VISUALIZATION OF HYPERSPECTRAL IMAGERY BASED ON MANIFOLD LEARNING

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ABSTRACT

Displaying the abundant information contained in a hyperspectral image is a challenging task. Previous visualization approach focused only on preserving the structure in the original images. They ended up with presenting pseudo-color images and stopped short of adjusting the color of the images to retrieve more desirable visual effects. In this paper, a new visualization algorithm is proposed. It can be modeled as a two stage approach. At the first stage, Laplacian Eigenmaps algorithm is applied to reduce the dimension of the hyperspectral image. In this way we obtain a three dimensional image with pseudo-color. At the second stage, we transfer the natural color of a panchromatic image to the image obtained by the first step via manifold alignment. Experimental results show that the visualized image not only retains the structure of the hyperspectral image but also possesses natural colors.

***Index Terms*—** Hyperspectral imagery, visualization, manifold learning, color transfer

1. INTRODUCTION

Hyperspectral imagery (HSI) includes numerous continuous spectral bands. One of the goals of HSI visualization is to fuse the HSI into a three-band color image. Principal component analysis (PCA) is the most extensively accepted dimension reduction method applied in HSI visualization based on the assumption that the data is embedded almost linearly in the ambient space [1]. However, the HSI data may not exactly satisfy this assumption of linearity [2].

Nonlinear techniques such as Locally Linear Embedding [3], Isomap [4] and Laplacian Eigenmaps [5] aim to discover the nonlinear structure of the manifold. In recent years, some nonlinear dimension reduction methods were employed to address the nonlinearity of HSI, including Markov random field (MRF) fusion [2], nonlinear optimization [6], bilateral filtering [7], In this work, we apply Laplacian Eigenmaps algorithm [5], which is relatively insensitive to outliers and noise, to reduce the dimensionality of HSI.

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Besides dimension reduction, visual effect is another aspect which should be emphasized in HSI visualization. However, most of the fusion methods end up visualization with a pseudo-color image. As we know, pseudo-color differs greatly from natural color and brings counterintuitive results. For example, a blue lake can be shown in red in a pseudo-color image. In order to achieve better visual effects, we transfer the natural color of a corresponding panchromatic image to the pseudo-color image based on manifold alignment [8].

The entire visualization procedure consists of two steps. First, dimension reduction of HSI is accomplished via manifold learning, in this way we obtain a three dimensional pseudo-color image. Second, color transfer is performed based on manifold alignment. The pseudo-color image is aligned with a corresponding panchromatic image to adjust the pseudo color to natural color. Experimental results show that the image after the two steps preserves the structure of the original HSI and possess natural visual effects.

2. VISUALIZATION OF HSI BASED ON MANIFOLD LEARING

This section describes the algorithm of visualization of HSI based on manifold learning. The procedure mainly contains two steps:

1. Reduce the bands of HSI by Laplacian Eigenmap algorithm.
2. Transfer natural color to the pseudo-color image acquired by step1 by manifold alignment.

2.1. Manifold dimension reduction of HSI

HSI appears to be high dimensional but usually lies on low-dimensional manifold. Dimensionality reduction is beneficial for visualizing the intrinsic structure of HSI. We constrain that while reducing dimensionality, pixels which are close with respect to geodesic distance in the high dimensional space should maintain the close distance after being mapped to low dimensional subspace, that is, the local structure should be preserved. In this work, we apply Laplacian Eigenmaps for dimensionality reduction [5], which has the locality preserving property, to reduce the dimensionality of HSI.

Let $\mathcal{X}$ denotes the HSI data with N pixels, and D dimensions. $\mathbf{X}$ represents the data matrix of size $N \times D$. Each row of $\mathbf{X}$ corresponds to the spectral signature of a pixel. We first construct the adjacency graph G of $\mathcal{X}$. Each node of G corresponds to a pixel of HSI. A node is connected with its k nearest neighbors. The edges between two nodes i and j are weighted by geodesic distance along the manifold. The distance can be defined by following heat kernel:

$$\mathbf{W}_{ij} = e^{-\|\mathbf{X}_i - \mathbf{X}_j\|^2} \tag{1}$$

while $\mathbf{X}_i$ is the i-th pixel.

To maintain the local structure of the original space while dimension reduction, i.e., the pixels with large $\mathbf{W}$ value should stay closed in there embedding. Our goal is to find a transformation F , which reduces the HSI data from D dimensional space to three dimensional space. The loss function is defined as:

$$\mathbf{C}(\mathbf{F}) = \sum_{i \neq j} \|\mathbf{X}(i,\cdot)\mathbf{F} - \mathbf{X}(j,\cdot)\mathbf{F}\|^2 \mathbf{W}(i,j) \tag{2}$$

We constrain $\mathbf{F}'\mathbf{X}'\mathbf{D}\mathbf{X}\mathbf{F} = \mathbf{I}$ for nontrivial solutions to the optimization problem. The summation is taken over all pairs of pixels from the HSI data. $\mathbf{F}$ is a matrix of size $D \times 3$. $\mathbf{X}(i,\cdot)\mathbf{F}$ is the embedded coordinate of $\mathbf{X}(i,\cdot)$. Minimizing this equation constrains that two similar pixels $\mathbf{X}_i$ and $\mathbf{X}_j$ with a large $\mathbf{W}(i,j)$ should be closed to each other in the new latent space.

To solve the optimization problem, we compute the first 3 eigenvectors correspond to the first three non-zero minimum eigenvalue of the generalized eigenvector problem [5]:

$$\mathbf{X}'\mathbf{L}\mathbf{X}f = \lambda \mathbf{X}'\mathbf{D}\mathbf{X} \tag{3}$$

where $\mathbf{D}$ is a diagonal matrix with $\mathbf{D}(i,i) = \sum_j \mathbf{W}(i,j)$ and $\mathbf{L}$ is the Laplacian of the HSI data acquired by $\mathbf{L} = \mathbf{D} - \mathbf{W}$. $\mathbf{F}$ is formed by arranging the 3 eigenvectors by column. The original HSI data is transformed to three-dimensional data $\mathbf{X}_{(a)}$ via $\mathbf{X}_{(a)} = \mathbf{X}\mathbf{F}$.

2.2. Color transfer based on manifold alignment

After dimension reduction, a pseudo-color image is obtained in which the detail information of the HSI is largely preserved. As mentioned before, pseudo-color images always bring counterintuitive visual effects. Our goal is to replace the pseudo-color with natural color to achieve better visual experiences. In this paper, the natural color from a panchromatic image is transferred to the pseudo-color image via manifold alignment.

Consider a pseudo-color image $\mathbf{X}_{(a)}$ and a natural color image $\mathbf{X}_{(b)}$. We first find the correspondence between the two images by SIFT feature matching. Pixels of similar SIFT feature are selected as corresponding points. According to [8], the joint similarity matrix between $\mathbf{X}_{(a)}$ and $\mathbf{X}_{(b)}$ can be defined as:

$$\mathbf{W}'(i,j) = \begin{cases} \mathbf{W}_{ij} & \mathbf{X}(i,\cdot) \text{ and } \mathbf{X}(j,\cdot) \text{ are from the same dataset} \\ 1 & \mathbf{X}(i,\cdot) \text{ and } \mathbf{X}(j,\cdot) \text{ are corresponding points from } \mathbf{X}^{(a)} \text{ and } \mathbf{X}^{(b)} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Then two image data are aligned to a common space. The loss function can be defined as:

$$\mathbf{C}(\mathbf{F}) = \sum_{i \neq j} \|\mathbf{Y}(i,\cdot)\mathbf{F} - \mathbf{Y}(j,\cdot)\mathbf{F}\|^2 \mathbf{W}'(i,j) \tag{5}$$

where $\mathbf{Y} = [\mathbf{X}_{(a)}; \mathbf{X}_{(b)}]$ is the joint data matrix of the two image data. The summation is taken over all pairs of pixels from the two image data. By Equation 5, the individual locality within each image can be preserved. Besides, Equation 5 encourages corresponding pixels from different images to stay close in the new common space. The optimization problem can be solved by Equation 3. Then $\mathbf{F}$ is a matrix of size 6×3. The first 3 rows of $\mathbf{F}$ (denoted by $\mathbf{F}_a$)form the transformation matrix of $\mathbf{X}_{(a)}$, and the last 3 rows of $\mathbf{F}$ (denoted by $\mathbf{F}_b$)form the transformation matrix of $\mathbf{X}_{(b)}$. After manifold alignment, $\mathbf{X}_{(a)}$ is transformed to $\mathbf{X}'_{(a)}$ via $\mathbf{X}'_{(a)} = \mathbf{X}_{(a)}\mathbf{F}_a$, and $\mathbf{X}_{(b)}$ is transformed to $\mathbf{X}'_{(b)}$ via $\mathbf{X}'_{(b)} = \mathbf{X}_{(b)}\mathbf{F}_b$. Since $\mathbf{X}'_{(a)}$ and $\mathbf{X}'_{(b)}$ are close to each other, the color of $\mathbf{X}_{(b)}$ can be transferred to $\mathbf{X}_{(a)}$ via $\mathbf{X}'_{(a)}\mathbf{F}_b^{-1}$.

The overall color transfer algorithm can be summarized as follows:

1. Perform SIFT feature based image registration on the panchromatic image and the HSI to get $\mathbf{X}_{(b)}$. Find the corresponding points of the two images $\mathbf{X}_{(a)}$ and $\mathbf{X}_{(b)}$by SIFT feature matching.

2. Compute the joint similarity matrices $\mathbf{W}'$ by Eq. 4.

3. Calculate the joint Laplacian matrix by $\mathbf{L}' = \mathbf{D}' - \mathbf{W}'$. Find the 3 smallest nonzero eigenvectors of $\mathbf{Y}'\mathbf{L}'\mathbf{Y}f = \lambda\mathbf{Y}'\mathbf{D}'\mathbf{Y}$. Arrange the eigenvectors by column to form the joint linear transformation $\mathbf{F}$. $\mathbf{F}_a$ is the first three rows of $\mathbf{F}$ and $\mathbf{F}_b$ is the last three rows of $\mathbf{F}$.

4. Transfer the color of panchromatic image to the pseudo-color image by $\mathbf{X}_{(a)}\mathbf{F}_a\mathbf{F}_b^{-1}$.

3. EXPERIMENT RESULTS

In this section, we demonstrate the effectiveness of our algorithm on the HSI of Washington DC Mall. The Washington data contains 191 bands. Each band consists of 1208 scan lines with 307 pixels in each scan line. We resize the spatial resolution to 640×154 before experiment. The panchromatic

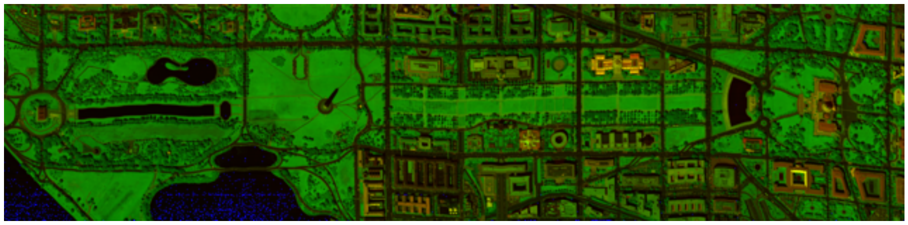

Fig. 1. Band 1, band 95 and band 191 of the original HSI represented by pseudo-color.

Fig. 2. The corresponding panchromatic image after registration.

Fig. 3. Dimension reduction result of the HSI via PCA.

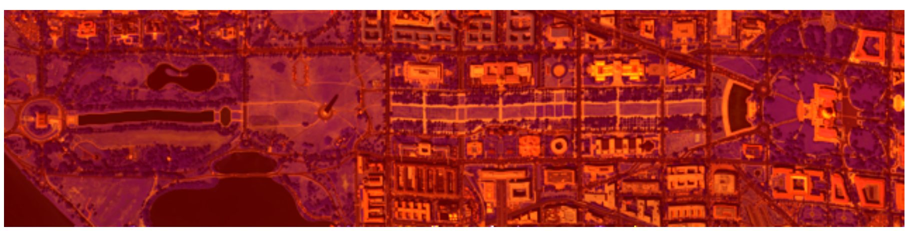

Fig. 4. Dimension reduction result of the HSI via manifold learning.

Fig. 5. The panchromatic image in the common new space.

image of Washington DC Mall is obtained from google maps and has a resolution of 5160×1640. Fig. 1 displays the original HSI by three randomly selected bands. Fig. 2 is the panchromatic image after image registration. Fig. 3 shows the

Fig. 6. The fused HSI in the common new space.

Fig. 7. The HSI with natural color after color transfer.

pseudo-color image after dimension reduction by PCA. We can see that some of the local structure are damaged. Fig. 4 presents the HSI after dimension reduction with Laplacian Eigenmaps. The local information are better preserved than PCA. However, the pseudo-color brings poor visual effects. Fig. 5 and Fig. 6 show the images after manifold alignment corresponding to panchromatic image and pseudo-color image respectively. We can see that the two images are much closed in color. Fig. 7 shows the fused HSI image after color transfer. This image retains largely the details of the original HSI. Besides, the natural color are more easy for people to understand the image.

4. CONCLUSIONS

This paper presents an approach to visualize hyperspectral images by manifold learning. The most important novelty of our approach is that it can not only preserve the details of the hyperspectral image, but also bring natural visual effects. To achieve this goal, we first apply manifold dimension reduction to the hyperspectral image. We obtain a three-band image with pseudo-color and retains the detail structure of the hyperspectral image. Then manifold alignment is applied on a panchromatic image and the pseudo-color image. In this way we replace the pseudo-color with a more desirable natural color. Experiment results demonstrate the effectiveness of our approach.

5. REFERENCES

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