I. L. THOMAS
Physics and Engineering Laboratory
Department of Scientific and Industrial Research
Private Bag, Lower Hutt, New Zealand

Spatial Postprocessing of Spectrally Classified Landsat Data

The technique, based on selecting the level of influence exerted on the central pixel by a predetermined set of nearest neighbors, uses a proximity function derived by analogy from a gravitational attractive force model.

ABSTRACT: *Usual spectrally based classification techniques make little allowance for the spatial relationship between surrounding picture elements. A process based on the evaluation of a proximity function is advanced that makes this allowance possible. This process reduces the classification "noise" brought about by a variable range of spectral signatures for a target over an extended area. The proximity function was derived by analogy with the scalar gravitational attractive force.*

INTRODUCTION

COMMON COMPUTER classification techniques (e.g., histogram parallepiped, minimum Euclidean distance, maximum likelihood, etc.) usually operate in spectral, rather than image, space (for further information, see Kanal (1974), Rosenfeld *et al.* (1978), Swain and Davis (1978), and others). Using these techniques, each picture element (pixel) is classified into a target category without reference to its spatial neighbors.

Variability in the spectral distribution for the same "training" target over an extended geographic area can lead to classification "noise" being introduced into a final thematic map. This variability can be produced by the influences of differing soil type, soil moisture regime, wind pressure on vegetation with the resultant change in radiance, individual farming practices, etc.

Consequently, some form of spatial postprocessing is often desirable to aggregate like-classified pixels together by 'filling in' the unclassified gaps between lesser aggregates and by rejecting, or changing, the ascribed class for pixels that have been possibly misclassified due to spectral noise.

A technique is described here for such spatial postprocessing of spectrally classfied data based on the evaluation of a "proximity function" for each pixel, for each target class, in the initially classified dataset. The possibly revised classification status for each pixel is then passed, after this spatial postprocessing, to an output dataset. This technique has been used by the New Zealand group since 1977 to good effect in land use, forestry, and bathymetric classification projects (Ellis *et al.*, 1978).

Davis and Peet (1977) used a "filling in" method in their "minimum area recognized" technique. The method outlined here considers internal consistency among the immediate nearest neighbors rather than filling in between classified conglomerates.

It remains for the user to choose the technique most appropriate to his application.

The human eye and brain, when viewing and classifying a scene, act as a multidimensional classifier. The combination senses color, shape, proximity of associated classes, and texture, among other information. Extensive work has been reported on the classification of features by shape and texture (Bernstein, 1978; and references

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therein). Goldstein and Rosenfeld (1964) described texture as a function of two parameters: detail—the spatial distribution of contrast—and shape. Haralick (1979) regarded some texture as being decomposable into two dimensions. The first dimension described the primitive elements that constituted texture and the second dimension addressed the spatial organization of the primitives. Extending these ideas into spectral classification: the spectrally classified pixel may be regarded as the first dimension, or primitive, in a spectrally and spatially ordered thematic map. The second dimension would then involve the spatial relationship between such spectrally classified primitives. It is expected that future classifiers will bring together textural and spectral systems just as the human eye and brain do now.

Method

Fu (1972) compared the use of a probability density function with other techniques in classifying data in spectral space. His probability function was based on the concept of electrostatic potential. Such a potential function existed for each target class over all pixels. Here we are considering the interaction between pixels that have already been classified into various target classes.

To avoid the possibility of uncontrolled edge growth, it was decided to use an inverse square distance relationship (Fu, 1972, similarly used an inverse square distance dependence). Consequently, a "proximity function" based on the scalar gravitational attractive force function was chosen, i.e., Equation 1. (The need to minimize computer time acted against the choice of other than such a simple relation. The weighting factors were also chosen as integers to further minimize computer time.)

The proximity function, Equation 1, is evaluated for a central pixel surrounded by nearest neighbors, for the set of classes. If the maximum value of the proximity function over the set of all target classes exceeds a user specified minimum value, then the central pixel is admitted as a member of the target set. Otherwise, it is rejected to the unclassified set. This applies whether or not the central pixel has already been classified as a member of the target set under consideration. (Weighting is used to favor the retention of the central pixel in its previously classified state, if classified. See later.)

In some cases previously unclassified pixels will be included by this process in the final target classification; and in others, classified pixels will be declassified and excluded. The outcome depends upon the maximum value of the proximity function over the complete target set for that pixel with respect to the predetermined minimum value.

The proximity function for each individual pixel is separately evaluated, in turn, from the 'raw' classification dataset and the result used to generate the revised pixel value, in turn, in the spatially postprocessed dataset.

The spatial postprocessing technique is only applied to a dataset where each pixel has been spectrally classified into one of j classes, or into the unclassified "zeroth" class. The proximity function F_j, for class j, for a central pixel P_5 in a 3 by 3 nearest neighbor matrix (Table 1) is evaluated from Equation 1 where only the non-diagonal neighbors are considered. (The non-diagonal neighbors—P_2, P_4, P_6, P_8—have the ability to be twice as effective as the diagonal members of the matrix (see Table A-1). This was considered to be cost effective from a computer time standpoint.)

$$F_j = \sum_i \frac{q_i q_5}{d^2_{i,5}} \quad i = 2,4,6,8 \qquad (1)$$

$$i = 2,4,6,8$$

where

- $d_{i,5}$ is the ground distance between the centers of the i^{th} and 5^{th} pixels ($d_{2,5} = d_{8,5} = 79$ m; $d_{4,5} = d_{6,5} = 57$ m);
- q_i and q_5 are arbitrary weighting values for the i^{th} and 5^{th} pixels. If the i^{th} pixel has been classified into the j^{th} class, then $q_i = 2$, and 0 if not. If the central pixel has been classified in the j^{th} class, then $q_5 = 2$, and 1 if not; and
- F_j is the value of the proximity function for class j.

The proximity function, F_j, is evaluated over all i for each j and the results compared. The central pixel is then reclassified as a member of the target class j_{max} corresponding to the maximum value of the proximity function $F_{j_{max}}$. If $F_{j_{max}}$ exceeds the predetermined minimum value, the central pixel passes, possibly reclassified, into the output dataset. If not, it is passed as a member of the unclassified 'zero' class.

The determination of the minimum value for the proximity function is discussed in the Appendix. A

Table 1. The 3 by 3 Nearest Neighbour Matrix Surrounding Pixel 5. Only the Non-Diagonal (Even Numbered) Pixels were Used in this Spatial Postprocessing Method. The Ground Level Dimensions of Each Pixel are Indicated.

←57m→

	1	2	3
↑ 79m ↓	4	5	6
	7	8	9

value of 12×10^{-4} m^{-2} was derived from considering the value of the proximity function for the three nearest neighbors $(P_2 + P_8 + P_4)$ where these neighbors were all members of class j, and P_5 was not. This value is also appropriate to $(P_4 + P_6)$ where sampling overlap along the scan line does occur. Such a value thus permits an improved classification representation of an extended class type.

If the value were set to 11×10^{-4} m^{-2}, edge growth, through the diagonal neighbors, would be introduced.

If 13×10^{-4} m^{-2} was selected for the value, excessive rejection would occur. This value would exclude the filling in of an extended feature, sited across scan lines, where P_5 had been omitted from the classified data set.

This spatial postprocessing procedure is applied to the complete spectrally classified data set with the exception of the first and last lines and the first and last pixels in each line. To minimize storage requirements, only three lines are read from disk store for operations on the central line. A further line is read later from disk following a line shuffle.

Evaluation

Unmodified supervised histogram parallepiped classification results are presented in Figure 1. (For details of the technique, see Swain and Davis (1978), and references therein. Thomas *et al.* (1979) provides details on this operational implementation.) Four targets were classified in this 2595 hectare subscene of Landsat scene 2282-21254 recorded over Central Canterbury, New Zealand on 31 October 1975. As outlined in the Appendix, these were the "noisy" targets Bare Ground and Kopara Wheat; the "medium" target Alfalfa (or Lucerne); and the "quiet" target Exotic Forest. (The "noise" of a target has been qualitatively defined as the departure from spectral signature homogeneity for each target class. That is, the Exotic Forest is here assumed to have a homogeneous unimodal spectral signature distribution.)

Following spatial postprocessing, using a discrimination value of 12×10^{-4} m^{-2} for the proximity function, the modified map for the same area, targets, and spectral signatures is presented as Figure 2.

The major tasks for the spatial postprocessing module are to reduce the noise and to improve the spatial coherency of the spectrally classified data.

However, the applicability of both the classification technique and the additional spatial postprocessing module to actuality must first be evaluated. The "quiet" target, Exotic Forest, is used for this evaluation with the expectation that, if the classification module is operating correctly, the areas deduced from ground measurements and

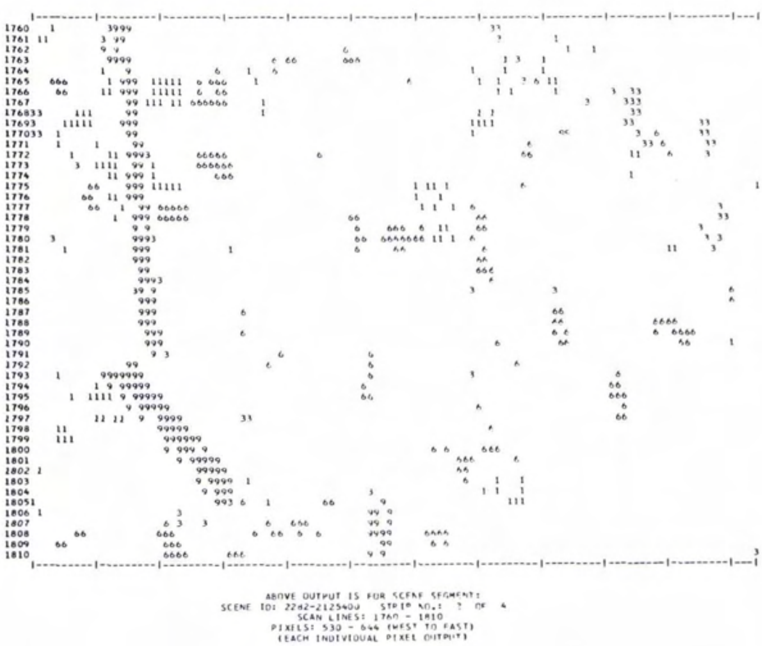

FIG. 1. Supervised histogram parallelepiped classification applied to the indicated agricultural subscene recorded over the Central Canterbury Plains on 31 October 1975. The character codes are as follows: (1)-Bare Ground, (3)-Kopara Wheat, (6)-Alfalfa (or Lucerne), and (9)-Exotic Forest.

FIG. 2. The same region as in Figure 1 has here been classified by the supervised histogram parallepiped method with identical spectral signatures to those used for Figure 1. Spatial postprocessing with a minimum proximity function discrimination level of $12 \times 10^{-4}m^{-2}$ has then been applied. In this case the character codes are (A)-Bare Ground, (C)-Kopara Wheat, (F)-Alfalfa (or Lucerne), and (I)-Exotic Forest.

from the computer classification should agree, within experimental limits. Further, if the spatial postprocessing module is functioning correctly, it should neither add nor subtract from the above area figures for such a "quiet" homogeneous target, again within experimental limits.

Within the sample region there are two major forest plantations. The plantation extending between scan lines 1761 and 1790 (portrayed in Figures 1 and 2) constitutes the 2.376 by 0.190 km shelter belt between Auchenflower and Homebush Roads on Sheet S75 of the NZMS 1 Map Series, Department of Lands and Survey, October 1973. This shelter belt is subsequently referred to as the Selwyn Forest. The other major plantation, which runs obliquely southeast from scan line 1791, has mean dimensions of 1.426 by 0.285 km and adjoins the West Coast Road on the same map sheet. (The other minor plantation, between scan lines 1806 and 1809, is excluded from the following evaluation as it is only partially included within the sample region, unlike the complete inclusion of the other two plantations.)

The known ground area of each forest is now compared with that estimated from both the raw classification and the additional spatial postprocessing process, for a discrimination value of 12×10^{-4} m^{-2}. The ground dimensions were checked by on-site inspection.

If one assumes that each picture element represents 79 by 57 m (across by along a scan line), then the Selwyn Forest maps to 30 ± 1 by 3 ± 1 pixels, where the uncertainties allow for pixels straddling target boundaries. Consequently, an area of 41 ± 15 ha could be expected to be recorded by Landsat. The raw classification process yielded an area for this forest of 36.9 ha, and after spatial postprocessing the area was found to be 38.3 ha.

The West Coast Road forest lies almost diagonally across the Landsat scan lines. Consequently, the mean forest dimensions are transformed into dimensions along and across the scan lines, in integral pixel units. Thus, the forest area, from the map and ground data, could be represented by 6 ± 1 pixels along 13 ± 1 scan lines. This led to predicted area of 35 ± 8 ha in comparison to a raw classification of Landsat data yielding 31.5 ha as against a spatially postprocessed result of 31.1 ha.

One can therefore conclude that the classification plus spatial postprocessing process has applicability to typing actual ground targets, with the qualification that a "quiet" homogeneous spectral signature has been assumed for the forest areas. The spatial postprocessing module, with a discrimination value of $12 \times 10^{-4}m^{-2}$, apparently functions also in the desired manner neither adding nor subtracting from actuality within experimental limits.

The questions of effectiveness in noise reduction and improvement in spatial coherency must now be considered.

This assessment of the capability of the spatial postprocessing module to reduce noise—misclassified pixels in the final thematic map—rests on the above conclusion that a discrimination value of $12 \times 10^{-4}m^{-2}$ is applicable to the spatial postprocessing of a "quiet" target. Classification noise is manifest as an increase or decrease in the classified area of a ground target with respect to actuality. The departure from the actual ground area of the target will increase as the spectral signature departs from the homogeneous unimodal state. For a "quiet" (possessing a homogeneous unimodal signature) target, the departure from actuality would be minimal and the spatial postprocessing would have minimal influence on the classified area. Such is the case for the "quiet" target in this test for a discrimination value of $12 \times 10^{-4}m^{-2}$ (see Table A-2). (The percentage decrease referred to in Table A-2 is obviously a combination of the exclusion of pixels initially misclassified into the target class and not surrounded by like classified pixels, together with those pixels initially excluded, but surrounded by consistently classified pixels, which were then included in the class by the spatial postprocessing procedure.)

For a value of $12 \times 10^{-4}m^{-2}$, the "noisy" targets (Bare Ground and Kopara Wheat) experienced a "noise" reduction between 30 and 55 percent and the "medium" target (Alfalfa) had a "noise" reduction of around 25 percent. These figures were confirmed by data from a ground truth visit to the area at the time of the satellite overpass. This visit took note of the location, type, and area of the test classes in the evaluation region and formed the base data for the above noise assessment study.

(Obviously the above figures will vary for other test areas and other targets. However, additional trials we have conducted support the results given here for the three target "noise" categories for the preset discrimination proximity function value of $12 \times 10^{-4}m^{-2}$.)

Spatial coherency improvement was qualitatively evaluated by visual comparison of line printer maps (e.g., Figures 1 and 2) for the range of discrimination values. Comparison was made against the unmodified histogram parallelepiped classified output. It was found that, for the "quiet" target, a discrimination value of $12 \times 10^{-4}m^{-2}$ yielded the closest agreement with the ground truth, as discussed earlier.

Conclusions

A procedure has been demonstrated for improving the target consistency in computer classified thematic maps.

The process also recognizes some of the spatial inter-relationships between picture elements that have been independently classified, in spectral space, into various target classes.

The simple supervised histogram parallelepiped classifier was here set up to evaluate the picture element into classes in a specified order (see Thomas *et al.*, 1979). The inclusion of the spatial postprocessing option permits some compensation for this sequential classification process to be included, if so desired.

The spatial postprocessing algorithm, based on a modified gravitational attractive force model with a minimum value for the permitted proximity function of $12 \times 10^{-4}m^{-2}$, has been found to be useful for New Zealand classification work. This value, based on selecting the level of influence exerted on the central pixel by a predetermined set of nearest neighbors, has been supported by operational examples.

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Appendix

Determination of the Discrimination Value for the Proximity Function

The minimum value for the proximity function $F_{j_{max}}$ was determined from the following analysis.

Comparative values for the function for varying selections of neighbors are presented in Table A-1.

An area of 2595 hectares of Central Canterbury, New Zealand, recorded on 31 October 1975 in Landsat scene 2282-21254, was classified by supervised histogram parallelepiped classification.

In determining the operational value for the discrimination level for the proximity function, spatial postprocessing was applied to this histogram parallelepiped classified data set with varying discrimination values. Four target classes were chosen. Bare Ground and Kopara Wheat were regarded as "noisy" targets, as each class included wide variations within each spectral signature parallelepiped. Alfalfa, or Lucerne, was regarded as a "medium" target and Exotic Forest as a "quiet" or "well defined" target.

The percentage decrease in the classified area for each value of the preset discrimination level for each target class was compared against the area for the unmodified parallelepiped results. This comparison is presented in Table A-2.

(In the analysis proceeding from Table A-2 the value for $P_1 + P_7 + P_4$ was excluded because, like $P_1 + P_3 + P_2$, it fell into an 'edge growth' situation. Alternatively, like $P_1 + P_3 + P_4$, it could be an unstable 'noise growth" state.)

As a result of the analysis discussed in the Evaluation section of this report and the data tabulated here, a minimum value of $12 \times 10^{-4}\text{m}^{-2}$ was selected for the discrimination level of the spatial postprocessing proximity function.

Table A-1. Proximity Function Values, from Equation 1, Summed over Specified Surrounding Pixels Referred to the Central Pixel P_5 for Two Cases: Where P_5 is of Class j_{max} (in which the Neighbours are Classified within Set j_{max}) and where P_5 is not of that Class.

Relationship	Proximity Function Value	$P_5 \neq j_{max}$ *10000 m^{-2}	$P_5 = j_{max}$ *10000 m^{-2}
3 nearest	$P_2 + P_8 + P_4$	12.6	25.1
	$P_2 + P_4 + P_6$	15.6	31.0
2 nearest	$P_2 + P_8$	6.4	12.8
	$P_2 + P_4$	9.4	18.7
	$P_4 + P_6$	12.4	24.6
2 diagonal	$P_1 + P_3$	4.2	8.4
3 diagonal	$P_1 + P_3 + P_7$	6.3	12.6
2 nearest plus 1 diagonal	$P_2 + P_4 + P_1$	11.5	22.9
2 diagonal plus 1 nearest	$P_1 + P_3 + P_2$	7.4	14.8
	$P_1 + P_7 + P_4$	10.4	20.7
4 nearest	$P_2 + P_4 + P_6 + P_8$	18.8	37.4
4 diagonal	$P_1 + P_3 + P_5 + P_7$	8.4	16.8

Table A-2. A Comparison of the Percentage Decrease in the Classified Areas between the Spatially Postprocessed Product and the Unmodified Histogram Parallepiped Classified Results for the Same Area with the Same Spectral Signatures. The Various Values of the Preset Proximity Function are Indicated. In 2595 Hectares, Histogram Parallepiped Classification Yielded 58.0 ha Bare Ground, 25.7 ha Kopara Wheat, 84.5 ha Alfalfa, and 74.8 ha Exotic Forest.

Preset Value for the Proximity Function ($\times$ 10000m^{-2})	Targets: Noisy — Bare Ground (% decrease)	Noisy — Kopara Wheat (% decrease)	Medium — Alfalfa (Lucerne) (% decrease)	Quiet — Exotic Forest (% decrease)
4	−76.9	−65.4	−84.3	−64.4
6	−76.9	−65.4	−84.3	−64.4
7	11.6	31.1	−3.2	−21.8
8	11.6	31.1	−3.2	−21.8
9	11.6	31.1	−3.2	−21.8
10	33.6	53.7	24.1	0.0
11	33.6	53.7	24.1	0.0
12	33.6	53.7	24.1	0.0
13	60.3	75.9	46.6	11.2
14	60.3	75.9	46.6	11.2
15	60.3	75.9	46.6	11.2
16	63.5	77.4	47.1	16.0
18	63.5	77.4	47.1	16.0
20	80.9	91.4	74.3	42.0
24	80.9	91.4	74.3	42.0
25	89.3	98.4	83.8	69.3
31	97.8	98.4	96.3	81.7
37	100.0	100.0	100.0	100.0