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COMPUTER RECOGNITION OF CITRUS INFESTATIONS

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ABSTRACT

A computer software system is described that uses digitized color information from aerial color infrared transparencies to detect the presence of citrus mealybug (Pseudococcus citri Risso), brown soft scale (Coccus hesperidum L.), and Rio Grande gummosis in individual citrus trees. The color coordinates at each spatial point, and color differences at adjacent points are used to locate the trees and to detect the infestations; and compensation is made for the variation in color characteristics between different transparencies. The system requires the input of four parameters: a flag denoting the presence of heavy shadows in the image, nominal tree size and spacing of the citrus trees, and a flag denoting the season of the year when the transparency was taken. An index of recognition, Iq, was defined and used as a measure of recognition effectiveness. For unknown data, Iq ranged from 43% to 81%, with nominal values of 60% to 80% for all three infestations.

I. INTRODUCTION

Each year in the United States, citrus mealybug, brown soft scale and Rio Grande gummosis cause serious economic losses to citrus growers in the form of damaged trees, lower yields, and depreciated fruit. Presently, this damage is assessed by formal or informal ground surveys, or by human interpretation of aerial color infrared (CIR) transparencies. Previous investigations[1-7] have found that many citrus infestations exhibit identifiable features in low altitude CIR images. Unfortunately, some of the infestations are not readily distinguishable from each other, however. Other work[8,9] has determined that machine recognition of citrus infestations is feasible, using an interactive processing system with an operator assisting in the decision-making process. The present study extends this work with the development of a software system that operates in a batch environment, recognizing the infestations using only four parameters as input. Brown soft scale, citrus mealybug, and Rio Grande gummosis were chosen for this processing since they tend to exhibit unique characteristics on CIR film, and because they cause damage in all of the growing areas of the United States. (Rio Grande gummosis is known by other names[10] in growing areas outside of Texas.)

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In color infrared transparencies, the infestations[1-3,11] are characterized primarily by changes in the light reflected from the leaves. Healthy tree foliage exhibits a bright red appearance due to strong reflectance of near infrared wavelengths. In contrast brown soft scale and citrus mealybug excrete a honeydew solution which provides an excellent growth site for the sooty mold fungus Capnodium citri Berk. and Desm. The presence of the mold is sensed by the film, since the reflectance from the foliage is greatly reduced in both the visible and near infrared spectral regions, giving a dark red or black appearance. The two infestations can be distinguished by the distribution of the mold: brown soft scale is characterized by a heavy coating of mold that appears black or dark red while mealybug causes an uneven coating that exhibits a mottled black and red appearance.

Gummosis is a disease that is caused by unknown agents that attack the main branches or upper trunk of the tree. Nutritional deficiencies cause leaves in the affected area to turn chlorotic (yellow-green) in color, increasing the reflectance in the visible light region. This increase is manifested in CIR film as a white or pink color.

The input data for the system consists of color transparancies that are digitized using a color[12] flying spot scanner, and transformed into a normalized[8,13] color coordinate system. At each spatial point, the normalized coordinate values are:

$$I = (R+G+B)/3 \quad (1)$$

$$X = 255 \cdot R/(R+G+B) \quad (2)$$

$$Y = 255 \cdot G/(R+G+B) \quad (3)$$

where

R, G and B are the red, green, and blue color intensities output by the scanner.

I is the intensity (brightness) coordinate value.

$$0 \leq I \leq 255$$

X and Y are the red and green chromaticity coordinates respectively; $0 \leq X \leq 255$ and $0 \leq Y \leq 255$, where X and Y are set to zero if $I = 0$.

The response for each spatial point is described by a three dimensional space, with two coordinates representing chromaticity, and the

third intensity.

II. DATA CHARACTERISTICS

In order to determine the general characteristics of the data, selected areas of the eight training slides identified in Table 1. were scanned to obtain their distributions in the (X,Y,I) space. The mean values of these distributions, normalized to a range of 0 to 1, are shown in Figure 1. Analysis[14] of this information determined that three classes of data could be defined and modeled in the (X,Y) plane as shown in Figure 2, since for each of the three infestations, coordinate values of the infested foliage clustered between those from background features, and from healthy tree foliage. Furthermore, since the slope of the class axis varied by only a small amount between different slides, a new chromaticity coordinate, W, was defined as a linear combination of X and Y:

$$W = 301X - 203Y + 54 \qquad (4)$$

This transformation simultaneously reduces the dimensionality of the data while maximizing the between class separation of the three classes. The effect of this transformation is shown in Figure 3, where the mean values from Figure 1 are replotted in the (W,I) domain.

SLIDE NUMBER	IDENTIFICATION	
1	G-5	G = gummosis
2	G-1	
3	BSS-5	BSS = brown soft scale
4	BSS-6	
5	BSS-12	
6	MB-4	MB = mealybug
7	MB-7	
8	MB-2	

Table 1 Training Slide Identification

Further processing determined that the training slides exhibited large variations in chromaticity and intensity characteristics in the (W,I) space due to differences in film exposure, ambient light conditions, and scanner gain levels during processing. However, by normalizing the coordinate values with respect to the maximum and minimum values of W and I, the coordinates for healthy and infested tree foliage clustered in four regions as shown in Figure 4. (As will be described shortly, these regions are used to determine the tree classification parameters.)

III. PROCESSING

The processing for detection and classification of the three infestations uses both spectral (color) and spatial information from the

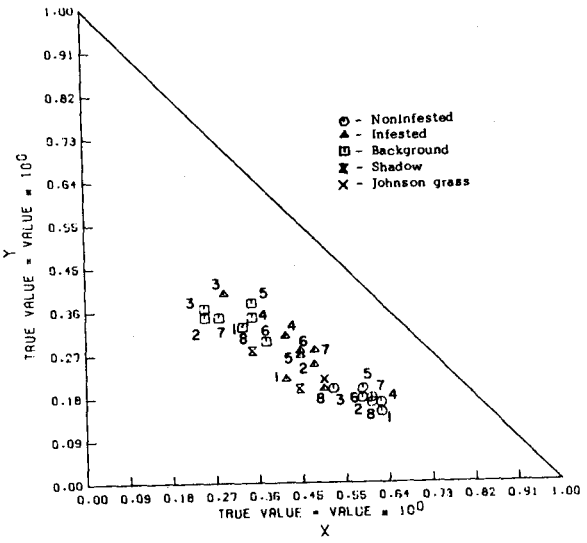

Figure 1 (a) Mean Values of the Training Slide Color Distributions in the X,Y Plane

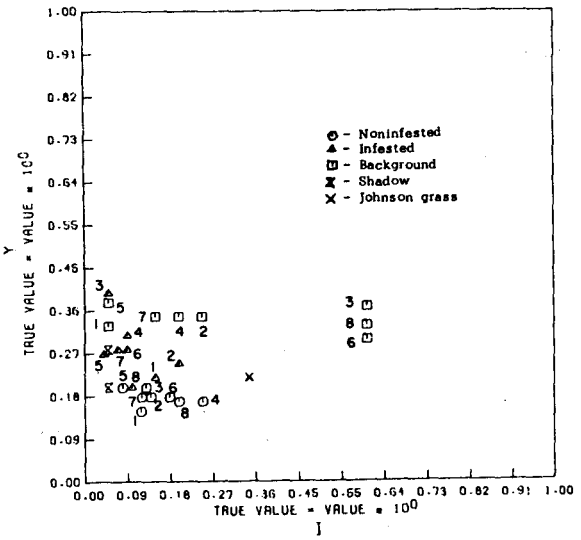

Figure 1 (b) Mean Values of the Training Slide Color Distributions in the I,Y Plane

image. Selective processing of the data is employed to reduce the amount of computation. The processing consists of three parts: location of individual citrus trees within rectangular boundaries, preprocessing to compensate for the variation in color characteristics between different slides and to determine the parameters needed for classification, and classification of

the health of each tree.

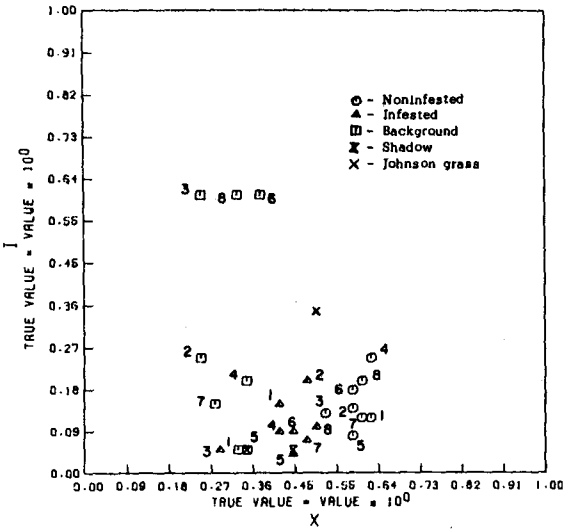

Figure 1 (c) Mean Values of the Training Slide Color Distributions in the X,I Plane

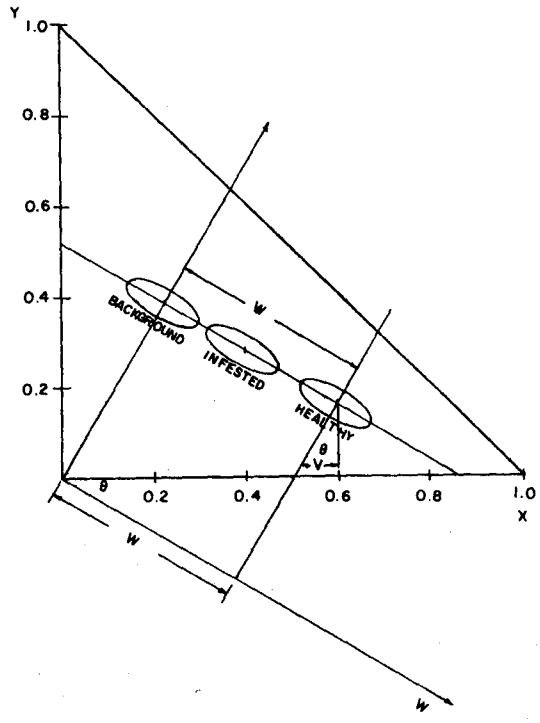

Figure 2 Coordinate Transformation

Tree location requires the input of two parameters: the nominal tree size and tree spacing; and restrictions on the input images that the citrus trees be planted in a regular pattern, that the individual trees not be completely grown together, and that the transparencies be taken at an altitude of 10,000 feet or less. Only the W coordinate is used in this step, since the background and tree foliage coordinates are separated primarily along the W axis as shown in Figure 3.

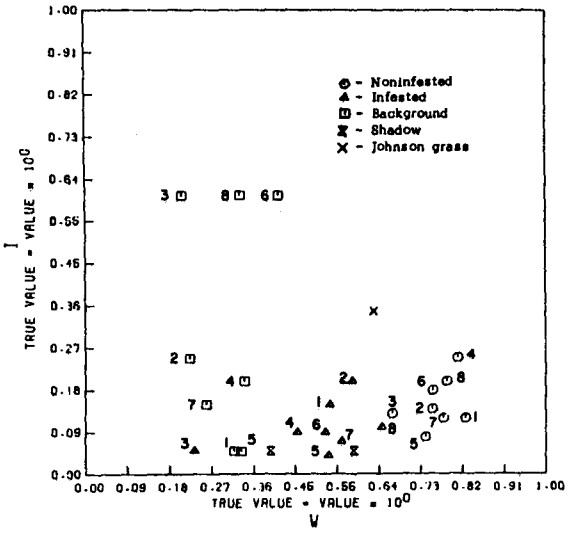

Figure 3 Mean Values of the Training Slide Color Distributions in the W,I Plane

The image is scanned in vertical strips as shown in Figure 5, using a directional derivative [15, 16] that is averaged across the width (one nominal tree size and one nominal tree spacing) of each strip to locate vertical edges:

$$DIF = \sum_{K=K1}^{K2} (W(J,K) - W(J-1,K)) \qquad (5)$$

where

DIF is the averaged directional derivative for row J of a given strip

K1, K2 are the column bounds for that strip

W(J,K) is the W coordinate value for location (J,K)

As the directional derivative is calculated down a strip, leading and trailing edges of treelike objects exhibit positive and negative peaks. If successive positive and negative peaks exceed preset thresholds, the vertical separation is calculated to determine whether it is within a

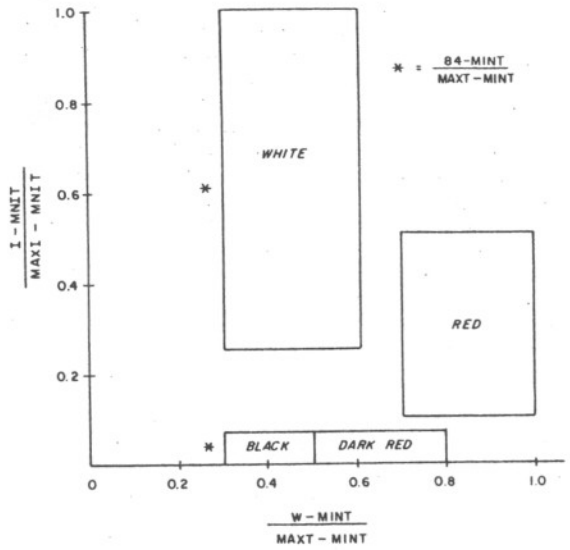

Figure 4 Color Search Regions

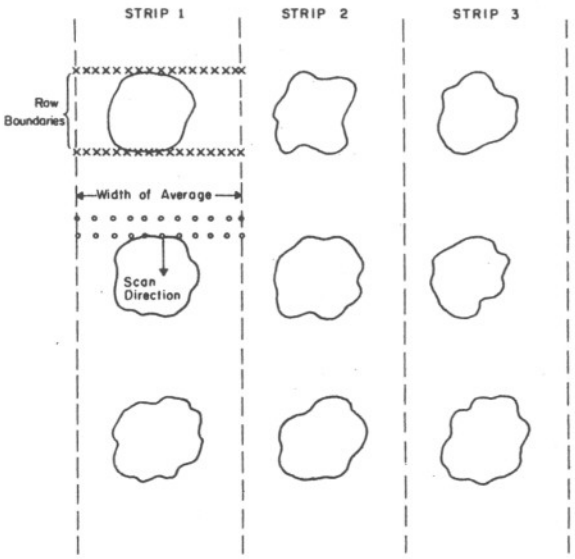

Figure 5 Vertical Scan

size window of 7/10 to 10/7 of a nominal tree size. If the size is acceptable, the edge coordinates are stored as vertical tree boundaries; otherwise, the scanning proceeds as before.

After all of the vertical strips have been scanned, the image is next scanned horizontally between the vertical boundaries, using the same process as previously. As before, if the thresholding and size criteria are satisfied, the left and right edge coordinates are stored with the top and bottom values.

Upon completion of the horizontal scan, ECN, a measure of the difference in vertical and horizontal size is calculated for each object in which the boundaries have been stored in the previous steps:

$$ECN = (TOP - BOT)/(RSIDE-LSIDE) \quad (6)$$

where

TOP is the top boundary

BOT is the bottom boundary

RSIDE is the right boundary

LSIDE is the left boundary

If the following inequality is satisfied:

$$0.6 \leq ECN \leq 1.66 \quad (7)$$

the vertical and horizontal size of the object are of the same order and the object is assumed to be a tree; otherwise, the four boundaries of the object are erased.

A citrus grove infested with mealybug is shown in Figure 6, and a plot of the averaged directional derivative for a vertical scan strip of this image is shown in Figure 7. Each tree row causes a positive peak at the top edge of a tree row that falls off rapidly, forming a negative peak at the bottom edge. Consequently, seven sets of positive and negative peaks are exhibited, one for each row of trees. The rectangular boundaries for the trees are shown in Figure 8.

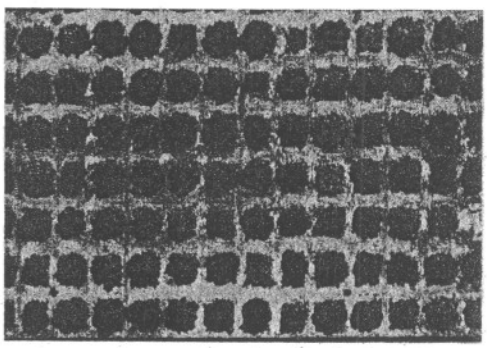

Figure 6 Slide MB-2

To preprocess the data, the spatial points within the tree boundaries are scanned in two passes. During the first pass, the maximum and minimum values of the W and I coordinates are determined. MAXT and MINT, and MAXI and MNIT are the maximum and minimum values for W and I respectively, as shown in Figure 4. To compensate for the variation in color characteristics, the coordinates at each spatial point can be normalized, or the fixed boundaries in the normalized

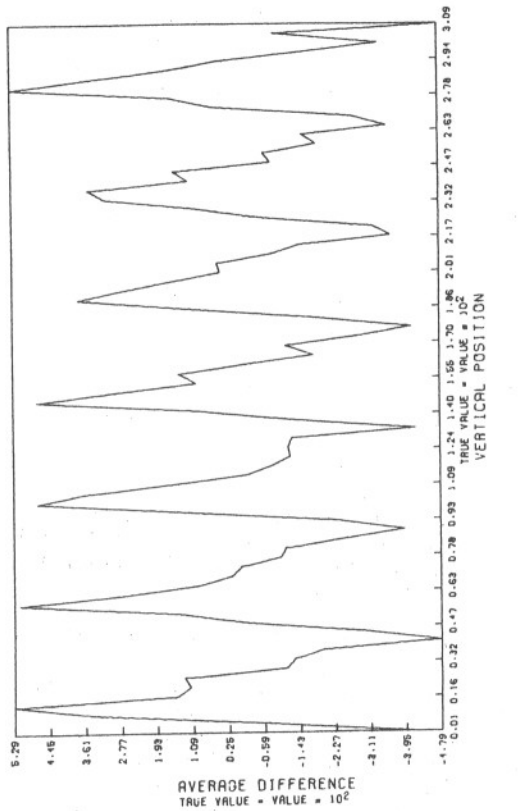

Figure 7 Fourth Vertical Scan Strip
K = 133 - 173

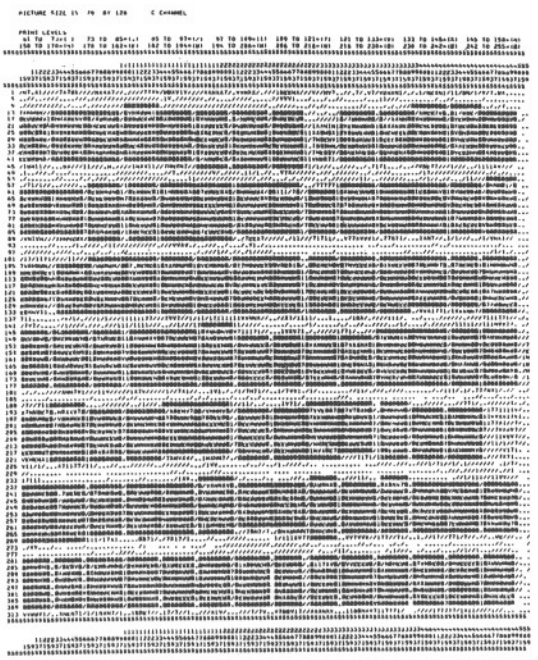

Figure 8 MB-2 Tree Boundaries

space can be calculated and then transformed back into the (W,I) space. In order to save processing, the second method is employed. A second pass is then made through the data to calculate the mean values of the data points whose coordinates are within the four color search regions. Pixels with coordinates outside of the four regions are not used in the calculations, since they are assumed to represent nontree information. The means are transformed into the (W,I) space and used as parameters in the decision functions which classify the trees in the next stage of processing. The transformed values are denoted by U(LK,C) LK = 1,2,3,4, and C = 1,2; where LK represents the color: 1 = red, 2 = dark red, 3 = white, and 4 = black; and C specifies the coordinate: 1 = W and 2 = I.

The values of the variance parameters, V(LK,C), LK = 1,2,3,4, and C = 1,2; are then calculated from the transformed widths of the four color search regions except for the following case. V(3,2) is calculated using the distance between U(3,2), the transformed intensity mean, and the transformed minimum intensity boundary for the white region, in order to limit the white response in the I direction. The variance parameter values are also used in the decision functions which subsequently classify the trees.

In the last stage of processing, the classification of each bounded object is determined. The classification is performed on an object by object basis, processing only pixels that lie within the rectangular boundaries. The values of two flags are required, one denoting the season of the year when the transparency was taken, the other denoting the presence or absence of heavy shadows.

The processing for each bounded area is as follows. First, TNUM, and the contents of arrays CLR, TPT, and CF, are set to zero. (The function of these variables will be described shortly.) Next, the state conditional probability density function[17] is calculated for each of the pixels within the boundary:

$$P(\underline{PXL}(J,K)/LK) \simeq DEN(LK) = \prod_{c=1}^{2} EXP(-((PXL(J,K,C)-U(LK,C))/V(LK,C))^2) \quad (8)$$

LK=1,2,3,4

where

$\underline{PXL}(J,K)$ is a vector composed of the (W,I) coordinate values at location (J,K).

LK denotes one of the four colors: red, dark red, white or black.

C denotes the coordinate.

PXL(J,K,C) is an element of $\underline{PXL}(J,K)$, and

specifies a value of W or I at location (J,K).

U(LK,C) is the mean value for color class LK, in coordinate C.

V(LK,C) is the variance for color class LK, in coordinate C.

The form of DEN(LK) was chosen to be gaussian since the flying spot scanner was found to have a gaussian output when digitizing a slide containing a single color (i.e. a neutral density or Kodak wratten filter).

At each spatial location, the density function with the maximum value is determined:

$$MAXCLS(J,K) = \max_{LK}(DEN(LK)). \quad (9)$$

If MAXCLS(J,K) exceeds a threshold value of 0.1, the pixel is classified as color $\underline{LK}$, the foliage color having the highest probability of causing $\underline{PXL}(J,K)$. MAXCLS(J,K) is then added to $CLR(\underline{LK})$; and $TPT(\underline{LK})$ and TNUM are incremented by one. Array CLR keeps a running total of the density values for each foliage color, TPT records the number of points receiving each color classification, and TNUM counts the total number of points within the boundary. If MAXCLS(J,K) does not exceed the threshold, no classification is made for that pixel, and no changes are made to CLR $(\underline{LK})$, or to $TPT(\underline{LK})$. TNUM, however, is incremented by one.

The threshold value was obtained by assuming that the distance from the mean was equal to the variance, and taking the resulting value, (0.36^2), as the threshold.

If pixels in two consecutive columns are both classified as color $\underline{LK}$, the corresponding continuity function, $CF(\underline{LK})$, is also incremented by one. (The last pixel in a row is consecutive with the first pixel in the next row.) CF keeps a running count of the relative size of continuous color areas that are contained within the boundary.

After all of the pixels within a given tree boundary have been processed, the color information is averaged over all of the points within the boundary:

$$TCLR(LK) = CLR(LK)/TNUM \simeq P(\underline{PXL}(J,K)/LK)P(LK)$$
$$LK = 1,2,3,4 \quad (10)$$

where

$$P(\underline{PXL}(J,K)/LK) \simeq CLR(LK)/TPT(LK)$$

$$P(LK) \simeq TPT(LK)/TNUM$$

Consequently, TCLR(LK) gives a relative measure of the amount of the characteristic color, LK, that is exhibited by the bounded object.

Before further processing is performed, the following ratio is calculated to verify that the bounded object exhibits treelike color characteristics:

$$TS = \sum_{LK=1}^{4} (TPT(LK))TNUM \quad (11)$$

TS gives a total measure of the four characteristic foliage colors that are contained within the boundary. If TS is less than a threshold value, D2, the object is classified as a nontree, as shown in Table 2. This eliminates objects (i.e. patches of Johnson grass) that are similar in shape as the trees, but which exhibit different spectral characteristics. A nontree classification causes the classification to be stored, the following steps to be skipped, and processing to continue with the next boundary.

CONDITION	DECISION
TS < D2	NONTREE
DEC(3) > D3 AND DEC(3) > DECM·D4	GUMMOSIS
D5 ≤ DECM ≤ D6 AND DECM > DEC(3)·D7	MEALYBUG
DECM > D6 AND DECM > DEC(3)·D7	BROWN SOFT SCALE
OTHERWISE	HEALTHY

Table 2 Classification Decision Table

For the bounded objects that exhibit treelike spectral characteristics, the following decision functions are calculated:

$$DEC(LK) = TCLR(LK)/TCLR(1), \quad LK = 2,3,4 \quad (12)$$

These functions are a modified form of the maximum likelihood ratio, and are formed from the ratio of the infested foliage colors to red, the healthy tree color.

A modified decision function, DECM, is calculated that combines the effect of the dark red and black foliage colors, and employs the continuity functions to assist in the separation of continuous dark color areas (brown soft scale), and areas that are mottled (mealybug):

$$DECM = DEC(2) + DEC(4) + 0.1(CF(2) + CF(4))/CF(1) \quad (13)$$

Since shadows affect the value of DECM, a flag, SHAD, is set if the transparency contains heavy shadows. This causes DECM to be reduced by a factor of D1, so as to compensate for the extra dark information. Otherwise, the value of DECM is not affected. A second flag, SEAS, is also employed in order to prevent new foliage from being mistakenly identified as gummosis, since both have similar spectral characteristics during the spring and summer months. If SEAS is set, a classification of gummosis is prevented

in the following steps. Otherwise, the transparency was taken during the fall or winter months, and the classification is not affected.

DEC(3) and DECM are used to classify bounded (treelike) objects as shown in Table 2, using threshold values D3-D7. The derivation of the threshold levels is described in reference 14. Each object exhibiting treelike spectral characteristics is classified one of four ways: healthy, or containing gummosis, brown soft scale, or citrus mealybug. After each bounded object is classified, the result is stored, and after all of the bounded areas have been processed, the results are output in both tabular and pictorial (overprint) form.

IV RESULTS AND CONCLUSIONS

In order to test the recognition process, three of the training slides, MB-2, G-1, and BSS-19, were used to set the classification threshold levels, D2-D7, shown in Table 2. The system was then used to analyze six slides of unknown data. All of the slides contained only one type of infestation. The results were tabulated using the following index of recognition as a measure of recognition effectiveness:

$$I_q = N_q \times 100/(N_q + M_q + L_q) \qquad (14)$$

where

- I_q is the index of recognition for the qth class of patterns, $0 \le I_q \le 100$ percent.
- N_q is the number of patterns in class q that are correctly classified.
- M_q is the number of patterns in class q that are misclassified into other classes.
- L_q is the number of patterns in other classes that are misclassified into class q.

This index gives a measure of both commission and ommission errors and is maximized if patterns in class q are not missed, and if patterns in other classes are not misclassified into class q. Note that non q classes of patterns are not individually specified in this expression.

The classification results for three typical slides are shown in Figures 9-11 in overprint form, and the results for all of the slides are tabulated in Tables 3-5. The classification key for the overprint output is shown in Table 6.

Tables 3-5 are tabulated by individual infestation, and also as infested/noninfested. In the latter case, no differentiation is made between the individual infestations in the infested catagory. Iq is calculated for the different classes shown in each table, using the corresponding values of Nq, Mq, and Lq. As an example, for slide MB-2 in Table 3, MB denotes that class q represents trees infested with mealybug. Forty six trees containing mealybug were correctly classified, 6 were misclassified into other classes, and 3 healthy trees were misclassified as infested with mealybug, giving an index of recognition of 84%.

CLASS	N_q	M_q	L_q	I_q(%)
MB-2				
MB	46	6	3	84
HEALTHY	35	3	5	81
ALL	81	9	8	83
INFESTED	47	5	3	85
NONINFESTED	35	3	5	81
ALL	82	8	8	84
MB-13				
MB	47	11	0	81
HEALTHY	0	0	4	0
ALL	47	11	4	76
INFESTED	51	7	0	88
NONINFESTED	0	0	4	0
ALL	51	7	4	82
MB-20				
MB	75	63	5	52
HEALTHY	83	20	17	69
ALL	158	83	22	60
INFESTED	120	18	5	84
NONINFESTED	83	20	17	69
ALL	203	38	22	77

Table 3 Index of Recognition of Mealybug

CLASS	N_q	M_q	L_q	I_q(%)
G-1				
GUM	18	7	0	72
HEALTHY	50	1	4	91
ALL	68	8	4	85
INFESTED	18	7	0	72
NONINFESTED	50	1	4	91
ALL	68	8	4	85
G-2				
GUM	13	5	0	72
HEALTHY	39	13	2	72
ALL	52	18	2	72
INFESTED	13	5	13	42
NONINFESTED	39	13	2	72
ALL	52	18	15	61
G-4				
GUM	12	11	5	43
HEALTHY	18	21	10	37
ALL	30	32	15	39
INFESTED	13	10	21	30
NONINFESTED	18	20	10	38
ALL	30	30	31	33

Table 4 Index of Recognition of Gummosis

Slide G-4 received the lowest recognition rate. It contained very heavy shadows, and several of the trees were surrounded with Johnson grass, an indication that the grove was not well taken care of. The shadow information caused many of the healthy trees to be classified as infested with mealybug, while many of the trees infested with gummosis were classified as healthy, since the ratio of white to dark information was shifted to below the gummosis threshold. Also, several of the trees surrounded with Johnson grass

received the classification of gummosis, because of the extra white information introduced by the grass. For this slide, the index of recognition for healthy trees was 37%, while the value for infested trees was 43%.

CLASS	N_q	M_q	L_q	I_q (%)
BSS-19				
BSS	15	2	0	88
HEALTHY	1	0	0	100
ALL	16	2	0	89
INFESTED	16	1	0	94
NONINFESTED	1	0	0	100
ALL	17	1	0	94
BSS-18				
BSS	14	15	1	47
HEALTHY	7	0	2	78
ALL	21	15	3	54
INFESTED	26	3	1	87
NONINFESTED	7	0	2	78
ALL	33	3	3	85
BSS-20				
BSS	52	15	5	72
HEALTHY	0	1	0	0
ALL	52	16	5	71
INFESTED	52	15	5	72
NONINFESTED	0	1	0	0
ALL	52	16	5	71

Table 5 Index of Recognition of Brown Soft Scale

GRAPHICAL REPRESENTATION	CLASSIFICATION
BLACK BORDER	HEALTHY
GRAY RECTANGLE	MEALYBUG
BLACK RECTANGLE	BROWN SOFT SCALE
WHITE RECTANGLE	GUMMOSIS
WHITE BORDER	NONTREE

Table 6 Classification Key

Another problem was the cross classification of citrus mealybug with brown soft scale. Slide BSS-18 contained infestations of brown scale that ranged from very light to very heavy. Many of the lightly infested trees had the appearance of being infested with citrus mealybug, and were misclassified into that category. In contrast, slide MB-20 contained infestations of mealybug with very heavy concentrations of sooty mold, and many of the infested trees were misclassified as containing brown soft scale. When the results were reclassified using the infested/noninfested classes, the index of recognition changed from 47 to 87%, and from 52 to 84%, respectively, for the two slides.

Unknown slides MB-13, G-2, and BSS-20 returned values of Iq for the three infestation classes that were higher than in the previous examples. The images contained only light to moderate shadows, and were taken of citrus groves that were well maintained; slides BSS-20 and MB-13 contained infestations of brown soft scale and citrus mealybug that exhibited distinctive visual characteristics. The index of recognition values for these slides ranged from 72 to 81% for the three infestations. (The value for healthy trees was zero for MB-13 which contained no healthy trees, and for BSS-20 which contained only one healthy tree.) These results used in conjunction with the previous values, show that the system achieves nominal recognition values of 60 to 80% for each of three infestations.

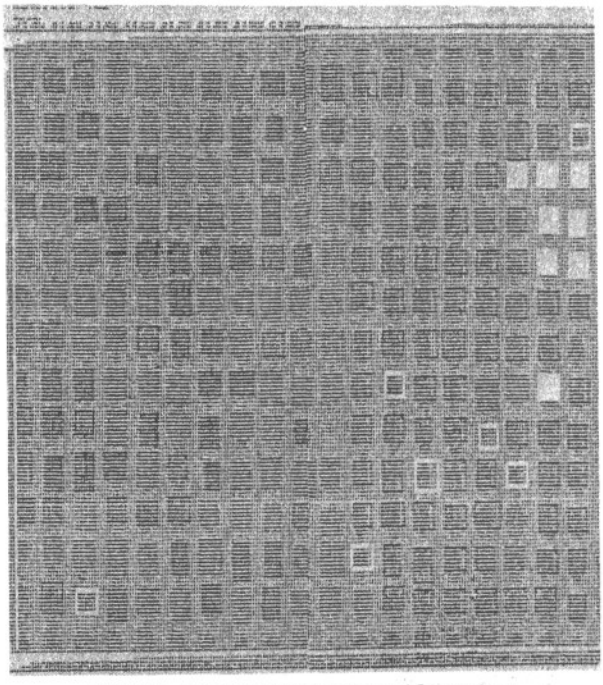

Figure 9 MB-20 Tree Classification

In conclusion, the system detects the presence of citrus mealybug, brown soft scale, and Rio Grande gummosis in individual citrus trees using only four parameters as input. Moderate shadows had no undue effect upon the classification process, but heavy shadows caused a significant increase in the classification error rate. Moderate infestations of mealybug were separated from moderate to heavy infestations of brown soft scale, however, heavy infestations of mealybug, and light infestations of brown soft scale were not effectively separated by the system. The spectral information is the primary feature that is used to recognize the infestations. Although three times as much data must be initially processed in comparison to black and white values, typically, less than 1.5 times as much data is required for the majority of processing.

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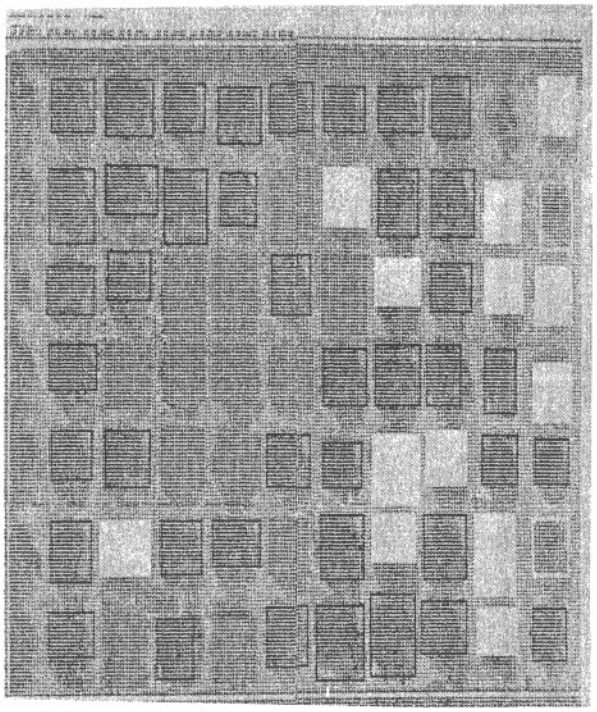

Figure 10 G-2 Tree Classification

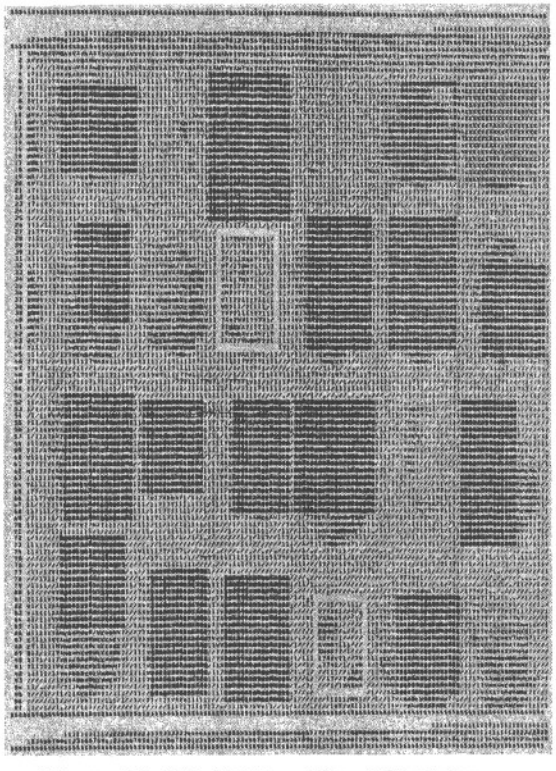

Figure 11 BSS-19 Tree Classification

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