE

The analyst working on the Kenosha Pass area used his list of class pairs having interclass divergence values less than or equal to 1000 to construct a separability diagram. He had already annotated the list, as discussed in the last section, to prevent confusion about symbols. The annotated list is reproduced as Figure 8-8 for your convenience.

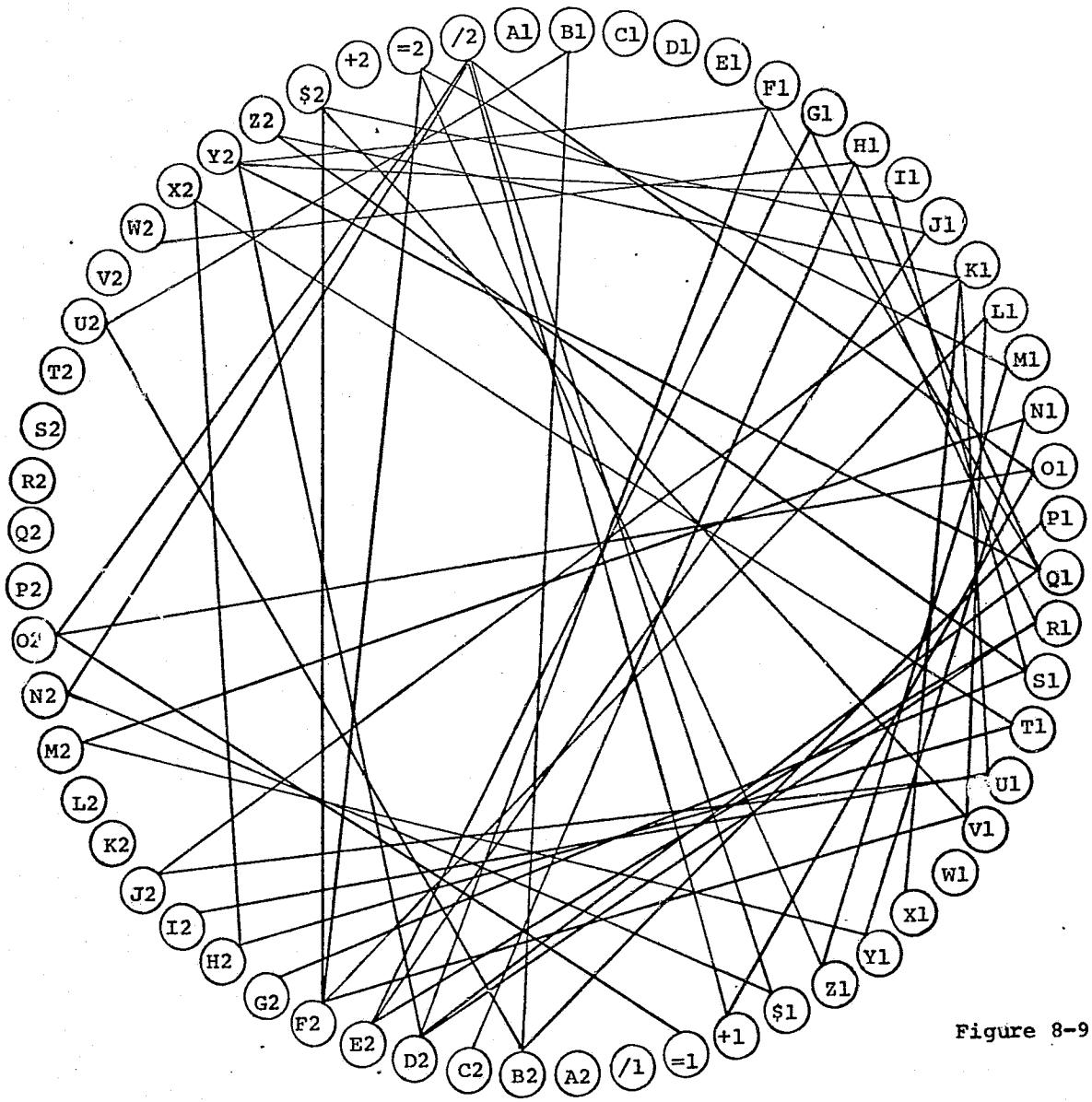
If the analyst had chosen to diagram the information in a circle, Figure 8-9 would have resulted. However, he chose instead to construct the diagram shown in Figure 8-10. (Don't be surprised if your first few diagrams do not look so orderly -- you can redraw them if they look too confusing.)

CASE STUDY

Using the SEPARABILITY output you generated in the last section, construct a separability diagram. Discuss the results of this operation with your instructor.

BB	945.	B1-B2
BU	838.	B1-U2
FQ	950.	F1-Q1
FD	489.	F1-D2
FY	740.	F1-Y2
GR	284.	G1-R1
GE	874.	G1-E2
HQ	932.	H1-Q1
HC	394.	H1-C2
HW	887.	H1-W2
IS	671.	I1-S1
IY	988.	I1-Y2
JE	634.	J1-E2
J$	797.	J1-$2
KU	690.	K1-U1
KX	995.	K1-X1
KJ	541.	K1-J2
KZ	544.	K1-Z2
LV	343.	L1-V1
LF	462.	L1-F2
MZ	518.	M1-Z1
M=	834.	M1-=2
NY	866.	N1-Y1
NM	593.	N1-M2
O+	473.	O1-+1
OO	704.	O1-O2
O/	397.	O1-/2
PB	152.	P1-B2
QD	599.	Q1-D2
QY	413.	Q1-Y2
RD	996.	R1-D2
RE	814.	R1-E2
SG	754.	S1-G2
SZ	931.	S1-Z2
TH	847.	T1-H2
TX	340.	T1-X2
UI	493.	U1-I2
UJ	873.	U1-J2
VF	468.	V1-F2
V$	658.	V1-$2
YM	597.	Y1-M2
Z=	421.	Z1-=2
$N	271.	$1-N2
$/	959.	$1-/2
+/	507.	+1-/2
=O	203.	=1-O2
BU	850.	B2-U2
DY	238.	D2-Y2
F$	957.	F2-$2
F=	753.	F2-=2
HX	581.	H2-X2
N/	646.	N2-/2
O/	666.	O2-/2

Figure 8-8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O1
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R1
S1
T1
U1
V1
W1
X1
Y1
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+1
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A2
B2
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+2
=2
/2

Figure 8-9

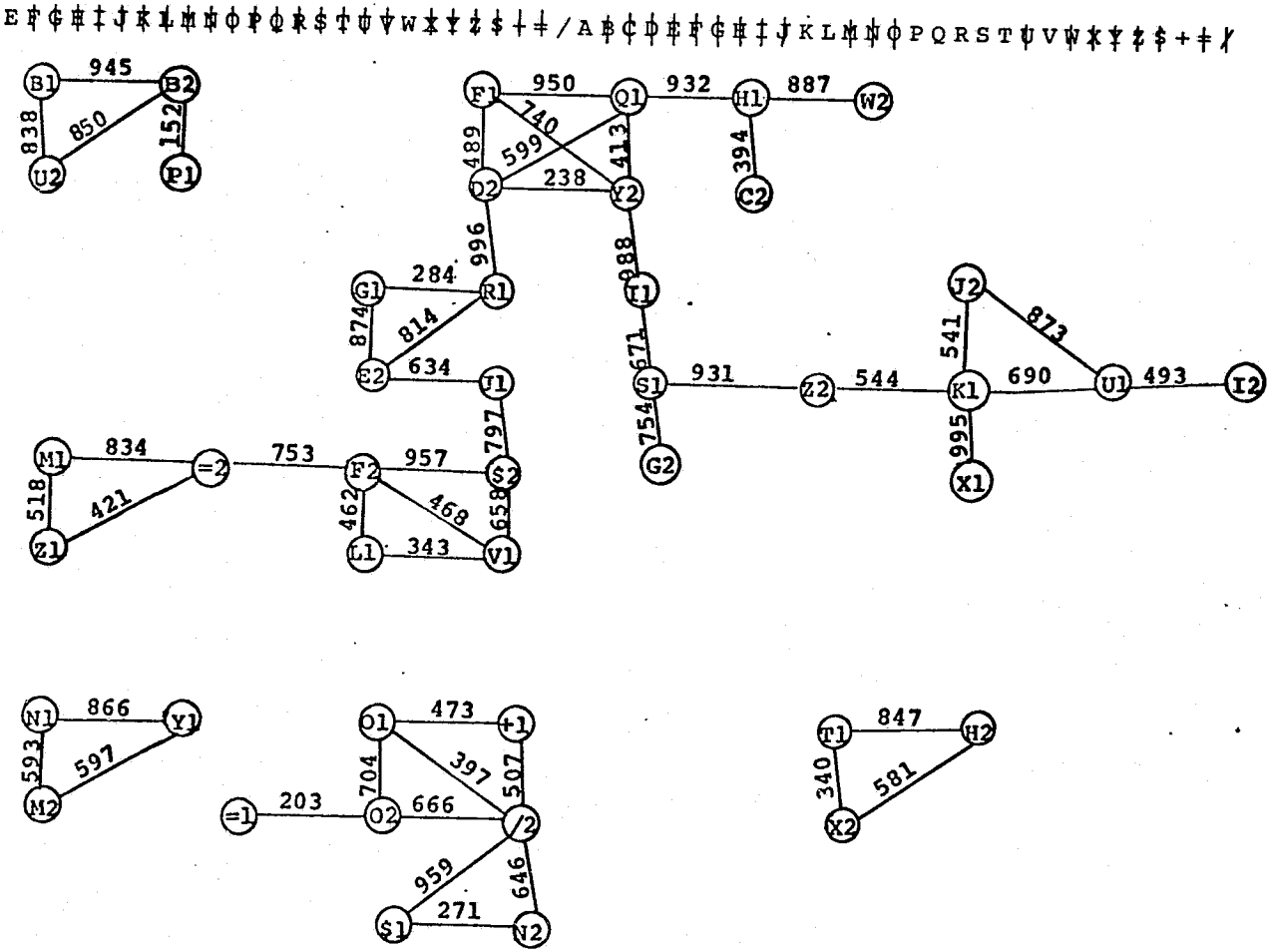


Figure 8-10. Separability diagram for Kenosha Pass example.

Section 9. SELECTION OF TRAINING CLASSES

Upon completion of this section, you should be able to select training classes for use in classification, given a separability diagram and a list of cluster-class/information-class associations (and an analysis objective).

This section describes the last step in the process of refining the candidate training areas to obtain training samples. So far, refinement of candidate training areas has included clustering the areas, associating cluster classes with information classes (cover types), calculating statistics of the clusters, running SEPARABILITY to get a measure of the distance between clusters, and constructing a separability diagram. In this section, training classes will be selected from the cluster classes. To select training classes, the separability information diagramed in Section 8 and the cluster-class/information-class associations determined in Section 5 will be used.

First, analysis objectives should be reviewed, to bring clearly to mind the cover types of interest.

There are a number of ways the problem of selecting training classes from cluster classes could be approached. A few possibilities will be suggested in general terms in the discussion, and then one of the possibilities will be pursued in detail in the example.

One possibility would be to begin by transferring the cluster class identification information onto the separability diagram. Then, group together cluster classes from the same cover type whose interclass statistical distances are less than the chosen threshold (e.g., a transformed divergence $\leq$ 1000). When cluster classes from the same cover type have a pairwise statistical distance greater than the chosen threshold, the conclusion would be that the cluster classes are spectrally distinct subclasses of that cover type. When cluster classes from DIFFERENT cover types are spectrally similar, as shown by a small statistical distance, there is a problem. Possible courses of action include the following: the classes could be clustered again to refine them further; the identification of cluster classes could be

checked to verify that the cluster classes are indeed from different cover types; the confusion between classes could be accepted and no action taken. Another possible course of action is more easily described by an example: assume that an analyst is interested in classifying an urban area, and has discovered that a cluster class identified as urban is similar to a cluster class identified as agriculture. He could decide that for his purposes, the error of classifying some agriculture data points as urban would not be too troublesome, while the error of classifying some urban points into agriculture would be disastrous. In that case, the analyst could choose to eliminate the cluster class identified as agriculture from any subsequent processing.

Another possible way to select training classes would again begin with the transfer of cluster class identification information onto the separability diagram. Then, when cluster classes from the same cover type have interclass statistical distances less than the chosen threshold, just one of those clusters would be chosen to represent that cover type, and the rest would not be used. The philosophy behind this approach is that the single cluster class will have a smaller variance than would a group of cluster classes, and therefore the single class would be less likely to be confused with other cover type classes. However, a criticism of this approach is that the number of data points is not as large as it would be if all clusters were used, and in general a larger number of data points in a training class is more representative.

Again if cluster classes from DIFFERENT cover types have a small interclass distance, the same problem arises as before, and one of the previously mentioned ways of dealing with the situation can be chosen.

A third possible approach to the selection of training samples would begin with the separability diagram. Tentative class groupings would be determined on the basis of the statistical distances without reference to the cover type identifications of the clusters. After cluster groupings have been determined on the basis of statistical distances, then the cluster class identification information is transferred onto the diagram. Then the groupings are inspected to see if the spectrally similar clusters are from the same cover type. The difference between this approach and the first one is rather subtle and can best be understood by trying both ways.

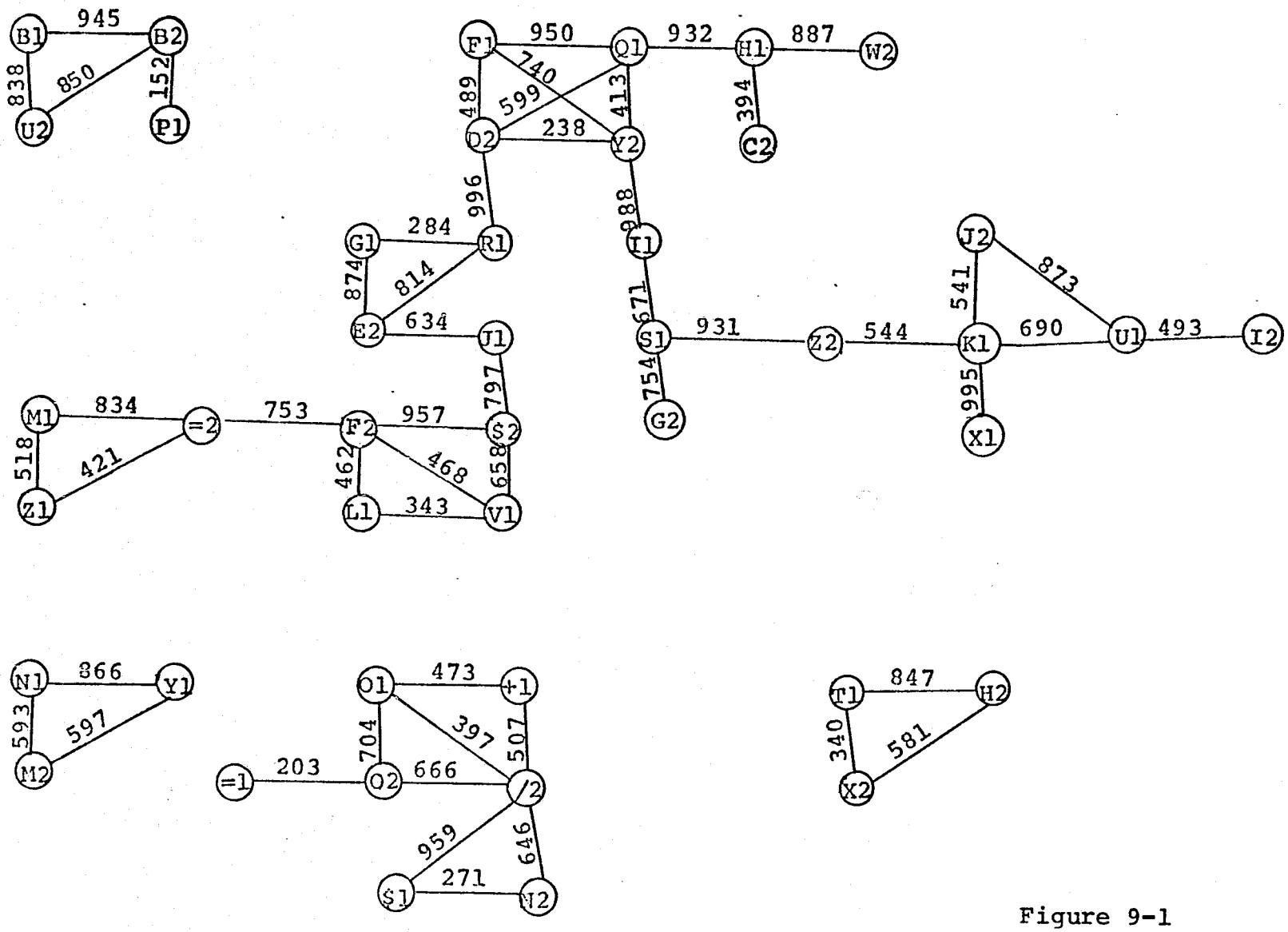
One point which should be apparent by now is that there is no single correct way to progress through an analysis sequence. As you increase your understanding of the pattern recognition concepts used in LARSYS and gain experience in analysis, you may even develop new procedures yourself.

This section has described ways in which training samples can be selected from the cluster classes generated earlier. The techniques described make use of the separability diagram constructed in the last section and the cluster class-information class associations determined earlier.

The techniques described here are still subject to a great deal of investigation. The construction of the separability diagram can be expressed in terms of a programmable algorithm, and the numerical criteria for grouping clusters together could be programmed. Experimental work along these lines is in progress at this writing.

EXAMPLE

In the Kenosha Pass example, remember that the analyst constructed the separability diagram shown in Figure 9-1. We will now go through a step-by-step interpretation of that diagram to convey the kinds of thinking an analyst does.


B1
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U2
P1
F1
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Q1
932
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W2
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413
394
D2
238
Y2
C2
996
988
G1
284
R1
I1
J2
874
814
541
873
671
931
544
690
493
E2
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J1
S1
Z2
K1
U1
I2
754
797
G2
995
M1
834
=2
753
F2
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X1
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462
468
658
Z1
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343
V1
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Y1
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M2
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704
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959
646
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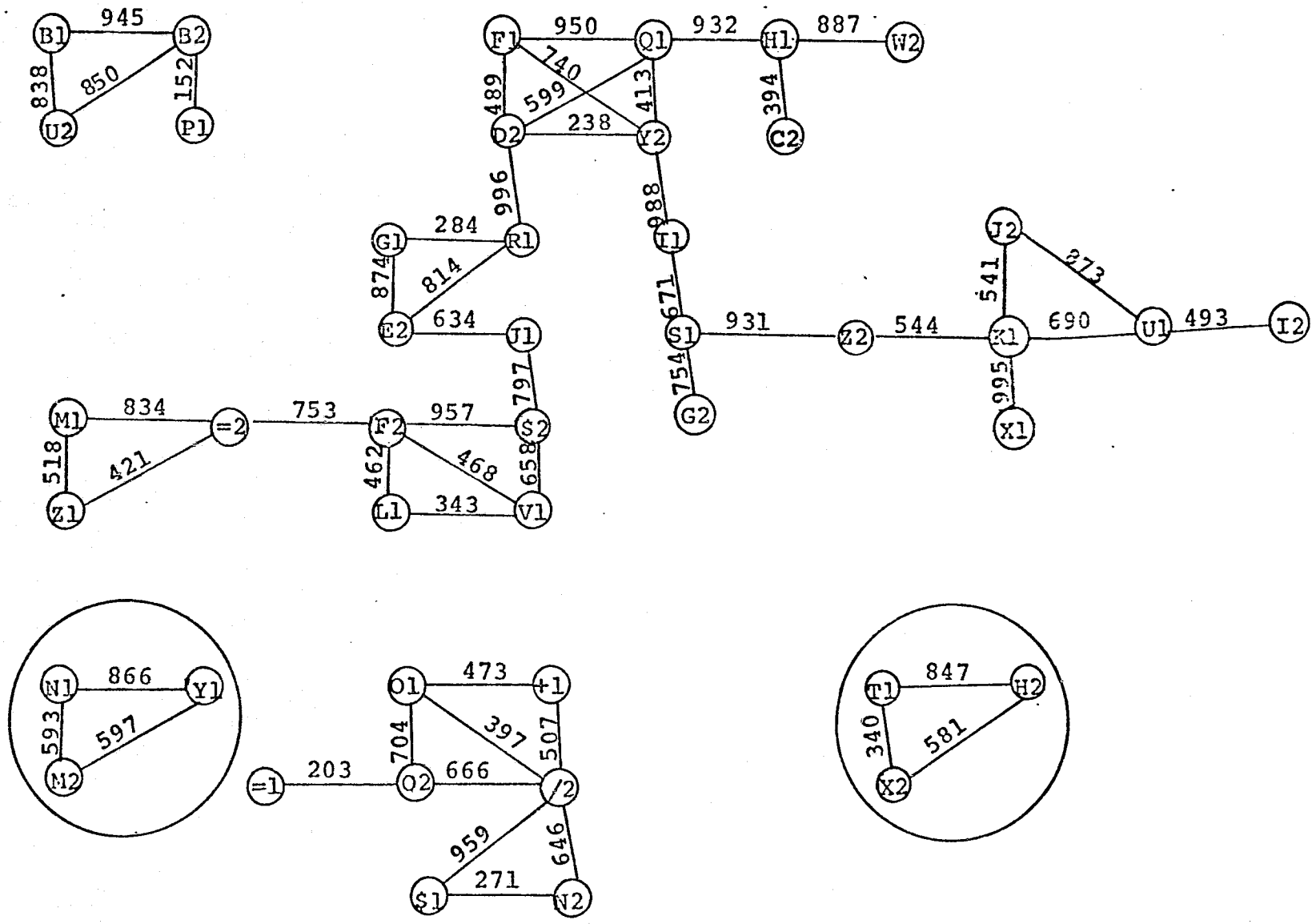
271
T1
847
H2
340
581
X2

Figure 9-1

The analyst who did this work chose to begin by looking at the statistical distances first without reference to the cover type identification of the various clusters. Two of the cluster groups were straightforward. Look in the lower left-hand corner at the N1-Y1-M2 group. It was not connected to any other group and every pair of clusters in the group has transformed divergence less than 1000. Similarly, the T1, X2 and H2 clusters were close to each other while being separate from any other clusters. The analyst then interpreted those by circling those two groups as shown in Figure 9-2.


B1
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D2
Y2
C2
996
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G1
284
R1
J2
874
814
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541
273
E2
634
J1
S1
931
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X1
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U1
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I2
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M1
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F2
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507
=1
203
O2
666
/2
959
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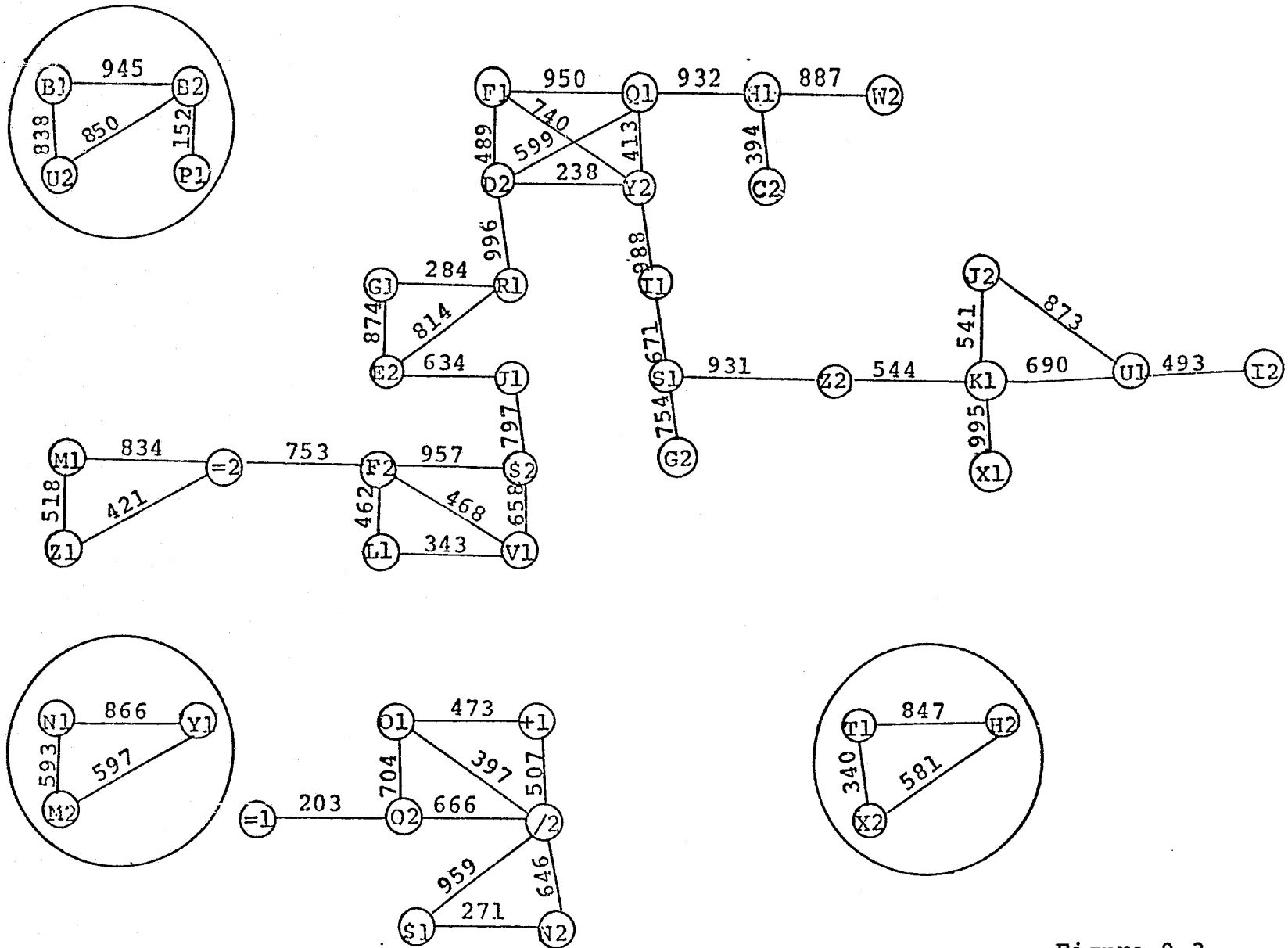
$1
N2
T1
847
H2
340
581
X2

Figure 9-2

Then what? Look at the B1-B2-U2-P1 group in the upper left-hand corner. Since the transformed divergence values between B1 and P1 and between U2 and P1 were greater than 1000, how did this group get handled? The analyst who did this work set a second criterion for cases such as this. This criterion will be expressed in terms of an example. Suppose you have three clusters a, b, and c. The a-b distance is less than 1000 and the a-c distance is less than 1000, but the b-c distance is greater than 1000. If this b-c distance is less than 1500 go ahead and group all three together. If the b-c distance is greater than 1500 only group together a-b or a-c, whichever pair has the smaller transformed divergence.

Now to return to the B1-B2-P1-U2 group, the analyst went back to his SEPARABILITY output to find the transformed divergences for B1-P1 and U2-P1. The B1-P1 distance was 1312 and the U2-P1 distance was 1117. Both of these were less than 1500 so the analyst grouped all four clusters together and his separability diagram looked like Figure 9-3.


B1
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887
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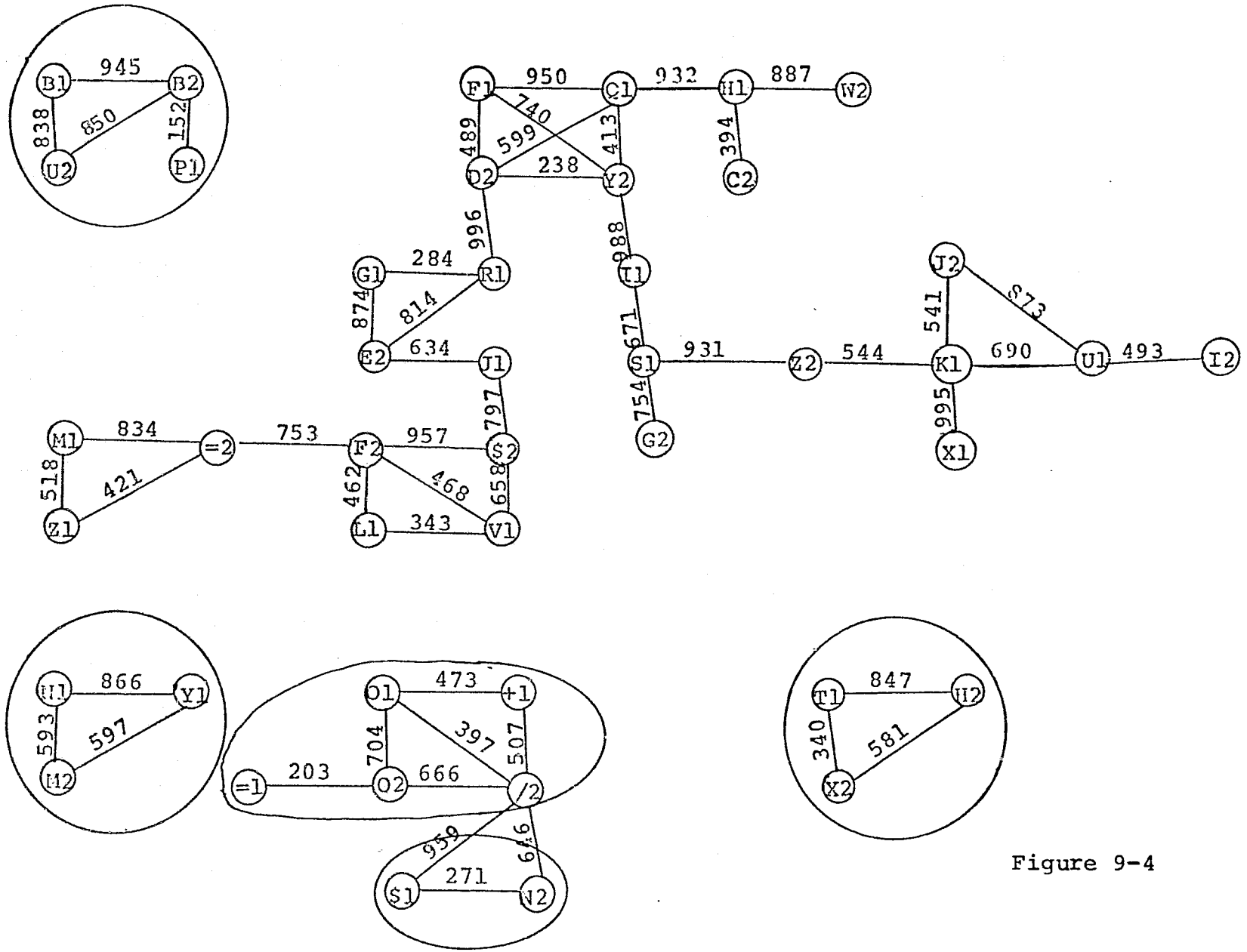
X2

Figure 9-3

Next go the the bottom of the page,the 01,+1,=1,02,/2,$1 and N2 group. In order to decide how to handle this the analyst again had to go back to his SEPARABILITY output to find the transformed divergences associated with some of the other class pairs. To help in following the discussion, draw in the indicated distances with dashed lines on Figure 9-3. The 01-=1 distance was 1170. The 02-+1 distance was 1072. The 02-N2 distance was 1579. The 02-$1 distance was 1747. The =1-$1 distance was 1850. Since the =1-$1 distance, 02-$1 distance and the 02-N2 distance were all greater than 1500 the analyst decided that the clusters represented by $1 and N2 belonged together in a group separate from the other clusters. For thoroughness the analyst also inspected the =1-+1 distance, 1470, and the =1-/2 distance, 1131. Both were less than 1500 so the 01,+1,=1,02,/2 clusters were all grouped together. At this point the separability diagram looked like Figure 9-4.


B1
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G1
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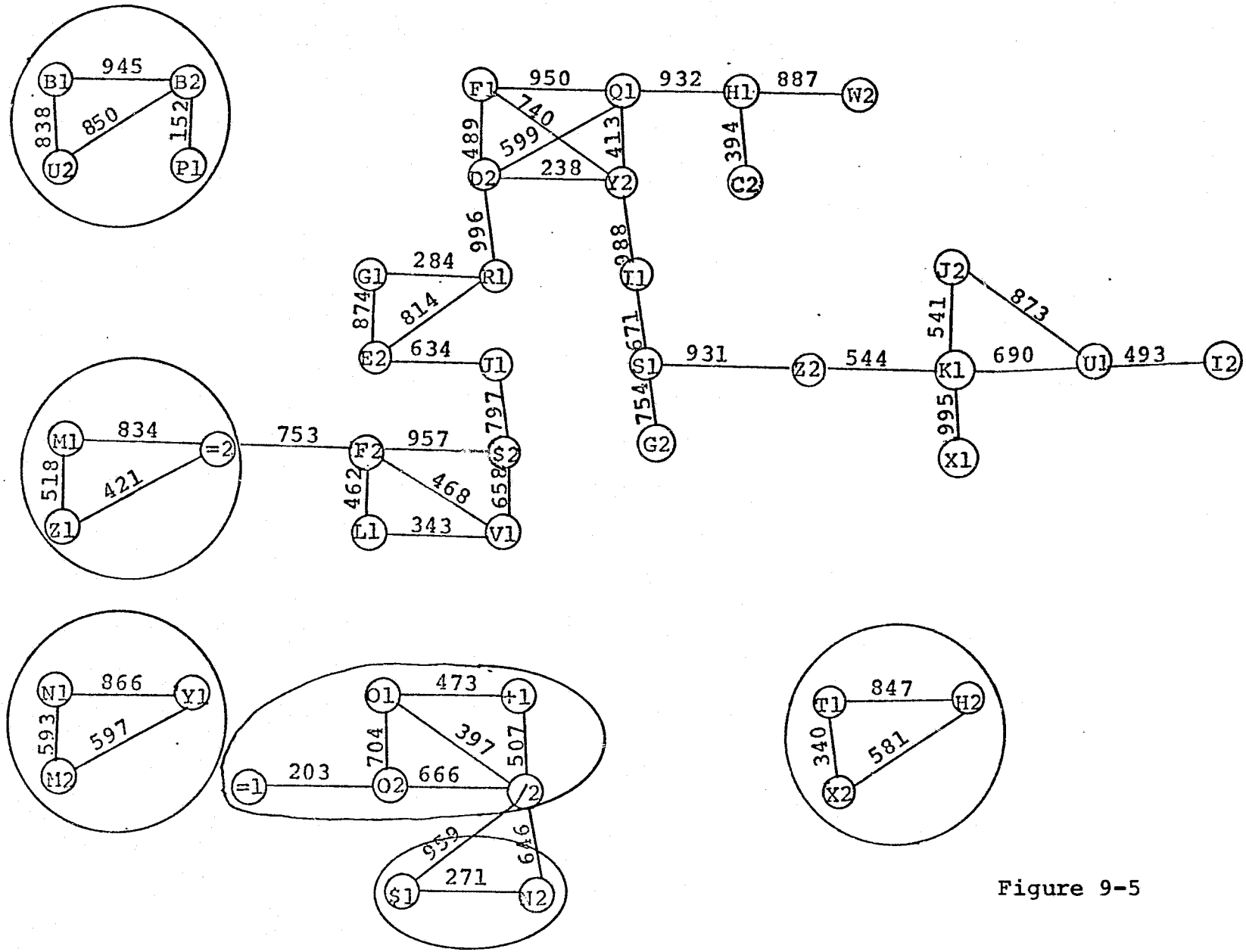
Figure 9-4

Now how did he interpret this string that is left? Start at the left end with the M1-Z1-=2 group. Should it be combined with other clusters or not? Going back to his SEPARABILITY output, the analyst found that the M1-F2 distance, 1073, and the Z1-F2 distance, 1266, were both less than 1500. However, the M1-L1 distance, 1538, and the Z1-L1 distance, 1731, both exceeded 1500 so these three clusters became a separate group. The separability diagram looked like Figure 9-5.


B1
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F1
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Figure 9-5

To proceed with the interpretation, the F2-L1-V1-$2 group is next. Again the analyst had to go back to his SEPARABILITY output to find out some more distances. The L1-$2 distance was 1197, the V1-J1 distance was 1611, and the F2-J1 distance was 1683. The V1-J1 distance and the F2-J1 distance were both greater than 1500 so the F2-$2-L1-V1 group was separated from the rest of the string. However the analyst wasn't yet ready to circle this group and finish with it. He looked at the mean and standard deviation of the clusters as plotted on the coincident spectral plot which he got as part of his STATISTICS output. He decided that the cluster represented by $2 would cause confusion so he chose to delete that cluster. His separability diagram then looked like Figure 9-6.

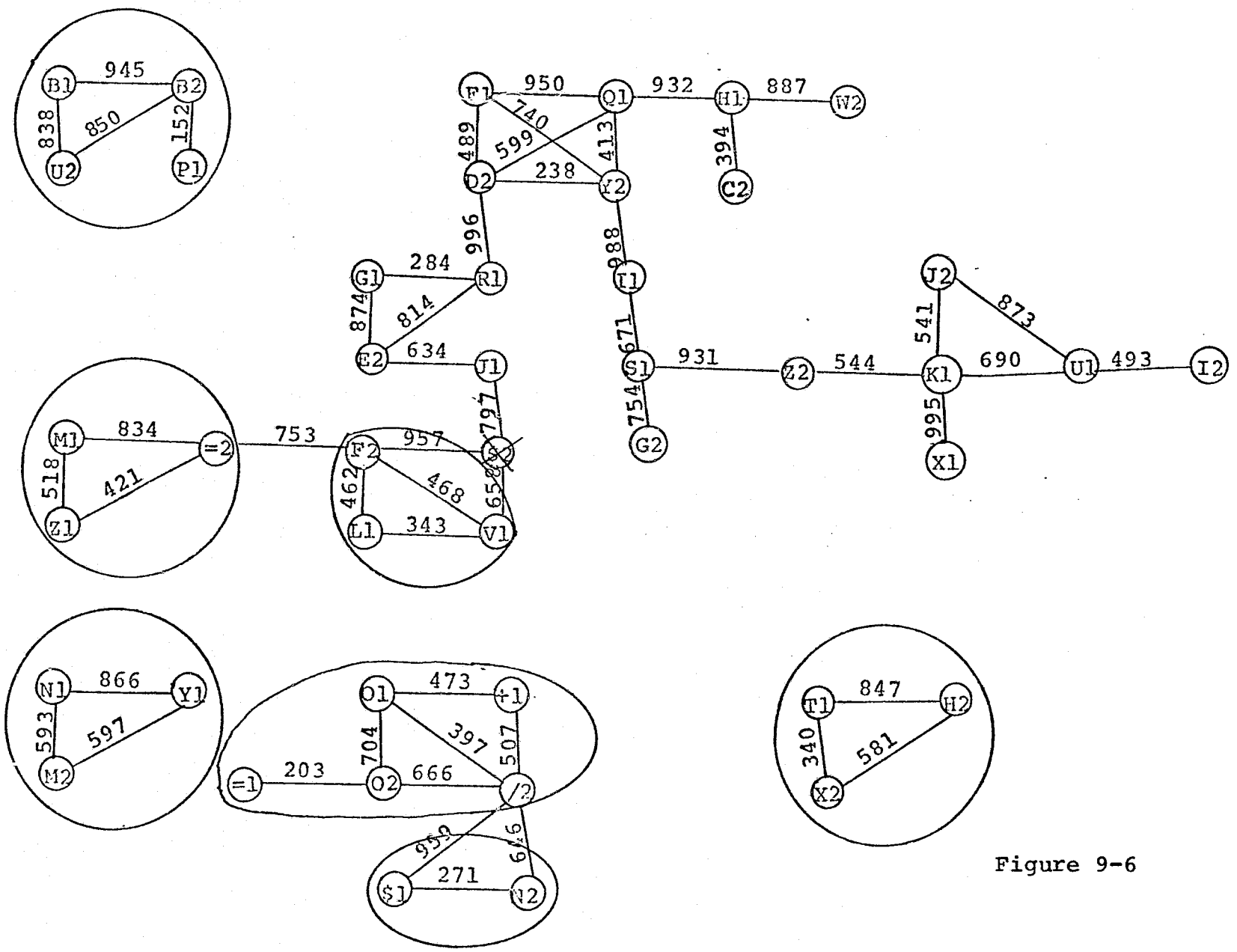
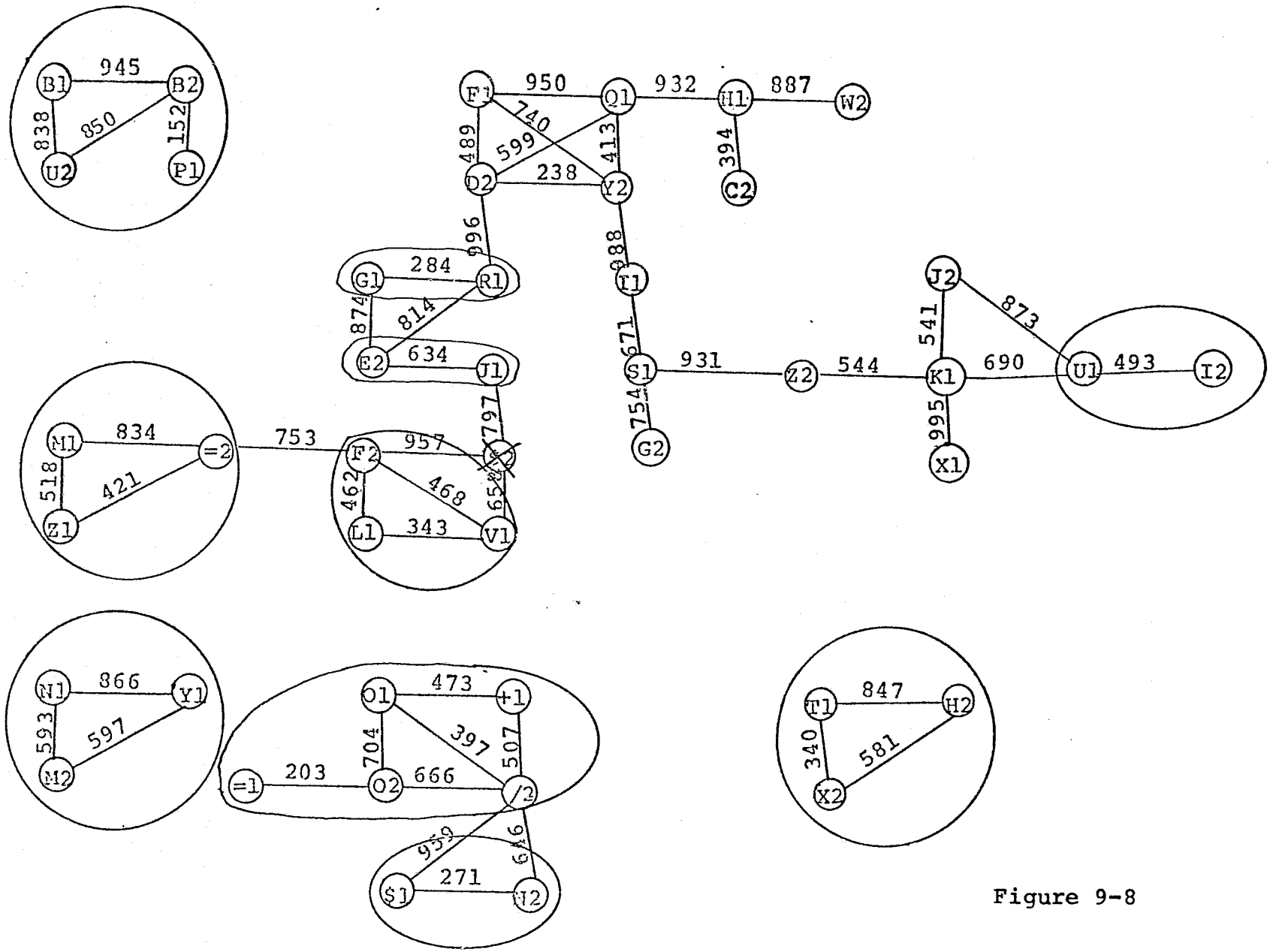


Figure 9-6

The next part of this string is the J1-E2-G1-R1 group. Other distances of interest include the G1-J1 distance, 1703, the R1-J1 distance, 1464, and G1-D2, 1612. Since the G1-D2 distance and the G1-J1 distance were both greater than 1500, the analyst grouped E2 and J1 together in one group, and made a separate group of G1 and R1. The separability diagram at this point looked like Figure 9-7.

Figure 9-7

Next, move to the right-hand side of the diagram, the part that has the I2, U1, J2, K1, and X1 clusters. The analyst again went back to his SEPARABILITY output to find out some more distances. The J2-I2 distance was 1675, the X1-U1 distance was 1797, and the X1-I2 distance was 1970. Because the J2-I2, the X1-I2, and the X1-U1 distances were all greater than 1500, only U1 and I2, the pair with the smallest transformed divergence, got grouped together. The diagram then looked like Figure 9-8.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541
873
E2
634
J1
S1
931
Z2
544
K1
690
U1
493
I2
754
797
M1
834
=2
753
F2
957
518
421
462
468
655
Z1
L1
343
V1
G2
995
X1
N1
866
Y1
593
597
M2
O1
473
+1
397
507
704
=1
203
O2
666
/2
959
646
271
$1
I2
T1
847
H2
340
581
X2

Figure 9-8

Moving to the left of the U1-I2 group, what about the J2, K1, X1 clusters? Well, the J2-X1 distance was 1404 so those three clusters at least could be put together. But how did Z2 fit in? Well the Z2-J2 distance was 1228, the Z2-X1 distance was 1079. The Z2-I1 distance was 1586 and the Z2-G2 distance was 1119. Z2 was closer to the J2-K1-X1 group than to the other clusters and all pairwise distances for Z2, J2, K1 and X1 were less than 1500 so the analyst grouped those four clusters together. The separability diagram in Figure 9-9 shows the interpretation to this point.

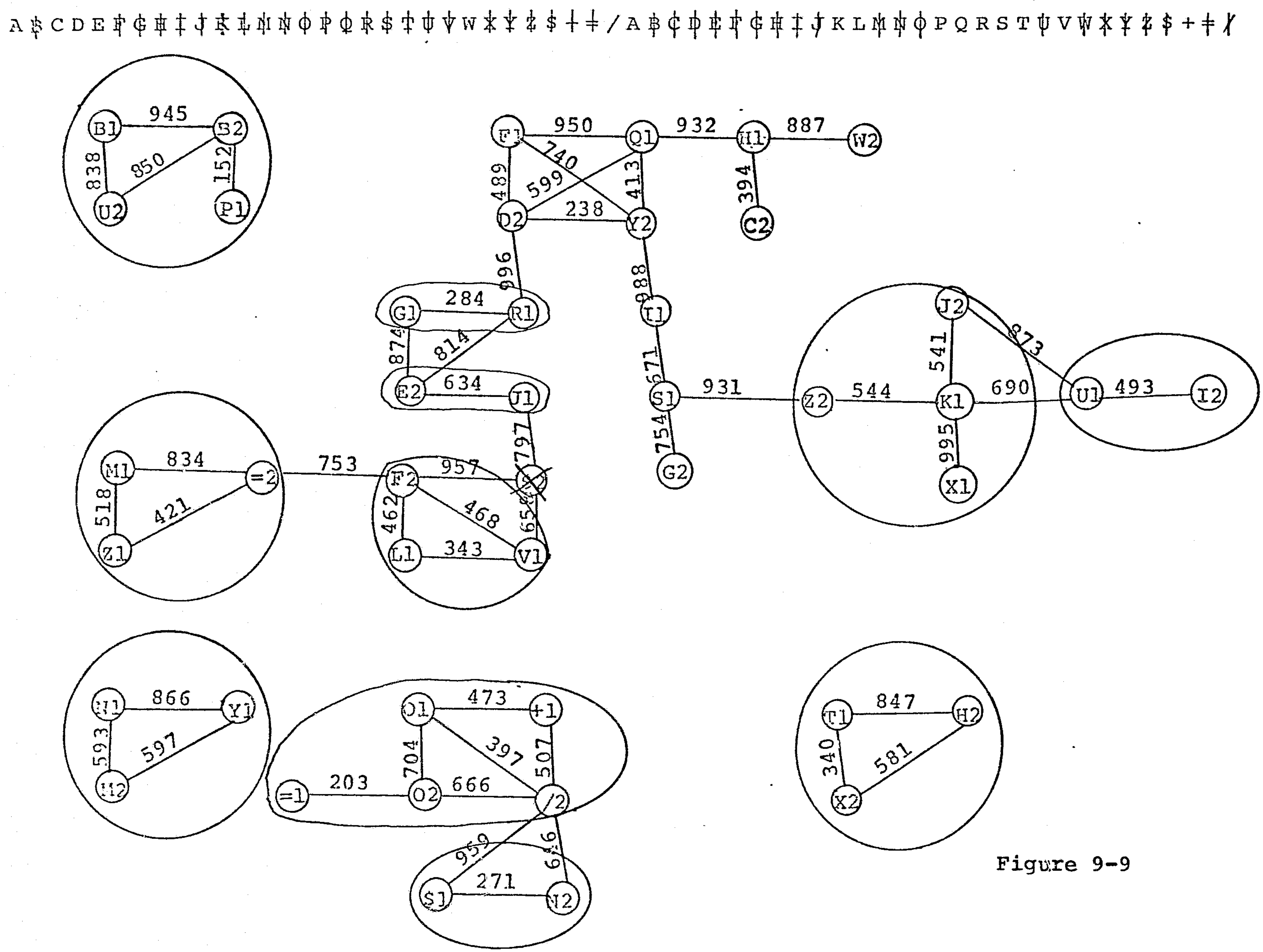
B1
B2
U2
P1
945
838
850
152
F1
Q1
H1
W2
C2
D2
Y2
950
932
887
740
599
413
489
394
238
996
988
G1
R1
E2
J1
284
874
814
634
797
S1
G2
671
754
931
J2
K1
Z2
U1
I2
X1
541
873
544
690
493
995
M1
Z1
=2
834
518
421
753
F2
L1
V1
957
462
468
343
N1
Y1
M2
866
593
597
O1
+1
O2
=1
/2
473
397
704
507
203
666
$1
N2
959
271
T1
H2
X2
847
340
581

Figure 9-9

Next look at the G2-I1 distance. The analyst found on his SEPARABILITY output that that was 1121. Since it was less than 1500, G2, S1 and I1 all went into one group. What about Y2? How did it fit with this group? The Y2-S1 distance, 1578, was greater than 1500 so Y2 did not go with this group. The separability diagram looked like Figure 9-10.

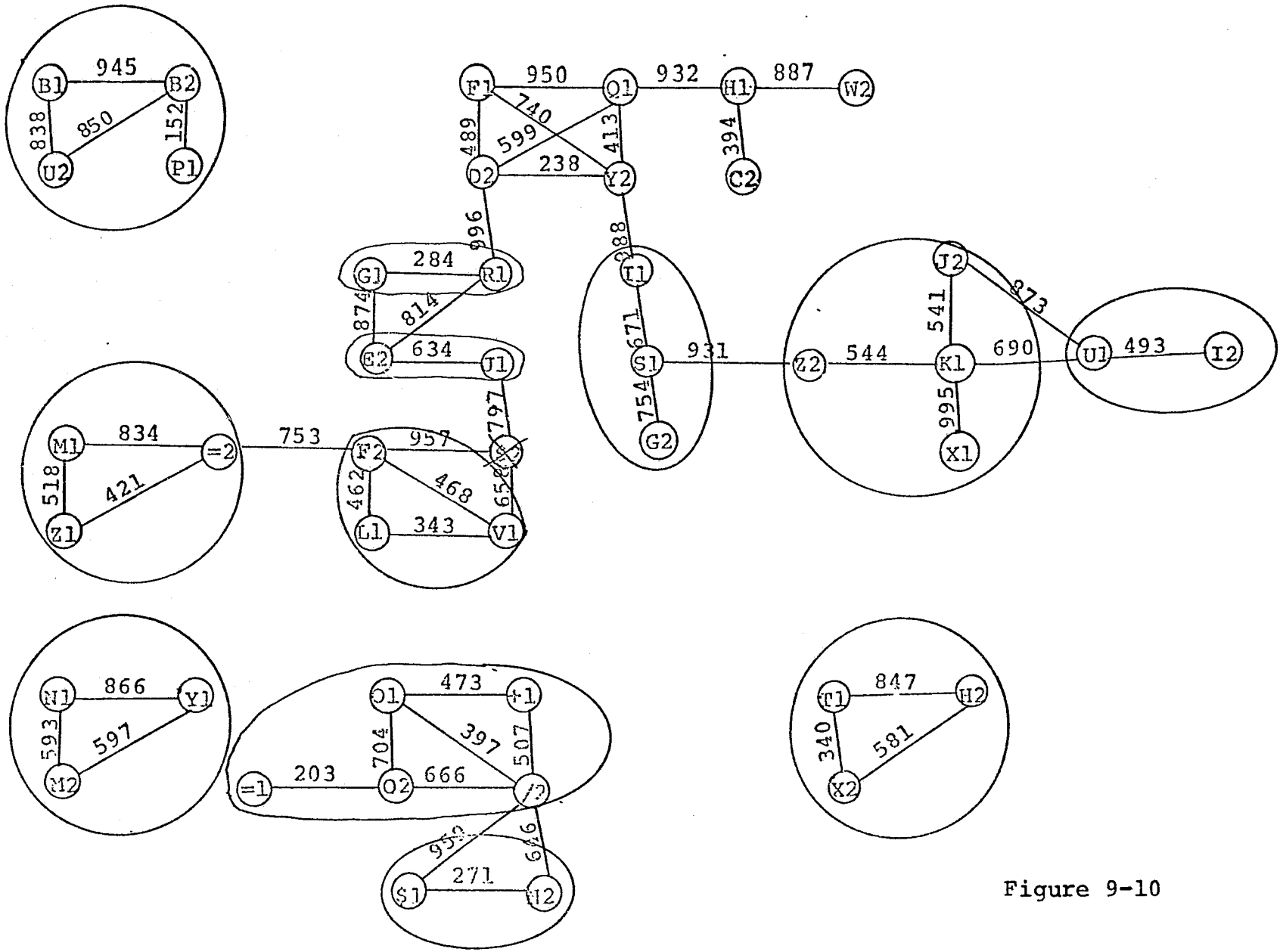
B1
945
B2
838
850
152
U2
P1
F1
950
Q1
932
H1
887
W2
740
489
599
413
394
238
D2
Y2
C2
996
288
G1
284
R1
T1
874
814
671
E2
634
J1
S1
931
Z2
544
K1
690
U1
493
I2
J2
541
873
754
G2
995
X1
M1
834
=2
753
797
F2
957
518
421
462
468
L1
343
V1
Z1
N1
866
Y1
593
597
M2
O1
473
+1
704
397
507
203
666
=1
O2
/2
271
$1
H2
847
T1
340
581
X2

Figure 9-10

Now did W2 go with C2 and H1? The C2-W2 distance was 1230, but the analyst looked at the means and standard deviations of the clusters and decided that the W2 cluster would cause too much confusion so the W2 cluster was deleted. Now, did H1 and C2 go with the F1-D2-Q1-Y2 group? The H1-Y2 distance, 1459, and the Q1-C2 distance, 1031, were less than 1500. The Y2-C2 distance was 1500. The F1-H1 distance, 1860, and the D2-C2 distance, 1745, were so large as to prevent C2 and H1 from being included in that group. Therefore H1 and C2 became a separate cluster group and the diagram looked like Figure 9-11.

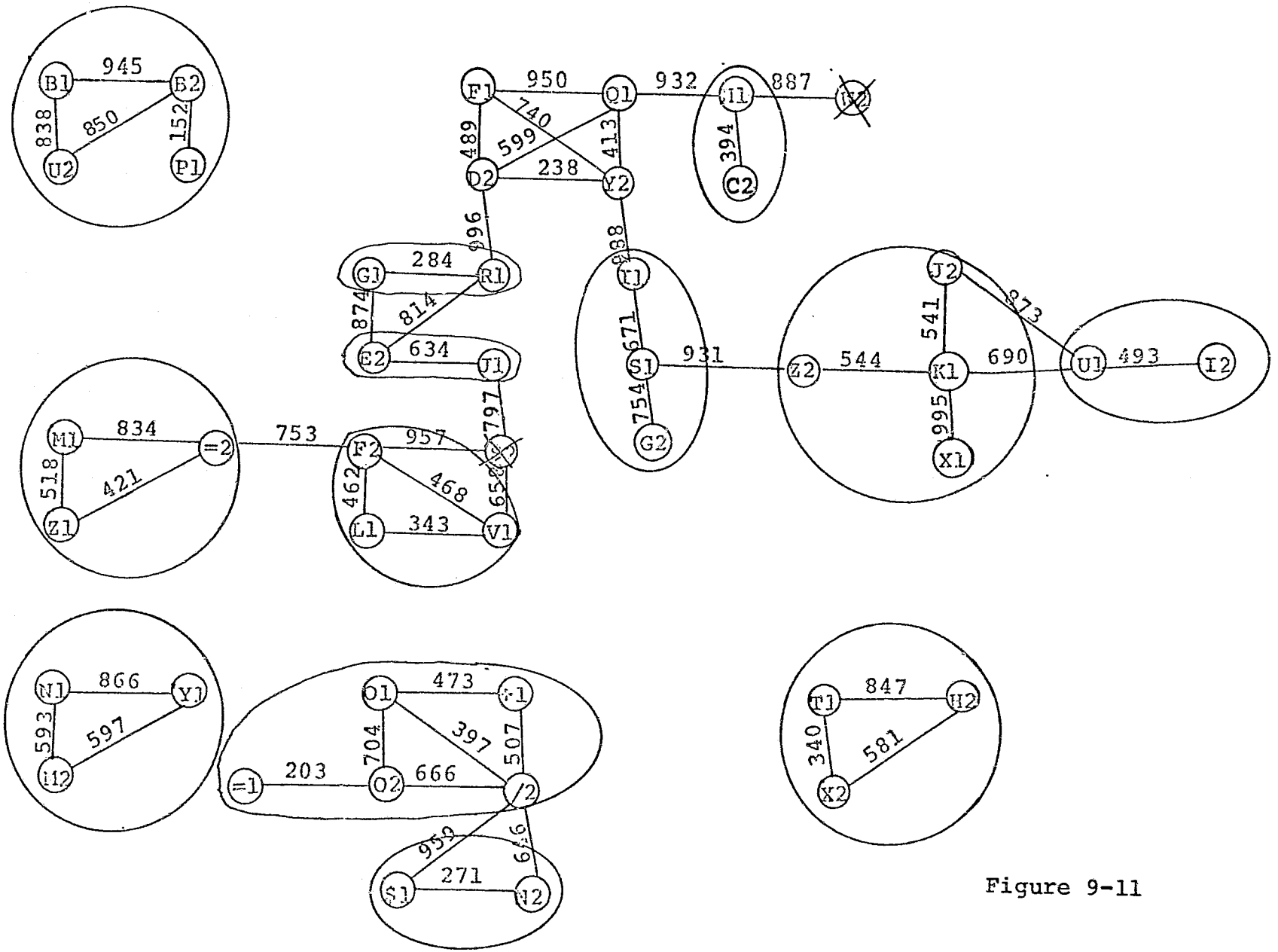
B1
945
B2
838
850
152
U2
P1
F1
950
Q1
932
I1
887
M2
740
489
599
413
238
O2
Y2
394
C2
996
988
G1
284
R1
874
814
T1
671
J2
541
873
E2
634
J1
S1
931
Z2
544
K1
690
U1
493
I2
754
G2
995
X1
797
M1
834
=2
753
F2
957
518
421
462
468
658
Z1
L1
343
V1
N1
866
Y1
473
O1
=1
593
597
704
397
507
203
O2
666
/2
T1
847
H2
340
581
X2
959
676
S1
271
H2

Figure 9-11

Before circling the F1, Q1, D2, Y2 clusters and calling them a cluster group the analyst reviewed the cluster means and standard deviations and found that the Q1 cluster was likely to cause confusion with the H1-C2 group, so that cluster was also deleted. Figure 9-12 was the result of the interpretation to this point.

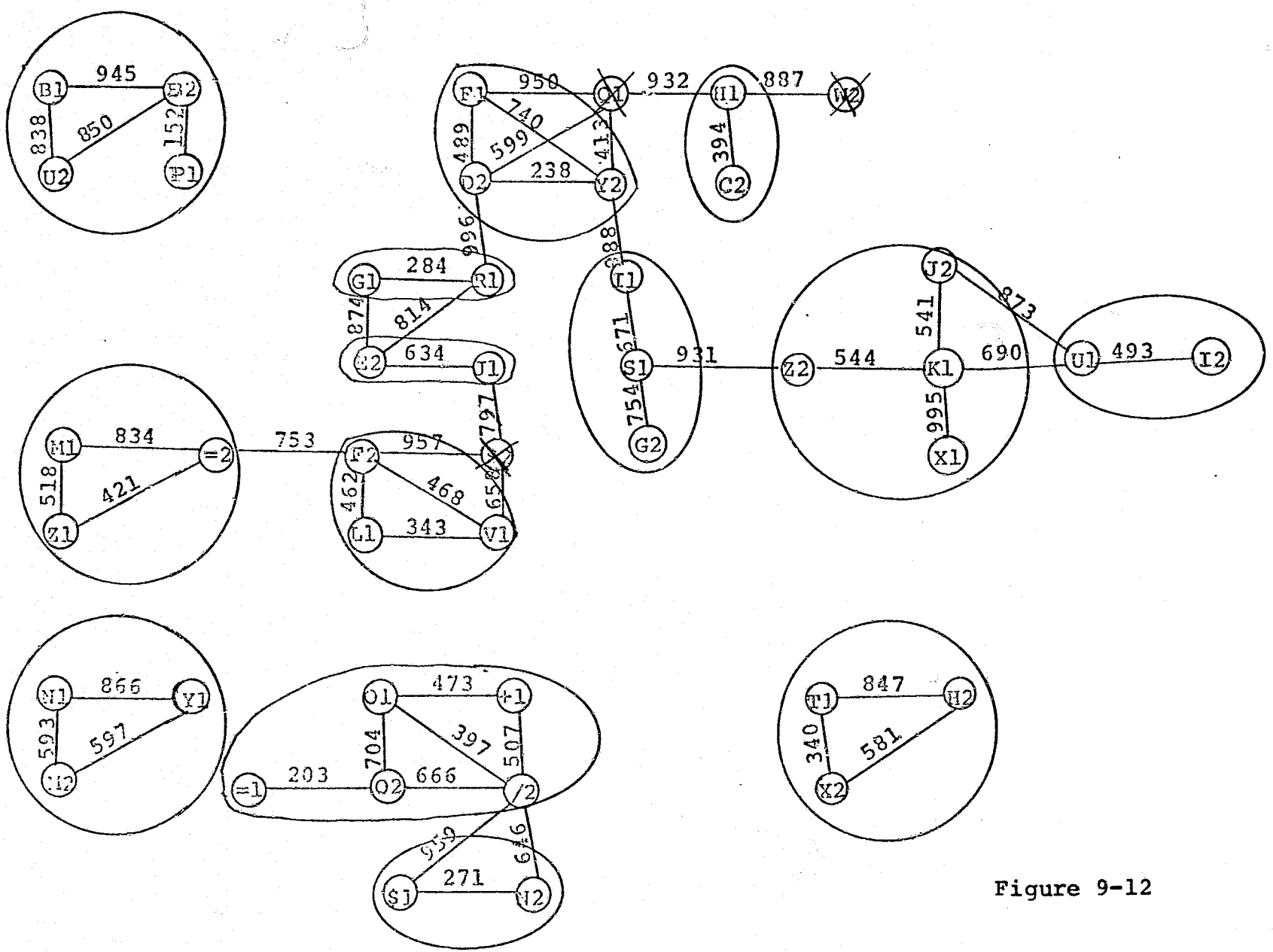

Figure 9-12

The line across the top of Figure 9-12 shows that several symbols were not crossed off, indicating that the clusters they represented were still classes by themselves. The rest of Figure 9-12 shows how the analyst had decided to combine clusters. This iteration reduced the number of classes from 60 to 30, but 30 is still a large number of classes for an analysis with an objective of differentiating five cover types.

The analyst combined clusters, assigned new symbols to all classes, and ran STATISTICS and SEPARABILITY over again.

Table 9-1 shows how the 60 classes were combined into 30, and the new symbols corresponding to the 30 classes are shown.

Table 9-1.

symbols in first iteration	new symbols	symbols in first iteration	new symbols
A1	A	B1,B2,P1,U2	Q
C1	B	F1,D2,Y2	R
D1	C	H1,C2	S
E1	D	G1,R1	T
W1	E	J1,E2	U
/1	F	I1,S1,G2	V
A2	G	K1,X1,J2,Z2	W
K2	H	U1,I2	X
L2	I	M1,Z1,=2	Y
P2	J	L1,V1,F2	Z
Q2	K	N1,Y1,M2	$
R2	L	O1,+1,=1,O2,/2	+
S2	M	T1,H2,X2	=
T2	N	$1,N2	/
V2	O		
+2	P		

Figure 9-13 shows the information from Table 9-1 put on the separability diagram. The analyst combined the Field Description Cards from CLUSTER in the manner indicated, and added to those cards a set of Field Description Cards describing clouds, cloud shadows, and water, chosen from outside the Kenosha Pass area boundaries. Then he took all these Field Description Cards, ran STATISTICS again, ran SEPARABILITY again, and constructed another separability diagram, the one shown in Figure 9-14.

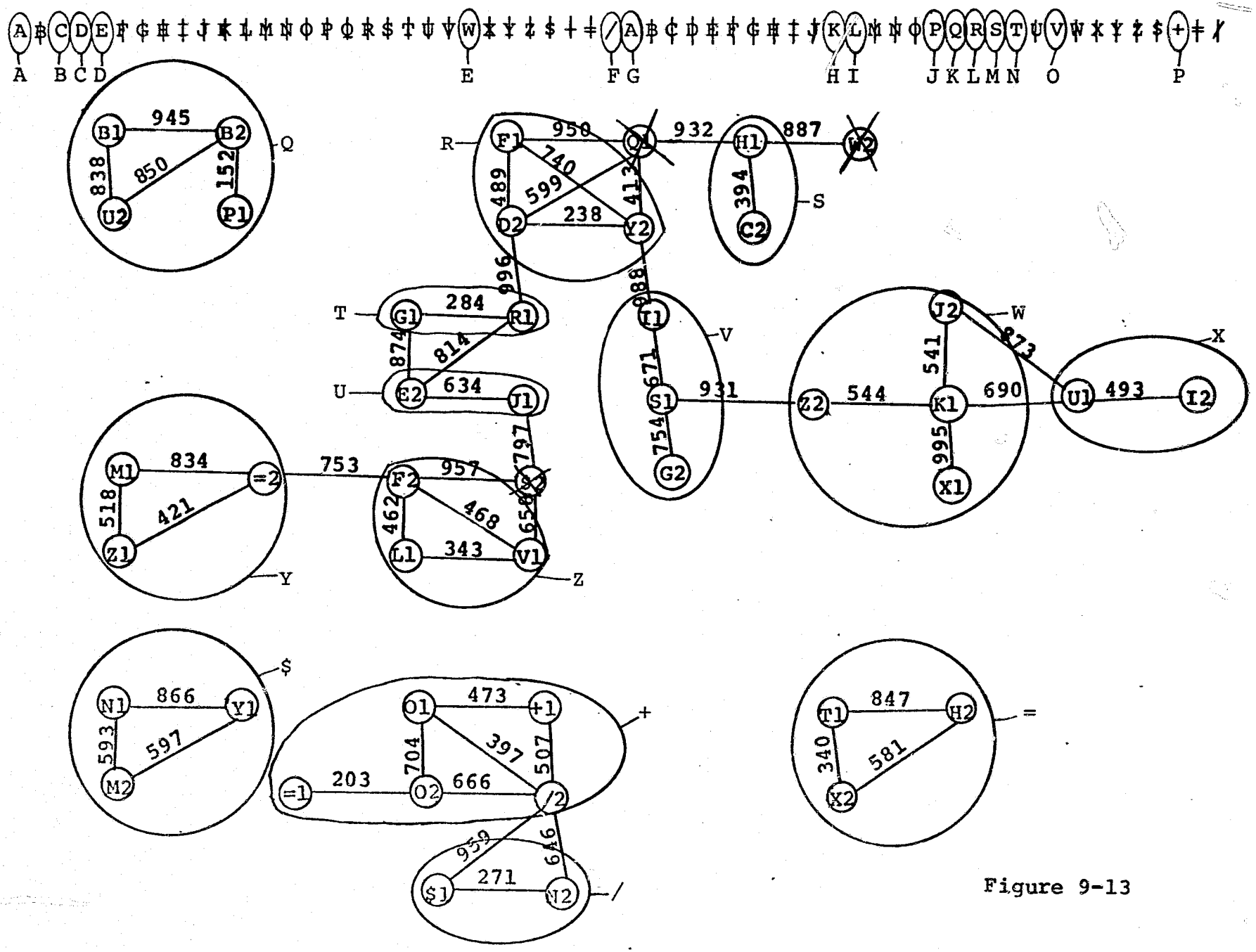
A B C D E F G H I J K L M N O P
B1 945 B2 Q
838 850 152
U2 P1
R F1 958 O1 932 H1 887 W2
489 140 599 413
D2 238 X2 394 C2 S
996 988
T G1 284 R1
874 814
U E2 634 J1
T1 V
671
S1 931
754
G2
J2 W
541 873
Z2 544 K1 690 U1 493 I2 X
995
X1
M1 834 =2 753 F2 957 X1
518 421 462 468 797 658
Z1 L1 343 V1 Y Z
$
N1 866 Y1
593 597
M2
+
O1 473 +1
704 397 507
=1 203 O2 666 /2
959 646
$1 271 N2 /
=
T1 847 H2
340 581
X2

Figure 9-13

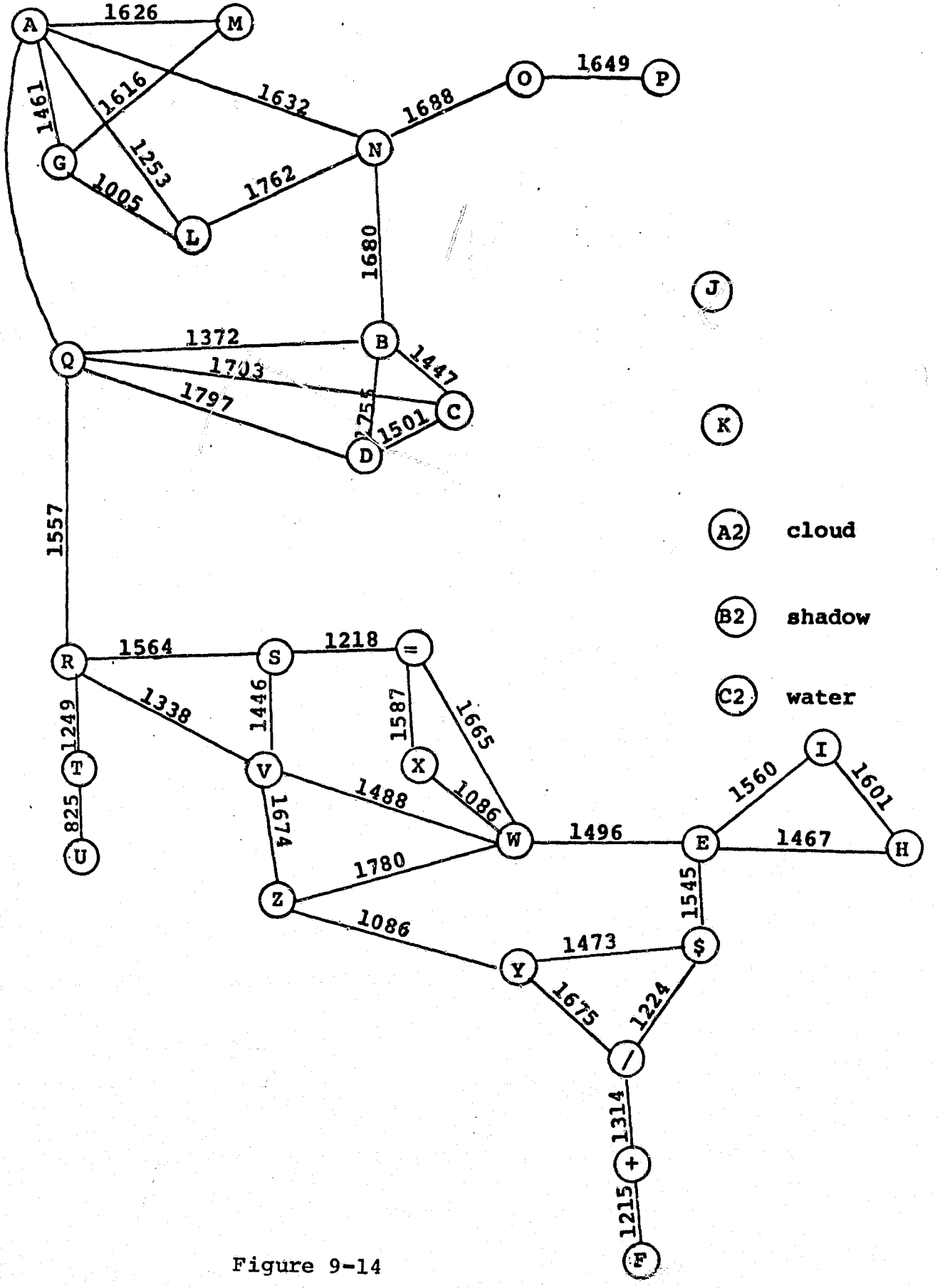
A
M
O
P
G
N
L
J
B
Q
C
D
K
A2
cloud
B2
shadow
C2
water
R
S
=
T
V
X
I
H
W
E
U
Z
$
Y
/
+
F
1626
1649
1461
1616
1632
1688
1253
1762
1005
1680
1372
1447
1703
1797
1501
1557
1564
1218
1338
1446
1587
1665
1249
1560
1601
1488
1086
1674
825
1496
1467
1780
1545
1086
1473
1675
1224
1314
1215

Figure 9-14

To interpret this diagram the analyst started by putting the cluster class identification information on the diagram. The result is shown in Figure 9-15.

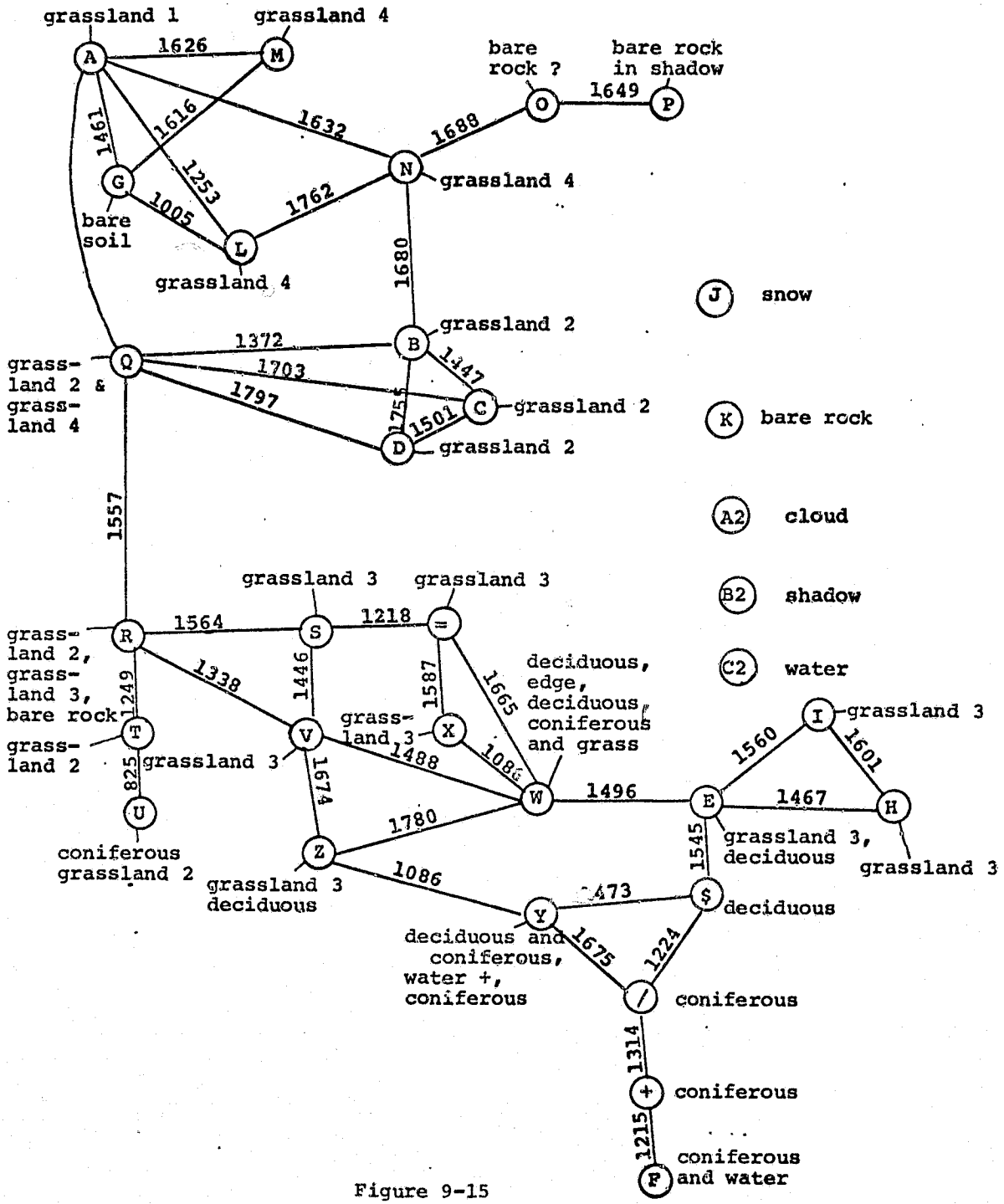

Figure 9-15

To interpret the diagram, classes J, K, A2, B2 and C2 were rather straight-forward. They were not connected to any other clusters, so they could each be circled individually and maintained as clusters.

The next thing the analyst did was to delete any classes composed of more than one cover type. For instance, R represented grassland 2, grassland 3, and bare rock, so it was deleted. U represented both coniferous and grassland 2, so it was deleted. Z was deleted, and W, E, Q and Y were deleted. The diagram then looked like Figure 9-16.

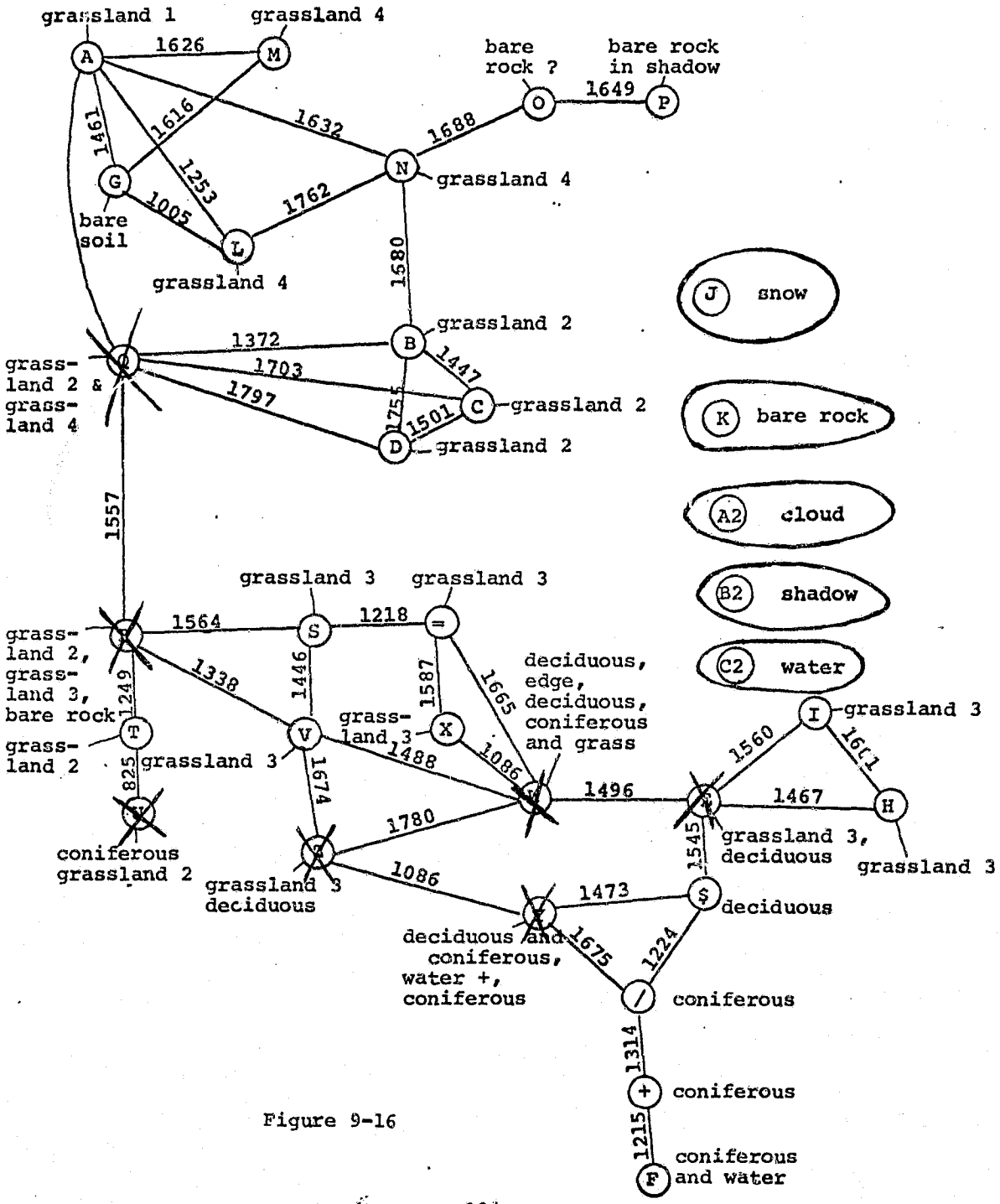
grassland 1
grassland 4
A
1626
M
bare rock ?
bare rock in shadow
1649
O
P
1461
1616
1632
1688
G
1253
N
grassland 4
bare soil
1005
1762
L
grassland 4
1580
J snow
grassland 2
B
1372
1447
grass-land 2 & grass-land 4
1703
1797
1755
1501
C
grassland 2
K bare rock
D
grassland 2
1557
A2 cloud
grassland 3
grassland 3
B2 shadow
1564
S
1218
grass-land 2, grass-land 3, bare rock
C2 water
1338
1446
1587
1665
deciduous, edge, deciduous, coniferous and grass
1249
grass-land 2
grassland 3
grass-land 3
1488
1086
1496
1560
1611
I
grassland 3
825
1674
1780
1467
H
1545
grassland 3, deciduous
coniferous grassland 2
grassland 3 deciduous
1086
1473
$
deciduous
deciduous and coniferous, water +, coniferous
1675
1224
coniferous
1314
coniferous
1215
coniferous and water

Figure 9-16

In this iteration, when classes of the same cover type had transformed divergence values less than 1750, the analyst grouped them together. As the interpretation of the rest of the diagram is discussed, you may wish to annotate Figure 9-16 to indicate the interpretation. Let's start at the bottom. Cluster F was coniferous and water. The next cluster up was coniferous. F was kept separate and by itself. Then the + and / were both coniferous, so they were grouped together. The $ was deciduous, so that became a class by itself. The I and H were both grassland 3, so they got grouped together. The S,=,V, and X classes were all grassland 3 and they were all connected to each other, so the analyst grouped them together into a single class. The X was also grassland 3 but it was not close to V or S, so it became another subclass of grassland 3. T, grassland 2, became a class by itself. Moving up to the B and D and C classes, the B-D distance was rather large and by inspection of the coincident spectral plot from STATISTICS the analyst decided that C was between B and D and therefore would cause confusion. He interpreted these classes by deleting class C, having B a separate class, and D as a separate class.

Look next at cluster A in the corner. It was identified as grassland 1 so it became a class by itself. The class G, bare soil, looked rather suspicious because it was close to class A, grassland 1, and would cause confusion. Also there is a class M, of grassland 4, and a class N of grassland 4, so the analyst felt that grassland 4 could be adequately represented without L, and it was deleted also. Them M became one grassland 4 subclass and N was the second grassland 4 subclass. O was a class of bare rock by itself and P was another class of bare rock. The interpretation of the diagram is shown completed in Figure 9-17.

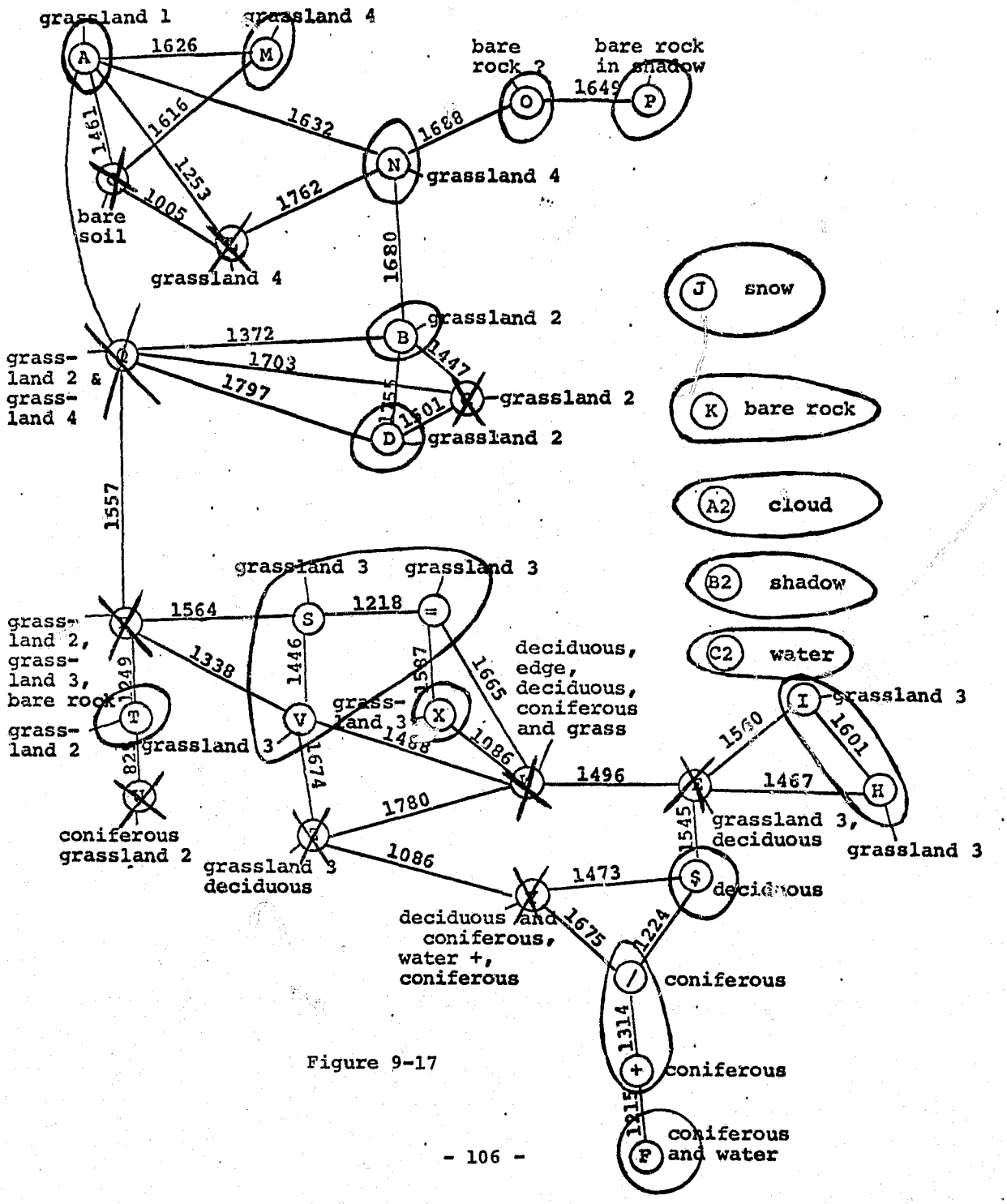

Figure 9-17

Using this diagram the analyst went back to his Field Description Cards again and did the combining and deleting indicated in Figure 9-17 to get together the description of all the training classes to be used to classify the Kenosha Pass test site.

CASE STUDY

Using the procedure illustrated in the example, interpret the separability diagram you created at the end of the preceding section, using the cluster class identification information you derived earlier, and keeping in mind your analysis objectives. You will have to decide how many iterations are necessary.

You should arrange to discuss your progress with your instructor at this time.

Section 10. CALCULATION OF STATISTICAL CHARACTERISTICS OF TRAINING CLASSES

Upon completion of this section, you should be able to do the following:

Explain why statistics are needed at this point in the analysis.

Use the LARSYS processing function to obtain statistics of training classes.

The analysis sequence so far has resulted in a set of Field Description Cards indicating the coordinates of data to be used for training. Before the classification can be performed, the STATISTICS processing function must be run on this final training set. The classifier available in LARSYS for classifying data on a point-by-point basis (CLASSIFYPOINTS) is based on the assumption that the training classes can be represented by multivariate Gaussian probability density functions, defined by mean vectors and covariance matrices. The STATISTICS processing function calculates the mean vectors and covariance matrices for the data described on Field Description Cards.

A detailed description of the input and output of the STATISTICS processor can be found on pages STA-1 to STA-22 in Volume 2 of the LARSYS User's Manual.

EXAMPLE

After the analyst had defined training patterns as discussed in the last section, he was ready to generate statistics for training. The control cards listed on the next page gave him the output he wanted:

```
-COMMENT KENOSHA PASS FINAL TRAINING STATISTICS
-RUNTABLE
DATA
RUN(73057902), TAPE(253), FILE(1)
END
*STATISTICS
CHANNELS 1,2,3,4
PUNCH
PRINT HIST(C), CORRE(C)
SCALE SPCINT(1)
DATA
CLASS GRASLND1
  .
  .
  field description cards for Dry Grass
  .
  .
CLASS GRASLND4
  .
  .
  field description cards for first Tundra subclass
  .
  .
CLASS GRASLND4
  .
  .
  field description cards for second Tundra subclass
  .
  .
CLASS BAREROK1
  .
  .
  field description cards for first subclass of Bare Rock
  .
  .
CLASS BARESHAD
  .
  .
  field description cards for Bare Rock in Shadow
  .
  .
CLASS GRASLND2
  .
  .
  field description cards for first subclass of
  Mountain Bunch Grass
  .
  .
CLASS GRASLND2
  .
  .
  field description cards for second subclass of
  Mountain Bunch Grass
  .
  .
CLASS GRASLND2
  .
  .
  field description cards for third subclass of
  Mountain Bunch Grass
  .
  .
```

```
CLASS GRASLND3
  •
  •
  field description cards for first subclass of Wet Meadow
  •
  •
CLASS GRASLND3
  •
  •
  field description cards for second subclass of Wet Meadow
  •
  •
CLASS GRASLND3
  •
  •
  field description cards for third subclass of Wet Meadow
  •
  •
CLASS DECIDOUS
  •
  •
  field description cards for Deciduous
  •
  •
CLASS CONIFER1
  •
  •
  field description cards for first subclass of
  Conifer
  •
  •
CLASS CONIFER2
  •
  •
  field description cards for second subclass of
  Conifer
  •
  •
CLASS BAREROK2
  •
  •
  field description cards for second subclass of Bare Rock
  •
  •
CLASS SNOW
  •
  •
  field description cards for Snow
  •
  •
CLASS CLOUD
  •
  •
  field description cards for Clouds
  •
  •
CLASS C SHADOW
  •
  •
  field description cards for Cloud Shadows
  •
  •
CLASS WATER
  •
  •
  field description cards for Water
  •
  •
END
```

This time the analyst wanted to see the histograms of the classes and the correlation matrices of the classes. Again, he used the SCALE card so that the coincident spectral plot would have a scale appropriate to LANDSAT data.

After running STATISTICS, the analyst ran SEPARABILITY one more time for the purpose of checking on probability of correct classification. The transformed divergence between all class pairs was greater than 1750, which generally corresponds to better than 90% probability of correct classification for training data. The analyst considered this acceptable, and decided that he was ready to classify the data, so the punched statistics deck from this job was saved for use in the next analysis step.

EXERCISES

1. Explain why statistics are needed at this point in the analysis.

CASE STUDY

Set up the control cards to run the STATISTICS processing function with your Field Description Cards from CLUSTER combined in the way determined in Section 9. Remember to request punched output.

Section 11. CLASSIFICATION, RESULTS DISPLAY, AND EVALUATION

Upon completion of this section, you should be able to do the following:

Name and briefly describe the decision rule implemented in the CLASSIFYPOINTS processing function.

Identify the kind of distribution training classes are assumed to have, and name the two parameters needed to define such distributions.

Given a statistics deck and the coordinates of an area to be classified, set up the control cards and run the CLASSIFYPOINTS processing function.

Set up control cards for PRINTRESULTS to display the classification, and run the job.

Given an example of a class performance matrix, indicate points correctly classified, errors of omission, and errors of commission for a specified class.

The CLASSIFYPOINTS processing function classifies multispectral (and multitemporal) data one point at a time into classes defined by the training statistics. This is the last major step in the process of deriving useful information from remote sensing data. Of course, an analyst may decide that the first classification produced is not satisfactory for the objectives to be met. In that case, decisions made in previous steps would have to be revised. The first few times an analyst deals with the spectral properties of cover types by using the pattern recognition techniques available in LARSYS, it may be necessary to go all the way back to the step where candidate training areas were selected. However, with experience and increased analysis skill, such drastic revisions can be avoided.

The decision rule implemented in LARSYS is called a maximum likelihood classification rule. Each data point to be classified is compared to all of the training classes, and is assigned

to the most likely class. To express the concept of a classifier in a quantitative way so that the computer can do the work, we would like to have a set of functions corresponding to the training classes. These functions would have the property that when a data vector to be classified is substituted into all of them, the function having the largest value corresponds to the class to which the data vector belongs. This would provide a quantitative way of discriminating between classes. Such functions are called discriminant functions. One way to get such a set of functions (the way LARSYS gets discriminant functions) is to start with training classes, and assume that they have multivariate Gaussian (or multivariate normal) probability density functions. Then the mean vector and covariance matrix define the distribution of the training data. The discriminant functions are expressed in terms of the mean vector and covariance matrix, which were calculated for all training classes by use of the STATISTICS processing function in the last section.

For more detailed information about the classification algorithm, see pages CLA-25 through CLA-29 of Volume 2 of the LARSYS User's Manual and also LARS Information Note 111572, Pattern Recognition: A Basis for Remote Sensing Data Analysis by Philip H. Swain.

The classification which is produced is stored on disk or tape (whichever you specify). In order to access and evaluate classification results, another LARSYS processing function is used. The PRINTRESULTS processing function can provide an alphanumeric printout, and it has a capability for providing quantitative information about a classification in the form of tables. The analyst can specify the coordinates of areas of interest, called "test fields." The computer then examines and tabulates the classification decision for each data point, and prints out a summary by fields, or classes, or both, as specified by the analyst. An example of tabular results for classes is shown in Figure 11-1. Such a table can be called a test class performance matrix.

	NO OF SAMPS	PCT. CORCT	OATS	CORN	WHEAT	SOYB	GRASS
OATS	66	98.5	65	0	0	1	0
CORN	93	93.5	0	87	0	6	0
WHEAT	69	100.0	0	0	69	0	0
SOYB	57	93.0	2	0	0	53	2
GRASS	31	90.3	0	3	0	0	28
TOTAL	316		67	90	69	60	30

Figure 11-1. Test class performance matrix

What do the numbers in the performance matrix tell you about the classification? Look first at the 66 samples of OATS. The table indicates that 65 of those points, or 98.5%, were correctly identified. Looking across that row, the table also indicates that one data point which the analyst knows to be oats was incorrectly classified as soybeans. That is, there was one error of omission for the 66 oats samples. Looking down the column labelled OATS, there were two errors of commission for the class oats. That is, two samples were called oats that should not have been.

The diagonal elements of the matrix can be summed, and that total divided by the total number of samples. The result is called overall performance. For Table 11-1, the overall performance is (65+87+69+53+28) ÷ 316 = 95.5%.

Another way of evaluating the classification is to sum the percent correct for each class, and divide by the number of classes. This result is called average performance by class. The average performance by class in Table 11-1 is (98.5+93.5+100.0+93.0+90.3) ÷ 5 = 95.1%.

The capability to get tabular results for a specified area can be used to obtain area estimates for the cover types in a classification. To do this, the coordinates of the entire area can be put in as a test field. Then the output, instead of being the usual performance matrix, will be a one-line table indicating the number of data points classified into each cover type. Given the total number of data points and the total area, the area per data point can be calculated. Then this area per data point multiplied by number of data points per cover type will give area per cover type.

Furthermore, the information in the performance matrix about the error rates associated with a classification can be used to adjust areal estimates derived from the classification, so that they more nearly estimate the true amounts of each cover type. More detailed information about this use of the performance matrix can be found in Appendix A, material extracted from the final report for Contract NAS5-21773: A Study of the Utilization of ERTS-1 Data from the Wabash River Basin by Marvin E. Bauer, titled Identification and Area Estimation of Agricultural Crops by Computer Classification of ERTS-1 MSS Data.

For the Kenosha pass example, the analyst used the following control cards to classify the data:

```
-COMMENT KENOSHA PASS CLASSIFICATION
-RUNTABLE
DATA
RUN(73057902), TAPE(253), FILE(1)
END
*CLASSIFYPOINTS
RESULTS TAPE(TTT), FILE(F)
CARDS READSTATS
CHANNELS 1,2,3,4
DATA
  .
  .
  .
punched statistics file from STATISTICS processing function
  .
  .
  .
DATA
RUN(73057902), LINE(197,531,1), COL(401,803,1)
END
```

Note that the analyst specified that his results were to go onto tape, where they remain until he writes over them. When you classify the case study data, you should put your results on disk. However, this means that you must run your PRINTRESULTS job in the same terminal session (or batch job) as the CLASSIFY-POINTS, because disk results are cleared at logout.

When you do need to keep results on tape, check with your supervisor to learn the numbers of any tapes assigned to you.

The next control card, CARDS READSTATS, indicates that the statistics (mean vectors and covariance matrices) of the training classes are to be read from punched cards.

The CHANNELS card of course specifies which channels are to be used for classification. The analyst chose to classify with all four channels. If a subset of channels had been desired (for instance, if one of the channels had striping so bad it couldn't be used), this is where the subset would be specified.

The first data deck contains the statistics of the training classes. The second data deck indicates the area to be classified.

To display the results, the analyst used the following control card setup:

```
-COMMENT PRINTOUT OF KENOSHA PASS
*PRINTRESULTS
RESULTS TAPE(TTT), FILE(F)
PRINT TRAIN(C)
SYMBOLS +,+,+,-,-,+,+,+,+,+,+,/,0,0,-, , ,$,W
GROUP GRASSLND(1/1,2,3,6,7,8,9,10,11/)
GROUP BARREN(2/4,5,15/),DECIDOUS(3/12/)
GROUP CONIFER(4/12,14/),SNOW(5/16/),CLOUD(6/17/)
GROUP C SHADOW(7/18/),WATER(8/19/)
END
```

The analyst specified that training class performances were to be printed out. Since CLASSIFYPOINTS stores the coordinates of the training data at the beginning of the results file, the analyst did not have to include a data deck to get training performance as he would have for test performance.

On the SYMBOLS card, alphanumeric symbols were assigned to the classes in the order that the classes appeared in the statistics deck. Using the same symbol for all subclasses of a single cover type simplified the printed map. By the way, a blank can be used as the symbol for a class (for example, classes 16 and 17 above).

The next four cards the analyst used were GROUP cards. Notice that the conventions for continuing function control cards include repeating the key word, not ending with a comma, and not punching past column 72. These cards provide special instructions to the computer about how results are to be tabulated. The first GROUP card, for instance, indicates that if a data point specified to the computer as grassland was classified into class 1,2,3,6,7,8,9,10 or 11, it was correctly classified. Similarly, if a point specified to the computer as barren was classified into class 4 or class 5 or class 15, it was correctly classified.

For this Kenosha Pass study, the analyst did not have adequate reference data to specify the coordinates of test fields. The training class performance provided one indication of accuracy. The training class performance matrix is shown in Figure 11-2.

Notice that the headings across the top of Figure 11-2 include water, cloud, and cloud shadow, but the column on the side doesn't. The explanation is that the column on the side lists only those groups of classes for which there are training fields within the area classified. Remember that the analyst selected training data for water, clouds, and cloud shadows from outside the Kenosha Pass area.

GROUP	NO OF SAMPS	PCT. CORCT	WATER	CLOUD	C SHADOW	SNOW	GRASSLND	DECIDOUS	CONIFER	BARREN
SNOW	8	100.0	0	0	0	8	0	0	0	0
GRASSLND	3185	99.7	0	0	0	0	3175	0	0	10
DECIDOUS	552	93.3	0	0	0	0	9	515	28	0
CONIFER	823	95.7	0	0	2	0	0	33	788	0
BARREN	306	98.7	0	0	0	1	3	0	0	312
TOTAL	4874		0	0	2	9	3187	548	812	312

OVERALL PERFORMANCE (4788/4874) = 98.2

AVERAGE PERFORMANCE BY CLASS (487.4/5) = 97.5

Figure 11-2. Training class performance, Kenosha Pass example.

Further evaluation of the results was not available for the Kenosha Pass area at this writing. However, the Forest Service, Rocky Mountain Forest and Range Experiment Station had provided evaluation information for two other areas. Since the two available areas, Manitou and Eleven Mile, are similar to Kenosha Pass, the evaluation procedure and results for those two areas will be discussed.

Test fields were found by the following procedure: In each area, the part corresponding to a 1:50,000 color infrared aerial photograph was used for evaluation. A grid of cells, each the same size as a 4 x 4 block of data points, was superimposed on the photography, and the grid was sampled systematically. Sample cells which were completely within one cover type became test fields. To minimize possible location errors, only the results of the interior 2 x 2 block of data points were tabulated. For the Manitou area, the hand-calculated results table is shown in Figure 11-3. The other area which was evaluated by this procedure, the Eleven Mile area, had the results (or test class performance matrix) shown in Figure 11-4.

You have followed the Kenosha Pass example through classification, results display, and evaluation, the topics of this section. However, since you will be instructed to use test fields to evaluate your classification, another example will be shown.

An example of the PRINTRESULTS processing function where test fields have been included for evaluation purposes will be presented. The analysis was done on MSS data collected from aircraft altitude over an agricultural scene. The analyst has already examined data quality, coordinated MSS data with reference data, selected candidate training areas, refined the candidate training areas, and calculated statistics for training classes. We will just look over his shoulder to see how he set up his card deck to classify the data and display the results.

Photointer-pretation Category	Number of Samples	Percent Correct	Computer classification category: Grassland	Deciduous Forest	Coniferous Forest	Water
Grassland	257	84.4	217	10	30	0
Deciduous Forest	21	23.8	8	5	8	0
Coniferous Forest	1239	86.1	146	26	1067	0
Water	3	66.7	0	0	1	2
Total	1520	84.9*	371	41	1106	2

*overall performance=number correct/total number of samples

Figure 11-3. Hand-tabulated test class performance matrix for Manitou area.

Photointer-pretation Category	Number of Samples	Percent Correct	Grassland	Deciduous Forest	Coniferous Forest	Water	Barren
Grassland	433	80.1	347	7	74	0	5
Deciduous Forest	94	51.1	35	48	11	0	0
Coniferous Forest	739	66.0	76	175	488	0	0
Water	60	95.0	0	0	3	57	0
Barren	54	1.9	34	1	18	0	1
Total	1380	68.2*	492	231	594	57	6

*overall performance = number correct/total number of samples.

Figure 11-4. Hand-tabulated test class performance matrix for Eleven Mile area.

He used the following card deck:

```
-COMMENT CLASSIFY, DISPLAY, AND EVALUATE 66000652
-RUNTABLE
DATA
RUN(66000652), TAPE(TTT), FILE(F)
END
*CLASSIFYPOINTS
RESULTS DISK
CARDS READSTATS
CHANNELS 1,6,8,12
DATA
 .
 .
 .
 stat deck from previous STATISTICS run
 .
 .
 .
DATA
RUN(66000652), LINES(1,950,2), COL(1,222,2)
END
*PRINTRESULTS
RESULTS DISK
PRINT OUTLINE (TRAIN,TEST), TRAIN(F,C),TEST(F,C,P)
SYMBOLS O,O,O,C,C,C,C,W,W,W,S,S,S,G,G,G,G
GROUP OATS(1/1,2,3/), CORN(2/4,5,6,7/), WHEAT(3/8,9,10/)
GROUP SOYBEANS(4/11,12,13/), GRASS(5/14,15,16,17/)
DATA
TEST 1
 .
 .
 .
 Field Description Cards for OATS test fields
 .
 .
 .
 TEST cards and Field Description Cards for corn,wheat,and soybeans
 .
 .
 .
TEST 5
 .
 .
 .
 Field Description Cards for Grass test fields
 .
 .
 .
END
```

There are several points to be observed about this deck. The CLASSIFYPOINTS and PRINTRESULTS jobs are being run "back-to-back". The classification results file is to be stored on disk. Training and test fields are to be outlined on the PRINTRESULTS display map. If your training fields are small, three- or four-point fields, outlining them may not be desirable. Training field and class performances are to be printed out (again, if your training fields are small, you would probably print performances for classes, not fields). Test field, class, and percentage tables are to be printed out.

Also observe that the group number on the GROUP cards determines the order in which the test fields appear in the data deck.

EXERCISES

1. Name and briefly describe the kind of decision rule implemented in the CLASSIFYPOINTS processing function.

2. Identify the kind of distribution training classes are assumed to have, and name the two parameters needed to define such distributions.

3. In Figure 11-1 indicate the points correctly classified, errors of omission, and errors of commission for soybeans.

CASE STUDY

Using the punched STATISTICS deck you generated in the last section, set up the control cards to run the CLASSIFYPOINTS processing function, putting your results on disk. The area to be classified is from line 30 to 430, and from column 112 to 333.

Also set up the control cards to run the PRINTRESULTS processing function. Your instructor has a set of test fields which you can use to evaluate your classification. Ask for any output products you think would be useful.

Run the CLASSIFYPOINTS and PRINTRESULTS jobs. Consider the possibility of running more than one PRINTRESULTS job. For instance, you might wish to assign every class and subclass a different symbol on one map, while on another map you could assign the same symbol to all subclasses of a class. If one cover type is of particular interest to you, you could assign a symbol to it, and blanks to all other classes.

If your overall test performance is not satisfactory, consider what you could do to improve the classification. Discuss the possibilities with your instructor.

Section 12. INFORMATION EXTRACTION AND INTERPRETATION

Upon completion of this section, you should be able to do the following:

Name at least two kinds of information that can be extracted from a classification.

Give an example of useful information extracted from multispectral classifications in your discipline.

The final and most important step is interpretation of results. The classification results themselves are not usually the product of interest. Instead, the objective of an analysis is usually to gain information for use in such things as forest management or land use planning. For instance, the objective usually involves learning where specific cover types are located, or what proportion of the area belongs to each cover type.

To complete the analysis, the original objectives must be reviewed, and the desired information extracted.

Examples of results analysis and the extraction of useful information from multispectral data classifications may be found in several journals, including those listed here:

Remote Sensing of the Environment
IEEE Transactions on Geoscience Electronics
Remote Sensing in Ecology
Journal of Soil and Water Conservation
Photogrammetric Engineering and Remote Sensing
Agronomy Journal
Applied Optics

Samples can also be found in a number of LARS Information Notes, published proceedings of remote sensing conferences, etc.

The objectives of the Kenosha Pass analysis were 1) to classify and inventory the area into these cover types: water, snow, grassland, deciduous forest, coniferous forest, barren (bare rock and bare soil); 2) to produce a classification map of these cover types; 3) to evaluate the classification accuracy.

The third objective, evaluation of accuracy, was discussed in the previous section. The analyst requested training class performance from PRINTRESULTS, and overall performance was 98.2%. Test performance was determined manually, rather than by submitting test field coordinates to PRINTRESULTS.

The second objective was to produce a classification map of the cover types of interest. The control cards used to produce the map were listed and discussed in the previous section.

And now for the first objective--a classification and inventory of the cover types. In addition to the map showing how cover types were distributed, an inventory of the amount of each cover type was needed. To get this information, the analyst ran PRINTRESULTS again, and input the coordinates of the entire area as a test field. Then the output, instead of being the usual performance matrix, was a one-line table indicating the number of data points classified into each cover type.

The control cards used are listed here:

```
-COMMENT KENOSHA PASS INVENTORY
*PRINTRESULTS
RESULTS TAPE(TTT), FILE(F)
PRINT TEST(C), MAPS(0)
GROUP GRASSLND(1/1,2,3,6,7,8,9,10,11/)
GROUP BARREN(2/4,5,15/), DECIDOUS(3/12/)
GROUP CONIFER(4/13,14/), SNOW(5/16/), CLOUD(6/17/)
GROUP C SHADOW(7/18/), WATER(8/19/)
DATA
TEST 1
RUN(73057902), LINE(197,531,1), COL(401,803,1)
END
```

The table produced by these cards contained the following information:

NUMBER OF SAMPLES CLASSIFIED INTO

GRASSLND	BARREN	DECIDOUS	CONIFER	SNOW	CLOUD	C SHADOW	WATER
97742	3597	13519	19640	38	196	253	20

Since the total number of data points (135,005) and the total area in acres (154,965) are known, the number of acres per data point could be determined (154965÷135005=1.14785), and from this the number of acres classified into each cover type was calculated.

The analyst has carried out an analysis sequence which met his objectives.

EXERCISES

1. Name at least two kinds of information that can be extracted from a classification.

2. Check with your instructor on the availability of the listed references, and skim through one or more of them. Then give an example of useful information extracted from multispectral classification.

CASE STUDY

Study your classification analysis results. Did you meet your analysis objectives? What information can you extract from the results? Based on your results, would you say that the cover type classes you initially selected were sufficiently distinct spectrally to provide adequate classification accuracy? Would you consider it worthwhile to use these classes as the basis for a "real life" application of remote sensing?

Discuss your results and conclusions with your instructor.

Appendix A

The following material has been reprinted from Section 2 of Identification and Area Estimation of Agricultural Crops by Computer Classification of ERTS-1 MSS Data, the final report for Contract NAS5-21773: A Study of the Utilization of ERTS-1 Data from the Wabash River Basin.

2.333 UNBIASING CLASSIFICATION RESULTS

Experience has shown that it is inevitable that some points are incorrectly identified by the maximum likelihood classifier. In this experiment, only about 80% of the test samples were correctly classified. The primary source of these errors is overlapping density functions for two or more classes. For example, some corn "looks" like soybeans and some soybeans are spectrally similar to corn. As described above, prior probability information or class weights can be used to good advantage to at least partially reduce the effects of such circumstances. A second procedure which can be used after the classification has been performed is to unbias or adjust the results based on the correct classification proportions and error rates. The latter procedure was first used during the 1971 Corn Blight Watch Experiment.

The source of the correct classification proportions and error rates are the matrices of test field classification performance such as shown in Table 2.6. From such information, we can determine the proportions, for instance, of corn classified as corn and non-corn and the proportions of non-corn classified as non-corn and corn. With this information, it is then possible to unbias or adjust the classification results for a county or several counties so that they more nearly estimate the true amounts of each class present in the classified area.

Theoretically, if the true values of the error rates of omission and commission were known, the classification results could be adjusted so that in effect the area estimates based on the classification closely approximated the true amounts of each crop present. In practice, of course, this situation is seldom found. The primary limitation is that the test samples are not completely representative of the total area classified and only provide estimates of the true error rates. Possible causes of non-representative test samples are that samples come from only a small part of the total area being classified and that many cover types such as farmsteads, idle land, roads, and urban areas generally have not been included in the set of test fields.

The method we have used for unbiasing classification results involves multiplying the county classification results (Table 2.7) by the inverse of the test field classification performance matrix (Table 2.6) as follows:

$$A = CP^{-1}$$

Table 2.6 Classification of corn, soybean, and "other" test fields, DeKalb, Ogle, and Lee Counties, Illinois, with and without the use of prior probability information in the classification decision rule.

(a) No prior probability information used, equal class weights assumed.

CLASS	NO. POINTS	NO. POINTS CLASSIFIED AS			PERCENT CORRECTLY CLASSIFIED
		CORN	SOYBEANS	"OTHER"	
Corn	9290	7546	973	771	81.2
Soybeans	2235	244	1732	259	77.5
"Other"	1121	150	307	664	59.2
TOTAL	12646	7940	3012	1694	78.6

(b) Prior probability information used, unequal class weights.*

CLASS	NO. POINTS	NO. POINTS CLASSIFIED AS			PERCENT CORRECTLY CLASSIFIED
		CORN	SOYBEANS	"OTHER"	
Corn	9290	7983	382	925	85.9
Soybeans	2235	395	1556	284	69.6
"Other"	1121	206	220	695	62.0
TOTAL	12646	8584	2158	1904	80.9

*Class weights were 44, 16, and 40 for corn, soybeans, and "other", respectively.

Table 2.7 Number of samples classified into corn, soybeans, and "other" for DeKalb, Ogle, and Lee Counties, Illinois.

(a) Equal Class Weights

	No. Points Classified As		
County	Corn	Soybeans	"Other"
DeKalb	131,451	85,148	74,311
Ogle	146.108	112,385	135,058
Lee	150,992	122,101	120,266
TOTAL	428,551	319,634	329,635

(b) Unequal Class Weights

DeKalb	No. Points Classified As		
County	Corn	Soybeans	"Other"
DeKalb	152,920	54,948	83,042
Ogle	170,220	74,940	148,391
Lee	178,177	80,241	134,941
TOTAL	501,317	210,129	366,374

where, C is the classification vector with n crops or classes, P^{-1} is the inverse of the n x n classification performance matrix, and A is a 1 x n vector of the crop acreages.

The results of applying this correction procedure are presented in Table 2.8 and discussed in the next section along with further results on the use of prior probabilities to the classification function.

2.334 ACREAGE ESTIMATION

The classification performance indicated by 80% correct recognition of test fields is believed to be adequate for satisfactorily estimating crop acreages. To determine how well crop acreages could be estimated from the ERTS classification, the ERTS coordinates of the three counties were obtained, the counties were classified, and the number of pixels classified into each class tabulated (Table 2.7). In Table 2.8, four acreage estimates based on the ERTS classifications are compared to each other and to estimates made by the Illinois Cooperative Crop Reporting Service (SRS/USDA). The ERTS estimates are the four combinations of using prior probability information in the classification decision rule and unbiasing the classification results as discussed in the previous two sections.

The standard to which the ERTS classifications are compared is the acreage estimates (shown as percentage of total land area) made by SRS/USDA. The mean squared differences between the SRS/USDA estimates and the several ERTS estimates are shown as a means of comparing the overall goodness of each ERTS estimate.

One of the most difficult aspects of remote sensing technology is quantitatively evaluating classification results. It is physically impossible to collect sufficient ground data of crop identification and acreage over large areas, to determine how accurate area estimates made from the ERTS classification are. We have therefore used the USDA county estimates as the reference for comparison. However, the crop surveys conducted by the USDA are designed to achieve prescribed levels of accuracy at only the national and state levels. For this reason the USDA does not publish accuracy figures for their county estimates. However, in those states, including Illinois, in which an annual farm census is conducted, the acreage estimates are considered to be quite accurate. Their estimates are probably within three to five percent of the actual acreages.

The ERTS estimates, particularly those adjusted for classification bias, are very close to those made by the USDA. It seems clear that the USDA and ERTS estimates are of the same parameter. The estimates agree best for the total of the three counties. There is more variation between the two estimates for the individual counties. However, this is simply a result of having a larger sample and can be expected as long as there is not a consistent bias in one direction in the ERTS classification, eg., corn is always over-estimated.

Table 2.8. Comparison of crop acreage estimates by USDA and estimates based on ERTS classifications. The results of utilizing prior probability information in classification and bias correction of classifications are shown.

County	Class	SRS-USDA	ERTS			
			Uncorrected		Bias Corrected	
			Equal Wts.	Non-Eq. Wts.	Equal Wts.	Non-Eq. Wts.
			(Percent of Total Land Area)			
DeKalb	Corn	41.5	45.2	52.6	47.6	50.8
	Soybeans	21.3	29.3	18.9	19.9	14.3
	"Other"	37.2	25.5	28.5	32.5	34.9
	r.m.s.*		6.5	6.9	8.3	8.5
Ogle	Corn	41.3	37.1	43.3	35.5	37.0
	Soybeans	11.5	28.6	19.0	14.4	10.2
	"Other"	47.2	34.3	37.7	50.1	52.8
	r.m.s.		12.6	7.1	4.1	4.1
Lee	Corn	37.9	38.4	45.3	37.6	40.0
	Soybeans	21.9	31.0	20.4	19.9	14.0
	"Other"	40.2	30.6	34.3	42.5	46.0
	r.m.s.		7.6	5.5	1.8	5.8
Total for all Counties	Corn	40.2	39.8	46.5	39.6	41.8
	Soybeans	18.0	29.6	19.5	17.8	12.7
	"Other"	41.8	30.6	34.0	42.6	45.5
	r.m.s.		9.3	5.8	0.6	3.9

*r.m.s.-root mean square difference between USDA and ERTS estimates

Two additional things are clear from the results: (1) the use of class weights or prior probability information in classification gave substantially better estimates of the amounts of corn and soybeans present (reduction of the r.m.s. difference from 9.3 to 5.8) and (2) the application of the unbiasing procedure after classification further improved the ERTS estimates (reduction of r.m.s. difference to 3.9 and 0.6) for the classification with and without class weights, respectively. In conclusion, these two procedures should be used whenever possible in making crop acreage estimates from classifications of ERTS type data.

CREDITS

The analysis example was done by Michael D. Fleming, LARS. Information about evaluation procedures and results was provided by Dr. Richard S. Driscoll, Rocky Mountain Forest and Range Experiment Station.