VISION-OPTIMIZED IMAGE-ADAPTED PROJECTIONS FOR VISUALIZATION OF HYPERSPECTRAL IMAGERY

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1. INTRODUCTION

Hyperspectral data visualizations are useful as a background layer to labeling information in the hyperspectral scene such as classification information, locations, or geographic features. Given a hyperspectral image H, where the ith-jth pixel H_{ij} is a d-dimensional vector representing reflectance at d wavelengths, any dimensionality-reduction method an be used to reduce the d dimensions down to three dimensions, and then display the three dimensions as the R, G, and B channels of a standard display.

In particular, principal components analysis is a standard method for hyperspectral visualization, dating back to 1973 [1]. However, problems with PCA and most image-adaptive visualizations to date include:

1. colors do not have a natural interpretation, for example, green does not mean vegetation,
2. colors do not have a consistent interpretation across images (because they are image-adaptive),
3. perceived color differences do not have an interpretable meaning,
4. colors tend to be bright and saturated and this makes it difficult to judge color differences and to judge when colors are close (and whether that means spectra are close).

Another problem with PCA and most image-adaptive visualizations is the computation time required to find the principal components (or other quantity used for adaptation). The approach proposed here still requires finding the first three principal components, and thus the computation time is roughly equivalent to PCA visualization.

Jacobson and Gupta described a number of goals they believed would be useful in a visualization [2], including perceived color differences corresponding to actual hyperspectral differences, colors having a consistent and natural interpretation, minimization of unplanned pre-attentive features, and the colors having a natural palette because human vision is optimized to perceive and consistently quantify differences in unsaturated greens, grays, and browns. They recommend that bright saturated colors be used for labels, and for extra layers of information such as highlighting pixels belonging to classes of interest [3].

Jacobson et al. [3] constructed linear basis functions that could be used for any hyperspectral image, and which were designed to satisfy the human-vision based goals, as well as make optimal use of the sRGB gamut (the set of colors available with the standardized sRGB monitor setting). Their proposed linear basis functions do not adapt to the image content.

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Our goal is to create visualizations with good human vision properties but that also adapt their emphasis to the image. We use an approach proposed by Jacobson et al. [3] to adapt a set of basis functions for differing SNR in each wavelength. However, instead of adapting for the SNR, we adapt the images based on image content. Any useful measure of image content would work; here we use the first three principal components, and the cosine basis functions proposed by Jacobson et al. [3]. We adapt the r, g, and b basis functions to the second, first, and third principal component separately (green is closest to human's photopic sensitivity, and so should be related to the most important information). Principal components can be negative, but a large negative value for a dimension still signifies that dimension is important, so we use the magnitude of the principal component vector (pc vector) to do the adaptation.

Specifically, given a basis function and the principal component being used to adapt it, construct each row of the adapting matrix A as follows: begin at the leftmost column which does not yet sum to one, and add to it until the column sums to one or until the row sum is equal to the adapting function for that component. If the adpating function for that row is not exhausted but the column sums to one, then add the remainder (up to one) to the next element in that row.

Here is an example for adapting a five-component hyperspectral image, for the green basis function. Let the first pc vector's magnitude be:

$$pc1 = \begin{bmatrix} .3 \\ .2 \\ 1 \\ 2.25 \\ 1.25 \end{bmatrix}, \text{ then } A = \begin{bmatrix} .3 & 0 & 0 & 0 & 0 \\ .2 & 0 & .0 & 0 & 0 \\ .5 & 0.5 & 0 & 0 & 0 \\ 0 & 0.5 & 1 & .75 & 0 \\ 0 & 0 & 0 & .25 & 1 \end{bmatrix}.$$

Also, we propose white-balancing these visualizations. White-balancing is done automatically by the human visual system when we view scenes, and is part of the image processing pipeline of many commercial digital color cameras. We white-balance our visualizations using the so-called "grayworld assumption", so that the average linear sRGB value is equal to a neutral gray value. This removes any color cast in the visualization and centers the colors of the visualization around the neutral axis, where human vision is most sensitive.

Fig. 1 shows examples of AVIRIS hyperspectral images visualized with standard PCA (left) and with the proposed white-balanced PCA-adapted cosine basis functions.

2. REFERENCES

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[2] N. P. Jacobson and M. R. Gupta, "Design goals and solutions for the display of hyperspectral imagery," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 43, no. 11, pp. 2684–2692, November 2005.

[3] N. P. Jacobson, M. R. Gupta, and J. B. Cole, "Linear fusion of image sets for display," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 45, no. 10, pp. 3277–3288, 2007.

[4] R. O. Green et al., "Imaging spectroscopy and the airborne visible/infrared imaging spectrometer (AVIRIS)," *Remote Sensing of Environment*, vol. 65, pp. 227–248, 1998, AVIRIS signal to noise curve is given in Figure 9.

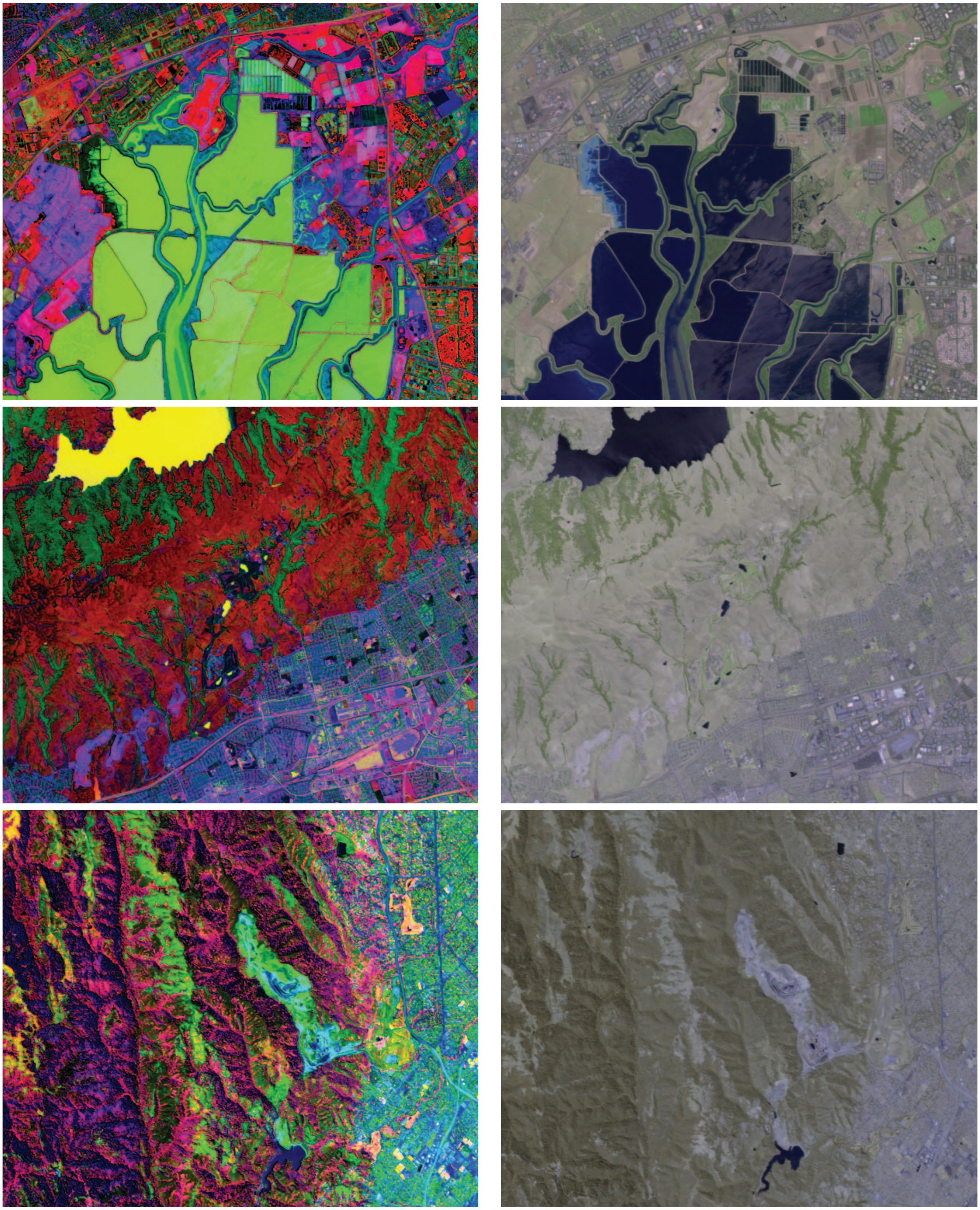

Fig. 1. *(Figure designed to be viewed with a calibrated sRGB display)* Example of standard PCA visualizations (left) and white-balanced PCA-adapted cosine-basis function visualizations (right). Images are projections of 190-band AVIRIS images of Moffet field and Jasper ridge. [4].