Analysis of Classification Results of Remotely Sensed Data and Evaluation of Classification Algorithms

Xin Zhuang, Bernard A. Engel, Xiaoping Xiong, and Chris J. Johannsen

Abstract

Classification results of remotely sensed data are usually summarized as confusion matrices, and various classification algorithms are used to improve results. Confusion matrices should be normalized to assess classification accuracies of remotely sensed data, and multiple comparisons are required to evaluate the classification algorithms. The classical iterative proportional fitting procedure, including eliminating zero counts, was scrutinized to normalize confusion matrices. The Tukey multiple comparison method was used for the comparison of results from three classification algorithms: minimum distance, maximum likelihood, and an artificial neural network. Normalized confusion matrices provided uniform margins and accuracies for each classification category. The Tukey comparisons of the three algorithms were made simultaneously; results provided the overall classification accuracy for each algorithm and showed no differences among the algorithms at a risk level of 5 percent. Normalized confusion matrices can be compared entry by entry because of their uniform margins. Results of this study indicate that classification algorithms can be evaluated with the Tukey method, and the multiple comparisons of the algorithms should be made based on normalized category accuracies obtained with the iterative proportional fitting procedure. Normalized confusion matrices provide a unified measure of producer's and user's accuracies.

Introduction

Classification results of remotely sensed data are usually summarized as confusion matrices (contingency tables). However, the contingency tables are unable to assess classification accuracies completely because the tables do not provide the accuracies for each classification category. Story and Congalton (1986) studied marginal statistics of a contingency table and thereby defined the user's accuracy and producer's accuracy for the table. According to the definitions, the user's accuracy measures commission errors for each classification category, whereas the producer's accuracy measures omission errors for each classification category. The user's accuracy is the ratio of the number of correctly classified samples in a category to the total number of samples that were classified as in that category (row total for the category). The producer's accuracy is the ratio of the number of correctly classified samples from a category to the total number of reference samples of that category (column total for the category). Usually, a user's accuracy does not equal the corresponding producer's accuracy. Based on these definitions, a user's accuracy or a producer's accuracy is not the accuracy for a given classification category.

Congalton *et al.* (1983) and Rosenfield and Fitzpatrick-Lins (1986) measured the agreement of classified data with reference data using *Kappa*. Kappa is a measure of agreement of a contingency table (Cohen, 1960). Congalton (1991) reviewed the method for accuracy assessment of classification results for remotely sensed data. However, both the marginal and the Kappa statistics do not directly include the effects of off-diagonal entries on the accuracies of individual classification categories and overall classification. Fienberg (1971) developed an iterative proportional fitting procedure to normalize a contingency table and include the effects. This procedure was applied to the accuracy assessment of classification results for remotely sensed data (Congalton *et al.*, 1983; Congalton, 1991). However, the details of the procedure should be addressed, including eliminating zero counts in contingency tables.

Although multiple comparisons such as the Tukey multiple comparison have been studied for many years, they have not yet been applied to evaluating classification algorithms (classifiers) in the area of remote sensing. However, a pairwise comparison based on the *Kappa* statistics was used to investigate the difference of means between a pair of classifiers (Congalton *et al.*, 1983; Congalton, 1991). Various new classifiers have been developed as advanced techniques are applied to remote sensing. Therefore, multiple comparisons of results from the new classifiers with those from conventional classifiers are needed.

The objectives of this study were to scrutinize the iterative proportional fitting procedure, including eliminating zero counts, and to apply the Tukey multiple comparison method to evaluating classification results obtained with

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Photogrammetric Engineering & Remote Sensing,
Vol. 61, No. 4, April 1995, pp. 427–433.

0099-1112/95/6104-427$3.00/0

maximum-likelihood, minimum-distance, and an artificial neural network classifier.

Materials and Methods

Data and Classifiers Used

The data used in this study were the classification results of a Landsat Thematic Mapper scene acquired 29 July 1987. The scene covered approximately 10.36 km², including sections 3, 4, 9, and 10 located in T28N, R5E of Richland township, Miami County, Indiana. The six categories of land cover for these sections included corn, soybeans, forest, pasture, bare soil, and river. The scene was classified with the following classifiers: maximum likelihood, minimum distance, and an artificial neural network (Tables 1, 2, and 3, respectively). These three classifiers were trained with the same data set.

Elimination of Zero Counts in Contingency Tables

Fixed and *random* zeros are two types of zero counts in a contingency table. A fixed zero occurs because of a zero probability, whereas a random zero occurs because of a small probability. In the contingency tables of classification results for remotely sensed data, random zeros are usually encountered. The zero counts in Table 1 may differ from one another. Before implementing a normalization, we adjusted the table to find an estimate for each of these zero counts. Fienberg and Holland (1970) developed a method of "smoothing with pseudo-counts" for eliminating zero counts. Based on an observation table, the approach used a Bayesian estimator to produce pseudo-counts and was formulated as

$$\hat{p}_{ij} = \frac{N}{N + k}(X_{ij} + k\lambda_{ij})$$

where X_{ij} is an entry in the i-th row and the j-th column of the table, $\hat{p}_{ij}$ is the Bayesian estimator of p_{ij}, and N is the sum of all entries ($N = \sum_{i,j} X_{ij}$). According to the Bayesian statistical analysis, an entry probability p_{ij} is regarded as a random variable and has a prior density, $\pi(p_{ij})$, proportional to $p_{i,j}^{k\lambda_{i,j}-1}$. λ_{ij} is the expectation of p_{ij} ($\lambda_{ij} = E_\pi(p_{ij})$), and k is the number of pseudo-counts to be added to a contingency table. The joint distribution of $\{p_{ij}\}$ is proportional to $\prod_{i,j} p_{i,j}^{k\lambda_{i,j}-1}$.

Empirical optimal λ_{ij} and k are calculated by

$$\lambda_{ij} = \frac{X_{i.}X_{.j}}{N^2}$$

where $X_{i.}$ is the i-th row margin and $X_{.j}$ is the j-th column margin, and

$$k = \frac{N^2 - \sum_{i,j} X_{ij}^2}{\sum_{i,j}(N\lambda_{ij} - X_{ij})^2}.$$

For smoothing a contingency table with pseudo-counts, first we calculated the "expected value," $N\lambda_{ij}$, instead of λ_{ij} for the simplicity of computation. Next, k was computed with the formula given above. Third, the k pseudo-counts were allocated to the individual entries of the *expected value* table, and the entries were multiplied by the ratio k/N. Finally, the contingency table was added to the table obtained in the third step entry by entry, and the result was multiplied by $N/(N+k)$ to preserve the original total of N. The elimination of zero counts can be done easily within a spreadsheet. Tables 1, 2, and 3 were adjusted by using the method of smoothing with pseudo-counts (Tables 4, 5, and 6).

Normalization of Contingency Tables

With the iterative proportional fitting procedure, a contingency table can be standardized to have uniform margins for both rows and columns in order to examine the association or interaction of the table (Fienberg, 1971). After a contingency table was smoothed with pseudo-counts, the iterative proportional fitting procedure was then applied to the table. The iterative proportional fitting procedure made the row and column margins consecutively equal one. To do this, the first step was to multiply the entries in a row by the ratio of one over the corresponding row margin. The second step was to multiply the entries in a column by the ratio of one over the corresponding column margin. Because each entry was adjusted during the first step, the column margins were changed. The first cycle of the iterative proportional fitting procedure was complete. Because the row margins were no longer equal to one after the second step, the operation including steps 1 and 2 was repeated. The repetition formed the second cycle of the iterative proportional fitting procedure. The process converged after a finite number of cycles (Fienberg, 1970). The iterative proportional fitting procedure is supported by the SAS software (SAS Institute, 1988a). Specifying the stopping criteria and the maximum iterations is optional. Tables 4, 5, and 6 were normalized with the iterative proportional fitting procedure (Tables 7, 8, and 9). These normalized classification results showed uniform margins and the accuracies (highlighted entries) for individual classification categories.

Multiple Comparisons

Each classification technique examined in this study had a contingency table. By extracting the correct percentages of each classification category in a normalized contingency table, we developed a summary table of classifier performance (Table 10).The summary table represented a two-factor experiment with only one observation per entry. Montgomery (1991) defined a statistical model to describe the experiment: i.e.,

$$y_{ij} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk}\ (i = 1,2,\ldots,I; j = 1,2,\ldots,J; k=1)$$

(I = the number of classifiers; J = the number of categories)

where

y_{ij} = performance of the classifiers being compared,
μ = overall mean of the correct percentages,
α_i = the effect of the i-th classifier,
β_j = the effect of the j-th category,
$(\alpha\beta)_{ij}$ = the effect of the interaction between α_i and β_j, and
ε_{ijk} = random errors.

The following assumptions were made in this study: (1) probabilities that individual categories were correctly classified were inherent for a classifier, (2) classification of pixels in category A did not depend on classification of pixels in category B, and (3) classification of pixels with classifier I did not depend on classification of pixels with classifier II. Based on these assumptions, columns of a summary table were independent, entries in each column were approximately independent, and the standard deviation in each entry y_{ij} was univariable and approximately $\sqrt{\frac{p_{ij}(1 - p_{ij})}{m_i}}$, where p_{ij} was the underlying true probability (the probability

TABLE 1. CLASSIFICATION RESULTS OBTAINED WITH THE MINIMUM DISTANCE ALGORITHM.

Classification Categories	Corn	Soybeans	Forest	Pasture	Bare Soil	River	Row Total	User's Accuracy (%)
	Reference categories (pixels)							
Corn	722	4	53	0	0	0	779	92.68
Soybeans	0	580	0	43	0	0	623	93.10
Forest	8	0	396	0	0	1	405	97.78
Pasture	0	1	0	195	105	1	302	64.57
Bare Soil	0	1	0	0	12	0	13	92.31
River	0	0	0	0	0	26	26	100.00
Column Total (pixels)	730	586	449	238	117	28	2148	
Producer's Accuracy (%)	98.90	98.98	88.20	81.93	10.26	92.86		

TABLE 2. CLASSIFICATION RESULTS OBTAINED WITH THE MAXIMUM-LIKELIHOOD ALGORITHM.

Classification Categories	Corn	Soybeans	Forest	Pasture	Bare Soil	River	Row Total	User's Accuracy (%)
	Reference categories (pixels)							
Corn	712	0	12	0	0	0	724	98.34
Soybeans	0	584	2	26	0	0	612	95.42
Forest	18	0	434	0	0	0	452	96.02
Pasture	0	1	0	212	105	0	318	66.67
Bare Soil	0	1	0	0	12	1	14	85.71
River	0	0	1	0	0	27	28	96.42
Column Total (pixels)	730	586	449	238	117	28	2148	
Producer's Accuracy (%)	97.53	99.66	96.66	89.08	10.26	96.43		

TABLE 3. CLASSIFICATION RESULTS OBTAINED WITH THE NEURAL NETWORK ALGORITHM.

Classification Categories	Corn	Soybeans	Forest	Pasture	Bare Soil	River	Row Total	User's Accuracy (%)
	Reference categories (pixels)							
Corn	725	8	21	11	1	1	767	94.52
Soybeans	1	555	32	13	0	1	602	92.19
Forest	3	4	393	3	0	0	403	97.52
Pasture	0	18	2	211	29	0	260	81.15
Bare Soil	0	1	0	0	87	0	88	98.86
River	1	0	1	0	0	26	28	92.86
Column Total (pixels)	730	586	449	238	117	28	2148	
Producer's Accuracy (%)	99.32	94.71	87.53	88.66	74.36	92.86		

that a given pixel in the i-th category was correctly classified by the j-th classifier), and m_i was the sample size in the i-th category. Because of one observation per entry, the effects of the interaction and the errors were confounded. We could assume no interaction effects between classifiers and classification categories (*i.e.*, $(\alpha\beta)_{ij}=0$). But we tested whether the interaction existed by "isolating" the component with one degree of freedom from the residual sum of squares because the effects of rows and columns were not additive (Tukey, 1949). Montgomery (1991) has documented the detailed procedure of the isolation. In addition, an effect α_i as defined by computing the difference between the corresponding classifier mean, μ_i, and the average of all classifier means: i.e.,

$$\mu_i - \frac{1}{I}\sum_{l=1}^{I} \mu_l \ (i = 1, 2, \ldots, I).$$

TABLE 4. CLASSIFICATION RESULTS ADJUSTED BY THE METHOD OF SMOOTHING WITH PSEUDO-COUNTS. THE ORIGINAL CLASSIFICATION WAS DONE WITH THE MINIMUM-DISTANCE ALGORITHM.

Classification Categories	Reference Categories						Row Total
	Corn	Soybeans	Forest	Pasture (pixels)	Bare Soil	River	
Corn	720.910	4.497	53.262	0.206	0.101	0.024	779
Soybeans	0.505	579.022	0.311	43.062	0.081	0.019	623
Forest	8.309	0.265	395.258	0.107	0.053	1.010	405
Pasture	0.245	1.194	0.007	194.615	104.789	1.007	302
Bare Soil	0.011	1.006	0.007	0.003	11.973	0.003	13
River	0.021	0.017	0.013	0.007	0.003	25.939	26
Column Total (pixels)	730	586	449	238	117	28	2148

TABLE 5. CLASSIFICATION RESULTS ADJUSTED BY THE METHOD OF SMOOTHING WITH PSEUDO-COUNTS. THE ORIGINAL CLASSIFICATION WAS DONE WITH THE MAXIMUM-LIKELIHOOD ALGORITHM.

Classification Categories	Reference Categories						Row Total
	Corn	Soybeans	Forest	Pasture (pixels)	Bare Soil	River	
Corn	710.964	0.435	12.310	0.178	0.088	0.021	724
Soybeans	0.463	583.072	2.280	26.093	0.074	0.018	612
Forest	18.302	0.274	433.245	0.111	0.055	0.013	452
Pasture	0.240	1.191	0.148	211.607	104.809	0.009	318
Bare Soil	0.011	1.006	0.007	0.005	11.975	0.998	14
River	0.021	0.017	1.011	0.007	0.003	26.941	28
Column Total (pixels)	730	586	449	238	117	28	2148

TABLE 6. CLASSIFICATION RESULTS ADJUSTED BY THE METHOD OF SMOOTHING WITH PSEUDO-COUNTS. THE ORIGINAL CLASSIFICATION WAS DONE WITH THE NEURAL NETWORK ALGORITHM.

Classification Categories	Reference Categories						Row Total
	Corn	Soybeans	Forest	Pasture (pixels)	Bare Soil	River	
Corn	723.856	8.496	21.343	11.182	1.101	1.022	767
Soybeans	1.502	554.037	32.231	13.132	0.081	1.017	602
Forest	3.330	4.261	392.239	3.103	0.054	0.013	403
Pasture	0.218	18.131	2.129	210.551	28.963	0.008	260
Bare Soil	0.074	1.057	0.045	0.024	86.797	0.003	88
River	1.021	0.019	1.012	0.008	0.004	25.937	28
Column Total (pixels)	730	586	449	238	117	28	2148

Therefore, it could be reported whether the performance of a classifier was higher or lower than the average after the computation.

The Tukey multiple comparison method can be applied to comparisons of classifiers. We made multiple comparisons by computing the Tukey critical distance (ω) (Mendenhall and Sincich, 1989): i.e.,

$$\omega = q_\alpha(p, v)\frac{s}{\sqrt{n}}$$

where

$q_\alpha(p, v)$ = critical value of the Studentized range at a given risk level, α;
p = number of classifiers;
v = number of degrees of freedom associated with MSE;
s = $\sqrt{\text{MSE}}$ (mean square of errors); and
n = number of observations in each of the p classifiers.

Any two population means of classifiers were judged to be different from one another if the difference of the corresponding sample means was greater than the distance, ω.

The Tukey multiple comparison method is also supported by SAS software (SAS Institute, 1988b). The results of the Tukey multiple comparisons for Table 10 provided the overall classification accuracy for each classifier and showed no differences among the three classifiers at a risk level of 5 percent.

TABLE 7. NORMALIZED RESULTS FOR THE CLASSIFICATION RESULTS OBTAINED WITH THE MINIMUM-DISTANCE ALGORITHM.

Classification Categories	Reference Categories						Row Total
	Corn	Soybeans	Forest	Pasture	Bare Soil	River	
Corn	**0.955**	0.005	0.039	0.000	0.000	0.000	0.999
Soybeans	0.001	**0.865**	0.000	0.134	0.000	0.000	1.000
Forest	0.036	0.001	**0.955**	0.001	0.000	0.007	1.000
Pasture	0.001	0.003	0.000	**0.863**	0.129	0.004	1.000
Bare Soil	0.002	0.126	0.001	0.001	**0.871**	0.000	1.001
River	0.001	0.000	0.000	0.001	0.000	**0.999**	1.000
Column Totals	0.996	1.000	0.995	0.999	1.000	1.010	6.000

TABLE 8. NORMALIZED RESULTS FOR THE CLASSIFICATION RESULTS OBTAINED WITH THE MAXIMUM-LIKELIHOOD ALGORITHM.

Classification Categories	Reference Categories						Row Total
	Corn	Soybeans	Forest	Pasture	Bare Soil	River	
Corn	**0.970**	0.004	0.021	0.004	0.001	0.000	1.000
Soybeans	0.000	**0.890**	0.001	0.109	0.000	0.000	1.000
Forest	0.032	0.003	**0.962**	0.003	0.000	0.000	1.000
Pasture	0.000	0.002	0.000	**0.875**	0.123	0.000	1.000
Bare Soil	0.000	0.094	0.000	0.001	**0.871**	0.034	1.000
River	0.000	0.002	0.021	0.002	0.000	**0.975**	1.000
Column Total	1.002	0.995	1.005	0.994	0.995	1.009	6.000

TABLE 9. NORMALIZED RESULTS FOR THE CLASSIFICATION RESULTS OBTAINED WITH THE NEURAL NETWORK ALGORITHM.

Classification Categories	Reference Categories						Row Total
	Corn	Soybeans	Forest	Pasture	Bare Soil	River	
Corn	**0.957**	0.007	0.012	0.018	0.000	0.005	0.999
Soybeans	0.004	**0.911**	0.034	0.041	0.000	0.010	1.000
Forest	0.019	0.016	**0.942**	0.022	0.000	0.000	0.999
Pasture	0.001	0.042	0.003	**0.918**	0.035	0.000	0.999
Bare Soil	0.002	0.022	0.001	0.001	**0.973**	0.000	0.999
River	0.010	0.000	0.004	0.000	0.000	**0.986**	1.000
Column Total	0.993	0.998	0.996	1.000	1.008	1.001	5.996

Discussion

As shown in Tables 4, 5, and 6, the pseudo-counts were allocated to the individual entries in Tables 1, 2, and 3, and the "zeros" were different from one another. We adjusted Tables 1, 2, and 3 without changing the original margins. This is the advantage of eliminating zero counts with the method of pseudo-count *smoothing*. Other methods such as adding 1, 1/2, or 1/4 pseudo-counts to all entries cannot preserve the original margins, although they preserve the total number of entries (Fienberg and Holland, 1970).

After implementation of the iterative proportional fitting procedure, the original contingency tables were normalized and fitted with uniform margins each equal to one. The computation precision of the computer caused the column totals in Tables 7, 8, and 9 not to equal exactly one. The normalized tables can be compared to one after another entry by entry because of the uniform margins. The iterative proportional fitting procedure included the effects of the off-diagonal entries in Tables 1, 2, and 3 on the accuracies of individual classification categories and overall classification. Therefore, the diagonal entries in Tables 7, 8, and 9 were not the ratios (producer's accuracies) of the diagonal entries in Tables 1, 2, and 3 over the corresponding column margins, indicating that a conclusion based on the original classification results could be biased. After implementing the procedure, we can assess the accuracy of a classification based on the normalized category accuracies. However, if we apply the method of the producer's accuracy and the user's accuracy to a contingency table, we must interpret the table in both row and column directions because of the definitions of the accuracies. Because the iterative proportional fitting procedure produces uniform margins and accuracies for each

TABLE 10. PERFORMANCE SUMMARY OF THE MINIMUM-DISTANCE, THE MAXIMUM-LIKELIHOOD, AND THE NEURAL NETWORK CLASSIFIERS.

Classification Categories	Classifiers: Minimum Distance	Maximum Likelihood	Neural Network
Corn	0.955	0.970	0.975
Soybeans	0.865	0.890	0.911
Forest	0.955	0.962	0.942
Pasture	0.863	0.875	0.918
Bare Soil	0.871	0.871	0.973
River	0.999	0.975	0.986

Table 11. SAS Output from the Multiple Comparisons of the Minimum-Distance, the Maximum-Likelihood, and the Neural Network Classifiers.

General Linear Models Procedure
Tukey's Studentized Range (HSD) Test for variable: Y
NOTE: This test controls the type I experimentwise error rate, but generally has a higher type II error rate than REGWQ.
$\alpha = 0.05$ df= 9 MSE= 0.0004
$q_{\alpha}(p, v) = 3.948$
$\omega = 0.033$
Means with the same letter are not significantly different.

Tukey Grouping	Means	N	Classifiers
A	0.948	6	Neural Network
A			
A	0.924	6	Maximum Likelihood
A			
A	0.918	6	Minimum Distance
average	0.930		

Classifiers	Classifier Effects	Relative Classifier Effects*
Minimum Distance	−0.012	−1.3%
Maximum Likelihood	−0.006	−0.7%
Neural Network	0.018	2.0%

*classifier affect/average

classification category, we can average the category accuracies to obtain an overall classification accuracy.

The major advantage of Tukey multiple comparisons is that the comparisons can be done all at once. However, if we apply pairwise comparisons to n classifiers, we need $n(n-1)/2$ pairwise comparisons. Another advantage is that the risk level, α, can be modified until the significant classifier differences are examined. We have to apply the modification to every pair of comparisons if we use pairwise comparisons. Pairwise comparisons are made according to the *Kappa* statistics. Kappa only provides an overall accuracy for a classification rather than accuracies for each classification category. As for the results of the Tukey multiple comparisons, not only were the classifiers evaluated, but the overall classification accuracy for each classifier was also provided. The results shown in Table 11 illustrated multiple Tukey comparisons could be made, and the performance of each classifier versus the average performance of all classifiers used could be estimated.

Acknowledgments

This research was supported by NASA Research Grant NAGW-1472 and the Laboratory for Applications of Remote Sensing at Purdue University. Special thanks go to Dr. Charles Bracker and Dr. Eric Gustafson for their helpful review of earlier drafts of this manuscript.

Journal Paper Number 13918 of the Purdue University Agricultural Research Programs.

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(Received 19 October 1992; revised and accepted 10 August 1993; revised 6 October 1993)

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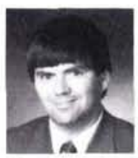

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15th Biennial Workshop on Color Photography and Videography in Resource Assessment

Indiana State University
Terre Haute, Indiana
May 1-3, 1995

Approximately 30 papers will be presented addressing state-of-the-art airborne video systems, digital cameras, and color photography, including applications of these systems for resource assessment.

Seven non-concurrent sessions and a panel discussion which includes video systems, digital cameras, data pre-processing, forestry resources, agricultural resources, wetlands/water applications, fisheries habitat, and land use resources will be presented.

Preliminary Schedule

1 May	6:30 - 8:00 p.m.	Informal Conversation/Tour of the Remote Sensing/GIS Lab
2 May	7:30 - 8:30 a.m. +	Registration
	8:30 - Noon	Sessions
	Noon - 1:30 p.m.	Luncheon
	1:30 - 5:00 p.m.	Sessions
	6:00 - 9:00 p.m.	Keynote/Dinner/Social
3 May	8:30 - Noon	Sessions
	Noon - 1:30 p.m.	Luncheon
	1:30 - 3:30 p.m.	Sessions
	3:30 - 5:00 p.m.	Panel Discussion/Closing

The Workshop cost is $175 which includes registration, a copy of the proceedings, continental breakfasts, luncheons, keynote dinner, and refreshments. Student registration is $75 which does not include dinner or a copy of the proceedings. For technical questions about the program contact Paul Mausel (Tel. 812-237-2254; FAX 812-237-8029). For registration information, registration forms, and accommodations information contact:

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