A CLASS-SEPARABILITY-BASED METHOD FOR MULTI/HYPERSPECTRAL IMAGE COLOR VISUALIZATION

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ABSTRACT

In this paper, a new color visualization technique for multi- and hyperspectral images is proposed. This method is based on a maximization of the perceptual distance between the scene endmembers as well as natural constancy of the resulting images. The stretched CMF principle is used to transform reflectance into values in the CIE L*a*b* colorspace combined with an \textit{a priori} known segmentation map for separability enhancement between classes. Boundaries are set in the a*b* subspace to balance the natural palette of colors in order to ease interpretation by a human expert. Convincing results on two different images are shown.

Index Terms— Color display, Segmentation, Human visual perception, Multi/hyperspectral imaging, Visualization

1. INTRODUCTION

Multi/hyperspectral images are constituted of tens or hundreds of grayscale images, depicting the radiance or reflectance values of a given scene at several ranges of wavelengths. Their use is very common in fields such as remote sensing, art or medicine. When it comes to the task of visualizing such an image on a traditional display device, a dimensionality reduction step is required so that no more than three channels remain to map the components towards the widely used Red-Green-Blue (RGB) colorspace. This results in an inevitable loss of information, hence the need for feature extraction algorithms that aim at projecting the data towards a reduced space that better highlight the relevant information in the image. The latter relevance can be measured by criteria such as energy [1, 2, 3], Signal-To-Noise Ratio [3] or independence of the components [4, 5]. However, focusing on the informative content alone does not allow optimal interpretation by a human expert because resulting images are generally highly contrasted and then are not respectful of the natural palette of colors. Hence the necessity to take into account how the human eye interpret color. In [6], the CIE Color Matching Functions (CMF) are used to combine spectral channels in such a way that the result is a representation of what a human eye would see if it was not limited to the visible range of wavelengths. Other color basis were used in [7] and appeal for the human eye is also considered in [8]. However, in those methods, class-separability is not fully considered. Indeed, another way to make human interpretation easier is by clearly highlighting and separating the endmembers of the scene. One of the most well-known method for class-separability-based dimensionality reduction is Fisher’s Discriminant Analysis (FDA) [9]. However, it does not take into account the perceptual distance between classes and the produced images rarely respect the natural palette of colors. In [10], the authors propose a band-selection scheme based on the FDA. It ranks the bands according to their class-separability power. Even though the method is not visualization-oriented, the number of selected bands can be chosen to be equal to three, in order to map them towards the RGB colorspace for instance. Selecting a subset of spectral bands instead of computing linear (or non-linear) combinations of them allows the resulting channels to keep their physical meaning. Hence natural-like representations, provided the descending order of the Red, Blue and Green ranges of wavelengths are respected during the mapping. However, in this method, no further processing is applied to the image and then the class-separability is not optimal. Moreover, band selection methods result in a very high loss of information due to the complete removal of but a triplet of bands.

In this paper, both class separability and natural constancy are considered. We propose to use the CIE L*a*b* colorspace in order to perceptually separate the endmembers given an \textit{a priori} known segmentation map. The L*a*b* components are computed thanks to the stretched CMF principle. Each group of pixels from a same class is then shifted in the L*a*b* space according to a equidistant scale on each axis. Constraining the minimal and maximal values on each scale allow to control the natural constancy of the resulting image.

The remainder of this paper is as follows : first, the dimensionality reduction step is described. Then, the perceptual class-separability enhancement is explained. Results are presented and discussed before conclusion.
2. DIMENSIONALITY REDUCTION

As explained earlier, high dimensionality pixels are vectors sampling the reflectance values along a given range of wavelengths. The reflectance of a given object is the proportion of light reflected by it, given a known illuminant. It takes its values between 0 and 100%. The dimensionality reduction step consists in converting a reflectance vector into a 3-D vector in a perceptual color space. At this aim, we used Jacobson’s stretched CMFs. The CIE Color Matching functions (see figure 1) are the numerical description of the chromatic response of the human eye. They are used to compute the transformation from reflectance to the XYZ colorspace, resulting in an approximation of how the human eye would see the corresponding scene.

![Fig. 1. Color matching functions](image)

Initially, the CMF bounded in the visible spectrum (400-700nm). Jacobson et al. proposed to extend these functions to all the wavelengths available, so that no part of the acquired data is neglected. Examples of resulting color representations can be found in section 4. The resulting XYZ components are then converted into L*a*b* using a standard CIE illuminant. L*a*b* is a perceptual colorspace, device-independent, and developed in 1976 by the Commission Internationale de l’Energie. It defines color through three components:

- **L**, the lightness. L = 0 yields black whereas L = 100 yields white.
- **a**, the red/green opposition
- **b**, the yellow/blue opposition

In this paper, values of a and b will be considered in \([-110; +110]\].

3. PERCEPTUAL SEPARATION OF ENDMEMBERS

First, a suitable segmentation map is required. It can be computed by means of any supervised or unsupervised classification algorithm. In this paper, we used the well-known \(K\)-means method which consists in clustering pixels according to their respective distances. Although it is an unsupervised method, it requires an input parameter which is \(K\), the number of clusters to be computed. Figure 2 shows examples of segmentation maps for the images described in the next section. Each gray level represents one class. The segmentation step is performed before dimensionality reduction. For each of the \(K\) classes, a centroid \(C_k (k \in [1..K])\) is computed in L*a*b*.

![Fig. 2. Segmentation maps for \(K = 5\)](image)

In order to perceptually separate those endmembers, we use a contrast stretching in each component of L*a*b*.

- On the L axis, the centroids are ranked by ascendant lightness and then translated separately so that they are equidistant. The translation applied on \(C_k\) is then applied to all pixels in the \(k^{th}\) class. The translations have to be made so that the resulting pixels lightness takes its values in the whole range \([0..100]\). Let \(s_L\) be the size of this range, 50% being its middle value. In most cases, \(s_L = 100\) can be used as a default value. However, in case of low dispersions of lightness inside the classes, if an entire set of similar pixel is translated towards very high or very low lightness, difference between them will become less and less perceptible. Indeed, as stated earlier, if L* = 0 or L* = 100, no matter what values have the a and b components, the user will only see black or white. In this particular case, one should consider to reduce \(s_L\). Figure 3 shows an illustrative example with \(K = 4\) and \(s_L = 100\). The red squares represent class centroids and the green dots are pixels.

- In the a*b* subspace, the same principle is applied. Here again, a parameter \(s_{ab}\) sets the range of colors. In order to keep a color constancy between the original and enhanced images, the origin of the range is taken as the centroid of the whole original image. Let \(\bar{a}\) and \(\bar{b}\) be its coordinates. As discussed in the next section, \(s_{ab}\) is of great influence on the natural aspect of the results, it can be used by the expert enduser to adjust the visualization according to its own needs. Figure 4 shows
an illustrative example with $K = 4$ and $s_{ab} = 120$. The orange square represents the image centroid. The left image shows the position of all the pixels before translation while the right one depicts the translations (arrows) performed on each centroid in the grey disc, which represents the bounded range of colors set by $s_{ab}$.

![Fig. 3. Class separation on the L* axis: initial state, scaling, after translation](image)

![Fig. 4. Class separation in the a*b* subspace: before (left) and after translation (right)](image)

### 4. EXPERIMENTS AND RESULTS

#### 4.1. Data sets

For the experiments, two images have been used. The first one is a portion of the well-known AVIRIS Jasper Ridge hyperspectral image, available at [http://aviris.jpl.nasa.gov/html/aviris.freedata.html](http://aviris.jpl.nasa.gov/html/aviris.freedata.html). It contains 220 bands, and we have considered 5 different endmembers, based on an expert analysis: 3 kinds of vegetation, shade and soil. The second dataset, which will be referred to as ‘Mural’ is a 35 bands (400-740nm) multispectral image of a 16th century mural painting from the Brömser Hof in Rudesheim, Germany, acquired with a rotating-wheel-based multispectral camera. Apart from the MacBeth CC target, the scene also contains 5 different endmembers which are 5 different types of paints. As a pre-processing step, bands with average reflectance value below 2% and those with low correlation (below 0.8) with their neighboring bands have been removed.

#### 4.2. Results

Figures 5 and 6 show the resulting color representations of both datasets. The stretched-CMF representations have been taken as initial images for perceptual class-separability enhancement and also as references for quality assessment of the proposed method.

![Fig. 5. Jasper Ridge scene - (a) stretched CMF representation, without class-separability enhancement (b) $s = 20$ (c) $s = 40$ (d) $s = 80$ (e) $s = 120$ (f) $s = 160$](image)
algorithm in L*a*b*. Moreover, endmembers have been considered equally important in the visualization process. However, it would be interesting to lead further investigations about the effect of different segmentation techniques as well as about the adaptive weighting of endmembers, in respect to their respective sizes, saliencies, and application-related importances.

5. CONCLUSIONS

A new class-separability-based method for multi/hyperspectral images color visualization has been proposed. First, dimensionality reduction is performed with the stretched CMF principle, then, pixels of each class are translated in the L*a*b* perceptual colorspace in order to enhance their perceptual separability. Natural constancy is balanced by setting boundaries in the a*b* subspace. Results on one multispectral and one hyperspectral images show that those boundaries are of great influence on the results and then can be used as a tradeoff parameter for the expert enduser to adjust according to its needs. Further investigations will be conducted on those boundaries and how to best balance natural constancy and perceptual class separability, according to the respective content and importance of each class.

6. ACKNOWLEDGEMENTS

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7. REFERENCES


