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Optical Power Spectrum Analysis: Scale and Resolution Effects

Land-use classification using optical power spectrum analysis is tested as a function of photo scale and resolution.

ABSTRACT: *Optical power spectrum measurements were made on three sets of photos differing in scale and resolution. The effects of these variables on power spectrum measurements and automatic land-use classification accuracy were determined.*

For the values tested (20 lp/mm and 35 lp/mm), resolution had no appreciable effect on classification but did shift the power curve in the expected direction. Scale had a direct effect on classification accuracy; results were poorest at the smallest scale (1/48,000) because of the difficulty in obtaining "pure" sample areas.

A stepwise multiple discriminant analysis program produced classification accuracies of 56 percent to 100 percent depending on scale and number of variables. With five variables, accuracy ranged from 66 percent to 92 percent for a six-category classification and from 88 percent to 100 percent for classification as man-made versus natural. A cross-validation analysis showed accuracies of 78 percent to 92 percent for four-category classifications and 91 percent to 100 percent for two categories.

INTRODUCTION

RECENT RESEARCH on automatic land-use classification has dealt extensively with digital processing of Landsat multispectral imagery. Results have been successful, but unfortunately are not readily applicable to conventional aircraft mapping photography. During the 1972-1974 time period, about 1200 Landsat images were obtained over the State of Washington. In this same period, over 20,000 aircraft photos were obtained, ranging in scale from 1/3,000 to 1/420,000.

Conventional mapping photography typically is obtained with panchromatic rather than multispectral systems and is an analog rather than a digital representation. The multispectral approach used by Landsat relies on color or tone differences occurring in two or more limited wavelength bands. Spatial information (size, shape, texture) is used sparingly, if at all. The reverse tends to hold true with conventional mapping photos. The broad band response of panchromatic film provides ambiguous tonal response; spatial characteristics tend to be more useful in classification.

Early attempts at automatic shape and texture classification using densitometric scanning and analog signal analysis met with somewhat limited success.[1,2] More promising results have been shown recently with image transforms in the spatial frequency domain.

When a beam of coherent light is passed through an image and a transform lens, a diffraction pattern is formed that is the optical equivalent of a Fourier Transform (Figure 1). The pattern may be photographed for subsequent analysis[3] or imaged on a detector whose output can in turn be digitized.[4-9]

The diffraction pattern shows the relative distribution of energy as a function of spatial frequency and direction or alignment. Figure 2 illustrates some representative pat-

PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING,
Vol. 43, No. 9, September 1977, pp. 1117-1125.

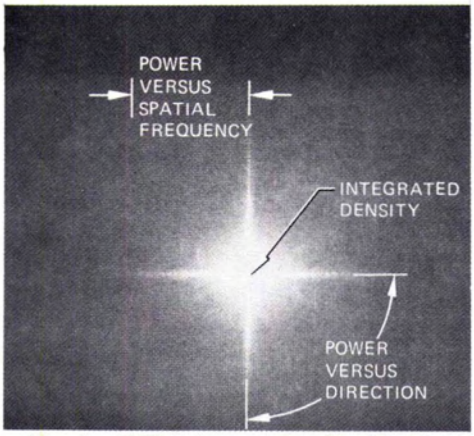

FIG. 1. Diffraction pattern of parking lot.

terns. Scene linearity (street patterns, for example) is denoted by the presence of peaks in the energy distribution. Spatial frequency (cycles per mm) increases away from the center of the pattern. The intensity of the pattern as a function of distance from the center (optical power spectrum) provides a means of feature classification.

Success has been achieved in classifying land use on Landsat imagery[6,7] using the optical power spectrum approach to spatial frequency analysis, but only limited data are available on larger-scale aircraft imagery.[5,8] In this study, three sets of large- and medium-scale panchromatic aircraft photos were analyzed to determine the applicability of optical power spectrum analysis and to investigate the effects of scale/resolution differences.

METHOD

A series of measurements were made on three sets of aerial photos using a Recognition Systems Incorporated Model 110 recording optical power spectrum analyzer (ROSA). The three sets of photos differed in scale and ground resolution but covered the same ground area.

For each image sample measurement, 64 data points were produced. The first 32 defined relative power as a function of spatial frequency; the second 32 defined relative power as a function of direction. These values were used in comparisons of scale/resolution effects as well as in multidiscriminant analysis routines designed to test classification accuracy.

PHOTOS

The three sets of panchromatic photos used (each set containing two to four photos) were obtained over an area south of Seattle, Washington (Figure 3). Original taking scales were 1/12,000 and 1/24,000; the 1/48,000-scale material was a two-diameter reduction of the 1/24,000-scale material. Ground resolutions were approximately 0.6 meters, 1.2 meters, and 1.4 meters, respectively.

The area covered by the photos consists of a deeply incised mature river flood plain undergoing transition from agriculture to light industry and commercial use. Valley walls tend to be wooded, and residential areas are located on surrounding hills. Two interstate highways bisect the area in N-S and E-W directions.

A six-category classification system was adopted for the study. The categories were approximately equivalent to Anderson Level

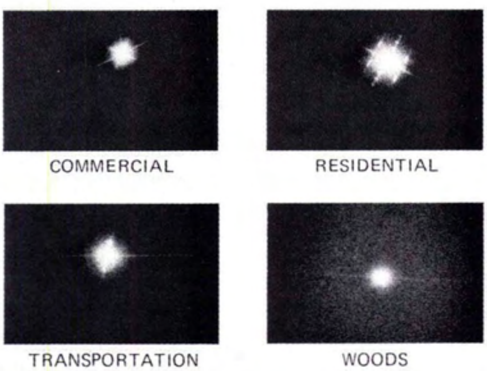

FIG. 2. Representative diffraction patterns taken from 1/24,000 scale panchromatic photo.

FIG. 3. Example of photo used in study—original scale of 1/12,000.

II classification[10] and consisted of residential, commercial, transportation, wooded, pasture, and open. The transportation category included railroads, interstate highways, and the adjacent rights-of-way. Pasture and open areas differed only in that the pasture areas contained vegetation and the open areas had little or none. Commercial areas contained shopping centers, warehouses, and light industry. Residential areas were predominantly single family housing.

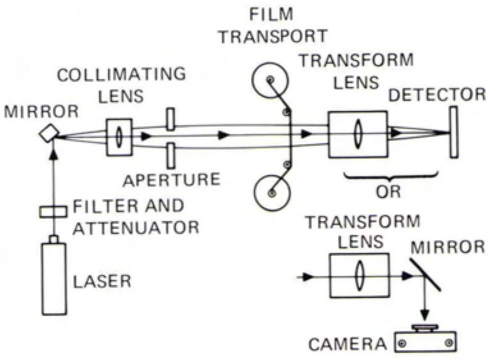

FIG. 4. Diagram of recording optical power spectrum analyzer (ROSA).

SAMPLE DESCRIPTION

A total of 252 image areas were sampled. Samples on the 1/24,000-scale photos were distributed in accordance with the overall distribution of the categories on the photos. A first set of samples on the 1/48,000-scale photos was made by following the same approach except that, because of scale, it was more difficult to find homogeneous open and pasture areas. Classification ambiguities arising with the first set of 1/48,000-scale data prompted the second set of readings at the same scale. Major emphasis here was in sampling unambiguous areas, i.e., areas that fell into a single land-use classification.

Samples on the 1/12,000-scale images were selected to cover a sub-set of the same ground areas covered on the 1/24,000-scale images. Selection was restricted by the smaller ground area coverage of the 1/12,000-scale imagery.

MEASUREMENTS

Sample areas were measured using the ROSA detector. A diffraction pattern is formed by passing coherent light (NE:He laser) through an aperture, the film plane, a transform lens, and the pattern focused on a detector (Figure 4). Aperture size, which controls the size of the sample area, is variable from 4.8 to 25.4 mm. All readings were obtained using a 6.4 mm circular aperture. The ground area coverage was thus 1.12, 4.5, and 18.0 acres at the three scales.

The focal length of the transform lens controls the range of spatial frequencies handled. In this study, a 495 mm focal length lens was used, providing a range of 1 to 49 cycles/mm.

The detector (Figure 5) contains 64 elements: 32 rings and 32 wedges. The rings record relative energy as a function of distance from the center of the diffraction pattern, which in turn is a function of spatial frequency.

Since diffraction patterns are symmetrical, the rings need cover only half the diffraction pattern. The other half provides data for the 32 wedges. The wedges record relative energy as a function of direction (azimuth). Each wedge covers a 5-degree segment.

On the detector used in this study, the wedges and rings were separated by a 20-degree segment called the scratch block. The scratch block filters out spatial noise due to film scratches and also provides space for connecting the individual rings and wedges to their amplifiers.

Energy recorded by each ring and wedge is fed to an amplifier. The amplified relative energy values are then fed to a keypunch where they are recorded on four punched cards. The system used in this study was time-limited by the keypunch; about two seconds were required for each sample reading. The detector itself can provide readings in 20 μsec.

ANALYSIS

The output for each sample reading consisted of two punched cards showing ring values and two showing wedge values. Ring data were normalized to ring 1 and 31 values and corrected for aperture and gain effects. Ring 32 values were dropped because of an amplifier noise problem. New cards were

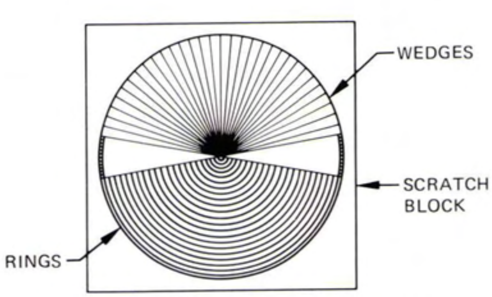

FIG. 5. Diagram of ROSA detector.

generated in this process that listed relative log power for rings 2 through 30.

Wedge data were treated by finding the mean and variability of each set of sample readings and converting all readings to Z scores (mean reading divided by standard deviation). Z scores values of 3 or more were defined as peaks, and the number of positive and negative peaks were listed on a separate card. In addition, wedge variability and ring 1 values were listed on the same card. Ring 1 values are a rough measure of relative film density within the sample area.

Two general types of data analysis were performed. In the first, analyses were made on the transformed ring and wedge values as a function of scale/resolution and land-use class. In the second, a multi-discriminant classification program was used to evaluate land-use classification accuracy for each of the four scale/resolution sample sets.

Results

Analysis of the effects of scale/resolution and land-use category on ring and wedge values showed rather strong consistency across scale and no obvious benefits of a particular scale/resolution combination. Strong correlations between ring 1, rings 2 through 30, and wedge variability values were found. The correlations of these three types of data appeared to be a function of true scene differences rather than a failure in data normalization.

Because ring and wedge value correlation negated the use of factor and cluster analysis techniques for classification purposes, a stepwise multiple discriminant analysis was employed. Classification accuracy values of 56 percent to 100 percent were achieved. Accuracy varied as a function of the number of variables employed and the particular sample involved. Two cross-validation tests showed similar accuracies.

Scale/resolution comparisons

A comparison of corrected ring values for the wooded category at each of the three scales employed is shown in Figure 6. Other categories provided similar results. A comparison of relative log power over the series of rings provides an indication of image quality. The 1/48,000-scale imagery, at an estimated resolution of about 35 cycles/mm, showed higher values for a given ring than the other two scales. The 1/12,000-scale material appeared to be of consistently better quality than the 1/24,000-scale material, although the difference was relatively small.

On an overall basis, the 1/12,000- and

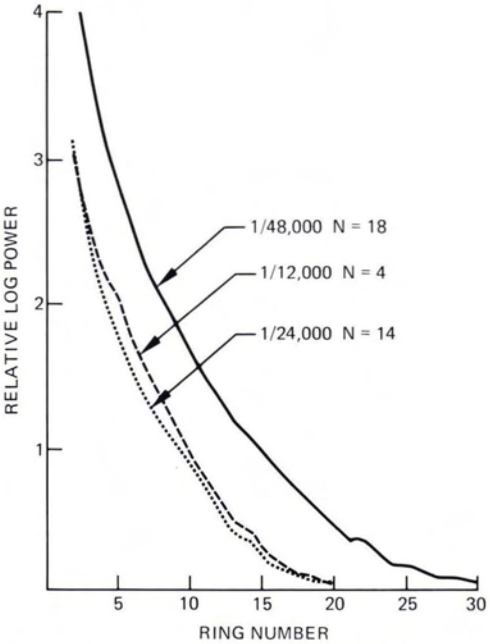

Fig. 6. Mean ring values—woods category.

1/24,000-scale materials showed little useful information beyond rings 17 to 19. These rings correspond to spatial frequencies of 16 to 21 cycles/mm. The 1/48,000- scale material appears to contain useful information out to a range of 33 to 40 cycles/mm. The 2:1 difference between the two sets of data is consistent with the results expected from the photoreduction process employed.

The 2:1 difference exhibited at the highest frequencies also was maintained at lower frequencies. A given level of relative log power on the 1/24,000-scale material tended to occur at half the spatial frequency of the 1/48,000-scale material.

A comparison of relative power plots for each category showed good agreement in terms of category separation or differences. In Figure 7, for example, the general relationship of the commercial and open categories are the same for both scales shown. With the exception of the transportation category at the 1/48,000 scale, the same phenomena held for other categories and scales. It thus was evident that the distribution of energy as a function of spatial frequency for each land-use category was generally consistent across scales.

The data shown in Figures 6 and 7 compare scales at the same image spatial frequencies (cycles/mm or rings). The same data were analyzed with matching done in terms of ground resolution (ground size).

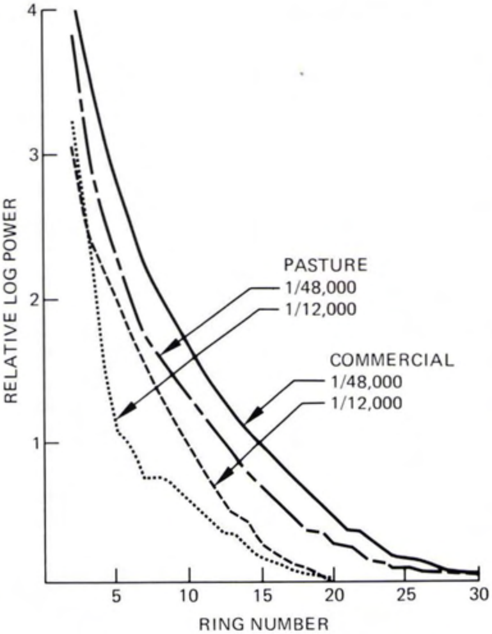

FIG. 7. Comparison of commercial and pasture ring means at two scales.

Different ring values were selected at each scale such that ring frequencies, expressed in meters-per-cycle × scale, were approximately equal.

A rather consistent trend was found in terms of scale effects. Relative log power at the 1/12,000 scale was consistently higher than for the other two scales at ground sizes of 0.5 to 5.0 meters (Figure 8). At larger ground sizes, the same difference occurred for all but the pasture and open categories. This suggests that the pasture and open categories contain little information beyond frequencies of 5 meters.

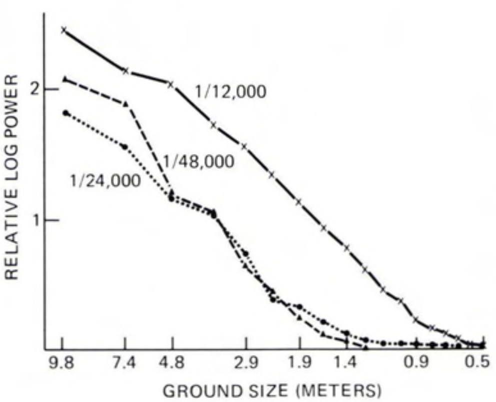

FIG. 8. Effects of scale and ground size on power—commercial category.

The 4- to 5-meter ground size range appeared to be significant in the comparison of 1/24,000- and 1/48,000-scale data. At smaller sizes, relative log power was roughly equivalent; at larger sizes, the 1/48,000-scale output was larger. The divergence was believed to represent the effects of a change in film gamma. An increase in gamma for the 1/48,000 scale would produce the effect shown; such an increase did in fact occur.

A tabulation of ring 1 data for each category and scale is shown in Table 1. Ring 1 readings are very roughly equivalent to energy transmission averaged over the sample area (6.4 mm circle). Typically, 60 percent to 80 percent of the total energy is ready by ring 1. No attempt was made to process the different scales to the same average density; comparisons of absolute values can thus not be made across scale. The relationship of average values for land-use categories can be compared within scales, however. The data in Table 1 indicate that wooded areas consistently showed the lowest transmission and open and commercial areas the highest. The second 1/48,000-scale sample (B) shows the effect of reducing, with the attenuator, the amount of energy from the laser. The separation among categories was reduced. The attenuator is used to avoid saturating the lower rings (low frequency) while still maintaining some power at the higher rings.

An examination of distributions about the mean showed considerable positive and negative skewing. Direction of skewing was not consistent across scales for different land-use categories.

A tabulation of wedge data is shown in Table 2. The data shown represent the mean variability of wedge readings about the mean and the standard deviation of the variability values. High variability is associated with strong directionality. The wedge readings were normally distributed, and wedge variability distributions for each land-use category were positively skewed.

The data in Table 2 show consistent category differences across scales. Manmade categories or features show high variability; natural features tend to show low variability. In addition, natural features often show greater consistency in variability (lower σ).

The final step in the analysis of wedge data involved the counting of peaks. The mean and variability of each set of wedge readings was computed and each reading in turn transformed to a Z score (distance from mean expressed in standard deviations). A

TABLE 1. RING 1 VALUES.

Land-Use	1/12,000		1/24,000		1/48,000 A		1/48,000 B	
Category	Mean	σ	Mean	σ	Mean	σ	Mean	σ
Residential	370	86	429	87	663	185	255.7	81.6
Commercial	495	102	625	162	737	216	316.8	65.5
Woods	168	47	223	57	242	75	—	—
Transportation	499	187	630	156	816	196	278.14	69.6
Pasture	331	164	416	115	346	156	269.9	138.0
Open	490	313	812	148	765	291	—	—

peak was then defined as a wedge value exceeding a Z score of ±3. Linear features such as roads would be expected to show a single strong peak. Intersecting road patterns found in commercial areas would show two peaks at right angles to each other. Areas without sharp boundaries, such as woods and pasture, would not be expected to show any peaks.

The commercial and transportation categories both tended to show a single peak; for the remainder of the categories such peaks were much less prevalent. The sharpest difference occurred between the transportation and wooded categories.

Reviewing both the ring and the wedge data, no particularly strong differences were found as a function of scale (constant film resolution). The 1/12,000-scale material showed a consistent tendency to exhibit slightly more power at a given frequency. This may represent a failure of the normalizing function, a bias related to the data collection procedure (data were collected at different times), a scene content difference (rather unlikely because of the consistency across land-use categories), or a film processing (gamma) difference.

Varying resolution and scale by photoreduction shifted the power curve to the right (as would be expected) and may have increased power at lower frequencies because of gamma changes. Ring 1 and wedge values showed no obvious effects related to either scale or resolution that could be separated from scene content differences.

CATEGORY DISCRIMINATION

The second phase of the analysis involved the testing of the usefulness of the power spectrum data in performing land-use classification. A stepwise multidiscriminant analysis routine (BMD)[11] was used to perform classification. Analyses were run on an IBM 360/65J.

The stepwise multidiscriminant analysis program develops a set of linear classification functions by selecting variables in a stepwise manner. Variables are selected by using one of four available criteria (based on F values or distance functions). A variable is deleted when the F value becomes too low. Output includes a table showing classification of each case, the *a posteriori* probability of each case belonging to each group, and a two-dimensional plot of the first canonical variable against the second.

Results of the analysis of each of the four samples are shown in Table 3. The number of variables listed is based on significant F ratios. For all but one of the 1/48,000-scale samples, between three and five variables were required to classify with 80 percent to 90 percent accuracy. With the one 1/48,0000-scale sample (A), overall accuracy was quite poor. The major portion of the error occurred in the commercial and trans-

TABLE 2. WEDGE VARIABILITY.

Land-Use	1/12,000		1/24,000		1/48,000 A		1/48,000 B	
Category	Mean	σ	Mean	σ	Mean	σ	Mean	σ
Residential	49.4	18.4	51	51	44.2	18.5	41.1	18.5
Commercial	73.0	74.6	58	56	45.3	41.3	41.8	25.6
Woods	16.1	10.9	22	22	20.7	7.3	—	—
Transportation	85.3	34.2	91	41	67.4	37.9	65.9	35.1
Pasture	15.9	8.9	10	5	13.8	9.0	13.1	4.6
Open	21.3	27.2	12	12	18.3	10.5	—	—

TABLE 3. STEPWISE MULTIPLE DISCRIMINANT ANALYSIS RESULTS.

Scale	Step	Variables Added	N	Errors: Commercial	Errors: Residential	Errors: Transportation	Errors: Woods	Errors: Pasture	Errors: Open	Total Accuracy	2-Category[a] Accuracy
1/12,000	3	R_1, W, R_7	38	3	2	1	1	3	2	67%	97%
	5	R_4, R_{27}	38	1	1	1	0	3	1	81%	100%
1/24,000	3	R_1, R_8, R_{11}	85	6	1	3	2	4	1	79%	94%
	5	R_{10}, R_3	85	5	0	1	0	3	0	89%	96%
1/48,000 A	3	R_{11}, R_1, R_6	82	17	4	8	2	2	3	56%	80%
	5	R_{13}, R_{29}	82	14	3	3	2	2	2	68%	89%
1/48,000 B	3	R_6, R_{15}, R_{11}	44	1	1	1	–	–	0	92%	100%
	5	R_{17}, R_{19}	44	0	2	1	–	–	0	92%	100%

[a] Cultural versus natural.

portation categories, and errors more often resulted from confusion within the cultural categories. An examination of the 1/48,000-scale imagery on which the sample readings were based showed that many of the sample areas contained more than one category of land use. The size of the sample areas (300-meter-diameter circle) was apparently too large to obtain "pure" samples consistently. In the second set of samples taken at the 1/48,000 scale (B), greater care was taken in placement of the sample areas, and the results showed greater accuracy.

Results at both the 1/24,000 and 1/48,000 scales indicated that the commercial category was most difficult to discriminate accurately. For the most part, this category was confused with the residential or transportation category.

The specific variables selected and the order in which they were selected varied from sample to sample (Table 3). The difference was probably partly due to scale differences and partly due to differences in the number of samples within each category. However, for all but the second 1/48,000-scale sample (B), the ring 1 variable was among the first three selected. The remaining selections included ring values corresponding to ground resolutions of 60 inches, 10 to 20 inches, 3 to 6 inches, and one ring at the highest available spatial frequency. For the second 1/48,000-scale sample, selections were in the 10- to 20-inch and 60-inch range only. The attenuator setting probably precluded any usefulness for ring 1 values.

VALIDATION

Using the multidiscriminant analysis program, two validation studies were performed. In the first, a cross-validation was obtained using regression equations developed independently on two halves of the 1/24,000-scale sample. All categories with more than ten observations were randomly divided into two subsamples, each having the same number of observations. Multidiscriminant analysis was performed on each sample half and the resulting regression equation was used to test observations from the opposite sample half. The program was allowed to select ten variables. The first three variables selected in each case accounted for almost 100 percent of the total dispersion and only those three were used in the cross-validation process. Results are shown in Table 4.

The second validation study involved a test of the regression equation developed on the 1/48,000-scale sample B against the original 1/48,000-scale sample A. Three variables were employed in the regression equation since they accounted for 100 percent of the total dispersion. Results are shown in Table 5.

In both the validation exercises, some difficulty was experienced with the commercial category. About 50 percent of the errors resulted from misidentification of this category, but only four of 16 such errors resulted in assignment to a non-cultural category.

CONCLUSIONS AND RECOMMENDATIONS

With the use of optical power spectrum data, reasonable success was achieved in classifying land use on photos at three different scales. Scale appeared to have little effect on the relationships observed among the land-use classes, although it appeared that the aperture size at the 1/48,000-scale covered too large an area. Without a great deal of care in sampling, many areas tended to contain two or more land-use categories. At the larger scales (1/24,000 and 1/12,000), the probability of obtaining a pure sample was much greater. It was concluded that a sample area of 4 to 5 acres is best for areas and land-use categories of the type tested. This

TABLE 4. CROSS-VALIDATION RESULTS (1/24,000 SCALE).

		Original Classed as:				Cross-Validation Classed as:				
		Commercial	Residential	Woods	Pasture	Commercial	Residential	Woods	Pasture	
A	Commercial	[6]	1			[5]	1		1	*B*
	Residential	1	[7]				[7]	1		
	Woods			[6]	1			[6]	1	
	Pasture		1		[9]			1	[9]	
		Total Accuracy = 88%				Total Accuracy = 84%				
		Natural versus Culture = 97%				Natural versus Cultural = 94%				
B	Commercial	[5]		1	1	[4]	3			*A*
	Residential		[8]				[8]			
	Woods		1	[5]	1		1	[6]		
	Pasture				[10]	1	1	1	[7]	
		Total Accuracy = 88%				Total Accuracy = 78%				
		Natural versus Cultural = 91%				Natural versus Cultural = 91%				

value would be expected to vary as a function of land-use pattern and classification categories.

Image processing differences (gamma) introduced artifacts that affected the comparisons of scale/resolution differences, but characteristic shapes of the relative power plots for each land-use category were generally preserved across scales. The influence of processing differences and sample area size could not be separated. Resolution differences shifted the power curves in the expected direction but had no clearcut effect on classification.

The multidiscriminant analysis program performed well and was relatively inexpensive to run. Cross-validation showed considerably less shrinkage than might have been expected because of the small samples involved.

Classification was achieved using spatial frequency (ring) data and a measure related to image transmission (ring 1). Directional (wedge) data did not appear particularly useful. However, only a few of the potential transforms of such data were evaluated.

The number of variables employed for classification was limited by the number of samples. Additional variables (beyond the five reported) did in fact improve classification but potentially capitalized on chance and thus were not used. Larger samples would allow additional variables to be evaluated.

Experience in this effort—as well as in previous work—suggests that the whole concept of land-use mapping, whether it be done automatically, by a photointerpreter, or on the ground, is not well defined. Even if one assumes that land use can be determined by visual observation of a section of terrain (either directly or remotely), there is often no obvious mathematical basis for classification assignment. Residential areas in this study, for example, contained houses, trees (woods), grass-covered areas (pasture), empty lots (open), and streets (transportation). Similarly, pasture, open, and agricultural areas contained buildings, trees, and roads. Although little difficulty was encountered in visual classification of each sample area, it is suspected that this mixture of features within use categories may well account for some of the difficulty in automatic classification using both spectral and spatial techniques.

Results from this study showed classification accuracies comparable to those

TABLE 5. 1/48,000-SCALE VALIDATION RESULTS.

	Original				Validation			
	Transportation	Residential	Open	Commercial	Transportation	Residential	Open	Commercial
Transportation	[5]			1	[7]	2		1
Residential		[14]		1		[18]		
Open			[7]				[10]	2
Commercial		1		[9]	2	3	1	[9]
	Total Accuracy = 92%				Total Accuracy = 80%			
	Natural versus Cultural = 100%				Natural versus Cultural = 95%			

achieved when using multispectral techniques. Only a single panchromatic coverage of the ground area was used and direct digital encoding of the scene was not required. Optical power spectrum analysis offers considerable promise in automatic analysis of the great mass of aircraft photography currently being collected.

Prior to large-scale implementation of the technique, three areas require further investigation. The first is the category definition problem previously discussed. A second and related question is one of defining optimum sample area size. What constitutes a homogeneous land use unit and how do these units vary as a function of terrain and culture differences? Finally, for many applications, it does not appear necessary to measure every square millimeter of film. A sampling scheme would provide adequate data at a considerable reduction in time and cost; the optical power spectrum technique is well suited to such an approach. Optimum sample techniques need to be defined.

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Articles for Next Month

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John E. Estes, Michael R. Mel, and *John O. Hooper,* Measuring Soil Moisture with an Airborne Imaging Passive Microwave Radiometer.

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J. J. Ulliman and *D. W. French,* Detection of Oak Wilt with Color IR Aerial Photography.

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