An Efficient Method for the Visualization of Spectral Images Based on a Perception-Oriented Spectrum Segmentation

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Abstract. We propose a new method for the visualization of spectral images. It involves a perception-based spectrum segmentation using an adaptable thresholding of the stretched CIE standard observer color-matching functions. This allows for an underlying removal of irrelevant channels, and, consequently, an alleviation of the computational burden of further processings. Principal Components Analysis is then used in each of the three segments to extract the Red, Green and Blue primaries for final visualization. A comparison framework using two different datasets shows the efficiency of the proposed method.

1 Introduction

Most of today's visualization devices are based on the paradigm that a combination of three primary colors (roughly red, green and blue) is sufficient for the human eye to characterize a color [1]. However, in many applications such as remote sensing, medical or art imaging, measuring the electromagnetic behavior of a scene has to be made with more spectral precision. Analogously to the need for a high spatial resolution for an enhanced separation of the different elements of a scene, a high spectral resolution allows for a better estimation of its reflectance, and thus, a better characterization of its color properties, regardless of the conditions of acquisition (illuminant, acquisition device). Spectral imaging consists of acquiring more than three spectral components from a scene, usually dozens, each one of them representing a reduced range of wavelengths, for better spectral precision (analogously to a pixel covering a small area of the space).

However, multispectral display devices are not yet of common use and the RGB strategy is still the most widespread. Therefore, when it comes to the task of visualizing a spectral image on a traditional computer screen, only three channels can be used, which implies a dimensionality reduction.

Tri-stimulus representation of multi and hyperspectral images for visualization is an active field of research which has been thoroughly investigated over the past decades. One of the most common approaches is probably the one referred to as *true color*. It is basically achieved by use of the CMF-based band transformation: each primary (R,G and B) is the result of a distinct linear combination of spectral channels in the visible range of wavelengths (400-700nm).

Even though it generally yields a natural visual rendering, this approach does not adapt itself to the data at all, therefore, noise and redundancy are not accurately handled.

Another very common approach for dimensionality reduction is Principal Components Analysis (PCA), which has been extensively used for visualization purposes. In [2], Durand and Kerr proposed an improved decorrelation method, aiming at maximizing both the Signal-to-Noise-Ratio (SNR) and the color contrast. Later, Tyo *et al.* [3], investigated PCA for N-to-3 dimensionality reduction towards the HSV colorspace. An automatic method to find the origin of the HSV cone is also proposed in order to enhance the final color representation. Tsagaris *et al.* [4] proposed to use the fact that the red, green and blue channels, as they are interpreted by the human eye, contain some correlation, which is in contradiction to the underlying decorrelation engendered by the PCA. For that reason, the authors proposed a constrained PCA-based technique in which the eigendecomposition of the correlation matrix is forced with non-zero elements in its non-diagonal elements. Scheunders [5] proposed to achieve a spatial decorrelation by first performing a simple image segmentation before using PCA and neural-network-based transformation in each region, distinctively. In [6], Du *et al.* compared seven feature extraction techniques in terms of class separability, including PCA, Independent Components Analysis (ICA) and Linear Discriminant Analysis (LDA).

However, due to the correlation matrix computation and manipulation, PCA is known to have a poor computational efficiency. For that reason, Jia *et al.* [7] proposed to segment the image's spectrum into contiguous subgroups of bands, in order to divide the complexity of PCA. Their method takes advantage of the block-structure of the correlation matrix of the spectral image to find the different subgroups. Zhu *et al.* [8] investigated spectral segmentation techniques (equal subgroups, correlation coefficients and RGB-based) together with ICA for visualization purposes. Segmented PCA is also investigated in [9], including equal subgroups, maximum energy and spectral-signature-based partitionings. However, none of these spectrum segmentation methods accurately handles the human perception of color. Moreover, we believe that gathering only contiguous bands and not allowing a band to belong to several segments is very restrictive and does not allow for an accurate exploitation of the perceptual correlation between the three primary colors.

In this paper, we propose an efficient visualization technique for the visualization of spectral images. It involves a fast perception-oriented spectrum segmentation, based on a thresholding of the CIE standard observer CMF. Three segments are formed and each one can then be used for the extraction of the Red, Green and Blue components. Segments are allowed to overlap and to be non-contiguous, so that a band can belong to several segments. Depending on the value of the thresholding parameter, a certain amount of bands is excluded, hence an underlying removal of irrelevant channels, and, consequently, an alleviation of the computational burden of further processings. In the remainder of this paper, the spectrum segmentation technique is first presented and the dimensionality reduction problem is briefly tackled. Then, the experimental framework is detailed and results are subjectively and objectively discussed before conclusion.

2 The proposed method

2.1 Spectrum segmentation

Spectrum segmentation aims at regrouping spectral channels so that bands of a same group are considered similar in some way. This allows for an alleviation of the computational burden of the feature extraction, in a divide-and-conquer fashion. In the related works mentioned in the previous section, segmentation is performed based on different criteria that we do not believe to allow for a good handling of human perception of color. Therefore, we propose to measure similarity taking such property into account. At this aim, we propose to use the CIE 1964 Supplementary Standard Colorimetric Observer Color Matching Functions (CMF) [10] which are descriptors of the chromatic response of the human eye (see figure 1).

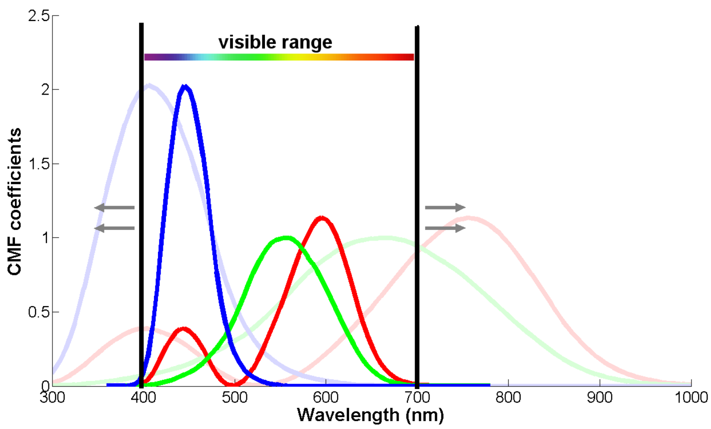


Fig. 1. The stretched CMF principle: In strong colors, the original functions. In light colors, the same ones stretched to fit a larger range of wavelengths.

The CMF are usually used to linearly combine spectral channels towards a tristimulus representation corresponding to how a human eye would see the scene [11]. In other words, each spectral channel $i \in [1..N]$ is associated with three weighting coefficients $x(i), y(i), z(i)$ roughly corresponding to its contributions to the perception of the red, green and blue. For clarity purposes, let us use the following notations $W_i^R = x(i), W_i^G = y(i), W_i^B = z(i)$.

We propose to interpret this statement as follows: the higher the weighting coefficient W_i^p, the higher the relevance for i to be a good representative of p.

Consequently, we propose to cluster the CMF coefficients into two classes, by means of a binarizing threshold τ. Coefficients above τ depicts the relevant wavelengths for band selection. We note the ensemble of the corresponding channels Seg_p^τ, $p \in \{R, G, B\}$.

The spectrum segmentation is performed using normalized functions so that $max_i(W_i^p) = 1, \forall P$. Figure 2 illustrates the technique as well as the role of τ.

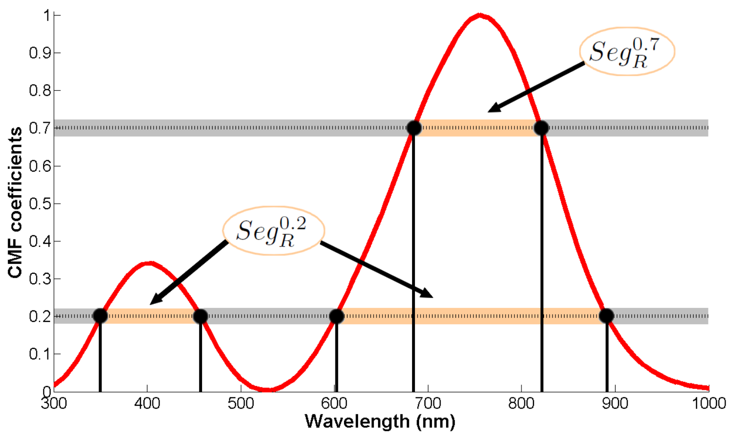


Fig. 2. The role of τ, example on the red function for $\tau = 0.2$ and $\tau = 0.7$. In both cases, the grey segments highlight the removal areas.

A problem appears when the spectral image contains channels outside the visible range of wavelengths (400-700nm). Indeed, the CMF are designed only for this part of the electromagnetic spectrum. As a solution to this, Jacobson *et al.* [12] proposed to stretch the CMF so that the entire image spectrum is covered, no matter what wavelengths it ranges in. This stretched CMF principle is illustrated by figure 1, for an image covering the range [300..1000] nanometers. In the case of a non-constant spectral sampling step, either the lacking channels must be replaced by interpolation methods, or the CMF coefficients must be adjusted. For computational ease, we recommend the latter solution.

Eventually, three segments are obtained, depending on the binarization threshold: Seg_R^τ, Seg_G^τ and Seg_B^τ in which the feature extractions for the red, green and blue channels will be performed, respectively.

Consequently, for a growing value of τ, the size of segments gets smaller and:

$$\tau_1 > \tau_2 \rightarrow Seg_p^{\tau_2} \in Seg_p^{\tau_1}, \forall p \in \{R, G, B\} \quad (1)$$

According to its nature, τ allows for the moderation of the aforementioned hypothesis. If it is set to 0, the hypothesis is rejected and band selection is totally unconstrained. On the contrary, if $\tau = 1$, the hypothesis is considered perfectly relevant and there is no need to proceed with band selection since, in that case, the size of each segment is reduced to 1. As will be seen and discussed in the results section, τ also allows one to moderate the natural aspect of the representation, and hence can be manually adjusted, according to the user's need.

2.2 Dimensionality reduction

Dimensionality reduction aims at finding a small set of bands which most accurately represents the whole spectral image. In this work, we used Principal Components Analysis (PCA), also known as Principal Components Transform (PCT) or Karhunen–Loève Transform (KLT). PCA is based on the eigendecomposition of the correlation matrix of the data, that is, in our case, the correlation matrix of a group of spectral channels. It is well-known the first PC contains generally more than 95% of the data energy. Therefore, we extract the first PC of each one of the three subgroups created by the previous step. Eventually, we obtain three highly-informative channels which are used for RGB visualization.

3 Experiments and results

Since the spectrum segmentation part is the core of our method, we propose to use several different segmentation techniques coupled with PCA in order to focus on the partitioning aspect. The other techniques we used are the following:

- The "equal subgroups" partitioning investigated for instance by Zhu *et al.* [8] simply consists of creating three contiguous subgroups of equal size.
- The "correlation-based" segmented PCA proposed by Jia *et al.* [7] consists of taking advantage of the block structure of the correlation matrix of spectral images. It achieves partitioning by segmenting the correlation matrix into three contiguous subgroups.
- The "maximum energy" segmented PCA, proposed by Tsagaris *et al.* [9] consists of partitioning the spectrum in a way that maximizes the eigenvalue corresponding to the first PC in each contiguous subgroup.

Objective comparison of the results has been achieved by considering two aspects:

- The *natural rendering*, in order to measure how appealing it can be for human vision. The evaluation of this criterion is quite challenging since there is no consensus on what is a natural color or a natural contrast, even though there have been some attempts to define those [13]. We propose to use a pseudo *true color* representation of the image as a reference for natural rendering. Even if a *true color* image is generally obtained by neglecting the non-visible ranges of wavelengths, we used the stretched CMF to compute the latter representation, in order to make the comparison relevant. As for a comparison metric, we used the euclidean norm in the CIE L*a*b* colorspace, also known as the CIE76 ΔE^*_{ab}. Transformation to the L*a*b*

colorspace was achieved by first converting reflectance data to XYZ vectors and then L*a*b* vectors by using a D65 standard illuminant for white point estimation. We insist on the fact that these representations are used only to assess the natural rendering, by supposing that they represent the best possible natural results. However, as stated in the introduction, using only the CMF does not allow for an accurate handling of the intrinsic properties of the image, since it is a data-independent transformation. This metric will be referred to as **NR** (Natural Rendering).
- The *perceptual class separability*, in order to measure the visual informative content of the representation, as suggested by Du *et al.* in [6]. At this aim, we manually selected 20 pixels by class, in each image. A class has been defined as a distinct visual feature (see description of the datasets). Then, each class centroid has been identified and projected in L*a*b*. The ΔE^*_{ab} distances between each couple of centroids have then been averaged. This metric will be referred to as **ICPD** (Inter-Class Perceptual Distance).

For our experiments, we used two different spectral images:

- 'Oslo' is a 160 bands remote sensing hyperspectral image, it represents a urban area in the neighborhood of Oslo (Norway). It was acquired with the HySpex VNIR-1600 sensor, developed by the Norsk Elektro Optikk (NEO) company in Norway. The sensor ranges from the early visible (400nm) to the near infrared (1000nm) with a spectral resolution of 3.7 nm. more information can be found on the constructor's website [14]. Based on a human expertise, we considered 5 classes in this image: vegetation, road, roof tops (two kinds) and cars.
- 'Flowers' is a 31 bands multispectral image from the database used in [15]. The sensor ranges only in the visible spectrum (400-720nm) with a 10nm spectral resolution. Three classes are present in this image: flower, leaves and background.

Figure 3 shows the pseudo *true color* representations of the images and results are presented on figures 4-7. Tables 1 and 2 gives the average perceptual distances with the pseudo *true color* references. Ranges of the colorspace are: $L* \in [0..100]$, $a* \in [-110.. + 110]$ and $b* \in [-110.. + 110]$.

We can see that the results from the presented technique are more naturally contrasted and thus allow for a more accurate interpretation by the human expert/enduser. As a result, the NR values are considerably better for the CMF-based segmentation than for the three other techniques. The worst natural renderings are obtained with the Maximum-ernergy-based segmented PCA. The evolution of the thresholding parameter does not yield any constant increase or decrease of the NR rate, however, we can see that the worst result is obtained for $\tau = 1$ on both images. This reveals that, by constraining too much the spectrum segmentation, the quality of the results lowers. Still, our results show that the CMF-based technique allows for the closest representations to the pseudo *true color* versions. Regarding the class-separability results, the maximum-energy-based segmented PCA gives the best results. The CMF-based method comes

(a) (b)

Fig. 3. Pseudo *true color* representations of the test images

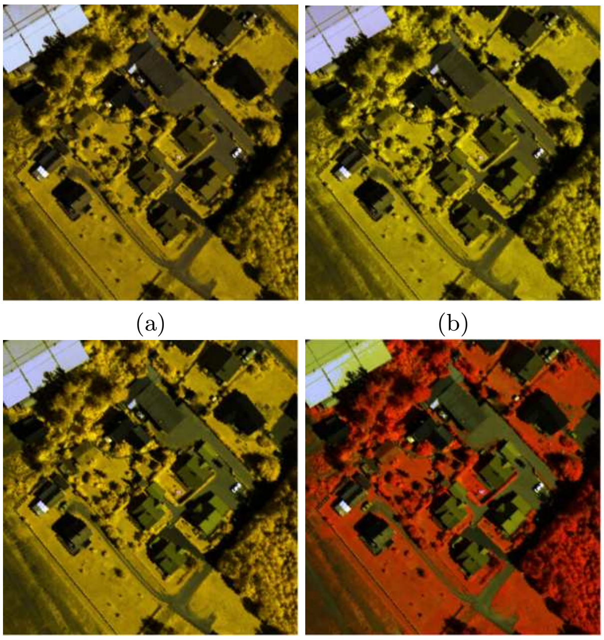
(a) (b) (c)

Fig. 4. RGB visualization of the 'Oslo' image according to different spectrum segmentation techniques: (a) Equal subgroups (b) Correlation-based (c) Maximum Energy

Segmentation technique	**NR**	**ICPD**
Equal subgroups	53.76	205.22
Correlation-based	90.87	226.72
Maximum energy	101.03	**243.21**
CMF-based, $\tau = 0.1$	**7.65**	222.01
CMF-based, $\tau = 0.5$	14.40	227.36
CMF-based, $\tau = 0.8$	11.96	224.55
CMF-based, $\tau = 1$	19.62	242.45

Table 1. Results for the 'Oslo' image

second and gives its best results for $\tau = 1$. However, considering the major improvement of NR brought by our approach, this latter gives an overall much better tradeoff between both metrics. Subjectively, if we look at the flower in figure 6c, even if the perceptual class-separability is obviously high, the one in 7d is much less disturbing and allows for a better quicker understanding of the endmembers of the scene.



(a) (b) (c) (d)

Fig. 5. RGB visualization of the 'Oslo' image according to the CMF-based segmented PCA with $\tau = 0.1$, 0.5, 0.8 and 1, respectively

(a) (b) (c)

Fig. 6. RGB visualization of the 'Flowers' image according to different spectrum segmentation techniques: (a) Equal subgroups (b) Correlation-based (c) Maximum Energy

The main drawback coming with an increase of the thresholding parameter is the loss of spectral channels, and thus the loss of information, which is done independently to the data itself. For that reason, one can see τ as a trade-off parameter, allowing for the balance between natural constancy and visual informative content.

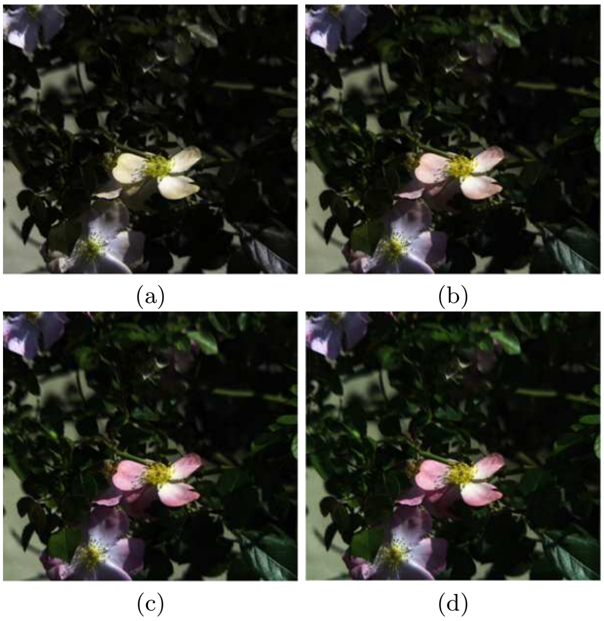


Fig. 7. RGB visualization of the 'Flowers' image according to the CMF-based segmented PCA with $\tau = 0.1$, 0.5, 0.8 and 1, respectively

Segmentation technique	NR	ICPD
Equal subgroups	12.37	101.34
Correlation-based	13.34	109.71
Maximum energy	22.50	**117.42**
CMF-based, $\tau = 0.1$	4.24	94.48
CMF-based, $\tau = 0.5$	**1.73**	96.33
CMF-based, $\tau = 0.8$	3.81	100.73
CMF-based, $\tau = 1$	5.70	112.30

Table 2. Results for the 'Flowers' image

4 Conclusion

A new method for the visualization of spectral images involving a spectrum segmentation technique based on a thresholding of color-matching functions has been introduced. Contrary to other spectral segmentation techniques, it allows for an underlying removal of irrelevant bands for visualization and thus allows for computational burden alleviation. The thresholding parameter allows for balancing the following hypothesis: the higher the color matching coefficient, the higher the relevance for the corresponding band to be a good representative of the corresponding primary. It also allows for balancing between natural constancy of the representation and the amount of bands to be removed. The results obtained by the presented technique are more naturally contrasted and thus make interpretation easier and quicker. Moreover, they contain a high class separability which reveals the presence of important visual information.

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References

1. Grassmann, H.: On the theory of compound colors. Phil. Mag **7** (1854) 254–64
2. Durand, J., Kerr, Y.: An improved decorrelation method for the efficient display ofmultispectral data. IEEE Trans. on Geoscience and Remote Sensing **27** (1989) 611–619
3. Tyo, J., Konsolakis, A., Diersen, D., Olsen, R.: Principal-components-based display strategy for spectral imagery. IEEE Trans. on Geoscience and Remote Sensing **41** (2003) 708–718
4. Tsagaris, V., Anastassopoulos, V.: Multispectral image fusion for improved rgb representation based on perceptual attributes. International Journal of Remote Sensing **26** (2005) 3241–3254
5. Scheunders, P.: Multispectral image fusion using local mapping techniques. In: International conference on pattern recognition. Volume 15. (2000) 311–314
6. Du, Q., Raksuntorn, N., Cai, S., Moorhead, R.: Color display for hyperspectral imagery. IEEE Trans. on Geoscience and Remote Sensing **46** (2008) 1858–1866
7. Jia, X., Richards, J.: Segmented principal components transformation for efficient hyperspectral remote-sensing image display and classification. IEEE Trans. on Geoscience and Remote Sensing **37** (1999) 538–542
8. Zhu, Y., Varshney, P., Chen, H.: Evaluation of ica based fusion of hyperspectral images for color display. In: Information Fusion, 2007 10th International Conference on. (2007) 1–7
9. Tsagaris, V., Anastassopoulos, V., Lampropoulos, G.: Fusion of hyperspectral data using segmented pct for color representation and classification. IEEE Trans. on Geoscience and Remote Sensing **43** (2005) 2365–2375
10. [online]: http://www.cie.co.at/main/freepubs.html (last check : Sept. 11, 2010)
11. Trussell, H.: Color and multispectral image representation and display. Handbook of image and video processing (2005) 411
12. Jacobson, N., Gupta, M.: Design goals and solutions for display of hyperspectral images. IEEE Trans. on Geoscience and Remote Sensing **43** (2005) 2684–2692
13. Ruderman, D.: The statistics of natural images. Network: computation in neural systems **5** (1994) 517–548
14. [online]: http://www.neo.no/hyspex/ (last check : Sept. 11, 2010)
15. Nascimento, S., Ferreira, F., Foster, D.: Statistics of spatial cone-excitation ratios in natural scenes. Journal of the Optical Society of America A **19** (2002) 1484–1490