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THE APPLICATION OF PATTERN RECOGNITION TECHNIQUES TO A REMOTE SENSING PROBLEM [1,2]

by

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Abstract

Pattern recognition techniques are being applied to the analysis of data gathered from a multiband optical mechanical scanner mounted on an aerospace platform. The purpose of the system is to provide automated techniques for making surveys of earth resources such as agricultural crop status, forest inventories, bodies of water, etc. This paper describes techniques used in the research including aspects of categorizer design, feature selection algorithms, and other methods suitable for carrying out research in a high data volume environment.

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2 Presented at the Seventh Symposium on Adaptive Processes, UCLA, Los Angeles, Calif., Dec. 16-18, 1968.

THE APPLICATION OF PATTERN RECOGNITION TECHNIQUES TO A REMOTE SENSING PROBLEM

I. Introduction

Remote sensing technology is concerned with the identification and determination of characteristics of physical objects through the analysis of measurements taken at a distance from these objects. The need for information systems for the field of agriculture and natural resources has been previously developed.[1] One of the major problems in agricultural remote sensing is the characterization and classification of measurements taken from various agricultural situations.[2] This aspect of the problem essentially falls into the general problem of pattern recognition. The spectral, spatial, and temporal variations of energy reflected and absorbed by physical objects are a function of the characteristics of the objects. Particularly, in agricultural situations, remote multispectral sensing is used to detect and record reflected and emitted (electromagnetic radiation) energy from specific target areas in many discrete, relatively narrow spectral bands in several regions of the electromagnetic spectrum. Such bands of electromagnetic radiation may be sensed and recorded using one or a combination of several types of devices, including cameras with diverse film-filter combinations, scanning radiometers with data stored on magnetic tapes, and microwave radiometric methods including radar systems. A particularly useful set of these bands lie between 0.3 and 14 microns wavelength. Based on the multispectral data, the problem now is to characterize and classify the data into categories useful from the agricultural viewpoint.

II. Data Collection and Preprocessing

The data used in the following discussion were measured and recorded from aircraft flights at 1500 to 7500 ft.* Scanning radiometers were used to obtain relative measurements of the energy reflected from the ground in twelve different wavelength bands as follows: 0.40-0.44 μ, 0.44-0.46 μ, 0.46-0.48 μ, 0.48-0.50 μ, 0.50-0.52 μ, 0.52-0.55 μ, 0.55-0.58 μ, 0.58-0.62 μ, 0.62-0.66 μ, 0.66-0.72 μ, 0.72-0.80 μ, and 0.80-1.0 μ. The last two wavelength bands are in the reflective infrared portion of the spectrum; the other bands encompass the visible wavelengths. These twelve measurements are recorded on a twelve-channel magnetic tape, and they constitute the basic twelve feature measurements for classification purposes. The recorded twelve-channel data are first digitized for the purpose of digital processing. Techniques have been developed to calibrate, format and edit the data so that it is conveniently available to the researcher.[3]

The statistical properties of the twelve-dimensional feature measurement vectors or samples for each pattern class (each kind of crop or ground cover, in this case) were investigated. Ground truth information was provided initially for the (training) samples used to estimate the statistical characteristics for each class. Univariate histograms were compiled for each class. It was noted that, in most cases, the histograms were unimodal in shape. It seemed reasonable, during the initial phase of study, to approximate the conditional probability density functions of the feature measurements for each class by multivariate gaussian density functions. The mean vectors

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* The airborne scanning equipments used in this research were made available by the U.S. Army Electronics Command on a no-cost basis to the University of Michigan who operated it. The flights were funded by USDA and flown to Purdue specifications. The details concerned with instrumentation are beyond the scope of this paper.

and covariance matrices for each class were estimated by the sample means and the sample covariances calculated from training samples. Bimodal density functions may usually be delt with by hypothesizing them to be a mixture of two gaussian density functions in which each mode is represented by a gaussian subclass. In addition to the data itself, ground truth information such as different planting dates for a given crop type very frequently suggests the validity of this assumption. Thus, the assumption of gaussianly distributed feature measurements is still a reasonably good approximation if the subclasses can be appropriately selected. Typical histograms for soybeans and wheat are shown in Fig. 1 and Fig. 2, respectively.

From the gaussian assumption, the following mathematical formulation can be made. For m pattern classes (e.g., m kinds of agricultural crops) $\omega_1, \omega_2, --- \omega_m$, the feature measurement vectors, X, for each class are distributed according to a multivariate gaussian density function, i.e.,

$$p(X/\omega_i) = \frac{1}{(2\pi)^{N/2}|K_i|^{1/2}} \exp\left[-\frac{1}{2}(X-M_i)^T K_i^{-1}(X-M_i)\right]$$

$$i = 1, --- m \qquad (1)$$

where X is an N-dimensional vector (N = 12), M_i and K_i are the mean vector and covariance matrix for the i^{th} class, ω_i, respectively. Based on the above formulation, the classification task can be easily performed by applying the maximum liklihood classification rule[4,5] (or the Bayes decision rule with (0,1) loss function).

III. Feature Selection

It was found that excessive computation time was required for classification purposes if all twelve feature measurements were used. Furthermore, it is always desirable to know the relative importance of these measurements from the classification viewpoint. These considerations suggest the study of feature selection, the selection of subsets of feature measurements from the complete set. Divergence has been suggested as a feature selection criterion in two-class classification problems with gaussianly distributed patterns.[6] For multiclass cases, the criterion of maximizing the minimum of pairwise divergence and maximizing the expected divergence have been proposed.[4,7,8] A direct generalization of the divergence criterion to multiclass problems with unequal covariance matrices using minimax linear discriminants has been investigated and applied to crop classification problems.[9,10] In the following, the approach is briefly described. Typical test results are given in Section VI to illustrate its applicability.

Consider that, in a multiclass classification problem, the classification performance can be measured in terms of a weighted sum of all pairwise misclassifications, i.e.,

$$P(e) = \frac{2}{m(m-1)} \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} P_{ij}(e) \qquad (2)$$

where $P(e)$ is the overall performance measure and $P_{ij}(e)$ is the pairwise probability of misclassification for classes ω_i and ω_j. Let $g_i(X)$ be the discriminant function of class ω_i, $i=1,\ldots,m$, then

$$P_{ij}(e) = \Pr\{g_i(X) > g_j(X) \mid \omega_j\} + \Pr\{g_i(X) < g_j(X) \mid \omega_i\} \qquad (3)$$

Suppose that a family of linear discriminant functions is chosen for $g_i(X)$:

$$g_i(X) = B_i^T X - c_i \,, \quad i = 1, \ldots, m \tag{4}$$

where B_i is an N-dimensional vector and c_i is a constant. Let $g_i(X) - g_j(X) = (B_i - B_j)^T X - (c_i - c_j) = B_{ij}^T X - c_{ij}$; then (3) becomes

$$P_{ij}(e) = \Pr\{B_{ij}^T X > c_{ij} | \omega_j\} + \Pr\{B_{ij}^T X < c_{ij} | \omega_i\} \tag{5}$$

After defining a standardized variable, refer to Anderson and Bahadue[11], (5) can be written as

$$P_{ij}(e) = 2 - \Pr\{\xi < d_j\} - \Pr\{\xi < d_i\} \tag{6}$$

where

$$d_i = \frac{B_{ij}^T M_i - c_{ij}}{(B_{ij}^T K_i B_{ij})^{1/2}} \tag{7}$$

and

$$d_j = \frac{c_{ij} - B_{ij}^T M_j}{(B_{ij}^T K_j B_{ij})^{1/2}} \tag{8}$$

ξ is the standardized gaussian random variable. Since, for linear classification procedures, the minimax procedure is admissible,[11] it is used here to determine an appropriate criterion for feature selection in multiclass classification problems. From (2) and (6), the condition of minimizing the maximum of P(e) is

$$d_i = d_j = d_{ij} \tag{9}$$

Then it follows from (7), (8) and (9) that

$$d_{ij} = \frac{B_{ij}^T(M_i - M_j)}{(B_{ij}^T K_i B_{ij})^{1/2} + (B_{ij}^T K_j B_{ij})^{1/2}} \tag{10}$$

The value of B_{ij}, which maximizes d_{ij} is of the form

$$B_{ij} = [\lambda_{ij} K_i + (1 - \lambda_{ij}) K_j]^{-1} (M_i - M_j) \tag{11}$$

where λ_{ij} is a Lagrange multiplier which can be calculated by solving the equation

$$B_{ij}^T [\lambda_{ij}^2 K_i - (1 - \lambda_{ij})^2 K_j] B_{ij} = 0 \tag{12}$$

with $0 < \lambda_{ij} < 1$. Finally, (6) becomes

$$P_{ij}^*(e) = 2[1 - \Pr\{\varepsilon < d_{ij}\}] \tag{13}$$

It is noted from, (13) that a monotonic functional relationship exists between $P_{ij}^*(e)$ and d_{ij}. The quantity d_{ij} is a measure of separability between class ω_i and class ω_j. In the case $K_i = K_j$, the equal covariance matrix case, this separability measure becomes equivalent to the divergence criteria.

Based on the separability measure d_{ij}, it is proposed that the feature selection criterion is to maximize the expected separability measure for all pairs of classes, i.e.,

$$\operatorname{Max} \left\{ \sum_{i=1}^{m} \sum_{j=i+1}^{m} d_{ij}\, P(\omega_i) P(\omega_j) \right\}$$

If there are several feature subsets satisfying the above criterion, the subset which minimizes the maximum variance of the separability measure for all pairs of classes is selected.

IV. Classification

As noted in Section II, the maximum liklihood classification rule (or Bayes decision rule with (0,1) loss function) is used for the classification task. Assuming equal a priori class probabilities with the gaussian assumption given in (1), the discriminant function corresponding to the maximum liklihood classification rule is[5]

$$g_i(X) = \log P(\omega_i) - \frac{N}{2}\log 2\pi - \frac{1}{2}\log|K_i|$$

$$- \frac{1}{2}[(X - M_i)^T K_i^{-1}(X - M_i)],\ i = 1, \ldots, m \tag{14}$$

Or, by removing terms constant over i,

$$g_i(X) = -\frac{1}{2}\log|K_i| - \frac{1}{2}[(X - M_i)^T K_i^{-1}(X - M_i)],$$

$$i = 1, \ldots, m \tag{15}$$

The classification rule is then reduced to the following: Classify X as belonging to class ω_i if

$$\log|K_i| + (X - M_i)^T K_i^{-1}(X - M_i) \leq \log|K_j|$$

$$+ (X - M_j)^T K_j^{-1}(X - M_j)$$

$$\text{for all } j \neq i \tag{16}$$

However, for the agricultural problem the total number of possible pattern classes is very difficult to determine beforehand. Some of the input samples may not belong to any of the m pre-determined classes (for example, roads, farmsteads, etc.). One possible way in which such samples could be treated is to establish a separate class (the (m + 1)th class ω_{m+1}) for "everything else". Unfortunately, it is usually rather difficult to obtain representative samples from this class for training. A more practical approach is to form a rejection class by not classifying a sample into any of the m classes if the value of the discriminant function computed from this sample is less than some threshold value. Mathematically then, a sample X is classified as from class ω_i if

$$\text{(i)} \qquad g_i(X) > g_j(X) \quad \text{for all } j \neq i \tag{17}$$

and

$$\text{(ii)} \qquad g_i(X) \geq T_i \tag{18}$$

where T_i is the threshold for the class ω_i.

The setting of an appropriate threshold depends on the criterion used. One useful criterion is to set the threshold so that most of the known samples fall into the correct classes, i.e. are not affected by the threshold. For the case considered, from (16), a sample X is rejected from class ω_i if

$$\log|K_i| + (X - M_i)^T K_i^{-1}(X - M_i) > T_i' \tag{19}$$

The quantity $(X - M_i)^T K_i^{-1}(X - M_i)$ has a chi square distribution $C_N(\chi^2)$ of N degrees of freedom. Therefore, for a given threshold setting, the percentage of samples from class ω_i being rejected can be determined from the percentage tabulation of the chi square distribution. For example, if it is desired that at least 95% of four-feature sample vectors from class ω_i not be rejected by the threshold setting T_i', then the threshold should be chosen by the rule

$$T_i' \geq \log|K_i| + \{\chi^2 \text{ for which } C_4(\chi^2) = 0.95\} \quad (20)$$

or

$$T_i' \geq \log|K_i| + 9.49 \quad (21)$$

V. Implementation of the System

The implementation of the characterization and classification processes described in previous sections is carried out on an IBM 360/44 system. For research purposes, it is necessary to have at hand an efficient and flexible system of computer programs for performing the statistical analysis, feature selection and classification processes. This system of computer programs is briefly described in the following.[12] An important feature of the system is the considerable degree of user-computer interaction through which is achieved the flexibility required by the research environment.

Fig. 3 shows a block diagram of the overall data flow for the system LARSYS (Laboratory for Agricultural Remote Sensing Data Processing System). The principal data input is the multispectral (twelve-channel) data. The Aircraft Data Handling Processor (LARSYSAH) prepares the data for use by the researcher. The data are digitized, calibrated and recorded on digital tape in a packed format (to reduce the physical volume). To make the data reedily accessible to the user, line-sample coordinates (much like x-y coordinates) are added during the process of digitization, and a special computer subroutine is used to read any desired area of data, specified by a set of line-sample coordinates, into core memory and transfer it to the user's program in unpacked form. Also available as part of LARSYSAH is a program which prints grey-level displays of selected data on a computer line printer. These displays, which are similar to black and white photographs of the ground areas over which the data were collected, are useful in coordinating the ground truth information with the multispectral scanner data.

The other form of data utlilized is ground truth information, which is collected on film and in the form of detailed written field reports. This information, including crop species, crop varieties, soil types, percentage of ground cover, etc., is cataloged and made available in convenient form by the Ground Truth Processor (LARSYSGT).

The Aircraft Data Analysis and Classifier Design System (LARSYSAA) is the major portion of the implemented system. Fig. 4 shows the control structure of the LARSYSAA system, which is composed of a monitor and four distinct processors. Each processor is directed by its own supervisor. The multiphase structure results largely from the need to minimize the amount of core memory occupied at any one time by program instructions in order to maximize the amount of memory available for data. In fact, for the same reason the individual processors are also decomposed into multiple phases which are only called into core memory by the respective supervisors as needed.

Three major reasons why the user-computer interface has received considerable attention in the development of the overall system are:

1. An optimal design of the overall system requires a substantial amount of interaction between the various phases (statistical analysis, feature selection, training and classification) of the designed system. At the present state-of-the-art, this interaction is best coordinated by the researcher.

2. Remote sensing applications invariably involve huge masses of data. As a result, the quantity of data input, the processing and the output required for a classification task consumes a considerable amount of computer time. It is essential, therefore, that the system be largely immune from user errors, so that errors in the later stages of processing will not result in loss of all the work which has gone before.

3. In the face of the two requirements already noted, the experimental status of the remote sensing problem makes it desirable that most or all of the processing system be written in a high level compiler language so that modifications to the system may be made quickly and easily by the researcher.

FORTRAN IV has been used to satisfy the third requirment (except for a few minor utility functions which can be accomplished most efficiently through use of assembly language). The flexibility of the program is achieved by (a) dynamic storage allocation, (b) inter- and intra-program communication via common storage areas, (c) residence of the source language program on a tape which is easily modified by an editing program, and (d) a self-directed System Construction Program which, one initiated, performs all of the steps necessary to go from source language to operational program. When modifications of the program become desirable, the system structure is such as to allow the changes to be implemented easily with the aid of the System Construction Program. A "conversational mode" of operation which is of particular value in the research environment has been achieved through the development of techniques which optimize man-machine communication and minimize the inefficiencies which usually result from a high level on-line user-computer interaction.

VI Experimental Results

Experiment 1: The classification scheme discussed in Section IV was tested using a nine-class crop classification problem. The nine classes were wheat, oats, corn, soybeans, alfalfa, red clover, rye, bare soil and water. The classification results using all twelve features (spectral bands) are given in Table 1 and Table 2. The training samples were used as test samples for classification (Table 1), but a completely different set of test samples for classification were also used in order to test the classifier's generalization capability, (Table 2). The difference in classification accuracy is probably due to the fact that the training samples used were not completely representative and the number of training samples was inadequate. The computer printout of the test results is shown in Fig. 5. A conventional panchromatic airphoto is shown in Fig. 6. This photo shows (manually added) ground truth to aid in evaluating the classifier's generalization.

Fig. 5 and Fig. 7 viewed together show the effect and usefulness of threshold settings; Fig. 7 shows the classification result of the nine-class, twelve-feature problem with no constraint (i.e., $T_i' = 0$) while the blanks in Fig. 5 (with threshold) indicate the points subsequently rejected by thresholding. These rejected points were from areas such as roads, farmsteads, and areas where the crop or ground cover was poorly developed. Note, for example, the effect of the sand due beginning at the right edge of the printout Fig. 5 at line 201 and running diagonally to the left (southwest) down the printout.

Table 3 and Table 4 shows the classification results corresponding to Table 1 and Table 2 respectively, but with only four features (arbitrarily selected) used. These results illustrate the effect on classification accuracy when a subset of features is used.

Experiment 2: The feature selection algorithm proposed in Section III was tested along with the scheme using the weighted sum of pairwise divergences for a five-class crop classification problem. The five classes of crops were: soybeans, corn, oats, wheat and red clover. The effectiveness of the features selected was tested by computing the percentage of correct classifications from 14,000 test samples using the maximum-liklihood classification rule. The results of this feature selection experiment are shown in Fig. 8, Table 5 and Table 6.

The solid line in Fig. 8 indicates the result using the proposed procedure, i.e., the features were selected using the criterion of maximizing the expected separability measure d_{ij}. The dotted line shows the result using the criterion of maximizing the expected divergence over all pairs of classes. The dashed line was obtained by selecting features directly on the basis of their contributions to the classification accuracy. In all three cases, the maximum liklihood classification rule was used for the classifier.

It is noted from the test results that it is possible for subsets of features to result in better classification performance than that produced by the complete set of features. This is probably mainly due to the deviation of the actual feature distributions from the assumed gaussian distribution and the error involved in the estimation of parameters*. Similar results on other forms of data have been obtained also by Estes,[13] Allais[14] and Hughes.[15]

* The mean vectors and covariance matrices were estimated from 400 training samples per class.

VII. Conclusions and Further Remarks

The applicability of pattern recognition techniques to agricultural remote sensing problems has been demonstrated in this paper. Preliminary studies have shown quite satisfactory results. Several problems which need immediate attentions are:

1. To develop nonparametric techniques for feature selection and classification to compare against the gaussian assumption originally used.[16,17]

2. To apply advanced techniques to the analysis of data so that more information can be obtained about the statistical structure of the multispectral data.

3. To develop mode estimation techniques so that the total number of pattern classes for a given classification task can be more accurately determined.[18]

More basic problems such as the study of the effectiveness of using measurements other than twelve-feature multispectral data should also be considered.

A digital display will be added to the present computer system so that the data editing procedure can be much faster than the printout technique presently in use. It will also be useful for studying other problems in man-data communication. Among these are included such questions as the spatial, spectral, and gray scale resolutions required for contrast enhancement schemes necessary when manual image interpretation techniques must be used in conjunction with pattern recognition techniques.

References

1. R. B. MacDonald and D. Landgrebe, "Remote Sensing for Agriculture and Natural Resources from Space", Proceeding of the 1967 National Symposium of the American Astronautical Society, Huntsville, Alabama, June 1967.

2. "Remote Multispectral Sensing in Agriculture", Vol. No. 1, No. 2, and No. 3, The Laboratory for Agricultural Remote Sensing, Purdue University, Lafayette, Indiana.

3. D. Landgrebe and T. Phillips, "A Multichannel Image Data Handling System for Agricultural Remote Sensing", Society of Photo Optical Instrumentation Engineers, Proceeding of the Seminar on Computerized Image Handling Techniques, Washington, D.C., June 26-27, 1967.

4. K.S. Fu, Sequential Methods in Pattern Recognition and Machine Learning, Academic Press, 1968.

5. N.J. Nilsson, Learning Machines, McGraw-Hill, 1965.

6. T. Marill and D.M. Green, "On the Effectiveness of Receptor in Recognition Systems", IEEE Transactions on Information Theory, Vol. IT-9, No. 1, pp. 11-17, 1963.

7. T.L. Grettenberg, "Signal Selection in Communication and Radar System", IEEE Transactions on Information Theory, Vol. IT-9, No. 4, pp. 265-275, 1963.

8. K.S. Fu and C.H. Chen, "Sequential Decisions, Pattern Recognition and Machine Learning", Technical Report TR-EE65-6, School of Electrical Engineering, Purdue University, April 1965.

9. P.J. Min, D.A. Landgrebe and K.S. Fu, "On Feature Selection in Multiclass Pattern Recognition", Proc. Second Annual Princeton Conference on Information Sciences and Systems, pp. 453-457, 1968.

10. P.J. Min, "On Feature Selection in Multiclass Pattern Recognition", Ph.D. Thesis, Purdue University, January 1969, LARS Information Note 080568, L-A-R-S, August 1968; TR-EE68-17.

11. T.W. Anderson and R.R. Bahadue, "Classification into Two Multivariate Normal Distributions with Different Covariance Matrices", Ann. Math. Stat., Vol. 33, No. 2, pp. 420-431, 1962.

12. P.H. Swain and D.A. Germann, "On the Application of Man-Machine Computing Systems to Problems in Remote Sensing", Proc. Eleventh Midwest Symposium on Circuit Theory, May 13-14, 1968, Notre Dame, Indiana; see also Software Age, Vol. 2, pp. 13-20, August 1968.

13. S.E. Estes, "Measurement Selection for Linear Discriminants Used in Pattern Classification", IBM Research Report RJ-331, San Jose, April 1965.

14. D.C. Allais, "The Selection of Measurements for Prediction", Tech. Report No. 6103-9, Stanford Electronics Laboratory, November 1964.

15. G.F. Hughes, "On the Mean Accuracy of Statistical Pattern Recognizers", IEEE Transactions on Information Theory, Vol. IT-14, No. 1, pp. 55-62, 1968.

16. R.R. Lemke and K.S. Fu, "On the Application of the Potential Function Method to Pattern Classification and System Identification", Proc. 1968, National Electronics Conference.

17. P.H. Swain and K.S. Fu, "On the Application of a Nonparametric Technique to Crop Classification Problems", Proc. 1968, National Electronics Conference.

18. E.G. Henrichon and K.S. Fu, "On Mode Estimation in Pattern Recognition", Proc. Seventh Symposium on Adaptive Processes, December 16-18, 1968, Los Angeles, California.

CAPTIONS

Figure 1. Example Histograms of Three Features From a Unimodal Class.

Figure 2. Example Histograms of Three Features From a Bimodal Class.

Figure 3. Block Diagram of Data Flown in LARSYS.

Figure 4. Block Diagram Showing Control Structure of LARSYSAA.

Figure 5. A Printout in Map Form of Classification Results. The symbols and their corresponding classes are as follows: O-Oats, S-Soybeans, R-Red Clover, C-Corn, Y-Rye, A-Alfalfa, I-Water, and X-Bare Soil. The outlined fields are those used for Table 2.

Figure 6. Conventional Panchromatic Airphoto of the Area Shown in Figure 5 and Showing the Correct Ground Truth.

Figure 7. A Printout of 12-feature Classification Results Without Thresholding. The outlined areas are the samples used for training.

Figure 8. Results of the Feature Selection Experiment.

Table 1. Quantitative Tabulation of Classification Results for Training Samples Used in Experiment 1. See Areas Outlined in Figure 7.

Table 2. Quantitative Tabulation of Classification Results for Test Samples Outlined in Figure 5.

Table 3. Quantitative Tabulation of 4-feature Classification Results for Training Samples.

Table 4. Quantitative Tabulation of 4-feature Classification Results of Test Samples.

Table 5. Quantitative Tabulation of 3-feature Classification Results for Experiment 2.

Table 6. Quantitative Tabulation of 12-feature Classification Results for Experiment 2.

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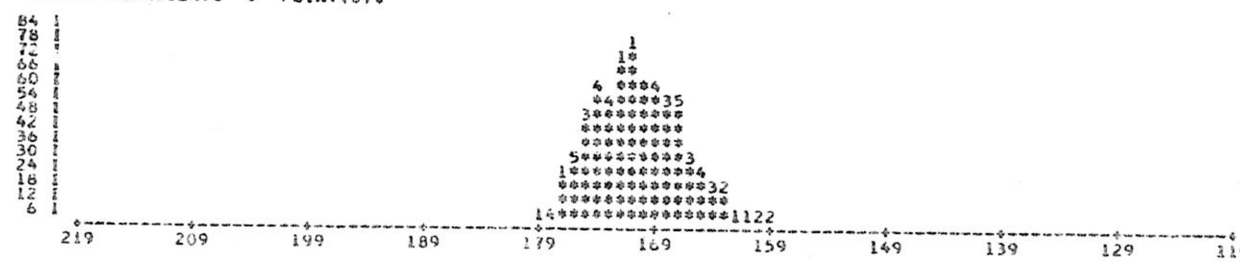
SOYBEANS

HISTOGRAM FOR ... SOYBEANS

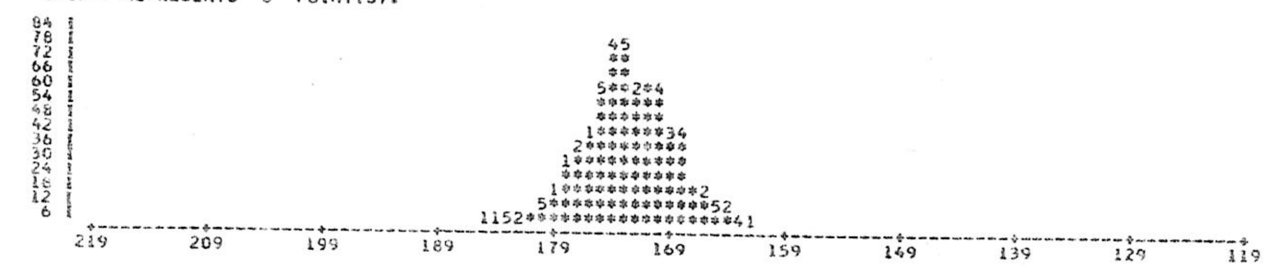
CHANNEL 10 0.66 - 0.72 MICRONS

EACH * REPRESENTS 6 POINT(S).



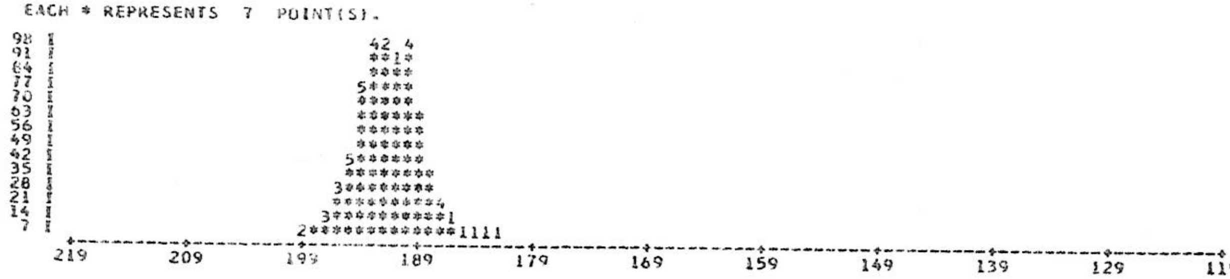
CHANNEL 11 0.72 - 0.80 MICRONS

EACH * REPRESENTS 6 POINT(S).



CHANNEL 12 0.80 - 1.00 MICRONS

EACH * REPRESENTS 7 POINT(S).



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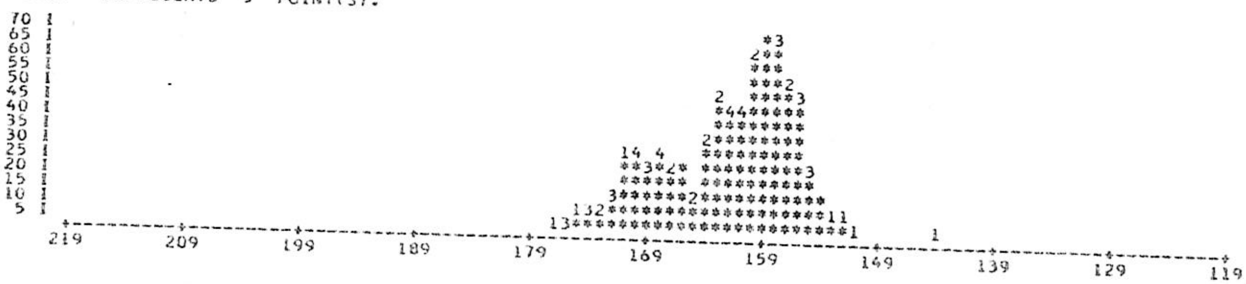
WHEAT

HISTOGRAM FOR ... WHEAT

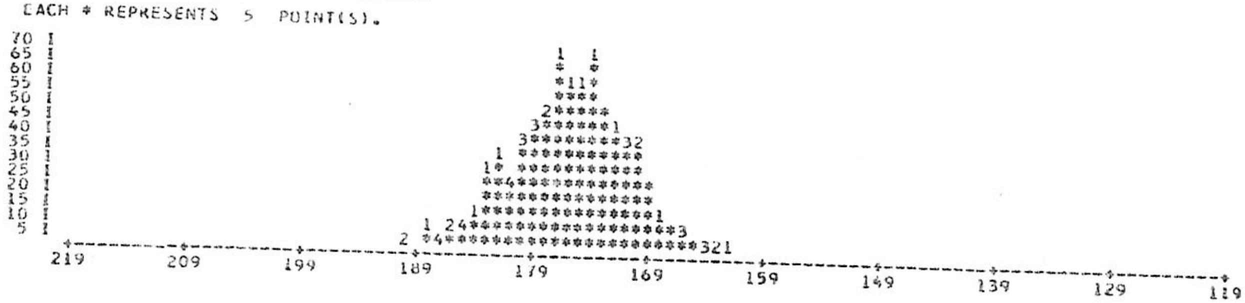
CHANNEL 10 0.66 - 0.72 MICRONS

EACH * REPRESENTS 5 POINT(S).



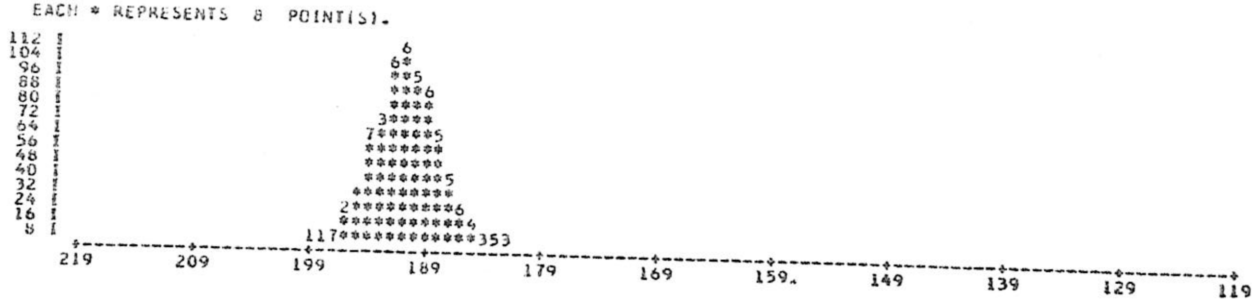
CHANNEL 11 0.72 - 0.80 MICRONS

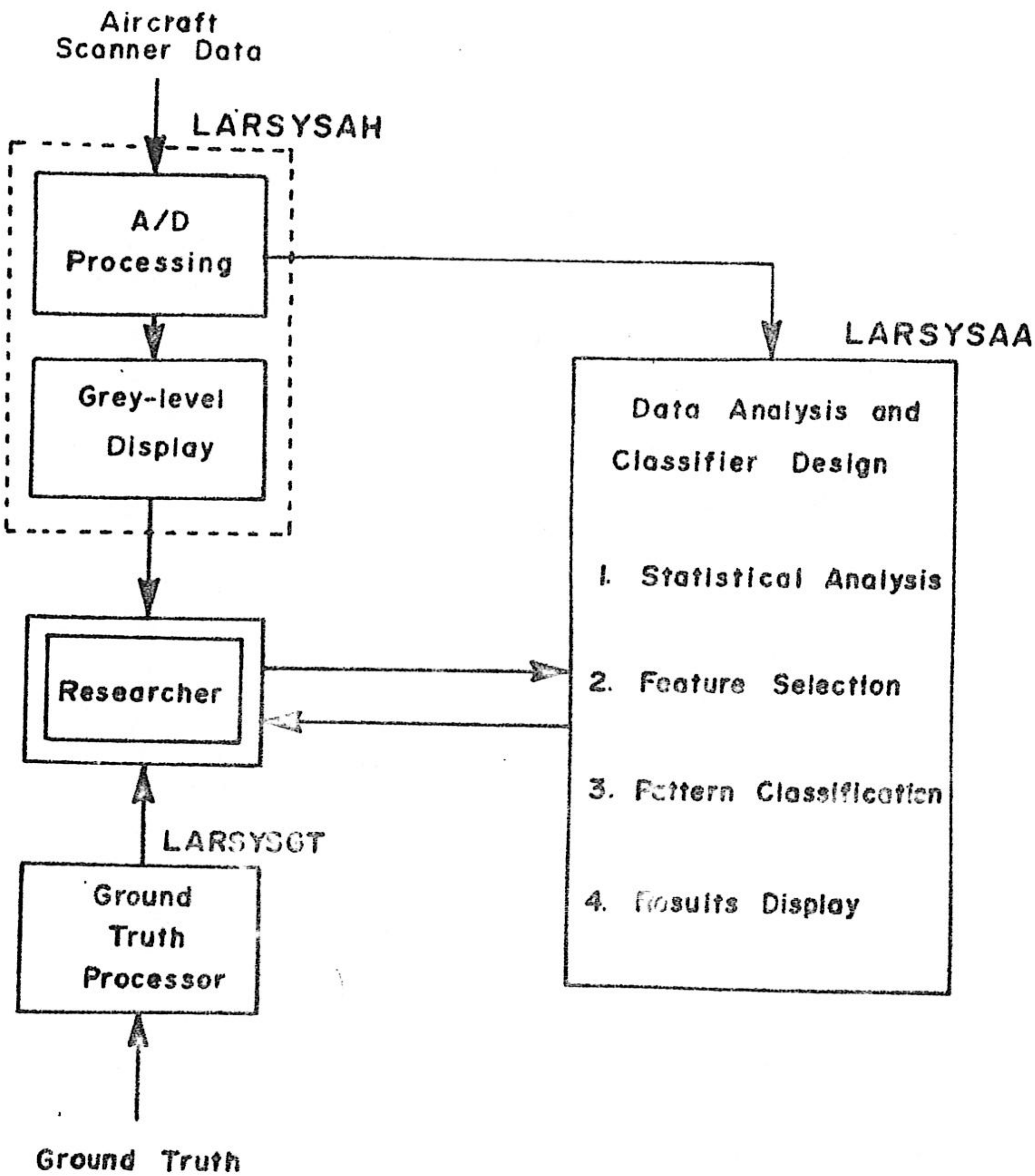
EACH * REPRESENTS 5 POINT(S).

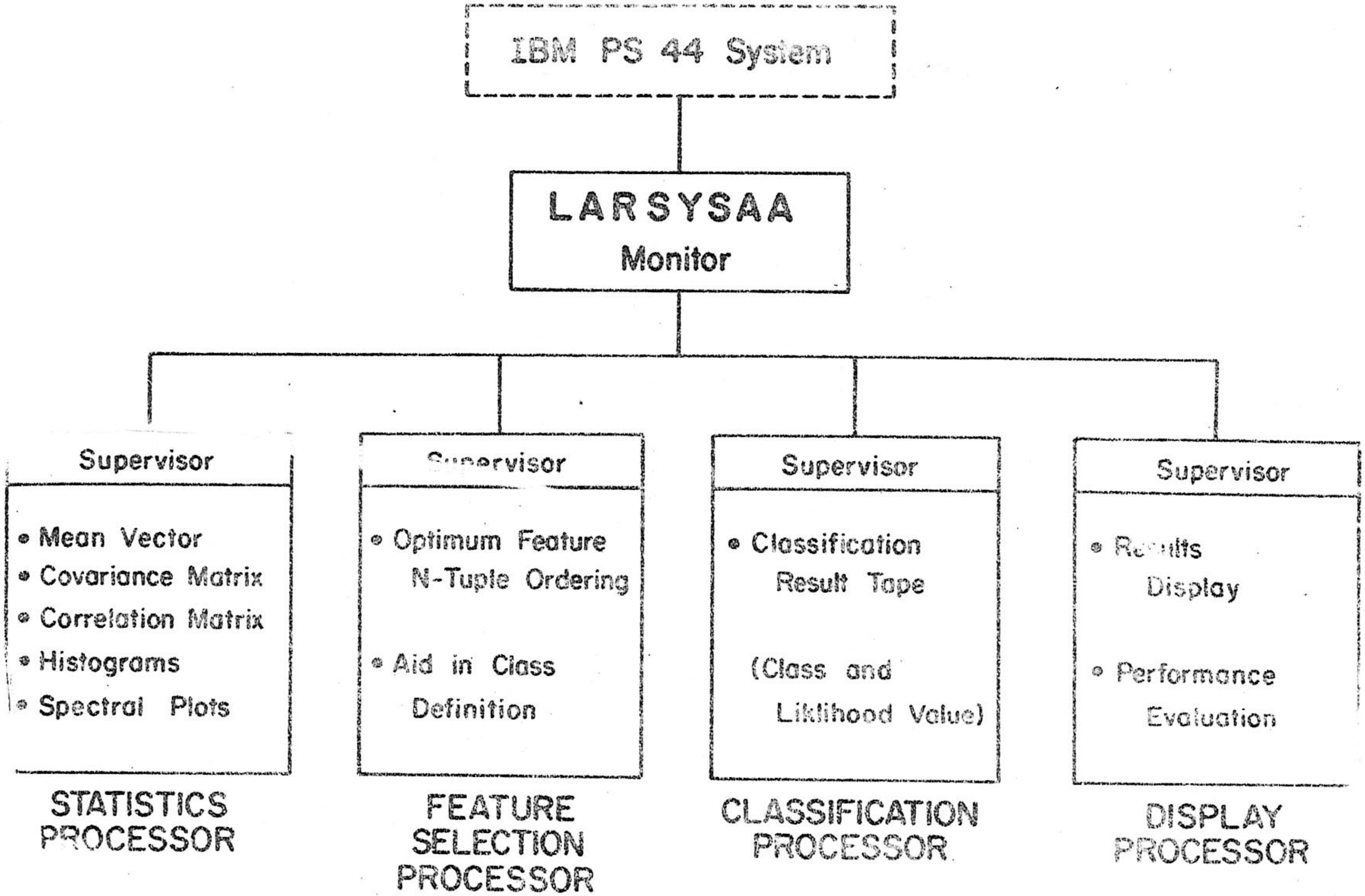


CHANNEL 12 0.80 - 1.00 MICRONS

EACH * REPRESENTS 8 POINT(S).




Aircraft Scanner Data
LARSYSAH
A/D Processing
Grey-level Display
Researcher
LARSYSGT
Ground Truth Processor
Ground Truth
LARSYSAA
Data Analysis and Classifier Design
1. Statistical Analysis
2. Feature Selection
3. Pattern Classification
4. Results Display


IBM PS 44 System
LARSYSAA
Monitor
Supervisor
• Mean Vector
• Covariance Matrix
• Correlation Matrix
• Histograms
• Spectral Plots
STATISTICS PROCESSOR
Supervisor
• Optimum Feature N-Tuple Ordering
• Aid in Class Definition
FEATURE SELECTION PROCESSOR
Supervisor
• Classification Result Tape
(Class and Liklihood Value)
CLASSIFICATION PROCESSOR
Supervisor
• Results Display
• Performance Evaluation
DISPLAY PROCESSOR

LARS / PURDUE

SERIAL NUMBER [illegible]   DATE OF CLASSIFICATION [illegible]

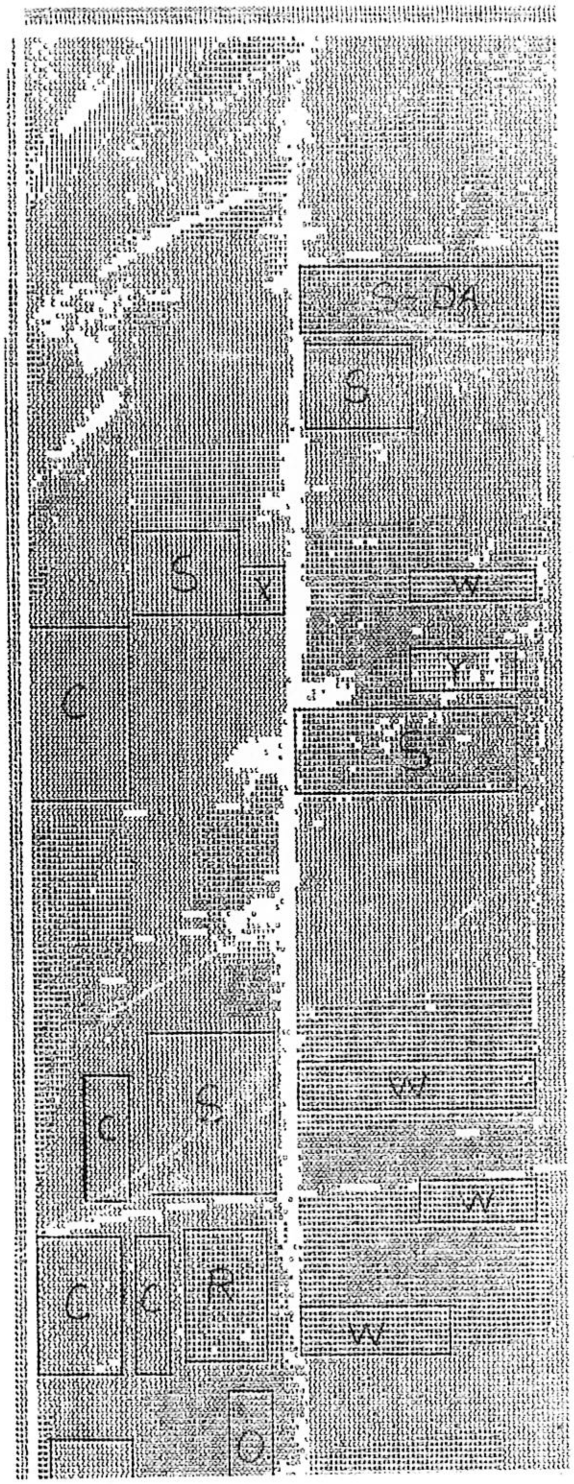
RUN NUMBER-----[illegible]   DATE------ [illegible]

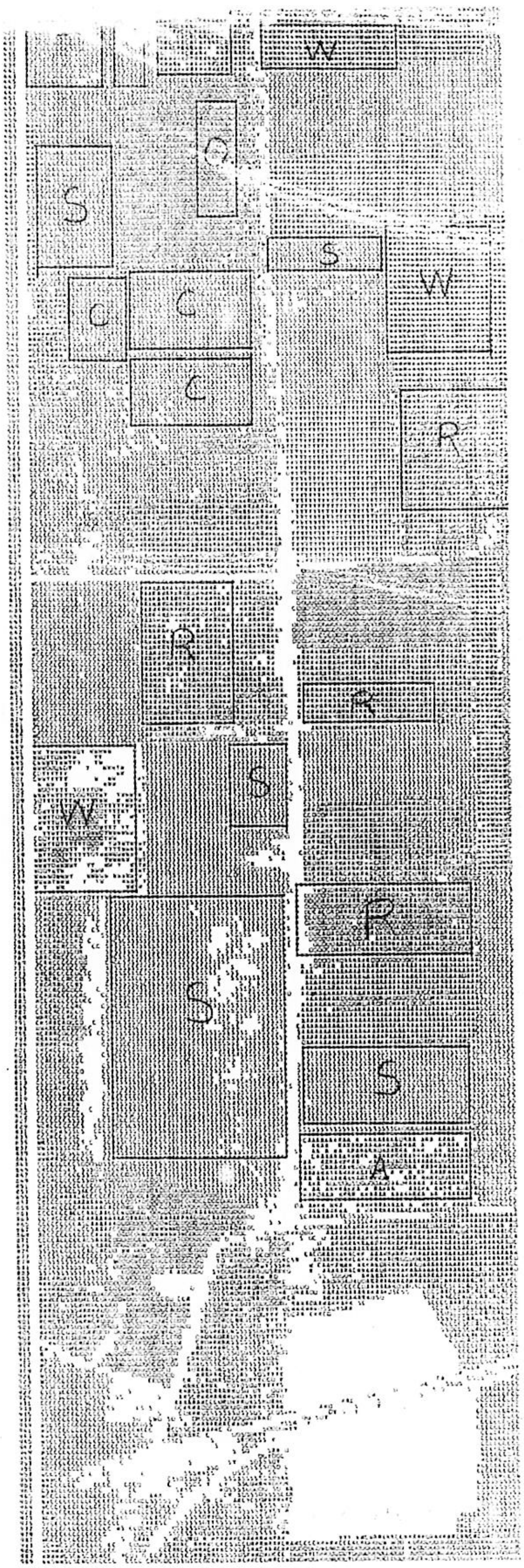
FLIGHT LINE----- [illegible]   TIME--------[illegible]

TAPE NUMBER----- [illegible]

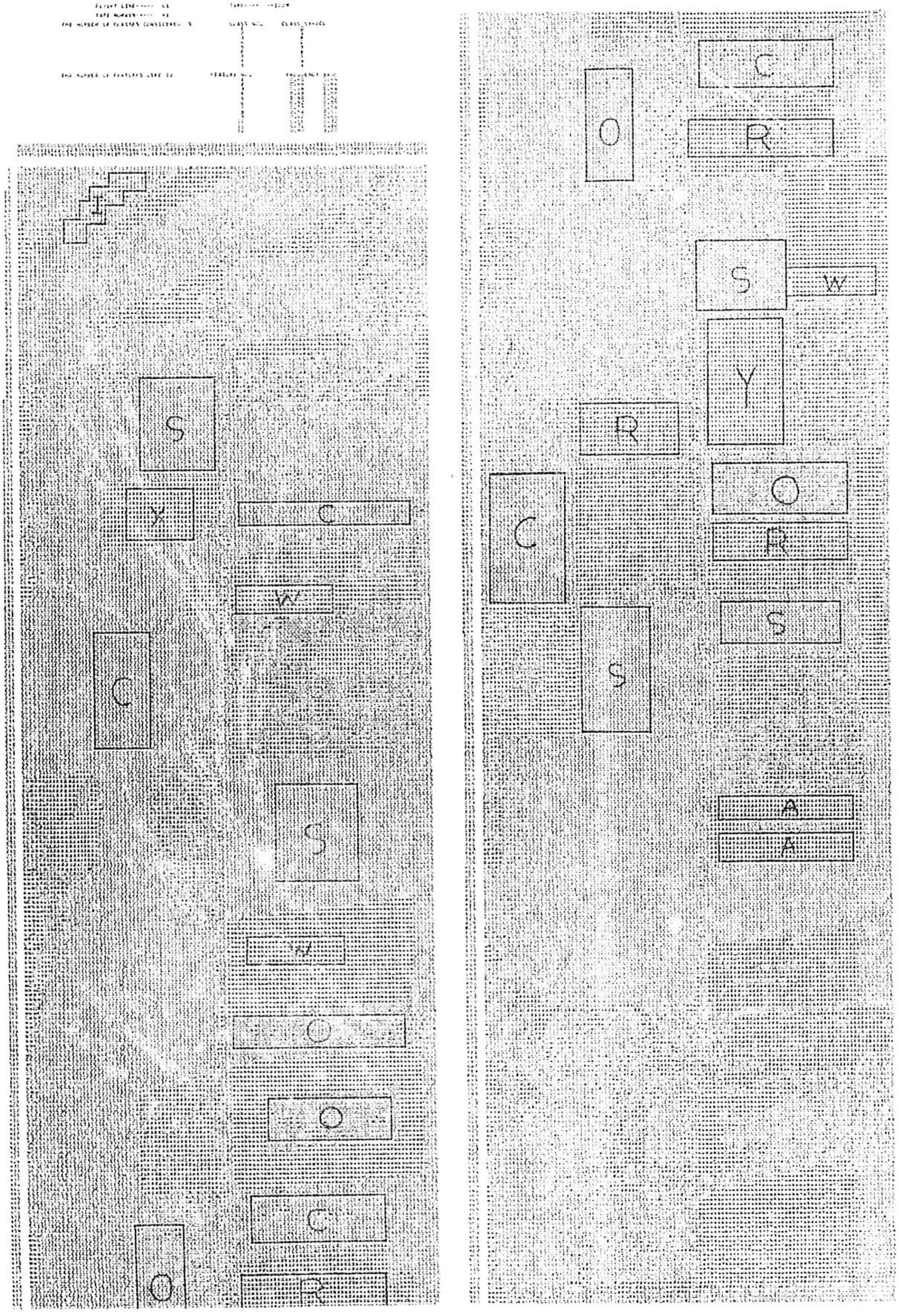
THE NUMBER OF CLASSES CONSIDERED 9   CLASS NO.   CLASS SYMBOL   THRESHOLD

THE NUMBER OF FEATURES USED 12   FEATURE NO.   FREQUENCY BAND





C-1
C-2
DA-S
DA.-B.S.
BS
DA-R
H-A
H-A.
DA-O
R.C.-T
DA-O
DA.-R
P-O
DA.-T
P-A-R.C.
H-A
H-A
DA RC
H RC
Woods


S
X
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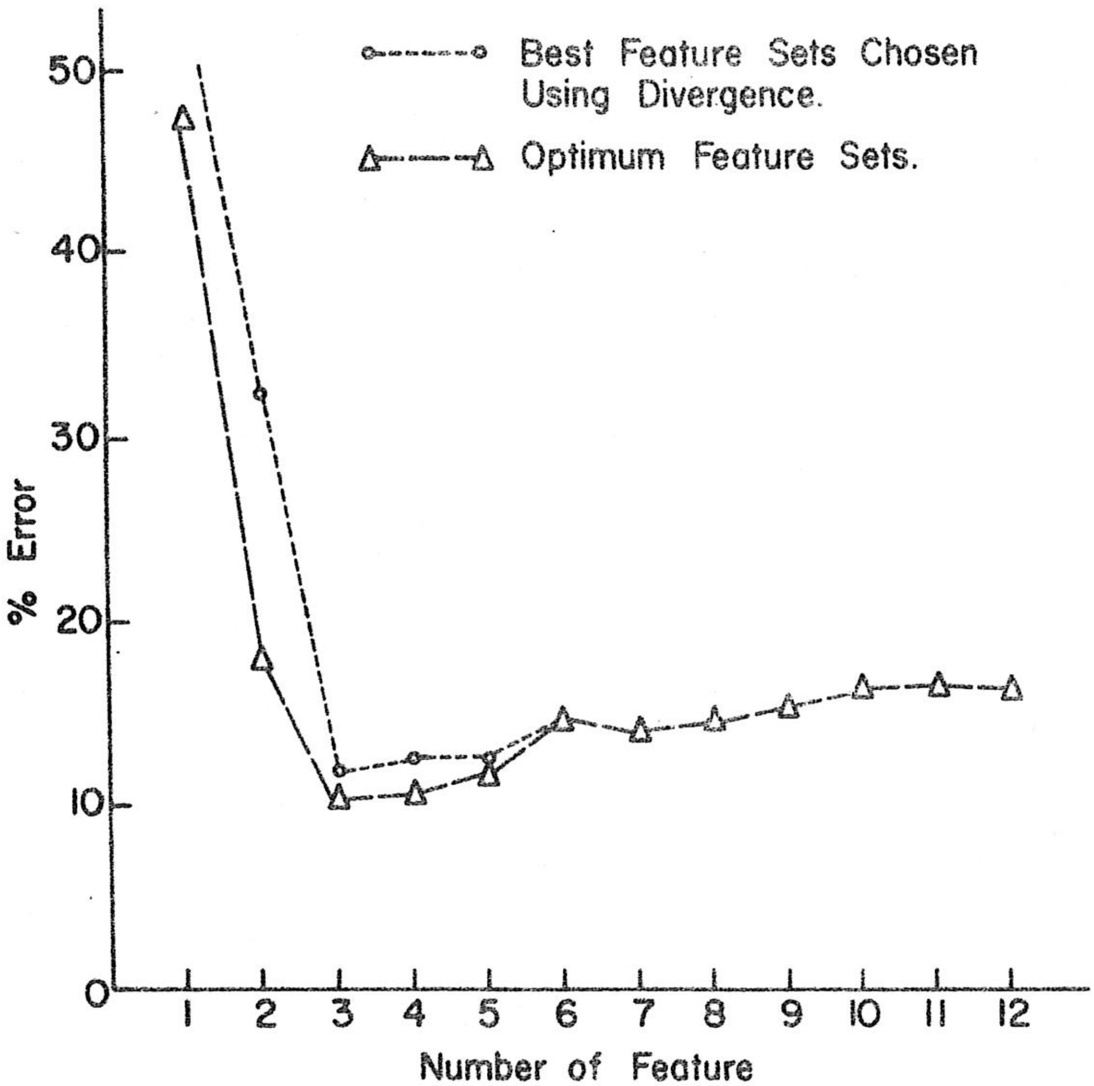

Best Feature Sets Chosen Using Divergence.
Optimum Feature Sets.
50
40
30
20
10
0
% Error
1
2
3
4
5
6
7
8
9
10
11
12
Number of Feature

LABORATORY FOR AGRICULTURAL REMOTE SENSING
PURDUE UNIVERSITY

CLASSIFICATION STUDY SERIAL NO. 10 DATE OF CLASSIFICATION July 8, 1967

RUN NUMBER——26600060 DATE—— 6/28/66

FLIGHT LINE—— C1 TIME——1229

TAPE NUMBER—— 41 ALTITUDE— 2600 FEET

CLASSES CONSIDERED

SYMBOL	CLASS	THRESHOLD
O	OATS	-50.45
S	SOYBEANS	-49.52
R	RED CL	-49.99
C	CORN	-50.53
Y	RYE	-48.65
A	ALFALFA	-49.17
I	WATER	-44.98
W	WHEAT	-51.09
X	BARE SOIL	-46.47

FEATURES CONSIDERED

FEATURE NO.	SPECTRAL BAND (MICRONS)	
1	0.40	0.44
2	0.44	0.46
3	0.46	0.48
4	0.48	0.50
5	0.50	0.52
6	0.52	0.55
7	0.55	0.58
8	0.58	0.62
9	0.62	0.66
10	0.66	0.72
11	0.72	0.80
12	0.80	1.00

CLASSIFICATION SUMMARY BY TEST CLASSES

			NO OF SAMPLES CLASSIFIED INTO									
CLASS	PCT. CORCT	NO OF SAMPS	O	S	R	C	Y	A	I	W	X	THRESH
OATS	92.9	1152	1070	1	32	11	0	0	0	38	0	0
SOYB	99.0	1819	5	1800	0	13	0	1	0	0	0	0
RED	96.9	771	15	0	747	3	0	6	0	0	0	0
CORN	94.3	1344	12	43	16	1267	0	1	0	0	0	5
RYE	99.8	494	1	0	0	0	493	0	0	0	0	0
ALFA	96.5	315	2	1	6	0	0	304	0	0	0	2
WATE	100.0	95	0	0	0	0	0	0	95	0	0	0
WHEA	94.2	365	19	1	0	0	1	0	0	344	0	0
BR S	100.0	170	0	0	0	0	0	0	0	0	170	0
TOTAL	97.1	6525	1124	1846	801	1294	494	312	95	382	170	7

LABORATORY FOR AGRICULTURAL REMOTE SENSING
PURDUE UNIVERSITY

CLASSIFICATION STUDY . . SERIAL NO. 10 DATE OF CLASSIFICATION July 8, 1967

RUN NUMBER——26600060
FLIGHT LINE—— C1
TAPE NUMBER—— 41

DATE——— 6/28/66
TIME——— [illegible]229
ALTITUDE— [illegible] FEET

CLASSES CONSIDERED

SYMBOL	CLASS	THRESHOLD
O	OATS	-50.45
S	SOYBEANS	-49.52
R	RED CL	-49.99
C	CORN	-50.53
Y	RYE	-48.65
A	ALFALFA	-49.17
I	WATER	-44.98
W	WHEAT	-51.09
X	BARE SOIL	-46.47

FEATURES CONSIDERED

FEATURE NO.	SPECTRAL BAND (MICRONS)	
1	0.40	0.44
2	[illegible]	0.46
3	[illegible]	0.48
4	[illegible]	0.50
5	[illegible]	0.52
6	0.52	0.55
7	0.55	0.58
8	0.58	0.62
9	0.62	0.66
10	0.66	0.72
11	0.72	[illegible].80
12	0.80	[illegible].00

CLASSIFICATION SUMMARY BY TEST CLASSES

CLASS	PCT. CORCT	NO OF SAMPS	NO OF SAMPLES CLASSIFIED INTO O	S	R	C	Y	A	I	W	X	THRESH
OATS	95.0	160	152	0	3	2	0	0	0	2	0	1
SOYB	69.9	5214	261	3644	380	662	1	84	0	1	15	166
RED	70.1	1982	294	3	1390	[illegible]	1	140	0	4	0	49
CORN	65.5	2020	19	662	2	1324	2	0	0	0	0	11
RYE	66.7	126	15	6	0	0	84	0	0	2	0	19
ALFA	51.7	418	35	3	99	3	0	216	0	0	0	62
WHEA	76.6	1888	85	1	0	8	175	0	0	1446	0	173
BR S	100.0	56	0	0	0	0	0	0	0	0	56	0
TOTAL	74.4	11864	861	4319	1874	2100	263	440	0	1455	71	481

LABORATORY FOR AGRICULTURAL REMOTE SENSING
PURDUE UNIVERSITY

CLASSIFICATION STUDY . . SERIAL NUMBER 13 — DATE OF CLASSIFICATION July 25, 1967

RUN NUMBER——26600060 — DATE—— 6/28/66

FLIGHT LINE—— C1 — TIME——1229

TAPE NUMBER—— 41 — ALTITUDE— 2600 FEET

CLASSES CONSIDERED

SYMBOL	CLASS	THRESHOLD
O	OATS	-23.84
S	SOYBEANS	-23.15
R	RED CL	-23.73
C	CORN	-23.80
Y	RYE	-22.20
A	ALFALFA	-22.78
I	WATER	-20.33
W	WHEAT	-23.94
X	BARE SOIL	-21.08

FEATURES CONSIDERED

FEATURE NO.	SPECTRAL BAND (MICRONS)	
2	0.44	0.46
6	0.52	0.55
9	0.62	0.66
11	0.72	0.80

CLASSIFICATION SUMMARY BY TEST CLASSES

			NO OF SAMPLES CLASSIFIED INTO									
CLASS	PCT. CORCT	NO OF SAMPS	O	S	R	C	Y	A	I	W	X	THRESH
OATS	86.8	1152	1000	23	57	18	5	0	0	49	0	0
SOYB	96.9	1819	13	1763	0	40	3	0	0	0	0	0
RED	84.7	771	12	0	653	41	0	64	0	0	0	1
CORN	83.7	1344	35	66	109	1125	0	7	0	0	0	2
RYE	99.0	494	4	1	0	0	489	0	0	0	0	0
ALFA	94.3	315	1	1	14	2	0	297	0	0	0	0
WATE	100.0	95	0	0	0	0	0	0	95	0	0	0
WHEA	93.8	595	33	3	0	0	1	0	0	558	0	0
BR S	100.0	170	0	0	0	0	0	0	0	0	170	0
TOTAL	93.2	6755	1098	1857	833	1226	498	368	95	607	170	3

LABORATORY FOR AGRICULTURAL REMOTE SENSING
PURDUE UNIVERSITY

CLASSIFICATION STUDY . . SERIAL NO. 13 — DATE OF CLASSIFICATION July 25, 1967

RUN NUMBER——26600060
FLIGHT LINE—— C1
TAPE NUMBER—— 41

DATE—— 6/28/66
TIME——1229
ALTITUDE - 2600 FEET

CLASSES CONSIDERED

SYMBOL	CLASS	THRESHOLD
O	OATS	-23.84
S	SOYBEANS	-23.15
R	RED CL	-23.73
C	CORN	-23.80
Y	RYE	-22.20
A	ALFALFA	-22.78
I	WATER	-20.33
W	WHEAT	-23.94
X	BARE SOIL	-21.08

FEATURES CONSIDERED

FEATURE NO.	SPECTRAL BAND (MICRONS)	
2	0.44	0.46
6	0.52	0.55
9	0.62	0.66
11	0.72	0.80

CLASSIFICATION SUMMARY BY TEST CLASSES

			NO OF SAMPLES CLASSIFIED INTO									
CLASS	PCT. CORCT	NO OF SAMPS	O	S	R	C	Y	A	I	W	X	THRESH
OATS	91.9	160	147	7	5	0	0	0	0	0	0	1
SOYB	66.1	5214	116	3446	447	630	92	66	0	1	21	395
RED	59.8	1982	233	13	1186	226	1	297	0	2	0	24
CORN	53.2	2020	28	878	6	1074	18	1	0	0	1	14
RYE	77.8	126	5	10	0	0	98	0	0	0	0	13
ALFA	48.3	418	23	9	118	63	0	202	0	0	0	3
WHEA	76.2	1888	72	14	0	4	154	0	0	1439	0	205
BR S	100.0	56	0	0	0	0	0	0	0	0	56	0
TOTAL	71.7	11864	624	4377	1762	1997	363	566	0	1442	78	655

LABORATORY FOR AGRICULTURAL REMOTE SENSING
PURDUE UNIVERSITY

CLASSIFICATION STUDY . . SERIAL NO. 218806801
CLASSIFICATION DATE . . FEBRUARY 18, 1968

RUN NUMBER------26600080 DATE------ 6/28/66
FLIGHT LINE---- C2 TIME------1237
TAPE NUMBER---- 44

CLASSES CONSIDERED

SYMBOL	CLASS
S	SOYBEANS
C	CORN I
O	OATS
W	WHEAT I
R	RED CL I

FEATURES CONSIDERED

FREQUENCY NO.	SPECTRAL BAND (MICRONS)	
1	0.40	0.44
10	0.66	0.72
11	0.72	0.80

CLASSIFICATION SUMMARY BY TEST CLASSES

				NO OF SAMPLES CLASSIFIED INTO					
	CLASS	NO OF SAMPS	PCT. CORCT	SOYB	CORN	OATS	WHEA	RED	THRS
1	SOYB	2827	88.8	2510	304	12	0	1	0
2	CORN	2807	84.5	170	2372	88	0	177	0
3	OATS	2823	89.8	5	44	2536	0	238	0
4	WHEA	2803	91.8	7	3	218	2572	3	0
5	RED	2811	86.6	4	220	152	0	2435	0
	TOTAL	14071		2696	2943	3006	2572	2854	0

OVERALL PERFORMANCE = 88.3

AVERAGE PERFORMANCE BY CLASS = 88.3

LABORATORY FOR AGRICULTURAL REMOTE SENSING
PURDUE UNIVERSITY

CLASSIFICATION STUDY . . SERIAL NO. 218807304
CLASSIFICATION DATE . . FEBRUARY 18, 1968

RUN NUMBER——26600080　　DATE—— 6/28/66

FLIGHT LINE—— C2　　TIME——1237

TAPE NUMBER—— 44　　ALTITUDE— 2600 FEET

CLASSES CONSIDERED

SYMBOL	CLASS
S	SOYBEANS
C	CORN I
O	OATS
W	WHEAT I
R	RED CL I

FEATURES CONSIDERED

FREQUENCY NO.	SPECTRAL BAND (MICRONS)	
1	0.40	0.44
2	0.44	0.46
3	0.46	0.48
4	0.48	0.50
5	0.50	0.52
6	0.52	0.55
7	0.55	0.58
8	0.58	0.62
9	0.62	0.66
10	0.66	0.72
11	0.72	0.80
12	0.80	1.00

CLASSIFICATION SUMMARY BY TEST CLASSES

				NO OF SAMPLES CLASSIFIED INTO					
	CLASS	NO OF SAMPS	PCT. CORCT	SOYB	CORN	OATS	WHEA	RED	THRS
1	SOYB	2827	72.7	2055	758	11	0	3	0
2	CORN	2807	85.1	167	2388	144	0	108	0
3	OATS	2823	92.7	1	59	2618	0	145	0
4	WHEA	2803	80.4	8	15	527	2253	0	0
5	RED	2811	86.2	9	95	283	0	2424	0
	TOTAL	14071		2240	3315	3583	2253	2680	0

OVERALL PERFORMANCE = 83.4

AVERAGE PERFORMANCE BY CLASS = 83.4