SNR-ADAPTIVE LINEAR FUSION OF HYPERSPECTRAL IMAGES FOR COLOR DISPLAY

Nathaniel P. Jacobson and Maya R. Gupta

natejake@ee.washington.edu, gupta@ee.washington.edu
Dept. of Electrical Engineering
University of Washington
Seattle, WA 98195

ABSTRACT

A set of three fixed basis functions is proposed for the linear projection of hyperspectral images into a set of three images that can be displayed on the red, green, and blue channels of a standard display. The proposed basis functions were designed to meet specific criteria for maximizing interpretability of the visualization and correspondence of the perceived visualization to the original hyperspectral data. The constraints of the standardized display-device colorspace sRGB were taken into account, and the design was optimized using the perceptual colorspace CIELab. This work improves upon a previous fixed basis function method, the Stretched CMF basis functions. A method for taking into account the different SNR of each frequency band is also proposed. Example visualizations are shown for AVIRIS hyperspectral imagery.

Index Terms— hyperspectral, color, CIELab, sRGB

1. INTRODUCTION

A *hyperspectral image* is a set of images where each component image corresponds to a particular wavelength band, just as a color image is a set of three images corresponding to red, green, and blue wavelengths. In this paper, the problem of displaying a hyperspectral image on a standard color monitor is considered. The approach is to reduce the dimensionality of the hyperspectral image by linearly projecting the hyperspectral image onto three basis functions: a red basis function, a green basis function, and a blue basis function. That is, given a hyperspectral image with N component images, and N-component discrete basis functions r, g, and b, then a normalized N-dimensional hyperspectral pixel x_{ij} is projected down to scalar color components R_{ij}, G_{ij}, B_{ij}:

$$R_{ij} = r^T x_{ij}, \;\; G_{ij} = g^T x_{ij}, \;\; B_{ij} = b^T x_{ij}.$$

Then, the three projected images R, G, and B are displayed as the red, green, and blue components of one color image. As a final step, the image is gamma corrected by converting it to the nonlinear sRGB color space.

Linear projection is analogous to how human vision maps the continuous visible spectrum of light onto the L, M, and S cones, corresponding roughly to the color sensations of red, green, and blue. In human vision the basis functions are (probabilistic) spectral sensitivities of each cone type. Human vision is an effective way to view the world, and motivates linear projections of hyperspectral images into color images. Humans can quickly interpret color images, including fast searching, useful comparisons, and shape and object recognition.

The main disadvantage to mapping hyperspectral image pixels to display colors is the loss of information. Given an hyperspectral image with N component images, a $N \rightarrow 3$ linear projection to one RGB color image is a many-to-one mapping such that some output RGB color values could correspond to many different N-dimensional hyperspectral pixels. Human color vision suffers from the same problem; two different visible spectra can cause the same color sensation. However, such metameric spectra from different objects can usually be distinguished by context, shapes formed in the image, and other visual clues. In fact, a common method for displaying hyperspectral images is to pick three spectral bands of the hyperspectral image and map those three bands' images to the R, G, and B components.

Another common approach to displaying hyperspectral images is to calculate the first three principal component analysis (PCA) basis functions for the hyperspectral dataset, project the hyperspectral image onto the PCA basis functions, and then map the resulting three PCA images to the RGB or HSV colorspace and display the final color image [1, 2]. Using PCA for image display has a number of disadvantages (see [3] for more detail on these points): the visualization can be difficult to interpret because the colors change drastically depending on the data, color differences do not correlate strongly with data differences, orthogonal principal components are usually mapped to the non-orthogonal RGB display channels, the colors may be distractingly pre-attentive, the standard contrast stretch used in PCA display leads to simultaneous contrast problems, and the computational complexity is high. Using other adaptive statistical approaches such as MNF and ICA for display has similar disadvantages.

In this paper we consider the design of projection basis functions such that the resulting color image provides useful, interpretable information to the human viewer about the original hyperspectral dataset. First, design goals for this visualization problem are discussed in Section 2. Based on the presented design goals, a new set of linear basis functions is proposed and analyzed in Section 3. In Section 4, a new method is given to adapt a basis to the data signal-to-noise (SNR) ratio.

2. DESIGN GOALS

In this section we consider some design goals for fusing a set of images to preserve information and enable interpretability.

1. **Summarization:** The visualization accurately summarizes the original data.
2. **Consistency of Visualization:** Hyperspectral data are projected in a sufficiently consistent way such that colors have consistent, interpretable meanings.
3. **Computational ease:** The computation is fast enough to enable real-time usage or interactivity.
4. **System-optimized design:** The design is optimized for characteristics of the display and the human visual system.
5. **Natural palette:** The visualization creates a natural palette of colors, producing pre-attentive colors (such as bright saturated colors) only when informative.
6. **Equal-energy white point:** A data vector with the same value for each component appears gray.
7. **Equal Luma Data Components:** Define a Kronecker data point to be a vector with all component values zero, except one component, which has value 1. If all Kronecker data points map to colors with the same CIELab luminance value, then the visualization has *equal luma* data components. In effect, this means that every data component (i.e., every spectral band) contributes equally to the perceived brightness of the visualization.
8. **Informative Hue Differences:** If the hue difference between any two same-length Kronecker data points is an increasing function of the distance between their non-zero components the visualization has informative hue differences.

3. FIXED BASIS FUNCTION SETS

We briefly review a previously proposed fixed basis function set, called the Stretched CMF basis (where CMF stands for color matching function), and then propose an improved design, the Constant-Luma Border basis. The bases can be sampled for an arbitrary number of data components N to be used with any hyperspectral imagery. Code to implement these basis function sets in Matlab is available at idl.ee.washington.edu/projects.php.

3.1. Stretched CMF

In previous work we proposed a basis inspired by human vision to reduce the dimensionality of hyperspectral images for display [3, 4]. The proposed Stretched CMF basis synthesized what the human eye would see if its range of perceived wavelengths were stretched to cover the hyperspectral range of interest. Figure 1 shows the Stretched CMF basis functions, and the rendered colors of Kronecker data pixels (data pixels where all components are zero except for one component) projected onto the basis. Some aspects of the Stretched CMF basis make it suboptimal for general use. First, the luminance and saturation of the middle data components are emphasized. Second, the change of hue across components is uneven, as shown by the colorbar of Figure 1 (top), the displayed color of Kronecker data points at each data component. Third, the Stretched CMF basis can produce RGB colors that are outside of the sRGB gamut, which must be clipped in order to be displayed on a standard sRGB monitor.

3.2. Constant-Luma Border

The Constant-Luma Border basis was designed for the goal of equal luma data components, while balancing the goal of equal chromatic differences with making the best use of the sRGB gamut. Kronecker data points are rendered in colors that follow the curve defined by linear mixtures (in linear sRGB space) between three pseudo-primaries that lie in the $L = 50$ Luma plane. Figure 2 shows the Constant-Luma Border basis functions, and the rendered colors of Kronecker data pixels (data pixels where all components are zero except for one component) projected onto the basis. The curve progresses from blue (R=0.122, G=0.122, B=1) to green (R=0, G=0.256, B=0) to red (R=0.866, G=0, B=0). Points along the curve are sampled at approximately constant ΔE.

The basis functions do not sum to the same value, so the equal energy white point goal is not well-met: data points with the maximum value for each component are rendered as off-white.

3.3. Data scaling

In order to fit the available gamut, it is necessary to scale the hyperspectral data in a consistent way. A raw data vector z is normalized as follows to create the normalized vector x that is then linearly projected: $x[n] = \frac{1}{k}(z[n] - \widehat{min}_z)/(\widehat{max}_z - \widehat{min}_z)$, where $k = max(\sum_{n=1}^{N} r[n], \sum_{n=1}^{N} g[n], \sum_{n=1}^{N} b[n])$ and $\widehat{min}_z$ and $\widehat{max}_z$ are the smallest and largest expected values of the data.

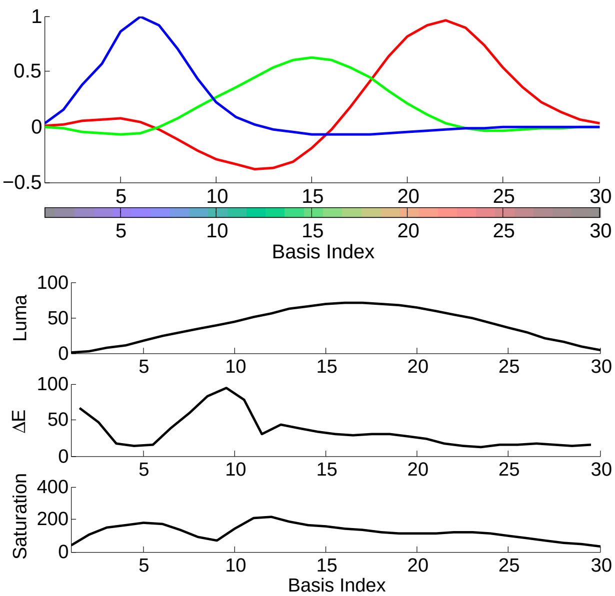

Fig. 1. Stretched CMF basis for $N = 30$ components.

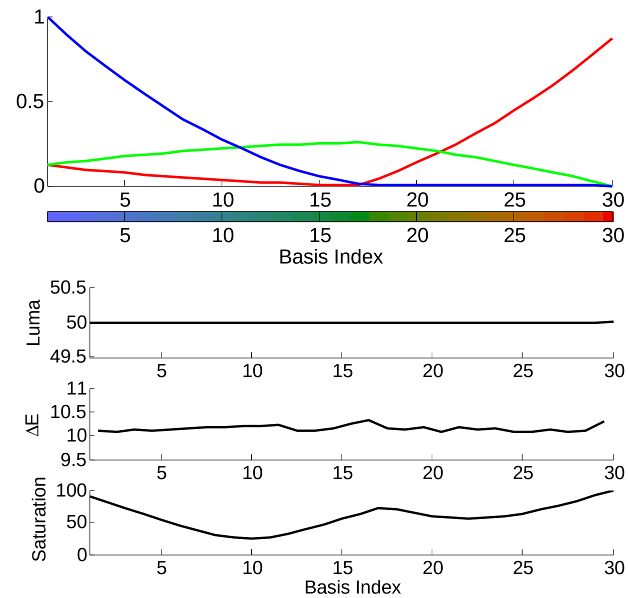

Fig. 2. Constant-Luma Border basis for $N = 30$ components

3.4. Interpreting the color

Figures 3 and 4 are examples of image sets projected with the proposed bases. Each basis enables the following consistent interpretation of colors to some extent:

Luminance: Luminance corresponds to the sum of the data vector components.

Hue: Hue indicates which data components are strongest. The colorbars, which show the rendered colors of unnormalized Kronecker data points, act as a legend that tells the viewer what components are strongest given a particular hue in the rendered image.

Saturation: A saturated color response corresponds to relatively few strong neighboring components. Similarly, a desaturated (gray) color indicates that all data components are equally strong.

4. ADAPTING BASES TO DATA SNR

In some sensor systems the signal to noise ratio (SNR) varies significantly over the data components. For hyperspectral images captured by NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) the SNR is affected by atmospheric scattering and the sensitivity of the component spectrometers of the system. Often, bands with low SNR are ignored as they contain little usable signal.

We developed a method to adapt a basis for varying SNR. Given original basis functions r, g, b, the reweighted basis functions are: Ar, Ag, Ab, where A is a reweighting matrix.

The matrix A is designed to transfer weight from components with low SNR to components with high SNR, so that high SNR components appear brighter and have greater hue changes between them. Elements of A are initialized to zero. Then, starting from the top left and proceeding row-by-row, each element is assigned the maximum value subject to the following constraints:

1. The sum of the ith row of A is equal to the SNR of the ith component.

2. The sum of each column of A is 1.

The following example shows how these constraints are satisfied for a given SNR vector (normalized to have a mean value of 1):

$$SNR = \begin{bmatrix} .3 \\ .1 \\ 2.3 \\ 1.3 \end{bmatrix}, \quad \text{then } A = \begin{bmatrix} .3 & 0 & 0 & 0 \\ .1 & 0 & 0 & 0 \\ .6 & 1 & .7 & 0 \\ 0 & 0 & .3 & 1 \end{bmatrix}.$$

The SNR-optimized basis functions have the same total sum as without the SNR optimization. Figure 4 shows an example of the difference between ignoring low-SNR bands and using an SNR-optimized basis (note that images were designed to be viewed on a standard sRGB display).

5. DISCUSSION

Using human vision as a model for a dimensionality-reduction system, in this paper we proposed a new solution for the lossy visualization of a hyperspectral image that is interpretable by humans in terms of perceived luminance, saturation, and hue.

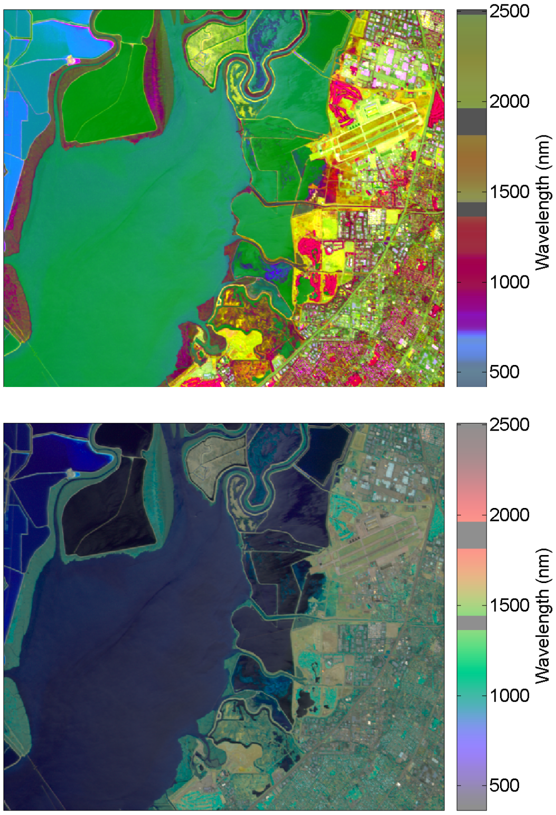

Fig. 3. AVIRIS hyperspectral visualizations; bands with poor SNR are not included in the projections. **Top:** Projected using PCA basis, top and bottom 2% of pixels saturated for each color component, with no gamma correction. **Bottom:** Projected using Stretched CMF basis.

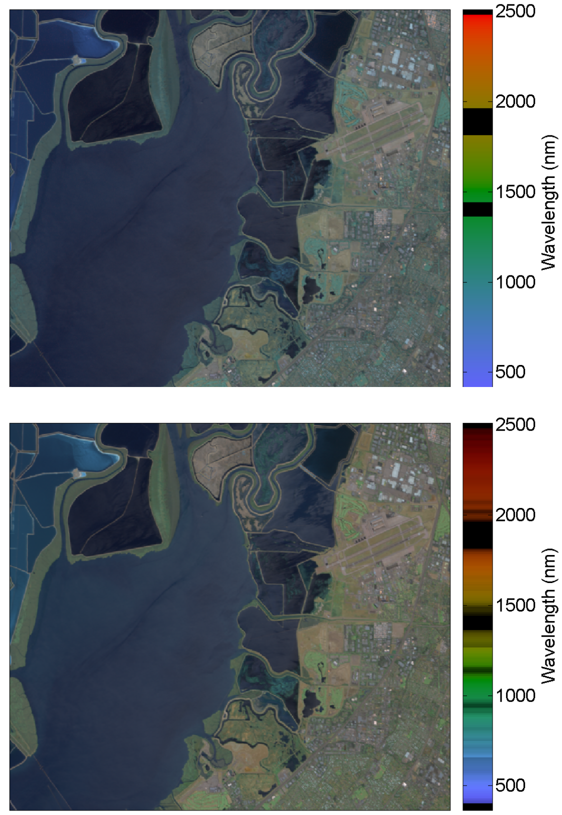

Fig. 4. AVIRIS hyperspectral visualizations. **Top:** Projected using Constant-Luma Border basis. Bands with poor SNR are not included in the projection. **Bottom:** Projected using the AVIRIS SNR-adapted Constant-Luma Border basis. All bands are included in calculating the color visualization of the hyperspectral image.

The proposed Constant-Luma border basis is optimized for the standard sRGB color monitor and for the characteristics of the human visual system, assuming all data components are equally important/noise-free. We proposed a method for adjusting any linear projection basis for the common case that the SNR varies for different data components. This SNR-adjustment method could also be used to adjust for differences in importance of different data components.

The proposed Constant-Luma border basis dimensionality-reduction technique and SNR-adaption technique can be applied to the visualization of other image sets. In particular, image sets where there are strong correlations between the components of the multi-dimensional pixels will work well. The value of this kind of visualization for a particular task would need to be evaluated by a user study.

6. REFERENCES

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