

# Remote Sensing Image Visualization Using Double Layers

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**Abstract**—Remote sensing imagery has relatively low spatial resolution. Since different materials/objects may be present in the area covered by a pixel, the pixel reflectance can be considered as the linear mixture of reflectance of these materials/objects (i.e., endmembers). Thus in remote sensing image processing we deal with mixed pixels instead of pure pixels as in traditional digital image processing. A multi-spectral or hyper-spectral image has tens to hundreds of spectral bands. How to display the plentiful information contained in such a 3D image cube is a challenging problem. In this paper, we will propose a visualization technique that employs two layers to integrate the mixture information (i.e., endmembers and their functional abundances) in each pixel. With user-friendly interactive tools, images can be displayed at any desired level of details.

*Keywords:* Hyperspectral image visualization; unsupervised classification; Linear unmixing.

## I. INTRODUCTION

A hyperspectral imaging sensor uses hundreds of co-register channels to acquire images from the same area on the earth. Although a hyperspectral sensor offers high spectral resolution, its spatial resolution is still limited as in other remote sensing devices. Therefore, different materials or objects may be presented in the area which is covered by a single pixel, and the pixel reflectance can be taken as the linear reflectance combination of different materials or objects (i.e., endmembers). It is a challenging work to display the plenty of information contained in these hundreds of spectral bands.

Remote sensing visualization can be considered as a multi-variant visualization problem. Currently existing techniques can be divided into two categories: one includes pre-processing approaches, and the other post-processing

approaches. The most common method in the first category is gray mapping. Gray mapping is useful to display only one band. One way to solving this problem is to introduce “color” into images. In Jacobson’s work [1], fixed linear spectral weighting envelopes were introduced to create natural-looking imagery that provides the display consistency for materials in the original data. This approach can provide good classification result when a remote region is combined by solid “blocks”, but it is difficult to provide the endmembers relationship if the region is mixed. As a post-processing method, a false color strategy has been introduced based on the first three principal components using principal component analysis (PCA) [2]. This approach can help observers make a quick classification and clustering decisions about different material/object distribution. But it is difficult to provide accurate classification information.

Multi-variant visualization has been researched for decades [3, 4]. In [3], high variants are mapped to different textures and it is displayed several variants successfully in one surface. 3D surface shape and texture mapping have been employed to displayed multi-variants data in [4]. Automatic color indices were assigned to hierarchically structured classified images [5]. All of these methods take the multi-variants as independent variables. Therefore, these methods cannot reveal the relationship between the variables.

In this paper we present a new approach that uses double layers to visualize remote sensing image. It employs two layers to visualize the mixed pixel information with different levels of details. Since it uses the processing result of linear unmixing, it is a post-processing approach. This approach reveals more accurate classification information, and displays the relationship between endmembers (i.e., multi-variants) at the subpixel level.

## II. CLASSIFICATION

### A. Linear Mixture Model (LMM)

Linear mixture analysis is a widely used method to classify and quantify multispectral/hyperspectral imagery. Since a pixel contains components acquired at different spectral wavelengths, each pixel in hyperspectral imagery can be represented as a vector  $\mathbf{r}$  whose dimension is  $l \times 1$ , where  $l$  is the number of spectral bands. Assume the number of endmember materials is  $n$ . Let  $\mathbf{M}$  be the signature matrix of these materials denoted as  $\mathbf{M} = [\mathbf{m}_1 \ \mathbf{m}_2 \ \dots \ \mathbf{m}_n]$ , where  $\mathbf{m}_j$  is an  $l \times 1$  vector corresponding to the signature of the  $j$ -th material. According to the linear mixture model (LMM), the pixel  $\mathbf{r}$  can be represented as

$$\mathbf{r} = \mathbf{M}\mathbf{p} + \mathbf{n} \quad (1)$$

where  $\mathbf{p} = (p_1, \dots, p_i, \dots, p_n)^T$  is  $n \times 1$  column vector called fractional abundance (FA) vector, whose  $i$ -th element represents the proportion of the  $i$ -th endmember materials in the pixel  $\mathbf{r}$ . Here,  $\mathbf{n}$  is an  $l \times 1$  column vector which is an additive noise or sensor measurement error.

Since  $\mathbf{p}$  represents the proportion of endmembers,  $p_i$  for  $1 \leq i \leq n$  should be a position number. Also, the whole pixel is constructed by all of endmembers. Hence,  $\mathbf{p}$  should be constrained by:

$$\sum_{i=1}^n p_i = 1 \quad \text{and} \quad 0 \leq p_i \leq 1 \quad (2)$$

### B. Iterative Error Analysis (IEA)

LMM constrained by (2) can be taken as fully constrained LMM model. IEA is a successful method to find the optimal results for the fully constrained LMM. The procedure of this approach can be described as follows.

1. Randomly select two pixels with the maximum and minimum norm from the image, and denote them as  $\mathbf{m}_1$  and  $\mathbf{m}_2$ , then use quadratic programming to solve the  $p_1$  and  $p_2$  that satisfy Eq. (2).
2. Calculate the error,  $e$ , between the reflectance vector,  $\mathbf{r}$ , and its estimate:  $\mathbf{e} = |\mathbf{r} - \mathbf{M}\mathbf{p}|$ .
3. Find the pixel that produces the maximum reconstruction error, take it as the next endmember, and add into the

signature matrix, i.e.,  $\mathbf{M} = [\mathbf{m}_1 \ \mathbf{m}_2 \ \mathbf{m}_3]$ . Then use the quadratic programming again to estimate fractional abundances in  $\mathbf{p}$ .

4. Go to step 2 for error calculation and repeat step 3 for a new endmember, until the error is less than a given threshold  $\zeta$  or reach the maximum number of endmembers.

## III. VISUALIZATION

The resulting FAs from the linear mixture analysis in Section II provide the spatial distribution of each endmember material in the image scene. Traditionally, each FA is displayed as a gray scale image. If there are  $n$  endmember materials, then  $n$  FA images will be generated. The drawback for visualizing FA image as separate gray scale image is that viewers need to observe the  $n$  FA images side by side.

Comparing to gray scale images, it is more intuitive to display FA images by a color image. Although the visualization by color works very well for pure pixels, it cannot display the proportional details of endmembers for mixed pixels. In this section we will introduce a novel approach to display classified images by using double layers, where layer I is to display the general information of FA images and layer II is for the details of each pixel in FA images. The overall image display is generated by overlaying Layer II on Layer I. This approach is particularly useful for the visualization of mixed pixels, which are dominant in a remote sensing image.

### A. Layer I --- Background Layer

Layer I, referred to as the background layer, is formed by pre-assigning a color to each of the  $n$  FA images and merging them using a linear transformation. In order to make the endmembers more distinguished in the final image, colors are chosen in different color category [7].

Each pixel in FA images can be presented as a vector  $\mathbf{p} = (p_1, \dots, p_i, \dots, p_n)^T$  constrained by (2). A color satisfying the rule in [7] was selected to represent  $p_i$ , which is a  $3 \times 1$  vector, denoted as  $\mathbf{c}_i = (r_i \ g_i \ b_i)^T$ . Then a color matrix for FA image color display can be constructed as:

$$\mathbf{C} = \begin{bmatrix} \mathbf{c}_1^T \\ \vdots \\ \mathbf{c}_i^T \\ \vdots \\ \mathbf{c}_n^T \end{bmatrix} = \begin{bmatrix} r_1 & g_1 & b_1 \\ \vdots & \vdots & \vdots \\ r_i & g_i & b_i \\ \vdots & \vdots & \vdots \\ r_n & g_n & b_n \end{bmatrix}. \quad (3)$$

The final color for pixel  $\mathbf{p}$  in layer I can be achieved by multiply the pixel vector and color matrix, i.e.,

$$\mathbf{c} = \mathbf{p}^T \mathbf{C}. \quad (4)$$

Since  $\mathbf{p}$  was constrained by (2), the final color will be within the normal range of color components.

### B. Layer II --- Detail Layer

In Layer II, referred to as detail layer, each endmember is represented by a fan chart. Without the pre-knowledge about the classification endmembers, each member is considered as equally important. Therefore, the endmember can be randomly assigned to the  $i$ -th fan region.

In general, the first endmember is chosen to assign the first region, and so on. The area of a fan-shaped region for the  $i$ -th endmember is proportional to the angle  $\theta_i$ , which is determined by its fractional abundance  $p_i$ , i.e.,

$$\theta_i = p_i \cdot 360^\circ \quad (5)$$

Its starting and ending positions can be represented as

$$\beta_i^s = \sum_{j=1}^{i-1} \theta_j \quad \text{and} \quad \beta_i^e = \sum_{j=1}^i \theta_j \quad (6)$$

respectively. They can be related by  $\theta_i = \beta_i^e - \beta_i^s$ , and

$\beta_1^s = 0^\circ$ . Because  $\mathbf{p}$  are constrained by (2), a pixel is shown as a full disk, i.e.,  $\beta_n^e = 360^\circ$ .

### C. Blending

After colors have been assigned to the two layers, the color in the final image is automatically blending in OpenGL. The blending equation is described as:

$$\mathbf{c}_{final} = \alpha \mathbf{c}_I + (1 - \alpha) \mathbf{c}_{II} \quad (7)$$

where  $\alpha$  is within the range  $[0, 1]$ . Therefore, the color of the final image is between the  $[\mathbf{c}_I, \mathbf{c}_{II}]$ .  $\alpha$  is associated with the zooming parameter to display the overall distribution and mixed detail information at the same time.

## IV. INTERACTION

Interactive operation is designed for observers to look through the details of the data. By selecting a region of interest (ROI) one can obtain the desired degree of details. For example, by selecting a large area, Layer I will dominate the display, whereas the mixing details of each pixel are more visible if a small ROI is chosen. If a very small area is selected, the precise quantitative mixing information of each individual pixel can be seen. A sample viewer to allow an analyst to interactively select a ROI has been developed.

As requested by observers, a legend box can be displayed to indicate the endmember spectral information, the associated materials, etc.

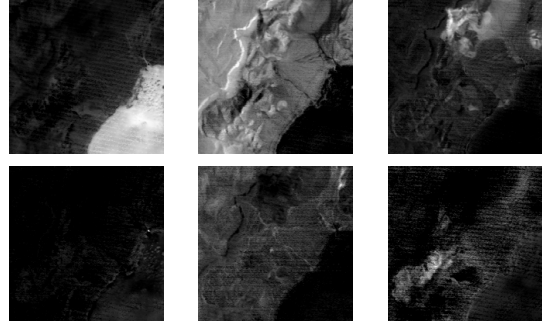


Figure 1: The abundance images of six materials.

## V. EXPERIMENT

A subimage (200×200) of AVIRIS Lunar Lake data was used to illustrate the proposed approach. After water absorption bands and low SNR bands were removed, 158 bands remained for processing. Fig. 1 shows the gray scale images of the six material abundances which were found by the IEA algorithm in Section II. The images were shown in gray scale, and a bright pixel means a large abundance of the specific material resident in this location. Although the general distribution of one particular material is clearly displayed, it is difficult to visualize the construction of a pixel.

An easy way to solve this problem is to use color image. Fig. 2 is the color image, in which each material was assigned a different color. In Fig. 2, the six materials can be easily distinguished by color, such as white, blue, red, yellow, green,

and cyan. In particular, an anomaly was detected in Fig. 1 and shown in blue in Fig. 2. Fig. 2 can display the overall material distribution and the fuzzy memberships of a pixel.

However, such a color display still cannot represent the detailed portions of materials within each pixel. For example, in the white area, it is difficult to see if other materials exist in this area and their portions. These cannot be resolved by only one color image. By introducing a second layer, such detailed information can be revealed.

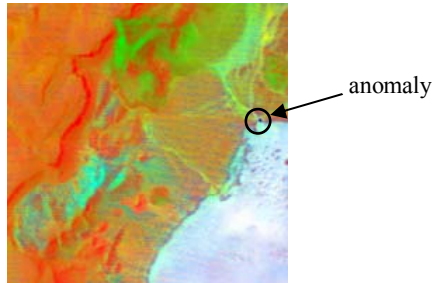


Figure 2: The color image displays the abundance of six materials.

Fig. 3 shows the visualized images of Layer I, Layer II, and double layers. The first column is when only Layer I was used to visualize the six endmembers; the second column is when only Layer II was used, and the third column is the results which was visualized by double layers. Fig. 3(a) shows the overall images using different layers, and Fig. 3(b) is the zoomed-in image, where some disks were popped out. As described in Section III, each disk represents one pixel, and the fan charts in the disk represents the abundance of materials. We can see that Layer I conveys the overall distributions of the endmembers, Layer II displays the details of the materials abundances in individual pixels, and the double layers can displays the overall distribution and pixel details at the same time.

## VI. CONCLUSION

Compared to the traditional one-layer image display, the proposed double-layer remote sensing image visualization technique can simultaneously display the overall endmember spatial distribution and their composition at the sub-pixel level. Since the visualization is based on the unsupervised linear unmixing result, where noise and interference information in the original image has been well suppressed, it creates informative and detailed images that provide the necessary information in a succinct form for practical decision-making.

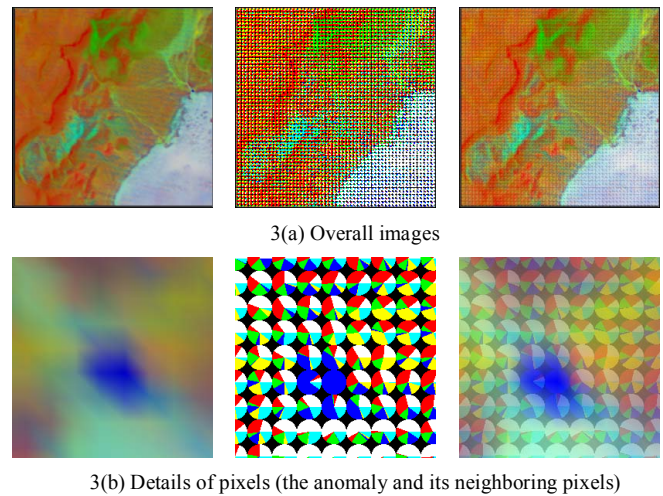


Figure 3: Visualization results (from left to right: Layer I, II, Double Layers).

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