LOCAL DETAIL ENHANCED HYPERSPECTRAL IMAGE VISUALIZATION

Jialu Fang, Yuntao Qian

College of Computer Science, Zhejiang University, Hangzhou, China

ABSTRACT

A new method for hyperspectral image (HSI) visualization is proposed in this paper, which emphasizes on pairwise distance preservation and detail enhancement. It includes two sequential steps. The first reduces the high dimensional spectral space of HSI to 3-D color space by distance preservation method, and then enhances the detailed information by Laplacian pyramid. Distance preservation is an optimization problem that minimizes the difference between the pairwise pixel distances in the original spectral space and the corresponding color space. In general, solving this optimization problem is always very time and storage consuming. A multi-resolution multidimensional scaling algorithm is proposed in this paper to mitigate this hardness. Obviously the loss of some local details is not avoided in multidimensional scaling. In order to enhance the spatial distinction of different scene objects, Laplacian pyramid is used to draw the locally details from the original HSI, and embed it into the color image. The proposed HSI visualization method takes the global and local information of spectral and spatial distribution in HSI into account for visualization, which makes the color display of HSI carry as much original information as possible.

***Index Terms*—** hyperspectral image, visualization, multi-resolution multidimensional scaling, Laplacian pyramid

1. INTRODUCTION

Nowadays, with the development of remote sensing techniques, hyperspectral imaging sensors are widely used to acquire images with hundreds of spectral bands. Hyperspectral images (HSI) make material detection, classification, identification and quantification more accurate. However, its high dimensional spectral space is unsuitable for visualization. The goal of HSI visualization is to integrate multiple spectral bands into RGB space which is more suitable for display instrument and human visual system [1]. By fast browsing, viewers can acquire the information of ground objects easily. However, reducing hundreds spectral bands to three dimensional color space suffers from information loss inevitably. It is crucial to create a visualized image that preserves both spectral and spatial information as much as possible.

The simplest way of HSI visualization is to select three specific input bands and map them to RGB channels respectively, but the remaining spectral bands are totally discarded. More sophisticated mappings created through data driven linear dimension reduction, e.g., principal component analysis (PCA) and independent component analysis (ICA) are applied to obtain the prime information of original data. An alternative idea for visualization is to use nonlinear methods for dimension reduction, such as locally linear embedding (LLE) and isometric feature mapping (ISOMAP). However, these nonlinear methods are fairly time consuming. Some researchers seek to create natural-looking visualized images. Color-matching functions (CMFs) are used to project HSIs onto a basis inspired by human vision and specify how much each of three primary colors (e.g., a red, a green, and a blue primary) should be mixed to create the color sensation at a particular wavelength, but it is sensor-dependent. In [2], the feature-level semisupervised manifold alignment is used to transfer the RGB information of a color image to a HSI over the same scene, so that a natural dispaly of HSI can be obtained. However, sometimes it is difficult to get the reference color image for HSI.

Preserving the distance of pairwise spectral vectors and their corresponding distance in color image is faithful to the raw HSI, so many state-of-the-art distance preservation methods have been presented in recent years [3, 4]. For example, in [3] an interactive visualization based on convex optimization is proposed for preserving the distance while considering the boundaries of the hue, saturation, and value (HSV) color space. [4] gave a nonstationary multiresolution Markov model to solve the optimization of distance preservation. Compared with other HSI visualization approaches, pairwise distance preservation methods always demonstrates the competitive performance, but solving the optimization problem of minimizing the pairwise distance between HSI and color spaces is not easy.

Distance preserved dimension reduction can be seen as a problem of multidimensional scaling (MDS) [5]. However, most of MDS algorithms are only applicable to small-size images due to their heavy computation and storage load, even though we transform MDS to an eigendecomposition problem. To overcome this obstacle, a coarse-to-fine multi-

Thanks to the National Science and Technology Support Program (No.2011BAD24B03) and the National Natural Science Foundation of China (No. 61171151) for funding.

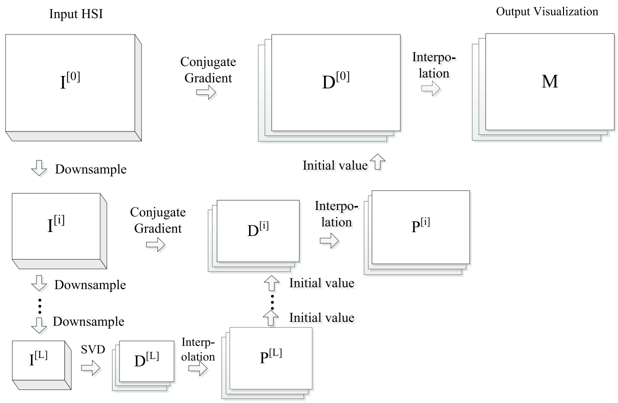


Fig. 1. Structure of Multi-resolution MDS

resolution MDS algorithm is proposed in this paper. This method reduces the spectral dimension of HSI in the sequential resolution levels. At the lowest resolution level, MDS is used to obtain a coarse solution and a conjugate-gradient algorithm is then used to find a more precise solution for each higher resolution levels. The solution in lower level is used as an initialization for the adjacent higher level until the full resolution level is reached.

Furthermore, in order to enhance the spatial distinction of different scene objects, Laplacian pyramid is used to draw the locally details from the original HSI, and embed it into the intermediate color image that is generated by multi-resolution MDS. In this procedure, the local details that are represented by a weighted combination of images at different pyramid levels are transfered from the original HSI to the visualized color image. In summary, the proposed HSI visualization method includes two sequential steps. The first reduces the high dimensional spectral space of HSI to 3-D color space by multi-resolution MDS algorithm, and then enhances the detailed information by Laplacian pyramid.

2. MULTI-RESOLUTION MDS

MDS is a dimension reduction method which constructs low dimensional samples whose pairwise distances are similar to those in high-dimensional space. It tries to minimizes the optimization problem with the following function:

$$E(\mathbf{u}) = \sum_{s \neq t} (\|\mathbf{v}_s - \mathbf{v}_t\|_2 - \|\mathbf{u}_s - \mathbf{u}_t\|_2)^2 \tag{1}$$

where $\mathbf{v}_s$, $\mathbf{v}_t$ denote spectral vectors in the spatial locations s and t, respectively. $\mathbf{u}_s = (R_s, G_s, B_s)^T$, $\mathbf{u}_t = (R_t, G_t, B_t)^T$ denote the pixel vectors in the corresponding locations in color space.

However, heavy computation and memory loads limit its use in high-resolution image processing. In order to overcome this disadvantage, multi-resolution MDS is proposed in this paper, which is based on the multi-resolution pyramid. An L-level multi-resolution pyramid is constructed by downsampling original HSI I. Let $I^{[i-1]}$ denote the image at level i, satisfying $I^{[0]} = I$, and size($I^{[i]}$) = size($I^{[0]}$)$/4^{i-1}$ ($i = 1, 2, ..., L$), which means the multi-resolution is only applied to the spatial dimensions but not spectral dimension. The structure of multi-resolution MDS algorithm is presented in Fig. 1.

At the lowest resolution level (level L), $I^{[L]}$ is transformed to a corresponding color image $D^{[L]}$ by the traditional MDS algorithms such as SVD based method, since the size of image in this level is very small compared to the original HSI. This result is used as the initial solution for the next higher resolution level.

At this time, as the initial solution of MDS has been derived from the lower level, a conjugate-gradient algorithm can be used to to solve MDS problem. The conjugate-gradient algorithm has state of the art performance among the existing MDS algorithms.

In order to update the initial solution to approach optimal value, gradient descent of objective function $E(\mathbf{u})$ is used.

$$\mathbf{u}^{[l+1]} = \mathbf{u}^{[l]} + \gamma d^{[l]} \tag{2}$$

where l means number of iterations, γ is the step size of gradient and d represents the direction.

$$d^{[l]} = -\nabla E\left(\mathbf{u}^{[l]}\right) + b^{[l-1]} d^{[l-1]} \tag{3}$$

where

$$b^{[l]} = \frac{< \nabla E\left(\mathbf{u}^{[l]}\right) - \nabla E\left(\mathbf{u}^{[l-1]}\right), \nabla E\left(\mathbf{u}^{[l]}\right) >}{< \nabla E\left(\mathbf{u}^{[l-1]}\right), \nabla E\left(\mathbf{u}^{[l-1]}\right) >} \tag{4}$$

At the level i (i=1,2,...,L), an interpolation method is used to get the initial solution $P^{[i]}$ for the conjugate-gradient algorithm at level $i-1$, which takes into account the inherent spatial dependencies between neighboring spectral vectors [4]

$$\mathbf{u}_s^{[i-1]} = \sum_{t \in N_s} w(s,t) \mathbf{u}_t^{[i]} \tag{5}$$

where N_s is a square neighborhood with fixed size centered around the pixel s. The weight $w(s,t)$ depends on the similarity between the spectral vectors located at s and t.

$$w(s,t) = \frac{1}{Z(s)} \exp\{-\frac{||I^{[i-1]}(s,.) - I^{[i-1]}(t,.)||_2^2}{h}\} \tag{6}$$

where $I^{[i-1]}$ is the HSI at level $i-1$ and $Z(s)$ is the normalizing constant ensuring $\sum_t w(s,t) = 1$. The parameter h acts as a degree of filtering.

Finally, the three dimensional image M is obtained at the highest resolution level.

3. LAPLACIAN PYRAMID BASED DETAIL ENHANCEMENT

The preservation of spectral pairwise distance alone does not guarantee that the local details are well preserved at the same time. As human visual system is sensitive to the visual discontinuous regions, the local detail enhancement is required to improve the visualization quality. The detail enhancement is always manipulated in HSL (Hue, Saturation, Lightness) color space, especially color saturation, as well as lightness, plays an key role in achieving good image enhancement. In this paper, Laplacian pyramid is proposed to restore details in lightness (L) and saturation (S) channels [6], and linearly stretch is used simultaneously to enhance the contrast in Hue (H) channel.

For channels L and S, Laplacian pyramid based detail enhancement is used respectively. The Laplacian pyramid is a sequence of images h_1, h_2, ..., h_N, each is the difference between two adjacent levels of the Gaussian pyramid [7]. Thus, for $0 \leq i < N$

$$h_i = g_i - \mathrm{expand}(g_{i+1}) \tag{7}$$

where g_i is the image of Gaussian pyramid at level i, and expand (g_{i+1}) means expanding g_{i+1} to the same size with g_i.

In our method, Laplacian pyramids are built for each band image of HSI. As the same method is applied for the enhancement of L and S channel respectively, we only introduce the enhancement method on L channel. The detail enhanced L channel image E_L can be calculated as

$$E_L = M_L + \sum_{i=1}^{N} \lambda_i h_i M_L \tag{8}$$

where M_L is the L channel of the color image derived from MDS method, which is also called intermediate image. The weight parameters λ_i are used to control the intensity of detail enhancement, which can be estimated as

$$\lambda_i = \left(\frac{\sqrt{\sum_{k=1}^{d} h_i(I_k)^2}}{|h_i(L_M)|} \right)^p \tag{9}$$

where I_k is the kth band image of HSI, and the parameter $0 \leq p \leq 1$ is used to remap the values to a non-linear scale so that weaker details can be enhanced without over emphasizing stronger details.

To further enhance the contrast of different regions, linearly stretch is used in the H channel so that 2% of pixels are at the minimum and 2% are at the maximum display value. The minimum and maximum pixels are then assigned 0 and 1, respectively, while the hue of remaining pixels are calculated as:

$$E_H = \frac{M_H - M_{H\,\min}}{M_{H\,\max} - M_{H\,\min}} \tag{10}$$

Table I. Comparison of correlation γ/δ for AVIRIS images

Image	PCA	CMF	Intermediate Result	Final Result
MF1	0.55/ **139**	0.72/ 129	**0.97**/ 44	**0.91/ 113**
MF2	0.47/ 142	0.78/ **150**	**0.98**/ 45	**0.96/ 143**
MF3	0.55/ 134	0.73/ **137**	**0.99**/ 39	**0.95/ 135**
JR1	0.64/ **146**	0.71/ 134	**0.91**/ 52	**0.90/ 109**
JR2	0.65/ **150**	0.70/ 142	**0.81**/ 43	**0.82/ 145**
JR3	0.53/ **149**	0.66/ 145	**0.94**/49	**0.93/ 137**
JR4	0.55/ **150**	0.68/ 146	**0.88**/ 30	**0.86/ 135**
C1	0.48/ **136**	0.73/ 130	**0.97**/ 48	**0.96 104**
C2	0.41/ **149**	0.74/ 142	**0.95**/ 56	**0.95/ 123**
C3	0.36/ **157**	0.64/ 143	**0.95**/ 57	**0.91/ 122**
C4	0.45/ **148**	0.61/ 133	**0.95**/ 41	**0.89/ 112**
LL1	0.31/ 138	0.50/ **142**	**0.96**/ 45	**0.95/ 123**
LL2	0.39/ **128**	0.52/ 123	**0.96**/ 57	**0.94/ 103**

where M_H is the H channel of the intermediate image, and $M_{H\,\max}$, $M_{H\,\min}$ are the maximal and minimal values of M_H respectively.

4. EXPERIMENTS

To evaluate the performance of the proposed HSI visualization method, AVIRIS data have bee used, including three images from Moffett Field, four images from Jasper Ridge, four images from Cuprite, and two images from Lunar Lake. Pairwise distance preservation γ and separability of features δ are used as quantitative metrics to measure the performance of HSI visualization [3].

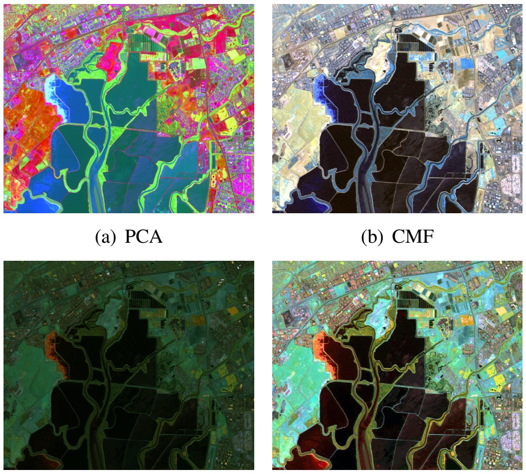
$$\gamma = \frac{X^T Y/|X| - \overline{X}\,\overline{Y}}{\mathrm{std}(X) \cdot \mathrm{std}(Y)} \tag{11}$$

where X is the distance vector between each pairwise spectral vectors in HSI, and Y is their corresponding distances vector in the visualized color space. X^T, $|X|$, $\overline{X}$ and $\mathrm{std}(X)$ denote the transpose, cardinal, mean and standard deviation of X respectively. In the ideal case, the normalized correlation is desired to be 1.

$$\delta = |Y|_1 / |Y| \tag{12}$$

where $|Y|_1$ denotes the L_1 norm. It should be as large as possible.

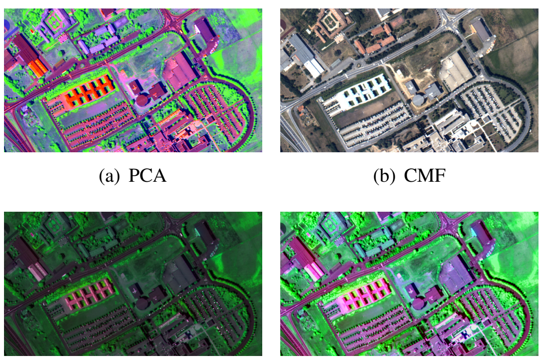
Compared with PCA and CMF approaches, the proposed detail enhanced HSI visualization method provides better results (see Table I). The intermediate results obtained by multi-resolution MDS have good performances of distance preservation but unfavourable separability. After detail enhancement, feature separability is improved significantly with a little sacrifice of distance preservation. From Fig. 2, it is found that edges and some color regions in the result of PCA method seem bright (see Fig. 2(a)) and colors of the result of CMF method are more natural-looking, but edges can not be well



(a) PCA (b) CMF

(c) Intermediate Result (d) Final Result

Fig. 2. Visualizations of Moffet02



(a) PCA (b) CMF

(c) Intermediate Result (d) Final Result

Fig. 3. Visualization of Pavia University

distinguished (see Fig. 2(b)). The intermediate result of proposed method seems too dark for human visual system (see Fig. 2(c)) and the final result has a greater perceptive display with more distinguished edges (see Fig. 2(d)).

Furthermore, we use classification to measure the effect of information preservation of visualization. Pavia University data set which acquired by the Reflective Optics System Imaging Spectrometer (ROSIS-03) optical sensor over the University of Pavia is used in our experiment. There are nine land cover classes and the corresponding labeled samples in the data set, whose details can be found in [8]. The number of training samples is set as 50 per class. The classification accuracy of proposed method is better than those of PCA and CMF (see Table II), which means our method has a better preservation of structure and details.

Table II. Classification on 3-D color images

method	γ	δ	OA	κ
PCA	0.64	**135**	49.64%	39.73%
CMF	0.71	118	35.26%	26.43%
Intermediate Result	**0.95**	51	**62.33%**	**52.50%**
Our method	0.90	112	62.16%	52.33%

5. CONCLUSION

The method proposed in this paper consists of two sequential steps. First step is multi-resolution MDS based distance preservation, and second step is the Laplacian pyramid based local detail enhancement which restores spacial details from HSI. By combining these two steps, a competitive visualization performance is achieved.

6. REFERENCES

[1] N. Jacobson and M. Gupta, "Design goals and solutions for display of hyperspectral images," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 11, pp. 2684–2692, 2005.

[2] D. Liao, Y. Qian, and J. Zhou, "Visualization of hyperspectral imaging data based on manifold alignment," *22nd Int. Conf. on Pattern Recogn. (ICPR)*, pp. 70–75, 2014.

[3] M. Cui, A. Razddan, J. Hu, and P. Wonka, "Interactive hyperspectral image visualization using convex optimization," *IEEE Trans. Geosci. Remote. Sens.*, vol. 47, no. 6, pp. 1673–1684, 2009.

[4] M. Mignotte, "A multiresolution markovian fusion model for the color visualization of hyperspectral images," *IEEE Trans. Geosci. Remote. Sens.*, vol. 48, no. 12, pp. 4236–4247, 2010.

[5] I. Borg and P. JF Groenen, *Modern multidimensional scaling: Theory and applications*, Springer Science & Business Media, 2005.

[6] K. Smith, P. E. Landes, J. Thollot, and K. Myszkowski, "Apparent greyscale: A simple and fast conversion to perceptually accurate images and video," in *Comput. Graph. Forum*. Wiley Online Library, 2008, vol. 27, pp. 193–200.

[7] P. J. Burt and E. H. Adelson, "The laplacian pyramid as a compact image code," *IEEE Trans. Commun.*, vol. 31, no. 4, pp. 532–540, 1983.

[8] Y. Qian, M. Ye, and J. Zhou, "Hyperspectral image classification based on structured sparse logistic regression and three-dimensional wavelet texture features," *IEEE Trans. Geosci. Remote Sens.*, vol. 51, no. 4, pp. 2276–2291, 2013.