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PERFORMANCE TESTS OF SIGNATURE EXTENSION ALGORITHMS

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ABSTRACT

Comparative tests were performed on seven signature extension algorithms to evaluate their effectiveness in correcting for changes in atmospheric haze and Sun angle in a Landsat scene. Four of the algorithms were cluster matching, and two were maximum likelihood algorithms. The seventh algorithm determined the haze level in both training and recognition segments and used a set of tables calculated from an atmospheric model to determine the affine transformation that corrects the training signatures for changes in Sun angle and haze level. Three of the algorithms were tested on a simulated data set, and all of the algorithms were tested on consecutive-day data. The classification performance on the data sets using the algorithms is presented, along with results of statistical tests on the accuracy and proportion estimates. The three algorithms tested on the simulated data produced significant improvements over the results obtained using untransformed signatures. For the consecutive-day data, the tested algorithms produced improvements in most but not all cases. The tests indicated also that no statistically significant differences were noted among the algorithms.

1. INTRODUCTION

Signature extension is the process of using signatures from a given segment† (the training segment, or T-SEG) to classify another segment (the recognition segment, or R-SEG). If such a procedure gave classification accuracies and proportions that were comparable to those obtained with local training, it would save much time and effort in a project such as the Large Area Crop Inventory Experiment (LACIE), where many segments must be classified. The simplest approach is to use the untransformed (UT) signatures from the T-SEG. Generally, this does not work well because these signatures are different from the signatures in the R-SEG as a result of differences in haze level, Sun angle, and various factors which affect target reflectance, such as soil color and growth stage.

In this study, comparative tests were performed on seven signature extension algorithms to evaluate their effectiveness in correcting for changes in atmospheric haze and Sun angle in a Landsat scene. The evaluation criteria were classification accuracy and proportion estimation. The algorithms tested were the Maximum Likelihood Estimation of Signature Transformation (MLEST), the University of Houston Maximum Likelihood Estimator (UHMLE), the Optimal Signature Correction Algorithmic Routine (OSCAR), modified OSCAR (MOD OSCAR), the Rank Order Optimal Signature Transformation Estimation Routine (ROOSTER), modified ROOSTER (MOD R), and the Atmospheric Correction (ATCOR) program.

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†A segment in this paper is a 9-by-11-kilometer ground area.

2. THE DATA SETS

Two data sets were used – one consisting of simulated data (section 2.1) and the other a set of acquisitions on consecutive days (section 2.2). The simulated data provided for a controlled experiment in which the transformations were known and in which the problems of nonnormal distributions and nonrepresentative statistics were avoided. The consecutive-day data set provided for a test of the capability of the algorithms to correct for atmospheric effects when effects caused by differences in the training and recognition targets are eliminated. The algorithms ROOSTER, UHMLE, and MLEST were tested on the simulated data. All the algorithms were tested on the consecutive-day data set.

2.1 SIMULATED DATA

The 1975 data base of the Earth Resources Interactive Processing System (ERIPS) contains four passes of four-channel simulated data for each of segments 429 and 432. Each segment has 117 lines and each line 196 pixels. The field coordinates reside in the ERIPS field data base. Four classes exist within each segment: wheat (W), barley (B), stubble (S), and grass (G). Each class is divided into two subclasses.

The data were generated from means and covariance matrices determined from training fields in Hill County, Montana. An algorithm was used to generate multivariate normal data with the same statistics. This was done separately for the four passes of segment 429. Each pass of segment 432 was created from the distributions used in the corresponding pass of segment 429 by transforming them with an affine transformation so that the data corresponded to a different Sun angle. Segment 429 was chosen to be the T-SEG and segment 432 the R-SEG. All classifications were made in four channels. Four data sets correspond to the four passes: SIM1, SIM2, SIM3, and SIM4.

2.2 CONSECUTIVE-DAY DATA

Seven sets of consecutive-day passes of Landsat-1 data from intensive test sites in Ellis, Finney, and Saline Counties, Kansas, were tested. The first set is denoted F1709-8. (The F indicates Finney County; 1709-8 indicates the dates of the training and recognition passes, respectively; i.e., the training pass was made 1709 days and the recognition pass 1708 days after the launch of Landsat-1.) In all, four sets from the Finney, two from the Saline, and one from the Ellis County test sites were used.

Ground truth was available for all fields in all test sites. A subset was selected for training fields, and fields were grouped into subclasses with the aid of cluster maps. In general, the rectangular ground-truth areas were not oriented so that their sides were parallel to the scan lines in the Landsat-1 data. To facilitate the application of the various algorithms, a "signature extension area" was defined (the smallest rectangular area with sides parallel to the Landsat scan lines) that included the ground-truth area in each case. For Finney County, this included the entire 9- by 11-kilometer segment (117 lines, 196 pixels) containing the ground-truth area. For Saline County, it included lines 26 to 91 and pixels 27 to 146; for Ellis, it included lines 24 to 109 and pixels 49 to 144.

3. APPROACH

The overall approach was to make signature extension runs using these algorithms and to compare the results with local classification results or ground truth. The algorithms were to provide modified training statistics which then were used to classify the recognition area. The UHMLE computes these modified statistics directly; all the other algorithms compute an affine transformation which is then used to modify the training statistics.

3.1 THE ALGORITHMS

The descriptions given here provide only a very rough idea of how these algorithms work. References are given to more detailed discussions. In the case of the consecutive-day data, the algorithms were usually run using the data from the signature extension area defined above. Exceptions will be noted.

3.1.1 MLEST. The MLEST technique [1] uses an iterative gradient optimization procedure (the Davidon-Fletcher-Powell algorithm) to obtain maximum likelihood estimates for the affine transformation assumed to relate the training and recognition statistics. The training subclass *a priori* probabilities and statistics are input to the program, which outputs the maximum likelihood estimate of the affine transformation.

3.1.2 UHMLE. The UHMLE [2] takes sublcass statistics from a T-SEG and image data from an R-SEG and computes maximum likelihood estimates of subclass proportions and statistics for the R-SEG. Two versions of UHMLE were used. The first, UH all, uses the ground-truth area as input data; when this version is used to obtain maximum likelihood estimates of proportions generated internally by UHMLE, it is referred to as UH all MLE. The second, UH fields, uses only the training fields within the R-SEG; when this version is used to obtain maximum likelihood estimates of proportions generated internally by UHMLE, it is referred to as UH fields MLE. The second version was introduced to eliminate the effect of insufficient training. The statistics generated by UHMLE are used to classify the ground-truth area in the R-SEG.

3.1.3 OSCAR. The OSCAR [3] considers every possible transformation defined by four cluster means: two in the T-SEG and two in the R-SEG. From these transformations, the algorithm selects those that are "best" able to match the training clusters with the recognition clusters. The amount of computation is kept to a manageable level (1) by rejecting pairings judged to be unreasonable on the basis of rankings and (2) by testing the remaining transformations, using each to transform all the training clusters, and calculating a measure based on the distance of the transformed training clusters from the recognition clusters. The five transformations giving the "best" measure are then averaged.

3.1.4 MODIFIED OSCAR. The MOD OSCAR [4], in effect, defines a transformation for each pair of clusters – one in the R-SEG and one in the T-SEG. Each cluster is used with its projection onto the soil line[1] to define a transformation. The transformations are evaluated as in OSCAR, and the best transformation is output.

3.1.5 ROOSTER. To perform signature extension with ROOSTER [5], one first obtains a set of class means for the T- and R-SEG's. These class means, called mean vectors, are obtained by clustering or by deriving class statistics from training fields.

The first step is to derive rank vectors corresponding to each of the mean vectors. These rank vectors are obtained by computing for each channel the rank of each mean relative to the others for that segment. The rank vectors are used to match the classes (or clusters) in the training area with those in the recognition area. Then, a regression analysis is used to determine the affine transformation which best transforms the mean vectors from the training area into the corresponding mean vectors from the recognition area.

In this study, the ROOSTER was used in three different ways: The first, R(C), consisted of using clusters to define the class means for both segments; the second, R(S), used subclass means derived from training fields for both segments (It is expected to provide an estimate of how well ROOSTER would do if an ideal clustering algorithm were available.); and the third, R(S/C), used subclass statistics for the T-SEG and clusters for the R-SEG. This is an alternate way of using ROOSTER operationally, since subclass statistics are always available for the training area.

3.1.6 MODIFIED ROOSTER. The MOD R [4] is identical to ROOSTER except that the regression line is computed with the cluster means and the projections of the cluster means onto the soil line.

3.1.7 ATCOR. The ATCOR program [6] is designed to correct for differences in haze level and Sun angle between the training and recognition data sets. The program processes each of these data sets separately. In each case, the input is the Landsat-1 data and the solar zenith angle. The ATCOR program determines the haze level from the brightness of certain dark targets in the scene and uses an atmospheric model to calculate a set of coefficients relating the Landsat data for that scene to the reflectance of the targets on the ground. The coefficients obtained from the training and recognition data sets are then used to compute the affine transformation to be applied to the training data.

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[1]The soil line is the "bottom of the tasselled cap" or that part of channel space containing bare soil.

3.1.8 REGRES. Rather than a signature extension algorithm, the REGRES program is a method for finding the optimum affine transformation to be applied to the statistics of the consecutive-day data. In each channel, a scatter plot is made of the second-day data versus the first-day data. A straight line is then fitted to the data which minimizes, in the least squares sense, the perpendicular distance from the points to the line. In principle, this line represents the best affine transformation for the training statistics.

3.2 CLASSIFICATION AND EVALUATION

After obtaining the modified statistics, we used standard LACIE classification procedures and the Laboratory for Applications of Remote Sensing System (LARSYS) implemented on the Univac 1108 computer to classify the R-SEG's. A two-class classifier was used with equal *a priori* probabilities for wheat and nonwheat. Within each class, the subclasses had equal *a priori* probabilities. A 1-percent chi-squared threshold was used. For the simulated data, entire areas were classified; for the consecutive-day data, the ground-truth areas were classified.

3.2.1 CLASSIFICATION ACCURACY. The classification accuracy was determined for wheat and nonwheat by using the training fields defined in section 2 as test fields. From these, the overall accuracy was computed. This is given by:

$$\text{Overall accuracy} = q_w p(w/w) + q_\phi p(\phi/\phi) \tag{1}$$

where $p(w/w)$ = wheat accuracy, $p(\phi/\phi)$ = nonwheat accuracy, q_W = wheat proportion in ground-truth area, and q_ϕ = nonwheat proportion in ground-truth area. The proportions q_W and q_ϕ were known from ground truth. The wheat, nonwheat, and overall accuracies were compared with the results obtained from local classification (section 4).

3.2.2 WHEAT PROPORTIONS. The classification results yielded wheat proportions for the ground-truth areas defined in section 2. In addition, the UHMLE program yielded a maximum likelihood estimate of the wheat proportions. These results were compared with the ground-truth proportions and the results obtained from local classification.

4. RESULTS

The results of this processing are given in tables 1 to 11. Table 1 gives the A and B coefficients determined for the consecutive-day data by those algorithms which produce an affine transformation. The algorithms are listed in the order in which they performed in the accuracy test.

Based on numerical calculations using an atmospheric model [6], certain constraints are expected to apply to the A and B coefficients corresponding to a change in the haze level. These should apply to the consecutive-day data if the haze levels present are uniform. Among these constraints, which apply to all channels, are the following:

1. If there is no difference in haze level between the T-SEG and the R-SEG, $A = 1.0$ and $B = 0.0$.

2. If the T-SEG has more haze than the R-SEG, $A > 1.0$ and $B < 0.0$.

3. If the T-SEG has less haze than the R-SEG, $A < 1.0$ and $B > 0.0$.

In many cases, the data in table 1 do not obey these rules. Examples can be found in the following anomalies:

1. $A > 1.0$ for some channels and $A < 1.0$ for others; e.g., R(S) for F1655-4.

2. $A > 1.0$ and $B > 0.0$; e.g., MLEST for F1673-2.

3. $A < 1.0$ and $B < 0.0$; e.g., R(C) for F1726-7, channel 2.

These failures to obey the constraints probably are due in part to nonuniform haze levels in the data and to changes in the look angle.

Tables 2, 3, 4, and 5 give the accuracy results for wheat and nonwheat using both data sets. The accuracy obtained with signature extension is expressed as a percentage difference from the local result; i.e.,

$$\text{Percentage difference} = \frac{\text{signature extension accuracy - local accuracy}}{\text{local accuracy}} \times 100\% \qquad (2)$$

Tables 6 and 7 give similar results for overall accuracy.

Tables 8 to 11 give the differences for both data sets (1) between results obtained using signature extension and local classification and (2) between results obtained using signature extension and ground truth. The means and standard deviations were obtained using the absolute values of the numbers in the tables.

5. ANALYSIS

In this section, a statistical analysis is performed on the data in tables 6 and 10. Data for the UHMLE algorithm were not included because of their large variances.

First, an analysis of variance was performed on the data in table 6. The purpose of an analysis of variance is to separate a response variable into component parts. In this way, the test for a particular factor will become more sensitive because variations due to other causes have been removed. In this experiment, two factors were present: signature extension algorithms and the seven consecutive-day acquisitions. The second factor could have been grouped several different ways, on the bases of days, sites, and presence of haze.

The last alternative was chosen. Each pass was classified as either clear or hazy by visually inspecting the images of the data produced by ERIPS. The results are shown in table 12. Three T-SEG-R-SEG combinations occurred; namely, haze-clear, clear-haze, and clear-clear. It was assumed that each combination would produce different results (classifications), thus the need for this factor in the analysis.

The interaction between the algorithms and haze combinations (A×H) was also expected to be present; that is, one algorithm might have performed well for the clear-haze consecutive-day acquisitions and poorly for the haze-clear days, whereas the opposite results might have occurred for another algorithm.

The model for the experiment was

$$y_{ijk} = \mu + a_i + h_j + ah_{ij} + e_{ijk} \qquad (3)$$

where μ = overall mean, a_i = contribution of the ith algorithm, h_j = contribution of the jth haze level, ah_{ij} = contribution of algorithm i and haze level j to the interaction, e_{ijk} = error term for the kth observation for the ith algorithm and the jth haze level, and y_{ijk} = response variable. In the analysis of variance for overall accuracy, y_{ijk} = percentage accuracy difference; that is, the quantity given in table 6.

The results of this analysis of variance are given in table 13, where significant differences between the algorithms and between the haze conditions are apparent.

Table 14 gives the average accuracy difference over the algorithms for each haze condition. Because the analysis of variance indicated significant differences between haze conditions, we can infer from table 14 that the presence of haze over the T-SEG is significantly different from the other two conditions.

The results for the different haze conditions were plotted as a function of the algorithms (fig. 1). The condition with haze over the T-SEG shows consistently better results than the other two conditions. A similar analysis was performed for the wheat proportions. In this case, y_{ijk} was the quantity given in table 10. R(S/C) was not included because of its large variance. The results show a significant difference between the haze conditions but not between the algorithms (table 15). Table 16 gives the average proportion difference over the algorithms for each haze condition, and figure 2 shows the performance of each algorithm for each of the three haze conditions. Here again, the haze-clear condition seems to give the best results.

6. CONCLUSIONS

The results of these tests are summarized in table 17. The first two columns list the algorithms in the order in which they performed on the accuracy test for the simulated and consecutive-day data. The numbers given are the mean percentage differences between the accuracy obtained using the algorithms and local accuracy (see tables 6 and 7). The minus signs indicate that the algorithm was less accurate than local classification. A statistical analysis was performed on the accuracy results for the consecutive-day data with the exception of data for the three versions of UHMLE (which were omitted because of large variances). The analysis indicated (1) no significant differences among the algorithms and (2) that the results obtained when the T-SEG appeared hazier than the R-SEG were better than in the other two conditions observed; i.e., when both were clear or the R-SEG was hazier.

The comparison of wheat proportion differences (between ground truth and local results) in the last four columns of table 17 shows the performance order of the algorithms to be the same for simulated data but quite different for consecutive-day data. This was because local results were quite different from ground-truth results for the consecutive-day data. These four columns of numbers are the means of the absolute values of the differences as given in tables 8, 9, 10, and 11. A statistical analysis was performed on the consecutive-day data for wheat proportion differences from local results. Data from R(S/C) and the three versions of UHMLE were not used because of large variances. The results given in table 15 indicate no significant differences among the algorithms tested. Here again, the best results were obtained when the T-SEG appeared hazier than the R-SEG.

Finally, it must be mentioned that, because of time limitations, this test was performed using the currently available algorithms. Subsequently, it has been discovered that some of the algorithms show better performance when later versions are used. For example, the program UHMLE has a later version that begins with the transformation (x + b) before estimating the R-SEG statistics. However, the results presented in this paper provide illustrative information which can be used in solving the signature extension problem.

7. REFERENCES

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TABLE 1. A AND B COEFFICIENTS FOR CONSECUTIVE-DAY DATA

Data	R(S)		MLEST		OSCAR		REGRES		MOD R		R(C)		MOD OSCAR		ATCOR		R(S/C)	
	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
F1709-8	1.20	-7.1	1.06	-2.32	1.12	-4.4	1.24	-9.1	1.03	-0.9	1.12	-5.1	1.06	-2.6	1.12	-6.6	1.05	-3.6
	1.18	-5.4	1.02	-0.9	1.08	-3.0	1.14	-5.2	1.04	-1.7	1.09	-4.5	1.05	-2.6	1.10	-5.4	0.99	-3.2
	0.99	2.2	1.05	-1.4	1.01	1.1	1.15	-6.6	1.03	0.1	1.03	0.5	1.05	-1.8	1.08	-5.8	1.23	-10.5
	0.99	1.3	1.06	-0.7	0.98	1.5	1.12	-2.1	1.03	0.3	1.02	0.9	1.05	-0.8	1.07	-2.3	1.23	-4.2
F1673-2	0.98	0.1	1.05	0.1	0.84	4.5	0.78	5.2	0.94	1.0	0.84		0.89	3.4	0.95	2.8	0.99	0.2
	0.99	-0.9	1.06	0.0	0.90	1.8	0.82	2.4	0.94	0.3	0.88	1.5	0.98	0.5	0.96	2.4	1.01	-0.7
	1.15	-8.6	1.10	0.6	1.10	-8.8	1.3	-17.6	0.98	-1.2	1.04	-5.6	0.95	1.6	0.96	2.4	1.13	-6.3
	1.16	-5.2	1.19	0.8	1.06	-3.3	1.5	-13.3	1.00	-0.8	1.06	-3.3	0.94	1.6	0.97	1.0	1.16	-4.0
F1655-4	1.06	-0.1	1.36	-8.9	1.04	-0.1	1.05	-0.2	1.05	-0.2	1.00	1.6	1.07	-1.0	0.92	4.7	1.30	-8.1
	1.08	-0.1	1.24	-2.3	1.03	0.5	1.04	1.0	1.06	0.0	1.00	1.7	1.03	0.6	0.94	4.3	1.26	-5.9
	0.92	6.5	1.12	-0.8	0.98	3.1	0.93	5.5	1.02	0.8	0.81	12.1	1.04	-0.8	0.94	3.8	1.22	-6.2
	0.95	2.2	1.35	-5.5	1.00	0.9	1.05	0.2	1.03	0.3	0.89	3.9	1.04	-0.6	0.95	1.4	1.16	-1.7
F1726-7	0.91	0.0	0.94	-1.6	0.80	0.3	0.92	-0.9	0.88	0.4	0.89	0.1	0.86	2.0	0.94	3.3	1.00	-3.6
	0.93	-0.6	0.99	-3.5	0.81	0.5	0.94	-1.2	0.89	0.6	0.91	-0.8	0.88	1.9	0.95	2.8	1.07	-6.1
	0.91	0.6	1.22	-14.8	1.02	-6.0	1.06	-8.6	0.90	0.2	1.03	-6.4	0.87	2.1	0.96	2.5	1.33	-18.7
	0.95	-0.6	1.17	-5.5		0.5	0.98	-1.6	0.91	-0.3	0.80	3.8	0.87	1.3	0.97	0.9	1.17	-3.9
S1455-4	1.22	-4.9	0.98	0.4	0.89	2.1	0.94	1.0	0.91	1.3	0.88	2.2	0.91	2.1	0.98	0.8	2.12	-25.3
	1.18	-3.9	0.98	0.1	0.93	0.6	1.13	-3.0	0.92	0.6	0.90	1.2	0.92	1.5	0.98	0.6	1.58	-11.7
	1.08	-1.9	1.02	0.0	0.92	1.1	0.99	-0.2	0.97	-1.3	1.00	-2.3	0.92	1.2	0.98	0.5	1.33	-7.0
	1.14	-1.4	0.97	0.5	0.91	0.6	0.98	-0.2	0.96	-0.8	0.98	-1.3	0.92	0.3	1.00	0.2	1.32	-3.5
S1725-4	0.95	3.5	0.99	1.7	1.01	1.2	1.01	1.4	1.05	-0.3	0.80	8.5	1.00	1.1	0.94	3.3	1.19	-4.9
	0.98	2.9	1.03	0.7	1.01	1.3	1.04	0.9	1.06	-1.0	0.81	8.1	1.06	-0.7	0.95	2.8	1.22	-5.5
	0.97	3.4	1.04	1.2	1.01	2.2	1.02	1.8	1.04	-0.3	0.98	2.9	1.04	0.1	0.96	2.5	1.31	-4.4
	1.02	0.5	1.04	0.6	1.00	1.1	1.00	1.0	1.05	-0.6	0.96	1.5	1.03	0.2	0.97	0.9	1.32	-1.7
E1726-5	1.06	-0.5	1.03	0.1	0.99	2.1	1.04	0.6	0.96	3.5	0.95	3.7	0.96	2.6	0.92	4.7	1.20	-6.4
	1.06	-0.3	1.02	0.0	0.94	4.4	1.00	2.3	0.95	4.4	0.93	4.8	1.06	-1.5	0.94	4.3	1.17	-5.9
	1.03	0.3	1.01	0.0	0.99	3.0	0.97	3.7	0.98	3.1	0.99	2.9	1.03	-0.6	0.94	3.8	1.13	-4.2
	1.08	-0.7	1.02	0.0	1.01	1.0	1.01	1.0	1.01	1.2	1.01	1.1	1.02	0.5	0.95	1.4	1.15	-2.0

TABLE 2. WHEAT ACCURACY FOR SIMULATED DATA*

Data	Local	Percentage difference between local accuracy and that obtained with various algorithms				
		R(S)	MLEST	UH fields	R(C)	UT
SIM1	84.4	-2.0	6.3	-100	-28.4	-100
SIM2	97.1	0.0	1.2	-2.9	0.0	-26.3
SIM3	94.8	0.2	3.5	2.8	-12.8	-84.4
SIM4	87.9	-0.1	6.5	-13.5	-1.7	-28.0
Mean	91.1	-0.5	4.4	-28.4	-10.7	-59.7
Std. dev.	5.9	1.0	2.5	48.2	13.1	38.1

TABLE 3. NONWHEAT ACCURACY FOR SIMULATED DATA*

Data	Local	Percentage difference between local accuracy and that obtained with various algorithms				
		R(S)	MLEST	UH fields	R(C)	UT
SIM1	96.4	0.5	-6.3	-0.2	-30.0	-99.1
SIM2	99.1	0.0	-0.5	-0.1	0.0	-15.8
SIM3	97.7	0.0	-1.1	-2.3	-2.9	-39.5
SIM4	94.3	-0.1	-6.0	-2.4	-3.2	-3.2
Mean	96.9	0.1	-3.5	-1.3	-9.0	-39.4
Std. dev.	2.0	0.3	3.1	1.3	14.1	42.5

TABLE 4. WHEAT ACCURACY FOR CONSECUTIVE-DAY DATA*

Data	Local	Percentage difference between local accuracy and that obtained with various algorithms											
		R(S)	MLEST	OSCAR	REGRES	MOD R	R(C)	MOD OSCAR	ATCOR	UH fields	UT	R(S/C)	UH all
F1709-8	96.7	0.5	1.1	0.7	1.2	0.7	1.1	1.3	1.2	-15.6	1.1	2.0	-21.9
F1673-2	97.3	-0.8	0.9	-3.9	-6.6	-2.6	-3.8	-2.9	-2.9	-3.9	-0.6	0.2	-2.2
F1655-4	93.5	-15.5	2.7	-12.8	-11.1	-12.7	-17.8	-14.5	-19.3	-9.6	-17.8	-1.8	-49.4
F1726-7	82.6	-3.3	-6.7	-2.3	-3.0	-5.9	-10.9	-1.9	-1.1	-27.4	-2.4	-8.4	-6.4
S1455-4	92.0	1.0	1.6	-4.0	-2.7	-7.1	-11.7	-6.1	-0.7	-16.8	0.0	-2.1	-42.6
S1725-4	79.7	7.3	2.0	4.6	7.0	-0.9	8.8	1.8	-0.6	1.8	-20.2	-13.6	21.3
E1726-5	92.6	-1.9	1.1	-0.3	-2.3	-1.5	0.4	-0.4	-6.2	-50.9	-1.0	3.6	-49.2
Mean	90.6	0.1	0.4	-2.6	-2.5	-4.3	-4.8	-3.2	-4.2	-17.5	-6.8	-5.2	-21.5
Std. dev.	6.8	3.5	3.2	5.4	5.7	4.6	9.1	5.6	7.0	17.5	9.5	8.3	27.2

*A minus sign means the algorithm was less accurate than local classification.

TABLE 5. NONWHEAT ACCURACY FOR CONSECUTIVE-DAY DATA*

Data	Local	Percentage difference between local accuracy and that obtained with various algorithms											
		R(S)	MLEST	OSCAR	REGRES	MOD R	R(C)	MOD OSCAR	ATCOR	UH fields	UT	R(S/C)	UH all
F1709-8	73.9	-8.5	-6.8	-10.3	-10.6	-11.2	-12.0	-11.5	-12.4	10.7	-12.0	-18.7	19.9
F1673-2	95.7	-2.3	-1.0	-3.0	-11.5	1.6	-0.9	0.1	-5.7	-27.2	0.3	-2.3	-30.8
F1655-4	95.4	0.4	-3.4	1.4	0.7	0.4	-0.5	0.6	1.4	-0.9	0.6	-4.4	-4.0
F1726-7	79.1	3.7	3.9	5.8	7.6	-0.4	2.3	3.9	-7.5	10.6	-10.5	-6.6	-6.8
S1455-4	78.9	-2.3	-5.1	-2.8	-0.5	3.0	7.6	3.0	1.3	-4.6	0.0	-5.8	-8.0
S1725-4	93.5	-6.5	-3.5	-7.7	-8.4	-6.1	-14.7	-5.7	-9.7	-11.8	-7.0	-8.1	-23.5
E1726-5	45.2	-5.1	-17.3	-9.3	-5.3	-2.2	-11.1	-25.2	3.1	86.1	-28.5	-31.4	61.3
Mean	80.2	-2.9	-2.2	-3.7	-4.0	-2.1	-4.2	-5.0	-4.2	9.0	-9.5	-11.0	1.2
Std. dev.	17.9	4.2	12.4	5.9	6.9	5.0	8.4	10.4	6.1	36.5	10.7	10.4	31.0

TABLE 6. OVERALL ACCURACY FOR CONSECUTIVE-DAY DATA*

Data	Local	Percentage difference between local accuracy and that obtained with various algorithms											
		R(S)	MLEST	OSCAR	REGRES	MOD R	R(C)	MOD OSCAR	ATCOR	UH fields	UT	R(S/C)	UH all
F1709-8	79.5	-5.8	-4.4	-7.0	-7.1	-7.6	-8.1	-7.8	-8.5	2.7	-8.2	-12.5	7.3
F1673-2	96.1	-2.0	-0.5	-3.2	-10.2	0.5	-1.7	-0.7	-5.0	-21.3	0.1	-1.7	-23.7
F1655-4	94.9	-3.3	-1.8	-2.1	-2.1	-2.7	-4.7	-3.0	-3.6	-3.1	-3.8	-3.8	-15.0
F1726-7	80.0	1.9	1.7	3.8	4.9	-1.9	-1.1	2.4	-5.9	0.9	-8.5	-7.1	-6.8
S1455-4	86.5	-0.2	-0.9	-3.5	-1.8	-3.2	-4.4	-2.5	0.1	-12.1	0.0	-3.5	-29.5
S1725-4	85.4	1.1	-0.5	-0.9	0.0	-3.2	-1.9	-5.0	-4.7	-4.3	-14.1	-11.0	0.9
E1726-5	66.2	-3.2	-6.0	-3.8	-3.5	-1.8	-4.1	-9.8	-2.7	1.4	-11.5	-9.8	-7.3
Mean	84.1	-1.6	-1.8	-2.4	-2.8	-2.8	-3.7	-3.8	-4.3	-5.1	-6.6	-7.1	-10.6
Std. dev.	10.2	2.7	2.6	3.3	4.9	2.5	2.4	4.2	2.7	8.7	5.5	4.2	13.1

TABLE 7. OVERALL ACCURACY FOR SIMULATED DATA*

Data	Local	Percentage difference between local accuracy and that obtained with various algorithms				
		R(S)	MLEST	UH fields	R(C)	UT
SIM1	93.5	0.0	-3.5	-21.7	-29.6	-99.3
SIM2	98.6	0.0	0.0	-0.7	0.0	-18.3
SIM3	97.0	0.1	0.0	-1.0	-5.2	-50.0
SIM4	92.8	-0.1	-3.2	-5.0	-2.9	-8.8
Mean	95.5	0.0	-1.7	-7.1	-9.4	-44.1
Std. dev.	2.8	0.1	1.9	9.9	13.6	40.8

TABLE 8. WHEAT PROPORTIONS FOR SIMULATED DATA AS DETERMINED USING LOCAL RESULTS

Data	Local	Signature extension proportion minus local proportion					
		R(S)	R(C)	MLEST	UH fields MLE	UH fields	UT
SIM1	24.3	-0.5	-1.9	0.6	-16.8	-22.3	-24.3
SIM2	24.7	0.0	0.0	0.6	-1.0	-1.1	-3.2
SIM3	24.9	0.1	-3.1	1.5	1.7	1.6	-20.0
SIM4	24.2	0.0	-0.2	6.8	-0.3	-0.6	-6.3
Mean absolute values		0.2	1.3	2.4	5.0	6.4	13.5
Std. dev.		0.2	1.5	3.0	7.9	10.6	10.3

TABLE 9. WHEAT PROPORTIONS FOR SIMULATED DATA AS DETERMINED USING GROUND TRUTH

Data	Ground truth	Signature extension proportion minus ground-truth proportion					
		R(S)	R(C)	MLEST	UH fields MLE	UH fields	UT
SIM1	23.9	-0.1	-1.5	1.0	-16.4	-21.9	-23.9
SIM2	23.9	0.8	0.8	1.4	-0.2	-0.3	-2.4
SIM3	23.9	1.1	-2.1	2.5	2.7	2.6	-19.0
SIM4	23.9	0.3	0.1	7.1	-0.3	-0.3	-6.0
Mean absolute values		0.8	1.1	3.0	4.9	6.3	12.8
Std. dev.		0.4	0.9	2.8	7.8	10.5	10.3

*A minus sign means the algorithm was less accurate than local classification.

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TABLE 10. WHEAT PROPORTIONS FOR CONSECUTIVE-DAY DATA AS DETERMINED USING LOCAL RESULTS

Acquisition	Local	Signature extension proportion minus local proportion												
		R(S)	REGRES	OSCAR	MOD R	UT	MLEST	ATCOR	MOD OSCAR	R(S/C)	R(C)	UH all	UH fields	UH all MLE
F1709-8	35.4	5.9	7.5	9.0	9.4	9.8	7.8	10.7	10.3	16.5	10.3	-8.9	-8.5	-5.2
F1673-2	28.9	3.1	-2.0	0.6	-2.0	1.9	5.0	-1.6	-1.9	4.4	-1.5	20.7	13.3	22.5
F1655-4	27.7	-2.2	-2.2	-2.1	-1.6	-4.7	3.9	-4.9	-2.8	2.8	-3.8	1.6	4.6	5.8
F1726-7	28.8	-1.0	-2.0	-1.4	-1.4	3.1	-0.4	2.6	-1.4	1.9	-2.6	-2.4	-13.7	-2.8
S1455-4	53.7	0.5	-3.3	-3.5	-8.6	-2.0	4.8	-3.0	-7.6	-0.3	-13.3	-11.4	-10.6	-8.3
S1725-4	35.3	4.6	5.0	5.3	2.9	-0.8	2.6	4.4	3.6	-0.9	9.6	19.6	5.5	20.7
E1726-5	61.9	1.8	1.4	3.3	0.9	6.6	4.9	-3.2	6.0	9.8	3.6	-25.1	-36.1	-29.7
Mean absolute values		2.7	3.3	3.6	3.8	4.1	4.2	4.3	4.8	5.2	6.4	12.8	13.2	13.6
Std. dev.		1.9	2.2	2.9	3.6	3.2	2.3	3.0	3.3	5.9	4.6	9.2	10.7	10.6

TABLE 11. WHEAT PROPORTIONS FOR CONSECUTIVE-DAY DATA AS DETERMINED USING GROUND TRUTH

Data	Ground truth	Signature extension proportion minus ground-truth proportion												
		R(S)	REGRES	OSCAR	MOD R	UT	MLEST	ATCOR	MOD OSCAR	R(S/C)	R(C)	UH all	UH fields	UH all MLE
F1709-8	24.6	16.7	18.3	19.8	20.2	20.6	18.6	21.5	21.1	27.3	21.1	1.9	2.3	5.6
F1673-2	24.6	7.4	2.3	4.9	2.3	6.2	9.3	2.7	2.4	8.7	2.8	25.0	17.6	26.8
F1655-4	24.6	0.9	0.9	1.0	1.5	-1.6	7.0	-1.8	0.3	5.9	-0.7	4.7	7.7	8.9
F1726-7	24.6	3.2	2.2	2.8	2.8	7.3	3.8	6.8	2.8	6.1	1.6	1.8	-9.5	1.4
S1455-4	58.3	-4.1	-7.9	-8.1	-13.2	-6.6	0.2	-7.6	-12.2	-4.9	-17.9	-16.0	-15.2	-12.9
S1725-4	58.3	-18.4	-18.0	-17.7	-20.1	-23.8	-20.4	-18.7	-19.4	-23.9	-13.4	-3.4	-17.5	-2.3
E1726-5	44.2	19.5	19.1	21.0	18.6	24.3	22.6	14.5	23.7	27.5	21.3	-7.4	-18.4	-12.0
Mean absolute values		10.0	9.8	10.8	11.2	12.9	11.7	10.5	11.7	14.9	11.3	8.6	12.6	10.0
Std. dev.		7.9	8.4	8.5	8.8	9.6	8.8	7.8	9.9	10.7	9.3	8.7	6.2	8.7

TABLE 12. HAZE CONDITIONS ON CONSECUTIVE-DAY DATA AS DETERMINED BY INSPECTION OF IMAGES

Data	T-SEG	R-SEG
F1709-8	Clear	Clear
F1673-2	Haze	Clear
F1655-4	Clear	Clear
F1726-7	Haze	Clear
S1455-4	Clear	Clear
S1725-4	Clear	Haze
E1726-5	Clear	Haze

TABLE 13. ANALYSIS OF VARIANCE FOR OVERALL ACCURACY

Source	Degrees of freedom	Sum of squares	Mean square	F-factor	Significance
Algorithm (A)	9	217.61	24.18	2.02	6% or 7%
Haze (H)	2	113.69	56.85	4.74	5%
A×H	18	205.32	11.41	.95	NS
Error	40	480.17	12.00		
Total	69	1 016.79			

TABLE 14. ACCURACY PERCENTAGE FOR THE THREE DIFFERENT HAZE CONDITIONS

Haze condition		Percent accuracy difference
T-SEG	R-SEG	
Haze	Clear	-1.71
Clear	Clear	-4.26
Clear	Haze	-4.82

TABLE 15. ANALYSIS OF VARIANCE FOR WHEAT PROPORTIONS

Source	Degrees of freedom	Sum of squares	Mean square	F-factor	Significance
Algorithm (A)	8	59.77	7.47	X	NS
Haze (H)	2	156.27	78.14	9.42	1%
A×H	16	45.21	2.83	X	NS
Error	36	312.95	8.69		
Total	62	574.20			

TABLE 16. AVERAGE PROPORTION DIFFERENCES
FOR THE THREE HAZE CONDITIONS

Haze condition		Proportion difference
T-SEG	R-SEG	
Haze	Clear	2.0
Clear	Clear	5.8
Clear	Haze	3.9

TABLE 17. SUMMARY OF TEST RESULTS

Percentage difference between local accuracy and that obtained with various algorithms				Wheat proportions difference from local				Wheat proportion difference from ground truth			
Simulated data		Consecutive-day data		Simulated data		Consecutive-day data		Simulated data		Consecutive-day data	
R(S)	0.0	R(S)	-1.6	R(S)	0.2	R(S)	2.7	R(S)	0.8	UH all	8.6
MLEST	-1.7	MLEST	-1.8	R(C)	1.3	REGRES	3.3	R(C)	1.1	REGRES	9.8
UH fields	-7.1	OSCAR	-2.4	MLEST	2.4	OSCAR	3.6	MLEST	3.0	UH all MLE	10.0
R(C)	-9.4	REGRES	-2.8	UH fields MLE	5.0	MOD R	3.8	UH fields MLE	4.9	R(S)	10.0
UT	-44.1	MOD R	-2.8	UH fields	6.4	UT	4.1	UH fields	6.3	ATCOR	10.5
		R(C)	-3.7	UT	13.5	MLEST	4.2	UT	12.8	OSCAR	10.8
		MOD OSCAR	-3.8			ATCOR	4.3			MOD R	11.2
		ATCOR	-4.3			MOD OSCAR	4.8			R(C)	11.3
		UH fields	-5.1			R(S/C)	5.2			MLEST	11.7
		UT	-6.6			R(C)	6.4			MOD OSCAR	11.7
		R(S/C)	-7.1			UH all	12.8			UH fields	12.6
		UH all	-10.6			UH fields	13.2			UT	12.9
						UH all MLE	13.6			R(S/C)	14.9

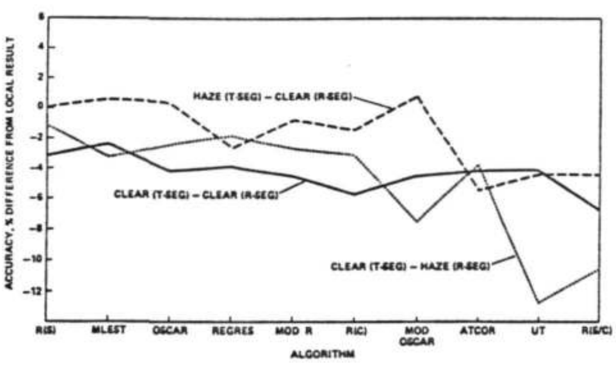

FIGURE 1. HAZE-BY-ALGORITHM INTERACTION. Overall accuracy difference is shown for the three haze conditions.

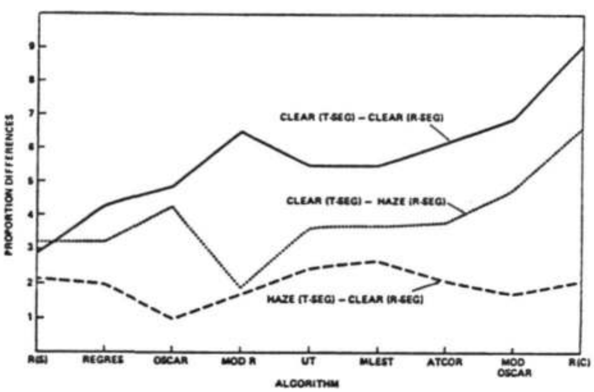

FIGURE 2. HAZE-BY-ALGORITHM INTERACTION. Proportion differences are shown for the three haze conditions.