An automated clustering/segmentation of hyperspectral images based on histogram thresholding

Jerry Silverman*, Charlene E. Caefer*, Jonathan M. Mooney**, Melanie M. Weeks*, Pearl Yip*
Air Force Research Laboratory, Hanscom AFB

ABSTRACT

A very simple and fast technique for clustering/segmenting hyperspectral images is described. The technique is based on the histogram of "divergence images": namely, single image reductions of the hyperspectral data cube whose values reflect spectral differences. Multi-value thresholds are set from the local extrema of such a histogram. Two methods are identified for combining the information of a pair of divergence images: a dual method of combining thresholds generated from 1D histograms; and a true 2D histogram method. These histogram-based segmentations have a built-in fine to coarse clustering depending on the extent of smoothing of the histogram before determining the extrema. The technique is useful at the fine scale as a powerful single image display "summary" of a data cube or at the coarser scales as a quick unsupervised classification or a good starting point for an operator-controlled supervised classification. Results will be shown for visible, SWIR, and MWIR hyperspectral imagery.

Keywords: hyperspectral data, clustering, segmentation, histograms, thresholds, unsupervised classification

1. INTRODUCTION

With hyperspectral data, the clear distinction in principle among the terms *clustering, segmentation,* and *classification* begins to blur. The desirability of *clustering* arises when masses of data points in multiple dimensions need simplification or compression by grouping into "natural" clusters[1]. *Segmentation* is typically a preliminary stage in image analysis and divides an image into meaningful or like regions[2]. Finally, *classification* is remote material identification through spectral signatures[3]. If we correctly cluster the hyperspectral data for a natural scene, and assign a common digital value to the pixels of a given cluster, we create in effect a representative segmented image of the scene as a consequence of the spatial correlations of the clusters. Further, given the tendency of the segmented regions to stem from the same or similar material, we have also in hand a good starting point to a full classification of the scene.

A standard technique of image segmentation is to use the histogram of an image whose intensities reflect different regions to determine multi-value thresholds.[2] In this paper, we extend this technique to the task of clustering/segmenting from a hyperspectral data cube. The histograms are generated from spectral divergence images whose values span the range of spectral variability among the data pixels. We will describe several ways to reduce the data cube to such divergence images, and techniques for establishing multi-value thresholds which use: a single 1-D histogram; a pair of 1-D histograms from two divergence images; and a 2-D histogram from two divergence images. We will use three scenes in the visible, the SWIR and the MWIR to illustrate our results.

2. THE TECHNIQUE

The basic steps in our clustering/segmentation process are:
1. Reduce the hyperspectral data cube to a single image, referred to as a divergence image, whose values group pixels according to spectral profile similarities.
2. Generate the histogram of the divergence image after suitable scaling or smoothing.
3. Determine a set of threshold values from the local extrema of this histogram and use to assign digital values to each pixel based on its place in the histogram.

*jerry.silverman@hanscom.af.mil; phone 781 377-3295; fax 781 377-4814; Sensors Directorate, Air Force Research Laboratory, AFRL/SNHI 80 Scott Rd. Hanscom AFB, MA, USA 01731; **Work accomplished while with AFRL currently with jon@solidstatescientific.com; Solid State Scientific Corporation 27-2 Wright Road, Hollis NH, USA 03049

We have identified several methods for generating such divergence images. One technique is to take the spectral distance of each pixel from a reference spectral profile using some standard measure of spectral differentiation such as Euclidean difference[3]. The reference profile could be that of a data pixel itself or that of a spectral eigenvector from a principal component analysis. Alternately, one can use one of the principal component (PC) images (suitably scaled) as the divergence image, thereby avoiding the use of a spectral distance measure. In Fig. 1, we show 4 divergence images, each scaled from 0 to 1000. Fig.1a is based on the first eigenvector as reference profile and Euclidean distance as measure; Fig. 1b is based on the second eigenvector with spectral information divergence as a measure[4]: Figs. 1c and 1d are directly the first and second PC images. While we have surveyed a wide range of divergence image types, we restrict our presentation

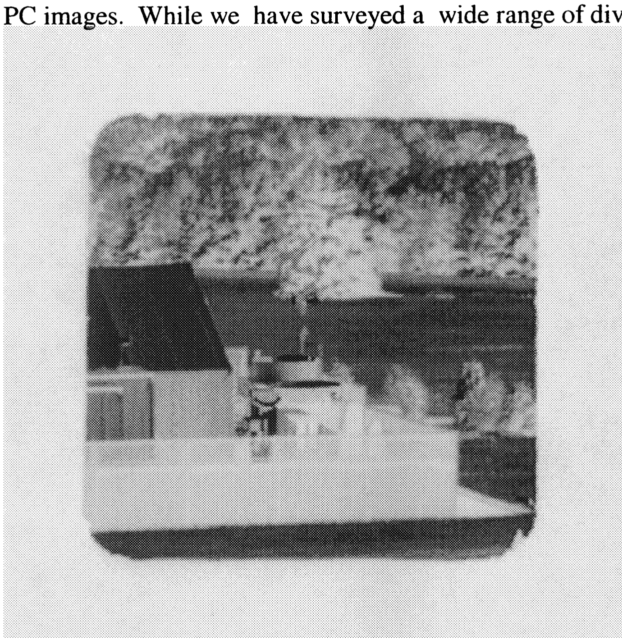

Fig. 1a. Divergence image from first eigenvector and Euclidean measure.

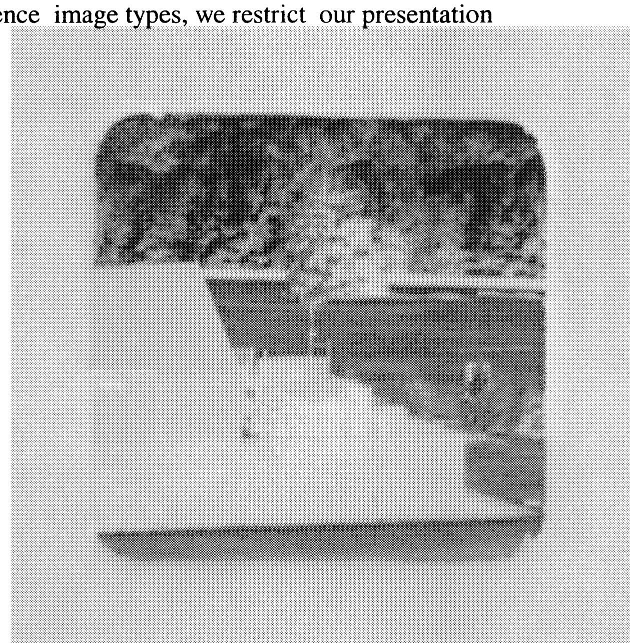

Fig. 1b. Divergence image from second eigenvector and spectral information divergence measure.

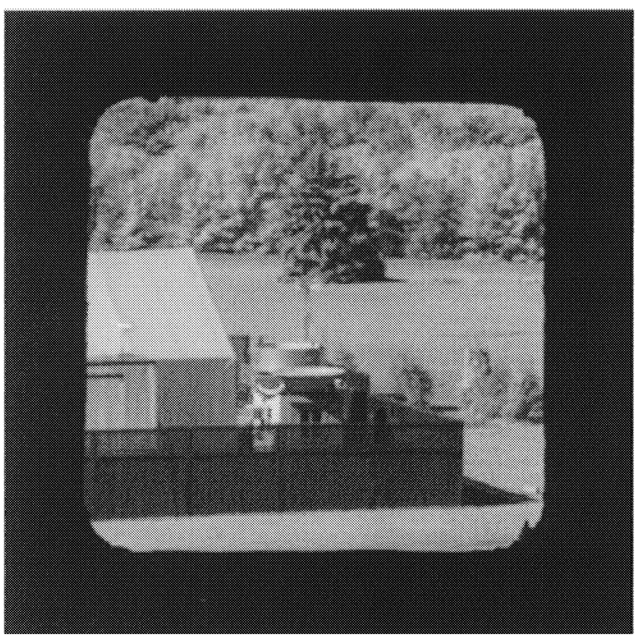

Fig. 1c. First principal component image used as divergence image.

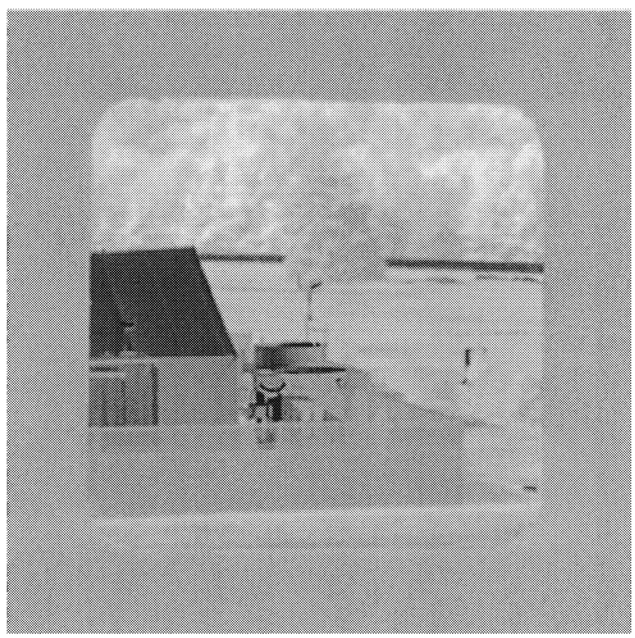

Fig. 1d. Second principal component image used as divergence image.

here to the PC images used as divergence images for reasons of simplicity and the advantage of the absence of a distance measure.

The histograms of the PC image in Fig. 1c is shown after smoothing with a narrow (Fig. 2a) and broad (Fig. 2b) Gaussian filter. The local minima of these histograms delineate the boundaries between one cluster group and another and form the basis of our multi-dimensional thresholding, i.e. pixels whose divergence values are bounded by two adjacent local minima are assigned the same digital value. We find that the degree of smoothing generates a range of fine to coarse segmentations (many to few discrete threshold values), as detailed by a later example (Fig. 9).

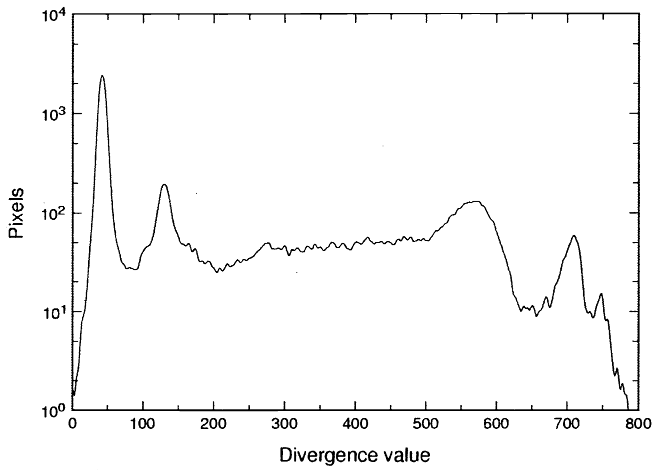

Fig. 2a. Histogram of image in Fig. 1c after smoothing with a narrow Gaussian filter.

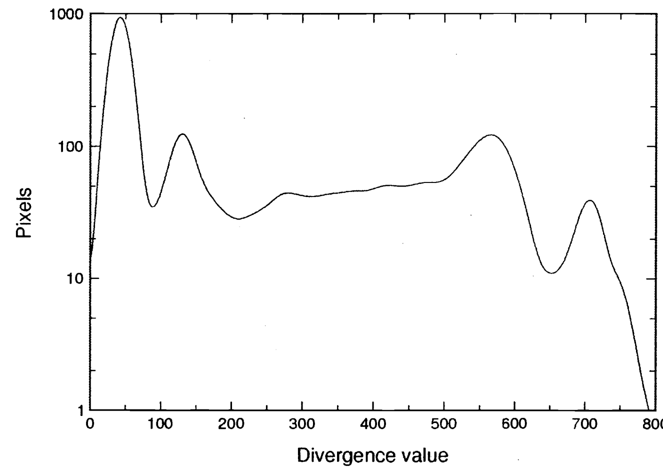

Fig. 2b. Histogram of image in Fig. 1c after smoothing with a broad Gaussian filter.

A segmentation based on a single divergence image may merge into one cluster or digital value a group of pixels which are distinguished in another image. For example, a road at the bottom of the background foliage in the Fig. 1 images is better discriminated in 1b and 1d than in 1a and 1c. We have identified two techniques for merging the information from two divergence images to improve spectral discrimination. The simpler is a dual 1D procedure in which the thresholds of two independent histograms from two divergence images are merged. The two sets of threshold values are plotted on a 2D grid and the grid elements actually occupied by pixels are assigned a new (somewhat arbitrary) digital value. The simple fictitious example in Fig. 3 demonstrates that the dual result chooses the finer discrimination from each image.

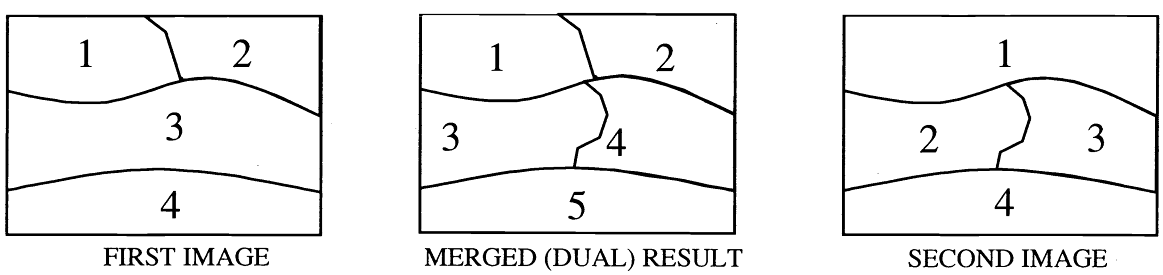

Fig. 3. The regions of a fictitious image are thresholded to 4 values in one independent segmentation (left) and 4 values in another independent segmentation (right) which are merged into the dual 5 level segmentation (center).

The second method for using a pair of divergence images is fully two-dimensional. One generates a 2D-histogram based on the dual values from the two divergence images of each pixel. The degree of smoothing of this histogram is indirectly carried out by integer quantization in scaling the original divergence images into an integer range. The peaks (local maxima) in this histogram are determined and then weeded so that neighboring peaks are replaced by a single representative peak. The final set of peaks are then somewhat arbitrarily numbered from 1 to N and the digital label which is assigned to each pixel is the number for the peak closest to the point of this pixel on the 2D-histogram.

Fig. 5a. First PC image of MWIR hyperspectral data.

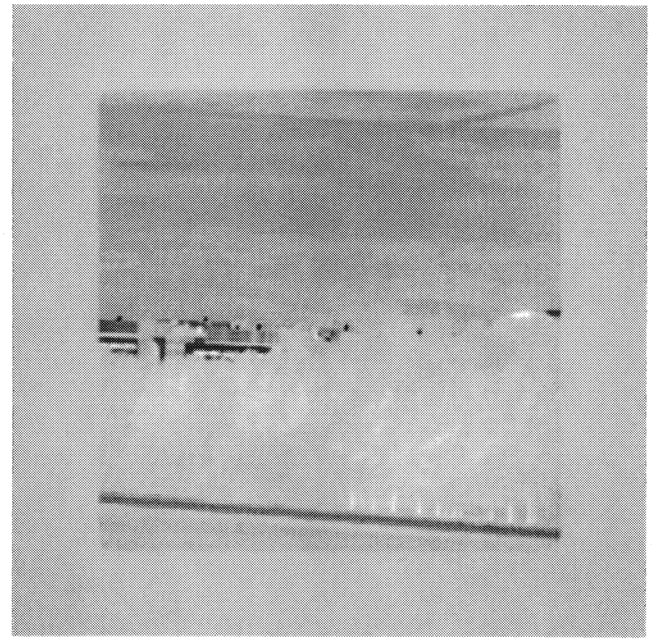

Fig. 5b. Second PC image.

Our final example is extracted from a HYDICE image in the SWIR provided by Spectral Information Technology Application Center (SITAC). HYDICE is a pushbroom imaging spectrometer with 210 spectral bands, which cover the full 0.4 to 2.5 μm spectral range. The array is a 320x210 element InSb array (Ref. 3, Chapter 1). The size of the extracted image is 187 by 259 pixels and was taken over the CART/ARM Site Lamont, OK in early evening at 11,400'.

Following the same format as in the previous examples, we show the first two PC images used as the divergence image pairs in Figure 7 and segmentation results in Figure 8. The image has a body of water (lower left), a set of panels, a road near the top, and a region of plowed and unplowed wheat fields. The 40 level dual result (Fig. 8c) is based on 18 by 10 independent thresholds from the 1D histograms of the first and second PC images. While similar generally to the 36 level 1D result, the 40 level dual result has a cleaner separation of the panels, particularly upper and lower halves of the larger panels. Again the full 2D result is superior overall as far as separating the water from most of the panels (only one small panel and the upper half of a large panel is assigned the same level as the water) and in differentiating realistically the textural difference of the plowed and unplowed fields.

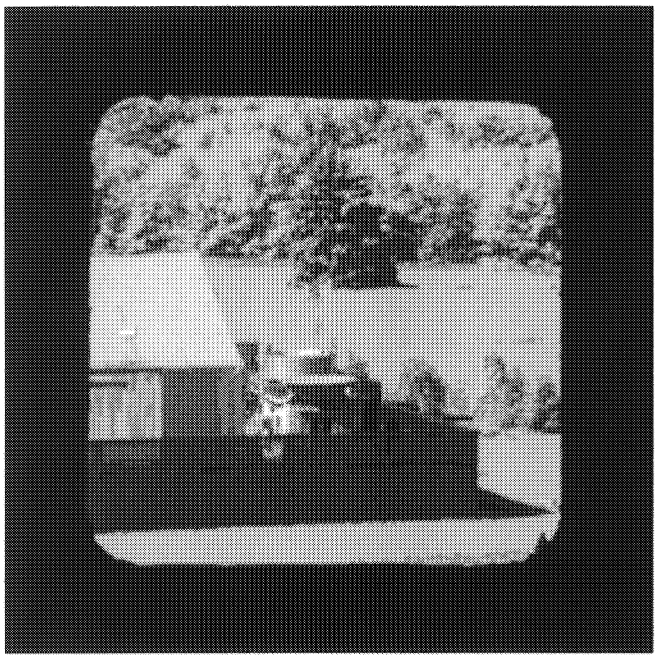

Fig. 4a. Segmentation to 12 levels based on the first PC image (Fig. 1c). Data from a visible hyperspectral camera.

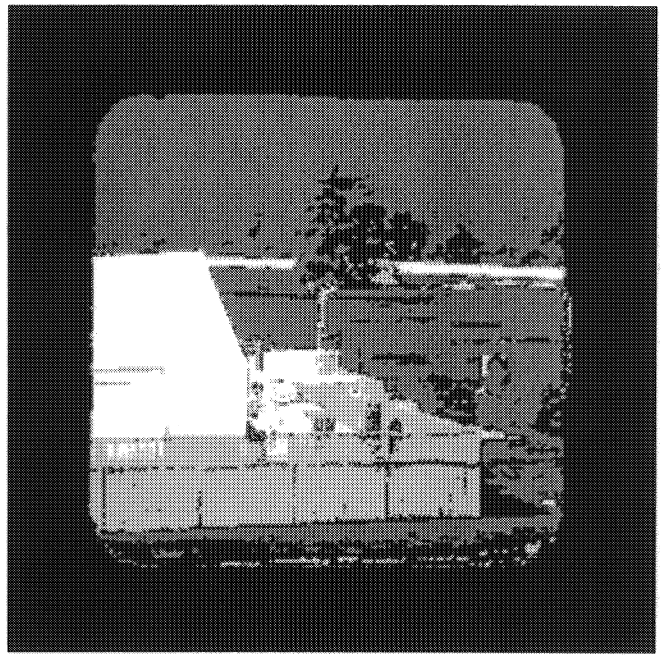

Fig. 4b. Segmentation to 12 levels based on the second PC image (Fig. 1d).

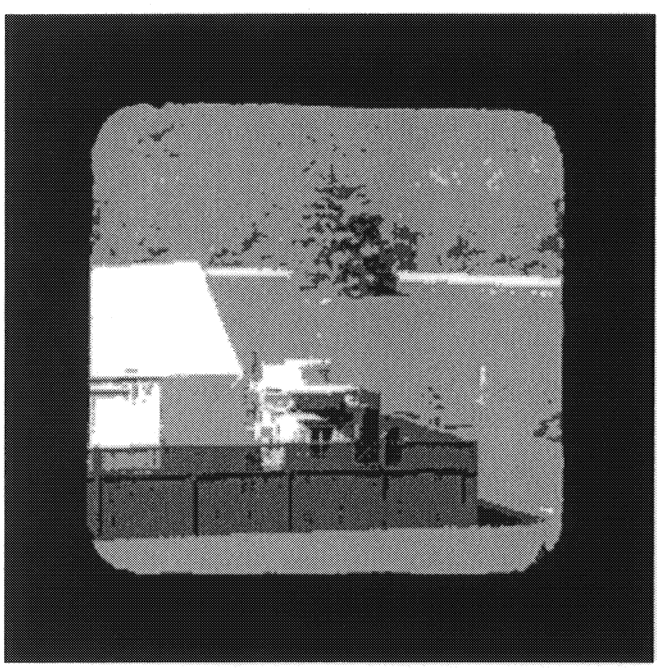

Fig. 4c. Dual segmentation to 12 levels based on the first two PC images.

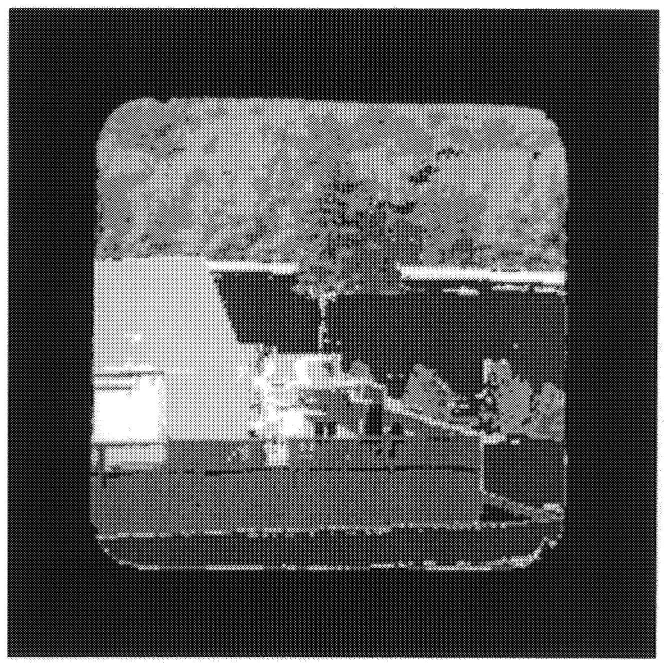

Fig. 4d. Segmentation to 12 levels based on a two-dimensional histogram from the first two PC images.

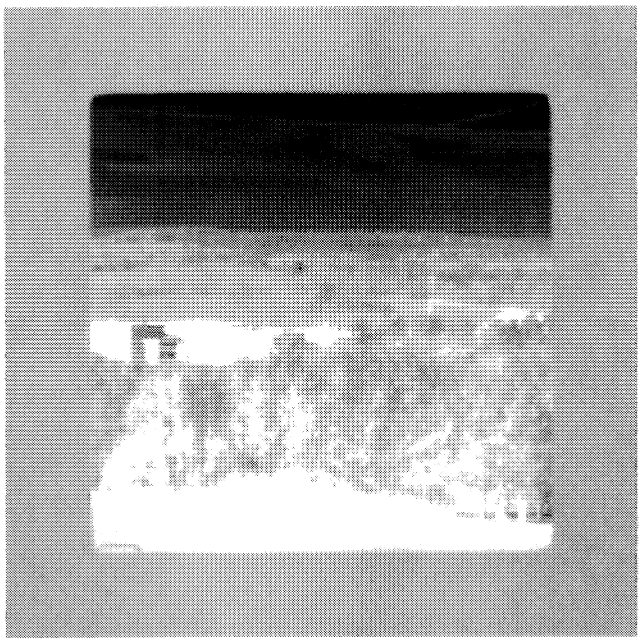

Fig. 5a. First PC image of MWIR hyperspectral data.

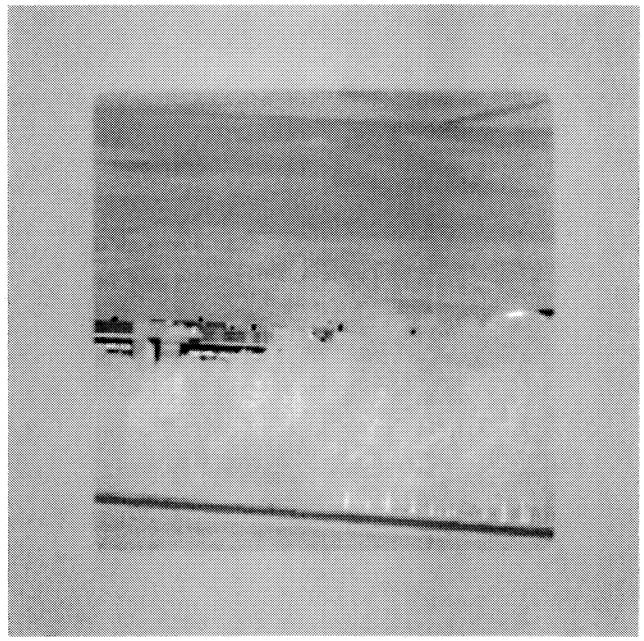

Fig. 5b. Second PC image.

Our final example is extracted from a HYDICE image in the SWIR provided by Spectral Information Technology Application Center (SITAC). HYDICE is a pushbroom imaging spectrometer with 210 spectral bands, which cover the full 0.4 to 2.5 μm spectral range. The array is a 320x210 element InSB array (Ref. 3, Chapter 1). The size of the extracted image is 187 by 259 pixels and was taken over the CART/ARM Site Lamont, OK in early evening at 11,400'.

Following the same format as in the previous examples, we show the first two PC images used as the divergence image pairs in Figure 7 and segmentation results in Figure 8. The image has a body of water (lower left), a set of panels, a road near the top, and a region of plowed and unplowed wheat fields. The 40 level dual result (Fig. 8c) is based on 18 by 10 independent thresholds from the 1D histograms of the first and second PC images. While similar generally to the 36 level 1D result, the 40 level dual result has a cleaner separation of the panels, particularly upper and lower halves of the larger panels. Again the full 2D result is superior overall as far as separating the water from most of the panels (only one small panel and the upper half of a large panel is assigned the same level as the water) and in differentiating realistically the textural difference of the plowed and unplowed fields.

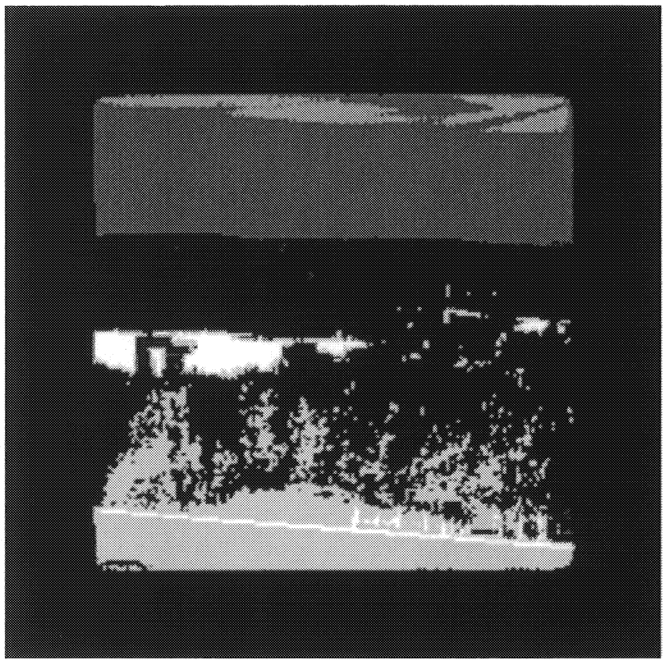
Fig. 6a. Segmentation to 34 levels based on the first PC image (Fig. 5a). Data from a MWIR hyperspectral camera.

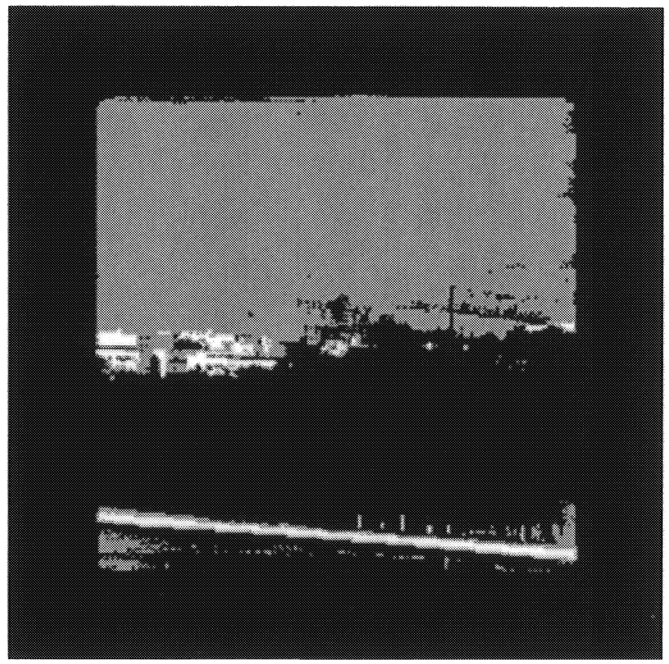
Fig. 6b. Segmentation to 31 levels based on the second PC image (Fig. 5b).

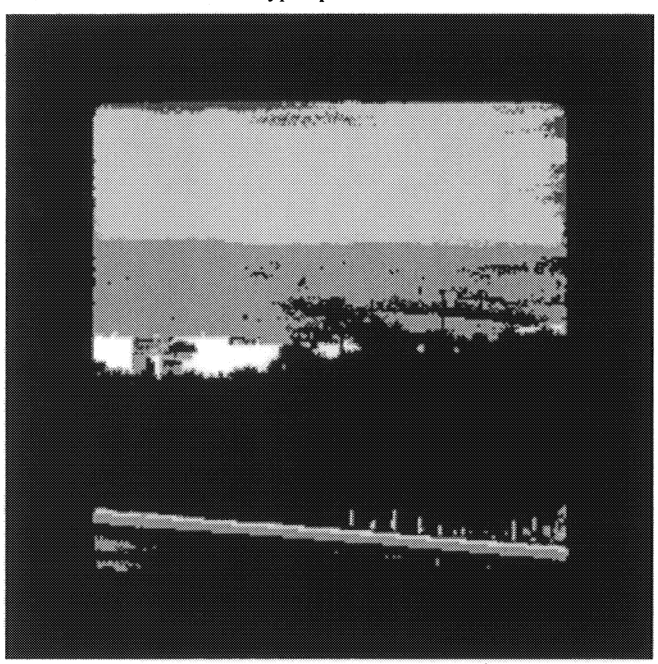
Fig. 6c. Dual segmentation to 32 levels based on the first two PC images.

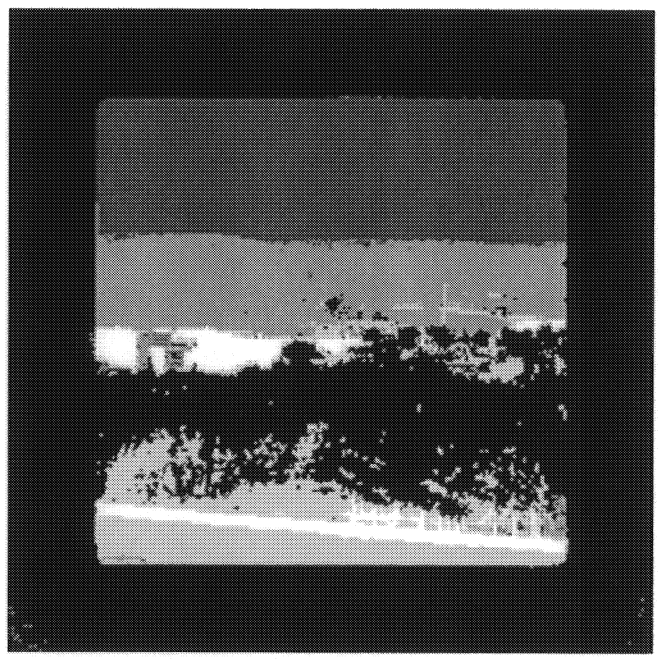
Fig. 6d. Segmentation to 34 levels based on a two-dimensional histogram from the first two PC images.

Fig. 7a. First PC image of HYDICE hyperspectral data.

Fig. 7b. Second PC image.

Our techniques have a natural scaling from coarse to fine clustering/segmentation based on the degree of histogram smoothing. For the 1D histograms this is implemented by the width of a Gaussian (or other averaging) filter, while for the 2D histograms, the smoothing is indirectly implemented by the effect of integer quantization in scaling a divergence image, created as a set of floats, to an integer range. In Figure 9, we show the 2D segmentation of our HYDICE image to 39 levels (as Fig. 8d), 23 levels, 16 levels, and 12 levels. As one goes from coarse to fine scale, the extra levels are utilized for more subtle details of the wheat fields, while the degree of panel discrimination remains largely unchanged in going to the finer scales (Our software is set up so that the user specifies the number of levels desired and a scaling parameter is iterated until the desired number is reached).

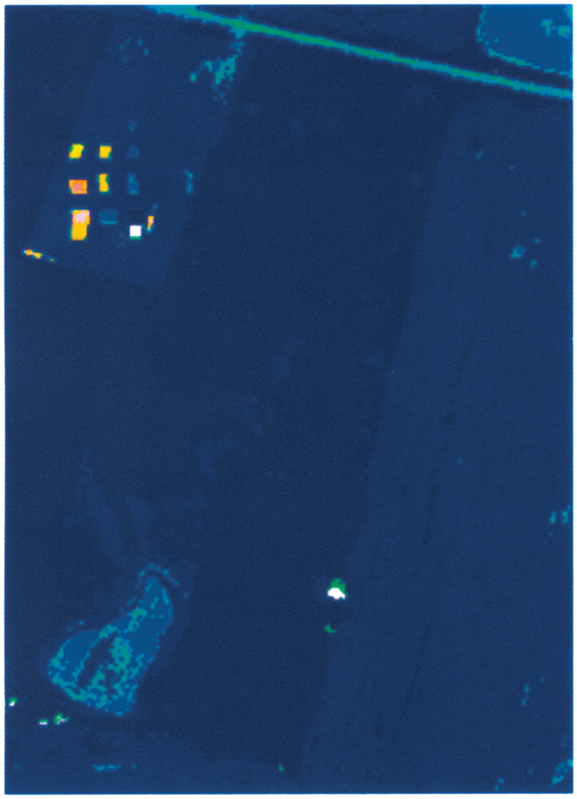

Fig. 8a. 36 level segmentation from first PC image.

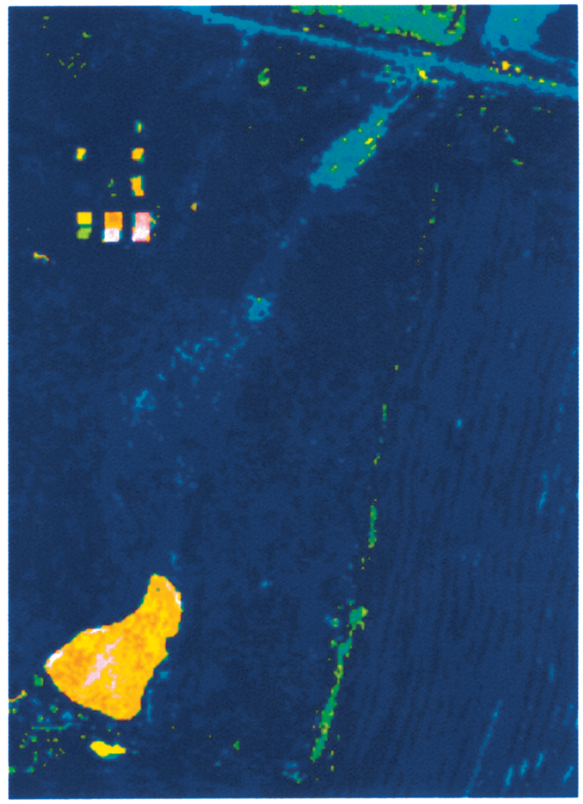

Fig. 8b. 35 level segmentation from second PC image.

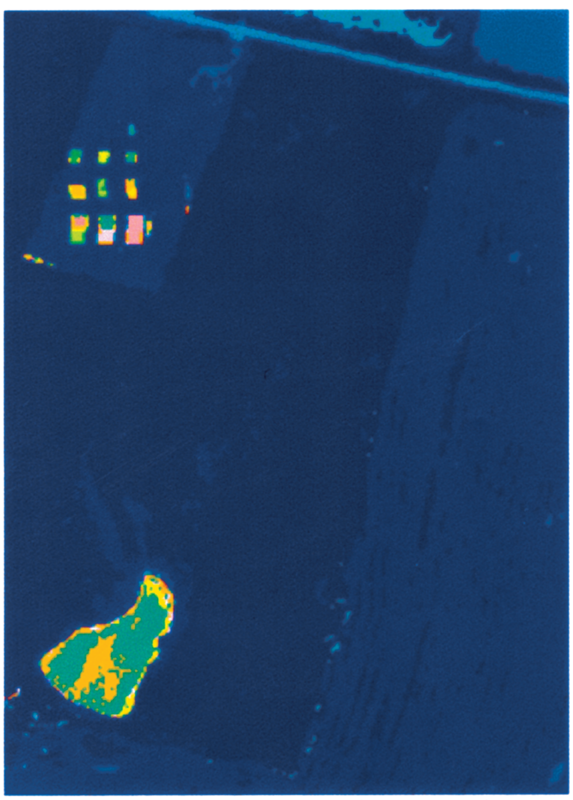

Fig. 8c. 40 level dual segmentation from two PC images.

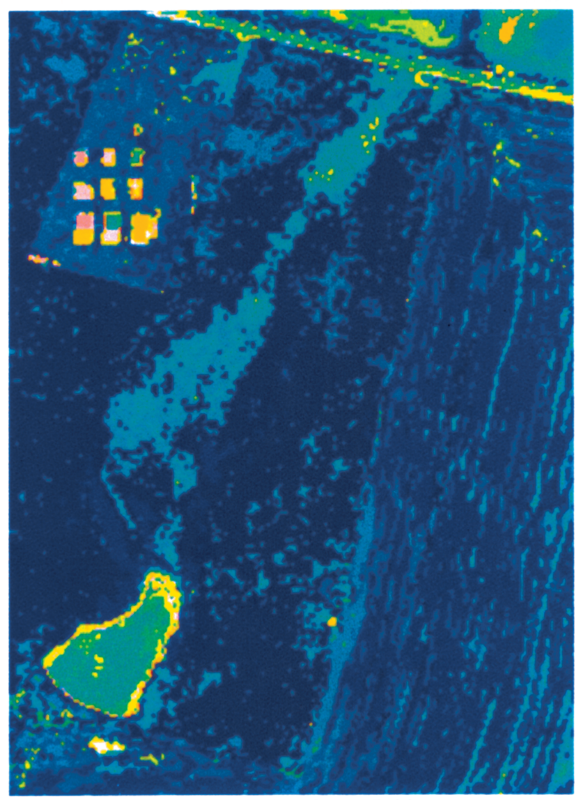

Fig. 8d. 39 level segmentation from 2D histogram.

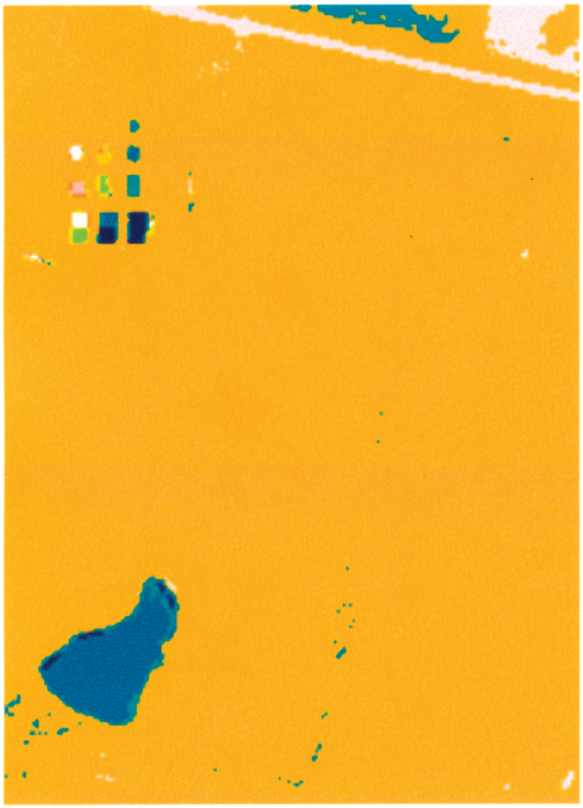

Fig. 9a. 12 level segmentation.

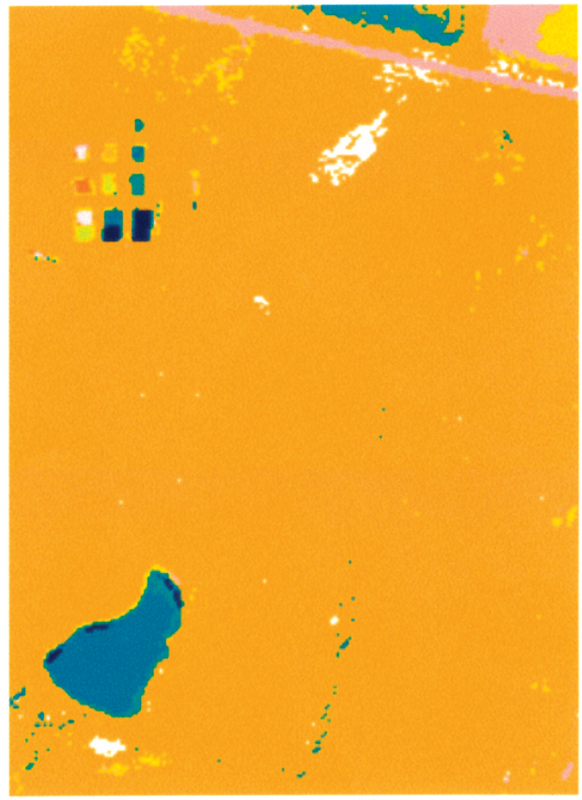

Fig. 9b. 16 level segmentation.

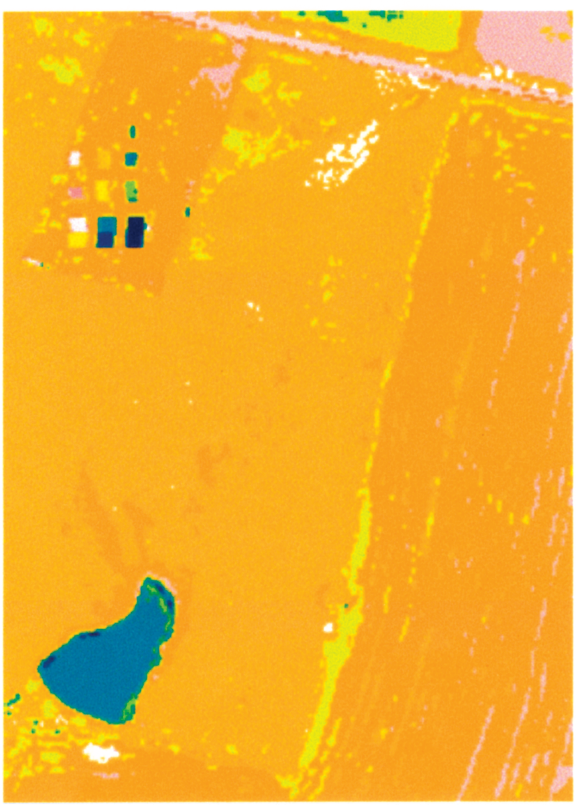

Fig. 9c. 23 level Segmentation.

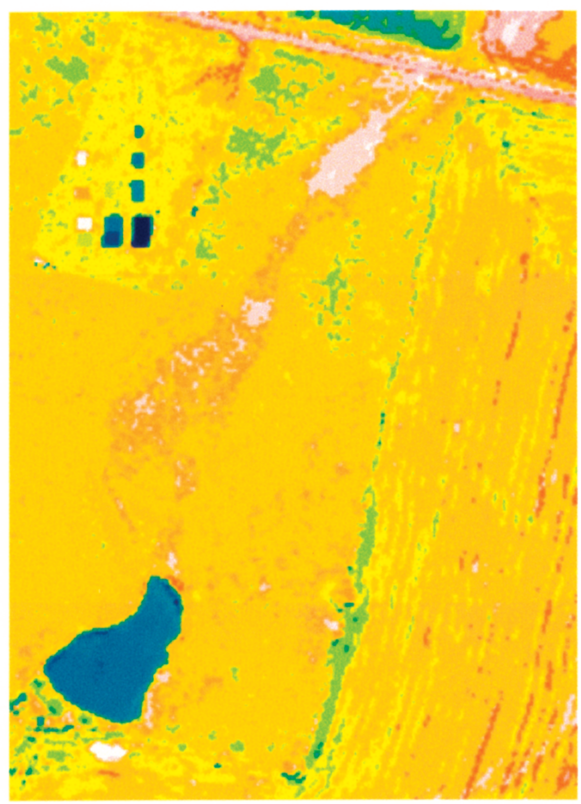

Fig. 9d. 39 level segmentation (as 8d).

4. CONCLUSIONS

We have described a set of simple and versatile techniques for clustering/segmenting hyperspectral images. The basic concept is to create single images (divergence images) whose values reflect spectral similarity or difference and threshold these images from the local extrema of their histograms. Methods of combining two independent divergence images have been identified, with the full 2D histogram technique preferred. A natural control on the fine to coarse degree of clustering/segmentation lies in the extent of histogram smoothing. The technique is useful at the fine scale as a powerful single image display "summary" of a data cube or at the coarser scales as a quick unsupervised classification or a good starting point for an operator-controlled supervised classification. Results were given for three images in the visible, MWIR, and SWIR bands respectively; each result was based on the first two PC in the role of divergent images.

The work is very rich in possible future extensions. Many alternative methods for creating divergence images could be explored. When merited by the quality of the data, one could fuse three divergence images by forming a 3D histogram and proceeding in analogy to our 2D treatment. Issues of spectral discrimination should be explored on data sets with more completely known ground truth than available with the present data.

ACKNOWLEDGMENTS

The cameras used to collect the visible and MWIR data were designed and fabricated by William Ewing, Toby Reeves and Steven DiSalvo. The HYDICE data was provided by Spectral Information Technology Application Center (SITAC). We are grateful to the following colleagues: Virgil Vickers for critical review of the manuscript, James Murguia and Andrzej Brodzik for technical discussions and Linda Bouthillette for graphic assistance. This work was carried out under Air Force Task 2305BN00.

REFERENCES

1. M. A. Bichel, "Adaptive Fast Fuzzy Clustering System", U. S. Patent 5,263,120, Nov. 16, 1993.
2. F. M. Wahl, *Digital Image Signal Processing*, Chap. 5, Artech House, Boston, 1987.
3. R. A. Schowengerdt, *Remote Sensing,* Chap. 9, Academic Press, Boston, 1997.
4. C. I. Chang, "An information-theoretic approach to spectral variability, similarity, and discrimination for hyperspectral image analysis", *IEEE Transactions on Information theory*, **46(5)**, pp. 1927-1932, 2000.
5. J. E. Murguia, T. D. Reeves, J. M. Mooney, W. S. Ewing, F. D. Shepherd, and A.K. Brodzik, "A compact visible/near infrared hyperspectral imager", *Proc. SPIE* , **4028**, 457-468, (2000).
6. J. M. Mooney, V. E. Vickers, M. An, and A.K. Brodzik, "High throughput hyperspectral infrared camera", *J. Opt. Soc. Am. A,* **14(11)**, pp. 2951-2961, 1997.
7. J. Silverman, "Signal processing algorithms for display and enhancement of IR images", *Proc. SPIE*, **2020**, 440-450, (1993).