SUPPLEMENTING HYPERSPECTRAL DATAWITH DIGITAL ELEVATION

Varun Madhok and David Landgrebe
School of Electrical & Computer Engineering
Purdue University
West Lafayette IN 47907-1285
Phone : (765)494-3486
Fax : (765)494-3358
e-mail: {madhok, landgreb}@ecn.purdue.edu

Reprinted from Proceedings of IEEE Geoscience and Remote Sensing Symposium, Hamburg Germany, June 28 - July 2, 1999.

ABSTRACT

This paper describes an experimental study where using a fusion of two essentially different types of data proves significantly superior to the individual use of either one or the other. The task is to identify and accurately delineate building roof-tops in a flightline of hyperspectral data of the Washington D.C. Mall. There are 210 channels of spectral data available, supplemented with a channel containing digital elevation map (DEM) data for each pixel of the scene.

Experiments using gradient-based algorithms on the DEM data show that its use alone is not sufficient to sharply delineate building boundaries. A spectral classifier does not have these problems. However, building roof-tops in this urban scene are constructed of different materials and are in various states of condition and illumination. This and the fact that, in some cases, the material used in roof-tops is spectrally similar to that used in streets and parking areas make this a challenging classification problem, even for hyperspectral data.

It is shown in this paper that combining hyperspectral and DEM data can substantially sharpen the identification of building boundaries, reduce classification error, and lessen dependence on the analyst for classifier construction.

INTRODUCTION

In the analysis of hyperspectral data, it has been shown [1] that a high accuracy in classification is readily achievable, provided the analyst has the ability to gather adequate training data from the scene, and label them correctly. The process, however, can be time-intensive and is dependent on the ability and judgment of the analyst. In this article we describe a scheme that demonstrates how the fusion of two essentially different types of data produces results superior to the use of either of the data individually.

DATA

The scene being analyzed is a flightline over the Washington D.C. mall. Hyperspectral data over the flightline was collected with the HYDICE system over 210 channels (0.4-2.4 μm). A three color representation of the data is shown in Fig. 1. The other data available to us is the digital elevation map (DEM) obtained photogrammetrically from B/W airborne photography. Fig. 2 is a representation of the DEM, with the lighter pixels representing portions of the ground at a higher elevation. The multispectral data and the DEM have been rectified and registered to one other.

ANALYSIS

As noted earlier, hyperspectral data is usually sufficient in most classification analyses. The first step in the identification of buildings (or rather building-rooftops) in the scene comprises a maximum likelihood classification scheme. Upon examination of the three color representation of the data (see Fig. 1), it is possible to identify the following scene classes - ROOFTOP, WATER, ASPHALT, GRAVEL PATH, LAWN, SHADOW and TREES. Training data is collected on each scene class and then used towards constructing a parametric classifier. The process described above was carried out via Multispec [3]. The analysis required approximately 2.5 minutes of CPU time on a Power Macintosh G3 machine and 27 minutes of analyst time. The results are shown in Fig. 3abc.

The information content in the DEM is in the rise in elevation of a given area-element in relation to its neighbor. The use of a gradient operator in identifying building pixels (presumably at higher elevation than ground level) is thus appropriate. A Sobel gradient operator [2] was used on the DEM. A gradient-threshold was applied to the result to obtain Fig. 4.

The analyses can now be compared:

- Spectral analysis focuses on pixel-wise identification of the class ROOFTOP. Note that the task desires the identification of a specific usage (rooftop) in the scene, rather than the material classification provided by spectral analysis. Thus, there is the possibility that spectrally similar materials will be identified with the roof class, regardless of the manner of their usage in the scene. Gradient operator based analysis identifies the building boundaries. In essence, the latter is a scheme to delineate building boundaries, while the other is a pixel classification scheme.
- The output in Fig. 4 outlines buildings as objects with thick boundaries. It is possible to thin the delineated scene objects by setting a high threshold on the output of the gradient operator. However this requires operand manipulation on the part of the analyst, and is inefficient.
- In general, spectral analysis is more robust over an extended scene. For instance, should the analyst note a different 'type' of building rooftop in isolation, the set of scene-classes can be enlarged and training data included appropriately. On the other hand, analysis of the DEM can be complicated by hilly terrain. In Fig. 2, note the rise to the Capitol Hill at the far right end of the DEM. It is evident that this particular section has to be processed in isolation.
- In Fig. 3c we can observe considerable speckle misclassifications in the output. In general there is some confusion in separating ROOFTOP - class data from spectrally similar classes ASPHALT and GRAVEL PATH.

In highlighting the shortcomings of the respective analyses it has been implicit that the problems associated with one technique can be alleviated through the use of the other. For instance, the last point in the discussion above leads to a significant conclusion. The emergence of inter-class confusion in classification is not a result of ‘wrong’ data. The material used in construction of building rooftops is, quite often, identical to that used in constructing roads, or laying paths. However, the scene-classes are functionally distinct, and this distinction is strikingly apparent in the DEM. This conclusion is key to the solution presented in the next section.

PROCEDURE

Given the disparity in the two types of the data, concurrent analysis is infeasible. Our analysis comprised maximum likelihood classification, as discussed earlier, followed by a thresholding operation on the elevation of all data elements identified as ASPHALT, GRAVEL PATH or ROOFTOP. The latter is designed as a Boolean-type operation in which all data (identified as one of the three classes listed above) below a certain elevation are said to be ground-level; the remaining filtered data are thus identified as building-rooftop.

Since there is a large amount of variation in scene elevation, the elevation threshold, discussed above, must be locally determined. The following procedure was adopted towards this task.

Centroid identification

The DEM was visually examined to identify zones or regions of relatively unchanging terrain. Pixels representative of these zones were identified as zone centroids.

Zoning

The pixel grid was then segmented into zones identified by their respective centroid. The process involved going through the grid and labeling each pixel according to the zone centroid closes to it. The metropolis distance metric was used. The partitioned image is shown in Fig. 5. Zone centroids have been highlighted as red dots in the figure. Note that only pixels identified as ROOFTOP, ASPHALT or GRAVEL PATH are identified in the zoned output. The remaining scene classes have been absorbed into the black background.

Threshold computation

For each zone, the median elevation for the pixels classified as ROOFTOP, ASPHALT or GRAVEL PATH is computed. In zones with an insufficient count of rooftop pixels, it is clear that threshold will be biased towards data at ground-elevations. The threshold for a given zone is thus chosen as the average of the median as calculated above, and the elevation of the zone-centroid.

Thresholding operation

The thresholds, thus computed, were used to get the result shown in Fig. 6 (compare with Fig. 3b). Note that the rooftops have been color-coded by the identifying zone.

DISCUSSION

In the above analysis, we identified the key attributes of the respective datasets available to us. Spectral data is best used in the identification of elemental composition, while the DEM identifies the data element in the functional sense. Data fusion is thus justifiable, with the analysis utilizing the respective attributes of the HYDICE data and the DEM towards the target application.

ACKNOWLEDGMENTS

HYDICE data rectification was performed by the School of Civil Engineering, Purdue University. The DEM was generated by Marconi Inc., San Diego CA. Work was supported in part by NASA Grant NAG5-3975 and ARO Grant DAAH04-96-1-0444.

REFERENCES

[1] D. A. Landgrebe, "Information Extraction Principles and Methods for Multispectral and Hyperspectral Image Data", in Information Processing for Remote Sensing, C. H. Chen, Ed. New Jersey: World Scientific, 1999.

[2] A. K. Jain, Fundamentals of Digital Image Processing, New Jersey: Prentice-Hall, 1989.

[3] D. A. Landgrebe, L. L. Biehl , "An introduction to Multispec", http://dynamo.ecn.purdue.edu/~biehl/MultiSpec/

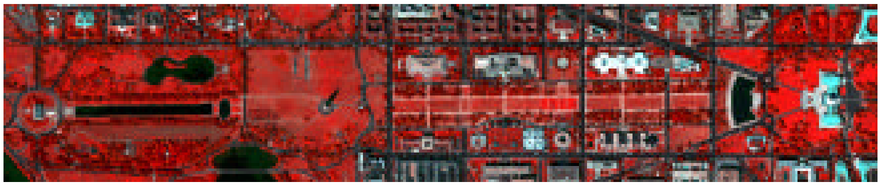

Figure 1 : Three color representation of spectral data. (Original in color)

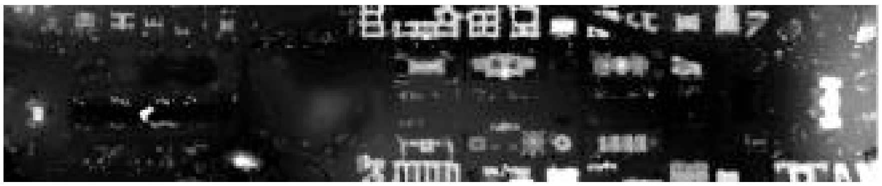

Figure 2 : Digital Elevation Map (DEM).

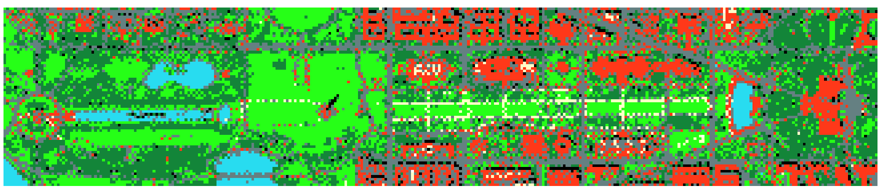

Figure 3a : Maximum likelihood classification of spectral data. (Original in color)

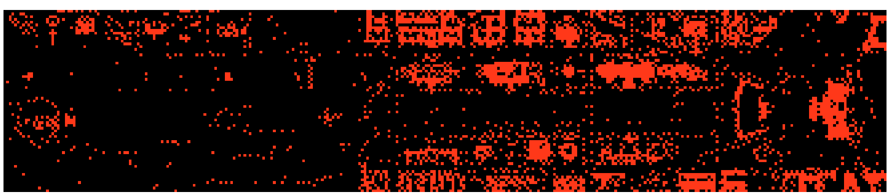

Figure 3b : Extracted rooftops from Fig. 3a.

Figure 3c : Section zoomed from Fig. 3b.

Figure 4 : Gradient operation on section of DEM.

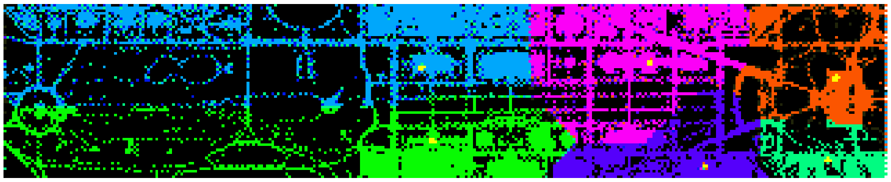

Figure 5 : Partitioned scene with centroid identification. (Original in color)

Figure 6 : Rooftops identified via data-fusion. (Original in color)