THE SYSTEM OF SEQUENTIAL CLASSIFICATION, CLUSTERING, AND COUNTING FRUIT TREES FROM DIGITALIZED AERIAL PHOTOGRAPHS

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by

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ACKNOWLEDGEMENT

The guidance throughout this study from Chapman Gleason of the Research Division was very much appreciated. He designed the automated system utilized in this study for his research in automated counting from ground photographs of mature oranges on trees.

INTRODUCTION

The purpose of this study was to determine if fruit trees in an orchard can be counted by computer techniques with digitalized data obtained from an infrared aerial photograph of an orchard. A system of sequential classification, clustering, and counting techniques was utilized to count fruit trees in an orchard. This system was initially developed to count mature oranges on photographs taken on the ground of a side view of a tree. The results of the tree yield study for mature oranges were encouraging, and it therefore seemed logical to test and possibly improve this system for other applications.

DATA COLLECTION

Data Source:

Data utilized in this study were developed from an infrared aerial photograph taken at an altitude of 600 feet of an orange grove. Total ground area in the photograph is 1,350 feet by 1,350 feet at a scale of approximately 1:1800.

A rectangular section of the aerial photograph with ground area 140 feet by 420 feet was digitalized for analysis using the Photometric Data Systems (PDS) microdensitometer.[1] Digitalized results were stored on magnetic tape in a form that could be processed by available analysis programs. The rationale in digitalizing only a subset of the aerial photograph was to keep computer costs at a minimum while still obtaining sufficient data for analysis. A rectangular section was chosen because it contained all groups in the infrared aerial photograph that were spectrally distinct to the human eye. Inspection of the photograph showed that 28 fruit trees were present in the rectangular section to be analyzed.

Microdensitometer:

The basic operation of the microdensitometer involves passing a beam of light through individual points on a color transparency. Each individual point, which is called a pixel or pixel reading, is comprised of a small area on the aerial photograph.

The beam of light passing through each pixel causes the relative intensity of the transparency to be measured for that pixel, and a voltage signal to be emitted by the photomultiplier tube. This is performed for a set of four filters (clear, red, green, and blue), which enhance various film layers. A linear response is produced if the scanning mode is transmission; a logarithmic response is produced if the scanning mode is density. The Digital Coordinate Readout System monitors the positioning of the scanning table, and initiates analog to digital conversions to the computer. The resulting intensity reading of each scanning mode and filter combination for each pixel is then stored on magnetic tape as a multivariate response, and thereby, made available for analysis.

Scanning Parameters:

There are several scanning parameters to be considered when digitalizing the aerial photograph. These scanning parameters include aperture shape, aperture size, scanning mode, and filter.

A square aperture achieves complete coverage of the area being scanned, while a circular aperture does not provide totality in coverage without overlapping pixels.

The aperture size and shape chosen was 240 microns square, which was sufficient for obtaining an accurate representation of the data. Therefore, each pixel area was 240 microns by 240 microns, which was equivalent to an area on the ground of 1.4 feet by 1.4 feet. A larger aperture could produce a pixel reading that would involve more than one spectrally distinct group. An aperture smaller than 240 microns by 240 microns would result in more pixel readings, and would therefore increase computer costs. For the rectangular section being analyzed, 100 pixels were digitalized per line. There were 300 lines scanned, and, therefore, a total of 30,000 pixels analyzed.

All filter and scanning mode combinations were used. Since there are four filters and two scanning modes, eight intensity readings for each pixel were stored as a multivariate response.

APPROACH

The system of sequential classification, clustering, and counting fruit trees in the rectangular section of the aerial photograph involves the following steps:

1. Digitalize the rectangular section of the aerial photograph using the PDS microdensitometer.
2. From the rectangular section, visually select sample areas from each spectrally distinct group. The pixels in each sample area will be used as training (labeled) data.
3. Using the training data, determine the discriminant functions required to identify the spectrally different groups, and classify each unlabeled pixel into one of the identified groups.
4. Retain all pixels that have been classified as fruit tree pixels by the classification procedure.
5. Cluster classified fruit tree pixels and count the classified fruit tree clusters for the rectangular section.
6. Apply discriminant analysis on the classified fruit tree clusters to separate fruit tree clusters from non-fruit tree clusters.

DATA ANALYSIS

Groups:

The seven groups represented in the rectangular section of the aerial photograph are: lake (L), hedges by the lake (H), canal (C), road (R), bushes (B), soil (S), and fruit trees (T). Examination of the training data in Figure 1 shows that a reduction in groups can be made. Canal, bush, and soil pixels were renamed as the group called other (O) because of their similarity in intensity readings with respect to the training data. Since lake and road pixels were clearly separated from fruit tree pixels, the area of the two-dimensional plot in Figure 1 containing these pixels was deleted from further analysis. That is, pixels with density-blue readings less than or equal to 23 were deleted to reduce computer expenses. Thus the original seven groups were reduced to three groups (fruit trees, hedges, and other).

Feature Selection:

The method of determining filter(s) and scanning mode(s) to be used in discriminant analysis is called the feature selection. Filter(s) and scanning mode(s) were selected by examining two-dimensional plots of the training data for each combination of the variables, which are all filter and scanning mode combinations.

Red and blue filters in the density scanning mode provided the best visual separation of fruit tree pixels from the remaining pixels. Figure 1 illustrates the discriminating potential of red and blue filters in the density scanning mode. Notice that the only overlap with fruit tree pixels occurred with hedge pixels. Hence, the variables for discriminant analysis have been determined.

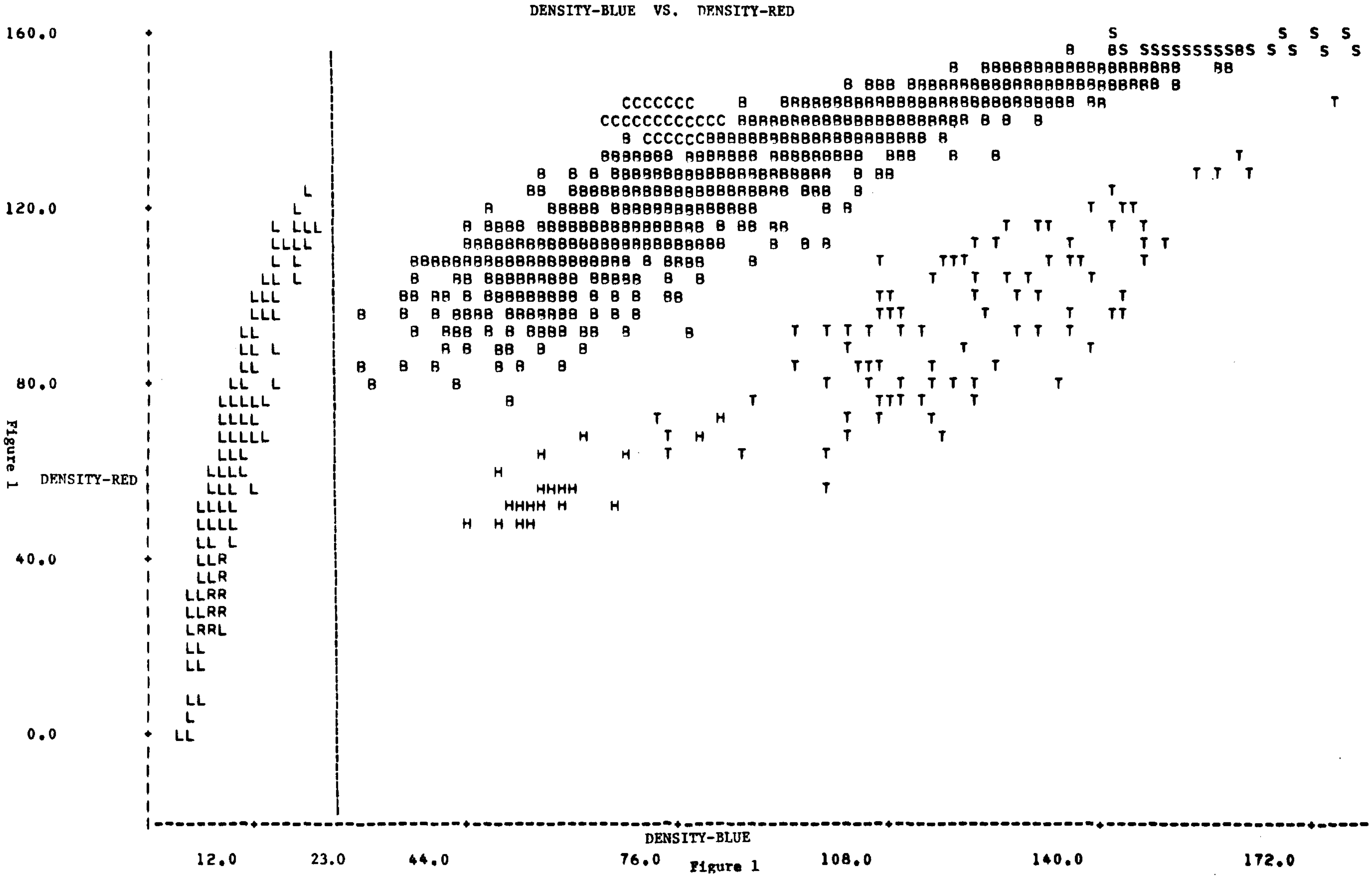
DENSITY-BLUE VS. DENSITY-RED

Figure 1

Discriminant Analysis Applied to Training Data for the Pixels:

Discriminant analysis makes use of the mean vector, covariance matrix, and prior probability of each group to develop a rule to assign each unlabeled pixel to one of the groups. Training data used to determine discriminant functions are represented in the following matrix:

$$\begin{array}{c|ccc|} & \text{Trees} & \text{Hedges} & \text{Other} \\ \text{Trees} & 90 & 0 & 0 \\ \text{Hedges} & 0 & 21 & 0 \\ \text{Other} & 0 & 0 & 1650 \end{array}$$

Quadratic discriminant functions, which were based on the selected variables for the three groups and on unequal prior probabilities determined by the relative frequency of each group in the training data, classified the three groups (fruit trees, hedges, and other) remarkably well. This successful classification suggests distinct spectral properties for the three groups. After the quadratic discriminant functions were determined, training pixels were treated as "unlabeled pixels" to test the classification procedure. The matrix representing the classification of the training data based on the quadratic discriminant functions is:

$$\begin{array}{c|ccc|} & \text{Trees} & \text{Hedges} & \text{Other} \\ \text{Trees} & 87 & \boxed{3} & 0 \\ \text{Hedges} & \boxed{2} & 19 & 0 \\ \text{Other} & 0 & 0 & 1650 \end{array}$$

Only three fruit tree pixels were incorrectly classified as hedge pixels, and two hedge pixels were incorrectly classified as fruit tree pixels. The remaining pixels in the training data were classified correctly into their respective groups.

Discriminant analysis was also performed on two categories (fruit tree pixels and remaining pixels). Results were as follows: using linear or quadratic discriminant functions with both equal and unequal prior probabilities all hedge pixels from the remaining category were incorrectly classified as fruit tree pixels. Therefore, discriminant analysis on these two categories did not successfully separate fruit tree pixels from remaining pixels.

However, a sequential two-stage procedure using discriminant analysis will separate fruit tree pixels from remaining pixels in the training data. In the first stage, fruit tree and hedge pixels are concatenated into one category, and the remaining pixels are combined into another category. After the first stage classification, fruit tree and hedge pixels are retained, and discriminated between in the second stage. Hence, the sequential two-stage procedure will obtain the same results as the single step procedure with three groups. Because of simplicity, the single stage three-group procedure was chosen.

As previously stated, lake and road pixels separated ideally from fruit tree pixels. Therefore, pixels with density-blue values less than or equal to 23 were removed from further analysis to reduce computer costs. This explains why discriminant analysis was not performed on four groups. By inspection of Figure 1 with lake and road pixels deleted, the three groups (fruit trees, hedges, and other) to be used for classification of unlabeled pixels are clearly represented.

Classification Results:

The classification procedure involves identifying each previously unlabeled pixel as a member of one of the specified groups. The discriminant procedure that minimized misclassification of the training data was chosen for classifying each unlabeled pixel (U).

Quadratic discriminant functions on three groups and the selected variables were used to classify each unlabeled pixels into one of the three groups. The classification matrix obtained with prior probabilities based on the relative frequency of each group in the training data was:

	Trees	Hedges	Other
Trees	87	3	0
Hedges	2	19	0
Other	0	0	1650
Unlabeled	2279	797	17932

Therefore, the number of pixels classified as fruit tree pixels was 2,368: (87 + 2 + 0 + 2279). The number of misclassifications in these 2,368 classified fruit tree pixels cannot be determined until clusters of these classified fruit tree pixels are generated in cluster analysis.

Cluster Analysis:

After unlabeled pixels have been classified, pixels classified as fruit tree pixels must be retained for cluster analysis. Procedure DISCOUT in SAS was used to save pixels labeled as fruit tree pixels.[2] DISCOUT is identical to procedure DISCRIM in SAS except DISCRIM cannot retain classification results on magnetic tape.

Prior to using cluster analysis, classified fruit tree pixels were blocked into subareas from the two-dimensional plot of x and y coordinates of classified fruit tree pixels. Each x and y coordinate corresponded to the actual position of a classified fruit tree pixel as recorded by the PDS microdensitometer. This blocking was performed to minimize computer costs when determining interpoint Euclidean distances by restricting the procedure MSTCLUS to a distinct subarea each time the procedure was performed.[3]

MSTCLUS clusters classified fruit tree pixels by computing interpoint Euclidean distances of each classified fruit tree pixel relative to all other classified fruit tree pixels in its block. Each distance is computed by taking the absolute value of the shortest distance between x and y coordinates of two classified fruit tree pixels. Clusters were obtained by removing edges that were considered inconsistent by MSTCLUS.

That is, the distance to adjacent pixels was too large to be a part of the same fruit tree canopy. Clusters of classified fruit tree pixels were then counted.

After obtaining clusters for classified fruit tree pixels, the next step is to determine which clusters were indeed fruit trees, and which clusters were not fruit trees due to pixels misclassified as fruit tree pixels by the classification procedure. The following is the classification by quadratic discriminant functions of the training data:

	Trees	Hedges	Other
Trees	87	3	0
Hedges	$\boxed{2}$	19	0
Other	0	0	1650

By observing this classification, it was known that two misclassifications were present in the fruit tree pixels. How many misclassifications were added by the classification of unlabeled pixels is not yet known.

As previously mentioned, there are 28 fruit trees in the rectangular section of the aerial photograph. However, 57 clusters were obtained by cluster analysis. Obviously, numerous misclassifications of the unlabeled data occurred. Therefore, a second classification procedure must be used to distinguish between fruit tree and non-fruit tree clusters.

Discriminant Analysis Applied to Training Data for the Clusters:

Since int[illegible] readings of the pixels were not sufficient to successfully discriminate among the three groups, as is illustrated by the 29 excess clusters, it was necessary to use another set of variables to discriminate between fruit tree clusters and non-fruit tree clusters.

Using as variables the characteristics of the clusters given by MSTCLUS (number of pixels, average edge length, and diameter), fruit tree clusters can be successfully separated from non-fruit tree clusters by discriminant analysis. All clusters were used as training data to determine if suitable discriminant functions could be obtained. Which of the two groups of clusters a particular cluster belonged in was determined by inspecting the two-dimensional plot of x and y coordinates of the classified fruit tree pixels. Therefore, training data were easily obtained.

The discriminating potential of these variables on the training data is verified by frequency distributions of the variables for each group, two-dimensional plots of all combinations of the variables and stepwise discriminant analysis in the Biomedical Computer Programs on the variables.[4] Figure 2 illustrates the separability of fruit tree clusters and non-fruit tree clusters using number of pixels in a cluster (NUMBER) and diameter of a cluster (DIAMETER) as variables.

Discriminating with all three variables (size, average edge length, and diameter) using quadratic discriminant functions, the classification matrix obtained for the training clusters was:

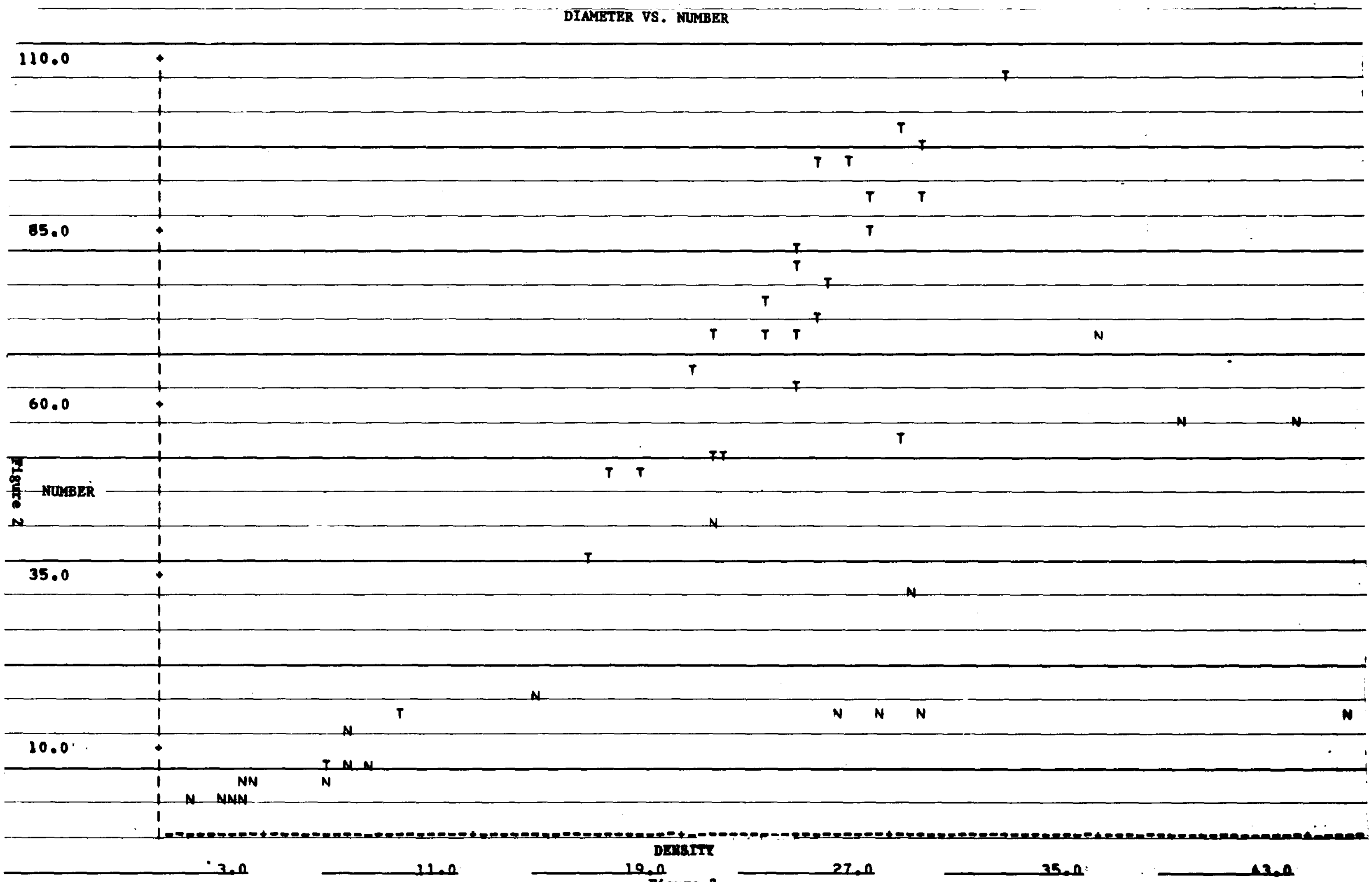
DIAMETER VS. NUMBER
110.0
85.0
60.0
35.0
10.0
NUMBER
DENSITY
3.0
11.0
19.0
27.0
35.0
43.0
T
N

Figure 2

$$\begin{array}{lcc} & \text{Trees} & \text{Non-Trees} \\ \text{Trees} & \underline{27} & 1 \\ \text{Non-Trees} & \underline{1} & 28 \end{array}$$

Only one misclassification of fruit tree clusters and one misclassification of non-fruit tree clusters exist in this matrix. There are 28: (27 + 1) fruit trees according to this analysis. Therefore, using quadratic discriminant functions, training clusters can be classified as fruit tree clusters or non-fruit tree clusters with a great deal of accuracy.

All clusters were extracted as training data to be used in discriminant analysis. Therefore, no unlabeled clusters remained to be classified.

The results of discriminant analysis when the measure for group separation is based on the generalized squared distance using quadratic discriminant functions were:

GROUPS: Fruit Tree Clusters and Non-Fruit Tree Clusters

EQUAL PRIOR PROBABILITIES

Variables:

Size and diameter:

$$\begin{array}{lcc} & \text{Trees} & \text{Non-Trees} \\ \text{Trees} & \underline{25} & 3 \\ \text{Non-Trees} & \underline{1} & 28 \end{array}$$

Size, diameter, and average edge length:

$$\begin{array}{lcc} & \text{Trees} & \text{Non-Trees} \\ \text{Trees} & \underline{27} & 1 \\ \text{Non-Trees} & \underline{1} & 28 \end{array}$$

Size, diameter, average edge length, and standard deviation:

$$\begin{array}{lcc} & \text{Trees} & \text{Non-Trees} \\ \text{Trees} & \underline{27} & 1 \\ \text{Non-Trees} & \underline{2} & 27 \end{array}$$

In conclusion, it is known that 28 fruit trees are present in the rectangular section under analysis. The system of sequential classification, clustering, and counting from imagery applied to this study produced 28 clusters that have been classified as fruit trees.

COST DISTRIBUTION

The cost of counting fruit trees in an orchard from digitalized aerial photographs by the system of sequential classification, clustering, and counting is positively correlated with the number of pixels utilized in the analysis.

In this study 30,000 pixels were analyzed. Approximately fifty percent of the costs occurred in the conversion of the PDS microdensitometer scan lines to SAS compatible observations, classification of the unlabeled pixels, and clustering of classified fruit tree pixels. The remaining costs were associated with analysis of the data to develop classification and clustering procedures, i.e. feature selection and determination of operative discriminant functions.

CONCLUSION

Given an infrared aerial photograph of an orchard, fruit trees in the orchard can be counted by the system of sequential classification by discriminant analysis, clustering by interpoint Euclidean distances, and counting. Therefore, spectrally distinct groups in an aerial photograph can be discriminated by their intensity readings recorded by the PDS microdensitometer and their characteristics as clusters produced by MSTCLUS.

The total number of trees in the selected area is 28, which is exactly what was obtained by this analysis.

COMMENTS

Further research to develop the best possible system of sequential classification, clustering, and counting from imagery should be pursued. Larger areas should be analyzed so that ample training data for clusters will be available. In this study, there were few clusters, and data from all clusters were used as training data.

An alteration in the software of MSTCLUS to retain cluster characteristics on magnetic tape is needed. This would eliminate keypunching the characteristics of the clusters.

More study is needed to determine a definite relationship between number of pixels analyzed and computer costs. Accurate cost estimates could then be formulated before a study is commenced. Further research to examine varying effects of different aperture sizes, aperture shapes, filters, and scanning modes is of the utmost necessity.

Each group in the training data should reflect the relative frequency of that group in the unlabeled data so that more accurate discriminant functions can be produced. In this study, the relative frequency of each group in the training data did not reflect the relative frequency of that group in the unlabeled data. Erroneous classification could have resulted, since the discriminant functions did not contain the correct prior probability of each group. However, preliminary results are quite encouraging since satisfactory results were obtained without using exact relative frequencies. This suggests the necessary information may be obtainable from the training data for developing a good classification, clustering, and counting system.

An alternative approach to this study could involve concatenating fruit tree pixels and hedge pixels into one group and remaining pixels into another group. Then, retain classified fruit tree and hedge pixels from the classification results, and cluster these pixels. Thus, long rows of hedges could easily be discriminated from the smaller, ellipsoidal pattern of fruit trees by using the characteristics of clusters as the discriminator. The problem with this approach is that inclusion of all hedge pixels in cluster analysis would result in higher computer costs.

Further analysis should now involve this system of sequential classification, clustering, and counting from imagery in other applications such as immature fruits rather than mature fruits. Thus, a system could be developed that would potentially have greater utility in surveys for forecasting crop yield.

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