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REDUCT -- A COLOR TRANSFORMATION OF LANDSAT MULTITEMPORAL MSS DATA

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ABSTRACT

The REDUCT algorithm was developed to display in a single image the results of analysis rooted in highly-dimensional data. Weights in the range $0 \le w_i \le 1$ are calculated for each pixel, the weights describing how strongly the pixel resembles the set of prototypes indexed by i. A base grey image $\underline{G}(x,y)$ and the colors for ideal prototypes $\underline{P}_i(x,y)$ are chosen. The color displayed is then

$$\underline{J}(x,y) = \underline{G}(x,y) + \sum_i w_i(x,y)[\underline{P}_i - \underline{G}(x,y)].$$

Imagery for a particular application is shown.

I. SUMMARY

A recurring problem in the use of multitemporal Landsat MSS data is the display of the data set and the results of digital analysis of the data. One wishes to view the results of multitemporal analysis as well, and being able to do so in a single image is advantageous. The REDUCT algorithm was designed to present in a single color image the results of a particular category of multitemporal analysis by using those results to modify a grey image of the scene. A base grey value for a pixel is moved toward certain bright colors, representative of individual prototypes or categories, according to how strongly the pixel's multitemporal behavior resembles that of the prototype. In the limit of each pixel's having an exact resemblance to a prototype and with separability among the prototypes, the display is the same as a classification map of the familiar sort, each pixel having assigned to it one of the bright colors. For no resemblance of any pixel to any prototype, the grey base image is unmodified. For behavior intermediate to these extremes, there is a continuum of color character of the display. To the extent that a pixel resembles more than one prototype, its color is produced by a linear combination of the controls for the resembled prototypes. If, then, the goal is to make highly visible the attempt to analyze differentially two features with similar behavior, their designated colors would be widely different. If on the other hand the goal is to show similar spectral objects by similar colors, prototypes with similar behavior would be given colors close together. The algorithm is expressed

$$\underline{J}(x,y) = \underline{G}(x,y) + \sum_i w_i(x,y)[\underline{P}_i - \underline{G}(x,y)]$$

in which $\underline{J}$ is the color control vector (in terms appropriate to the machine being driven; counts between 0 and 255 in blue, green, and red were used to make the imagery shown here), $\underline{G}$ is the base grey control vector for a pixel (here, MSS band 7 was linearly scaled onto the 0-255 grey range with $\pm 3\sigma$ from the mean falling onto the end points), $\underline{P}_i$ is the assigned bright color control vector for the i-th prototype, and w_i is the weight ($0 \le w_i \le 1$) describing how strongly the pixel's behavior resembles that of the i-th prototype. In this form the algorithm is adaptable to any quantitative analysis that produces weights in the specified range. The analysis need not be multitemporal (nor, we suppose, even multispectral), but its main utility will likely be the representation in only three color dimensions of much more highly dimensioned data. Thoughtful development of the weights should give insight as to the performance of the numerical analysis. The algorithm allows the numerical computation machinery to handle the part of the task it does better than the human analyst--simultaneous manipulation of many spectral variables for a pixel--while using the human analyst to best advantage where he does best--applying spatial evaluation to the image.

A specific application is demonstrated here. The profile model (ref. 1) of the spectral development of agricultural crops is employed to define spectral development curves for an arbitrarily large set of prototypes, and also to estimate the (assumed normal) distribution of the curves about the standard. For each time of acquisition, a pixel is compared against the development curve of each prototype, and its spectral distance from a curve is given in standard deviations. That distance is squared and summed for all the acquisitions, to form the quantity Q . Pixels resembling a particular prototype will have Q follow a chi-square distribution under the assumption of the normality mentioned above. The cumulative chi-square distribution function of appropriate degree of freedom is used to convert the quantity, Q , to a weight according to

$$u(Q) = \int_{Q}^{\infty} C.S.(x;n)dx$$

$$w(u) = \begin{cases} 4u, & 0 \leq u \leq 2 \\ \frac{1}{4}(u-0.2) + 0.8, & 0.2 \leq u \leq 1 \end{cases}$$

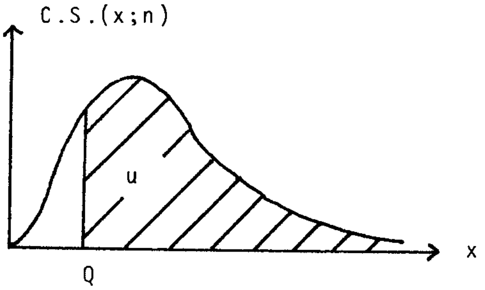
in which there are n degrees of freedom and C.S. is the chi-square density function. This transformation will have 'true' members of the i-th prototype class distributed uniformly in the interval $0 \leq u \leq 1$. The 80% of that population most closely approximating the prototype's behavior is uniformly distributed in $0.8 \leq w \leq 1$ and hence are close to the prototype's specified color (see Figure 2).

Two types of REDUCT imagery are shown. In the first, the spectral distances of a pixel (in standard deviation units) are taken from the mean of the actual pixels used to construct the crop profile for a prototype. In the second, the spectral distances are calculated from the calculated crop profile. A comparison of the two images' color patterns then shows how well the profiles actually represent the designated prototypes; where the first is brightly colored, the second is similarly colored to the extent that the profile accurately models the multispectral and multitemporal behavior of the prototype's pixels. The algorithm is useful for showing failures of the profile curves to represent individual fields' multispectral, multitemporal development.

II. REFERENCE

1. Badhwar, G.D., 1980. Crop Emergence Date Determination from Spectral Data, Photogrammetric Engineering and Remote Sensing, Vol. 46, 368.

Figure 1. Given $Q = \sum_{j=1}^{n+1} \left(\frac{x_j - \bar{x}}{S}\right)^2$, w results. There are (n+1) observations yielding average, $\bar{x}$, and sample standard deviation, S.



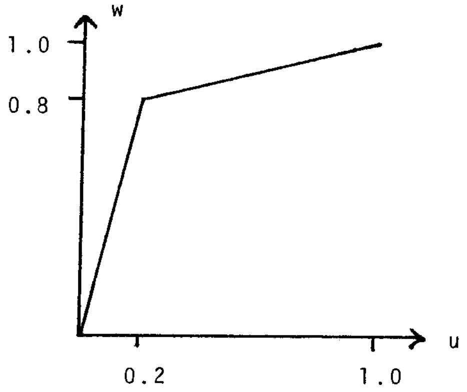
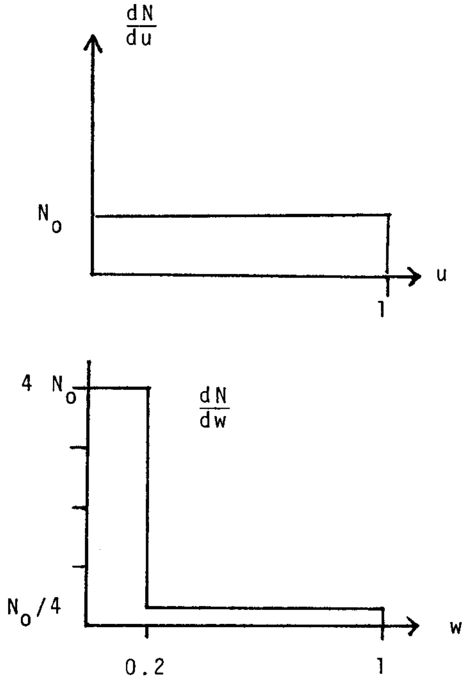


Figure 2. Densities of "true" members of prototype class if normally distributed.



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