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FINAL REPORT

DEVELOPMENT OF ADVANCED ACREAGE ESTIMATION METHODS

3. L. F. Guseman, Jr.

4. DEPARTMENT OF MATHEMATICS
TEXAS A&M UNIVERSITY
COLLEGE STATION, TEXAS 77843

FINAL REPORT

DEVELOPMENT OF ADVANCED

ACREAGE ESTIMATION METHODS

Contract NAS-9-14689

November 1, 1980 - June 30, 1982

Prepared for:

Earth Observations Division
NASA/Johnson Space Center
Houston, Texas 77058

by

L. F. Guseman, Jr.
Principal Investigator
Department of Mathematics
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L. F. Guseman, Jr.
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16. Abstract

Work carried out under this contract was concerned with:

Refinements and Documentation of the AMOEBA Clustering Algorithm

Rice Scene Radiation Characterization Applied Research

Spectral-Spatial Classification Algorithm Development

Use of the Akaike Information Criterion

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DEVELOPMENT OF ADVANCED ACREAGE ESTIMATION METHODS

INTRODUCTION

A practical application of remote sensing which is of considerable interest is the use of satellite-acquired (LANDSAT) multispectral scanner (MSS) data to conduct an inventory of some crop of economic interest such as wheat over a large geographical area. Any such inventory requires the development of accurate and efficient algorithms for analyzing the structure of the data. The use of multi-images (several registered passes over the same area during the growing season) increases the dimension of the measurement space. As a result, characterization of the data structure is a formidable task for an unaided analyst.

Cluster analysis has been used extensively as a scientific tool to generate hypotheses about structure of data sets. Sometimes one can reduce a large data set to a relatively small data set by the appropriate grouping of elements using cluster analysis. In some cases, the algorithm which effects the grouping becomes the basis for actual classification. In other cases, the cluster analysis produces groupings of the data which in turn serve as a starting point for other algorithms which produce acreage estimates. Additional uses of cluster analysis arise in conjunction with dimensionality reduction techniques which are used to generate displays for purposes of further interactive analysis of the data structure.

Work carried out under this contract dealt with algorithm development, theoretical investigations, and empirical studies. The algorithm development tasks centered around the refinement of the AMOEBA clustering/classification algorithm, and its subsequent use as a starting point for HISSE, a maximum likelihood proportion estimation procedure. Theoretical results were obtained

which form a basis for the maximum likehood estimation procedures. In addition, some investigations were made into the use of the Akaike information criterion (AIC) when applied to mixture models. Additional work was concerned with the development of a preliminary research plan which delineates some of the technical issues and associated tasks in the area of rice scene radiation characterization.

Specifically, investigations were carried out in the following areas:

Refinements and Documentation of the AMOEBA Clustering Algorithm

Rice Scene Radiation Characterization Applied Research

Spectral-Spatial Classification Algorithm Development

Use of the Akaike Information Criterion

Each of these investigations is discussed in turn in the sequel.

1. REFINEMENTS AND DOCUMENTATION OF THE AMOEBA CLUSTERING ALGORITHM

Detailed documentation of the AMOEBA clustering/classification algorithm for the version implemented on the HP-3000 System at EROS Data Center appears in an attached report entitled:

Jack Bryant, System support documentation--IDIMS FUNCTION--AMOEBA, Department of Mathematics, Texas A&M University, March, 1982.

Included throughout the documentation are comments which indicate where code changes could or should be made to transport the program to another system.

2. RICE SCENE RADIATION CHARACTERIZATION APPLIED RESEARCH

Work for this task was performed by Dr. James Heilman, Remote Sensing Center, Texas A&M University. The results of his investigations are presented in the attached report entitled:

James Heilman, Rice Scene Radiation Research Plan, Remote Sensing Center, Texas A&M University, December, 1981.

3. SPECTRAL-SPATIAL CLASSIFICATION ALGORITHM DEVELOPMENT

The objective of this study was to formulate and test algorithms based on a likelihood function which respected the integrity of some predetermined structure in the data.

For purposes of these investigations, the "pure field data" (patches) determined by the AMOEBA algorithm were used as the predetermined structure. A maximum likelihood parameter estimation procedure (HISSE) was designed to respect (take into account) field integrity.

A mathematical description and implementation of the procedure, along with results from preliminary tests, appear in the report:

Charles Peters and Frank Kampe, Numerical trials of HISSE, Contract NAS-9-14689, SR-HO-00477, Department of Mathematics, University of Houston, August, 1980.

Theoretical results underlying the approach used in the HISSE algorithm are discussed in the report:

Charles Peters, On the existence, uniqueness, and aymptotic normality of a consistent solution of the likelihood equations for nonidentically distributed observations--applications to missing data problems. Contract NAS-9-14689, SR-HO-00492, Department of Mathematics, University of Houston, September, 1980.

Additional theoretical results were obtained which address the convergence of a particular iterative form of the likelihood equations in the case of a mixture of densities from (possibly distinct) exponential families. These results appear in the report:

Richard A. Redner, An iterative procedure for obtaining maximum likelihood estimates in a mixture model, Contract NAS-9-14689, SR-T1-0481, Division of Mathematical Sciences, University of Tulsa, September, 1980.

Use of a modification of the HISSE model for the case of pure LANDSAT agricultural data sets are discussed in the attached report:

Charles Peters, On possible modifications of the HISSE model for pure agricultural data, Contract NAS-9-14689, SR-H1-04037, Department of Mathematics, University of Houston, February, 1981.

4. USE OF THE AKAIKE INFORMATION CRITERION

The objective of this study was to investigate the application of the Akaike Information Criterion (AIC) to a mixture model. In particular, investigations were carried out concerning the use of the AIC in selecting the number of components of a mixture model. The results of these investigations are discussed in the attached report:

Richard A. Redner, The Akaike information criterion and its application to mixture proportion estimation, Contract NAS-9-14689, SR-T1-04207, Division of Mathematical Sciences, University of Tulsa, November, 1981.

ATTACHED REPORTS

D1 Jack Bryant, System support documentation--IDIMS FUNCTION--AMOEBA, Department of Mathematics, Texas A&M University, March, 1982.

D2 James Heilman, Rice scene radiation characterization applied research, Remote Sensing Center, Texas A&M University, December, 1981.

D3 Charles Peters, On possible modifications of the HISSE model for pure agricultural data, Contract NAS-9-14689, SR-H1-04037, Department of Mathematics, University of Houston, February, 1981.

D4 Richard A. Redner, Genshiro Kitagawa, and William A. Coberly, The Akaike information criterion and its application to mixture proportion estimation, Contract NAS-9-14689, SR-T1-04207, Division of Mathematical Science, University of Tulsa, November, 1981.

D/

SYSTEM SUPPORT DOCUMENTATION

IDIMS FUNCTION

AMOEBA

Jack Bryant
Texas A&M University
College Station, Texas

March 1982

COMPUTER PROGRAM ABSTRACT

Sites At Which Developed: Texas A&M University and EROS Data Center

Symbolic Name: AMOEBA

Parent System: IDIMS

Language: FORTRAN 100%

Key Words: Clustering, Boundary detection, Classification, Spatial model, Pair probability of misclassification

Contact: Jack Bryant, Department of Mathematics, Texas A&M University, College Station, TX, 77843, 713-845-3169
Susan K. Jenson, Applications Branch, EROS Data Center, Sioux Falls, South Dakota

Status: Completed

ABSTRACT

AMOEBA is a clustering program based on a spatial-spectral model for image data. It is fast and automatic (in the sense that no parameters are required), and classifies each picture element into classes which are determined internally. As an IDIMS function, no limit on the size of the image is imposed.

TABLE OF CONTENTS

1. INTRODUCTION

AMOEBA is a clustering program designed during the Large Area Crop Inventory Experiment in 1977-78. The original idea* was developed in an agricultural setting (large fields, few real classes). It was a nice surprise to discover that the program solves other problems. It has an uncanny ability to discover structure in image data, at least when the structure exists. Because of the nature of the method, it operates efficiently on small (16 bit) computers lacking floating point hardware. In some sense, the smaller the computer the better it works.

Bugs? Before going on, we report a problem experienced at the EROS Data Center (EDC), a U.S. Geological Survey installation at Sioux Falls, South Dakota. Unquestionably correct FORTRAN source code produces nonsensical results. The bug is easily demonstrated, and may be related to the file management system of IDIMS. It is not encountered unless huge images with many bands are being processed. We do not know whether it is FORTRAN, IDIMS, the operating system, or local hardware. We do know it is not a problem in the source code. The source code is believed to be without error. Scores of hours with the Hewlett-Packard IDIMS-DEBUG utility only prove the program is lost. We welcome suggestions of any kind whatever which may indicate what is wrong. Fortunately, the bug shows up as a simple failure with meaningless cluster centers, or a bounds violation where, according to the source, none is possible. That is, it seems unlikely that the bug causes real damage since the user will be informed of garbage answers. A cynical systems programmer could suggest that a disappointed user use ISOCLS instead. A diligent one would find the bug, whatever it is. We are neither. We are only exhausted, and wish you luck if you look for it.

The Program. The idea underlying the program is easy to state. A full description is given in Appendix A. Here we sketch the idea. Our goal is to sort the pixels of an image into classes that will show an

---

*Jack Bryant, On the clustering of multidimensional pictorial data, Pattern Recognition 11, pp. 115-125, 1979.

analyst the structure of the image. Suppose one has two partitions of a set into a family of disjoint subsets. A measure of the distance between the partitions is the probability that points are clustered alike in the first and differently in the second, plus the probability they are classified alike in the second and differently in the first. Using a boundary finding algorithm, we can extract samples from the data we believe are alike. These will reside in spatially connected patches in the complement of the boundary. By ordering samples on some one-dimensional attribute, we are able to find some we believe are likely to be in different real classes. The samples, called test pixels, come in test sets of five each, and are used to evaluate our clustering. Test set means form starting cluster centers.

The number of clusterings of an image is astronomical. Rather than evaluate all clusterings, AMOEBA successively eliminates cluster centers which are involved in nearest neighbor assignments that split pairs from the same test set, or gather pairs from widely separated test pixels. Clusters are never combined, chained, or split. They are merely eliminated, starting with the set of test set means, and ending with a set of clusters between the user-supplied maximum and minimum numbers.

There are a number of general features about the program which have nothing to do with the clustering and classification method, but which do make the program harder to understand (harder, that is, than the big system original version in which data was assumed to be all in memory at once). Before we start detailed documentation, we comment on some of the trickier details which apply to more than one component. Nomenclature for the following:

COUNT -- a counter of the number of elements in each class.

ND -- the dimensionality or number of bands.

REJECT -- a vector of thresholds used to check classification based on a spatial mixture model.

Wide Image Logic. There is no limit to the size of input image which can be processed (other than disk storage). Yet there is a severe limitation on data storage: subroutines START and CLASSIFY each require three lines of data storage and three lines of labels. About 20,000 words

are available, so the maximum width is about 20,000/((ND+3)*3). If ND is 4, for example, fewer than 1000 samples per line can be processed. Therefore, the program segments the image into strips of width NC, with the actual width NZ being passed to various subroutines.

The Mask. In IDIMS, imagery is organized in rectangular arrays; however, the image itself is often not rectangular. The value 0 is usually stored in each band or channel of the "Mask". In AMOEBA, a logical flag MASK (optional parameter, default .TRUE.) is used to tell the program whether a value 0 in channel 1 is to be used as a mask. If set, no processing is wasted on these pixels. They are labelled with the label 99 and counted in COUNT(100). If some are found, their count is printed at the conclusion of the program.

Four Neighbors. Each pixel inside an image with rectangular organization has exactly four nearest neighbors. There are concepts for which more than the four neighbors can be considered. Discrete connectedness, however, is not one of them. AMOEBA uses discrete connectedness to form patches in the complement of the boundary. More precisely, a path is a sequence $p_1,\ldots,p_n$ of pixels such that p_i is a neighbor of p_{i+1} for $i = 1,\ldots,n-1$. A set of pixels is said to be connected if each pair of points in the set is contained in a path lying entirely in the set. For example, a singleton (a set containing only one pixel) is a connected set, as is the entire image. In this discrete setting, the concept is simple, but has considerable power. Let A be an arbitrary set of pixels. For each a in A, the set of all elements of A which can be joined to a by a path within A is a connected subset of A, and is, in fact, the largest (maximal) connected subset of A containing a. Maximal connected subsets of a set are called components of the set. The patches of AMOEBA are the components of the complement of the boundary. For this to work, only the four nearest neighbors can be considered when deciding what a path is.

In the classification step, again only four neighbors are considered. Here, however, we are really making a concession to the relatively low resolution of Landsat MSS data, to poor registration of multi-temporal imagery, and to computer-time spent in classification. It would

certainly be possible to consider 8 neighbors; this has, in fact, been done in areas dominated by agricultural activity, but for general usage with Landsat resolution four neighbors are enough.

Circular Buffers. The boundary-finding and classification sections of the program require not only a pixel but the neighborhood of the pixel. With only the four nearest neighbors to consider, three lines suffice. Rather than move the data or maps around, we simply switch pointers, rolling old labels or maps out to disk and new data in. The logic is simple, and is programmed as follows: Initially, pointers I1, I2, and I3 are 1, 2, and 3. I1 is the eldest, I2 the current time to be processed, and I3 the newest. After a line has been processed, the line pointed to by I1 is stashed, data is read into the data slot pointed to by I1, and the data buffer is "rotated" by saving I1, setting I1 = I2, I2 = I3, and then I3 = the old I1.

Tricking FORTRAN. Short FORTRAN integers are 16 bits long; in the HP-3000, this is the word size. Other than 16 bit processing consumes time all out of porportion to the benefit. An obvious case is floating point processing, but long (32 bit) integer processing is also expensive.

However, standard FORTRAN two's complement arithemtic is simply not adequate. We "trick" FORTRAN by biasing all distance calculations by -32768 (in octal, 100000, in hex 8000). That is, "zero" is actually the bit pattern 1 followed by 15 zeros, and numbers grow from there to the largest two's complement integer, 32767. The same trick is used in forming labels for patches of sure pixels. We allow for 64K labels by starting the labels at -32767 (-32768 is used to mark boundary). In several places, the bias needs to be removed, and care must be taken to insure this is properly executed.

Rejection Thresholds. Boundary pixels come in two flavors: pure and contaminated. The pure ones are rare (usually not more than 20% of the image), but are easy to model. Consider the spectral picture in which a pixel represents the sensor-average of two pure classes. This we call a pure boundary pixel. A case can be made for classification of such a pixel in the nearer of the classes of which it is a mixture. Obviously, such a pure mixture is nearer the one to which it is assigned than half the distance between. This is the basis underlying the

Rejection Thresholds. For each cluster, the Rejection Threshold (calculated in subroutine REJECTH and kept in REJECT(ND)) is half the distance between this cluster and the other cluster the greatest distance away. (Actually, the square of the distance, biased by -32768, is maintained.)

The model is strictly applicable in the absence of registration error, but the model can be extended. The result, easily obtained from Jensen's inequality, is: for registration errors, the otherwise uncontaminated distances should be no farther than $\sqrt{2}$ times the pure model. Pixels which fail this test are not classified (or reclassified). However, test pixels are believed to be pure, particularly the third in a test set of five. Therefore, in MOREQUES, the stricter test is imposed. New classes are introduced when the center test pixel fails the strict test.

Memory Management and Subroutine Linkage. Although the HP-3000 system allows dynamic array definition, we only use this in opening files (these routines must be changed to move the program to another system anyway). Memory is managed in the main program in an interger array called WORK (which is equivalenced to a logical array LWORK). This gets memory managed but makes subroutine linkage difficult to follow. As an aid to the Systems Analyst who must maintain the program, we give the exact calling sequences as they appear in MAIN, the subroutine version, and the various values of memory management parameters.

THRFND (finds integer vector thresholds, returned in WORK(1))

```
CALL THRFND (NFL,WORK(MM1), WORK(MM3), UICB, IND, WORK(MM4), NR, NC,
ND, MASK, IMGIN)

SUBROUTINE THRFND(NFL,INTTHR, SCANLINE, UICB, IND, DOUNT, NR, NC, ND,
MASK, IMGIN)
```

MM1 = 1	WORK(MM1)	INTTHR(ND)
MM3 = MM1 + ND	WORK(MM3)	SCANLINE(NC,ND)
MM4 = MM3 + ND*NC	WORK(MM4)	KOUNT(ND)

START (using the thresholds, estimate the boundary and create a disk file of boundary labels and patch labels)

```
CALL START(WORK(MM1), ND, NR, NC, NZ, WORK(MM3), WORK(MM4), WORK(MM5),
     UICB, IND, IMGIN, IMGCLAS, LABF, MASK)

SUBROUTINE START(INTTHR, ND, NR, NC, NZ, DATBUF, LABBUF, ISCAN, UICB,
                 IND, IMGIN, IMGCLAS, LAD, MASK)

MM1,3 as before              WORK(MM1)          INTTHR(ND)
MM4 = MM3+NC*ND*3            WORK(MM3)          DATBUF(NC,ND,3)
MM5 = MM4+CN*3               WORK(MM4)          LABBUF(NC,3)
                             WORK(MM5)          ISCAN(1)
```

Note: Parameters NC and NZ and their interaction are described in the documentation to START.

ASELECT (select test sets and write on temporary disk file)

```
CALL ASELECT(WORK(MM2), WORK(MM3), WORK(MM4), NL, NS, NR, NC, NZ, ND,
     NTS, WORK(MM5), WORK(MM6), FILENO, UICB, IND, IMGEN, IMGCLAS)

SUBROUTINE ASELECT(DAT, LAB, KNT, NL, NS, NR, NC, NA, ND, NTS, DATA,
                   LABEL, FILENO, UICB, INC, IMGEN, IMGCLAS)

  MM2 = MM1+ND                WORK(MM2)        DAT(NL,ND,NS)
  MM3 = MM2+NL*ND*NS          WORK(MM3)        LAB(NL)
  MM4 = MM3+NL                WORK(MM4)        KNT(NL)
  MM5 = MM4+NL                WORK(MM5)        DATA(NC,ND)
  MM6 = MM5+NC*ND             WORK(MM6)        LABEL(NC)
```

Note: Parameters NL and NS are described in the documentation to ASELECT.

THINTSTM ("thin" test sets and form mean vectors)

```
CALL THINTSTM(WORK(MM2), WORK(MM3), LWORK(MM4), WORK(MM5), WORK(MM6),
     N25, N60, N288, N140, N388, N428, ND, NTS, FILENO, UICB, IND)
```

```
SUBROUTINE THINTSTM(MP, TSP, TTP, CLASS, COUNT, N25, N60, N288, N140,
     N388, N428, ND, NTSI, FILENO, UICB, IND)

MM2   as before              WORK(MM2)        MP(ND,N140)
MM3 = MM2+ND*N428            WORK(MM3)        TSP(ND,5,N428)
MM4 = MM3+ND*N428*5          LWORK(MM4)       TTP(ND,5,N25
MM5 = MM4+N25*ND*5           WORK(MM5)        CLASS(N25)
MM6 = MM5+MM428              WORK(MM6)        COUNT(N140)
```

Note: N25, N60, N140, N428, N388, and N288 are described in the documentation to THINTSTM.

SORT (sorts test pixel sets in average odd channel order)

```
CALL SORT(WORK(MM3), WORK(MM4), WORK(MM5), ND, N428T5, N428)

SUBROUTINE SORT(TSPXL, DUMMY, INDEX, ND, NP, NP5)

MM3   as before              WORK(MM3)        TSPXL(ND,NP)
MM4 = MM3+ND*N428T5          WORK(MM4)        DUMMY(NP5)
MM5 = MM4+NP5                WORK(MM5)        INDEX(NP5)
N428T5 = N428*5
```

NUMCLU (determines the number of clusters and their centers)

```
CALL NUMCLU(WORK(MM2), ND, N140, N428T5, WORK(MM3), NFCLUS, MINCLN,
     MAXCLN, WORK(MM4), WORK(MM5), WORK(MM6), WORK(MM7), WORK(MM8), WORK(MM9),
     UICB, IND, WORK(MM10))

SUBROUTINE NUMCLU(MEAN, ND, NP5, NP, TSPXL, NFCLUS, MINCLN, MAXCLN,
     CLASS, COUNT, ERROR, SAVE, DUM, CSAVE, UICB, IND, NUM)

MM2, MM3 as before           WORK(MM2)        MEAN(ND,NP5)
N140 and N428 were modified  WORK(MM3)        TSPXL(ND,NP)
MM4 = MM3+ND*N428T5          WORK(MM4)        CLASS(NP)
MM5 = MM4+N428T5             WORK(MM5)        COUNT(NP5)
MM6 = MM5+N140               WORK(MM6)        ERROR(NP5)
MM7 = MM6+N140               WORK(MM7)        SAVE(NP5)
MM8 = MM7+N140               WORK(MM8)        DUM(NP5)
MM9 = MM8+N140               WORK(MM9)        CSAVE(NP)
MM10 = MM9+N428T5            WORK(MM10)       NUM(NP5)
```

MOREQUES (Classifies center test pixel and adds more clusters if they are needed; also initializes REJECT)

```
CALL MOREQUES(WORK(MM2), WORK(MM3), MAXCLUS, NFCLUS, ND, N428T5, WORK(MM5))

SUBROUTINE MOREQUES(MEANS, TESTS, MAXCLUS, NFCLUS, ND, NTS, REJECT)
```

MM2, MM3 as before	WORK(MM2)	MEANS(ND, MAXCLUS)
MM5 = 20900	WORK(MM3)	TESTS(ND, NTS)
	WORK(MM5)	REJECT(MAXCLUS)

CLASSIFY (performs a spatially checked per pixel nearest neighbor classification)

```
CALL CLASSIFY(WORK(MM3), WORK(MM2), WORK(MM4), NR, NC, NZ, ND, WORK(MM5),
     NFCLUS, UICB, IND, IMGIN, IMGCLAS, MAXCLUS, COUNT, MASK)

SUBROUTINE CLASSIFY(PIXELS, CLUSTERS, LABELS, NR, NC, NZ, ND, REJECT,
     NFCLUS, UICB, IND, IMGIN, IMGCLAS, MAXCLUS, COUNT, MASK)
```

MM2 as before	WORK(MM3)	PIXELS(NC,ND,3)
MM3 = MM2+N288*ND	WORK(MM2)	CLUSTERS(ND,MAXCLUS)
MM4 = MM3+NC*ND*3	WORK(MM4)	LABELS(NC,3)
MM5 as before	WORK(MM5)	REJECT(MAXCLUS)
COUNT is INTEGER*4	COUNT(100)	COUNT(100)

These comments should make it easier to follow subroutine linkage and memory management.

Organization of Detailed Documentation. There are only five subroutines with logic complex enough to require a detailed description of the algorithm. These are THRFND, START, ASELECT, THINTSTM, and NUMCLU, and will receive more attention in the documentation which follows. As for the main program, IDIMS parameter prompting and file management is easily followed from the source. Because of the elaborate interface IDIMS puts between the user and the outside world, the I/O portion of the program is at least three times the length it would be in a normal FORTRAN environment. But mere length does not make a program hard to understand, and the main

program of AMOEBA is truly self-documenting. The remainder of this document consists of a listing of the main program followed by documentation of each subroutine (in alphebetical order). Appendix A contains a detailed description of the theoretical foundation of the program, Appendix B contains a summary of each of the system subroutines used in AMOEBA, with references to IDIMS and HP documentation, Appendix C contains IDIMS User documentation, Appendix D shows the listing obtained in an interactive sample use of the function, and Appendix E shows a batch job to use the function.

Acknowledgement. We would like to express our gratitude to each of the many scientists who took time to evaluate the results of AMOEBA clustering. Their suggestions and critical remarks led to several improvements.

2. MAIN

Program AMOEBA Listing

```
PAGE 0001   HP32102B.01.33 FORTRAN/3000 (C) HEWLETT-PACKARD CO. 1980  TUE, OCT 13, 1981,  9:35 AM

00001000  $CONTROL SEGMENT=ANDEBASEG
00002000  $CONTROL LIST,LOCATION,MAP
00333   00003000         SUBROUTINE ANDEBA(UICB,ZERO)
00333   00004000         INTEGER*2 RECSIZE,ERR,SNAMEB,TNINGEB
00333   00005000         CHARACTER*1 SYMBOL(59)
00333   00006000         INTEGER*2 UICB(1),ZERO(1),IND(4),WORK(21000),OUTTYPE,FILENO
00333   00007000         INTEGER*4 DLAB,COUNT(100)
00333   00008000         LOGICAL STATFILE,LWORK(21000),LA,LB,MASK,CHANINAP,LABLMAP,CLASMAP
00333   00009000         CHARACTER*1 EQCHMAP,EQLMAP,EQCLMAP,EQMASK
00333   00010000         CHARACTER*22 SNAME
00333   00011000         CHARACTER*64 EQNAM
00333   00012000         CHARACTER*72 TNING
00333   00013000         INTEGER*2 NAMES(8),ADDRS(8),CODES(8),FILNUM,CHNAP,LMAP,CLMAP
00333   00014000        +    ,BLKSIZE(1),IPCBAR(128),IMASK,PRINTSL,PRINTNL,PRINTSS
00333   00015000         EQUIVALENCE (LWORK(1),WORK(1)),(EQNAM,NAMES),(LA,IA),(LB,IB)
00333   00016000         EQUIVALENCE (SNAMEB,SNAME),(TNING,TNINGEB),(EQCHMAP,CHNAP)
00333   00017000        +    ,(EQLMAP,LMAP),(EQCLMAP,CLMAP),(EQMASK,IMASK)
00333   00018000         SYSTEM INTRINSIC FOPEN,FLNECK
00333   00019000         SNAME = '                      '
00334   00020000         NPARMS = 8
00336   00021000         EQNAM =
00336   00022000        +'STATFILEFCNTFLDSCHANINAPLABELMAPCLASSMAPMASK     MINCLUS MAXCLN'
00442   00023000         CODES(1) = %1003
00445   00024000         CODES(2) = %1
00451   00025000         CODES(3) = %103
00456   00026000         CODES(4) = %103
00461   00027000         CODES(5) = %103
00466   00028000         CODES(6) = %103
00467   00029000         CODES(7) = %1
00474   00030000         CODES(8) = %1
00477   00031000         ADDRS(1) = IADDRESS(SNAMEB)
00502   00032000         ADDRS(2) = IADDRESS(NFL)
00507   00033000         ADDRS(3) = IADDRESS(CHNAP)
00514   00034000         ADDRS(4) = IADDRESS(LMAP)
00521   00035000         ADDRS(5) = IADDRESS(CLMAP)
00526   00036000         ADDRS(6) = IADDRESS(IMASK)
00533   00037000         ADDRS(7) = IADDRESS(MINCLN)
00540   00038000         ADDRS(8) = IADDRESS(MAXCLN)
00545   00039000         BLKSIZE(1) = 512
00550   00040000         CALL ATHUDS(UICB,IND,1,BLKSIZE,IPCBAR,128)
00566   00041000         IF (IND(1) LT 0) CALL CHAIO(UICB,IND,1,BLKSIZE(1),IPCBAR(1),0,37)
00612   00042000  C -- INITIALIZE BEFORE CALL TO PARAMS
00612   00043000         NFL = 45
00616   00044000         STATFILE =  TRUE
00616   00045000         EQCHMAP = 'N'
00627   00046000         EQLMAP  = 'N'
00632   00047000         EQCLMAP = 'N'
00643   00048000         EQMASK  = 'Y'
00654   00049000         MINCLN = 10
00657   00050000         CHANINAP =  FALSE
00660   00051000         LABLMAP  =  FALSE
00662   00052000         CLASMAP  =  FALSE
00664   00053000         MASK =  TRUE
00666   00054000         MAXCLN = 90
00676   00055000         CALL PARAMS(UICB,NAMES,CODES,ADDRS,NPARMS)
00722   00056000         IF (MAXCLN LT 90 OR MAXCLN GT 90) MAXCLN = 90
00712   00057000         MIDS = UICB(61)
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PAGE 0002   AMOEBA

00715  00058000          NODS = UICB(62)
00720  00059000          IF (NIDS.NE.1) CALL PABORT(UICB,1,0)
00733  00060000          IF (NODS.NE.1) CALL PABORT(UICB,1,0)
00746  00061000  C  CHECK IF STATFILE NAME IS NOT SUPPLIED
00746  00062000          IF (CODES(1)(0:1).EQ.0) GO TO 1009
00754  00063000          DO 5 I = 8,1,-1
00761  00064000          IF (SNAME(I:1).NE.' ') GO TO 6
01002  00065000     5    CONTINUE
01002  00066000          CALL PABORT(UICB,-63,0)
01013  00067000     6    SNAME(I+1:7) = '.STATS '
01032  00068000          IA = 1
01034  00069000          IB = 1
01036  00070000          RECSIZE = 140 + 2*ND
01042  00071000  C  OPEN STATFILE AS OLD TO CHECK FOR DUPLICATE NAME
01042  00072000          FILNUM = FOPEN(SNAME,LA,LB,RECSIZE)
01053  00073000          CALL FCHECK(0,ERR,,,)
01060  00074000          IF (ERR.EQ.0) CALL PABORT(UICB,45,0)
01073  00075000          IA = 0
01075  00076000          FILNUM = FOPEN(SNAME,LA,LB,RECSIZE)
01106  00077000          CALL FCHECK(0,ERR,,,)
01113  00078000          IF (ERR.EQ.0) GO TO 1110
01120  00079000          CALL PABORT(UICB,45,0)
01130  00080000     1009 STATFILE = .FALSE.
01137  00081000     1110 CONTINUE
01132  00082000  C--   ASSIGN LOGICALS
01132  00083000          IF (EQCHMAP.EQ.'Y') CHANMAP = .TRUE.
01144  00084000          IF (EQLMAP .EQ.'Y') LABLMAP  = .TRUE.
01156  00085000          IF (EQCLMAP.EQ.'Y') CLASMAP  = .TRUE.
01170  00086000          IF (EQMASK .EQ.'N') MASK     = .FALSE.
01202  00087000  C -- DO MAPPING PARAMS
01202  00088000          IMGIN = 1
01204  00089000          IMGCLAS = -1
01206  00090000  C
01206  00091000  C  OPEN INPUT TO GET ND & NC, THEN CLOSE
01206  00092000          CALL OPENPI(UICB,IND,IMGIN,INTYPE,ND,NR,NC,1)
01227  00093000          IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGIN,ND,NR,NC,100)
01243  00094000          IF (ND.GT.16.OR.ND.LT.2) CALL PABORT(UICB,48,0)
01261  00095000          OUTTYPE = 2
01262  00096000          CALL CLOSEP(UICB,IND,IMGIN,0)
01274  00097000          IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGIN,1,2,3,99)
01317  00098000          IF ( NOT (CHANMAP.OR.LABLMAP.OR.CLASMAP)) GO TO 8
01326  00099000          NPARMS = 3
01330  00100000          PRINTSL = 1
01332  00101000          PRINTNL = NR
01334  00102000          PRINTSS = 1
01336  00103000          ECHAR = 'PRINTSL PRINTNL PRINTSS '
01362  00104000          CODES(1) = %1
01367  00105000          CODES(2) = %1
01372  00106000          CODES(3) = %1
01377  00107000          ADDRS(1) = IADDRESS(PRINTSL)
01411  00108000          ADDRS(2) = IADDRESS(PRINTNL)
01405  00109000          ADDRS(3) = IADDRESS(PRINTSS)
01412  00110000          CALL PARAMS(UICB,NAMES,CODES,ADDRS,NPARMS)
01424  00111000     8    CONTINUE
01424  00112000  C
01424  00113000  C  TAKE CARE OF WIDE IMAGES:
01424  00114000  C
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PAGE 0003   ANDEBA

01424  00115000  C  NZ IS ACTUAL WIDTH
01424  00116000  C  NC IS TARGET NUMBER GRABBED AT A TIME
01424  00117000  C  EACH SUBROUTINE MUST MANAGE ACTUAL PARAMETERS FOR
01424  00118000  C  READP, WRITEP, AND THEIR SUBROUTINES.
01424  00119000        NZ = NC
01426  00120000        NCT = 20000/(3*(ND+1))
01434  00121000        DO 1001 I = 1,99
01441  00122000          NC = NZ/I+1
01446  00123000          IF (NC LE NCT) GO TO 1002
01454  00124000   1001 CONTINUE
01455  00125000   1002 CONTINUE
01455  00126000  C
01455  00127000  C  INITIAL ESTIMATES FOR BUFFERS
01455  00128000  C  NBR -- NUMBER OF BUFFERS ON READ
01455  00129000  C  NBW -- NUMBER OF BUFFERS ON WRITE
01455  00130000  C  GET AS MANY READ AS POSSIBLE!
01455  00131000        NBR = MIN0(ND+2,2)
01464  00132000        NBW = 2
01466  00133000  C
01466  00134000  C  OPEN IMAGES FOR REAL NOW
01466  00135000  C  OPEN OUTPUT IMAGE
01466  00136000        CALL OPENPO(UICB,IND,IMGCLAS,ZERO,OUTTYPE,1,NR,NZ,NBW)
01505  00137000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGCLAS,NR,NZ,NBW,101)
01525  00138000  C OPEN INPUT -- TRY UNTIL NBR IS 2
01525  00139000   994  CALL OPENPI(UICB,IND,IMGIN,INTYPE,ND,NR,NZ,NBR)
01540  00140000        IF (IND(1).GE.0) GO TO 996
01545  00141000  C  OUT OF VIRTUAL MEMORY?
01545  00142000        IF (IND(2).NE.37) CALL CHKIO(UICB,IND,IMGIN,
01545  00143000       *  NBR,NBW,0,102)
01566  00144000        IF (NBR.LE.2) GO TO 995
01572  00145000        NBR = NBR - 1
01573  00146000        GO TO 994
01574  00147000  C  NBR IS LESS THAN OR EQUAL TO 2, SO..
01574  00148000   995  IF (NBW.EQ.1 AND NBR.EQ.1) CALL PABORT(UICB,17,0)
01612  00149000        IF (NBW.EQ.2) GO TO 993
01616  00150000        NBR = 1
01620  00151000   993  NBW = 1
01622  00152000  C REDO OUTPUT WITH FEWER BUFFERS & TRY AGAIN
01622  00153000        CALL CLOSEP(UICB,IND,IMGCLAS,1)
01633  00154000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGCLAS,0,0,0,89)
01655  00155000        CALL OPENPO(UICB,IND,IMGCLAS,ZERO,OUTTYPE,1,NR,NZ,NBW)
01674  00156000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGCLAS,NZ,NBW,NBR,103)
01714  00157000        GO TO 994
01715  00158000  C CAN'T DO IT - INPUT IMAGE TOO BIG
01715  00159000   997  CALL PABORT(UICB,17,0)
01725  00160000  C -- ALL OPENS COMPLETE AND SUCCESSFUL
01725  00161000   996   CONTINUE
01725  00162000  C
01725  00163000  C  TELL ME HOW MANY BUFFERS I GOT
01725  00164000        WRITE (TMING,1010) NBR,NBW
01750  00165000   1010 FORMAT(9H YOU HAVE,I3,19H READ BUFFER(S) AND,I2,
01750  00166000       * 17H WRITE BUFFER(S)  )
01750  00167000        CALL PRINTP(UICB,IND,1,TMINGE0,50,0,0,0,0,0,0,0,0)
01777  00168000  C  JOFX(-1) IS INTTHR -- USED BY START
01777  00169000  C
01777  00170000  C  DETERMINE IF THE DATA CONTAINS ANY VALUE  GE  128
01777  00171000  C  FIRST READ THE DATA
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PAGE 0004   AMOEBA

01777  00172000          MRS = 1+MR/99
02003  00173000          MCS = 1+MZ/199
02007  00174000          DO 32 IR = 1,MR,MRS
02014  00175000          DO 32 K = 1,MD
02021  00176000          CALL READP(UICB,IND,IMGIN,WORK,2,1,IR,1,MZ,IR,K+1,1,MZ)
02051  00177000          IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGIN,IR,MZ,R,82)
02071  00178000          DO 32 J = 1,MZ,MCS
02076  00179000          IF (WORK(J).GE.128) GO TO 33
02105  00180000       32 CONTINUE
02110  00181000          GO TO 34
02111  00182000       33 WRITE(TMING,35)
02130  00183000       35 FORMAT(38H YOUR IMAGE CONTAINS A VALUE OVER 127.)
02150  00184000          CALL PRINTP(UICB,IND,1,TMINGE0,38,0,0,0,0,0,0,0,0)
02157  00185000          WRITE(TMING,36)
02175  00186000       36 FORMAT(44H PLEASE USE MAP TO PUT INTO THE RANGE 0-127.)
02175  00187000          CALL PRINTP(UICB,IND,1,TMINGE0,44,0,0,0,0,0,0,0,0)
02224  00188000          CALL PABORT(UICB,40,0)
02234  00189000       34 CONTINUE
02234  00190000          X = (20760.-FLOAT(NC*(MD+1))/FLOAT(MD))
02245  00191000          ML = IFIX(SQRT(X))
02254  00192000          MS = IFIX((21000.-FLOAT(2*ML)-FLOAT(NC*(MD+1)))/FLOAT(MD*ML))
02272  00194000  C
02273  00195000  C  THRFND DOESN'T NEED AS MUCH ROOM...
02273  00196000          MCS = NC
02275  00197000          NC = NC*3
02300  00198000          IF (NC.GT.MZ) NC = MZ
02302  00199000          MM1 = 1
02307  00200000          MM3 = MM1+MD
02312  00201000          MM4 = MM3+MD*NC
02316  00202000          CALL THRFND(MFL,WORK(MM1),WORK(MM3),UICB,IND,WORK(MM4),
02316  00203000         * MF,NC,MD,MASK,IMGIN)
02337  00204000          DO 37 I = 1,MD
02344  00205000          IF (WORK(I).LE.0) WORK(I) = 1
02352  00206000       37 CONTINUE
02354  00207000          WRITE(TMING,1111) (WORK(K),K = 1,MD)
02404  00208000    1111 FORMAT(' INTTHR = ',1613)
02404  00209000          CALL PRINTP(UICB,IND,1,TMINGE0,10+3*MD,0,0,0,0,0,0,0,0)
02435  00210000  C
02435  00211000  C  RESTORE NC
02435  00212000          NC = MCS
02437  00213000          MM4 = MM3+NC*MD*3
02444  00214000          CALL SETSYM(SYMBOL)
02450  00215000          MM5 = MM4+NC*3
02454  00216000          CALL START(WORK(MM1),MD,MR,NC,MZ,WORK(MM3),WORK(MM4),WORK(MM5),
02454  00217000         * UICB,IND,IMGIN,IMGCLAS,LABF,MASK)
02511  00218000          DLAB = LABF
02515  00219000          DLAB = DLAB+32768
02521  00220000          WRITE(TMING,2222) DLAB
02542  00221000    2222 FORMAT(' DLABEL$ = ',I5)
02542  00222000          CALL PRINTP(UICB,IND,1,TMINGE0,18,0,0,0,0,0,0,0,0)
02571  00223000          IF(CHANIMAP)CALLMAPP(PRINTSL,PRINTNL,PRINTSS,UICB,IND,IMGIN,
02571  00224000         *  MF,MZ,SYMBOL)
02611  00225000    2033 IF(LABLMAP)CALLMAPP(PRINTSL,PRINTNL,PRINTSS,UICB,IND,IMGCLAS,
02611  00226000         *  MF,MZ,SYMBOL)
02631  00227000          MM2 = MM1+MD
02634  00228000          MM3 = MM2+ML*MD*MS
02641  00229000          MM4 = MM3+ML
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02644  00230000         MM5 = MM4+NL
02647  00231000         MM6 = MM5+NC*ND
02653  00232000         CALL ASELECT(WORK(MM2),WORK(MM3),WORK(MM4),NL,NS,NR,
02653  00233000        * NC,NZ,ND,NTS,WORK(MM5),WORK(MM6),FILENO,UICB,IND,INGIN,INGCLAS)
02704  00234000   C  NTS IS THE NUMBER OF TEST SETS STASHED BY SELECT
02704  00235000         WRITE(TMING,3333) NTS
02725  00236000    3333 FORMAT(' BTSTSTS = ',I9)
02725  00237000         CALL PRINTP(UICB,IND,1,TMINGE0,16,0,0,0,0,0,0,0,0)
02754  00238000         N25 = 25
02756  00239000         N60 = 60
02760  00240000         N140 = 140
02762  00241000         N428 = 3000/(ND+3)
02767  00242000         N388 = N428-40
02772  00243000         N288 = N388-100
02775  00244000         IF (N288.LT.100) N288 = 100
03002  00245000         MM3 = MM2+ND*N428
03006  00246000         MM4 = MM3+ND*N428+5
03013  00247000         MM5 = MM4+N25*ND*5
03020  00248000         MM6 = MM5+N428
03023  00249000   C  WORK(MM2) IS MEAN(ND,N140)
03023  00250000   C  WORK(MM3) IS TSTPXL(ND,N428+5)
03023  00251000   C  HOWEVER, ALLOW FOR N428 IN CASE WE HAVE FEW
03023  00252000         CALL TMINTSTM(WORK(MM2),WORK(MM3),LWORK(MM4),WORK(MM5),
03023  00253000        * WORK(MM6),N25,N60,N288,N140,N388,N428,ND,NTS,
03023  00254000        * FILENO,UICB,IND)
03033  00255000         N428TS = N428+5
03036  00256000         MM4 = MM3+N428TS*ND
03070  00257000         MM5 = MM4+N428
03073  00258000         CALL SORT(WORK(MM3),WORK(MM4),WORK(MM5),ND,N428TS,N428)
03107  00259000         MM5 = MM4+N428TS
03110  00260000         MM6 = MM5+N140
03113  00261000         MM7 = MM6+N140
03116  00262000         MM8 = MM7+N140
03121  00263000         MM9 = MM8+N140
03124  00264000         MM10 = MM9+N428TS
03127  00265000         CALL NUMCLU(WORK(MM2),ND,N140,N428TS,WORK(MM3),NFCLUS,
03127  00266000        * MINCLN,WORK(MM4),WORK(MM5),WORK(MM6),WORK(MM7),
03127  00267000        * WORK(MM8),WORK(MM9),UICB,IND,WORK(MM10),MAXCLN)
03164  00268000         MAXCLUS = 98
03166  00269000         MM5 = 20900
03170  00270000         CALL MCREQUES(WORK(MM2),WORK(MM3),MAXCLUS,NFCLUS,ND,
03170  00271000        * N428TS,WORK(MM5))
03203  00272000         CALL MSORT(WORK(MM2),ND,NFCLUS,WORK(MM6),WORK(MM7))
03214  00273000   C
03214  00274000   C  CLOSE TEMP IMAGE AND OPEN CLUSTER MAP
03214  00275000         CALL CLOSEP(UICB,IND,INGCLAS,1)
03225  00276000         IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGCLAS,0,0,0,77)
03247  00277000         CALL DELUDS(UICB,IND)
03254  00278000         IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGCLAS,0,0,0,78)
03276  00279000         INGCLAS = 2
03303  00280000         CALL OPENPO(UICB,IND,INGCLAS,ZERO,1,1,NR,NZ,NBW)
03320  00281000         IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGCLAS,ND,NR,NZ,79)
03340  00282000         MM3 = MM2+ND*N288
03344  00283000         MM4 = MM3+NC*ND*3
03351  00284000         CALL CLASSIFY(WORK(MM3),WORK(MM2),WORK(MM4),NR,NC,NZ,ND,
03351  00285000        * WORK(MM5),NFCLUS,UICB,IND,INGIN,INGCLAS,MAXCLUS,COUNT,MASK)
03461  00286000         NFF = ND+4+7
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PAGE 0006   AMOEBA

03405  00287000        WRITE(THING,222)NFCLUS
03426  00288000    222 FORMAT(' FINAL NUMBER OF CLUSTERS  =',I3)
03426  00289000        CALL PRINTP(UICB,IND,1,THINGE@,31,0,0,0,0,0,0,0,0)
03455  00290000        DO 10 I = 1,NFCLUS
03462  00291000        IF (COUNT(I+1).LE.0) GO TO 10
03475  00292000        WRITE(THING,333) COUNT(I+1),(WORK(K+I*ND)
03475  00293000       * ,K = 1,ND)
03534  00294000    333 FORMAT(I7,16I4)
03534  00295000        CALL PRINTP(UICB,IND,1,THINGE@,MPP,0,0,0,0,0,0,0,0)
03562  00296000     10 CONTINUE
03562  00297000        IF (COUNT(1).EQ.0) GO TO 445
03573  00298000        WRITE(THING,444) COUNT(1)
03616  00299000    444 FORMAT(' THERE ARE ',I7,' UNCLASSIFIED.')
03616  00300000        CALL PRINTP(UICB,IND,1,THINGE@,32,0,0,0,0,0,0,0,0)
03645  00301000    445 IF (COUNT(100).EQ.0) GO TO 556
03655  00302000        WRITE(THING,555) COUNT(100)
03700  00303000    555 FORMAT(18H THE MASK CONTAINS ,I7,8H POINTS.)
03720  00304000        CALL PRINTP(UICB,IND,1,THINGE@,33,0,0,0,0,0,0,0,0)
03727  00305000    556 CONTINUE
03727  00306000        IF(CLASNAP)CALLNAPP(PRINTSL,PRINTNL,PRINTSS,UICB,IND,INGCLAS,
03727  00307000       *  NR,NZ,SYMBOL)
03747  00308000        CALL CLOSEP(UICB,IND,INGCLAS,0)
03760  00309000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGCLAS,0,0,0,400)
04002  00310000        CALL CLOSEP(UICB,IND,INGIN,0)
04013  00311000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGIN,0,0,0,300)
04035  00312000  C-- WRITE STAT FILE
04035  00313000        IF (STATFILE) CALL AMSTATS (FILNUM,ND,WORK(MM2),COUNT,NFCLUS,UICB)
04051  00314000        R E T U R N
04052  00315000        END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
ADDRS	INTEGER	ARRAY	0+%17 ,I	AMOEBA		SUBROUTINE	
AMSTATS		SUBROUTINE		ASELECT		SUBROUTINE	
ATHNDS		SUBROUTINE		BLKSIZE	INTEGER	ARRAY	0+%23 ,I
CHANIMAP	LOGICAL	SIMPLE VAR	0+%113	CHKIO		SUBROUTINE	
CMMAP	INTEGER	SIMPLE VAR	0+%5 ,I	CLASMAP	LOGICAL	SIMPLE VAR	0+%107
CLASSIFY		SUBROUTINE		CLMAP	INTEGER	SIMPLE VAR	0+%11 ,I
CLOSEP		SUBROUTINE		CODES	INTEGER	ARRAY	0+%21 ,I
COUNT	INTEGER*4	ARRAY	0+%20 ,I	DELWDS		SUBROUTINE	
DLAB	INTEGER*4	SIMPLE VAR	0+%125	EOCHMAP	CHARACTER	SIMPLE VAR	0+%6 ,I
EOCLMAP	CHARACTER	SIMPLE VAR	0+%12 ,I	EOLMAP	CHARACTER	SIMPLE VAR	0+%10 ,I
EOMASK	CHARACTER	SIMPLE VAR	0+%14 ,I	EOMAP	CHARACTER	SIMPLE VAR	0+%16 ,I
ERR	INTEGER	SIMPLE VAR	0+%122	FCHECK		SUBROUTINE	
FILEMO	INTEGER	SIMPLE VAR	0+%104	FILNUM	INTEGER	SIMPLE VAR	0+%106
FOPEN	INTEGER	FUNCTION		I	INTEGER	SIMPLE VAR	0+%26
IA	INTEGER	SIMPLE VAR	0+%27	IADDRESS	INTEGER	FUNCTION	
IB	INTEGER	SIMPLE VAR	0+%30	IMASK	INTEGER	SIMPLE VAR	0+%13 ,I
INGCLAS	INTEGER	SIMPLE VAR	0+%31	INGIN	INTEGER	SIMPLE VAR	0+%73
IND	INTEGER	ARRAY	0+%22 ,I	INTYPE	INTEGER	SIMPLE VAR	0+%71
IPCBAP	INTEGER	ARRAY	0+%24 ,I	IP	INTEGER	SIMPLE VAR	0+%67
J	INTEGER	SIMPLE VAR	0+%70	K	INTEGER	SIMPLE VAR	0+%117
LA	LOGICAL	SIMPLE VAR	0+%27	LABF	INTEGER	SIMPLE VAR	0+%52

PAGE 0007 AMOEBA

LABELMAP	LOGICAL	SIMPLE VAR	0+%36
LMAP	INTEGER	SIMPLE VAR	0+%7 ,I
MAPP		SUBROUTINE	
MAXCLN	INTEGER	SIMPLE VAR	0+%63
MINCLN	INTEGER	SIMPLE VAR	0+%62
MP10	INTEGER	SIMPLE VAR	0+%103
MM3	INTEGER	SIMPLE VAR	0+%34
MM5	INTEGER	SIMPLE VAR	0+%37
MP7	INTEGER	SIMPLE VAR	0+%44
MP9	INTEGER	SIMPLE VAR	0+%50
MSORT		SUBROUTINE	
M25	INTEGER	SIMPLE VAR	0+%75
M388	INTEGER	SIMPLE VAR	0+%53
M428TS	INTEGER	SIMPLE VAR	0+%116
NAMES	INTEGER	ARRAY	0+%15 ,I
NBW	INTEGER	SIMPLE VAR	0+%61
NCS	INTEGER	SIMPLE VAR	0+%110
NE	INTEGER	SIMPLE VAR	0+%51
NFL	INTEGER	SIMPLE VAR	0+%121
NL	INTEGER	SIMPLE VAR	0+%72
NPARMS	INTEGER	SIMPLE VAR	0+%55
NR	INTEGER	SIMPLE VAR	0+%100
NS	INTEGER	SIMPLE VAR	0+%101
NUMCLU		SUBROUTINE	
OPENFI		SUBROUTINE	
OUTTYPE	INTEGER	SIMPLE VAR	0+%114
PARAMS		SUBROUTINE	
PRINTP		SUBROUTINE	
PRINTSS	INTEGER	SIMPLE VAR	0+%115
RECSIZE	INTEGER	SIMPLE VAR	0+%64
SNAME	CHARACTER	SIMPLE VAR	0+%2 ,I
SORT		SUBROUTINE	
START		SUBROUTINE	
SYMBOL	CHARACTER	ARRAY	0+%25 ,I
THINGER	INTEGER	SIMPLE VAR	0+%3 ,I
THRFND		SUBROUTINE	
WORK	INTEGER	ARRAY	0+%13 ,I
ZERO	INTEGER	ARRAY	0-%4 ,I

LB	LOGICAL	SIMPLE VAR	0+%30
LWORK	LOGICAL	ARRAY	0+%13 ,I
MASK	LOGICAL	SIMPLE VAR	0+%60
MAXCLUS	INTEGER	SIMPLE VAR	0+%76
MM1	INTEGER	SIMPLE VAR	0+%32
MM2	INTEGER	SIMPLE VAR	0+%33
MM4	INTEGER	SIMPLE VAR	0+%35
MM6	INTEGER	SIMPLE VAR	0+%41
MM8	INTEGER	SIMPLE VAR	0+%45
MOREQUES		SUBROUTINE	
M140	INTEGER	SIMPLE VAR	0+%57
M288	INTEGER	SIMPLE VAR	0+%54
M428	INTEGER	SIMPLE VAR	0+%102
M60	INTEGER	SIMPLE VAR	0+%40
NBR	INTEGER	SIMPLE VAR	0+%47
NC	INTEGER	SIMPLE VAR	0+%46
NCT	INTEGER	SIMPLE VAR	0+%112
NFCLUS	INTEGER	SIMPLE VAR	0+%120
NIDS	INTEGER	SIMPLE VAR	0+%42
NODS	INTEGER	SIMPLE VAR	0+%43
NFP	INTEGER	SIMPLE VAR	0+%74
NRS	INTEGER	SIMPLE VAR	0+%66
NTS	INTEGER	SIMPLE VAR	0+%56
NZ	INTEGER	SIMPLE VAR	0+%111
OPENPO		SUBROUTINE	
PABORT		SUBROUTINE	
PRINTNL	INTEGER	SIMPLE VAR	0+%65
PRINTSL	INTEGER	SIMPLE VAR	0+%105
READP		SUBROUTINE	
SETSYM		SUBROUTINE	
SNAME0	INTEGER	SIMPLE VAR	0+%1 ,I
SQRT	REAL	FUNCTION	
STATFILE	LOGICAL	SIMPLE VAR	0+%77
THING	CHARACTER	SIMPLE VAR	0+%4 ,I
THINTSTR		SUBROUTINE	
UIC0	INTEGER	ARRAY	0-%5 ,I
X	REAL	SIMPLE VAR	0+%123

PROGRAM UNIT AMOEBA COMPILED

3. DETAILED DOCUMENTATION OF SUBROUTINES

Parent: MAIN AMSTATS

AMSTATS(FILNUM,ND,MEAN,COUNT NFCLUS,UICB)

After the classification step, subroutine AMSTATS writes the means of the clusters to a disk file using the standard IDIMS format for statistics files.

Method: AMSTATS receives the means and counts as parameters. It then writes all the means and counts to a previously opened disk file, one mean vector per record. Vectors with count equal zero are not written. The file is written and closed using HP standard intrinsics. Since this statistics file does not contain a covariance matrix, it cannot be used in maximum likelihood classification or ellipse plotting.

Program Variables

BUFFER	INTEGER ARRAY I/O array
CLASS	CHARACTER Creator ID for statistics file
CONTROL	LOGICAL Carriage control bit mask for FWRITE
COUNT	DOUBLE INTEGER Pouplations of classes
FCLOSE	INTRINSIC To close files
FILNUM	INTEGER File number
FWRITE	INTRINSIC To write a record
I	INTEGER Index for number of classes loop
IM	INTEGER I minus 1
J	INTEGER Class number counter
K	INTEGER Index for number of dimensions loop
LBUFF	LOGICAL ARRAY Equivalenced to I/O array because FWRITE requires a logical array
MEAN	INTEGER ARRAY Array of mean vectors
ND	INTEGER Number of dimensions
NFCLUS	INTEGER Number of final clusters
NFCP	INTEGER Number of final clusters plus one
NUMPTS	INTEGER Field that must hold COUNT, overflow possible
PABORT	SYSTEM SUBROUTINE

RBUFF	REAL ARRAY Equivalenced to I/O buffer to allow stuffing of means in mandatory real format.
RESIZE	INTEGER Record size
UICB	INTEGER ARRAY User Information Control Block

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PAGE 0016   HEWLETT-PACKARD 32102B 01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:37 AM

00024  00493000  $CONTROL SEGMENT=AMOEBASEG
00024  00494000  C-- THIS SUBROUTINE WRITES THE STATISTICS FILE AT THE
00024  00495000  C-- COMPLETION OF THE PROGRAM
00024  00496000        SUBROUTINE ARSTATS(FILNUM,ND,MEAN,COUNT,NFCLUS,UICB)
00024  00497000        REAL RBUFF(1)
00024  00498000        SYSTEM INTRINSIC FWRITE,FCLOSE
00024  00499000        INTEGER*2 FILNUM,MEAN(ND,NFCLUS),RECSIZE,
00024  00500000       *  BUFFER(220),NUMPTS,UICB(1)
00024  00501000        INTEGER*4 COUNT(100)
00024  00502000        LOGICAL CONTROL,LBUFF(220)
00024  00503000        CHARACTER*8 CLASS
00024  00504000        EQUIVALENCE (BUFFER,CLASS),(BUFFER(5),NUMPTS),
00024  00505000       *  (BUFFER(141),RBUFF),(LBUFF,BUFFER)
00024  00506000        RECSIZE = 140+2*ND
00030  00507000        BUFFER(7) = 0
00033  00508000        NFCP = NFCLUS + 1
00036  00509000        CLASS = 'AMOEBA  '
00050  00510000        BUFFER(6) = ND
00053  00511000        CONTROL = FALSE.
00055  00512000        J = 1
00057  00513000  C  CLASS & COUNT 1 ARE UNCLASSIFIED PIXELS
00057  00514000  C
00057  00515000        DO 905 I = 2,NFCP
00064  00516000        IF (COUNT(I).EQ.0) GO TO 905
00073  00517000  C
00077  00518000  C -- NUMPTS CAN OVERFLOW  BUT THE CRUNNY STATFILE
00073  00519000  C -- HAS ONLY AN INTEGER*2 FIELD AVAILABLE
00073  00520000  C
00073  00521000        NUMPTS = COUNT(I)
00103  00522000        BUFFER(9) = J
00106  00523000        J = J + 1
00107  00524000        IN = I - 1
00112  00525000        DO 931 K = 1,ND
00117  00526000        RBUFF(K) = MEAN(K,IN)
00120  00527000   931  CONTINUE
00121  00528000        CALL FWRITE(FILNUM,LBUFF,RECSIZE,CONTROL)
00137  00529000        IF ( CC ) 903,905,903
00141  00530000   903  CALL FABORT(UICB,45,0)
00151  00531000   905  CONTINUE
00152  00532000        CALL FCLOSE(FILNUM,1,0)
00166  00533000        IF ( CC ) 907,909,907
00160  00534000   907  CALL FABORT (UICB,45,0)
00170  00535000   909  CONTINUE
00170  00536000        RETURN
00171  00537000        END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
ARSTATS		SUBROUTINE		BUFFER	INTEGER	ARRAY	0+233 ,I
CLASS	CHARACTER	SIMPLE VAR	0+234 ,I	CONTROL	LOGICAL	SIMPLE VAR	0+215
COUNT	INTEGER*4	ARRAY	0-236 ,I	FCLOSE		SUBROUTINE	
FILNUM	INTEGER	SIMPLE VAR	0-211 ,I	FWRITE		SUBROUTINE	
I	INTEGER	SIMPLE VAR	0+217	IN	INTEGER	SIMPLE VAR	0+210
J	INTEGER	SIMPLE VAR	0+212	K	INTEGER	SIMPLE VAR	0+214
LBUFF	LOGICAL	ARRAY	0+233 ,I	MEAN	INTEGER	ARRAY	0-217 ,I
ND	INTEGER	SIMPLE VAR	0-210 ,I	NFCLUS	INTEGER	SIMPLE VAR	0-219 ,I
NFCP	INTEGER	SIMPLE VAR	0+213	NUMPTS	INTEGER	SIMPLE VAR	0+235 ,I
FABORT		SUBROUTINE		RBUFF	REAL	ARRAY	0+236 ,I
RECSIZE	INTEGER	SIMPLE VAR	0+211	UICB	INTEGER	ARRAY	0-234 ,I

PROGRAM UNIT ARSTATS COMPILED

Parent: MAIN ASELECT
Calls: CLOSEC

ASELECT(DAT,LAB,KNT,NL,NS,NR,NC,NZ,ND,NTS,DATA,LABEL,FILENO,UICB,
IND,IMGIN,IMGCLAS)

Subroutine ASELECT takes a label map created by START and extracts test sets. Both the label map and test sets reside in temporary disk files. The test sets are passed to THINTSTM

Method. Using Wide Image Logic (see above), ASELECT segments the image into strips. Each strip is about 6666/(ND+1) elements wide. Within a strip, the labels map is scanned looking for samples having the same label. The data values are collected as encountered in a buffer DAT(NL,ND,NS). One scan line of data and labels, requiring NC*(ND+1) words of memory, are resident. For each label active, buffers KNT counting how many and LAB pointing to which are required. Thus NL*ND*NS+2*NL+NC+(ND+1) ≤ 21000 is required. If NL ≤ 120 is estimated, we have NL*NS ≤ (20760 - NC*(ND+1))/ND. We set NL equal to the square root of the right hand side, and NS as large as possible satisfying the first inequality. This memory allocation is performed in the main program. For example, suppose we are processing an image of NZ = 2048 elements wide. For ND = 2, 4, 8, 12, and 16, we tabulate NC, NL, and NS in Table 1. Even in the worst case, sufficient buffer space is available to collect 31 samples. Note that NC/NL is relatively constant, as is desirable. NC/NL is about 56.2 $\sqrt{ND}/(ND+1)$, and $\sqrt{ND}/(ND+1)$ varies slowly with ND, e.g. as ND goes from 4 to 16, NC/NL should vary from 11.6 to 13.2 (these estimates are for very large NZ).

Subroutine CLOSEC is called when:

(a) The number of elements KNT(J) in buffer J for a particular label equals NS; or,

(b) A new label is encountered and no slots are available to stash data having that label; or,

(c) in a new line, an old label is not found; or,

(d) a line with no labels whatever is found; or,

(e) when all lines have been processed.

CLOSEC performs the following functions:

(1) It closes buffer J by setting LAB(J) = Z (Z = -32768 marks no label).

(2) It shows another slot available by decrementing NA, the slot available pointer. (No slots are available if NA = NL.)

(3) If KNT(J) is at least 5, it selects five test pixels as spread out as possible and writes then on disk; a count is kept of this event, called NTS in ASELECT.

(4) It sets KNT(J) = 0.

In case (a), that slot is made avaiable. Action taken in (b) is to seek the eldest active label, close that one, and then begin the new label here. In case (c), each such buffer is closed (since this label will no longer be encountered). In (d) and (e), all active labels are closed.

In the Wide Image Logic, a boundary is generated when a new strip is started. This prevents the bottom labels of one strip from being joined to the top of the next, and also frees all buffers for a new start.

Program Variables

CHKIO	SYSTEM SUBROUTINE
CLOSEC	SUBROUTINE Writes test sets on disk after sampling, and frees buffer.
DAT(NL,ND,NS)	INTEGER ARRAY Used for accumulating patches by label (the first variable), dimension (second) and by count.
DATA(NC,ND)	INTEGER ARRAY One line of data.
FILENO	INTEGER The file of test pixels, opened and written by CLOSEC.

I,IREAD,J,JS,K	INTEGER DO loop index.
IMGCLAS	INTEGER Label map file number.
IMGIN	INTEGER Data file number.
IND(1)	INTEGER ARRAY Error indicator.
KN	INTEGER Count number.
INT(NL)	INTEGER ARRAY Running count of number of each label found.
LAB(NL)	INTEGER ARRAY Label of particular slot. Note: For each J, KNT(J) is the number found so far with label LAB(J); these samples are stored in DAT(J,.,1) through DAT(J,.,KNT(J)).
LABEL(NC)	INTEGER ARRAY A line of labels.
LOLD	INTEGER Used in finding oldest active label.
NA	INTEGER Used to indicate when a search for an available slot should be undertaken. When NA = NS, no slots are available.
NC,NW,NX,NY,NZ	INTEGER Used in Wide Image Logic.
ND	INTEGER Dimensionality.
ND5	INTEGER ND*5; used as a dimension parameter for CLOSEC.
NL	INTEGER Number of labels collected at once.
NR	INTEGER Number of lines.
NS	INTEGER Number of samples for each label.
NTS	INTEGER Number of test sets written.
READP	SYSTEM SUBROUTINE
TSP(80)	LOGICAL ARRAY Buffer for writing test sets to disk in CLOSEC.

UICB(1) INTEGER ARRAY User Information Control Block

Z INTEGER Boundary marker: -32768.

Table 1. Example of Memory Allocation for ASELECT
Number of Samples = 2048

ND	NC	NL	NS
2	2048	85	86
4	1025	62	63
8	683	42	43
12	513	34	34
16	342	30	31

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PAGE 0020   HEWLETT-PACKARD 32102B 01 03   FORTRAN/3000    TUE, OCT 13, 1981,  9:38 AM

00020  00840000  $CONTROL SEGMENT=ANDEBASEG
00020  00841000        SUBROUTINE ASELECT(DAT,LAB,KNT,ML,MS,MR,MC,MZ,MD,MTS,DATA,LABEL,
00020  00842000       * FILENO,UICB,IND,INGIN,INGCLAS)
00020  00843000        INTEGER*2 DAT(ML,MD,MS),LAB(ML),KNT(ML),DATA(MC,MD),LABEL(MC),
00020  00844000       * Z,FILENO,UICB(1),IND(1)
00020  00845000        LOGICAL CONTROL,TSP(80)
00020  00846000  C
00020  00847000  C
00020  00848000  C  PARAMETERS:
00020  00849000  C
00020  00850000  C    TSP -- BUFFER FOR ACLOSEC
00020  00851000  C    DAT -- DATA BEING SAVED
00020  00852000  C    LAB -- LABEL VECTOR
00020  00853000  C    KNT -- COUNT VECTOR
00020  00854000  C           KNT(I) = 0 MEANS SLOT I IS FREE
00020  00855000  C     ML -- MAX NUMBER OF LABELS
00020  00856000  C     MS -- MAX SAMPLES PER PATCH
00020  00857000  C     MD -- DIMENSIONALITY
00020  00858000  C     MC -- ELEMENTS PER SCAN LINE
00020  00859000  C     MZ -- ACTUAL NUMBER OF ELEMENTS PER SCAN LINE
00020  00860000  C     MU -- STARTING ELEMENT READ
00020  00861000  C     MY -- LAST ELEMENT READ
00020  00862000  C     MX -- NUMBER READ (MC IS TARGET, BUT MX IS ACTUAL NUMBER)
00020  00863000  C     MR -- NUMBER OF SCAN LINES
00020  00864000  C     MA -- NUMBER OF LABEL SLOTS BEING USED
00020  00865000  C    MTS -- RUNNING COUNT OF NUMBER OF TEST SETS
00020  00866000  C
00020  00867000  C  INITIALIZE
00020  00868000         MDS = MD*3
00023  00869000         Z = -32768
00032  00870000         CONTROL = TRUE
00034  00871000         MTS = 0
00036  00872000         MA = 0
00040  00873000         DO 10 I = 1,ML
00045  00874000         KNT(I) = 0
00050  00875000      10 LAB(I) = Z
00054  00876000  C
00054  00877000  C  PROCESS BY STRIPS ABOUT MC WIDE
00054  00878000         DO 96 MU = 1,MZ,MC
00061  00879000         MY = MU+MC-1
00068  00880000         IF (MY GT MZ) MY = MZ
00072  00881000         MX = MY-MU+1
00076  00882000  C
00076  00883000  C  PROCESS BY SCAN LINES
00076  00884000         DO 500 IREAD = 1,MR
00103  00885000  C
00103  00886000  C  SEE IF START OF A NEW STRIP
00103  00887000         IF (IREAD GT 1 OR MU EQ 1) GO TO 97
00114  00888000         DO 98 I = 1,MX
00121  00889000      98 LABEL(I) = Z
00125  00890000         GO TO 99
00126  00891000  C
00126  00892000  C  READ LABELS
00126  00893000      97 CALL READP(UICB,IND,INGCLAS,LABEL,2,1,IREAD,MU,MX,
00126  00894000       * 1,IREAD+1,MU,MX)
00155  00895000         IF (IND(1) LT 0) CALL CHKIO(UICB,IND,INGCLAS,IREAD,MU,MZ,525)
00175  00896000  C
```

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PAGE 0029   ASELECT

00175  00897000  C  SEE IF THERE WAS A LABEL THIS LINE.
00175  00898000     99 DO 50 I = 1,NX
00202  00899000           IF (LABEL(I).NE.Z) GO TO 99
00211  00900000     50 CONTINUE
00212  00901000  C
00212  00902000  C  SEE IF ANY ACTIVE.
00212  00903000        IF (NA.EQ.0) GO TO 500
00217  00904000  C
00217  00905000  C  CLOSE ALL ACTIVE LABELS.
00217  00906000        DO 60 J = 1,NL
00224  00907000          IF (LAB(J).NE.Z) CALL CLOSEC(Z,J,TSP,LAB,KNT,DAT,NL,
00224  00908000       *    NS,ND,NA,NTS,FILENO,UICB,IND,CONTROL,NDS)
00257  00909000     60 CONTINUE
00260  00910000        GO TO 500
00261  00911000  C
00261  00912000  C  CHECK FOR INACTIVE OLD LABEL
00261  00913000     99 DO 100 J = 1,NL
00266  00914000           L = LAB(J)
00271  00915000           IF (L.EQ.Z) GO TO 100
00275  00916000           DO 110 I = 1,NX
00302  00917000             IF (LABEL(I).EQ.L) GO TO 100
00310  00918000    110    CONTINUE
00311  00919000              CALL CLOSEC(Z,J,TSP,LAB,KNT,DAT,NL,NS,ND,NA,NTS,
00311  00920000       * FILENO,UICB,IND,CONTROL,NDS)
00340  00921000    100 CONTINUE
00341  00922000  C
00341  00923000  C  POINT TO START
00341  00924000        J = 1
00343  00925000  C
00343  00926000  C  READ DATA
00343  00927000        DO 607 K = 1,ND
00350  00928000        CALL READP(UICB,IND,INGIN,DATA(1,K),2,K,IREAD,NW,NX,
00350  00929000       * K+1,IREAD,NW,NX)
00400  00930000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGIN,K,IREAD,NC,530)
00420  00931000    607 CONTINUE
00421  00932000  C  PROCESS CURRENT SCAN LINE
00421  00933000  C
00421  00934000        DO 200 I = 1,NX
00426  00935000          L = LABEL(I)
00431  00936000          IF (L.EQ.Z) GO TO 200
00436  00937000  C
00436  00938000  C  LABEL FOUND.  LOOK FOR A DUPE
00436  00939000           IF (LAB(J).EQ.L) GO TO 210
00443  00940000           DO 220 J = 1,NL
00450  00941000             IF (LAB(J).EQ.L) GO TO 210
00456  00942000    220    CONTINUE
00457  00943000  C
00457  00944000  C  FELL THROUGH -- NO MATCH FOUND
00457  00945000  C  CHECK IF  THERE IS ROOM
00457  00946000        IF (NA.LT.NL) GO TO 300
00463  00947000  C
00463  00948000  C  NO ROOM. CLOSE THE ELDEST
00463  00949000        LOLD = LAB(1)
00466  00950000        J = 1
00470  00951000        DO 310 JS = 2,NL
00475  00952000          IF (LAB(JS).GE.LOLD) GO TO 310
00502  00953000            J = JS
```

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PAGE 0030   ASELECT

00304  00954000            LOLD = LAB(JS)
00307  00955000      310 CONTINUE
00310  00956000  C
00310  00957000  C     OLDEST IS POINTED TO BY J
00310  00958000        CALL CLOSEC(Z,J,TSP,LAB,KNT,DAT,NL,NS,ND,NA,NTS,
00310  00959000       * FILENO,UICD,IND,CONTROL,NDS)
00337  00960000        GO TO 330
00340  00961000  C
00340  00962000  C  CATCH UP ON LOGIC!  ROOM FOR MERE MERE
00340  00963000  C
00340  00964000  C  FIND A SLOT
00340  00965000      300 DO 320 J = 1,NL
00345  00966000            IF (LAB(J).EQ.Z) GO TO 330
00353  00967000      320 CONTINUE
00354  00968000      330 KNT(J) = 0
00357  00969000          LAB(J) = L
00362  00970000          NA = NA+1
00363  00971000      210 KN = KNT(J)+1
00367  00972000          KNT(J) = KN
00372  00973000          DO 400 K = 1,ND
00377  00974000      400 DAT(KN,K,J) = DATA(I,K)
00617  00975000  C
00617  00976000  C  CLOSE IF  KN = NL
00617  00977000          IF(KN.EQ.NL) CAL  CLOSEC(Z,J,TSP,LAB,KNT,DAT,NL,NS,ND,NA,NTS,
00617  00978000       * FILENO,UICD,IND,CONTROL,NDS)
00651  00979000  C
00651  00980000  C  COLUMN LOOP END
00651  00981000      200   CONTINUE
00652  00982000  C  SCAN LOOP END
00652  00983000      300 CONTINUE
00656  00984000  C
00656  00985000  C  STRIP LOOP END
00656  00986000      96 CONTINUE
00662  00987000  C
00662  00988000  C  CLOSE EVERYTHING IN SIGHT
00662  00989000          DO 600 J = 1,NL
00667  00990000            IF(LAB(J).NE.Z)CALL CLOSEC(Z,J,TSP,LAB,KNT,DAT,NL,NS,ND,NA,NTS,
00667  00991000       * FILENO,UICD,IND,CONTROL,NDS)
00722  00992000      600 CONTINUE
00723  00993000          R E T U R N
00724  00994000                    END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
ASELECT		SUBROUTINE		CHKIO		SUBROUTINE	
CLOSEC		SUBROUTINE		CONTROL	LOGICAL	SIMPLE VAR	0+223
DAT	INTEGER	ARRAY	0-224 ,I	DATA	INTEGER	ARRAY	0-212 ,I
FILENO	INTEGER	SIMPLE VAR	0-210 ,I	I	INTEGER	SIMPLE VAR	0+26
INDCLAS	INTEGER	SIMPLE VAR	0-24 ,I	INDIN	INTEGER	SIMPLE VAR	0-25 ,I
IND	INTEGER	ARRAY	0-26 ,I	IREAD	INTEGER	SIMPLE VAR	0+215
J	INTEGER	SIMPLE VAR	0+212	JS	INTEGER	SIMPLE VAR	0+211
K	INTEGER	SIMPLE VAR	0+221	KN	INTEGER	SIMPLE VAR	0+224
KNT	INTEGER	ARRAY	0-222 ,I	L	INTEGER	SIMPLE VAR	0+210
LAB	INTEGER	ARRAY	0-223 ,I	LABEL	INTEGER	ARRAY	0-211 ,I
LOLD	INTEGER	SIMPLE VAR	0+217	NA	INTEGER	SIMPLE VAR	0+27
NC	INTEGER	SIMPLE VAR	0-216 ,I	ND	INTEGER	SIMPLE VAR	0-214 ,I
NDS	INTEGER	SIMPLE VAR	0+213	NL	INTEGER	SIMPLE VAR	0-221 ,I
NR	INTEGER	SIMPLE VAR	0-217 ,I	NS	INTEGER	SIMPLE VAR	0-220 ,I
NTS	INTEGER	SIMPLE VAR	0-213 ,I	NU	INTEGER	SIMPLE VAR	0+214
NX	INTEGER	SIMPLE VAR	0+216	NY	INTEGER	SIMPLE VAR	0+220
NZ	INTEGER	SIMPLE VAR	0-215 ,I	READP		SUBROUTINE	
TSP	LOGICAL	ARRAY	0+25 ,I	UICD	INTEGER	ARRAY	0-27 ,I
Z	INTEGER	SIMPLE VAR	0+222				

PROGRAM UNIT ASELECT COMPILED

Parent: MAIN CLASSIFY
Calls: PERPIXEL, MARKUP, FIXUP

CLASSIFY(PIXELS,CLUSTERS,LABELS,NR,NC,NZ,ND,REJECT,NFCLUS,UICB,IND,
IMAGE,IMGCLAS,MAXCLUS,COUNT,MASK)

This subroutine performs a spatially supervised classification of multi-image data. The underlying spectral classifer is a nearest neighbor (Euclidean distance) per pixel classifer. Such a classifer behaves poorly on mixtures: a point on the spatial boundary between classes will sometimes be classified in another actual class. In CLASSIFY, the mildest possible reclassification is performed: only points classified unlike all four of their neighbors are reclassified, and even these are left alone if the nearest class of a neighbor is too far away.

Method: CLASSIFY uses: Wide Image Logic, the Mask, Four Neighbors, Circular Buffers, and Rejection Thresholds. These concepts are documented separately. Assuming they are understood, the method can be described briefly. In each (wide image) strip of data, a circular buffer of three scan lines of data and labels is formed. Initially, all three lines are classified (subroutine PERPIXEL). Then a big loop is entered (label 30), and the center, pointed to by I2, is marked (subroutine MARKUP) to indicate pixels classified like at least one neighbor. Subroutine FIXUP is entered to reclassify unmarked pixels like one of their solidly classified neighbors. (These subroutines could, of course, be differently restrictive.) Then the eldest label line, pointed to by I1, is written on disk, the buffer is rotated, and a new line of data is read and classified. When no more data can be read, the last two lines of labels are written, and the next Wide Image Strip is processed.

A count is kept of the number in each class. This is returned in vector COUNT, a long integer array. COUNT(1) is reserved for unclassified elements (which appear on disk with label 0). COUNT(2) through COUNT(99) are the number in class 1 through 98. COUNT(100) is the number of points in the Mask, given label 99 on disk.

The classification routine may introduce new classes; because the data is only scanned once, the new classes will not be attractors until they are formed. The reason for introducing new classes lies in the profound unpopularity of unclassified pixels, as well as the stubborn adherence to the mixture model. Since these classes are usually small, the percentage of errors is likely to be tiny.

Program Variables

CHKIO	SYSTEM SUBROUTINE
CLUSTERS(ND,MAXCLUS)	INTEGER ARRAY The cluster centers or attractors. Their actual number is NFCLUS, which may be changed in PERPIXEL.
COUNT(100)	LONG INTEGER ARRAY The count of the number in each cluster. COUNT(1) in the number unclassified, COUNT(100) is the number in the mask, and COUNT(I) is the number in the cluster I-1 for I = 2,...,99.
FIXUP	SUBROUTINE Processes points classified unlike each of their four neighbors, attempting reclassification according to the mixture model.
I	INTEGER DO loop index
I1,I2,I3	INTEGER Circular buffer pointers
IMAGE	INTEGER Input image number.
IMGCLAS	INTEGER Output image number.
IND(1)	INTEGER ARRAY Error indicator.
IREAD,IROW	INTEGER Line numbers on read and write, managed in each strip.
IT	INTEGER Scratch variable, used to rotate buffer.
JC	INTEGER Used to index into COUNT while counting LABELS.
JJ,K	INTEGER DO loop index.

LABELS(NC,3)	INTEGER ARRAY Circular buffer of classifications.
MARKUP	SUBROUTINE Adds 101 to the center label when that label is like at least one of the four neighbors.
MASK	LOGICAL If .TRUE., a value of 0 in channel 1 of the data is classified "mask" and labelled 99.
MAXCLUS	INTEGER The maximum number of clusters allowed.
NC	INTEGER Width of each strip.
ND	INTEGER Dimensionality of data.
NFCLUS	INTEGER Dynamic number of clusters.
NR	INTEGER Number of lines.
NW,NX,NY,NZ	INTEGER Used, in loop 96, to segment the image into strips.
PERPIXEL	SUBROUTINE Performs a per pixel nearest neighbor classification. Introduces new clusters when the nearest neighbor is too far away to fit the mixture model.
PIXELS(NC,ND,3)	INTEGER ARRAY One circular buffer of data in a strip.
READP	SYSTEM SUBROUTINE
REJECT(MAXCLUS)	INTEGER ARRAY The rejection thresholds.
UICB(1)	INTEGER ARRAY User Information Control Block
WRITEP	SYSTEM SUBROUTINE

```
00018  00538000  $CONTROL SEGMENT=AMOEBASEG
00018  00539000        SUBROUTINE CLASSIFY(PIXELS,CLUSTERS,LABELS,NR,NC,NZ,ND,REJECT,
00018  00540000       * NFCLUS,UICB,IND,IMAGE,IMGCLAS,MAXCLUS,COUNT,MASK)
00018  00541000        INTEGER*2 UICB(1),IND(1),REJECT(MAXCLUS),CLUSTERS(ND,MAXCLUS),
00018  00542000       * PIXELS(NC,ND,3),LABELS(NC,3)
00018  00543000        INTEGER*4 COUNT(100)
00018  00544000        LOGICAL MASK
00018  00545000        DO 1 I = 1,100
00022  00546000      1 COUNT(I) = 0
00027  00547000  C
00027  00548000  C WIDE IMAGE LOGIC
00027  00549000  C  NW IS STARTING COL IN IMAGE
00027  00550000  C  NY IS ENDING
00027  00551000  C  NX IS ACTUAL NUMBER READ
00027  00552000  C
00027  00553000        DO 96 NW = 1,NZ,NC
00034  00554000        NY = NW+NC-1
00040  00555000        IF (NY.GT.NZ) NY = NZ
00045  00556000        NX = NY-NW+1
00051  00557000  C
00051  00558000  C  SET READ/WRITE COUNTERS
00051  00559000  C
00051  00560000        IREAD = 3
00055  00561000        IROW = 1
00055  00562000  C
00055  00563000  C  SET UP CIRCULAR BUFFER POINTER
00055  00564000  C
00055  00565000        I1 = 1
00057  00566000        I2 = 2
00061  00567000        I3 = 3
00063  00568000  C
00063  00569000  C  GET STARTED!  READ 3 SCAN LINES DATA
00063  00570000  C
00063  00571000        DO 20 I = 1,3
00070  00572000        DO 10 K = 1,ND
00073  00573000        CALL READP(UICB,IND,IMAGE,PIX  3(1,K,I),2,K,I,NW,
00073  00574000       * NY,K+1,I,NW,NX)
00130  00575000        IF (IND(I).LT.0) CALL CNA:SCUICB,IND,IMAGE,I,K,NC,11)
00150  00576000     10 CONTINUE
00151  00577000  C
00151  00578000  C  CLASSIFY FIRST THREE SCAN LINES
00151  00579000  C
00151  00580000     20 CALL PERPIXEL(PIXELS(1,1,I),CLUSTERS,LABELS(1,I),
00151  00581000       * ND,NC,NFCLUS,REJECT,MAXCLUS,MASK,NX)
00201  00582000  C
00201  00583000  C  REFERENCE FOR BIG LOOP
00201  00584000  C
00201  00585000  C  MARK PIXELS CLASSED LIKE THEIR NEIGHBORS
00201  00586000  C
00201  00587000     30 CALL MARKUP(LABELS,NC,I1,I2,I3,NX)
00211  00588000  C
00211  00589000  C  USE CONTEXT TO ATTEMPT RECLASSIFICATION
00211  00590000  C
00211  00591000        CALL FIXUP(LABELS,NC,I1,I2,I3,PIXELS(1,1,I2),REJECT,
00211  00592000       * CLUSTERS,ND,MAXCLUS,NX)
00236  00593000  C
00236  00594000  C  WRITE A SCAN LINE OF LABELS
```

```
PAGE 0019   CLASSIFY

00236  00595000  C
00236  00596000        CALL WRITEP(UICB,IND,IMGCLAS,LABELS(1,I1),2,1,IROW,NW,NX,
00236  00597000       * 1 IROW+1,NW,NX)
00270  00598000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGCLAS,IROW,0,0,21)
00311  00599000        DO 2 JJ = 1,NX
00316  00600000        JC = LABELS(JJ,I1)+1
00326  00601000      2 COUNT(JC) = COUNT(JC)+1
00336  00602000  C
00336  00603000  C  POINT TO NEXT SCAN LINE
00336  00604000  C
00336  00605000        IROW = IROW+1
00337  00606000        IREAD = IREAD+1
00340  00607000        IF (IREAD.GT.NR) GO TO 1400
00344  00608000  C
00344  00609000  C  GRAB ANOTHER SCAN LINE
00344  00610000  C
00344  00611000        DO 40 K = 1,ND
00351  00612000        CALL READP(UICB,IND,IMAGE,PIXELS(1,K,I1),2,K,IREAD,
00351  00613000       * NW,NX,K+1,IREAD,NW,NX)
00404  00614000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMAGE,K,I1,IREAD,263)
00424  00615000     40 CONTINUE
00425  00616000  C
00425  00617000  C  ROTATE CIRCULAR BUFFER
00425  00618000  C
00425  00619000        IT = I1
00427  00620000        I1 = I2
00431  00621000        I2 = I3
00433  00622000        I3 = IT
00435  00623000  C
00435  00624000  C  CLASSIFY THE NEW CRITTER
00435  00625000  C
00435  00626000        CALL PERPIXEL(PIXELS(1,1,I3),CLUSTERS,LABELS(1,I3),ND,NC,
00435  00627000       * NFCLAS,REJECT,MAXCLUS,MASK,NX)
00464  00628000        GO TO 30
00466  00629000  C
00466  00630000  C  FINISH UP
00466  00631000  C
00466  00632000   1000 CONTINUE
00466  00633000        CALL WRITEP(UICB,IND,IMGCLAS,LABELS(1,I2),2,1,IROW,
00466  00634000       * NW,NX,1,IROW+1,NW,NX)
00520  00635000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGCLAS,I2,IROW,NC,282)
00540  00636000        DO 3 JJ = 1,NX
00545  00637000        JC = LABELS(JJ,I2)+1
00553  00638000      3 COUNT(JC) = COUNT(JC)+1
00562  00639000        CALL WRITEP(UICB,IND,IMGCLAS,LABELS(1,I3),2,1,IROW+1,
00562  00640000       * NW,NX,1,1,1,1)
00622  00641000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGCLAS,I3,IROW,NC,287)
00641  00642000        DO 4 JJ = 1,NX
00647  00643000        JC = LABELS(JJ,I3)+1
00657  00644000      4 COUNT(JC) = COUNT(JC)+1
00667  00645000     96 CONTINUE
00675  00646000        R E T U R N
00676  00647000                   END
```

PAGE 0020 CLASSIFY

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
CHK10		SUBROUTINE		CLASSIFY		SUBROUTINE	
CLUSTERS	INTEGER	ARRAY	0-%22 ,I	COUNT	INTEGER*4	ARRAY	0-%5 ,I
FIXUP		SUBROUTINE		I	INTEGER	SIMPLE VAR	0+%4
I1	INTEGER	SIMPLE VAR	0+%14	I2	INTEGER	SIMPLE VAR	0+%15
I3	INTEGER	SIMPLE VAR	0+%16	IMAGE	INTEGER	SIMPLE VAR	0-%10 ,I
IMGCLAS	INTEGER	SIMPLE VAR	0-%7 ,I	IND	INTEGER	ARRAY	0-%11 ,I
IREAD	INTEGER	SIMPLE VAR	0+%11	IROW	INTEGER	SIMPLE VAR	0+%6
IT	INTEGER	SIMPLE VAR	0+%7	JC	INTEGER	SIMPLE VAR	0+%20
JJ	INTEGER	SIMPLE VAR	0+%5	K	INTEGER	SIMPLE VAR	0+%17
LABELS	INTEGER	ARRAY	0-%21 ,I	MARKUP		SUBROUTINE	
MASK	LOGICAL	SIMPLE VAR	0-%4 ,I	MAXCLUS	INTEGER	SIMPLE VAR	0-%6 ,I
NC	INTEGER	SIMPLE VAR	0-%17 ,I	ND	INTEGER	SIMPLE VAR	0-%15 ,I
NFCLUS	INTEGER	SIMPLE VAR	0-%13 ,I	NR	INTEGER	SIMPLE VAR	0-%20 ,I
NU	INTEGER	SIMPLE VAR	0+%10	NX	INTEGER	SIMPLE VAR	0+%12
NY	INTEGER	SIMPLE VAR	0+%13	NZ	INTEGER	SIMPLE VAR	0-%16 ,I
PERPIXEL		SUBROUTINE		PIXELS	INTEGER	ARRAY	0-%23 ,I
READP		SUBROUTINE		REJECT	INTEGER	ARRAY	0-%14 ,I
UIC0	INTEGER	ARRAY	0-%12 ,I	WRITEP		SUBROUTINE	

PROGRAM UNIT CLASSIFY COMPILED

Parent: ASELECT CLOSEC

CLOSEC(Z,J,TSP,LAB,KNT,DAT,NL,NS,ND,NA,N,FILENO,UICB,IND,CONTROL,ND5)

In this subroutine, a patch of pure pixels is closed by selecting a test set from the patch (5 representative pixels) and writing the test set to disk.

Method: If the file has not yet been opened (i.e., if CONTROL is true), then it is opened. The file name is TSTPXL__ where __ is a number from 1 to 99, depending on how many test pixel files are currently open in concurrently running sessions. The test pixel file is job-temporary, that is it is deallocated when it is closed.

If possible, five test pixels are selected from the patch by choosing them at equally spaced intervals along the array. This test set is written to a disk record. The test set count is incremented and the count of occupied labels is decremented.

Program Variables

CONTROL	LOGICAL If CONTROL is true, the test pixel file is opened and CONTROL is set to false.
DAT(NL,ND,NS)	INTEGER ARRAY At J, contains the list of pixels (brightness values) that constitute the current patch.
FCHECK	SYSTEM INTRINSIC to check for I/O errors
FILEINX	INTEGER Part of test pixel file name
FILENO	INTEGER Test pixel file system file number
FILESIZE	INTEGER*4 Maximum number of records in test pixel file
FNAME	CHARACTER Test pixel file name
FOPEN	SYSTEM INTRINSIC Opens a file
FWRITE	SYSTEM INTRINSIC Writes a record
I,IS,K,KN	INTEGER Do Loop Index
IA	" File options bit mask
IB	" File access bit mask

IERR	INTEGER I/O Error code
IMSG	" ARRAY holds message to be printed
IND	" ARRAY IDIMS error indicators
ITSP	" Temporary test pixel storage
J	" The pointer into KNT and DAT for the current patch to be processed.
KNT	INTEGER ARRAY At J, the population of the current patch.
LA	LOGICAL File options bit mask
LAB	INTEGER ARRAY Label vector
LB	LOGICAL File access bit mask
LTSP	LOGICAL Test pixel temporary storage
MSG	CHARACTER Message to be printed
N	INTEGER Count of test sets written to disk
NA	" Count of occupied labels
ND	" Number of dimensions
ND5	" " " times five
NL	" " " lines
NS	" " samples in strip
PABORT	SYSTEM SUBROUTINE
PIXELND	" Counter for pixels written to a record (1 to 5*ND)
PRINTP	SYSTEM SUBROUTINE
TSP	LOGICAL ARRAY Test pixel record
UICB	INTEGER ARRAY User information control block
Z	" Absolute zero, see "Tricking Fortran"

```
00025  00776000  $CONTROL SEGMENT=ARDEBASEG
00025  00777000        SUBROUTINE CLOSEC(Z,J,TSP,LAB,KNT,DAT,NL,NS,ND,NA,N,FILENO,
00025  00778000       1    UICB,IND,CONTROL,NDS)
00025  00779000  C  THIS SUBROUTINE IS A PORTION OF THE ARDEBA IDIMS FUNCTION.
00025  00780000  C  IT CHOOSES TEST PIXELS FROM A PATCH THAT IS BEING CLOSED,
00025  00781000  C  AND RESETS APPROPRIATE COUNTERS.
00025  00782000  C
00025  00783000        LOGICAL LTSP,TSP(NDS),LA,LB,CONTROL
00025  00784000        INTEGER*4 FILESIZE
00025  00785000        INTEGER*2 Z,ITSP,DAT(NL,ND,NS),KNT(1),LAB(1),IMSG(39),FILEINX
00025  00786000        EQUIVALENCE (LTSP,ITSP)
00025  00787000        INTEGER*2 PIXELNO,IA,IB,UICB(1),IND(1),FILENO
00025  00788000        SYSTEM INTRINSIC FOPEN,FCHECK,FWRITE
00025  00789000        CHARACTER*74 MSG
00025  00790000        CHARACTER*9 FNAME
00025  00791000        EQUIVALENCE (LA,IA),(LB,IB),(IMSG,MSG)
00025  00792000        IF (.NOT.CONTROL) GO TO 3
00030  00793000        IA = 0
00032  00794000        FILESIZE = 65536
00034  00795000        IB = 4
00036  00796000        CONTROL = FALSE.
00040  00797000  C  OPEN THE DISK FILE
00040  00798000        FNAME = "TSTPXL  ."
00056  00799000        DO 6 FILEINX = 1,99
00063  00800000        FNAME[7:2] = STR(FILEINX)
00100  00801000        FILENO = 0
00102  00802000        FILENO = FOPEN(FNAME,LA,LB,NDS,,,2,,FILESIZE,16)
00120  00803000        IF (.CC.)2,3,2
00123  00804000   2    CONTINUE
00123  00805000        CALL FCHECK(FILENO,IERR)
00130  00806000        IF (IERR EQ.100.OR.IERR.EQ.101) GO TO 6
00140  00807000        MSG = " OPEN ERROR        ON TEST PIXEL DISK FILE"
00175  00808000        MSG[13:5] = STR(IERR)
00212  00809000        CALL PRINTP(UICB,IND,1,IMSG,41,0,0,0,0,0,0,0,0)
00242  00810000        CALL PABORT(UICB,45,0)
00272  00811000   6    CONTINUE
00272  00812000   3    CONTINUE
00272  00813000        KN = KNT(J)
00276  00814000        IF(KN.LT.5) GO TO 100
00262  00815000        IS = (KN-1)/4
00266  00816000        PIXELNO = 0
00270  00817000        DO 10 I = 1,KN,IS
00275  00818000        DO 10 K = 1,ND
00302  00819000        PIXELNO = PIXELNO + 1
00303  00820000        ITSP = DAT(I,K,J)
00315  00821000   10   TSP(PIXELNO) = LTSP
00322  00822000  C  WRITE TEST PIXELS TO DISK FILE
00322  00823000        CALL FWRITE(FILENO,TSP,NDS,CONTROL)
00330  00824000        IF (.CC.) 4,5,4
00332  00825000   4    CALL FCHECK(FILENO,IERR)
00337  00826000        MSG = " ERROR         DURING WRITE OF TEST PIXEL FILE"
00376  00827000        MSG[8:6] = STR(IERR)
00413  00828000        CALL PRINTP(UICB,IND,1,IMSG,45,0,0,0,0,0,0,0,0)
00442  00829000        CALL PABORT(UICB,45,0)
00452  00830000   5    CONTINUE
00452  00831000  C
00457  00832000  C INCREMENT COUNT OF TEST PIXEL GROUPS WRITTEN TO DISK
```

```
PAGE 0027   CLOSEC

00457  00833000          N = N + 1
00474  00834000   100    KNT(J) = 0
00457  00835000          LAB(J) = Z
00462  00836000   C DECREMENT COUNT OF OCCUPIED LABELS
00462  00837000          NA = NA-1
00463  00838000          RETURN
00464  00839000          END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS
CLOSEC		SUBROUTINE	
DAT	INTEGER	ARRAY	0-%16 ,I
FILEINX	INTEGER	SIMPLE VAR	0+%16
FILESIZE	INTEGER*4	SIMPLE VAR	0+%21
FOPEN	INTEGER	FUNCTION	
I	INTEGER	SIMPLE VAR	0+%7
IB	INTEGER	SIMPLE VAR	0+%11
IMSG	INTEGER	ARRAY	0+%5 ,I
IS	INTEGER	SIMPLE VAR	0+%12
J	INTEGER	SIMPLE VAR	0-%22 ,I
KN	INTEGER	SIMPLE VAR	0+%20
LA	LOGICAL	SIMPLE VAR	0+%10
LB	LOGICAL	SIMPLE VAR	0+%11
MSG	CHARACTER	SIMPLE VAR	0+%6 ,I
NA	INTEGER	SIMPLE VAR	0-%12 ,I
ND3	INTEGER	SIMPLE VAR	0-%4 ,I
NS	INTEGER	SIMPLE VAR	0-%14 ,I
PIXELNO	INTEGER	SIMPLE VAR	0+%13
TSP	LOGICAL	ARRAY	0-%21 ,I
Z	INTEGER	SIMPLE VAR	0-%23 ,I

NAME	TYPE	STRUCTURE	ADDRESS
CONTROL	LOGICAL	SIMPLE VAR	0-%5 ,I
FCHECK		SUBROUTINE	
FILENO	INTEGER	SIMPLE VAR	0-%10 ,I
FNAME	CHARACTER	SIMPLE VAR	0+%23 ,I
FWRITE		SUBROUTINE	
IA	INTEGER	SIMPLE VAR	0+%10
IERR	INTEGER	SIMPLE VAR	0+%14
IND	INTEGER	ARRAY	0-%6 ,I
ITSP	INTEGER	SIMPLE VAR	0+%17
K	INTEGER	SIMPLE VAR	0+%15
KNT	INTEGER	ARRAY	0-%17 ,I
LAB	INTEGER	ARRAY	0-%20 ,I
LTSP	LOGICAL	SIMPLE VAR	0+%17
N	INTEGER	SIMPLE VAR	0-%11 ,I
ND	INTEGER	SIMPLE VAR	0-%13 ,I
NL	INTEGER	SIMPLE VAR	0-%15 ,I
PABORT		SUBROUTINE	
PRINTP		SUBROUTINE	
UICB	INTEGER	ARRAY	0-%7 ,I

```
PROGRAM UNIT CLOSEC COMPILED
```

Parent: NUMCLU COLAPS

COLAPS(MAX,MEAN,SUM,ND)

In this subroutine, each vector in MEAN with corresponding index in SUM zero is eliminated. The calling program NUMCLU uses SUM to mark vectors in MEAN which are no longer in force. Classification is more efficient when needless branches on SUM(.) = 0 are avoided.

Method: The method is as simple-minded and as inefficient as a bubble sort. Any time SUM(.) = 0 is encountered, move the entire array down one slot. (But) It is self-documenting.

Program Variables

I,J,K,MM,IP1	INTEGER DO loop parameters
MAX	INTEGER Number of vectors in MEAN.
MEAN(ND,MAX)	INTEGER ARRAY The mean vectors, to be collapsed.
ND	INTEGER Dimensionality
SUM(MAX)	INTEGER ARRAY Pointer array; vectors in MEAN with SUM(.) = 0 should be eliminated.

```
PAGE 0060   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:41 AM

00006  02092000  $CONTROL SEGMENT=AMDEBASEG
00006  02093000        SUBROUTINE COLAPS(MAX,MEAN,SUM,ND)
00006  02094000  C
00006  02095000  C  PARENT PROGRAM:     NUMCLU
00006  02096000  C
00006  02097000  C  SUBROUTINE  COLAPS  GOES THRU THE CLUSTERS IN  MEAN
00006  02098000  C  AND DELETES ANY CLUSTER WITH  SUM(K) = 0, COMPRESSING
00006  02099000  C  THE ARRAY  MEAN ;  THIS ALLOWS SLIGHTLY MORE EFFICIENT
00006  02100000  C  SEARCH WHEN TRYING TO CLASSIFY A POINT.
00006  02101000        INTEGER*2 MEAN(ND,MAX),SUM(MAX)
00006  02102000        MM = MAX-1
00011  02103000        DO 1 I = 1,MM
00016  02104000        IF (SUM(I).NE.0) GO TO 1
00023  02105000        IP1 = I+1
00026  02106000        IF (I'1.EQ.MAX) R E T U R N
00032  02107000        DO 2 J = IP1,MAX
00037  02108000        IF (SUM(J).EQ.0) GO TO 2
00044  02109000        SUM(I) = SUM(J)
00050  02110000        SUM(J) = 0
00053  02111000        DO 3 K = 1,ND
00060  02112000      3 MEAN(K,I) = MEAN(K,J)
00075  02113000        GO TO 1
00077  02114000      2 CONTINUE
00100  02115000        R E T U R N
00101  02116000      1 CONTINUE
00102  02117000        R E T U R N
00103  02118000        END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
COLAPS		SUBROUTINE		I	INTEGER	SIMPLE VAR	Q+%3
IP1	INTEGER	SIMPLE VAR	Q+%7	J	INTEGER	SIMPLE VAR	Q+%4
K	INTEGER	SIMPLE VAR	Q+%6	MAX	INTEGER	SIMPLE VAR	Q-%7 ,I
MEAN	INTEGER	ARRAY	Q-%6 ,I	MM	INTEGER	SIMPLE VAR	Q+%5
ND	INTEGER	SIMPLE VAR	Q-%4 ,I	SUM	INTEGER	ARRAY	Q-%5 ,I

PROGRAM UNIT COLAPS COMPILED

Parent: START CONNCT

CONNCT(FINISHED,Z,N,A1,A2,BUF,IN,LAB)

This subroutine grows components from intervals.

Method: Label line A1 contains either Z or patch labels; Z marks boundary. Line A2 contains Z (boundary) or interval marks. A2 is scanned; when an interval is found, A1 is examined looking for a patch label. If a patch label is found, it is saved in BUF.

Then A2 is scanned again. An interval mark is replaced by the corresponding label in BUF. If none is found, the label counter LAB is incremented and LAB is stored as the new label. Labels begin at -32767 and are allowed to grow to as much as 32767. On reaching 32767, flag FINISHED is set to .TRUE. so the calling program will know the supply of patches has exhausted the labels.

"U" shaped components will not be found by this method. Rather, they will be pieced together as two different fields of labels. We do back up one line in loop 50, which sometimes removes single element patches.

Program Variables

A1(N),A2(N)	INTEGER ARRAY A1 is the elder line with patches already marked. A2 is the new line of intervals to be turned into patch labels. (The first patches are created in the calling program.)
BUF(IN)	INTEGER ARRAY Used to stash labels to be transfered to intervals.
FINISHED	LOGICAL When we run out of labels, FINISHED is set to .TRUE. The calling program uses this flag to terminate processing (gathering patches).
I,K	INTEGER DO loop index.

IN	INTEGER	Number of intervals in A2.
IS,IT	INTEGER	Temporary labels.
LAB	INTEGER	Current label pointer.
N	INTEGER	Number of elements in a line.
Z	INTEGER	Boundary marker, -32768.

```
PAGE 0037   HEWLETT-PACKARD 321020.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:39 AM


00007  01169000  $CONTROL SEGMENT=AMOEBASEG
00007  01170000        SUBROUTINE CONNCT(FINISHED,Z,N,A1,A2,BUF,IN,LAB)
00007  01171000        LOGICAL FINISHED
00007  01172000        INTEGER*2 Z,A1(N),A2(N),BUF(IN)
00007  01173000        DO 10 K = 1,IN
00014  01174000     10 BUF(K) = Z
00020  01175000        DO 20 I = 1,N
00025  01176000        IT = A2(I)
00030  01177000        IF (IT.EQ.Z) GO TO 20
00034  01178000        IS = A1(I)
00037  01179000        IF (IS.EQ.Z) GO TO 20
00043  01180000        BUF(IT) = IS
00046  01181000     20 CONTINUE
00047  01182000        DO 30 K = 1,IN
00054  01183000        IF (BUF(K).NE.Z) GO TO 30
00061  01184000        LAB = LAB+1
00062  01185000        IF (LAB.EQ.32767) GO TO 60
00070  01186000        BUF(K) = LAB
00073  01187000     30 CONTINUE
00074  01188000  C
00074  01189000  C  NOW TRANSFER ACTUAL LABELS
00074  01190000        DO 40 I = 1,N
00101  01191000        IT = A2(I)
00104  01192000        IF (IT.NE.Z) A2(I) = BUF(IT)
00113  01193000     40 CONTINUE
00114  01194000  C
00114  01195000  C  BACK UP AND CLEAN UP SINGLETONS (MAYBE)
00114  01196000        DO 50 I = 1,N
00121  01197000        IT = A2(I)
00124  01198000        IF (IT.EQ.Z) GO TO 50
00130  01199000        IF (A1(I).NE.Z) A1(I) = IT
00137  01200000     50 CONTINUE
00140  01201000        R E T U R N
00141  01202000     60 FINISHED = .TRUE.
00143  01203000        R E T U R N
00144  01204000                        END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS                NAME              TYPE        STRUCTURE   ADDRESS

A1                INTEGER     ARRAY       0-%10  ,I              A2                INTEGER     ARRAY       0-%7   ,I
BUF               INTEGER     ARRAY       0-%6   ,I              CONNCT                        SUBROUTINE
FINISHED          LOGICAL     SIMPLE VAR  0-%13  ,I              I                 INTEGER     SIMPLE VAR  0+%3
IN                INTEGER     SIMPLE VAR  0-%5   ,I              IS                INTEGER     SIMPLE VAR  0+%4
IT                INTEGER     SIMPLE VAR  0+%5                   K                 INTEGER     SIMPLE VAR  0+%6
LAB               INTEGER     SIMPLE VAR  0-%4   ,I              N                 INTEGER     SIMPLE VAR  0-%11  ,I
Z                 INTEGER     SIMPLE VAR  0-%12  ,I


PROGRAM UNIT CONNCT COMPILED
```

Parent: NUMCLU DIAMTR

DIAMTR(MEAN,ND,ITL,IDIAM)

This routine determines the square of the diameter of the vectors in array MEAN.

Method: Except for the bias of -32768, the method is self-documenting. The biased squared distance from MEAN(.,I) to MEAN(.,J), with $1 \leq I < J \leq ITL$, is computed, and the maximum such value is returned as IDIAM.

Program Variables

I,J,K,IP,ITLM	INTEGER	DO loop parameters.
IDIAM	INTEGER	Square of diameter of vectors in MEAN.
ITL	INTEGER	The total number of vectors in MEAN.
MEAN(ND,ITL)	INTEGER ARRAY	The array whose diameter is to be determined.

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PAGE 0039   HEWLETT-PACKARD 321020.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:41 AM

00005  02067000  $CONTROL SEGMENT=ANOEBASEG
00005  02068000        SUBROUTINE DIANTR(MEAN,ND,ITL,IDIAM)
00005  02069000  C
00005  02070000  C  PARENT PROGRAM:      NUMCLU
00005  02071000  C
00005  02072000  C  SUBROUTINE DIANTR FINDS THE SQUARE OF THE DIAMETER
00005  02073000  C  OF THE SET OF CLUSTER CENTERS IN MEAN
00005  02074000        INTEGER*2 MEAN(ND,ITL)
00005  02075000        ITLM = ITL-1
00010  02076000        IDIAM = -32768
00017  02077000        DO 1 I = 1,ITLM
00024  02078000        IP = I+1
00027  02079000        DO 1 J = IP,ITL
00034  02080000  C
00034  02081000  C  FIND THE DISTANCE **2 BETWEEN MEAN(.,I) AND MEAN(.,J)
00034  02082000        IS = -32767
00036  02083000        DO 2 K = 1,ND
00041  02084000        IF (IS.GE.16300) GO TO 1
00054  02085000        IT = MEAN(K,I)-MEAN(K,J)
00071  02086000      2 IS = IS+IT*IT
00076  02087000        IF (IS.LE.IDIAM) GO TO 1
00102  02088000        IDIAM = IS
00104  02089000      1 CONTINUE
00106  02090000        R E T U R N
00107  02091000        END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS                NAME              TYPE        STRUCTURE   ADDRESS

DIANTR                        SUBROUTINE                         I                 INTEGER     SIMPLE VAR  Q+%3
IDIAM             INTEGER     SIMPLE VAR  Q-%4   ,I               IP                INTEGER     SIMPLE VAR  Q+%4
IS                INTEGER     SIMPLE VAR  Q+%6                   IT                INTEGER     SIMPLE VAR  Q+%7
ITL               INTEGER     SIMPLE VAR  Q-%5   ,I               ITLM              INTEGER     SIMPLE VAR  Q+%10
J                 INTEGER     SIMPLE VAR  Q+%5                   K                 INTEGER     SIMPLE VAR  Q+%11
MEAN              INTEGER     ARRAY       Q-%7   ,I              ND                INTEGER     SIMPLE VAR  Q-%6   ,I


PROGRAM UNIT DIANTR COMPILED
```

Parents: START, MARKUPDN, MARKLR FILLLR

FILLLR(Z,LAB,N)

This subroutine works along a line of labels and replaces a label with its two neighbors marked boundary with the label boundary. It, so to speak, fills in left-right cracks in the boundary map.

Method: Only one tricky point is involved. LL, LR, and LM are used to save labels down a line. This minimizes indexing while preventing propogation of boundary down lines. As usual, Z = -32768 is used to mark boundary.

Program Variables

I	INTEGER DO loop index
IM	INTEGER Pointer to current position.
LAB(N)	INTEGER ARRAY The labels being processed.
LL,LM,LR	INTEGER Labels down the line.
N	INTEGER Number of labels.
Z	INTEGER Boundary: -32768

```
PAGE 0040   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:39 AM

00004  01245000  $CONTROL SEGMENT=ANOEBASEG
00004  01246000        SUBROUTINE FILLLR(Z,LAB,N)
00004  01247000        INTEGER*2 Z,LAB(N)
00004  01248000        IF (N LT 3) R E T U R N
00010  01249000        LL = LAB(1)
00013  01250000        LR = LAB(2)
00016  01251000        IN = 2
00020  01252000        DO 10 I = 3,N
00023  01253000        LR = LAB(I)
00030  01254000        IF (LR EQ Z.AND.LL.EQ.Z) LAB(IN) = Z
00041  01255000        LL = LR
00043  01256000        LR = LP
00047  01257000     10 IN = I
00050  01258000        R E T U P N
00051  01259000                   END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS                  NAME              TYPE        STRUCTURE   ADDRESS

FILLLR                        SUBROUTINE                           I                 INTEGER     SIMPLE VAR  0+22
IP                INTEGER     SIMPLE VAR  0+23                     LAB               INTEGER     ARRAY       0-25  ,I
LL                INTEGER     SIMPLE VAR  0+24                     LR                INTEGER     SIMPLE VAR  0+25
LR                INTEGER     SIMPLE VAR  0+26                     N                 INTEGER     SIMPLE VAR  0-24  ,I
Z                 INTEGER     SIMPLE VAR  0-26  ,I


PROGRAM UNIT FILLLR COMPILED
```

Parent: CLASSIFY FIXUP

FIXUP(LABELS,NC,I1,I2,I3,PIXELS,REJECT,CLUSTERS,ND,MAXCLUS)

This subroutine follows MARKUP and attempts reclassification of a pixel classified unlike each of its four neighbors. The attempt fails when each nieghbor is too far from the pixel to stand that reclassification.

Method: As in MARKUP, a circular buffer LABELS is maintained. I1 points to the eldest, I2 to the current (which may have been modified by the addition of 101), and I3 to the nearest (unchecked) line of labels. We regard the classifications in line I1 as final, those in I3 as tentative. Those in I2 marked over 100 are fixed by subtraction of the 101 added by FIXUP. Of the rest, note they are classed unlike any neighbor. Collect, from the four neighbors, the classes of each neighbor (a) in line I1, (b) in line I2 and marked, or (c) in line I3 and like at least one neighbor in that line. This gives up to four classes. Reclassify the pixel in the nearest unrejected class of those up to four classes. If no unrejected class exists, leave the classification alone. All distances are biased by -32768.

Program Variables

CLUSTERS(ND,MAXCLUS)	INTEGER ARRAY The cluster cneters.
FOUR(4)	INTEGER ARRAY Used to store the (up to) four classifications of OK neighbors.
I	INTEGER DO loop index.
I1	INTEGER Pointer to eldest label line.
I2	INTEGER Pointer to current label line.
I3	INTEGER Pointer to newest label line.
IM	INTEGER I-1; pointer to current slot.
IS	INTEGER Sum accumulator for distance.

ITT	INTEGER Scratch variable.
J	INTEGER Index into FOUR: DO loop index.
J4	INTEGER Value of FOUR(J) in loop.
K	INTEGER DO loop index.
L	INTEGER DO loop index.
LL	INTEGER Label on left.
LM	INTEGER Label in middle.
LR	INTEGER Label on right.
MAXCLUS	INTEGER Dimension for CLUSTERS.
NC	INTEGER Number of samples per line.
ND	INTEGER Dimensionality
NDIST	INTEGER Distance from nearest neighbor classifier, pixel to nearest of up to four.
NRST	INTEGER Index of nearest, or zero if all are too far away.
PIXELS(NC,ND)	INTEGER ARRAY One line of data along line I2.
REJECT(MAXCLUS)	INTEGER ARRAY Rejection thresholds.

```
00014  00669000  $CONTROL SEGMENT=AMOEBASEG
00014  00670000        SUBROUTINE FIXUP(LABELS,NC,I1,I2,I3,PIXELS,REJECT,
00014  00671000       * CLUSTERS,ND,MAXCLUS,MX)
00014  00672000        INTEGER*2 LABELS(NC,3),PIXELS(NC,ND),REJECT(MAXCLUS),
00014  00673000       * CLUSTERS(ND,MAXCLUS),FOUR(4)
00014  00674000        IF (MX.LT.3) R E T U R N
00020  00675000        LL = LABELS(1,I2)
00026  00676000        LR = LABELS(2,I2)
00033  00677000        DO 10 I = 3,MX
00042  00678000        LR = LABELS(I,I2)
00051  00679000        IM = I-1
00054  00680000        IF (LR.GT.100) GO TO 101
00060  00681000        J = 0
00062  00682000        ITT = LABELS(IM,I1)
00071  00683000        IF (ITT.EQ.0) GO TO 30
00075  00684000        J = 1
00077  00685000        FOUR(J) = ITT
00102  00686000     30 IF (LL.LE.100) GO TO 40
00106  00687000        J = J+1
00107  00688000        FOUP(J) = LL-101
00113  00689000     40 IF (LR.LE.100) GO TO 50
00117  00690000        J = J+1
00120  00691000        FOUR(J) = LR-101
00124  00692000     50 ITT = LABELS(IM,I3)
00137  00693000        IF (ITT.NE.LABELS(I-2,I3).AND.ITT.NE.LABELS(I,I3))GOTO60
00133  00694000        J = J+1
00136  00695000        FOUP(J) = ITT
00141  00696000     60 IF (J.EQ.0) GO TO 11
00145  00697000        NRST = 0
00147  00698000        NDIST = 32767
00171  00699000        DO 70 L = 1,J
00176  00700000        J4 = FOUR(L)
00201  00701000        IS = -32768
00210  00702000        DO 80 K = 1,ND
00215  00703000        IF (IS.GE.16383) GO TO 70
00226  00704000        ITT = PIXELS(IM,K)-CLUSTERS(K,J4)
00241  00705000        IS = IS+ITT*ITT
00247  00706000        IF (IS.GE.REJECT(J4)) GO TO 70
00253  00707000     80 CONTINUE
00256  00708000        IF (NDIST.LE.IS) GO TO 70
00262  00709000        NDIST = IS
00264  00710000        NRST = J4
00266  00711000     70 CONTINUE
00267  00712000        IF (NRST.NE.0) LABELS(IM,I2) = NRST
00301  00713000        GO TO 11
00302  00714000    101 LABELS(IM,I2) = LR-101
00312  00715000     11 LL = LM
00314  00716000     10 LM = LR
00317  00717000        R E T U R N
00320  00718000                  END
```

PAGE 0023 FIXUP

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
CLUSTERS	INTEGER	ARRAY	0-%7 ,I	FIXUP		SUBROUTINE	
FOUR	INTEGER	ARRAY	0+%4 ,I	I	INTEGER	SIMPLE VAR	0+%5
I1	INTEGER	SIMPLE VAR	0-%14 ,I	I2	INTEGER	SIMPLE VAR	0-%13 ,I
I3	INTEGER	SIMPLE VAR	0-%12 ,I	IA	INTEGER	SIMPLE VAR	0+%7
IS	INTEGER	SIMPLE VAR	0+%12	ITT	INTEGER	SIMPLE VAR	0+%11
J	INTEGER	SIMPLE VAR	0+%10	J4	INTEGER	SIMPLE VAR	0+%13
K	INTEGER	SIMPLE VAR	0+%16	L	INTEGER	SIMPLE VAR	0+%6
LABELS	INTEGER	ARRAY	0-%16 ,I	LL	INTEGER	SIMPLE VAR	0+%14
LM	INTEGER	SIMPLE VAR	0+%15	LR	INTEGER	SIMPLE VAR	0+%17
MAXCLUS	INTEGER	SIMPLE VAR	0-%5 ,I	MC	INTEGER	SIMPLE VAR	0-%15 ,I
MD	INTEGER	SIMPLE VAR	0-%6 ,I	MDIST	INTEGER	SIMPLE VAR	0+%21
MRST	INTEGER	SIMPLE VAR	0+%20	MX	INTEGER	SIMPLE VAR	0-%4 ,I
PIXELS	INTEGER	ARRAY	0-%11 ,I	REJECT	INTEGER	ARRAY	0-%10 ,I

PROGRAM UNIT FIXUP COMPILED

Parent: THINTSTM GETN25

GETN25(FRSTFLG,TTP,N25,NDS,FILENO,UICB,IND)

This program fetches N25 test sets from a disk file written by the subroutine CLOSEC.

Method: On the first call to the subroutine the disk file is rewound. On each call, N25 test sets are read from the file. A test set is five test pixels. The file is job-temporary.

Program Variables

FCHECK	SYSTEM INTRINSIC Error checking
FCONTROL	SYSTEM " Used to rewind file
FILENO	INTEGER System file number
FREAD	SYSTEM INTRINSIC File read
FRSTFLG	LOGICAL Marks first call
I	INTEGER DO loop index
ICALL	" Number of words returned by read
IERR	" Stuffed with error code
IMSG	" ARRAY Message to be printed
IND	INTEGER ARRAY Error code location
MSG	CHARACTER Message to be printed
N25	INTEGER Number of test sets requested
ND5	" 5 times number of dimensions
PABORT	SYSTEM SUBROUTINE
PRINTP	" " Prints a message
TTP	LOGICAL ARRAY Sutffed with test sets
UICB	INTEGER ARRAY User information control blcok
ZERO	LOGICAL Dummy argument for FCONTROL

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PAGE 0046   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:40 AM

00017  01497000  $CONTROL SEGMENT=ANOEBASEG
00017  01498000        SUBROUTINE GETN25(FRSTFLG,TTP,N25,ND5,FILENO,UICB,IND)
00017  01499000  C THIS SUBROUTINE FETCHES N25 SETS OF 5 TEST PIXELS FROM A DISK FILE THA
00017  01500000  C WAS CREATED EARLIER
00017  01501000  C
00017  01502000        INTEGER*2 UICB(1),IND(1),FILENO,
00017  01503000       *          IMSG(39)
00017  01504000        SYSTEM INTRINSIC FCONTROL,FREAD,FCHECK
00017  01505000        LOGICAL TTP(ND5,N25),ZERO,FRSTFLG
00017  01506000        CHARACTER*78 MSG
00017  01507000        EQUIVALENCE (IMSG,MSG)
00017  01508000  C
00017  01509000        IF ( NOT FRSTFLG) GO TO 10
00020  01510000        ZERO = FALSE
00022  01511000        FRSTFLG = FALSE
00024  01512000  C  ON FIRST CALL, REWIND FILE
00024  01513000        CALL FCONTROL (FILENO,3,ZERO)
00030  01514000        IF ( CC ) 6,10,6
00032  01515000   6    MSG = " FAILURE TO REWIND TEST PIXEL FILE"
00063  01516000        CALL PRINTP(UICB,IND,1,IMSG,34,0,0,0,0,0,0,0,0)
00113  01517000        CALL PABORT(UICB,45,0)
00122  01518000   10   CONTINUE
00122  01519000  C  READ N25 SETS OF 5 TEST PIXELS
00122  01520000        DO 30 I = 1,N25
00136  01521000        ICALL = FREAD(FILENO,TTP(1,I),ND5)
00142  01522000        IF (.NOT.) 20,30,20
00144  01523000   20   CALL FCHECK(FILENO,IERR)
00151  01524000        MSG = " ERROR @         ON TEST PIXEL FILE READ "
00205  01525000        MSG[10:6] = STR(IERR)
00222  01526000        CALL PRINTP(UICB,IND,1,IMSG,40,0,0,0,0,0,0,0,0)
00252  01527000        CALL PABORT(UICB,45,0)
00262  01528000   30   CONTINUE
00263  01529000        RETURN
00264  01530000                    END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
FCHECK		SUBROUTINE		FCONTROL		SUBROUTINE	
FILENO	INTEGER	SIMPLE VAR	Q-%6 ,I	FREAD	INTEGER	FUNCTION	
FRSTFLG	LOGICAL	SIMPLE VAR	Q-%12 ,I	GETN25		SUBROUTINE	
I	INTEGER	SIMPLE VAR	Q+%5	ICALL	INTEGER	SIMPLE VAR	Q+%7
IERR	INTEGER	SIMPLE VAR	Q+%6	IMSG	INTEGER	ARRAY	Q+%3 ,I
IND	INTEGER	ARRAY	Q-%4 ,I	MSG	CHARACTER	SIMPLE VAR	Q+%4 ,I
N25	INTEGER	SIMPLE VAR	Q-%10 ,I	ND5	INTEGER	SIMPLE VAR	Q-%7 ,I
PABORT		SUBROUTINE		PRINTP		SUBROUTINE	
TTP	LOGICAL	ARRAY	Q-%11 ,I	UICB	INTEGER	ARRAY	Q-%5 ,I
ZERO	LOGICAL	SIMPLE VAR	Q+%10				

PROGRAM UNIT GETN25 COMPILED

PARENT: MAPP IIIFN

FUNCTION IIIFN(I)

Maps -32768 to 32767 into 1 to 59 so that: -32768, 0, and 99 all map into 0; other integers I map to numbers between 2 and 59. This function is used by MAPP to index into SYMBOL. Special numbers -32768, 0, and 99 are all mapped to print as blanks. Others print as symbols so that when I and J are close, the symbols are different.

Method: Self-documenting.

Program Variables

I	INTEGER	Function argument

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PAGE 0015   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:37 AM

00001   00479000  $CONTROL SEGMENT=ANOEBASEG
00002   00480000        FUNCTION IIIFN(I)
00004   00481000        IF (I.GT.0) GO TO 3
00006   00482000        IF (I.EQ.0.OR.I.EQ.-32768) GO TO 4
00022   00483000        I = -I
00025   00484000        GO TO 5
00026   00485000      3 IF (I.EQ.99) GO TO 4
00032   00486000      5 I = MOD(I,60)
00036   00487000        IF (I.LE.1) I = I+30
00044   00488000        IIIFN = I
00046   00489000        R E T U R N
00047   00490000      4 IIIFN = 1
00051   00491000        R E T U R N
00054   00492000                  END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS                  NAME              TYPE        STRUCTURE   ADDRESS

I                 INTEGER     SIMPLE VAR  Q-24  ,I                 IIIFN             INTEGER     SIMPLE VAR  Q-25
IIIFN             INTEGER     FUNCTION


PROGRAM UNIT IIIFN COMPILED
```

Parent: MAIN MAPP

Calls: IIIFN

MAPP(N1,N2,N3,UICB,IND,IMAGE,NR,NC,SYMBOL)

Produces a quick look at a segment of data, labels map, or cluster map. Output is directed to the default device. This program is intended for debugging.

Method: The subroutine prints N2 lines in band one of an image, starting at line N1 sample N3. Because of the limitations of PRINTP, only 64 samples can be printed. Line numbers are printed, but not column numbers.

Program Variables

CHKIO	SYSTEM SUBROUTINE
IC	INTEGER DO loop index
IIIFN(IV)	INTEGER FUNCTION
IMAGE	INTEGER Image number.
IND(1)	INTEGER ARRAY Error information.
IPX(36)	INTEGER ARRAY Dummy array to compensate for the inadquacies of PRINTP. Equivalenced to PICTURE.
IR	INTEGER DO loop index.
N1	INTEGER Starting line number.
N1PN2	INTEGER Last line number to print.
N2	INTEGER Number of lines
N3	INTEGER Starting sample number
NC	INTEGER Number of samples in image.
NCL	INTEGER Last sample to be printed.
NCP	INTEGER Actual number printed.

NCP8	INTEGER NCP+8, the number sent to PRINTP.
NR	INTEGER Number of lines in image.
PICTURE	CHARACTER*72 area for core-to-core write under FORMAT control.
PRINTP	SYSTEM SUBROUTINE
READP	SYSTEM SUBROUTINE
SCAN(64)	INTEGER ARRAY Array to read from image.
SYMBOL(59)	CHARACTER*1 ARRAY The symbols printed; created by SETSYM.
UICB	INTEGER ARRAY

```
00026   00443000  $CONTROL SEGMENT=ANOEBASEG
00026   00444000        SUBROUTINE MAPP(N1,N2,N3,UICB,IND,IMAGE,NR,NC,SYMBOL)
00026   00445000        INTEGER*2 IPX(2),UICB(1),IND(1),SCAN(64)
00026   00446000        CHARACTER*72 PICTURE
00026   00447000        CHARACTER*1 SYMBOL(59)
00026   00448000        EQUIVALENCE(PICTURE,IPX)
00026   00449000        NIPN2 = N1+N2-1
00026   00450000        IF (NIPN2 GT NR) NIPN2 = NR
00027   00451000  C
00027   00452000  C  PRINT FROM COL N3 TO COL N3+63, ROWS N1 TO NIPN2.
00027   00453000        NCL = MIN0(NC,N3+63)
00046   00454000        NCP = NCL-N3+1
00051   00455000        NCP8 = NCP+8
00055   00456000        DO 100 IR = N1,NIPN2
00061   00457000        CALL READP(UICB,IND,IMAGE,SCAN,2,1,IR,N3,NCP,1,IR+1,N3,NCP)
00111   00458000        WRITE(PICTURE,111)IR,(SYMBOL(IIIFN(SCAN(IC))),IC = 1,NCP)
00121   00459000    111 FORMAT(I6,2X,64A1)
00151   00460000    100 CALL PRINTF(UICB,IND,1,IPX,NCP8,0,0,0,0,0,0,0,0)
00201   00461000        IF (IND(1) LT 0) CALL CHRIO(UICB,IND,1,IR,0,0,111)
00223   00462000        R E T U R N
00224   00463000                    END
```

Symbol map

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
CHRIO		SUBROUTINE		IC	INTEGER	SIMPLE VAR	Q+%5
IIIFN	INTEGER	FUNCTION		IMAGE	INTEGER	SIMPLE VAR	Q-%7 ,I
IND	INTEGER	ARRAY	Q-%10 ,I	IPX	INTEGER	ARRAY	Q+%1 ,I
IR	INTEGER	SIMPLE VAR	Q+%6	MAPP		SUBROUTINE	
N1	INTEGER	SIMPLE VAR	Q-%14 ,I	NIPN2	INTEGER	SIMPLE VAR	Q+%4
N2	INTEGER	SIMPLE VAR	Q-%13 ,I	N3	INTEGER	SIMPLE VAR	Q-%12 ,I
NC	INTEGER	SIMPLE VAR	Q-%5 ,I	NCL	INTEGER	SIMPLE VAR	Q+%7
NCP	INTEGER	SIMPLE VAR	Q+%10	NCP8	INTEGER	SIMPLE VAR	Q+%11
NR	INTEGER	SIMPLE VAR	Q-%6 ,I	PICTURE	CHARACTER	SIMPLE VAR	Q+%2 ,I
PRINTP		SUBROUTINE		READP		SUBROUTINE	
SCAN	INTEGER	ARRAY	Q+%3 ,I	SYMBOL	CHARACTER	ARRAY	Q-%4 ,I
UICB	INTEGER	ARRAY	Q-%11 ,I				

PROGRAM UNIT MAPP COMPILED

Parent: STARt MARKLR

Calls: FILLLR

MARKLR(Z,DATA,INTTHR,NC,ND,LABELS,MASK)

This subroutine marks boundary points left-right.

Method: A line of data is scanned. Points in the mask are marked boundary (under control of MASK). Points which, in any band, are closer to their left neighbor than INTTHR(.) are marked boundary. Finally, subroutine FILLLR is used to fill in a single point gap along the line.

Program Variables

DATA(NC,ND)	INTEGER ARRAY One line of data
FILLLR	SUBROUTINE Fills in gaps along a line.
I,K	INTEGER DO loop index
IM	INTEGER I-1
INTTHR(ND)	INTEGER ARRAY The thresholds for boundary finding.
LABELS(NC)	INTEGER ARRAY A line of labels
MASK	LOGICAL The mask flag. When .TRUE., zero in band 1 marks a point off the image, i.e., masked.
NC	INTEGER Number of samples per line.
ND	INTEGER Dimensionality
Z	INTEGER -32768, passed as a parameter, and used to mark boundary points.

Parent: CLASSIFY MARKUP

MARKUP(LABELS,NC,I1,I2,I3)

This subroutine "marks" pixels classified like at least one neighbor. This follows a nearest neighbor classification by PERPIXEL, and is followed by a possible reclassification of errant pixels by FIXUP.

Method: The pixel labels reside in a circular buffer LABELS of NC labels per line I1 points to the eldest label, I2 to the current label, and I3 to the newest. The eldest label may have been spatially modified, but labels along scan line I2 are not propagated down that scan line. The number 101 is added to any label classified like at least one of the four neighbors along scan line I2.

Program Variables

I	INTEGER DO loop index
I1	INTEGER Eldest line pointer.
I2	INTEGER Current line pointer.
I3	INTEGER Newest line pointer.
IM	INTEGER I-1
LABELS(NC,3)	INTEGER ARRAY The labels; LABELS(.,I2) is modified by adding 101 when at least one neighbor has the same label.
LL	INTEGER Label on left.
LM	INTEGER Label in middle.
RL	INTEGER Label on right
NC	INTEGER Number of samples per line.

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PAGE 0021   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:37 AM

00004  00648000  $CONTROL SEGMENT=AMOEBASEG
00004  00649000        SUBROUTINE MARKUP(LABELS,NC,I1,I2,I3,NX)
00004  00650000  C  THIS PROGRAM ADDS 1000 TO ANY CLASSIFICATION WHICH IS LIKE
00004  00651000  C  AT LEAST ONE NEIGHBOR     101
00004  00652000        INTEGER*2 LABELS(NC,?)
00004  00653000        IF (NX LT 3) R E T U R N
00010  00654000        IM = 2
00012  00655000        LL = LABELS(1,I2)
00020  00656000        LM = LABELS(2,I2)
00027  00657000        DO 10 I = 3,NX
00034  00658000        LR = LABELS(I,I2)
00043  00659000        IF (LM EQ 0) GO TO 30
00047  00660000        IF (LL.EQ.LM.OR.LR.EQ.LM) GO TO 20
00056  00661000        IF (LABELS(IM,I3) EQ LM) GO TO 20
00067  00662000        IF (LABELS(IM,I1) NE LM) GO TO 30
00100  00663000     20 LABELS(IM,I2) = LM+101
00110  00664000     30 LL = LM
00112  00665000        LM = LR
00114  00666000     10 IM = I
00117  00667000        R E T U R N
00120  00668000                   END
```

LABELS(IM,I1)- 101

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
I	INTEGER	SIMPLE VAR	Q+%2	I1	INTEGER	SIMPLE VAR	Q-%7 ,I
I2	INTEGER	SIMPLE VAR	Q-%6 ,I	I3	INTEGER	SIMPLE VAR	Q-%5 ,I
IM	INTEGER	SIMPLE VAR	Q+%3	LABELS	INTEGER	ARRAY	Q-%11 ,I
LL	INTEGER	SIMPLE VAR	Q+%4	LM	INTEGER	SIMPLE VAR	Q+%5
LR	INTEGER	SIMPLE VAR	Q+%6	MARKUP		SUBROUTINE	
NC	INTEGER	SIMPLE VAR	Q-%10 ,I	NX	INTEGER	SIMPLE VAR	Q-%4 ,I

PROGRAM UNIT MARKUP COMPILED

Parent: START MARKUPDN

Calls: FILLLR

MARKUPDN(Z,D1,D2,L1,L2,L3,NC,ND,INTTHR,MASK)

This subroutine marks boundary points up-down.

METHOD: If, in any band, data in D1 is closer to or equal to data in D2 than the threshold INTTHR, then labels L1 and L1 and L2 at that sample are marked by being set equal to Z. The reason for the "less than or equal to" rather than "less than" as appears in MARKLR is that the data is generally less variable down scan lines than across scan lines. Points off the image are also marked as boundary provided MASK is set. At conclusion of this scan through the data, FILLLR is called on center line L2.

Program Variables

D1(NC,ND) D2(NC,ND)	INTEGER ARRAY Two adjacent lines of data, D1 is the eldest, D2 newer.
FILLLR	SUBROUTINE Fills in gaps along a line.
I,K	INTEGER DO loop index.
INTTHR(ND)	INTEGER ARRAY Vector thresholds for deciding boundary.
L1(NC) L2(NC) L3(NC)	INTEGER ARRAY Three scan lines of labels. L1 is oldest, L3 newest.
MASK	LOGICAL Flag used to decide whether a value of 0 in D1(.,1) or D2(.,1) marks the mask. Mask points are marked boundary.
NC	Number of samples per line
ND	Dimensionality
Z	-32768, used to mark boundary.

```
PAGE 0030   HEWLETT-PACKARD 321028.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:39 AM

00012  01205000  $CONTROL SEGMENT=AMOEBASEG
00012  01206000        SUBROUTINE MARKUPDM(Z,D1,D2,L1,L2,L3,NC,ND,INTTHR,MASK,NX)
00012  01207000        INTEGER*2 Z,D1(NC,ND),D2(NC,ND),L1(NC),L2(NC),L3(NC),INTTHR(ND)
00012  01208000        LOGICAL MASK
00012  01209000        DO 10 I = 1,NX
00017  01210000        IF (L1(I).EQ.Z.AND.L3(I).EQ.Z) GO TO 20
00030  01211000        IF ( NOT MASK) GO TO 1
00033  01212000        IF (D1(I,1) EQ.0) L1(I) = Z
00043  01213000        IF (D2(I,1).EQ.0) L2(I) = Z
00057  01214000      1 DO 30 K = 1,ND
00064  01215000        IF (IABS(D1(I,K)-D2(I,K)).LE.INTTHR(K)) GO TO 30
00106  01216000        L1(I) = Z
00111  01217000        GO TO 20
00113  01218000     30 CONTINUE
00114  01219000        GO TO 10
00115  01220000     20 L2(I) = Z
00120  01221000     10 CONTINUE
00121  01222000        CALL FILLLR(Z,L2,NX)
00126  01223000        R E T U R N
00127  01224000                      END


  SYMBOL MAP

NAME              TYPE        STRUCTURE    ADDRESS          NAME              TYPE        STRUCTURE    ADDRESS

D1                INTEGER     ARRAY        0-%15 ,I         D2                INTEGER     ARRAY        0-%14 ,I
FILLLR                        SUBROUTINE                    I                 INTEGER     SIMPLE VAR   0+%3
INTTHR            INTEGER     ARRAY        0-%6  ,I         K                 INTEGER     SIMPLE VAR   0+%4
L1                INTEGER     ARRAY        0-%13 ,I         L2                INTEGER     ARRAY        0-%12 ,I
L3                INTEGER     ARRAY        0-%11 ,I         MARKUPDM                      SUBROUTINE
MASK              LOGICAL     SIMPLE VAR   0-%5  ,I         NC                INTEGER     SIMPLE VAR   0-%10 ,I
ND                INTEGER     SIMPLE VAR   0-%7  ,I         NX                INTEGER     SIMPLE VAR   0-%4  ,I
Z                 INTEGER     SIMPLE VAR   0-%16 ,I


PROGRAM UNIT MARKUPDM COMPILED
```

Parent: MAIN MOREQUES

Calls: REJECTH

MOREQUES(MEANS,TESTS,MAXCLUS,NFCLUS,ND,NTS,REJECT)

The purpose of MOREQUES is to detect when a necessary cluster has been lost and add it in. The test is based on the pure rejection thresholds applied to classification of the center (i.e., third of 5) test pixel in each test set.

Method: Initially, REJECTH is called to determine the pure rejection thresholds. Then a loop on center of test sets is entered. Each time no cluster center is closer than its rejection threshold to the test pixel, that test pixel is added as a new cluster center, the reject thresholds are calculated, and the next test set examined. On completion of all examinations, the reject thresholds are multiplied by 2 (effectively multiplying the Euclidean distance test by $\sqrt{2}$, preparing for misregistration mixtures). Since there is a bias of -32768, the actual calculation goes as follows: If r is the unbiased rejection threshold and R the biased, then $r = R + 32768$, so the new unbiased threshold 2r has its biased threshold $R' = 2r - 32768 = 2R + 32768$. (If R' is greater than 16000, use R' = 16000.)

Program Variables

A0	INTEGER*4 Long integer used to perform long calculations
I,J,K	INTEGER DO loop parameters
IS,IT	INTEGER Used in accumulating distance.
MAXCLUS	INTEGER Maximum number of clusters.
MEANS(ND,MAXCLUS)	INTEGER ARRAY The cluster centers.
ND	INTEGER Dimensionality
NFCLUS	INTEGER Current number of clusters.
NTS	INTEGER Number of test sets.

REJECT(MAXCLUS)	INTEGER ARRAY Rejection thresholds.
REJECTH	SUBROUTINE Calculates REJECT.
TESTS(ND,NTS)	INTEGER ARRAY Test pixels.

```
PAGE 0001   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:37 AM

00010  00719000  $CONTROL SEGMENT=ANOTHERSEG
00010  00720000        SUBROUTINE NOREDUES(MEANS,TESTS,MAXCLUS,NFCLUS,ND,NTS,REJECT)
00010  00721000        INTEGER*2 MEANS(ND,MAXCLUS),TESTS(ND,NTS),REJECT(MAXCLUS)
00010  00722000        INTEGER*4 A0
00010  00723000        CALL REJECTH(MEANS,ND,REJECT,NFCLUS,MAXCLUS)
00020  00724000        DO 10 I = 3,NTS,3
00023  00725000          DO 30 J = 1,NFCLUS
00032  00726000            IS = -32768
00041  00727000            DO 20 K = 1,ND
00046  00728000              IF (IS.GE.16383) GO TO 30
00056  00729000                IT = TESTS(K,I)-MEANS(K,J)
00073  00730000                IS = IS+IT*IT
00077  00731000                IF (IS.GE.REJECT(J)) GO TO 30
00105  00732000     20       CONTINUE
00106  00733000  C
00106  00734000  C  GETTING HERE MEANS WE SUCCESSFULLY CLASSIFIED TESTS(..I)
00106  00735000        GO TO 10
00110  00736000     30   CONTINUE
00111  00737000  C
00111  00738000  C  GETTING HERE MEANS WE DIDN'T.  ADD ONE.
00111  00739000        NFCLUS = NFCLUS+1
00112  00740000        DO 40 K = 1,ND
00117  00741000     40 MEANS(K,NFCLUS) = TESTS(K,I)
00134  00742000        CALL REJECTH(MEANS,ND,REJECT,NFCLUS,MAXCLUS)
00144  00743000        IF (NFCLUS.GE.MAXCLUS) GO TO 50
00151  00744000     10 CONTINUE
00152  00745000     50 DO 60 I = 1,NFCLUS
00157  00746000        A0 = REJECT(I)
00164  00747000        A0 = A0+2+32768
00174  00748000        IF (A0.GT.16000) A0 = 16000
00206  00749000     60 REJECT(I) = A0
00217  00750000        R E T U R N
00227  00751000        END


  SYMBOL MAP

NAME            TYPE        STRUCTURE   ADDRESS          NAME            TYPE        STRUCTURE   ADDRESS

A0              INTEGER*4   SIMPLE VAR  0+%11           I               INTEGER     SIMPLE VAR  0+%4
IS              INTEGER     SIMPLE VAR  0+%6            IT              INTEGER     SIMPLE VAR  0+%7
J               INTEGER     SIMPLE VAR  0+%5            K               INTEGER     SIMPLE VAR  0+%10
MAXCLUS         INTEGER     SIMPLE VAR  0-%10 ,I        MEANS           INTEGER     ARRAY       0-%12 ,I
NOREDUES                    SUBROUTINE                  ND              INTEGER     SIMPLE VAR  0-%6  ,I
NFCLUS          INTEGER     SIMPLE VAR  0-%7  ,I        NTS             INTEGER     SIMPLE VAR  0-%5  ,I
REJECT          INTEGER     ARRAY       0-%4  ,I        REJECTH                     SUBROUTINE
TESTS           INTEGER     ARRAY       0-%11 ,I


PROGRAM UNIT NOREDUES COMPILED
```

Parent: START MRKIVL

MRKIVL(Z,A,N,M)

This subroutine prepares the complement of the boundary for accumulation of components.

Method: Recall that boundary points are marked with Z (-32768). The rest are counted left-to-right along line A in intervals, replacing the slot in A by the interval number. For example, a 20 point line on input might be

Z Z 0 0 0 Z Z Z Z 0 Z 0 0 Z 0 Z Z Z 0 0

and the line returned would be

Z Z 1 1 1 Z Z Z Z 2 Z 3 3 Z 4 Z Z Z 5 5 .

On return, M is the number of intervals found.

Program Variables

A(N)	INTEGER ARRAY One line of boundary labels, in which intervals are to be found.
I	INTEGER DO loop index
IM	INTEGER I-1
M	INTEGER Interval counter.
N	INTEGER Number in a line
Z	INTEGER Boundary marker.

```
PAGE 0036   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:39 AM

00004  01150000  $CONTROL SEGMENT=AMOEBASEG
00004  01151000        SUBROUTINE MRKIVL(Z,A,M,N)
00004  01152000        INTEGER*2 Z,A(N)
00004  01153000        M = 1
00006  01154000        IF (A(1).EQ.Z) GO TO 10
00013  01155000        A(1) = M
0001C  01156000        M = M+1
00017  01157000     10 DO 20 I = 2,N
00024  01158000        IM = I-1
00027  01159000        IF (A(I).EQ.Z) GO TO 20
00034  01160000        IF (A(IM).EQ.Z) GO TO 30
00041  01161000        A(I) = A(IM)
00043  01162000        GO TO 20
00046  01163000     30 A(I) = M
00051  01164000        M = M+1
00052  01165000     20 CONTINUE
00053  01166000        M = M-1
00054  01167000        R E T U R N
00055  01168000                      END


  SYMBOL MAP

NAME              TYPE       STRUCTURE   ADDRESS                NAME              TYPE       STRUCTURE   ADDRESS

A                 INTEGER    ARRAY       Q-26  ,I              I                 INTEGER    SIMPLE VAR  Q+22
IM                INTEGER    SIMPLE VAR  Q+23                  M                 INTEGER    SIMPLE VAR  Q-24  ,I
MRKIVL                       SUBROUTINE                        N                 INTEGER    SIMPLE VAR  Q-28  ,I
Z                 INTEGER    SIMPLE VAR  Q-27  ,I


PROGRAM UNIT MRKIVL COMPILED
```

Parent: MAIN MSORT

Calls: SHELL

MSORT(MEAN,ND,NFC,DUM,INDX)

Sorts final clusters by average odd channels to aid interpretation of clustering.

Method: First the sums are accumulated. At the same time, an index is set so that INDX(I) = I. Then SHELL is called. On return from SHELL, the means are reordered by the permutation of INDX. The actual means are now switched in place.

Program Variables

DUM(NFC)	INTEGER ARRAY Used to accumulate sums in odd bands, and then as temporary storage to switch MEAN.
I	INTEGER DO loop index
INDX(NFC)	INTEGER ARRAY The pointer array, used by SHELL to indicate actual order of DUM.
J	INTEGER DO loop index.
K	INTEGER DO loop index.
MEAN(ND,NFC)	INTEGER ARRAY The means to be sorted.
ND	INTEGER Dimensionality of MEAN.
NFC	INTEGER Number of vectors in MEAN.
SHELL	SUBROUTINE Sorts vector in increasing order.

```
PAGE 0010  HEWLETT-PACKARD 32102B.01.07  FORTRAN/3000  TUE, OCT 13, 1981,  9:36 AM

00007  00360000  $CONTROL SEGMENT=AMOEBASEG
00007  00361000        SUBROUTINE MSORT(MEAN,ND,NFC,DUM,INDX)
00007  00362000        INTEGER*2 MEAN(ND,NFC),DUM(NFC),INDX(NFC)
00007  00363000        DO 1 I = 1,NFC
00014  00364000        DUM(I) = 0
00017  00365000        DO 1000 J = 1,ND,2
00023  00366000   1000 DUM(I) = DUM(I)+MEAN(J,I) -
00036  00367000      1 INDX(I) = I
00042  00368000        CALL SHELL(DUM,INDX,NFC)
00050  00369000        DO 110 K = 1,ND
00055  00370000        DO 120 I = 1,NFC
00062  00371000    120 DUM(I) = MEAN(K,INDX(I))
00074  00372000        DO 130 I = 1,NFC
00101  00373000    130 MEAN(K,I) = DUM(I)
00112  00374000    110 CONTINUE
00113  00375000        R E T U R N
00114  00376000                    END


  SYMBOL MAP

NAME              TYPE       STRUCTURE    ADDRESS          NAME              TYPE       STRUCTURE    ADDRESS

DUM               INTEGER    ARRAY        Q-%5  ,I        I                 INTEGER    SIMPLE VAR   Q+%3
INDX              INTEGER    ARRAY        Q-%4  ,I        J                 INTEGER    SIMPLE VAR   Q+%4
K                 INTEGER    SIMPLE VAR   Q+%5             MEAN              INTEGER    ARRAY        Q-%10 ,I
MSORT                        SUBROUTINE                   ND                INTEGER    SIMPLE VAR   Q-%7  ,I
NFC               INTEGER    SIMPLE VAR   Q-%6  ,I        SHELL                        SUBROUTINE


PROGRAM UNIT MSORT COMPILED
```

Parent: MAIN NUMCLU

Calls: COLAPS, DIAMTR, UNCLE

NUMCLU(MEAN,ND,NP5,NP,TSPXL,NFCLUS,MINCLN,MAXCLN,CLASS,COUNT,ERROR,SAVE, DUM,CSAVE,UICB,IND,NUM)

NUMCLU is the main clustering segment in AMOEBA. It carries out cluster formation according to the strategy suggested by the model (Appendix A).

Method: On entry to NUMCLU, the set of all possible means is MEAN, and the test sets are in TSPXL. Also furnished is MINCLN (which, if negative, requests exactly MINCLN (too many) clusters, or if positive at least MINCLN, and MAXCLN (which specifies the maximum number of clusters to seek). The following steps are carried out;

(1) Classify the first and last of each test set in the nearest cluster (Euclidian distance). Save the classification in CLASS and count it in COUNT. Set LIVING = the initial number NP5 of clusters.
(2) For each I, if COUNT(I) = 0, eliminate that cluster by setting NUM(I) = 0 and LIVING = LIVING -1.
(3) If fewer than 101 clusters are present, go to step (6), else set IE = 1.
(4) Eliminate successively each cluster I with COUNT(I) = IE; reclassify test pixels assigned to eliminated classes; exit (5) when the number of viable clusters falls below 101.
(5) Increment IE and repeat (4).
(6) Call COLAPS to remove eliminated centers.
(7) Call DIAMTR to determine the diameter of starting clusters.
(8) Set the initial elimination protection threshold IDIAMP. Except for the bias, IDIAMP is the diameter divided by 4*MINCLN.
(9) Classify each test pixel by nearest neighbor and save the classification.

(10) Set NERR, an error counter, to zero; also set ERROR(I) = 0, I = 1, ...,LIVING.

(11) Count the number of times a cluster attracts a pixel from a test set and a pixel from a "far away" test set (in the order inplied by the pre-sorting of test sets). Also accumulate in ERROR the count of this event per cluster.

(12) Count the number of times a pair from the same test set is split, and credit to each of the clusters by incrementing ERROR of each.

(13) Save the running minimum of NERR in MIN provided the current number of clusters is not greater than MAXCLN.

(14) Determine which cluster I has ERROR(I) maximum.

(15) Tentatively reassign test pixels assigned to class I; however, if any test pixel J is assigned more than IDIAMP away, execute (17).

(16) Now dummy eliminate class I, set IDIAMP = IDIAMP-ND, and decrement the running number of clusters. If this number is less than or equal to MINCLN, execute (18). (Similar logic implements exactly so many clusters.) Otherwise execute step (10).

(17) The biased distance is ID; set IDIAMP = (IDIAMP/3)*2 + ID/3 + ND and replace the mean in question by the (far away) test pixel. Replace the error counter here by half its former value and repeat step (14).

(18) Now actually eliminate the clusters to the minimum NERR (the earlier eliminations were only dummies), and again call COLAPS to move means to the beginning of MEAN. The number of clusters is now NFCLUS. Exit.

Program Variables

CHKIO	SYSTEM SUBROUTINE
CLASS(NP)	INTEGER ARRAY The class a test pixel is nearest.
COLAPS	SUBROUTINE Moves the vectors in MEAN to start, eliminating gaps.
COUNT(NP5)	INTEGER ARRAY. The number of classifications a mean receives.

CSAVE(NP)	INTEGER ARRAY Scratch array used to save classifications while checking distances.
DIAMTR	SUBROUTINE Finds biased square of diameter of starting clusters.
DUM(NP5)	INTERGER ARRAY Dummy, used to mark which are eliminated while computing the minimum number of errors.
ERROR(NP5)	INTEGER ARRAY Number of errors for each cluster center; see above.
I,J,K,	INTEGER DO loop index.
I1,I2,I3,I4,I5	INTEGER The classification of the first through fifth of each test set pixel.
IC	INTEGER The classification of a test pixel far away.
ID	INTEGER The biased distance returned by UNCLE.
IDIAM	INTEGER Square of diameter (biased) of starting cluster centers.
IDIAMP	INTEGER Elimination protection threshold (biased by -32768).
IE	INTEGER Number of classifications to eliminate (a DO loop index).
IN	INTEGER Running current number of clusters being tested.
IND(1)	INTEGER ARRAY Error indicator.
IPMC	INTEGER Estimate of PPMC (see Appendix A).
IPRINT	INTEGER IDIAM with bias removed.
IT	INTEGER Far away index.
LIVING	INTEGER Current number of living clusters.

MAXCLN	INTEGER Maximum number of clusters sought.
MEAN(ND,NP5)	INTEGER ARRAY The cluster centers.
MIN	INTEGER Running minimum number of errors found.
MINCLN	INTEGER Minimum number of clusters sought.
MJ	INTEGER The class with most errors during elimination.
MP	INTEGER Error count for seeking maximum number of errors.
ND	INTEGER Dimensionality
NERR	INTEGER Local count of number of errors each trial.
NFCLUS	INTEGER Final number of clusters.
NP	INTEGER Number of test pixels.
NP5	INTEGER Number of means.
NPA	INTEGER NP/4; 1/4 of the way through the set of test pixels.
NPA2	INTEGER NPA*2; 1/2 of the way.
NUM(NP5)	INTEGER ARRAY Indicator to point to classes eliminated. Used at first and last of the program.
PRINTEQ(66)	INTEGER ARRAY Used for PRINTP I/O.
PRINTIT	CHARACTER Used for core-to-core formated write.
PRINTP	SYSTEM SUBROUTINE
SAVE(NP5)	INTEGER ARRAY Used to save classes eliminated (tentatively) in order.
SEEK	LOGICAL Used to carry out logic for exactly so many clusters (if .TRUE.).
TSPXL(ND,NP)	INTEGER ARRAY The test pixels.
UICB(1)	INTEGER ARRAY User Information Control Block.
UNCLE	SUBROUTINE Finds closest MEAN with NUM ≠ 0 to TSPXL; distance is ID, class is I1.

```
00266  01637000  $CONTROL SEGMENT=ANOEBASEG
00266  01638000        SUBROUTINE NUMCLU(MEAN,ND,NPS,NP,TSPXL,NFCLUS,NINCLN,
00266  01639000       *  CLASS,COUNT,ERROR,SAVE,DUM,CSAVE,UICB,IND,NUM,MAXCLN)
00266  01640000  C
00266  01641000  C  PARENT PROGRAM:      MAIN
00266  01642000  C  DAUGHTER PROGRAMS:  UNCLE,COLAPS,DIANTR
00266  01643000  C
00266  01644000  C  ---PARAMETERS IN NUMCLU---
00266  01645000  C
00266  01646000  C   CLASS -- INTEGER*2 VECTOR USED TO STORE THE CLUSTER
00266  01647000  C             TO WHICH A TEST PIXEL (IN  TSPXL ) IS
00266  01648000  C             ASSIGNED.
00266  01649000  C
00266  01650000  C   COUNT -- INTEGER*2 VECTOR USED TO TALLY THE NUMBER
00266  01651000  C             OF TIMES A TEST PIXEL IS ASSIGNED TO
00266  01652000  C             EACH CLASS (IN  MEAN )
00266  01653000  C
00266  01654000  C   ERROR -- INTEGER*2 VECTOR USED TO ESTIMATE THE
00266  01655000  C             RELATIVE PERFORMANCE OF EACH CLUSTER
00266  01656000  C             VS.ALL THE OTHERS. NOTE
00266  01657000  C
00266  01658000  C      ERROR(K) IS:  INCREASED BY  1  WHEN
00266  01659000  C             CLUSTER  K  IS INVOLVED IN SPLITTING
00266  01660000  C             A PAIR FROM THE SAME PATCH)
00266  01661000  C
00266  01662000  C             INCREASED BY  1  WHEN
00266  01663000  C             CLUSTER  K  ATTRACTS A PAIR FROM
00266  01664000  C             DIFFERENT REAL CLASSES.
00266  01665000  C
00266  01666000  C  AT EACH ELIMINATION CYCLE, THE CLUSTER WITH  ERROR RELATIVELY
00266  01667000  C  LARGEST IS ELIMINATED)  THE AFFECT OF THIS IS
00266  01668000  C  THAT A CLUSTER SURVIVES IF IT
00266  01669000  C
00266  01670000  C             (A)  DOES NOT SPLIT PAIRS
00266  01671000  C             FROM THE SAME PATCH
00266  01672000  C
00266  01673000  C             (B)  DOES SPLIT PAIRS FROM
00266  01674000  C             DIFFERENT PATCHES.
00266  01675000  C
00266  01676000  C    SAVE -- INTEGER*2 VECTOR USED TO STORE THE ORDER
00266  01677000  C             IN WHICH CLUSTERS ARE TO BE ELIMINATED
00266  01678000  C             ONCE THEIR NUMBER IS DETERMINED.
00266  01679000  C
00266  01680000  C     DUM -- INTEGER*2 VECTOR USED TO MARK CLUSTERS
00266  01681000  C             WHICH WERE ELIMINATED IN THE INITIAL
00266  01682000  C             ELIMINATION CYCLE PRIOR TO THEIR
00266  01683000  C             ACTUAL ELIMINATION.
00266  01684000  C
00266  01685000  C   CSAVE -- TEMPORARY VECTOR USED TO SAVE CERTAIN CLASSIFICATIONS
00266  01686000  C             WHILE THE ENTIRE SET IS BEING CHECKED FOR ACCURACY.
00266  01687000  C
00266  01688000  C  LIVING -- PARAMETER MARKING THE CURRENT NUMBER
00266  01689000  C             OF CLUSTERS.
00266  01690000  C
00266  01691000  C    NERR -- THE NUMBER OF TEST PIXEL PAIRS WHICH
00266  01692000  C             ARE SPLIT PLUS THE NUMBER OF DIFFERENT
00266  01693000  C             PAIRS WHICH ARE JOINED DURING A CYCLE
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PAGE 0051   NUMCLU

00266  01694000  C
00266  01695000  C  MINCLN -- THE MINIMUM NUMBER OF CLUSTERS SOUGHT.
00266  01696000  C             IF  MINCLN  IS NEGATIVE, EXACTLY  -MINCLN
00266  01697000  C             CLUSTERS ARE SOUGHT (RATHER THAN GE.)
00266  01698000  C
00266  01699000  C  MAXCLN -- THE MAXIMUM NUMBER OF CLUSTERS SOUGHT (IN NUMCLU)
00266  01700000  C             IN THE CURRENT VERSION, MAXCLN = 98,
00266  01701000  C             ALTHOUGH IT COULD EASILY BE MADE A PROGRAM PARAMETER.
00266  01702000  C
00266  01703000  C    SEEK -- A FLAG TO SWITCH BETWEEN EXACTLY AND GE
00266  01704000  C             MINCLN CLUSTERS.
00266  01705000  C
00266  01706000  C   IDIAM -- THE SQUARE OF THE DIAMETER OF THE STARTING CLUSTER SET
00266  01707000  C
00266  01708000  C  IDIAMP -- AN ELIMINATION PROTECTION THRESHOLD WHICH PREVENTS
00266  01709000  C             THE LOSS OF CLUSTERS NEEDED FOR THE REASONABLE CLASS-
00266  01710000  C             IFICATION OF SOME TEST PIXELS.
00266  01711000  C
00266  01712000  C     MIN -- RUNNING MINIMUM NUMBER OF ERRORS.
00266  01713000  C
00266  01714000  C     MIN -- NUMBER OF CLUSTERS WITH  MIN  ERRORS.
00266  01715000  C
00266  01716000        INTEGER*2 TSPXL(ND,NP),MEAN(ND,NPS),NUM(NPS),CLASS(NP)
00266  01717000       * ,COUNT(NPS),ERROR(NPS),SAVE(NPS),DUM(NPS),CSAVE(NP)
00266  01718000       * ,PRINTE0(66),UIC0(1),IND(4)
00266  01719000        LOGICAL SEEK
00266  01720000        CHARACTER*72 PRINTIT
00266  01721000        EQUIVALENCE(PRINTIT,PRINTE0)
00266  01722000        MINCLN = MINCLN
00270  01723000        DO 1111 I = 1,NPS
00273  01724000  1111 NUM(I) = 1
00301  01725000  C
00301  01726000  C  THIS SEGMENT FOLLOWS ORDERS RE HOW MANY CLUSTERS ARE REQUIRED
00301  01727000        SEEK =.FALSE.
00302  01728000        IF (MINCLN.LT.0) GO TO 96
00307  01729000        IF (MINCLN.LT.2.OR.MINCLN.GT.100) MINCLN = 5
00317  01730000     97 WRITE(PRINTIT,98) MINCLN
00340  01731000        CALL PRINTP(UIC0,IND,1,PRINTE0,42,0,0,0,0,0,0,0,0)
00370  01732000        IF (IND(1).LT.0) CALL CMKIO(UIC0,IND,1,0,0,0,1200)
00413  01733000        GO TO 95
00415  01734000     96 MINCLN = -MINCLN
00420  01735000        IF (MINCLN.GT.100.OR.MINCLN.LT.2) MINCLN = 15
00430  01736000        SEEK = .TRUE.
00432  01737000        WRITE(PRINTIT,94) MINCLN
00457  01738000        CALL PRINTP(UIC0,IND,1,PRINTE0,32,0,0,0,0,0,0,0,0)
00503  01739000        IF (IND(1).LT.0) CALL CMKIO(UIC0,IND,1,0,0,0,1300)
00526  01740000     94 FORMAT('      EXACTLY',I3,' CLUSTERS SOUGHT.')
00526  01741000     98 FORMAT('      MINIMUM NUMBER OF CLUSTERS SOUGHT:',I3)
00526  01742000     95 MINCLN = MINCLN-1
00527  01743000  C     MAXCLN = 98       *******MAXCLN NOW A PROGRAM PARAM*************
00527  01744000  C
00527  01745000  C  PRINT STARTING CONDITIONS.
00527  01746000        WRITE(PRINTIT,100) NPS,NP
00552  01747000        CALL PRINTP(UIC0,IND,1,PRINTE0,47,0,0,0,0,0,0,0,0)
00602  01748000        IF (IND(1).LT.0) CALL CMKIO(UIC0,IND,1,0,0,0,1400)
00627  01749000   100 FORMAT('      START WITH',I4,' CLUSTERS,',I5,' TEST POINTS.')
00623  01750000  C
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PAGE 0032 NUNCLU

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00629  01791000  C  CLEAR A COUNTER OF THE NUMBER OF TIMES A CLUSTER IS HIT
00629  01792000  C  BY A TEST PIXEL IN THE INITIAL CLASSIFICATION.
00629  01793000        DO 2 I = 1,NPS
00632  01794000       2 COUNT(I) = 0
00636  01795000  C
00636  01796000  C  CLASSIFY AND COUNT THE CLASSIFICATION OF EVERY 9-TH TEST PIXEL.
00636  01797000  C
00636  01798000  C  VERSION II USES AS STARTING CLUSTERS PATCH CENTERS FROM PATCHES
00636  01799000  C  CONTAINING 9 OR MORE PIXELS. THIS MEANS THE TIME SPENT IN NUNCLU
00636  01800000  C  IS O(NP**3).
00636  01801000  C
00636  01802000        DO 1 I = 1,NP,9
00647  01803000        CALL UNCLE(TSPXL(1,I),MEAN,ND,NPS,II,NUM,ID)
00661  01804000        COUNT(II) = COUNT(II)+1
00665  01805000        CLASS(I) = II
00670  01806000        CALL UNCLE(TSPXL(1,I+4),MEAN,ND,NPS,II,NUM,ID)
00707  01807000        COUNT(II) = COUNT(II)+1
00713  01808000       1 CLASS(I+4) = II
00721  01809000  C
00721  01810000  C   LIVING  IS THE TEMPORARY NUMBER OF LIVING CLUSTERS.
00721  01811000        LIVING = NPS
00722  01812000        DO 3 I = 1,NPS
00736  01813000        IF (COUNT(I).GT.0) GO TO 3
00741  01814000  C
00741  01815000  C  ELIMINATE A CLUSTER TO WHICH NOTHING IS ASSIGNED.
00741  01816000        NUM(I) = 0
00744  01817000        LIVING = LIVING-1
00749  01818000       3 CONTINUE
00746  01819000  C
00746  01820000  C  REPORT HOW MANY CLUSTERS WE START WITH.
00746  01821000        WRITE(PRINTIT,101) LIVING
00767  01822000     101 FORMAT('    ',I4,' CLUSTERS HAVE NON VOID ASSIGNMENTS.')
00767  01823000        CALL PRINTP(UICB,IND,1,PRINTE0,4J,0,0,0,0,0,0,0,0)
01017  01824000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,1,0,0,0,1500)
01042  01825000  C
01042  01826000  C  WE ARE AIMING FOR NO MORE THAN 100 TO SAVE TIME IN THE BAD LOGIC
01042  01827000        IF (LIVING.LE.100) GO TO 7
01050  01828000        DO 4 IE = 1,100
01059  01829000        DO 5 I = 1,NPS
01062  01830000        IF (COUNT(I).NE.IE) GO TO 5
01067  01831000  C
01067  01832000  C  ELIMININATE AN UNPOPULAR CLASS AND...
01067  01833000        LIVING = LIVING-1
01076  01834000        NUM(I) = 0
01073  01835000  C
01073  01836000  C  ...RECLASSIFY PIXELS IN THAT CLASS.
01073  01837000        DO 6 J = 1,NP,9
01100  01838000        IF (CLASS(J).NE.I) GO TO 99
01105  01839000        CALL UNCLE(TSPXL(1,J),MEAN,ND,NPS,II,NUM,ID)
01123  01840000        CLASS(J) = II
01126  01841000        COUNT(II) = COUNT(II)+1
01132  01842000     99 IF (CLASS(J+4).NE.I) GO TO 6
01141  01843000        CALL UNCLE(TSPXL(1,J+4),MEAN,ND,NPS,II,NUM,ID)
01160  01844000        CLASS(J+4) = II
01167  01845000        COUNT(II) = COUNT(II)+1
01171  01846000       6 CONTINUE
01172  01847000  C
```

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PAGE 0053   NUMCLU

01172  01808000  C  SEE IF WE ARE FINISHED.
01172  01809000        IF (LIVING.LE.100) GO TO 7
01177  01810000      5 CONTINUE
01200  01811000      4 CONTINUE
01201  01812000  C
01201  01813000      7 CALL COLAPS(NPS,MEAN,NUM,ND)
01210  01814000        IF (MINCLM.GT.LIVING) GO TO 807
01215  01815000  C
01215  01816000  C  ESTIMATE THE DIAMETER OF THE STARTING SET OF CLUSTER CENTERS
01215  01817000        CALL DIAMTR(MEAN,ND,LIVING,IDIAM)
01223  01818000  C
01223  01819000  C  PRINT THE DIAMETER.
01223  01820000        IPRINT = IDIAM+32767+1
01227  01821000        IF (IPRINT.LT.0) IPRINT = 32767
01234  01822000        WRITE(PRINTIT,81) IPRINT
01255  01823000     81 FORMAT('     SQUARE OF DIAMETER OF STARTING CLUSTERS:',I6)
01255  01824000        CALL PRINTP(UICB,IND,1,PRINTE0.51,0,0,0,0,0,0,0,0)
01305  01825000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,1,0,0,0,1566)
01320  01826000  C
01320  01827000  C  SET THRESHOLD FOR ELIMINATION PROTECTION
01330  01828000        IDIAMP = IPRINT/MINCLM/4-32768
01345  01829000  C
01345  01830000  C  INITIALIZE A DUMMY VECTOR OF POINTERS TO ELIMINATED CLUSTERS.
01345  01831000        DO 8 I = 1,LIVING
01352  01832000      8 DUM(I) = 1
01356  01833000  C
01356  01834000  C  PREPARE TO COUNT ERRORS
01356  01835000        IN = LIVING
01360  01836000        MIN = 32767
01362  01837000  C
01362  01838000  C  NPA IS 1/4 OF THE WAY ON ONE SIDE OF THE POINT WE ARE WORKING ON
01362  01839000        NPA = NP/4
01365  01840000  C
01365  01841000  C  NPA2 IS 1/2 IN THE ORDER IMPLIED BY THE RESULT OF SORT.
01365  01842000        NPA2 = NPA*2
01370  01843000  C
01370  01844000  C  CLASSIFY ALL TEST POINTS PRIOR TO GETTING STARTED.
01370  01845000        DO 9 I = 1,NP
01375  01846000        CALL UNCLE(TSPXL(1,I),MEAN,ND,LIVING,II,DUM,ID)
01413  01847000      9 CLASS(I) = II
01417  01848000  C*****************************************************************
01417  01849000  C
01417  01850000  C  REFERENCE POINT FOR MAIN LOOP.
01417  01851000  C
01417  01852000  C  INITIALIZE LOCAL COUNT OF ERRORS.
01417  01853000     11 NERR = 0
01421  01854000        DO 40 I = 1,LIVING
01426  01855000     40 ERROR(I) = 0
01433  01856000  C
01433  01857000  C  GO THRU PATCHES (I.E.THRU TEST PIXELS IN SETS OF 5)
01433  01858000        DO 25 I = 1,NP,5
01437  01859000  C
01437  01860000  C  GRAB A TEST SET OF 5 FROM THE SAME PATCH.
01437  01861000        I1 = CLASS(I)
01442  01862000        I2 = CLASS(I+1)
01447  01863000        I3 = CLASS(I+2)
01454  01864000        I4 = CLASS(I+3)
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01461  01865000        I9 = CLASS(I+4)
01466  01866000  C
01466  01867000  C  MAKE AN INDEX INTO THE TEST PIXELS WHICH SHOULD BE FAR ENOUGH
01466  01868000  C  AWAY TO BE IN A DIFFERENT REAL CLASS (ALTHOUGH THIS CANNOT BE
01466  01869000  C  GUARANTEED). THEN CHECK IF IT IS OFF THE ARRAY.
01466  01870000        IT = I+NPA
01471  01871000        IF (IT.GT.NP) IT = I-NPA2
01477  01872000  C-----------------------------------------------------------------------
01477  01873000  C
01477  01874000  C  THIS SEGMENT COUNTS THE NUMBER OF TIMES A CLUSTER ATTRACTS A
01477  01875000  C  PIXEL FROM ONE OF THE TEST SETS AND FROM ONE IN THE FAR AWAY
01477  01876000  C  CLASS.  ONLY ONE CLUSTER IS INVOLVED IN THIS TYPE OF ERROR.
01477  01877000        DO 76 K = 1,2
01504  01878000        IC = CLASS(IT)
01507  01879000        IF (IC.NE.I1) GO TO 71
01520  01880000        ERROR(I1) = ERROR(I1)+1
01524  01881000        NERR = NERR+1
01529  01882000     71 IF (IC.NE.I2) GO TO 72
01531  01883000        ERROR(I2) = ERROR(I2)+1
01535  01884000        NERR = NERR+1
01536  01885000     72 IF (IC.NE.I3) GO TO 73
01542  01886000        ERROR(I3) = ERROR(I3)+1
01546  01887000        NERR = NERR+1
01547  01888000     73 IF (IC.NE.I4) GO TO 74
01553  01889000        ERROR(I4) = ERROR(I4)+1
01557  01890000        NERR = NERR+1
01560  01891000     74 IF (IC.NE.I5) GO TO 75
01564  01892000        ERROR(I5) = ERROR(I5)+1
01570  01893000        NERR = NERR+1
01571  01894000  C
01571  01895000  C  MAKE ANOTHER INDEX FAR AWAY.
01571  01896000     75 IT = I-NPA
01574  01897000        IF (IT.LE.0) IT = I+NPA2
01602  01898000     76 CONTINUE
01603  01899000  C-----------------------------------------------------------------------
01603  01900000  C
01603  01901000  C. . . . . .
01603  01902000  C
01603  01903000  C  THIS SEGMENT COUNTS THE NUMBER OF SAME PATCH -- DIFFERENT
01603  01904000  C  CLUSTER ERRORS.  EACH ERROR IS CREDITED TO TWO CLUSTERS
01603  01905000  C  SINCE WE CAN BE CONFIDENT THAT SAME PATCH SAMPLES ARE
01603  01906000  C  FROM THE SAME REAL CLASS.
01603  01907000        IF (I1.EQ.I2) GO TO 42
01607  01908000        NERR = NERR+2
01611  01909000        ERROR(I1) = ERROR(I1)+1
01615  01910000        ERROR(I2) = ERROR(I2)+1
01621  01911000     42 IF (I1.EQ.I3) GO TO 44
01623  01912000        NERR = NERR+2
01627  01913000        ERROR(I1) = ERROR(I1)+1
01633  01914000        ERROR(I3) = ERROR(I3)+1
01637  01915000     44 IF (I1.EQ.I4) GO TO 46
01643  01916000        NERR = NERR+2
01647  01917000        ERROR(I1) = ERROR(I1)+1
01651  01918000        ERROR(I4) = ERROR(I4)+1
01655  01919000     46 IF (I1.EQ.I5) GO TO 48
01661  01920000        NERR = NERR+2
01663  01921000        ERROR(I1) = ERROR(I1)+1
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PAGE 0055   HUNCLU

01667  01922000          ERROR(I5) = ERROR(I5)+1
01673  01923000       48 IF (I2.EQ.I3) GO TO 50
01677  01924000          NERR = NERR+2
01701  01925000          ERROR(I2) = ERROR(I2)+1
01705  01926000          ERROR(I3) = ERROR(I3)+1
01711  01927000       50 IF (I2.EQ.I4) GO TO 52
01715  01928000          NERR = NERR+2
01717  01929000          ERROR(I2) = ERROR(I2)+1
01723  01930000          ERROR(I4) = ERROR(I4)+1
01727  01931000       52 IF (I2.EQ.I5) GO TO 54
01733  01932000          NERR = NERR+2
01735  01933000          ERROR(I2) = ERROR(I2)+1
01741  01934000          ERROR(I5) = ERROR(I5)+1
01745  01935000       54 IF (I3.EQ.I4) GO TO 56
01751  01936000          NERR = NERR+2
01753  01937000          ERROR(I3) = ERROR(I3)+1
01757  01938000          ERROR(I4) = ERROR(I4)+1
01763  01939000       56 IF (I3.EQ.I5) GO TO 58
01767  01940000          NERR = NERR+2
01771  01941000          ERROR(I3) = ERROR(I3)+1
01775  01942000          ERROR(I5) = ERROR(I5)+1
02001  01943000       58 IF (I4.EQ.I5) GO TO 25
02005  01944000          NERR = NERR+2
02007  01945000          ERROR(I4) = ERROR(I4)+1
02013  01946000          ERROR(I5) = ERROR(I5)+1
02017  01947000    C
02017  01948000    C  ALL COMPUTED FOR THIS PATCH ..... .....
02017  01949000    C
02017  01950000    C  GET THE NEXT PATCH.
02017  01951000       25 CONTINUE
02024  01952000    C
02024  01953000    C  SEE IF ERRORS ARE LESS THAN BEFORE.
02024  01954000          IF (NERR.GE.MIN.OR.IN.GE.MAXCLN) GO TO 102
02027  01955000    C
02027  01956000    C  YES...UPDATE RUNNING MIN
02027  01957000          MIN = NERR
02031  01958000          MIN = IN
02033  01959000    C
02033  01960000    C  THIS SEGMENT CARRIES OUT THE LOGIC DICTATED BY THE NEED FOR
02033  01961000    C  EXACTLY 50 MANY CLUSTERS.  (IT JUST GREW THIS WAY.)
02033  01962000      102 IN = IN-1
02034  01963000          IF (SEEK) MIN = IN+1
02041  01964000          IF (IN.LE.MINCLN) GO TO 103
02043  01965000          MP = -32767
02047  01966000    C
02047  01967000    C  FIND THE CLUSTER WHICH SEEMS TO CAUSE THE MOST ERRORS.
02047  01968000          DO 61 J = 1,LIVING
02054  01969000          IF (DUN(J).EQ.0) GO TO 61
02062  01970000          IF (ERROR(J).LE.MP) GO TO 61
02067  01971000          MP = ERROR(J)
02072  01972000          MJ = J
02074  01973000       61 CONTINUE
02075  01974000    C
02075  01975000    C  STASH THE INDEX OF THIS MOST OFFENSIVE CRITTER
02075  01976000          SAVE(IN) = MJ
02100  01977000    C
02100  01978000    C  AND MARK IT DOOMED (IF NOT DEAD).
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PAGE 0036   NUNCLU

02100  01979000        DUN(NJ) = 0
02103  01980000  C  RECLASSIFY ALL POINTS WHICH WERE ASSIGNED TO THIS CLUSTER.
02103  01981000  C
02103  01982000  C  HOWEVER, IF A TEST PIXEL ASSIGNED TO THIS CLUSTER IS, AFTER THE
02103  01983000  C  ELIMINATION OF THIS CLUSTER, REASSIGNED TO ONE MORE THAN  IDIAMP
02103  01984000  C  AWAY, ELIMINATE THE CLUSTER WITH NEXT FEWEST ERRORS.
02103  01985000        DO 65 I = 1,NP
02110  01986000        IF (CLASS(I).NE.NJ) GO TO 65
02113  01987000        CALL UNCLE(TSPXL(1,I),MEAN,ND,LIVING,II,DUN,ID)
02133  01988000  C  SEE IF DISTANCE.LE.THRESHOLD
02133  01989000        IF (ID.GT.IDIAMP) GO TO 1000
02140  01990000  C
02140  01991000  C  SAVE THIS CLASSIFICATION.
02140  01992000        CSAVE(I) = II
02143  01993000     65 CONTINUE
02144  01994000        IDIAMP = IDIAMP-ND
02147  01995000  C
02147  01996000  C  YES, ALL DISTANCES ARE OK...
02147  01997000  C  NOW ACTUALLY CLASSIFY THE POINTS
02147  01998000        DO 66 I = 1,NP
02154  01999000        IF (CLASS(I).NE.NJ) GO TO 66
02161  02000000        CLASS(I) = CSAVE(I)
02164  02001000     66 CONTINUE
02165  02002000        GO TO 11
02167  02003000  C
02167  02004000  C  DON'T ZAP CLASS NJ AFTER ALL
02167  02005000   1000 IN = IN+1
02170  02006000        DUN(NJ) = 1
02173  02007000        ERROR(NJ) = ERROR(NJ)/2
02177  02008000  C     DO 813 K = 1,ND
02204  02009000  C 813 MEAN(K,NJ) = TSPXL(K,I)
02221  02010000  C
02221  02011000  C  INCR THE THRESHOLD TO INSURE NO INFINITE LOOP.
02221  02012000        IDIAMP = (IDIAMP/3)*2+ID/3+ND
02231  02013000        GO TO 102
02232  02014000  C*****************************************************************
02232  02015000  C
02232  02016000  C  I SUPOSE WE ARE THROUGH NOW...REPORT!
02232  02017000    103 NFCLUS = NIN
02234  02018000        WRITE(PRINTIT,10) NFCLUS
02255  02019000     10 FORMAT('      NUMBER OF CLUSTERS:',I4)
02255  02020000        CALL PRINTP(UICB,IND,1,PRINTB,28,0,0,0,0,0,0,0,0)
02305  02021000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,1,0,6,0,2000)
02330  02022000        IPNC = IFIX(25.*FLOAT(NIN)/FLOAT(NP))
02342  02022100        IPNC = IPNC*2/3
02346  02022200  C
02346  02022300  C  ALLOWS FOR COUNTING ERRORS TWICE... JUST AN ESTIMATE.
02346  02023000        WRITE(PRINTIT,104) IPNC
02367  02024000    104 FORMAT('      ESTIMATE OF PAIR PNC:',I4,' PERCENT.')
02367  02025000        CALL PRINTP(UICB,IND,1,PRINTB,39,0,0,0,0,0,0,0,0)
02417  02026000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,1,0,6,0,2100)
02442  02027000        NIN = NIN+1
02443  02028000        LVNGM = LIVING-1
02446  02029000  C
02446  02030000  C  ITS HARD TO SEE HOW THIS COULD HAPPEN, BUT...
02446  02031000        IF (NIN.GT.LVNGM) R E T U R N
02460  02032000  C
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C-2

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PAGE 0037   NUMCLU


02460   02033000  C  ACTUALLY PERFORM THE ELIMINATION NOW.
02460   02034000        DO 62 I = MIN,LYNGH
02463   02035000     62 NUM(SAVE(I)) = 0
02472   02036000  C
02472   02037000  C  AGAIN COLLAPSE THE ARRAY TO ALLOW MORE EFFICIENT SEARCH.
02472   02038000        CALL COLAPS(LIVING,MEAN,NUM,ND)
02501   02039000        R E T U R N
02502   02040000     807 NFCLUS = LIVING
02504   02041000        R E T U R N
02505   02042000        END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS

CHKIO                         SUBROUTINE
COLAPS                        SUBROUTINE
CSAVE             INTEGER     ARRAY       0-%10  ,I
DUM               INTEGER     ARRAY       0-%11  ,I
I                 INTEGER     SIMPLE VAR  0+%6
I2                INTEGER     SIMPLE VAR  0+%31
I4                INTEGER     SIMPLE VAR  0+%33
IC                INTEGER     SIMPLE VAR  0+%7
IDIAM             INTEGER     SIMPLE VAR  0+%36
IE                INTEGER     SIMPLE VAR  0+%11
IND               INTEGER     ARRAY       0-%6   ,I
IPRINT            INTEGER     SIMPLE VAR  0+%37
J                 INTEGER     SIMPLE VAR  0+%21
LIVING            INTEGER     SIMPLE VAR  0+%30
MAXCLN            INTEGER     SIMPLE VAR  0-%4   ,I
MIN               INTEGER     SIMPLE VAR  0+%40
MJ                INTEGER     SIMPLE VAR  0+%24
ND                INTEGER     SIMPLE VAR  0-%23  ,I
NFCLUS            INTEGER     SIMPLE VAR  0-%17  ,I
NINCLN            INTEGER     SIMPLE VAR  0-%16  ,I
NP3               INTEGER     SIMPLE VAR  0-%22  ,I
NPA2              INTEGER     SIMPLE VAR  0+%13
NUMCLU                        SUBROUTINE
PRINTIT           CHARACTER   SIMPLE VAR  0+%5   ,I
SAVE              INTEGER     ARRAY       0-%12  ,I
TSPXL             INTEGER     ARRAY       0-%20  ,I
UNCLE                         SUBROUTINE

NAME              TYPE        STRUCTURE   ADDRESS

CLASS             INTEGER     ARRAY       0-%15  ,I
COUNT             INTEGER     ARRAY       0-%14  ,I
DIANTR                        SUBROUTINE
ERROR             INTEGER     ARRAY       0-%13  ,I
I1                INTEGER     SIMPLE VAR  0+%27
I3                INTEGER     SIMPLE VAR  0+%32
I5                INTEGER     SIMPLE VAR  0+%34
ID                INTEGER     SIMPLE VAR  0+%10
IDIAMP            INTEGER     SIMPLE VAR  0+%15
IN                INTEGER     SIMPLE VAR  0+%16
IPNC              INTEGER     SIMPLE VAR  0+%41
IT                INTEGER     SIMPLE VAR  0+%23
K                 INTEGER     SIMPLE VAR  0+%35
LYNGH             INTEGER     SIMPLE VAR  0+%26
MEAN              INTEGER     ARRAY       0-%24  ,I
MINCLN            INTEGER     SIMPLE VAR  0+%17
MP                INTEGER     SIMPLE VAR  0+%25
NERR              INTEGER     SIMPLE VAR  0+%22
NI                INTEGER     SIMPLE VAR  0+%14
NP                INTEGER     SIMPLE VAR  0-%21  ,I
NPA               INTEGER     SIMPLE VAR  0+%12
NUM               INTEGER     ARRAY       0-%5   ,I
PRINTEG           INTEGER     ARRAY       0+%4   ,I
PRINTP                        SUBROUTINE
SEEK              LOGICAL     SIMPLE VAR  0+%20
UICB              INTEGER     ARRAY       0-%7   ,I


PROGRAM UNIT NUMCLU COMPILED
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Parent: CLASSIFY PERPIXEL

Calls: REJECTH

PERPIXEL(PIXELS,CLUSTERS,LABELS,ND,NC,NFCLUS,REJECT,MAXCLUS,MASK,NX)

Performs a per pixel classification of a line.

Method: This subroutine performs a checked per pixel classification of multidimensional data in PIXELS to classes in CLUSTERS. Nearest neighbor (Euclidean distance) classification is employed. However, when the distance is too great, the classification is rejected, and (generally) a new cluster center is added. On that event, the cluster reject thresholds are recomputed and this line classification is restarted. Labels (i.e. class numbers) are written in line LABELS.

The program is straightforward with the possible exception of the biased distances and the modification of rejection thresholds in loop 120. All distances are biased by -32768; the rejection thresholds are also biased by -32768 in REJECTH. We wish to make the test less severe than was applied to pure pixels (the test pixels), so we logically multiply the thresholds by 2 (which, in terms of distances, amounts to deciding reject on 0.7 * distance between competing classes rather than 0.5 * distance between). Thus, if r is the biased and R the logical threshold, we have r = R - 32768, so that

$$r' = 2R - 32768 = 2(R+32678) - 32768$$
$$= 2R + 32768 .$$

Program Variables

AO	INTEGER*4 Long integer to carry out the threshold arithmetic intermediate steps.
CLUSTERS(ND,MAXCLUS)	INTEGER ARRAY The clusters.
I,J,K	INTEGER DO loop index.
ICL	INTEGER Class number of nearest cluster.

IM	INTEGER Distance to nearest cluster
IS	INTEGER Accumulator for computing distance.
IT	INTEGER Temporary for computing distance.
JR	INTEGER Reject threshold of current class.
LABELS(NC)	INTEGER ARRAY The classification.
MASK	LOGICAL If .TRUE., a value 0 in channel 1 is used as a mask (i.e. not data), and the label 99 is stored in LABELS.
MAXCLUS	INTEGER Maximum number of clusters (current value, set in MAIN, is 98).
NC	INTEGER Number of samples per line.
ND	INTEGER Dimensionality.
NFCLUS	INTEGER Current number of clusters.
NX	INTEGER Actual number of samples per line (approximately NC, but often a little less). NC is used to dimension things; NX may vary from one call to the next.
PIXELS(NC,ND)	INTEGER ARRAY One line of data.
REJECT(MAXCLUS)	INTEGER ARRAY The reject thresholds.
REJECTH	SUBROUTINE Calculates REJECT.

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PAGE 0000   HEWLETT-PACKARD 321020.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:36 AM

00011  00316000  $CONTROL SEGMENT=ANOEBASEG
00011  00317000        SUBROUTINE PERPIXEL(PIXELS,CLUSTERS,LABELS,ND,NC,NFCLUS,
00011  00318000       * REJECT,MAXCLUS,MASK,NX)
00011  00319000        LOGICAL MASK
00011  00320000        INTEGER*4 A0
00011  00321000        INTEGER*2 PIXELS(NC,ND),CLUSTERS(ND,MAXCLUS),LABELS(NC),
00011  00322000       * REJECT(MAXCLUS)
00011  00323000    130 DO 10 I = 1,NX
00017  00324000        IF (.NOT MASK) GO TO 30
00022  00325000        IF (PIXELS(I,1).NE.0) GO TO 30
00023  00326000        ICL = 99
00024  00327000        GO TO 10
00027  00328000     30 CONTINUE
00030  00329000        IM = 32767
00032  00330000        ICL = 0
00041  00331000        DO 30 J = 1,NFCLUS
00046  00332000        IS = -32768
00052  00333000        JR = REJECT(J)
00060  00334000        DO 20 K = 1,ND
00065  00335000        IF (IS.GE.JR) GO TO 30
00072  00336000        IT = PIXELS(I,K)-CLUSTERS(K,J)
00112  00337000        IS = IS+IT*IT
00116  00338000        IF (IS.GE.JR) GO TO 30
00122  00339000     20 CONTINUE
00124  00340000        IF (IM.LE.IS) GO TO 30
00130  00341000        IM = IS
00132  00342000        ICL = J
00134  00343000     30 CONTINUE
00139  00344000        IF (ICL.EQ.0) GO TO 100
00141  00345000     10 LABELS(I) = ICL
00150  00346000        R E T U R N
00151  00347000    100 IF (NFCLUS.GE.MAXCLUS) GO TO 10
00155  00348000        NFCLUS = NFCLUS+1
00156  00349000        ICL = NFCLUS
00160  00350000        DO 110 K = 1,ND
00162  00351000    110 CLUSTERS(K,ICL) = PIXELS(I,K)
00202  00352000        CALL REJECTH(CLUSTERS,ND,REJECT,NFCLUS,MAXCLUS)
00212  00353000        DO 120 K = 1,NFCLUS
00217  00354000        A0 = REJECT(K)
00224  00355000        A0 = A0+2+32768
00234  00356000        IF (A0 GT 16000) A0 = 16000
00246  00357000    120 REJECT(K) = A0
00257  00358000        GO TO 130
00263  00359000                    END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
A0	INTEGER*4	SIMPLE VAR	Q+%14	CLUSTERS	INTEGER	ARRAY	Q-%14 ,I
I	INTEGER	SIMPLE VAR	Q+%4	ICL	INTEGER	SIMPLE VAR	Q+%12
IM	INTEGER	SIMPLE VAR	Q+%6	IS	INTEGER	SIMPLE VAR	Q+%10
IT	INTEGER	SIMPLE VAR	Q+%11	J	INTEGER	SIMPLE VAR	Q+%7
JR	INTEGER	SIMPLE VAR	Q+%5	K	INTEGER	SIMPLE VAR	Q+%13
LABELS	INTEGER	ARRAY	Q-%13 ,I	MASK	LOGICAL	SIMPLE VAR	Q-%5 ,I
MAXCLUS	INTEGER	SIMPLE VAR	Q-%6 ,I	NC	INTEGER	SIMPLE VAR	Q-%11 ,I
ND	INTEGER	SIMPLE VAR	Q-%12 ,I	NFCLUS	INTEGER	SIMPLE VAR	Q-%10 ,I
NX	INTEGER	SIMPLE VAR	Q-%4 ,I	PERPIXEL		SUBROUTINE	
PIXELS	INTEGER	ARRAY	Q-%15 ,I	REJECT	INTEGER	ARRAY	Q-%7 ,I
REJECTH		SUBROUTINE					

PROGRAM UNIT PERPIXEL COMPILED

Parents: MOREQUES, PERPIXEL REJECTH

REJECTH(CLUSTERS,ND,REJFCT,NFCLUS,MAXCLUS)

This subroutine determines the cluster-dependent classification rejection thresholds.

Method: Using a bias of -32768, the inter-cluster squared distance from cluster I to cluster J is maximized. The maximum over J, divided by four, is the classification rejection threshold for cluster I, and is stored in REJECT(I). To minimize round-off error, the division by four is carried out in two stages; the second accounts for the bias: R = D - 32768, so D/2 - 32768 = R/2 - 16384 should be stored as the twice halved square of distance.

Program Variables

CLUSTERS(ND,MAXCLUS)	Integer ARRAY The cluster centers.
I,J,K,	INTEGER DO loop index.
IM,IS,IT	INTEGER Used in calculation and maximization of distances.
MAXCLUS	INTEGER Maximum number of clusters.
ND	INTEGER Dimensionality
NFCLUS	INTEGER Actual number of clusters.
REJECT(MAXCLUS)	INTEGER ARRAY Rejection thresholds.

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PAGE 0025   HEWLETT-PACKARD 321020.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:37 AM

00006  00752000  $CONTROL SEGMENT=ANOEBASEG
00006  00753000        SUBROUTINE REJECTH(CLUSTERS,ND,REJECT,NFCLUS,MAXCLUS)
00006  00754000        INTEGER*2 CLUSTERS(ND,MAXCLUS),REJECT(MAXCLUS)
00006  00755000        DO 10 I = 1,NFCLUS
00013  00756000  C
00013  00757000  C  FIND THE CRITTER THE GREATEST DISTANCE AWAY
00013  00758000  C
00013  00759000        IR = -32768
00022  00760000        DO 20 J = 1,NFCLUS
00027  00761000        IF (I.EQ.J) GO TO 20
00035  00762000  C
00035  00763000  C  FIND DIST(I,J)**2
00035  00764000  C
00035  00765000        IS = -32768
00044  00766000        DO 30 K = 1,ND
00051  00767000        IT = (CLUSTERS(K,J)-CLUSTERS(K,I))/2
00067  00768000     30 IS = MIN0(16383,IS+IT*IT)
00100  00769000        IF (IS.LE.IR) GO TO 20
00105  00770000        IR = IS
00107  00771000     20 CONTINUE
00110  00772000        REJECT(I) = IR/2-16384
00115  00773000     10 CONTINUE
00116  00774000        R E T U R N
00120  00775000                   END


  SYMBOL MAP

NAME              TYPE        STRUCTURE     ADDRESS                NAME              TYPE        STRUCTURE     ADDRESS

CLUSTERS          INTEGER     ARRAY         0-%10  ,I              I                 INTEGER     SIMPLE VAR    0+%3
IR                INTEGER     SIMPLE VAR    0+%4                   IS                INTEGER     SIMPLE VAR    0+%6
IT                INTEGER     SIMPLE VAR    0+%7                   J                 INTEGER     SIMPLE VAR    0+%5
K                 INTEGER     SIMPLE VAR    0+%10                  MAXCLUS           INTEGER     SIMPLE VAR    0-%4   ,I
ND                INTEGER     SIMPLE VAR    0-%7   ,I              NFCLUS            INTEGER     SIMPLE VAR    0-%5   ,I
REJECT            INTEGER     ARRAY         0-%6   ,I              REJECTH                       SUBROUTINE


PROGRAM UNIT REJECTH COMPILED
```

Parent: MAIN SETSYM

SETSYM(SYMBOL)

Sets SYMBOL to the appropriate character set for display in MAPP.

Method: Because of the restrictions of HP FORTRAN-SEGMENTER and of IDIMS, this usually straightforward task is 14 lines long. The result is to set SYMBOL(1) equal to a blank and SYMBOL(2) to SYMBOL(59) (printable) ASCII characters between 33 and 90 (decimal).

Program Variables

CC(2)	CHARACTER*1 ARRAY Equivalenced to IC.
IC	INTEGER Used to transfer ASCII binary to characters.
J	INTEGER DO loop index.
NOX	INTEGER Index into SYMBOL.
SYMBOL(59)	CHARACTER*1 ARRAY The symbol set.

```
PAGE 0014   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:37 AM

00015  00464000  $CONTROL SEGMENT=ANOTHERSEG
00016  00465000        SUBROUTINE SETSYM(SYMBOL)
00017  00466000        CHARACTER*1 CC(2),SYMBOL(*)
00018  00467000        EQUIVALENCE (CC(1),IC)
00019  00468000        NOX = 2
00017  00469000        IC = 32
00021  00470000        SYMBOL(1) = CC(2)
00021  00471000     10 DO 20 J = 33,90
00023  00472000        IC = J
00024  00473000        SYMBOL(NOX) = CC(2)
00025  00474000        NOX = NOX+1
00021  00475000        IF (NOX.GT.59) R E T U R N
00027  00476000     20 CONTINUE
00026  00477000        GO TO 10
00029  00478000                   END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS          NAME              TYPE        STRUCTURE   ADDRESS

CC                CHARACTER   ARRAY       0+%2   ,1        IC                INTEGER     SIMPLE VAR  0+%1   ,1
J                 INTEGER     SIMPLE VAR  0+%4             NOX               INTEGER     SIMPLE VAR  0+%3
SETSYM                        SUBROUTINE                   SYMBOL            CHARACTER   ARRAY       0-%4   ,1


PROGRAM UNIT SETSYM COMPILED
```

Parent: MSORT, SORT SHELL

SHELL(KEY,INDEX,NUMBER)

Sorts KEY into increasing order; the elements of KEY are not interchanged. Rather, the array INDEX is permuted so that KEY(INDEX(I)) ≤ KEY(INDEX(J)) when I < J.

Method: See Shell, D. L., A high speed sorting program, Comm. ACM 2 (1959), 30-32.

Program Variables

INDEX(NUMBER)	INTEGER ARRAY On entry, INDEX(I) = I; on exit, INDEX is permuted.
KEY(NUMBER)	INTEGER ARRAY The list to be sorted.
NUMBER	INTEGER The number of items in the list.
I,IM,IT,J,K,M	INTEGER Internal variables

```
PAGE 0012   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:36 AM

00002  00412000  $CONTROL SEGMENT=ANOTHSEG
00003  00413000        SUBROUTINE SHELL(KEY,INDEX,NUMBER)
00004  00414000  C
00005  00415000  C  ENTRY PROGRAM:     SORT
00006  00416000        INTEGER*2 KEY(NUMBER),INDEX(NUMBER)
00007  00417000  C
00008  00418000  C  FAST SORT ROUTINE:  IT IS ASSUMED THAT INDEX(K) = K ON ENTRY
00009  00419000  C  ON EXIT, KEY(INDEX(I)) LE KEY(INDEX(I+1)) ,.I = 1,NUMBER-1.
00010  00420000  C
00011  00421000  C  REFERENCE:
00012  00422000  C
00013  00423000  C  SHELL, D.L., A HIGH SPEED SORTING PROCEDURE, COMM
00014  00424000  C       ACM, 2(1959),30-32.
00015  00425000  C
00016  00426000        M = NUMBER
00017  00427000     10 M = M/2
00018  00428000        IF (M EQ 0) R E T U R N
00019  00429000        K = NUMBER-M
00020  00430000        J = 1
00021  00431000     20 I = J
00022  00432000     30 IM = I+M
00023  00433000        IF (KEY(INDEX(I)) LE KEY(INDEX(IM))) GO TO 40
00024  00434000        IT = INDEX(I)
00025  00435000        INDEX(I) = INDEX(IM)
00026  00436000        INDEX(IM) = IT
00027  00437000        I = I-M
00028  00438000        IF (I GE 1) GO TO 30
00029  00439000     40 J = J+1
00030  00440000        IF (J GT K) GO TO 10
00031  00441000        GO TO 20
00032  00442000        END


  SYMBOL MAP

NAME              TYPE        STRUCTURE    ADDRESS              NAME              TYPE        STRUCTURE    ADDRESS

I                 INTEGER     SIMPLE VAR   Q+%2                IM                INTEGER     SIMPLE VAR   Q+%3
INDEX             INTEGER     ARRAY        Q-%5   ,I           IT                INTEGER     SIMPLE VAR   Q+%5
J                 INTEGER     SIMPLE VAR   Q+%4                K                 INTEGER     SIMPLE VAR   Q+%7
KEY               INTEGER     ARRAY        Q-%6   ,I           M                 INTEGER     SIMPLE VAR   Q+%6
NUMBER            INTEGER     SIMPLE VAR   Q-%4   ,I           SHELL                         SUBROUTINE


PROGRAM UNIT SHELL COMPILED
```

Parent: MAIN SORT

Calls: SHELL

SORT(TSPXL,DUMMY,INDEX,ND,NP,NPS)

Sorts TSPXL in increasing order of the sum of odd channels of the first test pixel in each test set. Sets are kept together.

Method: First the sums of odd bands of the first test pixel in each test set are accumulated, and an index into the sets is formed so that INDEX(I) = I. Then SHELL is called. On return from SHELL, the test sets are reordered by the permutation of INDEX induced by SHELL. The actual sets are now switched in place.

Program Variables

DUMMY(NP5)	INTEGER ARRAY Used to accumulate sums in odd bands of the first element of each test set, and then as a temporary vector while TSPXL is being reordered.
I	INTEGER DO loop index.
INDEX(NP5)	INTEGER ARRAY The pointer array, used by SHELL to indicate order of DUMMY.
J	INTEGER DO loop index
K	INTEGER DO loop index.
L	INTEGER DO loop index; note: the index into TSPXL is I * 5 + L - 5, where I is the test set number and L is the number, I = 1,...,NP5, L = 1,...,5.
ND	INTEGER Dimensionality of TSPXL.
NP	INTEGER Number of test pixels.
NP5	INTEGER Number of test sets (= NP/5).
SHELL	SUBROUTINE Sorts vector in increasing order.
TSPXL(ND,NP)	INTEGER ARRAY Test pixels, organized as vectors, then sets, then count of sets, to be reordered by increasing sum of odd bands.

```
PAGE 0011   HEWLETT-PACKARD 32102B.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:36 AM

00010  00377000  $CONTROL SEGMENT=ANOEBASEG
00010  00378000        SUBROUTINE SORT(TSPXL,DUMMY,INDEX,ND,NP,NP3)
00010  00379000  C
00010  00380000  C  PARENT PROGRAM:     MAIN
00010  00381000  C  DAUGHTER PROGRAM:  SHELL
00010  00382000  C
00010  00383000        INTEGER*2 TSPXL(ND,NP),DUMMY(NP3),INDEX(NP3)
00010  00384000  C
00010  00385000  C  THIS SUBROUTINE SORTS TSPXL INTO INCREASING ORDER
00010  00386000  C  ON SUM OF ODD CHANNELS ( =  AVERAGE BRIGHTNESS?)
00010  00387000  C
00010  00388000  C  PLACE THE AVERAGE BRIGHTNESS OF TEST PIXEL I IN DUMMY(K)
00010  00389000  C  WHERE I = 1+3*(K-1)  THE BRIGHTNESS IS ASSUMED TO BE IN ODD
00010  00390000  C  CHANNELS A LA KAUTH-THOMAS OR OTHER.
00010  00391000        K = 1
00012  00392000        DO 1 I = 1,NP,3
00017  00393000        DUMMY(K) = 0
00022  00394000        DO 1000 J = 1,ND,2
00027  00395000   1000 DUMMY(K) = DUMMY(K)+TSPXL(J,I)
00041  00396000        INDEX(K) = K
00044  00397000     1 K = K+1
00046  00398000  C
00046  00399000  C  SORT DUMMY
00046  00400000        CALL SHELL(DUMMY,INDEX,NP3)
00054  00401000  C
00054  00402000  C  NOW PERFORM ACTUAL SWITCHING
00054  00403000    100 DO 110 K = 1,ND
00061  00404000        DO 110 L = 1,3
00066  00405000        DO 120 I = 1,NP3
00073  00406000    120 DUMMY(I) = TSPXL(K,INDEX(I)*3-3+L)
00110  00407000        DO 130 I = 1,NP3
00115  00408000    130 TSPXL(K,I*3-3+L) = DUMMY(I)
00121  00409000    110 CONTINUE
00127  00410000        R E T U R N
00134  00411000        END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS          NAME              TYPE        STRUCTURE   ADDRESS

DUMMY             INTEGER     ARRAY       0-%10  ,I        I                 INTEGER     SIMPLE VAR  0+%4
INDEX             INTEGER     ARRAY       0-%7   ,I        J                 INTEGER     SIMPLE VAR  0+%6
K                 INTEGER     SIMPLE VAR  0+%7             L                 INTEGER     SIMPLE VAR  0+%5
ND                INTEGER     SIMPLE VAR  0-%6   ,I        NP                INTEGER     SIMPLE VAR  0-%5   ,I
NP3               INTEGER     SIMPLE VAR  0-%4   ,I        SHELL                         SUBROUTINE
SORT                          SUBROUTINE                   TSPXL             INTEGER     ARRAY       0-%11  ,I


PROGRAM UNIT SORT COMPILED
```

Parent: MAIN START

Calls: MARKLP, MARKKUPDN, MRKIUL, CONNCT

START(INTTHR,ND,NR,NC,NZ,DATBUF,LABBUF,ISCAN,UICB,IND,IMGIN,LMGCLAS,LAB, MASK)

START makes the vector boundary decisions and returns a map (on disk) of the components of the complement of the boundary.

Method: The program employs Wide Image Logic to segment the image into strips. Three lines of data and three lines of labels are active at any given time. Circular Buffers using pointers I1, I2, and I3, manage this; I1 always points to the eldest and I3 to the newest. Even so, we can't phrase the description of the method in absolute terms (i.e. as if the entire image were in memory at once). The initial phase must be described first.

Initially, a labels buffer is set to all one. Then the data is scanned, and points for which the vector gradient test is failed in the left-right direction are marked (subroutine MARKLR). Then up-down boundaries are located (subroutine MARKUPDN), and one-pixel gaps in the boundary map are filled (subroutine FILLR). Then, the logical OR of the first and second line replaces the first. (These are details, but this is detailed documentation, and FORTRAN loves it.) We now have an excellent estimate of the boundary in the first two lines and a fair first cut on the third. Subroutine MRKIVL is called to mark intervals in line 1. MRKIVL replaces each interval contained in the complement of the boundary along a line with (successively) 1,2,... . If any patch slices were found in this step, then the first line is initialized with patch labels (starting at -32767).

Now the big loop is entered. Intervals in line I2 are marked. If any patches are found here, subroutine CONNCT is used to transfer old labels to new intervals or to begin new labels. Row I1 labels are written and new data is read into DATBUF(.,.,I1). New labels are marked with 1 and the circular buffer pointers are rotated. (Now I3 is the newest). We now call MARKLR (I3) and then MARKUPDN, and return to the big loop. Exit

from the loop when we run out of data (or labels). If out of data (or at the bottom of a strip), process lines I2 then I3 and write on disk. If out of labels, simply paint the rest of the image boundary. (Since 64K labels are allowed, this seems unlikely to happen on even the largest natural images.)

The initialization phase guarantees labels are not propogated from the bottom of one strip to the top of the next.

Program Variables

CHKIO	SYSTEM SUBROUTINE
CONNCT	SUBROUTINE Transfers labels from one line to the next, and begins new labels when no connection exists.
DATBUF(NC,ND,3)	INTEGER ARRAY Three lines of data, organized as a circular buffer.
FILLLR	SUBROUTINE Replaces a boundary-not boundary-boundary gap by three boundary points along a line.
FINISHED	LOGICAL Returned .TRUE. by CONNCT when no more labels exist.
I,ITM,J,K	INTEGER DO loop index.
I1,I2,I3	INTEGER Circular buffer pointers
IMGCLAS	INTEGER Image number of the (temporary) labels-boundary disk maps.
IMGIN	INTEGER Image number of the data.
IN	INTEGER The number of intervals found by MRKIVL in a line.
IND(1)	INTEGER ARRAY Error indicator
INTTHR(ND)	INTEGER ARRAY The vector thresholds obtained by THRFND.
IROW	INTEGER Line number being read.
IROWOUT	INTEGER Line of labels being written
ISCAN(1)	INTEGER ARRAY Scratch array used by CONNCT to store labels.

IT	INTEGER Used to rotate pointers.
LAB	INTEGER Current label number.
LABBUF(NC,3)	INTEGER ARRAY Three lines of labels.
MARKLR	SUBROUTINE Mark left-right boundaries depending on vector thresholds.
MARKUPDN	SUBROUTINE Mark up-down boundaries.
MASK	LOGICAL The Mask flag.
MRKIVL	SUBROUTINE Mark intervals along a line in the complement of the boundary.
NC	INTEGER Number of columns in a strip.
ND	INTEGER Dimensionality
NW,NX,NY	INTEGER Used to partition the image into strips (see Wide Image Logic).
NZ	INTEGER Actual number of samples.
READP	SYSTEM SUBROUTINE
UICB(1)	INTEGER ARRAY User Information Control Block
WRITEP	SYSTEM SUBROUTINE
Z	INTEGER -32768; boundary marker.

```
00012  00995000  $CONTROL SEGMENT=ANOEBASEC
00012  00996000        SUBROUTINE START(INTTHR,ND,NR,NC,NZ,DATBUF,LABBUF,
00012  00997000       *ISCAN,UICB,IND,INGIN,INGCLAS,LAB,MASK)
00012  00998000        INTEGER*2 Z,INTTHR(ND),DATBUF(NC,ND,3),LABBUF(NC,3),ISCAN(1),
00012  00999000       * UICB(1),IND(1)
00012  01000000        LOGICAL FINISHED,MASK
00012  01001000        FINISHED = .FALSE.
00013  01002000        Z = -32768
00022  01003000        LAB = Z
00024  01004000  C
00024  01005000  C  PROCESS IN STRIPS ABOUT NC WIDE...
00024  01006000        DO 96 NU = 1,NZ,NC
00031  01007000  C
00031  01008000  C  NY IS LAST OF STRIP
00031  01009000        NY = NU+NC-1
00035  01010000        IF (NY.GT.NZ) NY = NZ
00042  01011000  C
00042  01012000  C  NX IS ACTUAL NUMBER GRABBED
00042  01013000        NX = NY-NU+1
00046  01014000        IRQU = 3
00050  01015000        IRQUOUT = 0
00052  01016000        I1 = 1
00054  01017000        I2 = 2
00056  01018000        I3 = 3
00060  01019000  C
00060  01020000  C  INIT LABELS BUFFER
00060  01021000        DO 10 I = 1,NX
00065  01022000        DO 10 J = 1,3
00072  01023000     10 LABBUF(I,J) = 1
00103  01024000  C
00103  01025000  C  READ 3 LINES DATA
00103  01026000        DO 20 J = 1,3
00110  01027000        DO 20 K = 1,ND
00115  01028000        CALL READP(UICB,IND,INGIN,DATBUF(1,K,J),2,K,J,NU,NX,K+1,
00115  01029000       +  J,NU,NX)
00150  01030000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGIN,NU,NX,K,1019)
00170  01031000     20 CONTINUE
00172  01032000  C
00172  01033000  C  MARK BOUNDARY 1_3 LR
00172  01034000        DO 30 J = 1,3
00177  01035000     30 CALL MARKLR(Z,DATBUF(1,1,J),INTTHR,NC,ND,LABBUF(1,J),MASK,NX)
00224  01036000  C
00224  01037000  C  MARK BOUNDARY 2 UD
00224  01038000        CALL MARKUPDN(Z,DATBUF(1,1,1),DATBUF(1,1,2),LABBUF(1,1),
00224  01039000       * LABBUF(1,2),LABBUF(1,3),NC,ND,INTTHR,MASK,NX)
00264  01040000  C
00264  01041000  C  FILL IN CRACKS 2
00264  01042000        CALL FILLLR(Z,LABBUF(1,2),NX)
00273  01043000  C
00273  01044000  C  DUP LABELS 2 TO 1
00273  01045000        DO 70 I = 1,NX
00300  01046000     70 IF (LABBUF(I,2).EQ.Z) LABBUF(I,1) = Z
00316  01047000        CALL MRKIVL(Z,LABBUF(1,1),NX,IN)
00326  01048000        DO 2222 I = 1,NX
00333  01049000        IF (LABBUF(I,1) NE Z) LABBUF(I,1)=LABBUF(I,1)+Z
00353  01050000   2222 CONTINUE
00356  01051000        LAB = LAB+IN
```

```
PAGE 0033   START

00365  01052000    1000 CONTINUE
00365  01053000   C
00365  01054000   C  MARK INTERVALS I2
00365  01055000         CALL MRKIVL(Z,LABBUF(1,I2),NX,IN)
00376  01056000   C
00376  01057000   C  SEE IF ANYTHING TO CONNECT
00376  01058000         IF (LAB.NE.Z) GO TO 81
00402  01059000         LAB = Z+IN
00405  01060000         DO 1111 I = 1,NX
00412  01061000         IF (LABBUF(I,I1).NE.Z) LABBUF(I,I1) = LABBUF(I,I1)+Z
00437  01062000    1111 CONTINUE
00440  01063000         GO TO 82
00441  01064000      81 IF (IN.EQ.0) GO TO 82
00445  01065000         CALL CONNCT(FINISHED,Z,NX,LABBUF(1,I1),LABBUF(1,I2),ISCAN,IN,LAB)
00467  01066000   C
00467  01067000   C  SEE IF FINISHED
00467  01068000         IF (FINISHED) GO TO 2000
00473  01069000   C
00473  01070000   C  WRITE I1 LABELS
00473  01071000      82 IROWOUT = IROWOUT+1
00474  01072000         CALL WRITEP(UICB,IND,IMGCLAS,LABBUF(1,I1),2,1,IROWOUT,NW,NX,
00474  01073000        *  1,IROWOUT+1,NW,NX)
00526  01074000         IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGCLAS,I1,NW,0,20)
00547  01075000   C
00547  01076000   C  READ NEXT
00547  01077000         IROW = IROW+1
00550  01078000         IF (IROW.GT.NR) GO TO 300
00554  01079000         DO 85 K = 1,ND
00561  01080000         CALL READP(UICB,IND,IMGIN,DATBUF(1,K,I1),2,K,IROW,NW,NX,
00561  01081000        *  K+1,IROW,NW,NX)
00614  01082000         IF (IND(1).LT.0) CALL CHKIO(UICB,IND,IMGIN,K,I1,NW,30)
00634  01083000      85 CONTINUE
00635  01084000   C
00635  01085000   C  MARK NEW LABELS
00635  01086000         DO 200 I = 1,NX
00642  01087000     200 LABBUF(I,I1) = I
00652  01088000   C
00652  01089000   C  ROTATE BUFFERS
00652  01090000         IT = I1
00654  01091000         I1 = I2
00656  01092000         I2 = I3
00660  01093000         I3 = IT
00662  01094000   C
00662  01095000   C  MARK
00662  01096000         CALL MARKLR(Z,DATBUF(1,1,I3),INTTHR,NC,NW,LABBUF(1,I3),MASK,NX)
00706  01097000         CALL MARKUPDN(Z,DATBUF(1,1,I1),DATBUF(1,1,I2),LABBUF(1,I1),
00706  01098000        * LABBUF(1,I2),LABBUF(1,I3),NC,ND,INTTHR,MASK,NX)
00757  01099000   C
00754  01100000   C  DO IT AGAIN
00755  01101000         GO TO 1000
00755  01102000   C
00755  01103000   C  FINISHED...PROCESS LAST TWO SCAN LINES
00755  01104000     300 CONTINUE
00755  01105000   C
00755  01106000   C  PROPOGATE I2 TO I3
00755  01107000         DO 310 I = 1,NX
00762  01108000         IF (LABBUF(I,I2).EQ.Z) LABBUF(I,I3) = Z
```

```
PAGE 0034   START

01001  01109000     310 CONTINUE
01002  01110000  C
01002  01111000  C  SCAN LINE I2 THEN I3
01002  01112000         DO 410 ITM = 1,2
01007  01113000         CALL MRKIVL(Z,LABBUF(1,I2),MX,IN)
01020  01114000  C
01020  01115000  C  JOIN I2 TO I1
01020  01116000         IF (IN.NE.0) CALL CONNCT(FINISHED,Z,MX,LABBUF(1,I1),LABBUF(1,I2),
01020  01117000        * ISCAN,IN,LAB)
01043  01118000         IF (FINISHED) GO TO 2000
01051  01119000  C
01051  01120000  C  STORE I1
01051  01121000         IROWOUT = IROWOUT+1
01052  01122000         CALL WRITEP(UICB,IND,INGCLAS,LABBUF(1,I1),2,1,IROWOUT,NW,MX,
01052  01123000        *  1,IROWOUT+1,NW,MX)
01104  01124000         IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGCLAS,I1,NW,0,40)
01125  01125000         I1 = I2
01127  01126000         I2 = I3
01131  01127000  C
01131  01128000  C  DO IT AGAIN (TWICE)
01131  01129000       410 CONTINUE
01132  01130000        96 CONTINUE
01136  01131000         R E T U R N
01137  01132000      2000 DO 2020 J = 1,MX
01144  01133000      2020 LABBUF(J,1) = Z
01153  01134000      2010 IROWOUT = IROWOUT+1
01154  01135000         DO 2040 I = IROWOUT,NR
01161  01136000         CALL WRITEP(UICB,IND,INGCLAS,LABBUF(1,1),2,1,I,NW,MX,
01161  01137000        * 1,I+1,NW,MX)
01212  01138000         IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGCLAS,I,NW,Z,750)
01232  01139000      2040 CONTINUE
01233  01140000  C
01233  01141000  C  SEE IF FINISHED
01233  01142000         IF (NY.GE.NZ) R E T U R N
01240  01143000         NW = NY+1
01243  01144000         NY = NY+NC
01246  01145000         IF (NY.GT.NZ) NY = NZ
01253  01146000         NX = NY-NW+1
01257  01147000         IROWOUT = 0
01261  01148000         GO TO 2010
01262  01149000                       END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
CHKIO		SUBROUTINE		CONNCT		SUBROUTINE	
DATBUF	INTEGER	ARRAY	0-%14 ,I	FILLLR		SUBROUTINE	
FINISHED	LOGICAL	SIMPLE VAR	0+%11	I	INTEGER	SIMPLE VAR	0+%3
I1	INTEGER	SIMPLE VAR	0+%16	I2	INTEGER	SIMPLE VAR	0+%17
I3	INTEGER	SIMPLE VAR	0+%20	INGCLAS	INTEGER	SIMPLE VAR	0-%6 ,I
INSIN	INTEGER	SIMPLE VAR	0-%7 ,I	IN	INTEGER	SIMPLE VAR	0+%7
IND	INTEGER	ARRAY	0-%10 ,I	INTTHR	INTEGER	ARRAY	0-%21 ,I
IROW	INTEGER	SIMPLE VAR	0+%6	IROWOUT	INTEGER	SIMPLE VAR	0+%4
ISCAN	INTEGER	ARRAY	0-%12 ,I	IT	INTEGER	SIMPLE VAR	0+%12
ITH	INTEGER	SIMPLE VAR	0+%5	J	INTEGER	SIMPLE VAR	0+%10
K	INTEGER	SIMPLE VAR	0+%21	LAB	INTEGER	SIMPLE VAR	0-%9 ,I
LABBUF	INTEGER	ARRAY	0-%13 ,I	MARKLR		SUBROUTINE	
MARKUPDN		SUBROUTINE		MASK	LOGICAL	SIMPLE VAR	0-%4 ,I
MRKIVL		SUBROUTINE		NC	INTEGER	SIMPLE VAR	0-%16 ,I
NO	INTEGER	SIMPLE VAR	0-%20 ,I	NR	INTEGER	SIMPLE VAR	0-%17 ,I
NW	INTEGER	SIMPLE VAR	0+%13	NX	INTEGER	SIMPLE VAR	0+%14
NY	INTEGER	SIMPLE VAR	0+%15	NZ	INTEGER	SIMPLE VAR	0-%15 ,I
READP		SUBROUTINE		START		SUBROUTINE	
UICB	INTEGER	ARRAY	0-%11 ,I	WRITEP		SUBROUTINE	
Z	INTEGER	SIMPLE VAR	0+%22				

PROGRAM UNIT START COMPILED

Parent: MAIN THINTSTM

Calls: GETN25

THINTSTM(MP,TSP,TTP,CLASS,COUNT,N25,N60,N288,N140,N388,N428,ND,NTSI,FILENO, UICB,IND)

Subroutine ASELECT creates a disk file of samples taken 5 at a time from the patches (the components of the complement of the bouncary). There will be many of these sets in a large image. The starting conditions for the clustering part of AMOEBA require relatively few. Further, the starting cluster centers have not been formed yet. Subroutine THINTSTM forms the starting cluster centers and "thins" the test sets.

Method: In MAIN, program variables N288, N388, and N428 are selected as large as possible depending on available menory (i.e. depending on ND). (If ND is 4, then N288 = 288, N388 = 388, and N428 = 428). If we start with NTS test sets (stored on disk by ASELECT), and if NTS < N428, then THINTSTM simply forms NTS means as starting cluster centers and returns N140 = NTS and N488 = NTS. Otherwise there are many test sets, and a complex procedure is followed to prevent the number of means and the number of test sets from growing too large.

1. If NTS < N25, go to step 7 (the finish). Otherwise read 25 test sets into the temporary buffer TTP.
2. Each test set has 5 test points; classify the 25 first elements in the class of nearest last element centers.
3. For each of the test sets classified correctly (i.e. in which the first element was nearer its last then the last of another of the 25), form the mean and add this mean to the mean pool MP, indicate the main pool is occupied with COUNT, and add the test set to the test set pool TSP, indicating it is occupied by CLASS. Count these events in NMP (the means) and NTSP (the test sets).
4. If there are more than 100 vectors in the mean pool, proceed to step 5. If there are more than N388 test sets, proceed to step 6. Otherwise go to step 1 and get more.

5. More than 100 vectors are in the mean pool. Classify all center test pixels in the classes of the mean pool and count the number of times a mean is hit. Eliminate each mean which was not hit. If NMP is greater than N60 (=60) after this operation, eliminate each with 1, 2, ... classification until NMP ≤ N60. At each elimination, reclassify center test pixels which were assigned to an eliminated mean and test if NMP < N60. When N60 is reached, test whether NTSP is greater than N388. If NTSP ≤ N388, return to step 1 to gather more, else proceed with step 6.
6. More than N388 test sets are in the test set pool, but fewer than 100 means are in the mean pool. Moreover, the majority of the test sets have been assigned to a class by the logic of step 5. (The ones just added haven't been, of course, so they are kept around a while longer.) Determine the mean which has the most test sets assigned. Test sets assigned to this mean are duplicates. Eliminate one (the first one found) and decrease the count. Repeat until fewer than N288 test sets are present, then go to step 1.
7. Close the disk file which contained the test sets, and compress and count the means and test sets; N140 is the number of means (starting cluster centers) and N428 is returned the number of test sets.

Program Variables

CLASS(N428)	INTEGER ARRAY The class to which a center test pixel is assigned.
COUNT(N140)	INTEGER ARRAY The number of center test pixels assigned to a mean.
FCLOSE	SYSTEM SUBROUTINE
FILENO	INTEGER File number of scratch disk file containing test sets.
FIRST	LOGICAL Switch used to jump around rewind of file in GETN25.

GETN25	SUBROUTINE Reads N25 test sets from disk.
I,II,J,K,L,LS,M	INTEGER DO loop index.
IA	INTEGER Class of nearest last test set element to first in batch of N25.
ICL	INTEGER Class of nearest mean to test set center.
IE	INTEGER Count of how unpopular a mean should be to be eliminated.
IM	INTEGER Distance to mean of a test set center.
IND(1)	INTEGER ARRAY Error indicator.
IS	INTEGER Distance accumulator.
IT	INTEGER Used to convert logical to integer. Also distance temporary.
IT1	INTEGER Distance temporary.
JS	INTEGER The test set center reclassified after a mean is eliminated.
JT	INTEGER A classification, tested to see of a duplicate test set has been found.
LIT	LOGICAL Equivalenced to IT; used to convert logical to integer to compensate for the inadequacy of the Segmenter.
MAX	INTEGER The running maximum count of classification in all means.
MP(ND,N140)	INTEGER ARRAY The mean pool, and, on return, the means.
N140	INTEGER On call, 140; on return, the number starting clusters.
N25	INTEGER The number of test sets read at a time.
N288	INTEGER Number of test sets sought after the iteration is started.
N388	INTEGER Test set iteration trigger.

N428	INTEGER Number of slots for test sets.
N60	INTEGER Means sought after iteration started.
ND	INTEGER Dimensionality.
ND5	INTEGER ND*5, for GETN25.
NDXM	INTEGER Pointer to mean pool, used in search for a free slot.
NDXP	INTEGER Pointer to test set pool.
NEAR	INTEGER Used in test set to test set smallest distance determination.
NMP	INTEGER Number in mean pool.
NTS	INTEGER Number of test sets on disk remaining.
NTSI	INTEGER Number of test sets on disk.
NTSP	INTEGER Number in test set pool.
TSP(ND,5,N488)	INTEGER ARRAY Test set pool.
TTP(ND,5,N25)	LOGICAL ARRAY Test sets for GETN25 to read into.
UICB(1)	INTEGER ARRAY User Information Control Block.

```
00019  01260000  $CONTROL SEGMENT=AMOEBASEG
00019  01261000        SUBROUTINE TMINTSTR(MP,TSP,TTP,CLASS,COUNT,M29,M60,
00019  01262000       * M280,M140,M350,M420,ND,NTSI,FILENO,UICO,IND)
00019  01263000        SYSTEM INTRINSIC FCLOSE
00019  01264000  C  SUBROUTINE TO REDUCE A LARGE NUMBER OF TEST SETS
00019  01265000  C  TO ABOUT M350, AND TO FORM ABOUT M280 MEAN VECTORS
00019  01266000  C  TO START NUMCLU
00019  01267000  C
00019  01268000  C  PARAMETERS:
00019  01269000  C
00019  01270000  C     MP -- MEAN POOL
00019  01271000  C    TSP -- TEST SET POOL
00019  01272000  C    TTP -- TEMPORARY TEST SET POOL
00019  01273000  C CLASS -- CLASSIFICATION OF TSP IN MP
00019  01274000  C COUNT -- COUNT OF MP CLASSIFICATIONS
00019  01275000  C     ND -- DIMENSIONALITY
00019  01276000  C   NTSI -- NUMBER OF TEST SETS INPUT
00019  01277000  C    NTS -- NUMBER OF TEST SETS
00019  01278000  C   NTSP -- NUMBER IN TEST SET POOL
00019  01279000  C    NMP -- NUMBER IN MEAN POOL
00019  01280000  C    M29 -- NUMBER OF TEST SETS GRABBED AT A TIME
00019  01281000  C    M60 -- MEANS SOUGHT AFTER ITERATION STARTED
00019  01282000  C  M280 -- MEAN ITERATION TRIGGER, AND
00019  01283000  C        -- TEST SETS SOUGHT AFTER ITERATION STARTED
00019  01284000  C  M140 -- ABSOLUTE MAX NUMBER MEANS
00019  01285000  C           ON RETURN, THIS PARAMETER IS THE ACTUAL NUMBER
00019  01286000  C  M350 -- TEST SET TRIGGER
00019  01287000  C  M420 -- ABSOLUTE MAX NUMBER OF TEST SETS
00019  01288000  C           ON RETURN, THIS PARAMETER IS THE ACTUAL NUMBER
00019  01289000  C  NDXM -- SEARCH INDEX IN MP LOOKING FOR NEW
00019  01290000  C  NDXP -- DITTO FOR TSP
00019  01291000  C
00019  01292000        LOGICAL LIT,TTP(ND,3,M29),FIRST
00019  01293000        EQUIVALENCE (IT,LIT)
00019  01294000        INTEGER*2 MP(ND,M140),TSP(ND,3,M420),
00019  01295000       * CLASS(M420),COUNT(M140),FILENO,UICO(1),IND(1)
00019  01296000  C INITIALIZE
00019  01297000        FIRST = TRUE
00017  01298000        ICL = 1
00021  01299000        JS = 1
00027  01300000        DO 10 I = 1,M140
00030  01301000     10 COUNT(I) = -1
00034  01302000        DO 20 J = 1,M420
00041  01303000     20 CLASS(J) = -1
00045  01304000        NMP = 0
00047  01305000        NTSP = 0
00051  01306000        NTS = NTSI
00053  01307000        NDXM = 0
00055  01308000        NDXP = 0
00057  01309000        NDS = ND*3
00062  01310000  C
00062  01311000  C  INITIALLY MEAN POOL AND TEST SET POOL ARE EMPTY
00062  01312000  C
00062  01313000  C  REFERENCE POINT FOR NEXT M29 TEST SETS
00062  01314000  C  GET M29 TEST SETS
00062  01315000  C  (RETURN IF NOT THAT MANY)
00062  01316000        IF (NTS GE M429) GO TO 2000
```

```
PAGE 0042   TWINTSTR

00066  01317000          N25 = NTS
00070  01318000          N140 = NTS
00072  01319000          N428 = NTS
00074  01320000          CALL GETN25(FIRST,TTP,N25,ND5,FILENO,UICB,IND)
00107  01321000          CALL FCLOSE(FILENO,4,0)
00112  01322000          DO 1 I = 1,NTS
00120  01323000          DO 2 K = 1,ND
00125  01324000            IS = 2
00127  01325000            DO 3 LS = 1,5
00134  01326000              LIT = TTP(K,LS,I)
00146  01327000              IS = IS+IT
00151  01328000        3   TSP(K,LS,I) = IT
00164  01329000        2 MP(K,I) = IS/5
00175  01330000        1 CONTINUE
00176  01331000          R E T U R N
00177  01332000     2000 IF (NTS LT N25) GO TO 6000
00204  01333000          CALL GETN25(FIRST,TTP,N25,ND5,FILENO,UICB,IND)
00217  01334000          NTS = NTS-N25
00222  01335000  C
00222  01336000  C  CLASSIFY FIRST PIXEL IN EACH TEST SET IN NEAREST
00222  01337000  C  LAST PIXEL CLASS
00222  01338000          DO 30 L = 1,N25
00227  01339000          NEAR = 16000
00231  01340000  C
00231  01341000  C  FIND CLOSEST TO L-TH CRITTER
00231  01342000          DO 40 K = 1,N25
00236  01343000          IS = -32768
00245  01344000          DO 50 K = 1,ND
00252  01345000          IF (IS.GT.NEAR) GO TO 40
00262  01346000          LIT = TTP(K,1,L)
00273  01347000          IT1 = IT
00275  01348000          LIT = TTP(K,5,M)
00306  01349000          IT = IT-IT1
00311  01350000       50 IS = IS+IT+IT
00316  01351000          IF (IS GE.NEAR) GO TO 40
00323  01352000          IA = K
00324  01353000          NEAR = IS
00326  01354000       40 CONTINUE
00327  01355000  C
00327  01356000  C  ZAP ANY SUCH THAT CLASS(K)<>K
00327  01357000          IF (IA NE L) GO TO 30
00333  01358000  C
00333  01359000  C  FIND A SLOT FOR MEAN AND TEST PIXELS
00335  01360000       70 NDXM = NDXM+1
00336  01361000          IF (NDXM GT N140) NDXM = 1
00341  01362000          IF (COUNT(NDXM) GE 0) GO TO 70
00345  01363000       90 NDXP = NDXP+1
00347  01364000          IF (NDXP GT N428) NDXP = 1
00354  01365000          IF (CLASS(NDXP) GE 0) GO TO 90
00361  01366000  C
00361  01367000  C  FORM MEANS, ADD TO MEAN POOL
00361  01368000  C  ADD TEST SETS TO TEST SET POOL
00361  01369000          DO 90 K = 1,NC
00366  01370000          IS = 2
00370  01371000          DO 100 LS = 1,5
00375  01372000          LIT = TTP(K,LS,L)
00407  01373000          IS = IS+IT
```

```
00412  01374000     140 TSP(K,LS,NDXP) = IT
00423  01375000      90 MP(K,NDXR) = IS/3
00436  01376000  C
00436  01377000  C  SHOW COVERED AND COUNT
00436  01378000         COUNT(NDXR) = 0
00441  01379000         CLASS(NDXP) = 0
00444  01380000         NMP = NMP+1
00445  01381000         NTSP = NTSP+1
00446  01382000     30 CONTINUE
00447  01383000  C
00447  01384000  C  DOES THE MEAN POOL CONTAIN MORE THAN 100 MEANS?
00447  01385000         IF (NMP.GE.100) GO TO 1000
00453  01386000  C*** YES! GO ELIMINATE (1000)
00453  01387000  C
00453  01388000  C***  NO!
00453  01389000  C  ARE THERE MORE THAN N300 TEST SETS?
00453  01390000   3000 IF (NTSP.LT.N300) GO TO 2000
00457  01391000  C***  NO! GO ITERATE (2000)
00457  01392000  C
00457  01393000  C*** YES! ZAP SOME
00457  01394000         MAX = -1
00461  01395000         DO 200 I = 1,N140
00466  01396000         MAX = MAX0(MAX,COUNT(I))
00475  01397000    200 CONTINUE
00476  01398000   9000 DO 210 J = 1,N425
00503  01399000         JT = CLASS(J)
00506  01400000         IF (JT.LE.0) GO TO 210
00512  01401000         IF (COUNT(JT).LT.MAX) GO TO 210
00517  01402000         CLASS(J) = -1
00522  01403000         COUNT(JT) = COUNT(JT)-1
00526  01404000         NTSP = NTSP-1
00527  01405000         IF (NTSP.LT.N300) GO TO 2000
00534  01406000    210 CONTINUE
00535  01407000         MAX = MAX-1
00536  01408000         GO TO 9000
00537  01409000  C  CLASSIFY ALL CENTER OF TEST SETS AND COUNT
00537  01410000  C
00537  01411000   1000 NP = 3
00541  01412000         DO 399 J = 1,N140
00546  01413000         IF (COUNT(J).GE.0)COUNT(J) = 0
00553  01414000    399 CONTINUE
00556  01415000  C  NOW CLASSIFY EM
00556  01416000         DO 300 J = 1,N425
00563  01417000         IF (CLASS(J).LT.0) GO TO 300
00570  01418000         IM = 16000
00572  01419000         DO 310 I = 1,N140
00577  01420000         IF (COUNT(I).LT.0) GO TO 310
00604  01421000         IS = -12760
00611  01422000         DO 320 K = 1,ND
00620  01423000         IF (IS.GE.IM) GO TO 310
00625  01424000         IT = TSP(K,NP,J)-MP(K,I)
00645  01425000    320 IS = IS+IT*IT
00652  01426000         IF (IS.GT.IM) GO TO 310
00656  01427000         IM = IS
00660  01428000         ICL = I
00662  01429000    310 CONTINUE
00667  01430000         CLASS(J) = ICL
```

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PAGE 0044   THIRTYTH

00666  01431000         COUNT(ICL) = COUNT(ICL)+1
00672  01432000     300 CONTINUE
00673  01433000  C
00673  01434000  C  ALL CLASSIFIED AND COUNTED. NOW SEE IF ANY MISSES
00673  01435000         DO 330 I = 1,N140
00700  01436000         IF (COUNT(I).NE.0) GO TO 330
00705  01437000         COUNT(I) = -1
00710  01438000         NRP = NRP-1
00711  01439000     330 CONTINUE
00712  01440000  C
00712  01441000  C  SEE IF WE'RE DOWN TO N60
00712  01442000         IF (NRP.LE.N60) GO TO 3000
00716  01443000  C  NO. SO ZAP SOME WITH 1,2,...CLASSIFICATIONS
00716  01444000  C
00716  01445000         IE = 1
00720  01446000    4000 DO 440 II = 1,N140
00725  01447000         IC = COUNT(II)
00730  01448000         IF (IC.NE.IE) GO TO 440
00734  01449000         NRP = NRP-1
00735  01450000         COUNT(II) = -1
00740  01451000  C  REMOVED.  NOW RECLASSIFY ITEMS ASSIGNED TO CLASS I
00740  01452000  C
00740  01453000         DO 450 J = 1,N428
00745  01454000         IF (CLASS(J).NE.II) GO TO 450
00751  01455000         IM = 16000
00754  01456000         DO 460 I = 1,N140
00761  01457000         IF (COUNT(I).LT.0) GO TO 460
00767  01458000         IS = -32768
00770  01459000         DO 470 K = 1,ND
01003  01460000         IF (IS.GE.IM) GO TO 460
01012  01461000         IT = TSP(K,3,J)-RP(K,I)
01021  01462000     470 IS = IS+IT*IT
01026  01463000         IF (IS.GT.IM) GO TO 460
01042  01464000         JS = J
01044  01465000         IM = IS
01046  01466000         ICL = I
01050  01467000     460 CONTINUE
01051  01468000         CLASS(JS) = ICL
01054  01469000         COUNT(ICL) = COUNT(ICL)+1
01060  01470000     450 CONTINUE
01061  01471000         IF (NRP.LT.N60) GO TO 3000
01067  01472000     440 CONTINUE
01070  01473000         IE = IE+1
01071  01474000         GO TO 4000
01072  01475000    6000 CALL FCLOSE(FILENO,4,0)
01076  01476000         L = 0
01100  01477000  C  NOW PUT EVERYTHING IN THE FIRST SLOTS OF RP AND TSP
01100  01478000  C
01100  01479000         DO 7000 I = 1,N428
01105  01480000         IF (CLASS(I).EQ.-1) GO TO 7000
01112  01481000         L = L+1
01113  01482000         DO 7010 K = 1,ND
01120  01483000         DO 7010 J = 1,3
01125  01484000    7010 TSP(K,J,L) = TSP(K,J,I)
01151  01485000    7000 CONTINUE
01152  01486000         N428 = L
01154  01487000         L = 0
```

```
PAGE 0043   THINTSTR

01175  01488000          DO 7020 I = 1,M160
01163  01489000          IF (COUNT(I).EQ.-1) GO TO 7020
01170  01490000          L = L+1
01171  01491000          DO 7030 K = 1,ND
01176  01492000    7030  AP(K,L) = AP(K,I)
01211  01493000    7020  CONTINUE
01214  01494000          M160 = L
01215  01495000          R E T U R N
01217  01496000          END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS	NAME	TYPE	STRUCTURE	ADDRESS
CLASS	INTEGER	ARRAY	0-220 .I	COUNT	INTEGER	ARRAY	0-217 .I
FCLOSE		SUBROUTINE		FILENO	INTEGER	SIMPLE VAR	0-26 .I
FIRST	LOGICAL	SIMPLE VAR	0+236	GETN2S		SUBROUTINE	
I	INTEGER	SIMPLE VAR	0+25	IA	INTEGER	SIMPLE VAR	0+27
IC	INTEGER	SIMPLE VAR	0+211	ICL	INTEGER	SIMPLE VAR	0+231
IE	INTEGER	SIMPLE VAR	0+213	II	INTEGER	SIMPLE VAR	0+215
IR	INTEGER	SIMPLE VAR	0+221	IND	INTEGER	ARRAY	0-24 .I
IS	INTEGER	SIMPLE VAR	0+223	IT	INTEGER	SIMPLE VAR	0+230
ITI	INTEGER	SIMPLE VAR	0+232	J	INTEGER	SIMPLE VAR	0+222
JS	INTEGER	SIMPLE VAR	0+216	JT	INTEGER	SIMPLE VAR	0+217
K	INTEGER	SIMPLE VAR	0+233	L	INTEGER	SIMPLE VAR	0+214
LIF	LOGICAL	SIMPLE VAR	0+230	LS	INTEGER	SIMPLE VAR	0+237
M	INTEGER	SIMPLE VAR	0+227	MAX	INTEGER	SIMPLE VAR	0+226
MP	INTEGER	ARRAY	0-223 .I	M160	INTEGER	SIMPLE VAR	0-213 .I
M23	INTEGER	SIMPLE VAR	0-216 .I	M200	INTEGER	SIMPLE VAR	0-214 .I
M300	INTEGER	SIMPLE VAR	0-212 .I	M420	INTEGER	SIMPLE VAR	0-211 .I
M60	INTEGER	SIMPLE VAR	0-219 .I	ND	INTEGER	SIMPLE VAR	0-210 .I
ND3	INTEGER	SIMPLE VAR	0+224	NDXR	INTEGER	SIMPLE VAR	0+26
NDXP	INTEGER	SIMPLE VAR	0+210	NEAR	INTEGER	SIMPLE VAR	0+235
NPP	INTEGER	SIMPLE VAR	0+212	NP	INTEGER	SIMPLE VAR	0+225
NTS	INTEGER	SIMPLE VAR	0+220	NTSI	INTEGER	SIMPLE VAR	0-27 .I
NTSP	INTEGER	SIMPLE VAR	0+234	THINTSTR		SUBROUTINE	
TSP	INTEGER	ARRAY	0-222 .I	TTP	LOGICAL	ARRAY	0-221 .I
UICB	INTEGER	ARRAY	0-25 .I				

PROGRAM UNIT THINTSTR COMPILED

Parent: MAIN THRFND

THRFND(NFL,INTTHR,SCANLINE,UICB,IND,KOUNT,NR,NC,NB,MASK,IMGIN)

Subroutine THRFND finds vector thresholds INTTHR so that about NFL percent of the scene is in patches. The thresholds are used in subroutine START to decide boundary; a boundary decision is made when any channel differs from its neighbor by more than that channel's INTTHR.

Method: Initially the data is sparsely sampled to estimate the variability. The initial thresholds are, for each channel K, .15 x (NFL+5) x A(K)/$\sqrt{ND}$, where A(K) is the average estimated in that channel of the difference of a point from its left-hand neighbor.

These initial thresholds are updated in an adaptive program which scans the data checking when a boundary decision would be made. A count is kept of the decisions non boundary (i.e. pure). When too few pure points are being found, the thresholds are increased (making it harder to be a boundary point and thus easier to be a pure point). When too many are found, the thresholds are decreased. Too many or few is decided by comparing the count NFND with the target TARGET.

Only one threshold is increased or decreased at a time. A count is kept of the number of boundary decisions which have been made per channel. When it is necessary to decrease the thresholds, that threshold which has the highest count is decreased. Dually, when the thresholds must be increased, that threshold with the lowest count is incremented. The effect is that the algorithm expects all channels to contribute equally in boundary-finding.

Flags UP and DOWN, initially .FALSE., control exit. When the thresholds are increased, UP is set .TRUE. When they are decreased, DOWN is set .TRUE. Another flag, BOTH (initially false) is tested after each outer loop (the data is scanned in a pattern which spreads the sparse sample), and then, after the test is set to UP.AND.DOWN. Thus one more scan of the data is taken after both flags have been set.

The scanning strategy has two phases: the initial phase sets NCS = the larger of 4 or NR*NC/557039. Then data is sampled by every eleventh line and every NCS sample along a line to estimate variability. When the sum exceeds 32245 in any channel or when the loop falls through, the initial INTTHR estimates are calculated and the second sampline phase is entered. Let

NSEL = (NR/100)*(NC/100)/2 + 1

N20 = 20 ; if N20 ≥ NC, N20 = NC/2 .

Then the loop structure is the following (in FORTRAN):

```
      DO 665 NN = 2, N20, NSEL
           DO 65 N = 1,20,5
                IS = N+NN
                IF(IS.GE.NR)IS = NR/2
                     DO 100 I + IS,NR,17
                          read data for line I
                          DO 60 J = NN,NC,5
                               count pure decisions and boundary
                               decisions per channel.
60                        CONTINUE
                     see if too many (→80), just right (→100)
                     or too few (here) (increase and go to 63)
80                   too many : decrease
63                   reset counters and target
100                CONTINUE
65         CONTINUE
                   test BOTH ; if .TRUE., RETURN
           set BOTH to UP.AND.DOWN
665   CONTINUE
      RETURN
```

As can be seen, the sample is not sparse: in particular, the 65 loop must be executed at least twice, first with NN = 2 and then NN = 2+NSEL (in a 512x512 image, NSEL = 13). Thus, the rows sampled are (with NSEL = 13)

3	,	20	,	37	,	54	,	71	,	88	,	...
8	,	25	,	42	,	59	,	76	,	93	,	...
13	,	30	,	47	,	64	,	81	,	98	,	...
18	,	35	,	52	,	69	,	86	,	103	,	...
16	,	33	,	50	,	67	,	84	,	101	,	...
21	,	38	,	55	,	72	,	89	,	106	,	...
26	,	43	,	60	,	77	,	94	,	111	,	...
31	,	48	,	65	,	82	,	99	,	116	,	... .

During the first four, every fifth line sample pair is sampled beginning at sample 2. During the second four, the starting sample is 15. This sampling strategy avoids staying in any place too long and is fast.

Program Variables

BOTH	LOGICAL A flag which, when true, means the thresholds have been increased and decreased.
CHKIO	SYSTEM SUBROUTINE
DELTGT	REAL (NFL+5)/100, used to increment TARGET when a test is made.
DOWN	LOGICAL A flag used to tell when the thresholds have been decreased.
FLAG	LOGICAL Used to tell when a pure point has been detected.
I,J,K,N,NN	INTEGER DO loop index.
IMGIN	INTEGER Input image number.
IND(1)	INTEGER ARRAY Error indicator.
INTTHR(ND)	INTEGER ARRAY The integer thresholds.
IS	INTEGER Starting row in loop 100.
IT	INTEGER Used to accumulate initial estimate of variability.
JM	INTEGER J-1; points to sample to left along a line.
KI	INTEGER Index of threshold to be increased or decreased.

KOUNT(ND)	INTEGER ARRAY Used to count the number of times a boundary decision would have been made in a channel if all were tested.
MASK	LOGICAL If .TRUE., a value of 0 in channel 1 is regarded as a mask (i.e. not image data).
MAX,MIN	INTEGER Used to find max or min of KOUNT to determine which channel threshold to adjust.
N20	INTEGER Loop 665 parameter: usually 20.
NC	INTEGER Number of samples.
NCS	INTEGER MAXØ(NR*NC/557039,4) used to sparsely sample on the initial estimate.
ND	INTEGER Dimensionality.
NFL	INTEGER Input parameter: percent of scene which user believes to be inside patches.
NFLD	INTEGER NFL+5; interval parameter which allows for "crack" fill in logic in start which adds boundary points not based on thresholding. This has been found to amount to about 5 percent.
NFND	INTEGER Running number of pure points found; tested against TARGET to decide if too many, too few, or about right during a pass through the data.
NR	INTEGER Number of lines.
NSEL	INTEGER (NR/100)*(NC/100)/2+1; used as loop 665 parameter.
NUM	INTEGER Counter during variability estimation phase.
OONUM	REAL Used to form initial threshold estimates.
READP	SYSTEM SUBROUTINE
SCANLINE(NC,ND)	INTEGER ARRAY One line of data.
TARGET	REAL Running count of the target percent pure points.

UICB(1)	INTEGER ARRAY User Information Control Block
UP	LOGICAL A flag which is set when the thresholds have been increased.

```
00019  01931000  $CONTROL SEGMENT=ANOEBASEG
00019  01932000        SUBROUTINE THRFND(NFL,INTTHR,SCANLINE,UICB,IND,KOUNT,NR,NC,ND,
00019  01933000       * MASK,INGIN)
00019  01934000        INTEGER*2 SCANLINE(NC,ND),INTTHR(ND),KOUNT(ND),UICB(1),IND(4),
00019  01935000       * BUFFER(NC)
00019  01936000        LOGICAL MASK,FLAG,UP,DOWN,BOTH
00019  01937000        NSEL = (NR/100)*(NC/100)/2+1
00023  01938000        NCS = IFIX(FLOAT(NR)*FLOAT(NC)/32767./17.)
00041  01939000        IF (NCS.LT.5) NCS = 4
00046  01940000        NUM = 1
00050  01941000        NFLD = MAX0(MIN0(NFL+5,80),25)
00063  01942000        NFND = 0
00065  01943000        TARGET = NFLD*0.01
00071  01944000        DELTGT = TARGET
00073  01945000        DO 20 K = 1,ND
00100  01946000     20 INTTHR(K) = 0
00104  01947000        IR = 1
00106  01948000        UP = .FALSE.
00110  01949000        DOWN = UP
00112  01950000        BOTH = UP
00114  01951000  C
00114  01952000  C  SAMPLE DATA TO GET INITIAL ESTIMATE
00114  01953000  C
00114  01954000        DO 30 I = 2,NR,11
00121  01955000  C
00121  01956000  C  EVERY 11 SCAN LINES
00121  01957000  C
00121  01958000        N20 = 20
00122  01959000        IF (N20.GE.NC) N20 = NC/2
00131  01960000        DO 25 K = 1,ND
00136  01961000        CALL READP(UICB,IND,INGIN,SCANLINE(1,K),2,K,I,1,NC,K+1,I,1,NC)
00170  01962000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGIN,IR,NC,I,50)
00210  01963000     25 CONTINUE
00211  01964000        DO 30 J = 2,NC,NCS
00216  01965000        JM = J-1
00221  01966000        IF (.NOT.MASK) GO TO 1
00232  01967000        IF (SCANLINE(J,I) EQ.0.OR.SCANLINE(JM,I).EQ.0) GO TO 30
00251  01968000      1 DO 40 K = 1,ND
00256  01969000        IT = INTTHR(K)+IABS(SCANLINE(J,K)-SCANLINE(JM,K))
00277  01970000        IF (IT.GE.32245) GO TO 660
00305  01971000     40 INTTHR(K) = IT
00311  01972000        NUM = NUM+1
00312  01973000     30 CONTINUE
00314  01974000    660 DONUM = 15.*DELTGT/SQRT(FLOAT(ND))/FLOAT(NUM)
00320  01975000        DO 50 K = 1,ND
00335  01976000     50 INTTHR(K) = IFIX(FLOAT(INTTHR(K))*DONUM)
00347  01977000        DO 66 K = 1,ND
00354  01978000     66 KOUNT(K) = 0
00360  01979000        DO 665 NN = 2,N20,NSEL
00365  01980000        DO 65 N = 1,20,5
00372  01981000        IS = N+NN
00375  01982000        IF (IS GE.NR) IS = NR/2
00403  01983000        DO 100 I = IS,NR,17
00416  01984000        DO 25 K = 1,ND
00419  01985000          CALL READP(UICB,IND,INGIN,SCANLINE(1,K),2,K,I,1,NC,K+1,I,1,NC)
00447  01986000        IF (IND(1).LT.0) CALL CHKIO(UICB,IND,INGIN,IR,NC,I,60)
00467  01987000     65 CONTINUE
```

```
PAGE 0048   THRFND

00470  01598000         DO 60 J = NN,NC,S
00473  01599000         JM = J-1
00300  01570000         IF (.NOT.MASK) GO TO 2
00302  01591000         IF (SCANLINE(J,1) EQ.0.OR.SCANLINE(JM,1).EQ.0) GO TO 60
00324  01592000       2 FLAG = .TRUE.
00326  01593000         DO 70 K = 1,ND
00333  01594000         IF (IABS(SCANLINE(J,K)-SCANLINE(JM,K)).LT.INTTHR(K)) GO TO 70
00339  01595000         KOUNT(K) = KOUNT(K)+1
00361  01596000         FLAG = FALSE.
00367  01597000      70 CONTINUE
00364  01598000         IF (FLAG) NFND = NFND+1
00367  01599000         TARGET = TARGET+DELTGT
00373  01600000      60 CONTINUE
00374  01601000         IT = IFIX(TARGET)
00601  01602000         IF (NFND.GT.IT+3) GO TO 80
00607  01603000         IF (NFND.GE.IT-3) GO TO 100
00613  01604000   C  TOO FEW--INCREASE
00615  01605000         MAX = KOUNT(1)
00620  01606000         KI = 1
00622  01607000         UP = .TRUE.
00624  01608000         DO 61 K = 2,ND
00631  01609000         IF (KOUNT(K).LE.MAX) GO TO 61
00636  01610000         MAX = KOUNT(K)
00641  01611000         KI = K
00643  01612000      61 CONTINUE
00644  01613000         INTTHR(KI) = INTTHR(KI)+1
00650  01614000         GO TO 63
00651  01615000   C  TOO MANY--DECREASE
00651  01616000      80 MIN = KOUNT(1)
00654  01617000         KI = 1
00656  01618000         DOWN = .TRUE.
00660  01619000         DO 81 K = 2,ND
00665  01620000         IF (KOUNT(K).GE.MIN) GO TO 81
00672  01621000         MIN = KOUNT(K)
00675  01622000         KI = K
00677  01623000      81 CONTINUE
00700  01624000         INTTHR(KI) = INTTHR(KI)-1
00704  01625000   C  RESTORE COUNTERS
00704  01626000      63 DO 83 K = 1,ND
00711  01627000      83 KOUNT(K) = 0
00715  01628000         NFND = 0
00717  01629000         TARGET = DELTGT
00721  01630000     100 CONTINUE
00722  01631000      65 CONTINUE
00723  01632000         IF (BOTH) GO TO 666
00727  01633000         BOTH = UP.AND.DOWN
00733  01634000     665 CONTINUE
00734  01635000     666 RETURN
00735  01636000         END
```

SYMBOL MAP

NAME	TYPE	STRUCTURE	ADDRESS
BOTH	LOGICAL	SIMPLE VAR	0+%21
CHRIO		SUBROUTINE	
DOWN	LOGICAL	SIMPLE VAR	0+%26
I	INTEGER	SIMPLE VAR	0+%4
IMD	INTEGER	ARRAY	0-%12 ,I
IR	INTEGER	SIMPLE VAR	0+%12
IT	INTEGER	SIMPLE VAR	0+%16
JR	INTEGER	SIMPLE VAR	0+%6
KI	INTEGER	SIMPLE VAR	0+%30
MASK	LOGICAL	SIMPLE VAR	0-%5 ,I
MIN	INTEGER	SIMPLE VAR	0+%31
N20	INTEGER	SIMPLE VAR	0+%11
NCS	INTEGER	SIMPLE VAR	0+%25
NFL	INTEGER	SIMPLE VAR	0-%16 ,I
NFND	INTEGER	SIMPLE VAR	0+%10
NR	INTEGER	SIMPLE VAR	0-%10 ,I
NUM	INTEGER	SIMPLE VAR	0+%24
READP		SUBROUTINE	
SQRT	REAL	FUNCTION	
THRFND		SUBROUTINE	
UP	LOGICAL	SIMPLE VAR	0+%7

NAME	TYPE	STRUCTURE	ADDRESS
BUFFER	INTEGER	ARRAY	0+%3 ,I
DELTGT	REAL	SIMPLE VAR	0+%36
FLAG	LOGICAL	SIMPLE VAR	0+%22
INSIN	INTEGER	SIMPLE VAR	0-%4 ,I
INTTHR	INTEGER	ARRAY	0-%15 ,I
IS	INTEGER	SIMPLE VAR	0+%14
J	INTEGER	SIMPLE VAR	0+%13
K	INTEGER	SIMPLE VAR	0+%27
KOUNT	INTEGER	ARRAY	0-%11 ,I
MAX	INTEGER	SIMPLE VAR	0+%23
N	INTEGER	SIMPLE VAR	0+%5
NC	INTEGER	SIMPLE VAR	0-%7 ,I
ND	INTEGER	SIMPLE VAR	0-%6 ,I
NFLD	INTEGER	SIMPLE VAR	0+%15
NN	INTEGER	SIMPLE VAR	0+%17
NSEL	INTEGER	SIMPLE VAR	0+%20
OONUM	REAL	SIMPLE VAR	0+%34
SCANLINE	INTEGER	ARRAY	0-%14 ,I
TARGET	REAL	SIMPLE VAR	0+%32
UICB	INTEGER	ARRAY	0-%13 ,I

PROGRAM UNIT THRFND COMPILED

Parent: NUMCLU UNCLE

UNCLE(TSPXL,MEAN,ND,MAX,NEAR,SUM,ID)

This program finds the cluster from MEAN nearest TSPXL. Only clusters with index I such that SUM(I) ≠ 0 are considered. The distance is returned as ID, the index as NEAR.

Method: Self-documenting.

Program Variables

ID	INTEGER The squared distance (biased by -32768) from TSPXL to the nearest cluster in MEAN.
IS,IT	INTEGER Used to compute the distance.
K,M	INTEGER DO loop index.
MAX	INTEGER The largest possible number of means. Inactive means have SUM(.) = 0.
MEAN(ND,MAX)	INTEGER ARRAY The cluster centers.
ND	INTEGER Dimensionality
NEAR	INTEGER Returned index of nearest cluster to TSPXL.
SUM(MAX)	INTEGER ARRAY An indicator that a cluster has been eliminated. If SUM(I) = 0, then cluster MEAN(.,I) is gone.
TSPXL(ND)	INTEGER ARRAY The point to be classified.

```
PAGE 0030   HEWLETT-PACKARD 321020.01.03   FORTRAN/3000    TUE, OCT 13, 1981,  9:41 AM

00007  02043000  $CONTROL SEGMENT=ANOEBASEG
00007  02044000        SUBROUTINE UNCLE(TSPXL,MEAN,MD,MAX,NEAR,SUM,ID)
00007  02045000  C
00007  02046000  C  PARENT PROGRAM:     NUNCLU
00007  02047000  C
00007  02048000  C  SUBROUTINE  UNCLE  FINDS THE CLUSTER  NEAR  FROM  MEAN
00007  02049000  C  WHICH IS CLOSEST TO  TSPXL  WITHOUT REGARD FOR HOW FAR
00007  02050000  C  THIS MIGHT BE.  ONLY CLUSTERS  K  WITH SUM(K) NOT ZERO
00007  02051000  C  ARE CONSIDERED.
00007  02052000        INTEGER*2 TSPXL(MD),MEAN(MD,MAX),SUM(MAX)
00007  02053000        ID = 16000
00011  02054000        DO 1 K = 1,MAX
00016  02055000        IF (SUM(K).EQ.0) GO TO 1
00024  02056000        IS = -32768
00031  02057000        DO 2 M = 1,MD
00040  02058000        IF (IS.GT.ID) GO TO 1
00047  02059000        IT = MEAN(M,K)-TSPXL(M)
00060  02060000      2 IS = IS+IT*IT
00069  02061000        IF (IS.GT.ID) GO TO 1
00071  02062000        ID = IS
00073  02063000        NEAR = K
00075  02064000      1 CONTINUE
00076  02065000        R E T U R N
00077  02066000        END


  SYMBOL MAP

NAME              TYPE        STRUCTURE   ADDRESS          NAME              TYPE        STRUCTURE   ADDRESS

ID                INTEGER     SIMPLE VAR  Q-%4  ,I         IS                INTEGER     SIMPLE VAR  Q+%3
IT                INTEGER     SIMPLE VAR  Q+%4             K                 INTEGER     SIMPLE VAR  Q+%6
M                 INTEGER     SIMPLE VAR  Q+%5             MAX               INTEGER     SIMPLE VAR  Q-%7  ,I
MEAN              INTEGER     ARRAY       Q-%11 ,I         MD                INTEGER     SIMPLE VAR  Q-%10 ,I
NEAR              INTEGER     SIMPLE VAR  Q-%6  ,I         SUM               INTEGER     ARRAY       Q-%9  ,I
TSPXL             INTEGER     ARRAY       Q-%12 ,I         UNCLE                         SUBROUTINE


PROGRAM UNIT UNCLE COMPILED
```

APPENDIX A

THE THEORETICAL FOUNDATION OF AMOEBA

The Assumptions. The clustering technique AMOEBA is based on three groups of theoretical statements. The first group concerns the relationship between the spatial and spectral behavior of the data. Roughly speaking, it is assumed that spectrally homogeneous groups of pixels found in spatially connected blobs represent the real classes. The second group contains a definition of a new concept (the pair probability of misclustering) and specifies that in clustering it is desired to minimize this probability The third group concerns the problem of handling the classification of pixels which are on the spatial boundary between two real classes.

Group A

A1 Real classes exist and can be distinguished using digital multi-imagery.

Discussion: While it might not be questionable that real classes exist, it is certainly not clear that this is the case for their representation in multi-image measurements. Assumption A1 may fail in clu tering if too much is hoped for in the identification of clusters in the data with real world classes. On the other hand, the assumption must certainly be held, at least implicitly, by all who would cluster the data looking for associations homologous to real classes.

It can also be observed that digital multi-image data consists of pixels at the atomic level. A consequence of assumption A1 is that, at least for some pixels, it is meaningful to ask what real class a pixel belongs to. It is clearly not possible to ask this of all pixels. Pixels on spatial boundaries display erratic statistical fluxuations which are generally difficult to model. This is particularly true of data which is one or more of

(a) data sampled in a particular scan line direction and subjected to significant band-width limited processing after sampling;

(b) pictorial imagery with sampling at a density comparable to the point-spread of the lens system;

(c) multi-temporal imagery in which imperfect registration has been performed: that is, multi-imagery in which spatial adjustments have been made so that pixels from various single images are samples from approximately the same spatial point.

(It can be noted that Landsat multi-temporal multi-spectral data enjoys all of these properties.) For digital multi-imagery, we can distinguish, at least in principle, between mixture pixels and pure pixels (the rest). Mixture pixels arise as a consequence of finite bandwidth ((a) or (b)) or imperfect registration (c). If the data is sampled efficiently and real classes are found in small groups then many pixels will be mixtures. On the other hand, if it is to be believed that an adequate spatial sample is available, then each real class must be represented in at least some pure pixel associations. In order to make this more precise, we introduce some terminology.

Let I denote the digital image. The next three assumptions concern the existence of a set $P \subset I$ of pixels such that neighboring pixels in the set are unusually like one another in measurement space. Call two pixels with spatial coordinates (i,j) and (n,m) neighbors if $|i - n| + |j - m| = 1$. (A pixel inside the image has four neighbors.) A path is an ordered sequence $p_1,\ldots,p_n$ such that p_{k-1} is a neighbor of p_k for $k = 2,\ldots,n$. A set Q is said to be connected if for each pair p,q in Q there is a path $p_1,\ldots,p_n$ in Q with $p_1 = p$ and $p_n = q$. It is easy to see that any non-void $P \subset I$ is a union of non-void maximal connected sets Q_i, $i = 1,\ldots,k$ with $Q_i \cap Q_j = \emptyset$ for $i \neq j$; the components Q_i are uniquely determined.

We assume that:

A2 A subset P of I has the property that each pixel $p \in P$ is a pure measurement from a real class.

Call the components of P patches; consequences of the purity assumption and the discussion above on sampling are the following two statements.

Rather than formalize the sampling discussion, we simply assume:

A3. All pixels from a given patch are measurements from the same real class.

A4. Each real class has at least one measurement pixel in P.

Group B

Consider a clustering $C = \{C_0,\ldots,C_m\}$ of the data. (It is convenient to include a cluster C_0 which one might call "unknown"; most classification rules allow a threshold in which a pixel is not assigned to any cluster.) In what follows, we call a clustering of a pixel p in C_i meaningful if and only if $i > 0$. Consider also the unknown real partition of data into pure real classes $\{R_1,\ldots,R_k\}$ plus a mixture class R_0. These are not simply unknown: they depend on the observer, and so are unknowable. In clustering, one might hope to minimize the "probability of misclassification." Unfortunately, since the clusters are not labelled and, indeed, no labels independent of an external observer exist, this concept is meaningless.

One observation we can make right away is the following: it is clearly an error if $p \in R_i$ for $i \neq 0$ and $p \in C_0$. This is actually a restriction on the "rejection thresholds", and is used in AMOEBA to determine when the clustering is going astray. Here we simply assume $R_i \cap C_0 = \emptyset$ when $i \neq 0$.

Consider a pair $\{p,q\}$ of pure pixels. Let $r(s)$ denote the real class a pixel s is in and $c(s)$ the cluster. Since $c(p) \neq 0$ and $c(q) \neq 0$, p and q are clustered in meaningful clusters, and there are four cases:

(i) $r(p) = r(q)$ and $c(p) = c(q)$;

(ii) $r(p) \neq r(q)$ and $c(p) \neq c(q)$;

(iii) $r(p) = r(q)$ and $c(p) \neq c(q)$;

(iv) $r(p) \neq r(q)$ and $c(p) = c(q)$.

The last two cases are errors.

B1 Definition. The probability that two pure pixels are in the same real class and are clustered differently plus the probability that two pure pixels are in distinct real classes and are clustered alike is called the pair probability of misclustering (PPMC).

B2 Objective. In clustering pure pixels, it is desired that
(a) each pure pixel be assigned to a meaningful cluster, and
(b) the PPMC is minimal.

Before examining just how these assumptions are developed into a clustering program, we consider the problem of handling mixture pixels.

Group C

The underlying classification rule used in AMOEBA is a nearest neighbor (Euclidean distance) to cluster center. A clustering program based on the model discussed above furnishes cluster centers. The pixels are tentatively classified by nearest cluster center and this classification is checked spatially. We assume:

C.1.a. The nearest cluster center classification is generally accurate.

b. Each pixel with two, three or four spatial neighbors in the same class is acceptably classified.

c. Each pixel with no neighbor in the same class is not correctly classified.

Assumption C.1 allows us to locate and mark pixels with one or no neighbor in the same class for examination. Most of these pixels are boundary pixels. To model this situation, we assume:

C.2 Each pixel on a spatial boundary is, as a measurement vector, a convex combination of the cluster centers in which two of its four neighbors are classified.

Although this model ignores both contaminated boundaries and registration errors, it leads to a method for reclassifying apparent errors and, unexpectedly, to a cluster-dependent rejection threshold. Note that, if $b = ap + (1 - a)q$ is a convex combination of vectors p and q,

then dist(b, nearer of p,q) $\leq \frac{1}{2}$ dist(p,q). Suppose p is a pixel which was marked as having no neighbor in the same class. Let q_1, q_2, q_3 and q_4 be the cluster centers of the classes of the four neighbors of p which are acceptably classified. (Usually at most two are distinct, and often only one neighbor is in a valid cluster at this point.) For each cluster i, let $r(i) = \frac{1}{2}\max_j \text{dist}(c_i, c_j)$ denote half the distance from cluster center c_i to the other furtherest away. Reclassify pixel p in class q_i provided $\text{dist}(p,q_i) < r(i)$ and $\text{dist}(p,q_i) \leq \min_{i \neq j} \{d : d = \text{dist}(p,q_j)$ and $d < r(j)\}$.

The IDIMS function AMOEBA represents one attempt to follow this model as far as it can take us. We only make two concessions to reality: First, the boundary estimation program is good but not perfect, so we do not actually classify patches as one unit. Second, registration errors blow the mixture $\sqrt{2}$ high (that is, in registration-error pixels, the α depends on the band, but, even so, the distance to the closest is more than $\sqrt{2} \cdot 1/2\ d(p,q) \simeq .7\ \text{dist}(p,q)$).

APPENDIX B

SYSTEM SUBROUTINES

*	ATHWDS	Authorize work data sets (temporary images)
*	CHKIO	Check for errors after an I/O is performed
*	CLOSEP	Close a picture file
*	DELWDS	Deauthorize work data sets
**	FCHECK	Check for I/O errors
**	FCLOSE	Close a file
**	FOPEN	Open a file
**	FWRITE	Write a record
*	OPENPI	Open the input image disk file
*	OPENPO	Open the output image disk file
*	Params	Prompt for user parameters
*	PRINTP	Print a message
*	READP	Read a portion of an image
*	WRITEP	Write a portion of an image

* Supplied by ESL. Reference "IDIMS Applications Programmers Guide" ESL-TM1047

** Supplied by Hewlett-Packard. Reference "MPE Intrinsics Reference Manual" Part No. 3000-90010.

APPENDIX C

IDIMS USER DOCUMENTATION

AMOEBA

A. PURPOSE

Performs completely unsupervised clustering and classification of a multispectral image using a spatial-spectral clustering algorithm.

B. INPUT AND OUTPUT

The input image must contain between 2 and 16 bands, and must contain no measurement less than zero or greater than 127. The output image is of type BYTE.

C. PARAMETERS

There are 7 optional parameters. They are:

STATFILE = Statistics file name (alphanumeric character) that output statistics data is to be stored in.

PCTFLDS = The user's estimate of the percent of the image contained in "fields"--spatially connected spectrally homogeneous areas; (integer)

Default = 45

CHAN1MAP* = Shall a map of band one of the image be sent to the user? (character)

Default = 'N'

LABELMAP* = Shall a map of labels be sent to the user? (character)

Default = 'N'

CLASSMAP* = Shall a classification map be sent to the user? (character)

Default = 'N'

MASK = Shall a value of 0 in band 1 be taken as a mask (i.e., not part of the image)? (character)

Default = 'Y'

MINCLUS = User's desired minimum number of clusters. If negative, exactly -MINCLUS clusters will be sought. If positive, at least MINCLUS clusters will be sought (integer)

Default = 10

MAXCLN = User's desired maximum number of clusters. May not exceed 98.

Default = 98

D. EXAMPLE

INIMAGE > AMOEBA > OUTCLUST

*These are primarily debugging aids to give the user a quick look at the data and follow the progress of the function. Additional parameters PRINTSL (starting line), PRINT NL (number of lines), and PRINTSS (starting sample) are required.

After prompting for parameters, messages to the user will appear as follows: (assume the image is NB bands and all default options are taken).

INTTHR = (list of boundary detection thresholds)

#LABELS = (number of distinct "fields" found; a field is defined as a connected area of non-boundary)

#TSTSTS = (number of "test sets" found. A test set is a set of 5 pixels collected from the same field).

Minimum number of clusters sought: 10 start with nn clusters, mm test points. kk clusters have non void assignments.
Square of diameters of starting clusters: sss
Number of clusters: cc
Estimate of Pair PMC: pp percent.
Final number of clusters = ff
(number in 1) ("center" of 1)

(number in ff) ("center" of ff)
There are uu unclassified.
The mask contains aa points.
End function--AMOEBA

The meaning of most of these outputs is explained in the algorithm documentation (F). The principal user output is the list of clusters "centers" (attractors is probably a better term) and the number of image elements assigned to that center.

E. DIAGNOSTIC MESSAGES

There are five messages AMOEBA may return:

1. Your image contains a value over 127. Please use MAP to put into the range 0-127. FUNCTION DOES NOT SUPPORT INPUT DATA TYPE

   A value over 127 was encountered.

2. NUMBER OF BANDS SPECIFIED NOT ALLOWED BY FUNCTION

   Number of bands must be at least 2 and at most 16.

3. EXTERNAL FILE COULD NOT BE ACCESSED

   The STATFILE name is already in use.

4. SPECIFIED NON-IMAGE FILE PREFIX INVALID

   The STATFILE name contains more than 8 characters, or is otherwise invalid.

5. INPUT IMAGE SIZE EXCEEDS FUNCTION CAPABILITIES

The input image is too wide for even one buffer on input and one on output. Use MOSAIC to segment the image into strips. (The number of bands and number of lines do not matter, only the number of samples).

Additional messages may be returned if I/O problems are encountered during operation of the function.

F. ALGORITHM

The clustering and classification function AMOEBA is based on a simple model for image data. In the model, the concepts of boundary, field, and classification are defined, and assumptions are made about the accuracy of a clustering in terms of the classification. The classification is based on a spatially modified nearest neighbor classifier (Euclidean distance); to train such a classifier, one needs to know only the number of classes and the class "centers". The actual function proceeds in steps as follows; subroutine names are given in parenthesis:

Find boundary detection vector thresholds (THRFND):

Boundary detection is based on vector gradient thresholds (rather than a norm threshold or other one-dimensional decision rule). Thus one threshold is determined for each band. Initially the image is sparsely sampled to estimate with each band contributing about the same number of boundary decision estimates. These thresholds are passed to the next step.

Find connected sets of non-boundary (START):

The data is scanned three lines at a time (in a circular buffer), and a circular buffer of labels is created. A boundary decision results when a point and its neighbor differ by more than the threshold in any band. "Cracks" are filled in, and intervals are located on each new labels line. These are then connected to the previous line of labels, and the previous line written to disk. The resulting intermediate image contains -32768 (the smallest 16 bit two's complement integer) marking boundary, or n (which starts at -32767 and is incremented) labeling connected sets of non-boundary. #LABELS = n is printed.

Extract test sets and store on disk scratch file (ASELECT)

The labels map and data are scanned, and as large a buffer as there is memory for is allocated to accumulate samples bearing the same label. When the buffer fills (or at end of the data), each same-label batch is sampled, taking every fifth point (from batches with at least 5), and the sample sets are stored on disk. There can be as many as 64K-1 such sets. These are passed to the next step. Their number is printed (#TSTSTS). The temporary labels map is deleted from disk.

Thin test sets and accumulate starting clusters (THINTSTM)

The starting clusters are to be means of samples taken from the same component of the complement of the boundary. Accordingly, they should be spectrally purer, since this tends to minimize registration errors and reduce noise. However, it is out of the question to classify 10,000

things in 2,000 classes, and then may be even more than this many test sets (i.e., more than 2,000) in a large image. We therefore reduce the number by (a) removing apparent duplicate means, (b) removing test sets in which the first sample is relatively unlike the last, and (c) removing apparent duplicate test sets. The final number of test sets is printed in the next step. The temporary test set file is deleted from disk.

Find the clusters and their number (NUMCLU)

First sort the test sets in increasing order based on the sum of the odd channel values. Samples from the same test set are in the same "field", and therefore are from the same real class (on the model assumptions). Samples spread out in this order tend to be from different real classes. Errors are made by the classifier when a center attracts points from different real classes or participates in the splitting of a pair from the same test set. Therefore, centers which make errors are eliminated. A running estimate is kept of the probability that a pair from different classes is clustered alike, plus the probability that a pair from the same real class is clustered differently. The minimum value of this estimate of the Pair PMC is used to determine the number of clusters and exactly what they are.

Classify and count (CLASSIFY)

A spatially modified nearest neighbor classification is now performed. Initially, each point is classified by nearest neighbor. Then this classification is checked for accuracy by looking at the classification of the four nearest neighbors. Points with one neighbor in the same class are deemed OK!. Not-OK points are examined with the view of reclassification in the class of OK - neighbors, provided this can be done consistently with the anticipated spectral appearance of a mixture pixel. No reclassification based on spatial content alone is performed. That is, all reclassification must fit the mixture and registration error model. Circular buffers are managed (similarly to START), and the checked nearest neighbor classification is written to disk as a type BYTE image.

Finish (AMSTATS)

The optional STATFILE is written.

G. COMMENT

The user is advised to be cautious about interpreting any clustering of image data. Many images, indeed, are not suitable for clustering. If AMOEBA is selected, the output parameter Pair PMC is a good indication of accuracy: more than 25 percent and the area was probably poorly clustered. Under 20 and clustering was at least self-consistent.

Users wanting to learn more about the method or the underlying model should consult the reference.

H. REFERENCE

Jack Bryant, "On the clustering of multidimensional pictorial data", Pattern Recognition 11, pp. 115-125 (1979).

APPENDIX D

SAMPLE INTERACTIVE SESSION

```
16    WASTE.BRTGRN(1 1 100 100))AMOEBA)SEPT28
17    PLEASE SUPPLY PARAMETER VALUES FOR FUNCTION AMOEBA
18    STATFILE CHAR STRING (DEFAULT= ):
19    PCNTFLDS SIMPLE INTEGER (DEFAULT=45):
20    CHANIMAP CHAR STRING (DEFAULT=N): Y
21    LABELMAP CHAR STRING (DEFAULT=N): Y
22    CLASSMAP CHAR STRING (DEFAULT=N): Y
23    MASK     CHAR STRING (DEFAULT=Y):
24    MINCLUS  SIMPLE INTEGER (DEFAULT=10): 2
25    MAXCLN   SIMPLE INTEGER (DEFAULT=98):
26    PRINTSL  SIMPLE INTEGER (DEFAULT=1): 50
27    PRINTNL  SIMPLE INTEGER (DEFAULT=100): 24
28    PRINTSS  SIMPLE INTEGER (DEFAULT=1): 50
29     YOU HAVE   2 READ BUFFER(S) AND 2 WRITE BUFFER(S).
30     INTTHR =    2  1
31     #LABELS =     63
32        50   '( ))(&&&''''''')--(&&&&(+,*('&&('''')))( )(( ))*******
33        51   ' )++(&'&''''&')/.(&'&&(+**''''''''''''(''(( ))*** )*+
34        52   ' )++*)('&&&&&'(--('('&'' )+)&&&&'( ))( )(((( ))))*)**
35        53   ( )++++)''&&&'(-.*'('&&( ))(&$$%'( ))*)*+)''(((( ))))( )
36        54   ( )+,,-,(&&''''(,-)&''&&'('( )&$$&'( ))( ))(''''''''''( )(
37        55   ))),,,,)''''(*+*('''&&'('(+(%@$&( ))'%%%%%&''&&' )*)(
38        56   ((++-0/+('''''(( )+)''&&&''''**(%@%'( )(%@$%$$&('''(**)
39        57   ( ))*+.1/*('' ))(*)((&'&''''((*+)%$%' ))&%%%@$$&''&'*,)
40        58   ))( )**,/1. ))*,./.+ ))(('''''&' ))&$%(+)$%%$$$$%&&&'*+(
41        59   ))(( )((+/0,,134430,,)'(((''''''&%(+-)$$$$$$$%&%' )*)'
42        60   ),*)*)&(.0//45433/-//-)(('('(((&)-,&$%%%%%%%%'(*)''
43        61   ,,,+,,)+,.//132/-*+050)'&''(((''*,)$%%%%%%$$$$%(*('&
44        62   ,,++,/.,,,01/000/-.-30'%%&'((((*,(%%%%$$$$$$%*,'&&
45        63   )**(),-,./10..02344/0-'$%%&*,*(),-)&%%%%%%%%%&*)&%'
46        64   ()(''(++./// .0113671+(&%%%&*-+)+1/'$&&%%&&%%'(&&&'
47        65   (('(' )*+,+,/10/0264,&%&&&%&))'-9(3*))''' &&&&''''''''
48        66   (''''(')***-/.+*,043-(%&'&&%&''+70;4,(( ))''''(((''''
49        67   ''''((')(*,,*(&')-0.)'&&''''&'''&%)296+&*20(' )))(((''''
50        68   '&&''''''(**('&&')--+''''(((''(('&%(170*-84))++**(((''
51        69   '&&''''''( ))(('''( )*++)( ))))))))''''(+21*)0.*****+*( )(
52        70   '&&''''( ))( ))( ))(( )**))**)*)''''&&(($%%)++***)( )( )
53        71   '&''''(('( ))))))(( )*))( )**))))))'(*)'&%'+,,*)(((( )
54        72   &&''''((&'( )***))*)**))))**)**,+*)*.-&%)))+**))( )*)
55        73   &''''(((( ))**)*)*****))*)))*********(,11/++++*))*-1/
56        50                LL                                    JJJJ
57        51                                                        JJ
58        52
59        53
60        54
61        55
62        56                                  GG                  FF
63        57                                  GG                FFFF
64        58   D                                                FFFFF
65        59   D                                                FFFFF
66        60                                                    FFFFF          B
67        61                                                  FFFFFF           B
68        62                                                  FFFFFFFF         B
69        63                                                  FFFFFFFF
70        64                                                    FFFFFF
71        65                                     )))              FF
72        66                                     )))))
73        67                                     )))))                      <<
74        68                                      ) )                       <<
75        69                                                                 <
76        70
```

```
 77        71
 78        72              99
 79        73              99
 80     0TSTSTS =      30
 81          MINIMUM NUMBER OF CLUSTERS SOUGHT:   2
 82          START WITH  30 CLUSTERS,  150 TEST POINTS.
 83          15 CLUSTERS HAVE NON VOID ASSIGNMENTS.
 84          SQUARE OF DIAMETER OF STARTING CLUSTERS:    165
 85          NUMBER OF CLUSTERS:   14
 86          ESTIMATE OF PAIR PMC:   32 PERCENT.
 87     FINAL  NUMBER OF CLUSTERS   = 19
 88          504    3    0
 89         1089    4    0
 90          543    6    0
 91          633    7    0
 92         1302    7    6
 93         4191   10    7
 94         1353   10    4
 95          334   11    9
 96          369   11   10
 97          474   11    4
 98          166   16    2
 99           71   18    8
100           39   29    8
101           23   42   13
102     THE MASK CONTAINS    1909 POINTS.
103          50   ++++)))))))))+..+)))+*..**((+))))++++++++,,,,,,,,
104          51   ++..+)))))))))0..+)+))***.+(((()+++))))+))*****,,,,,,
105          52   ++++++)))))))+..+)++))))+.+(((((++++++++++++++++,,--,
106          53   ****...)))))))**0+)+)+)+++((&&((+++++++*))******,,,*
107          54   ,**../..))++)*..+)+)+)+++++(&&(++++++++++++))))))***,
108          55   ,***.//..)))++...+++)))+++..((&&++++''''''++))))****
109          56   ******00.)))))***.+++)))))++..((&&++++'&&'&&++++++.. *
110          57   ++++++000++))***.+++))))))...+&&'+++''''&&&++(((( . +
111          58   +++++++00/++..000+++++)))))))++&&'+++&''&&&&'((((. . +
112          59   ++++++++0/..00000/...****))))))&+++(&&&&&&&'(((. .++
113          60   +.....**00//00000/////****)))*****.+(&'''&''&((+..+++
114          61   ..........////00///../0/++)))*****..+''''&'&&&'+..++(
115          62   ......//...00/////////0/(''))*****..(''''&&&&&&'...+((
116          63   ...++...//0/////000///(''''(..***.//(((''''''''''(..((+
117          64   ***))...////////000/.(((''(..***//(((((''((''''((((()))
118          65   **))))+.....////000.('((((...((+111+++(((((((+++(++)
119          66   *)))+)++....///...0///('(((((((((+1110.(((((((+++)))
120          67   )))++++++....(((+///(((((((((((+110.(.//((++++++))
121          68   )))+++(+...(((((+//.(((((((((((((((10/..1/'+**..+++)
122          69   )))++(+++++(((+++...++++++++++(((((///(.//..***.++++
123          70   +))++(+++++++++++++..+++..+++(((((((''.....*++++++
124          71   +))++++++++++++++++.++++..++++++(((((('.....++++++
125          72   )))++++++++...++*******..++.....///(('++...++++++
126          73   )))))+++++++++.++*******.+++.........////.....++++++/
127     END FUNCTION--AMOEBA
```

APPENDIX E

SAMPLE BATCH JOB

1. Create, using the Editor, and store the following file:

```
!JOB    jobcard
!IDIMS
inputimage>AMOEBA(parameterlist)>outputimage
>END
!EOJ
```

2. Exit the Editor and enter
   : STREAM filename.

3. Return later for results.

In some systems, it may be mandatory to store the input image (or perhaps both); someone should be around to respond to requests to hang tapes.

D2

RICE SCENE RADIATION

RESEARCH PLAN

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December, 1981

RICE SCENE RADIATION RESEARCH PLAN

The goal of rice scene radiation research is to develop an understanding of the functional relationships between rice and its spectral characteristics. These functional relationships will be integrated into spectral - agrometeorological models for use in crop identification, development stage estimation, and condition assessment.

CROP IDENTIFICATION

Introduction

Knowledge of the cultural and biophysical characteristics of crops and their relationships to spectral response are important inputs to the pattern recognition research effort. For crop identification, this research will provide information on what crops can and cannot be separated using the current and planned sensor technologies, what additional kinds of measurements are needed, and the important times and frequency of observations needed to enable crop discrimination and identification. For the sampling and estimation research effort, knowledge of the cultural and biophysical characteristics of crops which significantly affect spectral response is needed in order to account for the agronomic factors of importance in an advanced dynamic sampling and estimation approach.

Technical Issues

Scene radiation applied research issues in crop identification which have been defined are:

1. What are the key cultural and biophysical characteristics of crops (which are potentially observable from remotely sensed data) that

permit separability between crops and identifiability of crop types at harvest and earlier in the season?

2. How are the cultural and biophysical characteristics related to crop type manifested in the spectral response observed by existing and planned sensors such as MSS, TM, and other advanced sensors?
3. What new kinds of observations are needed to improve the estimates of key crop characteristics shown to permit separability between crops and identifiability of crop types?

Technical Approach

Crop identification research for rice involves: field research, canopy modeling, and Landsat data analysis. Field research data will include intensive agronomic and spectral measurements. Canopy geometry measurements and available information on leaf reflectance and transmittance will enable modeling of canopies and thus increase the range of canopy conditions which can be studied with confidence. Use of field measurements and canopy modeling will enable extension of that knowledge to the relationship with Landsat MSS and TM data.

Task Descriptions

Identify Cultural and Biophysical Characteristics Related to Crop Identification

The first technical issue has the following specific objectives:

* Determine the key difference between rice and its confusion crops in the timing and duration of key physiological and cultural events.
* Determine the key differences in canopy geometry among rice varieties and the optical properties of canopy components.

* Determine the cultural, regional, and environmental differences among rice and its confusion crops.
* Represent the distribution of the key crop characteristics by functional forms.

A literature review will be conducted to identify planting dates, regional crop calendars, soil surveys and other descriptions of management practices. The periodic observations acquired on sample segments in the United States will also be used to help detail management practices (e.g. row width, planting dates) and provide more localized information on planting date and development stage.

When the data have been compiled, the crop characteristics will be related to geographic region and to other scene characteristics and management practices. Functional forms will be found which describe the distributions within and across the geographic regions.

Relate Agronomic Characteristics to Spectral Response

The second objective is to determine how cultural and biophysical characteristics affect in the spectral response of rice observed by existing and planned sensors such as MSS, TM, and other advanced sensors, and has two sub-objectives.

* Determine the relationships among key crop characteristics, remote sensing observables (band means and transformations with current and planned sensor systems), and background effects (e.g., soil and water background, atmospheric haze, view angle, and sun angle).
* Determine which remote sensing observables are predominantly a function of the crop characteristics of interest and are least sensitive to background effects.

A set of remote sensing observables including MSS bands, tasselled cap components, MSS band ratios (e.g., 7/5), TM bands, transformations of TM bands, and bands of other sensors will be examined. For all sensors, research into appropriate bands or transformations for estimation of particular canopy characteristics will be conducted.

The relationships of these remote sensing observables to crop characteristics and to scene characteristics which are not of interest will be examined. To do this, both field-acquired data and data modeled using canopy geometry and leaf reflectance and transmittance measurements will be used. Correlations, regressions, and linear and nonlinear models will be used as appropriate to describe the relationship of the remote sensing observables to and the amount of variability due to: green leaf area index, percent soil cover, green biomass, development stage, and temporal trajectories.

After the functional relationships have been determined, sensitivity analyses will be conducted on the variables of interest to determine the change in spectral response given a certain change in the canopy variable. This will enable determination of which canopy and background variables are important in determining spectral response.

Finally, the "best" bands or transformations for each of the sensors will be determined to be those which maximize sensitivity to various individual crop characteristics and minimize sensitivity to undesired effects. The crop discrimination power of these sets of remote sensing observables will be tested using multivariate analysis on data from one or more intensive test sites.

Investigate Potential Improvements Due to New Data Types

The third objective is to determine what new kinds of observations are needed to immprove the estimates of key crop characteristics shown to permit separability between crops and identifiability of crop types. The specific objectives addressing this issue are:

* Determine the functional relationships among key crop characteristics, background effects, and spectral response observable in other spectral regions or with other types of measurements.
* Identify new data types which improve the relationships with key crop characteristics used for crop discrimination while minimizing background effects.

To address this issue, spectral measurements must be acquired in the field and over test sites with sensors other than the current and planned sensors. Helicopter spectrometer and/or aircraft scanner data covering other visible and near-to-middle IR regions, thermal measurements, microwave measurements, and illumination/view angle measurements are required. The approach for addressing this issue will parallel that of the second issue except for the measurements utilized.

Data Requirements

The selection of treatments consists of first identifying the major sources of variation in the growth, development, and spectral response of rice. These factors include: planting date, variety, plant population/row spacing, soil conditions, and weather. The levels of each factor will be selected to sample the range of expected conditions in commercial fields.

Spectral measurements will be made in controlled plots using the EXOTECH 100A radiometer and the Barnes multiband radiometer system (having the TM bands). Detailed agronomic measurements of the crop canopies including crop development stage, vegetation measurements, crop condition, soil background condition, and grain yield will be collected.

DEVELOPMENT STAGE ESTIMATION

Introduction

Crop development stage is important for crop identification and yield modeling. There are three approaches for estimating crop development stages: (1) average crop calendars based on accumulation of days between stages, (2) meteorological methods based on accumulation of thermal or photo-thermal units between stages, and (3) spectral methods based on changes in spectral response as a function of development stage. The goals of this task are to investigate the use of spectral measurements to determine crop development stage and to develop a meteorologically-driven stage of development model that will accept spectral inputs.

Technical Issues

Research issues for rice development stage estimation are:

1. What are the key biophysical characteristics of crops (which are potentially observable using remotely sensed data) that permit their development stage to be determined?
   a. What are the critical development stages of crops with respect to crop identification, condition assessment and yield prediction?

b. What are the key differences in timing and duration of key developmental events?

c. What are the key differences in canopy geometry and composition related to development stage?

d. How do these differences depend on cultural, environmental and geographical factors?

e. What are reasonably representative functional forms for the distribution functions of the key crop characteristics?

2. What are the functional relationships between development stage and the radiometric characteristics of crop canopies?

   a. MSS bands

   b. TM bands

   c. Transformations of MSS and TM data

   d. Other sensors

3. How are the functional relationships affected by cultural, environmental and geographic factors (e.g. variety, row width, soil type, moisture stress)?

4. How can spectrally derived development stage information best be utilized?

   a. Development of models which, given spectral plus weather data, predict development stage

   b. Development of models which, given development stage, agromet conditions, and canopy geometry, predict spectral response

5. What is the improvement in performance of large area crop growth and yield models by using spectrally derived inputs (i.e., evaluation of models in the context of a large area crop yield model).

Technical Approach

The general technical approach for addressing the research objectives in the crop development stage area will involve estimation theory. The radiometric characteristics of rice canopies will be modeled to determine functional relationships with development stage and/or time. This development will rely on both ground and satellite measured spectral data in the MSS and TM bands, and meteorological data. The trajectories of the development stage of crops in spectral space will be analyzed to identify variables with superior properties for estimating development stages of rice. Various estimators will be examined individually and together to determine their predictive abilities.

Task Description

Four research tasks must be completed in the area of estimating crop development stage. Agronomic information of rice must be obtained describing the key biophysical characteristics that permit development stage to be determined. The necessary information will be obtained from technical literature, Texas A&M agronomists and field measurements. The key biophysical characteristics are needed to gain a physical understanding of problems associated with using spectral measurements to estimate stage of development.

The second research task involves an analysis of multiyear agronomic, spectral, and meteorological data. The development stage trajectories of rice will be examined in spectral/agronomic space to identify worthwhile spectral estimators of crop development stage.

The third research task involves development of an agrometerological stage of development model that accepts spectral inputs. The model will be developed using agronomic and meteorological data obtained from rice experiment stations in three different climatic regions. The model will be developed to obtain a high degree of accuracy for the three maturity classes of rice.

The fourth task will consist of development of a framework for merging the spectral estimators of stage of development with the agrometerological model so that the spectral estimates of growth stage can be used to "correct" the model estimates, if necessary.

Data Requirements

To identify the form of relationship between crop development stage and spectral variables and to develop initial models, reflectance measurements and observations of development stage at all growth-development stages for a representative set of cropping practices and soils are required.

The specific data requirements are:

- Reflectance measurements in the Landsat MSS bands and TM bands.
- Rice develoment stage observations.
- All growth and development stages from pre-planting to post-harvest sampled.
- Frequency of observations at 5-7 day intervals.
- Representative treatments above sampled (i.e., several soil types, varieties and planting dates)
- Daily meteorological data, temperature, relative humidity, solar radiation, precipitation, etc.
- Atmospheric measurements on days spectral data are acquired.

After initial model forms have been developed, a larger data set is required to test and evaluate the models. This data set should be acquired over 3-5 additional domestic and international experiment stations at locations having difference soils, weather, and cropping practices.

CROP CONDITION ASSESSMENT

Introduction

Potentially, multispectral data contains additional information about crops other than identification. Relatively little research has been conducted on developing and exploiting the capability of multispectral data to provide information about crop condition and yield. For example, the ratio of near infrared to red reflectances and the greenness transformation have highly significant relationships with leaf area index (LAI). Agronomic variables, such as LAI and percent soil cover, are frequently required inputs to crop models which depict limitations imposed on crop growth and yields by weather. Additionally, measures of the presence and degree of stress, such as moisture and nutrient deficits and disease and insect infestations, are potentially important inputs to crop growth and yield models. Thus, if agonomic variables related to yield could be reliably estimated from multispectral satellite data, then physiologically-based crop growth and yield models can be implemented for large areas.

Technical Issues

The research and development program to assess crop condition and provide inputs to yield models will address the following issues:

- What are the important biophysical variables related to the condition and yield of rice? Which of these variables can be potentially estimated using remotely sensed data?
- How are the functional relationships between spectral variables and biophysical parameters of rice affected by variation in soil background, crop production practices, and environmental conditions?

Technical Approach

Field measurements which include stress (temperature and moisture) treatments will be used to determine the effect of stress on biophysical factors. The Suits reflectance model will be used to predict changes in reflectance due to the changes in the biophysical characteristics of rice. This information will be used to support crop identification and to develop techniques for using spectral estimates of crop condition in agrometerological yield models.

Task Description

The two research tasks in condition assessment are to determine the key biophysical description of crop condtion that can be observed by remotely sensed data, and two determine how these characteristics can be observed using remotely sensed data. These tasks will be addressed using literature reviews, historical data analysis, and field measurements.

Data Requirements

Data requirements are the same as in Development Stage Estimation.

N83 12497

D3

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POSSIBLE MODIFICATIONS OF THE HISSE MODEL FOR PURE LANDSAT AGRICULTURAL DATA

by

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SUMMARY.

This report explores an idea, due to A. Feiveson, for relaxing the assumption of class conditional independence of LANDSAT spectral measurements within the same patch (f'eld). Theoretical arguments are given which show that any significant refinement of the model beyond Feiveson's proposal will not allow the reduction, essential to HISSE, of the pure data to patch summary statistics. A slight alteration of the new model is shown to be a reasonable approximation to the model which describes pure data elements from the same patch as jointly qaussian with a covariance function which exhibits exponential decay with respect to spatial separation.

1. The Basic HISSE Model and its Modifications.

The original mathematical assumptions underlying HISSE are fully described in [7]. Briefly, they are:

a) The sampled pure pixels are organized into p patches (fields) and corresponding to each patch j, there is a set of spectral data measurements $X_j = (X_{j1}, \cdots, X_{jN_j})$, where X_{jk} is the (perhaps multitemporal) vector of spectral data from the kth pixel in the jth patch. For each patch j, there is also an unknown class designation $\theta_j \in \{1,\ldots,m\}$, where m is known.

b) The $\{(X_j,\theta_j)\}_{j=1}^{p}$ are treated as independent random variables. The θ_j have a common unknown discrete distribution Prob $[\theta_j = \ell] = \alpha_\ell > 0$, where $\sum_{\ell=1}^{m}\alpha_\ell = 1$.

c) Given that $\theta_j = \ell$, $X_{j1}, \cdots, X_{jN_j}$ are independently normally distributed with unknown mean μ_ℓ and unknown variance-covariance matrix Ω_ℓ.

A proposed modification due to A. Feiveson [3], introduces one additional matrix parameter for each class. Assumption (c) is changed to

c') Given that $\theta_j = \ell$, $X_{jk} = \mu_\ell + e_j + d_{jk}$, where $E(e_j) = E(d_{jk}) = 0$, var $(e_j) = \Sigma_\ell$, var $(d_{jk}) = \psi_\ell$ and the e_j's and d_{jk}'s are independent normal random variables. Thus the elements $X_{j1}, \cdots, X_{jN_j}$ of X_j are jointly normal with marginal distributions $X_{jk} \sim N(\mu_\ell, \Sigma_\ell + \psi_\ell)$, and constant within-patch covariance $\text{cov}(X_{jk}, X_{ji}) = \Sigma_\ell$, for $k \neq i$.

Notice that the original assumption (c) is a limiting case of (c') obtained by allowing $\Sigma_\ell = 0$.

For reasons discussed later, we will alter (c') to

(c") The constant within-patch covariance for elements of the jth patch is $\text{cov}\,(X_{jk}, X_{ji}) = \frac{1}{N_j}\Sigma_\ell$.

The effect of (c") is that data elements from large patches are considered more weakly correlated than those from small patches. Assumption (c') is perhaps more appropriate if the correlation between pixels of the same patch is really independent of their spatial separation, while (c") is better if the correlation falls off rapidly with spatial separation, on account of the preponderance of spatially distant pairs in larger patches. Calculations are presented in Section 4 to suggest that (c") is a reasonable approximation to the average covariance between pairs when the correlation decreases exponentially with spatial separation. In Section 3 theoretical arguments are given which severely restrict the covariance models for which the patch mean vector and scatter matrix are sufficient statistics without, however, eliminating (c') and (c"). This is an important consideration, since procedures like HISSE are feasible only if the spectral information in patches can be summarized in a small number of statistics.

2. Numerical Procedures for the Alternative Covariance Models.

The likelihood function and iterative procedure for the current version of HISSE are given in [7] and will not be repeated here. For covariance models (c') and (c"). The likelihood functions is

$$L = \sum_{j=1}^{p} \log \sum_{\ell=1}^{m} \alpha_\ell f_\ell(X_j) = \sum_{j=1}^{p} \log f(X_j)$$

where the model (c')

$$f_\ell(X_j) = |\psi_\ell|^{\frac{-N_j-1}{2}} |\psi_\ell + N_j\Sigma_\ell|^{-\frac{1}{2}} \exp[-\tfrac{1}{2} Q'_\ell(X_j)]$$

and $$Q'_\ell(X_j) = tr\psi_\ell^{-1}S_j + N_j(m_j-\mu_\ell)^T(\psi_\ell+N_j\Sigma_\ell)^{-1}(m_j-\mu_\ell),$$

while for model (c")

$$f_\ell(X_j) = |\psi_\ell|^{\frac{-N_j-1}{2}} |\psi_\ell + \Sigma_\ell|^{-\frac{1}{2}} \exp[-\tfrac{1}{2} Q''_\ell(X_j)]$$

and $$Q''_\ell(X_j) = tr\psi_\ell^{-1}S_j + N_j(m_j-\mu_\ell)^T(\psi_\ell+\Sigma_\ell)^{-1}(m_j-\mu_\ell).$$

In both these expressions m_j and S_j are, respectively the patch mean and scatter

$$m_j = \frac{1}{N_j}\sum_{k=1}^{N_j} X_{jk}$$

$$S_j = \sum_{k=1}^{N_j}(X_{jk}-m_j)(X_{jk}-m_j)^T.$$

Thus for both of these covariance models the patch mean and scatter are jointly sufficient.

The unconstrained likelihood equations for model (c") have the form

(1.1) $$\alpha_\ell = \frac{1}{p}\sum_{j=1}^{p}\frac{\alpha_\ell f_\ell(X_j)}{f(X_j)}$$

(1.2) $$\mu_\ell = \sum_{j=1}^{p} N_j \frac{f_\ell(X_j)}{f(X_j)} m_j \Big/ \sum_{j=1}^{p} N_j \frac{f_\ell(X_j)}{f(X_j)}$$

$$\psi_\ell = \sum_{j=1}^{p} \frac{f_\ell(X_j)}{f(X_j)} S_j \Big/ \sum_{j=1}^{p} (N_j - 1) \frac{f_\ell(X_j)}{f(X_j)} \tag{1.3}$$

$$\Omega_\ell = \sum_{j=1}^{p} \frac{f_\ell(X_j)}{f(X_j)} N_j (m_j - \mu_\ell)(m_j - \mu_\ell)^T \Big/ \sum_{j=1}^{p} \frac{f_\ell(X_j)}{f(X_j)} \tag{1.4}$$

where the new parameter Ω_ℓ is defined as $\Sigma_\ell + \psi_\ell$.

The expressions on the right of equations (1.1) - (1.4) are appealing in that they are averages of quantities whose expectations, given $\theta_j = \ell$, are the parameters on the left. In addition, the successive substitutions scheme suggested by equations (1.1) - (1.4) is a slight variation of the generalized E-M procedure of Dempster, Laird, and Rubin [2]. For covariance model (c'), the likelihood equations do not suggest a natural iterative procedure and it appears that the generalized E-M procedure has no simple formulation.

To be consistent with the original interpretation of the parameter Σ_ℓ as a variance-covariance matrix, it is necessary to maximize the likelihood subject to the additional inequality constraint $\Omega_\ell \geq \psi_\ell$. Since a solution of equations (1.1) - (1.4) need not satisfy this constraint, maximizing the likelihood subject to $\Omega_\ell \geq \psi_\ell$ requires a much more complicated numerical procedure. The condition $\Omega_\ell \geq \psi_\ell$ is equivalent to a set of scalar inequality and nonlinear equality constraints, and numerical procedures for such problems are generally very slow to converge. The unconstrained maximum likelihood procedure is appropriate if as in (c") we merely assume that $\text{cov}\,(X_{j1}, X_{jk})$ is the same for all i and k, without introducing random variables e_j and d_{jk}.

3. Covariance Models for which patch mean and scatter are sufficient.

Let $X = (X_1 | \cdots | X_N)_{n \times N}$ be a matrix whose columns are jointly normally

distributed n-vectors. We are interested in characterizing those families of distributions of X for which the statistic (m,S) is sufficient, where $m = X_1 + \cdots + X_N$ and $S = X_1X_1^T + \cdots + X_NX_N^T$. We begin by recalling the following definitions [4, p. 32].

Definition: Let G be a group of homeomorphisms on $\mathbb{R}^n$. A function T defined on $\mathbb{R}^n$ is invariant under G if $T(gx) = T(x)$ for all $x \in \mathbb{R}^n$, $g \in G$. T is a maximal invariant of G if T is invariant and $T(x) = T(y)$ implies that there is a $g \in G$ such that $y = gx$. A measure λ is invariant under G if $\lambda g = \lambda$ for all $g \in G$, where $\lambda g(E) = \lambda(g(E))$.

Lemma 1: Let elements of $\mathbb{R}^{nN}$ be represented as $x = (x_1|\cdots|x_N)$ and let $e^T = (1,1,\cdots,1)_{1xN}$. For each $N \times N$ real orthogonal matrix u satisfying $ue = e$, let $g_u(x) = xu$. Then $T(x) = (m,S) = (xe,xx^T)$ is a maximal invariant of the group $G = \{g_u\}$.

Proof: $T(g_ux) = (xue, xu(xu)^T) = (xe, xx^T) = T(x)$. Thus T is invariant. Suppose that $T(x) = T(y)$ so that $xe = ye$ and $xx^T = yy^T$. If $x^{(i)}$ and $y^{(i)}$ denote the ith rows of x and y then $x^{(i)}x^{(j)T} = y^{(i)}y^{(j)T}$ and $x^{(i)}e = y^{(i)}e$ for all i and j. This implies that corresponding rows of x and y have the same Euclidean norm and form the same angle with the vector e^T. In addition, the rows of x describe the same set of angles in $\mathbb{R}^N$ as do the corresponding rows of y. Thus, by carrying out parallel Gram-Schmidt procedures on $\{e^T, x^{(1)}, \cdots, x^{(n)}\}$ and $\{e^T, y^{(1)}, \cdots, y^{(n)}\}$, it is easy to construct an orthogonal matrix u such that $e^Tu = e^T$ and $x^{(i)}u = y^{(i)}$ for each i; that is, such that $y = g_ux$. Therefore T is a maximal invariant.

Example: Any linear function T defined on $\mathbb{R}^n$ is a maximal invariant under the group of translations by elements of the kernel of T. In fact, most of the results in [6] characterizing linear sufficient statistics depend only on this aspect of linearity.

If T is a maximal invariant then any invariant function on $\mathbb{R}^n$ is a function of $T(x)$. Moreover, a function $h \circ T$ on $\mathbb{R}^n$ is a maximal invariant if and only if h is one to one on the range of T. In the theorems which follow we shall require that T be a continuous open mapping, in addition to being a maximal invariant. The following lemma shows that to some extent T may be chosen for convenience, with affecting the property of openness.

Lemma 2: Let V be an open subset of $\mathbb{R}^n$, let G be a group of homeomorphisms from V to V and let T_1 and T_2 be continuous maximal invariants of G defined on V with values in $\mathbb{R}^m$. If T_1 is an open mapping then so is T_2.

Proof: Since T_2 and T_1 are maximal invariants, there is a one to one function $h: T_1(V) \to T_2(V)$ such that $T_2 = hT_1$. Since $h^{-1} = T_1 T_2^{-1}$ on $T_2(V)$, T_2 is continuous and T_1 is open, h is continuous. By the Brouwer invariance of domain theorem [8, p. 3] h is an open mapping. Therefore, T_2 is also open.

Theorem 1: Let V be an open subset of $\mathbb{R}^n$, let $\mathcal{M}$ be a homogeneous collection of finite Borel measures on $\mathbb{R}^n$, and let λ be a fixed element of $\mathcal{M}$. Suppose that $\lambda(V^c) = 0$ and $\lambda(U) > 0$ for each nonempty open subset U of V. Let G be a group of homeomorphisms from V to V such that $\lambda(gB) = 0$ whenever $\lambda(B) = 0$ and $g \in G$. Suppose that f_μ is a continuous representative of $\frac{d\mu}{d\lambda}$ for each $\mu \in \mathcal{M}$ and that $T: V \to \mathbb{R}^m$ is a continuous open maximal invariant of

G. Then T is a sufficient statistic for $\mathcal{M}$ if and only if each f_μ is invariant under G.

Proof: Suppose that T is sufficient. Then for each $\mu \in \mathcal{M}$ there exists a Borel measureable function k_μ such that $k_\mu \cdot T$ is a version of $d\mu/d\lambda$, [1].

Let $\mu \in \mathcal{M}$ and $g \in G$ be fixed. The set

$$U = \{x \in V \mid f_\mu(x) \neq f_\mu(gx)\}$$

is an open subset of $B \cup g^{-1}(B)$, where

$$B = \{x \in V \mid f_\mu(x) \neq k_\mu(T(x))\}.$$

Since $\lambda(B) = 0$, $\lambda(g^{-1}(B)) = 0$ and $\lambda(U) = 0$. Therefore, U is empty and it follows that f_μ is invariant. Conversely, if each f_μ is invariant, then for each $\mu \in \mathcal{M}$ there exists a function h_μ such that $f_\mu = h_\mu \cdot T$. Since f_μ is continuous and T is open, h_μ is continuous on $T(V)$. Therefore, by [1, Corollary 6.1] T is sufficient.

Corollary 1.1: Given the hypotheses of Theorem 1, if λ is invariant then T is sufficient if and only if each $\mu \in \mathcal{M}$ is invariant.

Proof: In general, a density with respect to λ of μg is $f_{\mu g} = (f_\mu \circ g)h$, where h is a version of $d\lambda g/d\lambda$. If λ is invariant, then we can take $h = 1$ to obtain $f_{\mu g} = f_\mu \circ g$ as a unique continuous density of μg, for each μ, g. By Theorem 1, T is sufficient if and only if $f_{\mu g} = f_\mu$, which is equivalent to $\mu g = \mu$.

Suppose that $\mu g \in \mathcal{M}$ for each $\mu \in \mathcal{M}$, $g \in G$ and that θ is an r-dimensional parameterization of $\mathcal{M}$; i.e., a one to one function from $\mathcal{M}$ onto $\Omega = \theta(\mathcal{M}) \subset \mathcal{R}^r$. Then there is a homomorphism $g \to \bar{g}$ from G onto a group $\bar{G}$ of transformations on Ω defined by $\bar{g}(\theta_0) = \theta(\theta^{-1}(\theta_0)g)$. The following corollary is clear.

Corollary 1.2. Given the hypothesis of Theorem 1, if λ is invariant then T is sufficient iff $\bar{G}$ is the trivial group consisting only of the identity mapping on Ω.

To apply these results to the characterization problem at hand, let $X = (X_1 | \cdots | X_N)$ be a random $n \times N$ matrix having one of a given family of normal distributions and let $X^{(i)}$ denote the ith row of X. We think of $X_1, \cdots, X_N$ as being the observed random vector, but at various times wish to consider the parameters

$$\mu_i = E(X_i)$$

$$\mu^{(i)} = E(X^{(i)})$$

$$C_{ij} = \operatorname{cov}(X_i, X_j)$$

$$R^{(ij)} = \operatorname{cov}(X^{(i)}, X^{(j)}).$$

For the open set V of Theorem 1, we take the set of regular points of $T(x) = (xe, xx^T)$; that is, the set of points x at which $T'(x)$ is surjective $T'(x)$ is surjective if the matrix $\begin{pmatrix} e^T \\ x \end{pmatrix}$ has rank $n + 1$, which is almost certainly true for any of the probabilities under consideration as soon as $N \geq n + 1$. Clearly any of the mappings g_u of lemma 1 is a homeomorphism from V onto itself and T is a continuous open mapping on V. $\mathcal{M}$ will be the given set of nN-variate

normal probability measures. The invariant measure λ of Corollary 1.2 will be that given by $\mu_i = 0$, $C_{ij} = 0$ if $i \neq j$, $C_{ii} = I_{n\times n}$. If λ is not already a member of $\mathcal{M}$, it may be added without affecting the sufficiency of T for $\mathcal{M}$. According to Corollary 1.2, and lemma 1, T is sufficient for $\mathcal{M}$ if and only if

$$\mu^{(i)}u = \mu^{(i)} \tag{2.1}$$

and

$$u\ R^{(i,j)}u^T = R^{(i,j)} \tag{2.2}$$

for all i,j and $u \in U = \{N \times N$ orthogonal matrices u such that $ue = e\}$.

Now, (2.1) holds if and only if each $\mu^{(i)} = \lambda_i e^T$ for some scalar λ_i, which is equivalent to $\mu_1 = \cdots = \mu_N$. In (2.2) U may be replaced by the larger set $U' = \{N \times N$ orthogonal matrices such that $ue = \pm e\}$. Let $P = \frac{1}{N} ee^T$ and $Q = I - P$. Then U' is the set of all orthogonal matrices which commute with P, and (2.2) states that each $R^{(i,j)}$ commutes with each $u \in U'$. Let w be an orthogonal matrix such that

$$wPw^T = \left[\begin{array}{c|c} 1 & 0_{1\times(N-1)} \\ \hline 0_{(N-1)\times 1} & 0_{(N-1)\times(N-1)} \end{array}\right].$$

Then U' is the set of all orthogonal matrices u such that wuw^T commutes with wPw^T and (2.2) holds iff $wR^{(i,j)}w^T$ commutes with wuw^T for each $u \in U'$. Elementary calculations show that wuw^T must be of the form

$$wuw^T = \left[\begin{array}{c|c} 1 & 0 \\ \hline 0 & v \end{array}\right]$$

where v is $(N-1)\times(N-1)$ orthogonal, and that for some scalars $\lambda_1^{(i,j)}$, $\lambda_2^{(i,j)}$.

$$ {}_{W}R^{(i,j)}{}_{W}{}^{T} = \left[\begin{array}{c|c} \lambda_1{}^{(i,j)} & 0 \\ \hline 0 & \lambda_2{}^{(i,j)}{}_{I} \end{array}\right]. $$

If follows that (2.2) is true iff each $R^{(i,j)}$ is a linear combination of P and Q. Therefore, (2.2) holds if and only if each $R^{(i,j)}$ has constant diagonal elements and constant off diagonal elements, which may depend on i and j. Thus, there are matrices $A = (a_{ij})$ and $B = b(_{ij})$ such that

$$ \operatorname{cov}(X_{ik},X_{j\ell}) = \begin{cases} a_{ij} & \text{if } k = \ell \\ b_{ij} & \text{if } k \neq \ell \end{cases} $$

That is,

$$ \operatorname{var}(X_k) = A \qquad \text{for all } k $$

and

$$ \operatorname{cov}(X_k,X_\ell) = B \qquad \text{if } k \neq \ell . $$

Consequently, A and B are symmetric and we have established

Theorem 2: Let $X_1, \cdots, X_N$ be jointly normally distributed n-vectors whose joint distribution is a number of a family $\mathcal{M}$. Then the mean and scatter matrix of the X_i's are sufficient for $\mathcal{M}$ if and only if for each member of $\mathcal{M}$, (a) the X_i's are identically distributed, and (b) $\operatorname{cov}(X_i,X_j)$ is independent of i and j.

4. Conclusion:

As we mentioned in Section 1 if one thinks of a patch as an approximation to a field then it is difficult to understand how the within-patch covariance of

spectral measurements from a given patch could be constant but dependent on the patch size as in (c"). According to the results of Section 3, there is no more sophisticated covariance model whose parameters can be estimated with optimum efficiency using only the patch means and scatters; however, there may be more realistic covariance models which are well approximated by (c') or (c"). For example, suppose that a patch is rectangular in shape with multidimensional spectral information $\{X_{ij} | i = 1 \cdots r;\ j = 1 \cdots c\}$ where i and j denote the spatial line and column number of the pixel producing X_{ij}. Suppose further that the correlation of two observations X_{ij} and $X_{k\ell}$ decays exponentially with their spatial separation; that is,

$$\operatorname{cov}(X_{ij}, X_{k\ell}) = \Omega^{\frac{1}{2}} A^{|i-k|} B^{|j-\ell|} \Omega^{\frac{1}{2}},$$

where Ω is their common variance matrix and A and B are symmetric commuting matrices of spectral radius less than 1. Let Σ be the average covariance over all pairs of distinct pixels. Then a simple calculation shows that for large r and s (large patch size) $rs\Sigma$ is nearly $4\Omega^{\frac{1}{2}} A(I-A)^{-1} B(I-B)^{-1} \Omega^{\frac{1}{2}}$, so that Σ is nearly inversely proportional to the patch size, as is required by (c"). If A and B are positive semidefinite, so that $z^T X_{ij}$ is always positively correlated with $z^T X_{k\ell}$ for any z, then the expression just given is an upper bound for the average within-patch covariance for any patch size. Therefore, the effect of approximating the exponential covariance model with the constant covariance model (c") may be predictable, and not serious.

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THE AKAIKE INFORMATION CRITERION AND ITS APPLICATION TO MIXTURE PROPORTION ESTIMATION

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Table of Contents

1. INTRODUCTION

Estimation of parameters in a statistical model is a familiar and well discussed topic, but a more important topic, and certainly a more difficult one, is the selection of the appropriate model. The AIC (Akaike's Information Criterion) is a useful tool in model selection. It is particularly important in selecting the order of the model or in selecting the number of free parameters in a model. This report discusses the use of the AIC in selecting the order of a model and we emphasize the use of the AIC in determining the number of components in a mixture model.

After introducing appropriate notation in section 2, we show that the AIC is an extension of the maximum likelihood principle, as well as an entropy maximization principle. Section 3 will discuss the derivation of the AIC. In section 4, we give applications of the AIC to model selection in a number of important problems and we also introduce the BIC which is discussed in Hannan [1980]. Section 5 will discuss the application of the AIC to the mixture models. In section 6, we will look at the effectiveness of the AIC in dealing with the order selection problem on some 1 and 2 dimensional mixture problems.

2. DESCRIPTION OF THE AIC

We want to introduce the AIC as an extension of the maximum likelihood method. Let's begin by explaining why such an extension is needed. If we consider the case where the order of a particular model is determined, then the maximum likelihood

method is an excellent method for obtaining an estimate for the unknown parameters. The maximum likelihood estimate, under weak assumptions, is a strongly consistent, asymptotically unbiased and an asymptotically minimum variance estimator of the unknown parameters (Zacks [1971]). However, in the case that the order of the model is not known, the maximum likelihood estimator no longer has all of these desirable properties. The cause of this difficulty is that the maximum likelihood estimator has a preference for models of high order. As the order of the model is increased, the value of the maximum likelihood function, evaluated at the maximum likelihood estimate for that order model, is increased. Therefore, the maximum likelihood estimator will always have too many parameters.

The use of the maximum likelihood estimator to estimate the order of the model will lead to an estimate which fits the data very well (in fact too well), but will be a very poor estimator of the true density function. In section 4, we will use histograms as a concrete example of this problem.

As a possible replacement for the maximum likelihood estimator, we wish to consider an entropy maximization principle. This approach to the AIC was introduced and developed by Akaike [1972b, 1973, 1977]. It has also been supported by a Bayseian approach in Akaike [1978, 1979, 1980].

Let X be a random variable with density function g(x). If f(x) is any other density function, we can define a measure of similarity of f and g by

$$B(g;f) \equiv E_x \log \frac{f(x)}{g(x)}$$

which equals $\int \{\log \frac{f(x)}{g(x)}\}\, g(x)dx$, in the case of a continuous random variable x, and which equals $\sum_{i=1}^{p} \log(\frac{f_i}{g_i})\, g_i$, in the discrete case. This measure is the entropy of f and g as defined by Kullback [1968]. It is non-positive and equals zero only in the case that f = g almost everywhere.

One interpretation of this, in the discrete case, is that for a sample of size N, the quantity $N \cdot B(g;f)$ is approximately the logarithm of the probability of obtaining the data distribution g(x) from the assumed model f(x).

Let f, a model for the data, be defined by

$$f(x) = \begin{cases} f_i & \alpha_i < x < \alpha_{i+1} \quad i = 1,\cdots,p \\ 0 & \text{otherwise} \end{cases}$$

where $(\sum_{i=1}^{p} f_i)(\alpha_{p+1} - \alpha_1) = 1$. Given that we have N independent observations $x_1, x_2,\cdots,x_N$ from f we define N_i $i = 1,\cdots,p$ to be the frequency of observations in the interval $\alpha_i < x < \alpha_{i+1}$ and define relative frequencies g_i $i = 1,\cdots,p$ by $g_i = N_i/N$.

The probability of observing the frequencies $\{N_1, N_2,\cdots,N_p\}$ from the model f is

$$w = \frac{N!}{N_1!\, N_2!\cdots N_p!}\, f_1^{N_1} f_2^{N_2}\cdots f_p^{N_p}.$$

From this we see that

$$\log w = \log N! - \sum_{i=1}^{p} \log N_i! + \sum_{i=1}^{p} N_i \log f_i$$

and using the fact that $\log N! \approx n \log n - n$, then

$$\log w \approx N \log N - N - \sum_{i=1}^{p} N_i \log N_i + \sum_{i=1}^{p} N_i + \sum_{i=1}^{p} N_i \log f_i$$

$$= -N \sum_{i=1}^{p} \frac{N_i}{N} \log \frac{N_i}{N} + N \sum_{i=1}^{p} \frac{N_i}{N} \log f_i$$

$$= N \sum_{i=1}^{p} g_i \log \frac{f_i}{g_i}$$

$$= N \cdot B(g;f).$$

So, $N \cdot B(g;f)$ is approximately the logarithm of the probability of obtaining the distribution g from the assumed model f.

From a statistical inference point of view, we wish to find a model f(y) which will maximize the expected entropy

$$E_x\, B(g;f(\cdot,\theta(x))) = E_x\, E_y \log\{\frac{f(y|\theta(x))}{g(y)}\}$$

and this idea is well motivated by example 1.

Let $\ell(\hat{\theta})$ denote the value of the log likelihood function, evaluated at the maximum likelihood estimate $\hat{\theta}$,

$$\ell(\hat{\theta}) = \frac{1}{N} \sum_{k=1}^{N} \log f(x_k, \hat{\theta}(x_1, \cdots, x_N))$$

and let k denote the number of free parameters in the model. We define the AIC function by

$$AIC = -2\ell(\hat{\theta}) + \frac{2k}{N}.$$

The factor of -2 is introduced for convenience, since in the normal case

$$-2 \log \exp(\frac{-(x-u)^2}{2\sigma^2}) = \frac{(x-u)^2}{\sigma^2}.$$

Observe, that

$$E_y \log\{\frac{f(y)}{g(y)}\} = E_y \log f(y) + c \qquad (1)$$

where c is independent of the choice of f. Also, it can be shown in many cases, that for $\hat{\theta}$ the maximum likelihood estimate of θ, we have

$$E_x E_y \log f(y,\hat{\theta}) \approx (\ell(\hat{\theta}) - K/N). \qquad (2)$$

By using (1) and (2), we see that an estimator which minimizes the AIC, should approximately maximize the entropy function. The AIC estimate is a choice of parameters (which includes the choice of the number of parameter) which minimizes the AIC.

There is a relationship between the AIC and certain classical hypothesis tests. Let ${}_m\hat{\theta}$ and ${}_{m+k}\hat{\theta}$ be the maximum likelihood estimates for the m and m + k order models. Under certain regularity conditions we have that $\ell({}_{m+k}\hat{\theta}) - \ell({}_m\hat{\theta})$ is asymptotically $\chi^2(k)$ (Rao [1973]). In the case that this holds, one can apply the Neyman-Pearson likelihood ratio test, and for a particular level of significance this would be equivalent to use of the AIC.

The Neyman-Pearson theory is designed to handle a particular type of composite hypothesis test and is not applicable to a variety of situations. In contrast to this, the AIC has wide applicability. It can be applied in the comparison of different types of models and can be applied when the Fisher Information matrix is singular. We consider the AIC as a simplification of the usual hypothesis testing approach to model building.

A second way to think about the AIC is as a penalized likelihood estimate. There have been a number of penalized approaches. Good and Gaskins [1971] and later Tapia [1978] introduced roughness penalties for estimators in infinite dimensional spaces. Redner [1980] and Rossback and Lennington [1978] discuss penalties on mixture models.

The AIC approach to the penalty term is appealing because of the simplicity and generality of the approach. However, the approximation in (2) is not valid for mixture models and we need to investigate this problem.

3. DERIVATION OF THE AIC

Let $g(x)$ denote the true density function and let $x_1, x_2, \cdots, x_N$ be an independent sample from $g(x)$. Let $f(x,\theta)$ be our model for $g(x)$ and let θ_0 be the value of the parameter θ such that $f(x, \theta_0) = g(x)$. We will let $\ell(\theta)$ denote the log likelihood function and $\hat{\theta}$ the maximum likelihood estimate. Finally we define

$$I(\theta_0) = E_x\{\frac{\partial}{\partial\theta} \log f(x,\theta_0) \cdot \frac{\partial}{\partial\theta} \log f(x,\theta_0)\}$$

as the Fisher information matrix and

$$J(\theta_0) = -E_x\{\frac{\partial^2}{\partial\theta\partial\theta'} \log f(x, \theta_0)\}$$

as the negative of the expected value of the Hessian of the log likelihood function.

If we assume that $I(\theta_0)$ is a nonsingular matrix, then under certain regularity conditions we observe that $I(\theta_0) = J(\theta_0)$ and furthermore that

$$\ell(\hat{\theta}) - \frac{1}{2N} \operatorname{tr}(J(\theta_0)\ I^{-1}(\theta_0))$$

is approximately an unbiased estimator for $E_x\ \ell(\theta_0)$. It also follows that

$$\ell(\hat{\theta}) - \frac{1}{N} \operatorname{tr}(J(\theta_0)\ I^{-1}(\theta_0))$$

is approximately an unbiased estimator for the entropy. (See appendix 1.)

Since $J(\theta_0) = I(\theta_0)$, then $k \equiv \operatorname{tr}(J(\theta_0)\ I^{-1}(\theta_0))$ is the number of parameters in the model and so

$$E_x\ \ell(\theta_0) \approx E_x\ \ell(\hat{\theta}) - \frac{k}{2N}$$

and

$$-2E_y\ E_x \log f(y, \hat{\theta}(x)) \approx -2\ E_x\ \ell(\hat{\theta}) + \frac{2k}{N}.$$

We have made two critical assumptions in these calculations and they are both quite significant. First, we have assumed that the Fisher information matrix is nonsingular. In the case that it is singular, then the statements above are no longer valid. What we can say is that

$$E_x\, \ell(\theta_0) \approx E_x\, \ell(\hat{\theta}) - \frac{1}{2N} \text{ rank } (I(\theta_0))$$

and $-2E_y\, E_x \log f(y,\hat{\theta}(x)) \approx -2E_x\, \ell(\hat{\theta}) + \frac{2}{N} \text{ rank } (I(\theta_0))$.

These facts will become important when we discuss finite mixtures, since in that case, the Fisher information matrix is often singular.

Now suppose that the true distribution of the data is not in the model. We distinguish between two different cases. Observe that the true distribution cannot be modelled if we use too few parameters, but this is not a problem. The maximum likelihood estimator rarely chooses a model with too few parameters, for these models do not fit the data. The problem is with eliminating models with too many parameters. But here we are concerned with models which do not contain the true distribution for any number of parameters. This is a case in which we almost always find ourselves. The model seldom (if ever) exactly fits the data. But this does not invalidate the use of the AIC.

Let us define a parameter θ_0 to be a choice of θ which maximizes $E_x \log f(x|\theta)$. When the true distribution $g(x)$ is in the model, then this implies $f(x,\theta_0) = g(x)$. Here we have only that

$$E_x \log f(x,\theta_0) = \max_{\theta} E_x\, f(x|\theta).$$

We then have that

$$E_x \log f(x|\theta_0) \approx E_x \ell(\hat{\theta}) - \frac{1}{2N} \operatorname{tr}(J^{-1}(\theta_0)\, I(\theta_0))$$

and so $E_x E_y \log f(y|\hat{\theta}(x)) \approx E_x \ell(\hat{\theta}) - \frac{1}{N} \operatorname{tr}(J^{-1}(\theta_0)\, I(\theta_0))$.

If the true distribution $g(x)$ is close to $f(x|\theta_0)$, then $J(\theta_0)$ will be close to $I(\theta_0)$, in which case, $\operatorname{tr}(J^{-1}(\theta_0)\, I(\theta_0)) \approx k$. In this case, we use the AIC and expect the AIC to choose a good estimator of θ_0.

If the true distribution is not well modelled by $f(x|\theta)$, then we should choose a better model, rather than alter the AIC.

4. APPLICATIONS

The simplicity and generality of the AIC procedure makes it particularly useful. There are many areas in which the AIC can be used. We want to discuss a very simple application of the AIC to demonstrate its use, and hopefully, in this simple environment, we can better understand how the AIC functions and perhaps judge its effectiveness.

We consider the problem of determining the bin size for a histogram of univariate data, and we recall, that for a fixed bin size, the traditional height of the bins is a maximum likelihood estimate. Given independent observations $x_1, \cdots, x_N$, and an interval of numbers $[a,b]$, we want to find the choice of bin size which minimizes the AIC. If the interval is divided into p bins and N_i $i = 1, \cdots, p$ is the number of observations in each bin, then the AIC equals (except for an additive constant)

$$-2\left(\sum_{i=1}^{p} N_i \log N_i - N \log p\right) + 2(p - 1).$$

In some examples involving normally distributed observations, we observe that the AIC chooses a conservative number of bins. In 5 examples, using 100 independent normally distributed observations for each case, the AIC chose from 5 to 8 bins. This is a reasonable, if perhaps conservative, number of bins. We can see from the examples in Figure 1, that the AIC provides a number of bins which gives a smooth histogram. A larger number of bins could be used, but not too much larger. Figure 1 is typical of other examples.

When the sample size is increased, the number of bins chosen by the AIC is also increased. In each case, the resulting histogram is a smooth histogram (see Figure 2).

That the number of bins increases with the sample size, at first appears to be a problem. How can we choose the order of the model, if the AIC chooses to use more and more parameters as the sample size increases.

To understand this situation, it is necessary to distinguish two cases. The first case is that the true density is in the model for some finite number of parameters. The histogram is an example of a second type, where the true density is not in the model. The normal density function cannot be expressed as a histogram using a finite number of bins. Therefore, for any finite sample, the AIC chooses a small number of bins relative to the sample size. As the sample is increased, the AIC can reject histograms which have only a small number of bins and uses histograms with smaller mesh size.

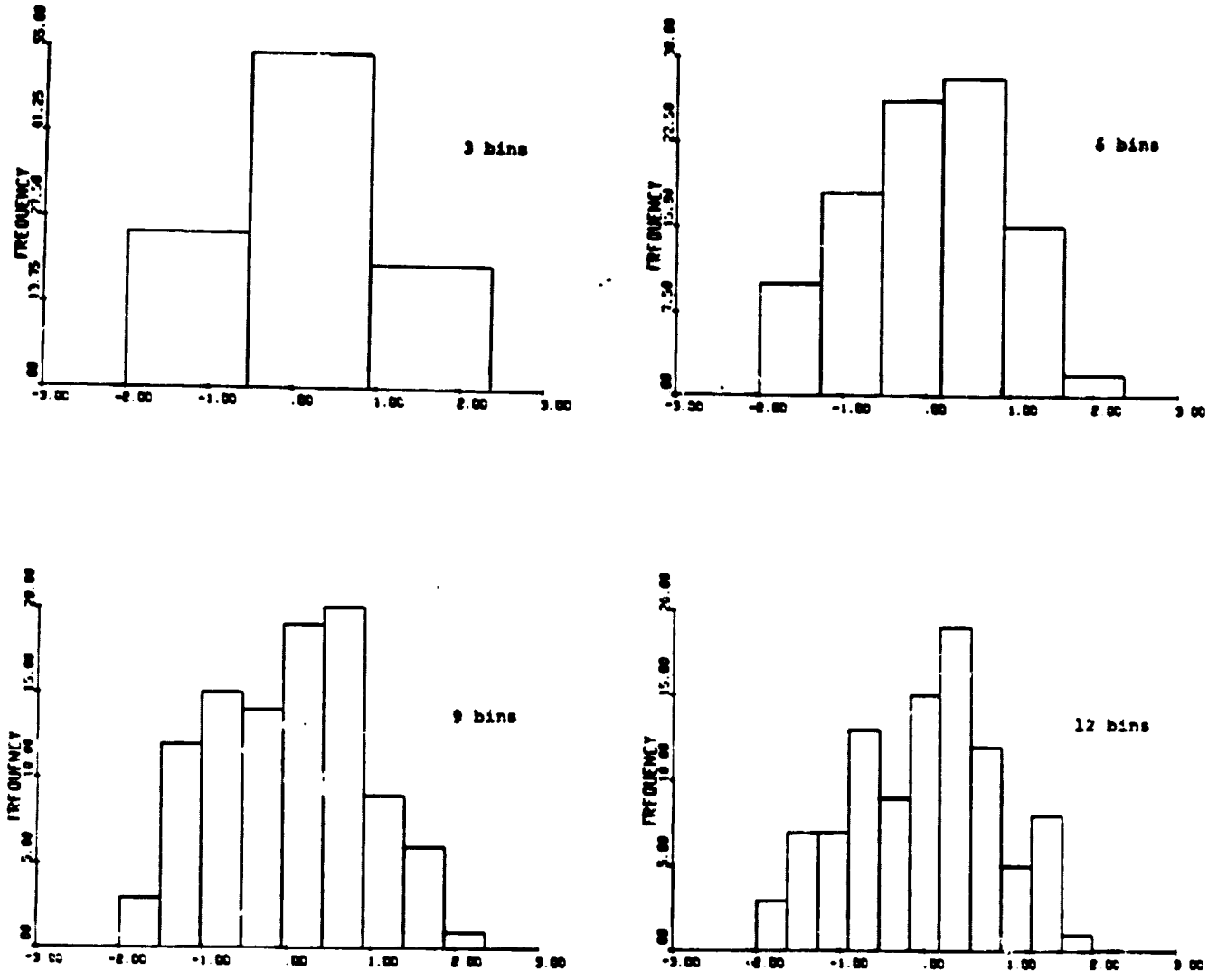

Figure 1. Graphs of histograms of normal data using different bin sizes.

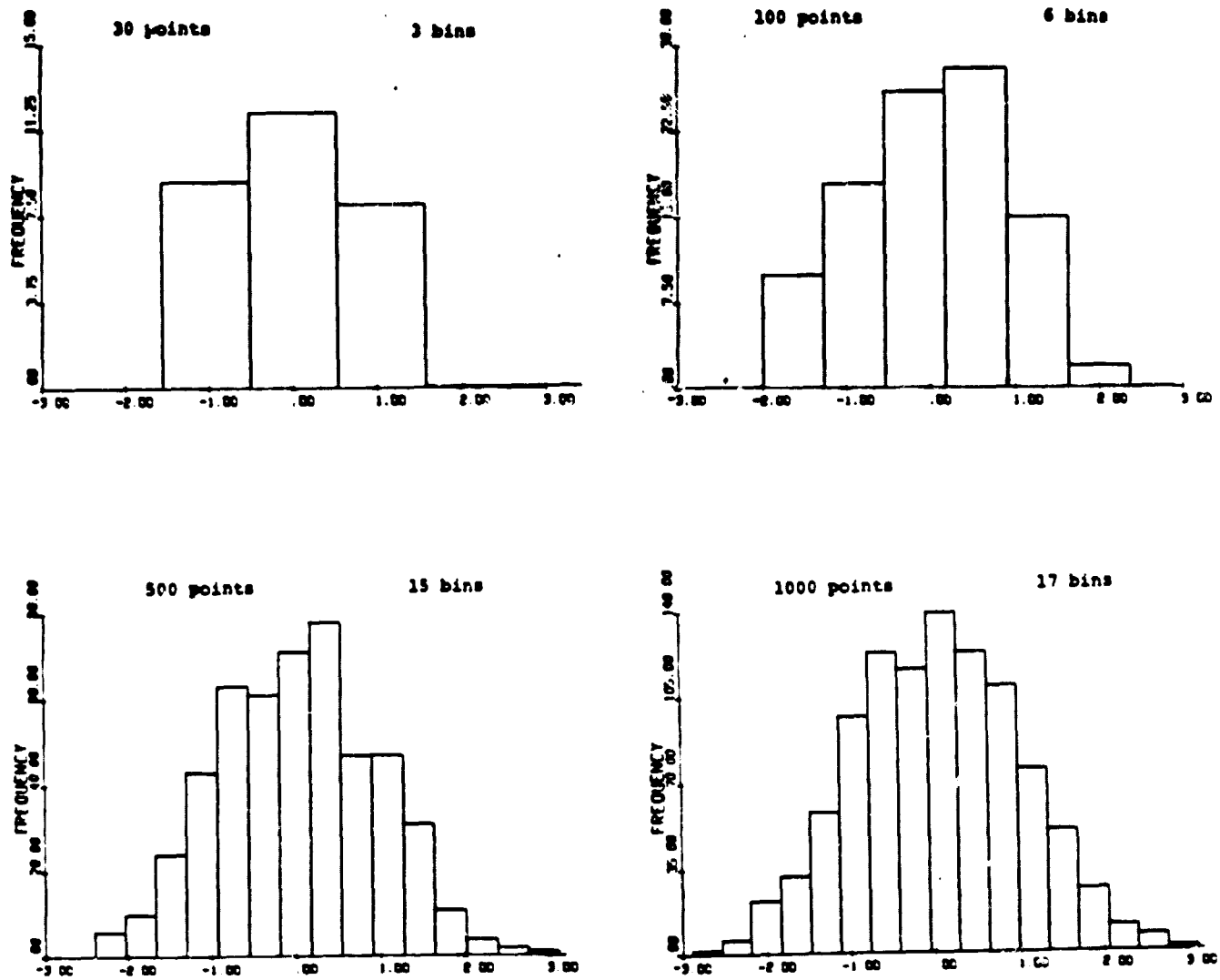

Figure 2. Graphs of histograms of normal data using AIC and different sample sizes.

The AIC tends to choose the correct number of parameters when the model matches the data. When the model does not match the data, the AIC chooses a reasonable number of parameters to fit the model, and this number increases with sample size.

We will return to this topic again when we discuss mixture models. But now let's consider other applications of the AIC. The theoretical arguments, might give the false impression that the AIC can only be used in a maximum likelihood density estimation setting, and we should dispense with that misconception at this time. While it is true that our theoretical justification of the AIC is based on the maximum likelihood density estimation situation, the AIC can be applied (with prudence) to many situations involving observations.

One of the first applications of the AIC was to time series analysis. Hipel [1981] gives a good set of references in this area and we will reproduce many of them here and add a few new entries. Autoregressive Moving Average (ARMA) process applications of the AIC have been presented by Akaike [1974], Ozaki [1977], and Lennox, McLeod and Hipel [1977a,b]. For the ARIMA process, see Ozake [1977]. Applications to the Autoregressive process were given by Akaike [1979] and Jones [1974]. Finally Kitagawa [1980] has applied the AIC to the difficult problem of modelling a time series which possesses a slowly changing spectrum.

There has been some recent work by Hannan [1980] on the estimation of the order of an ARMA process. In this paper, Hannan points out that the AIC is not a strongly consistent estimator of the order of an ARMA process. In fact it is not even a weakly

C-3

consistent estimator of the order. He defines two other criterion for estimating the number of parameters in an ARMA process. He considers the following measures. If p and q are the number of parameters in the AR and MA parts of the model, then

$$AIC = 2\ell(\hat{\theta}) + 2(p + q)$$

$$BIC = 2\ell(\hat{\theta}) + (p + q) \ln N$$

and

$$\phi(p,q) = 2\ell(\hat{\theta}) + (p + q)\, C \ln(\ln N) \qquad C > 2.$$

Hannan shows that BIC and $\phi(p,q)$ are strongly consistent.

While these are valuable theorems, they need to be properly understood. In the case that the model does not fit the true distribution exactly, the notion of 'correct order' becomes meaningless. What we want is a parsimonious use of parameters to obtain a reasonable fit to the data. This is our overall goal in many statistical settings. The AIC seems to perform very well in this environment and so should not be ruled out just because of these negative results. On the other hand, the AIC may provide too many parameters in large sample cases.

In Akaike [1973], the author considers factor analysis, principal component analysis, analysis of variance, and multiple regression, as other possible areas of application of the AIC. Kitagawa [1979] has used the AIC to detect outliers. Finally, choosing the order of a polynomial regression has been considered by Akaike [1972a] and Tanabe [1974].

The overall simplicity of the AIC makes it a valuable tool in model selection and helps integrate the model selection process into the estimation process. Because of these facts and the successful experience of many statistical investigators, the AIC appears to have a bright and useful future as a model selection tool.

5. MIXTURE MODELS

We will now focus our attention on the problem of estimating the number of classes in a mixture model. Let $X_1, \cdots, X_N$ be independent identically distributed observations from a mixture density. That is, X_1 has density function

$$P(x|\theta^0) = \sum_{i=1}^{m^0} \alpha_i^0 P_i(x|\theta_i^0)$$

where $\alpha_i^0 > 0 \quad i = 1, \cdots, m^0$

$$\sum_{i=1}^{m} \alpha_i^0 = 1$$

and $P_i(x|\theta_i)$ is a density function parameterized by $\theta_i \in \Omega$.

From the independent sample $\{x_k\}_{k=1}^N$ on R^n, we wish to estimate the number of classes m and $\theta = \{\alpha, \cdots, \alpha_m, \theta_1, \cdots, \theta_m\}$.

Given a fixed value of m, we can obtain maximum likelihood estimates of the remaining parameters in the model using the maximum likelihood approach. We will not discuss this optimization problem here, but the reader is referred to a discussion of the EM algorithm by Redner [1980].

Once we have obtained a maximum likelihood estimate for two or more classes, we select as our estimate of the number of classes, a choice of m which minimizes

$$AIC(m) = -2\ell({}_m\hat{\theta}) + 2\, k_m$$

where k_m is the number of free parameters in the model with m classes.

The application of the AIC to mixture models is not as straightforward as many other applications. The difficulties arise in several ways and we will now discuss them.

Let us suppose that the true model has m^0 classes. That is, the m^0 component density functions are identifiable in the sense of Teicher [1963], and they have a positive probability of being observed in an independent sample. Under these conditions it is reasonable to assume that the Fisher information matrix is non-singular. Although this is not always the case, it is usually satisfied. Now let us consider the rank of the Fisher information matrix for the model with $m^0 + 1$ classes, given that the true distribution has exactly m^0 classes.

What is the rank of the Fisher information matrix? Unfortunately that is not a well defined question, for its solution depends on how the m^{th} order model is embedded into the $m + 1^{st}$ order model.

Consider two alternative methods of embedding a one class model into a two class model and let θ_1 and θ_2 be one-dimensional parameters. The first alternative is that θ_1 equals θ_2, and α_1 and α_2 are arbitrary. In this case, the rank of the Fisher information matrix is 1. On the other hand, if we use another embedding, say $\alpha_2 = 0$ and θ_2 is arbitrary, then the rank of $I(\theta_0)$ is 2. In either case, we are estimating 3 free parameters.

This problem is compounded by the fact, that in practice we do not know the true order of the model, and the possibility exists that the $I(\theta_0)$ has full rank. In this case, it would be rank 3, if the two class model were actually correct.

Fortunately we can use the AIC as it stands and not worry about the rank of $I(\theta_0)$. Since its rank is not larger than the number of free parameters (since the number of free parameters is the dimension of the matrix) we use the AIC as stated.

We minimize

$$AIC(m) = -2\ell\,(\hat{\theta}) + 2\,k_m$$

where k_m is the number of free parameters in the m class model.

We propose to use the AIC even in the case that true distribution is not in the model. We have seen with histograms that the AIC is still an effective tool in selecting the order of a model and small changes in the data from the model should not have a strong effect on the performance of the AIC.

We will discuss some simulations that were performed using the AIC in the next section, but now we wish to consider other uses of the AIC in mixture problems. Let us consider the mixture of several multivariate normal densities. That is each n-dimensional observation has distribution

$$P(x) = \sum_{i=1}^{m} \alpha_i\, P_i(x,\, \mu_i,\, \Omega_i)$$

where $P_i(x,\, \mu_i,\, \Omega_i) = \frac{1}{\sqrt{2\pi}^n}\ \frac{1}{|\Omega_i|^{1/2}}\ e^{-\frac{1}{2}(x - \mu_i)^t\, \Omega_i^{-1}(x - \mu_i)}$

and $\sum_{i=1}^{m} \alpha_i = 1$ and $\alpha_i > 0 \quad i = 1, \cdots, m.$

The parameters in the model are $\{\alpha_i,\, \mu_i,\, \Omega_i\}_{i=1}^{m}$ and the number of mixing components m. We may add the additional assumption that, although the covariances are unknown, they are assumed to be equal.

Choosing between the free convariance model, and the unknown but equal covariance model, is a problem in choosing the order of the model. The number of parameters to be estimated in estimating

the covariance for an n-dimensional multivariate normal density is $\frac{n(n+1)}{2}$. We observe that the constraint requiring the covariance to be positive definite does not affect the number of free parameters, since given any positive definite matrix, all the parameters can be varied arbitrarily by some small amount without change to the positive definiteness.

If we have a model with m classes and n dimensions, then the number of free parameters in the m covariances is $k = \frac{m(n)(n+1)}{2}$, unless the covariances are assumed to be equal. Then we have that $k = \frac{n(n+1)}{2}$.

The AIC can be used to determine which of these two models should be used on any given data set.

6. MIXTURE SIMULATIONS

In order to understand the application of the AIC to mixture models, we have performed several simulations. The simulations in one dimension were designed to analyze the performance of the AIC as a function of class separation. The simulations were performed with relatively small data sets and we have observed that this causes the AIC to choose a conservative number of classes. This is similar to what was discovered in the histogram application.

The data which we generated was a mixture of two normal densities. The mixing proportions were equal and the true covariances were set equal to one. The only parameters which we varied were the sample size and the mean values. All of the parameters in the model were estimated. The covariances were estimated using the assumption they were equal but unknown. The tabulated results are in Figure 3 (all of the figures for this section are in appendix B).

From these data sets, we observe that the performance of the AIC is indeed a function of the class separation. When the classes are well separated (mean values 3 standard deviations apart) the AIC unerringly chose the correct number of classes. On the other hand, the AIC always chose the one class model when the class separations were small (mean values were less than or equal to 1 standard deviation apart). The AIC performed well for 2 units of separation.

To test the limits of the AIC, we considered another simulation. This simulation was composed of 10 repetitions of the one standard deviation separation with 300 observations. The results are contained in Table 1. We can observe two things in this table. Obviously the AIC consistently chose too few classes for the model. In fact, 8 out of 10 times too few classes were chosen, and the three class model was never chosen. The histograms and estimated density functions for the first two runs are in Figure 4.

One can estimate the performance of the AIC for larger sample sizes by considering Table 1. It appears that for sample sizes in the range of 2000 data points the AIC would choose the correct model about one-half of the time.

Our final calculations in one dimension involve Landsat data from one scan line of segment 1618. We use the AIC to estimate the number of classes in the model and the resulting answer was three classes. On consulting ground truth, we see that 88 percent of the data lie in three ground truth classes, and no other ground truth class comprised more than 5 percent of the scan line. The results for channel three and the brightness component are presented in Figures 5 and 6.

Table 1. AIC values for 10 simulations.

Run Number	No. of Classes		
1	911.0	914.2	918.0
2	* 918.0	915.1	918.0
3	924.8	927.0	931.0
4	931.4	935.4	939.2
5	* 894.6	891.0	892.2
6	890.6	894.6	898.6
7	933.2	936.0	938.8
8	924.2	927.2	931.0
9	886.6	888.4	892.2
10	907.0	911.0	914.8

The overall effect of these data sets is to show that the AIC chooses a reasonable number of classes, considering the sample size.

As a second stage in our investigation of the application of the AIC to mixtures, we investigated mixtures of bivariate normal density functions. These investigations consisted of simulations with three and five bivariate normal densities at several different separations, and also, the estimation of the number of normal classes in a portion of Landsat segment.

We initially investigated a mixture of three normal classes at various separation. For simplicity of the example, we generated classes which had equal probabilities and which each had the identity matrix as its covariance matrix. As in the one-dimensional examples, we varied the means in the simulations and estimated the covariances

under the hypothesis that they were equal but unknown. In Figures 7, 8 and 9, the true values of the means, the values of the AIC for the different models, and a graph of the true density function are displayed. From the table of AIC values in each of the tnree examples, one can see that the AIC chose the correct number of classes except in Case III where the true mean separation was small and Case IC. Although the classes are well separated in Case IC the AIC chose the fourth order model. This type of error is to be expected to happen a certain percentage of the time.

We extended our investigation to mixtures of five normal classes. Again the proportions of the classes were equal and the covariance of the five classes were equal to the identity matrix. In Figures 10 and 11, we see the true mean values, the values of the AIC for the different models and graphs of the true density function. One thousand sample points were used since we must estimate 17 parameters under the assumption that the covariances are unknown but are equal. Again we see that the AIC chose the correct number of classes when the populations are well separated and chose too few classes in the case that there is considerable overlap between classes.

Let us now consider a more realistic data set. We take a Landsat segment for this purpose and we selected segment 1633 for this test. Using ground truth data, we selected the pure elements of the scene. We define a pixel to be a pure pixel, if it has neighbors which are all of the same ground truth class. The data set was reduced in dimension by the use of the Kauth transformation to the greeness and brightness plane. We used the first 20 percent of this two dimensional data set to form our working data set.

We modelled this data set, which comprises 1966 data points, by a mixture of bivariate normal density functions. During some of our calculations of the maximum likelihood estimate, we observed that the maximum likelihood iteration was proceeding to a singularity of the likelihood function. This not only causes numerical problems but completely invalidates the use of the AIC to determine the number of classes. Singularities of the likelihood function must be avoided. There are several methods for avoiding the singularities of the likelihood function. The method which we implemented was an application of a penalty term. This penalty term forces the likelihood iteration to avoid the singularities of the likelihood function (see Redner (1980)).

This type of adjustment to the natural maximum likelihood iteration is often necessary. Since the data is discrete, that is the data takes on only integer values, this is a common problem.

With this adjustment, the maximum likelihood estimate for various numbers of classes was calculated. Table 2 contains the AIC values. It was not possible to completely determine the correct number of classes using the AIC due to limits on machine time. But the reader can observe from these numbers that the number of classes is quite large. With 15 classes in the model, the maximum likelihood estimate for each parameter is based on approximately 22 data points. Furthermore it appears that the true number of classes, as determined by the AIC, might be considerably larger than 15. This is unacceptable for the type of application for which this is intended. One would expect that the number of classes chosen by the AIC for a full Landsat segment would be much larger (perhaps two to four times as large).

Table 2. AIC values for Landsat Segment

No. of Classes	AIC Values	BIC Values
7	33194	33423
8	33130	33392
9	33126	33422
10	33078	33407
11	33078	33441
15	32954	33511

This brings us back to our previous remarks concerning the consistency of the AIC and the tendancy for the AIC to choose a large number of classes, when the true model is not a good approximation to the data. Because of the poor showing of the AIC in this example we extended the experiment to consider the BIC. The results of these calculations are also in Table 2. From these numbers, one can see that the trend of the AIC to choose a large number of classes, is not reflected in this table of BIC values. In fact, the choice of 8 classes by the BIC, appears to be a much better value for the types of applications for which the model is intended. Figure 12 contains the maximum likelihood estimates for the model with 8 classes and also contains the scatter plot of the 1966 data points.

In response to the poor showing of the AIC, we considered one final experiment. This estimate of the parameters and the number of classes proceeded in a three step process.

First the maximum likelihood estimate for models with different numbers of classes was calculated under the common covariance assumption. The maximization of the likelihood function with the equal

covariance hypothesis is a very stable optimization problem. It also has fewer local maxima and so it is much easier to find the global maxima.

The second phase of the procedure involved determination of the number of classes to use in the model using the AIC. In this case, the AIC chose 7 classes for the model. Table 3 contains the AIC values.

Since it appears that the common covariance assumption is not valid for Landsat data, in the final step we fixed the mean values and iterated on the proportions and the covariance. The covariances being allowed to vary independently. This provides a significant improvement to the fit to the data according to the AIC. The new AIC value is 33194.

Although the AIC has performed well in numerous applications, we observe, in the application of the AIC directly to a large portion of a Landsat segment, that it provides a model with a large number of classes. The cause of this problem is probably the unboundedness of the likelihood function. The use of the penalty term was not sufficient to completely rectify this situation. We should emphasize that it is the type of application which

Table 3. AIC values for the equal covariance model

No. of Classes	AIC
6	33546
7	33276
8	33280
10	33292

we have in mind and the large amount of computation which has to be done which causes us to conclude that the answer given by the direct application of the AIC, is not suitable. In addition, the ratio of the number of parameters being estimated and the number of data points available is not particularly large. All of these considerations lead us to consider possible alternatives. The most natural alteration of the AIC is the BIC, which gives us a more desirable number of classes along with some indication that it might consistently give the correct number of classes when the model is correct and when we have large data sets. The other possibility is given by the three step application of the AIC to the mixture problem. This approach is appealing because of the stability of the natural fixed point iteration if the covariances are assumed to be unknown but equal.

7. CONCLUDING REMARKS

The AIC has shown to be effective in a wide range of applications. These demonstrations now include the mixture density problems. For some data sets it appears that the BIC may provide more useful results than the direct application of the AIC. The authors are optimistic about the possible uses of the AIC and BIC in determing the number of components in a mixture model and in determining which of several mixture models to use.

On the other hand, we do not consider the simulations and examples presented in this paper as sufficient proof of the applicability of the AIC or BIC in model selection for the mixture problem. In particular the AIC and BIC have not been applied to a full Landsat segment and certainly many segments must be considered before a judgement on these criterion can be made.

It is hoped that experiments along these lines will be carried out in the near future. The application of the AIC and BIC to the HISSE procedure is a particular experiment that should be carried out as well as the application of these criterion to MLE methods applied to profile data.

There are numerous other areas which need to be considered in the application of the AIC and BIC to mixture models. The mechanics of applying the AIC and BIC to mixture models needs to be considered further. Since we are dealing with expensive non-linear optimization problems to obtain the likelihood estimates, we must consider the best way to find the AIC or BIC estimates. The suggestion by Wolf (1970) may be particularly applicable to this area. Wolf suggests the use of certain non-parametric clustering schemes to assist in obtaining initial guesses of the MLE.

Finally we reiterate that the AIC and BIC can be used in a wide range of applications. We have emphasized the use of the AIC and BIC in model selection for mixture problems because that is a problem in which we have a deep interest. However, the use of the AIC and BIC in other areas should not be neglected and it is hoped that the applications which we suggested in section 4 might lead to other uses of these criterion.

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APPENDIX A

Proofs of the approximations provided in section 3.

Let $g(x)$ denote the true density function for a random variable X and let $f(x,\theta)$ be a model for $g(x)$. Let θ_0 be a choice of parameters θ so that

$$E_x \log f(x,\theta_0) = \max_\theta E_x \log f(x,\theta).$$

In the case that the true density $g(x)$ is in the model, then this implies that $f(x,\theta_0) = g(x)$.

We also define

$$I(\theta_0) = E_x \{\frac{\partial}{\partial\theta} \log f(x,\theta_0) \cdot \frac{\partial}{\partial\theta} \log f(x,\theta_0)\}$$

to be the Fisher information matrix and define

$$J(\theta_0) = - E_x \{\frac{\theta^2}{\partial\theta\partial\theta'} \log f(x,\theta_0)\}$$

to be the negative of the expected Hessian of the log likelihood function. Let $\hat{\theta}$ be the maximum likelihood estimate where $\hat{\theta}$ is shorthand for $\hat{\theta}(x_1,\cdots, x_N)$, a function of the observations. Finally we define

$$\ell(\theta) = \frac{1}{N} \sum_{k=1}^{N} \log f(x_k,\theta)$$

to be the log likelihood function.

Assuming the true density function $g(x)$ to be in the model and assuming the necessary regularity conditions, we will show that

$$E_x \ell(\theta_0) \sim E_x \ell(\hat{\theta}) - \frac{1}{2N} \text{rank } (I(\theta_0)) \tag{1}$$

and $$-2 E_y E_x \log f(y,\hat{\theta}(x)) \sim -2 E_x \ell(\hat{\theta}) + \frac{2}{N} \text{rank } (I(\theta_0)) \tag{2}$$

Later on we will show that, in the case that $g(x)$ is not in the model and if $J(\theta_0)$ and $I(\theta_0)$ are nonsingular, then we have that

$$E_x \ell(\theta_0) \sim E_x \ell(\hat{\theta}) - \frac{1}{2N} \text{tr } \{J(\theta_0)^{-1} I(\theta_0)\} \tag{3}$$

and $$-2 E_y E_x \log f(y,\hat{\theta}(x)) \sim -2 E_x \ell(\hat{\theta}) + \frac{2}{N} \text{tr } \{J(\theta_0)^{-1} I(\theta_0)\}. \tag{4}$$

Recall that by the law of large numbers we have

$$\frac{1}{N}\sum_{k=1}^{N}\frac{\partial^2}{\partial\theta\partial\theta'}\log f(x_k,\theta_0) \to -J(\theta_0). \tag{5}$$

Using the central limit theorem we can observe that

$$\frac{1}{\sqrt{N}}\sum_{k=1}^{N}\frac{\partial}{\partial\theta}\log f(x_k,\theta_0) \to N(0,I(\theta_0)). \tag{6}$$

From the following equation

$$\frac{\partial}{\partial\theta}\ell(\hat{\theta}) = 0 = \frac{1}{N}\sum_{k=1}^{N}\frac{\partial}{\partial\theta}\log f(x_k,\hat{\theta})$$

$$\sim \frac{1}{N}\sum_{k=1}^{N}\frac{\partial}{\partial\theta}\log f(x_k,\theta_0) + \frac{1}{N}\sum_{k=1}^{N}\frac{\partial^2}{\partial\theta\partial\theta'}\log f(x_k,\theta_0)(\hat{\theta}-\theta_0)$$

we calculate, using (5) and (6), that

$$\sqrt{N}\,J(\theta_0)(\hat{\theta}-\theta_0) \sim N(0,I(\theta_0)).$$

If $J(\theta_0)$ (respectively $I(\theta_0)$) is a singular matrix, then we have a singular normal density. In this case let $P: R^m \to R^n$ for $m > n$ be a matrix that P^TP is the $n \times n$ identity matrix and PP^T is the projection onto the range of $J(\theta_0)$. Then

$$\sqrt{N}\,PJ(\theta_0)(\hat{\theta}-\theta_0) \sim N(0,PI(\theta_0)P^T)$$

where $PI(\theta_0)P^T = PJ(\theta_0)P^T$ is nonsingular. From the definition of P,

$$\sqrt{N}\,PJ(\theta_0)\,P^T\,P(\hat{\theta}-\theta_0) \sim N(0,PI(\theta_0)P^T)$$

and so

$$\sqrt{N}\,P(\hat{\theta}-\theta) \sim N(0,(PJ(\theta_0)P^T)^{-1}(PI(\theta_0)P^T)(PJ(\theta_0)P^T)^{-1}) \tag{7}$$

Now observe that

$$\frac{1}{N}\sum_{k=1}^{N}\log f(x_k,\theta_0) \sim \frac{1}{N}\sum_{k=1}^{N}\log f(x_k,\hat{\theta})$$

$$-\tfrac{1}{2}(\theta_0-\hat{\theta})\,J(\theta_0)(\theta_0-\hat{\theta})$$

and so by taking expectations

$$E_X \ell(\theta_0) \sim E_X \ell(\hat{\theta}) - \frac{1}{2} E_X (\theta_0 - \hat{\theta})^T J(\theta_0)(\theta_0 - \hat{\theta})$$

$$= E_X \ell(\hat{\theta}) - \frac{1}{2} E_X (\theta_0 - \hat{\theta})^T P^T P \, J(\theta_0) \, P^T P (\theta_0 - \hat{\theta})$$

$$= E_X \ell(\hat{\theta}) - \frac{1}{2N} E_X \operatorname{tr} \left[(PJ(\theta_0)P^T)(P(\theta_0 - \hat{\theta})(\theta_0 - \hat{\theta})^T P^T) \right]$$

Therefore,

$$E_X \ell(\theta_0) \sim E_X \ell(\hat{\theta}) - \frac{1}{2N} \operatorname{tr} \left[(PJ(\theta_0)P^T)(PJ(\theta_0)P^T)^{-1} \right.$$

$$\left. (PI(\theta_0)P^T)(PJ(\theta_0)P^T)^{-1} \right] \qquad (8)$$

$$= E_X \ell(\hat{\theta}) - \frac{1}{2N} \operatorname{rank} (I(\theta_0))$$

since $J(\theta_0) = I(\theta_0)$.

We see that $\ell(\theta)$ is a biased estimate of $\ell(\theta_0)$ and this bias is on the average equal to $\frac{1}{2N} \operatorname{rank} I(\theta_0)$.

We now proceed to establishing (2). First observe that

$$E_y \log f(y,\hat{\theta}) = \int \log f(y|\hat{\theta}) \, g(y) \, dy$$

$$\sim \int \log f(y,\theta_0) \, g(y) \, dy + \int \frac{\partial}{\partial \theta} \{\log f(y,\theta_0)\} \, g(y) \, dy (\hat{\theta} - \theta_0)$$

$$+ \frac{1}{2} (\hat{\theta} - \theta_0)^T \int \frac{\partial^2}{\partial \theta \partial \theta'} \{\log f(y,\theta_0)\} \, g(y) \, dy (\hat{\theta} - \theta_0)$$

$$= E_y \log f(y,\theta_0) - \frac{1}{2} (\hat{\theta} - \theta_0)^T J(\theta_0)(\hat{\theta} - \theta_0)$$

$$= E_y \log f(y,\theta_0) - \frac{1}{2} (\hat{\theta} - \theta_0)^T P^T P J(\theta_0) P^T P (\hat{\theta} - \theta_0)$$

Taking expectations we find that

$$E_x E_y \log f(y,\hat{\theta}) \sim E_x E_y \log f(y,\theta_0)$$

$$- \frac{1}{2N} \operatorname{tr} ((PJ(\theta_0)P^T)^{-1} (PI(\theta_0)P^T))$$

$$= E_x E_y \log f(y,\theta_0) - \frac{1}{2N} \text{rank } I(\theta_0).$$

$$= E_y \log f(y,\theta_0) - \frac{1}{2N} \text{rank } I(\theta_0).$$

We observe that equation (1) is equivalent to

$$E_y \log f(y,\theta_0) \sim E_x(\ell(\hat{\theta})) - \frac{1}{2N} \text{rank } I(\theta_0)$$

Putting these two estimates together

$$E_x E_y \log f(y,\hat{\theta}) \sim E_x \ell(\hat{\theta}) - \frac{1}{N} \text{rank } I(\theta_0)$$

which establishes (2).

Let us now consider the case that $g(x)$ is not in the model and so θ_0 is a choice of parameters which maximize $E_x \log f(x,\theta)$. Let us also assume that the Fisher information matrix $I(\theta_0)$ is nonsingular.

Observe that equation (6) still holds and we have immediately that

$$E_x \ell(\theta_0) \sim E_x \ell(\hat{\theta}) - \frac{1}{2N} \text{tr}\{(PJ(\theta_0)P^T)^{-1}(PI(\theta_0)P^T)\}$$

If $J(\theta_0)$ is nonsingular then

$$E_x \ell(\theta_0) \sim E_x \ell(\hat{\theta}) - \frac{1}{2N} \text{tr}(J(\theta_0)^{-1} I(\theta_0))$$

and this gives us equation (3).

We can also observe the (7) holds, that is

$$E_x E_y \log f(y,\hat{\theta}) \sim E_x E_y \log f(y,\theta_0)$$

$$- \frac{1}{2N} \text{tr}((PJ(\theta_0)P^T)^{-1}(PI(\theta_0)P^T)^{-1}$$

and also

$$E_x E_y \log f(y,\theta_0) \sim E_x \ell(\hat{\theta}) - \frac{1}{2N} \text{tr}((PJ(\theta_0)P^T)^{-1}(PI(\theta_0)P^T)^{-1}.$$

Combining these facts one gets that

$$E_x E_y \log f(y,\hat{\theta}) \sim E_x \ell(\hat{\theta}) - \frac{1}{N} \operatorname{tr}(PJ(\theta_0)P^T)^{-1}(PI(\theta_0)P^T)$$

Again if J is nonsingular, then P = I and

$$E_x E_y \log f(y,\hat{\theta}) \sim E_x \ell(\hat{\theta}) - \frac{1}{N} \operatorname{tr} J(\theta_0)^{-1} I(\theta_0)$$

and this establishes our final result.

APPENDIX B

Figures from section 6

100 DATA POINTS

No. of Classes	$\Delta = \mu_1 - \mu_2$ .5	1.0	2.0	3.0
1	295.0	322.2	352.0	407.2
2	295.4	321.6	340.0	402.6
3	299.0	325.4	343.0	405.6

200 DATA POINTS

No. of Classes	$\Delta = \mu_1 - \mu_2$ .5	1.0	2.0	3.0
1	273.4	303.4	330.8	418.2
2	277.4	303.8	331.2	406.6
3	280.8	307.8	335.2	410.6

300 DATA POINTS

No. of Classes	$\Delta = \mu_1 - \mu_2$ .5	1.0	2.0	3.0
1	871.2	886.6	1040.6	1213.2
2	875.2	888.4	1038.0	1171.8
3	878.6	892.2	1042.0	1175.8

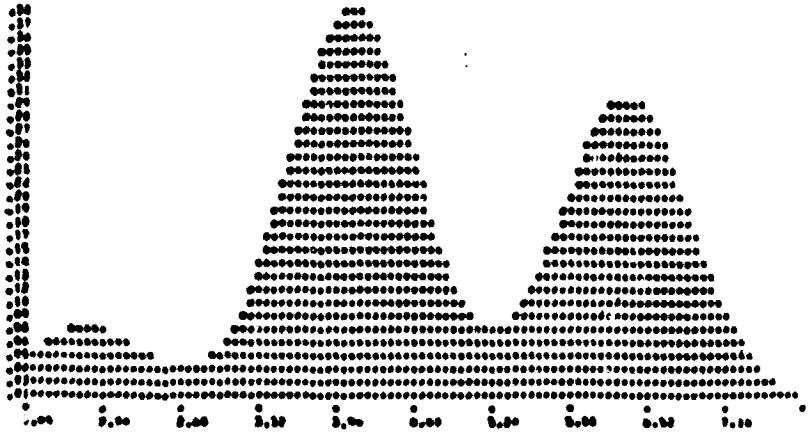
300 DATA POINTS

No. of Classes	$\Delta = \mu_1 - \mu_2$ .5	1.0	2.0	3.0
1	893.2	907.0	1052.6	1192.6
2	897.2	911.0	1034.0	1156.6
3	908.2	914.8	1038.0	1160.4

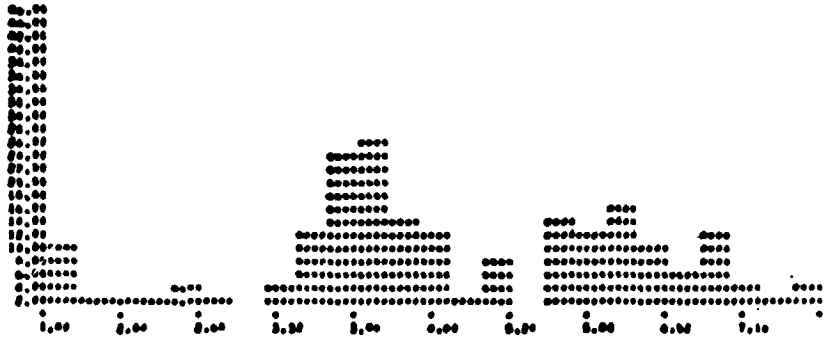
Figure 3. Tables of AIC values for 4 simulations. Each table contains AIC values for varying numbers of classes and class separation.

Figure 4. Graphs of histograms and estimated density functions for runs number one and two in table 1.

ESTIMATED DENSITY FUNCTION, WITH 3 CLASSES

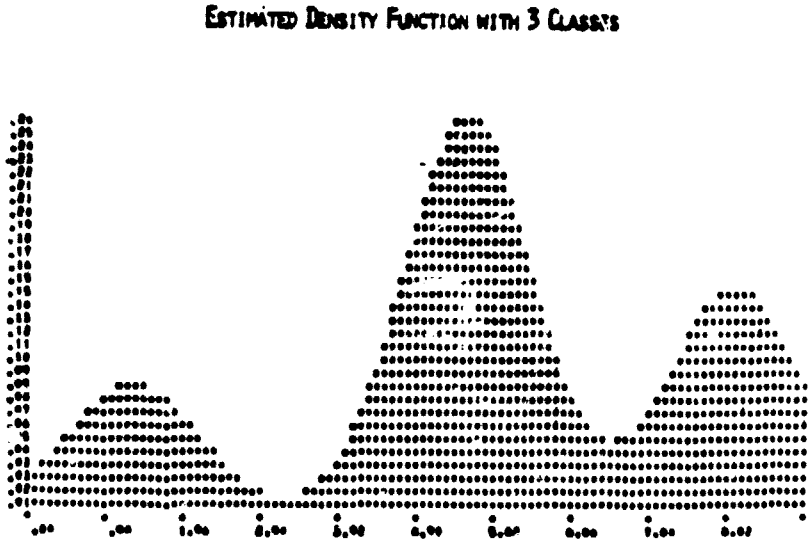


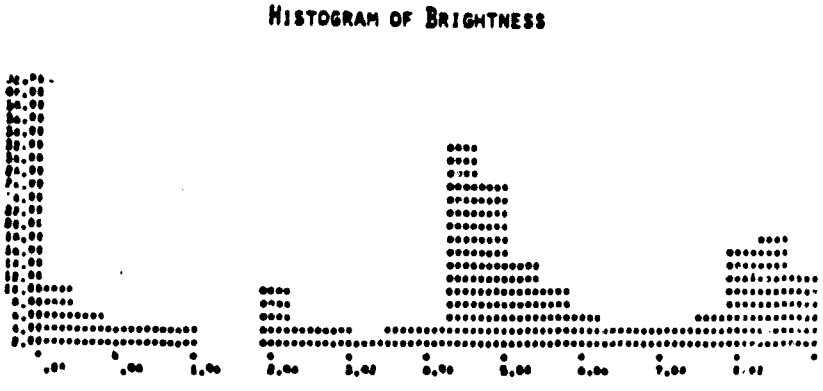
CHANNEL 3 HISTOGRAM



No. of Classes	AIC Values
1	721.3
2	725.3
3	662.9
4	666.9

Figure 5. Graphs and AIC values for segment 1618/235 line 62 channel 3.





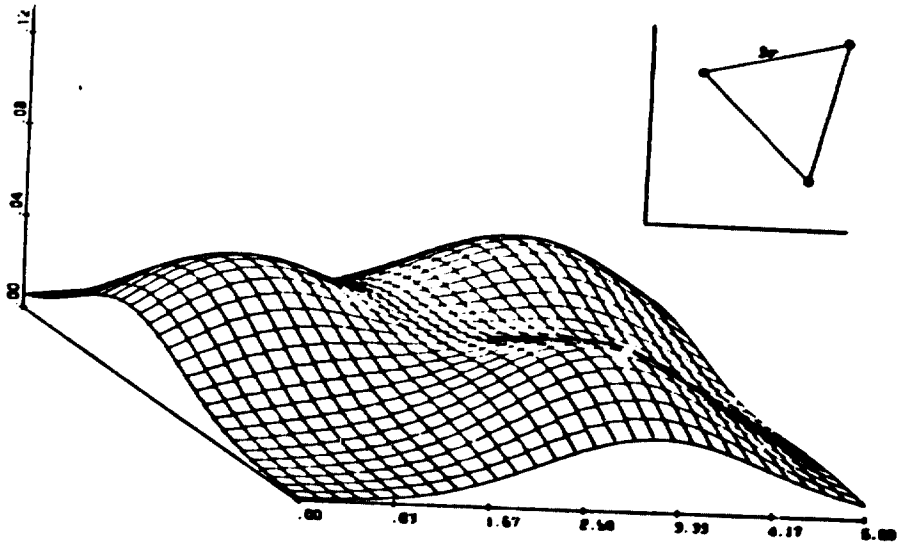
No. of Classes	AIC Values
1	941.8
2	927.5
3	857.1
4	861.2

Figure 6. Graphs and AIC values for segment 1618/235 line 62 brightness coordinate.

CASE I

TRUE MEAN VALUES

CLASS 1	3.12, 1.00
CLASS 2	1.00, 3.12
CLASS 3	3.90, 3.90



CASE I. MODEL MIXTURE DENSITY.

TABLE OF AIC VALUES (500 POINTS)

No. OF CLASSES	AIC VALUES
1	3699.8
2	3679.8
3	3600.8
4	3600.0 *

TABLE OF AIC VALUES (500 POINTS)

No. OF CLASSES	AIC VALUES
1	3729.1
2	3701.8
3	3642.7 *
4	3648.2

TABLE OF AIC VALUES (1000 POINTS)

No. OF CLASSES	AIC VALUES
1	7434.3
2	7366.6
3	7219.3 *
4	7224.4

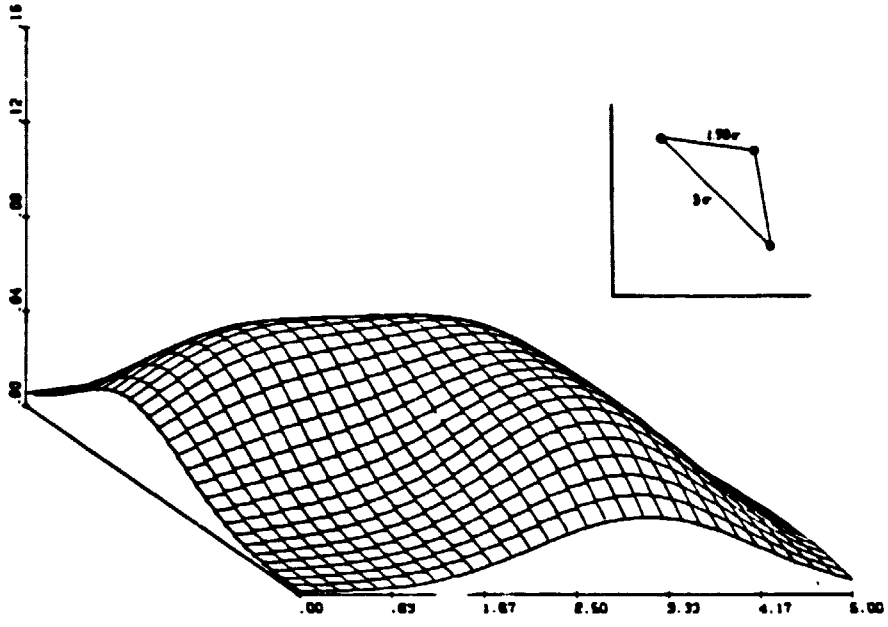
Figure 7. Mixture model density and tables of AIC values fcr 3 simulations (* denotes the minimum AIC values).

CASE II

	True Mean Values
Class 1	3.12, 1.00
Class 2	1.00, 3.12
Class 3	3.00, 3.00

TABLE OF AIC VALUES (500 POINTS)

No. of Classes	AIC Values
1	3514.4
2	3471.0
3	3467.4
4	3472.4



CASE II. MODEL MIXTURE DENSITY.

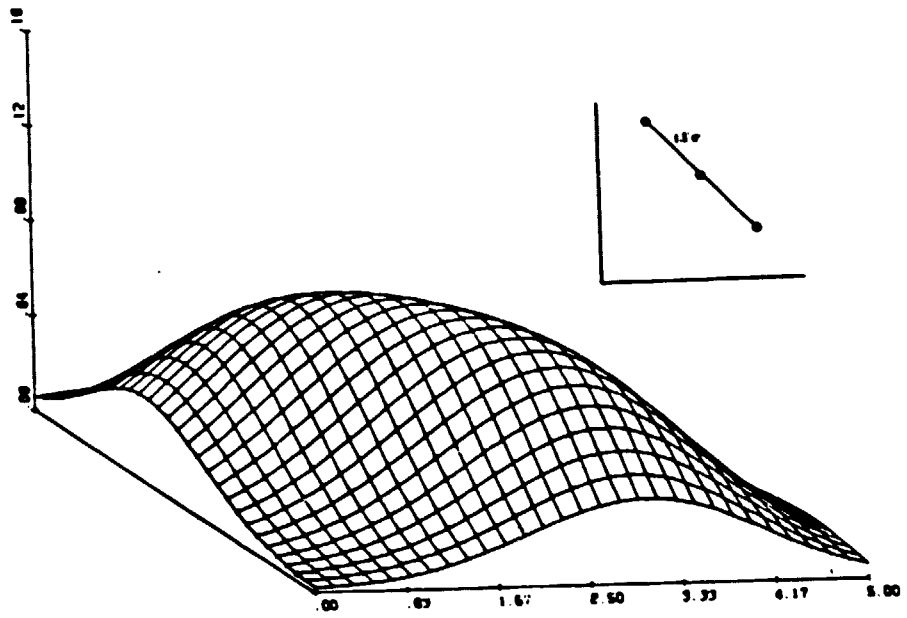
Figure 8. Mixture model density and table of AIC values.

CASE III

	True Mean Values
Class 1	3.12, 1.00
Class 2	1.00, 3.12
Class 3	2.06, 2.06

TABLE OF AIC VALUES (500 POINTS)

No. of Classes	AIC Values
1	3285.8
2	3250.2 *
3	3250.8 0
4	3256.4



CASE III. MODEL MIXTURE DENSITY.

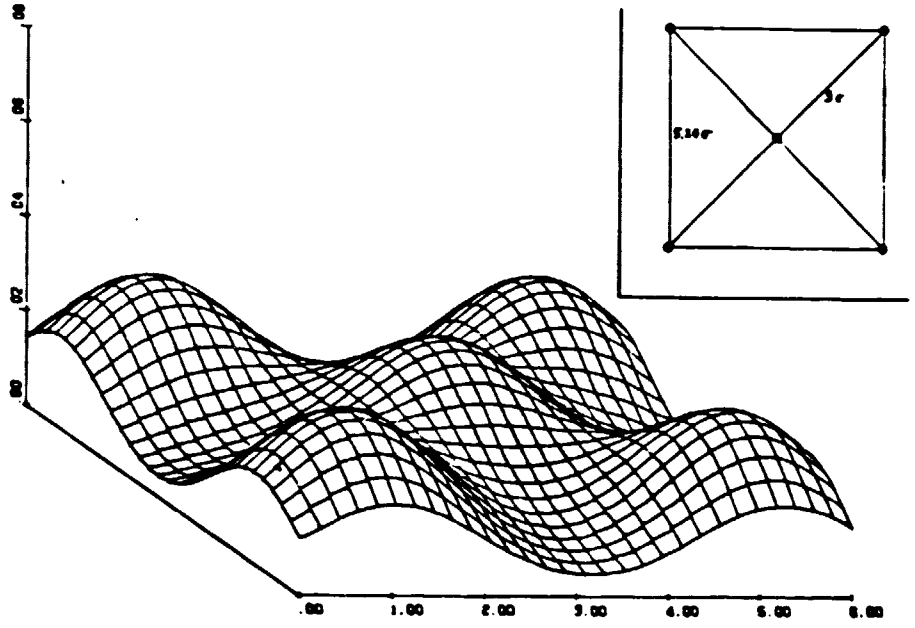
Figure 9. Mixture model density and table of AIC values.

CASE IV

	True Mean Values
Class 1	1.00, 1.00
Class 2	5.24, 1.00
Class 3	5.24, 5.24
Class 4	1.00, 5.24
Class 5	3.12, 3.12

TABLE OF AIC VALUES (1000 POINTS)

No. of Classes	AIC Values
1	8702.4
2	8560.6
3	8564.4
4	8411.4
5	8315.4
6	8321.6



CASE IV. MODEL MIXTURE DENSITY.

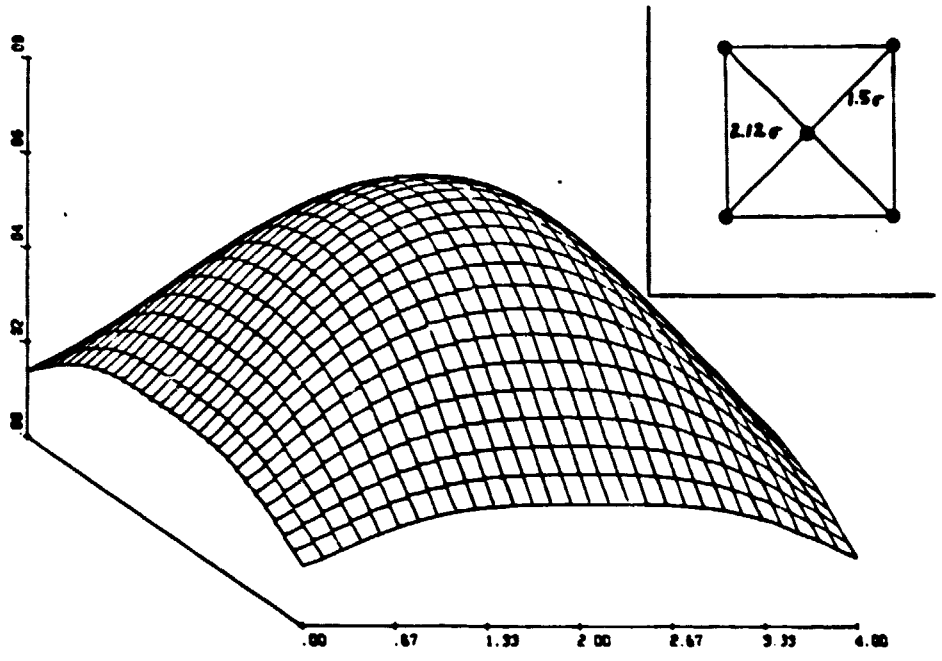
Figure 10. Mixture model density and table of AIC values.

CASE V

True Mean Values	
Class 1	1.00, 1.00
Class 2	3.12, 1.00
Class 3	3.12, 3.12
Class 4	1.00, 3.12
Class 5	2.06, 2.06

TABLE OF AIC VALUES (1000 POINTS)

No. of Classes	AIC Values
1	6803.8
2	6795.6 0
3	6801.6
4	6794.2 •
5	6796.8 0
6	6802.0



CASE V. MODEL MIXTURE DENSITY.

Figure 11. Mixture model density and table of AIC values.

MAXIMUM LIKELIHOOD ESTIMATES

CLASS NO.	PROPORTION	MEAN VALUES
1	.34	149, 26
2	.08	88, 12
3	.16	110, 28
4	.21	102, 42
5	.04	47, 6
6	.01	104, 87
7	.07	103, 35
8	.09	99, 62

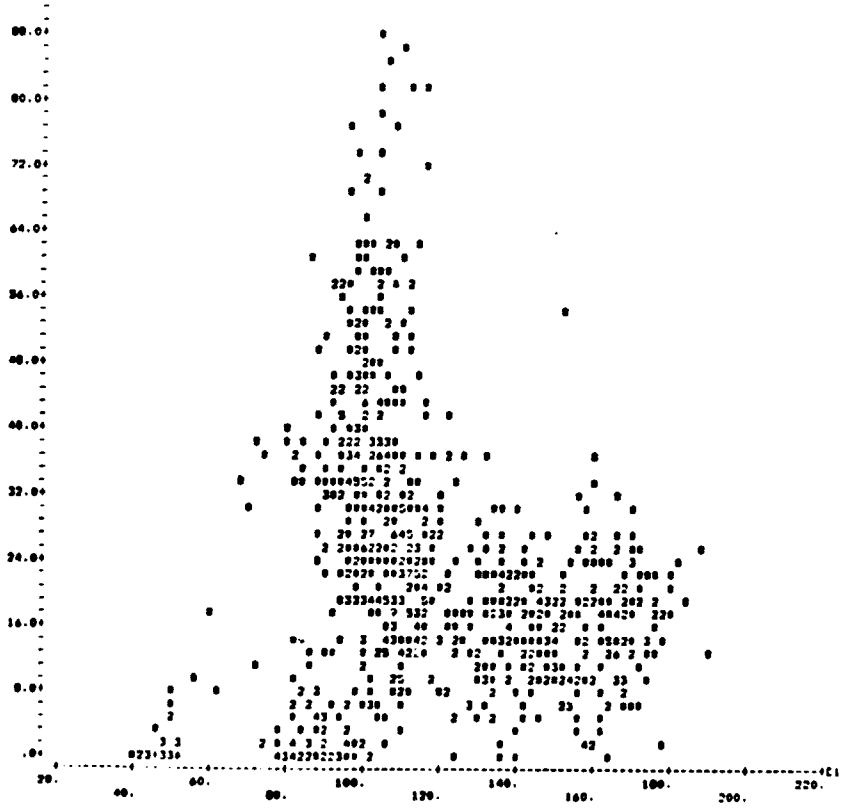


Figure 12. Maximum likelihood estimates with 8 class matter plot.