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Visualization of spectral images: a comparative study

Steven Le Moan^{1,2}, Alamin Mansouri¹, Jon Y. Hardeberg², Yvon Voisin¹

1 : Le2i - Université de Bourgogne, Auxerre, France

2 : The Norwegian Color Research Laboratory - Gjøvik University College, Gjøvik, Norway

Abstract—The dimensionality reduction of spectral images for visualization has been a quite active area of research recently. Given the variety of existing approaches, it can be very challenging to understand the actual advantages of one over another, especially in the absence of a very specific application. Moreover, there is no consensus on how to evaluate the general efficiency of such a method. In this paper, we propose a comparison framework not only to compare such techniques, but also to measure their intrinsic properties in terms of naturalness and informative content.

I. INTRODUCTION

Dimensionality reduction aims at reducing the number of spectral channels in an image. There are several motivations behind this. First, high-dimensional spaces are known to spawn rather particular properties [1] such as the decreasing meaningfulness of the euclidean distance, which can be problematic in many classification-related applications. Computational burden is another problem that is involved. Indeed, high spectral resolution often yields a large amount of data and therefore relatively large files. It can thus be seen as a means for compression. Sampling the spectrum with high precision also results in potential redundancy between “neighboring” channels (that is, with small wavelength step between them). This unnecessary information, as well as any kind of noise can be handled by dimensionality reduction. Last but not least, when it comes to display a spectral image, one does not have many options. If we set aside the not-so-common spectral display technologies, most of today’s visualization devices are based on the paradigm that a combination of three primary colors (generally red, green and blue) is sufficient for the human eye to characterize any color [2]. Hence the need to extract only three channels from the high-dimensional images. Generally speaking and without a very specific application, the resulting composite must convey as much information from the initial data as possible, while being relatively appealing to ease viewing and/or interpretation.

Dimensionality reduction methods can be roughly categorized into two categories, which, although one being an extension of the other, are based on two very different philosophies. *Band transformation* consists in linearly or nonlinearly combining spectral bands while *band selection* constraint the resulting composite to be a subset of the initial image. The latter technique somehow allows for a better interpretation of the dimensionality reduction by keeping the relation between one channel and its range of wavelengths intact.

The remaining of this paper is as follows: first, we review the state-of-the-art methods for dimensionality reduction of spectral images. Secondly, we describe more explicitly 6 of them that we aim at comparing. Evaluation metrics are then presented as well as the data used in this study. Finally, results are presented and discussed before conclusion.

II. A STATE OF THE ART IN DIMENSIONALITY REDUCTION FOR SPECTRAL IMAGES

Tri-stimulus representation of multi/hyperspectral images for visualization is an active field of research that has been thoroughly investigated over the past decades. One of the most common approaches is probably the one referred to as “true color”. It can basically be achieved in two different ways: one consists of selecting the bands at 700.0nm, 546.1nm and 435.8nm (or the closest) and mapping them to the three primaries: R,G and B, respectively. The other one uses the CMF-based band transformation [3] (each primary R,G and B is the result of a linear combination of spectral channels in the visible range of wavelengths). Even though it generally yields a natural visual rendering, this approach does not take the data itself into account at all, and thus noise, redundancy, etc. are not accurately handled.

Another very common approach for dimensionality reduction is Principal Components Analysis (PCA), which has been extensively used for visualization purposes. Tyo *et al.* [4], investigated PCA for N-to-3 dimensionality reduction into the HSV color space. An automatic method to find the origin of the HSV cone is also proposed in order to enhance the final color representation. Later, Tsagaris *et al.* [5] 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 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. Several other PCA-based visualization techniques can be found in the literature [6], [7], [8].

In order to alleviate the computational burden of the traditional PCA, Jia *et al.* [9] proposed a correlation-based spectrum segmentation technique so that principal components are extracted from different segments and then used for visualization. Other segmented PCA approaches are investigated in [10] including equal subgroups, maximum energy and spectral-signature-based partitioning.

In [11], Du *et al.* compared seven feature extraction techniques in terms of class separability, including PCA, Independent Components Analysis (ICA) and Linear Discriminant Analysis (LDA). ICA has also been studied by Zhu *et al.* [12] for spectral image visualization. They used several spectrum segmentation techniques (equal subgroups, correlation coefficients and RGB-based) to extract the first IC in each segment. The use of different color spaces for mapping of the PCs or ICs has been investigated by Zhang *et al.* [13].

In [14], [15], Jacobson *et al.* presented a band transformation method allowing the CMF to be extended to the whole image spectrum, and not only to the visible part. They proposed a series of criteria to assess the quality of a spectral image visualization. Later, Cui *et al.* [16] proposed to derive the dimensionality reduction problem into a simple convex optimization problem. In their paper, class separability is considered and manipulations on the HSV cone allow for color adjustments on the visualization. More recently, we have proposed a method based on class-separability in the CIELAB space for improved spectral image visualization [17].

All the previously presented approaches are *band transformation* techniques inasmuch as they produce combinations of the original spectral channels to create an enhanced representative triplet. As stated earlier, the often mentioned drawback of this kind of approach is the loss of physical meaning attached to a channel. That is, if, initially, a spectral band is implicitly linked to a range of wavelengths, what can we tell about a combination of them? A particular case of *band transformation* is called *band selection* and consists of linearly combining the channels while constraining the weighting coefficients in the duet $\{0, 1\}$. In other words, the resulting triplet is a subset of the original dataset. By doing this, one preserves the underlying physical meaning of the spectral channels, thus allowing for an easier interpretation by the human end user.

In [18], Bajcsy investigated several supervised and unsupervised criteria for band selection, including entropy, spectral derivatives, contrast, etc. Many signal processing techniques have been applied to band selection: Constrained Energy Minimization (CEM) and Linear Constrained Minimum Variance (LCMV) [19], Orthogonal Subspace Projection (OSP) [20], [21] or the One-Bit Transform (1BT) [22]. Also information measures based on Shannon's theory of communication [23] have been proven to be very powerful in the identification of redundancy in high-dimensional datasets. Mutual information was first used for band selection by Conese *et al.* [24]. In [25] and [26], two metrics based on mutual information are introduced in the context of image fusion evaluation. They measure how much information is shared by the original and the reduced datasets. In [27], mutual information is used to measure the similarity of each band with an estimated ground truth. Hence, irrelevant bands for classification purpose are removed. In [28], a normalized mutual information measures is used for hierarchical spectrum segmentation.

III. BENCHMARKING METHODS

We have selected 8 methods to compare, 5 are based on *band transformation* and 3 on *band selection*. Although not

all of them are specifically dedicated to visualization, we have applied them in this context:

- **CMF-based *True Color* (TCCMF)**. The Color Matching Functions model the tri-stimulus human perception of colors. They are applied as weighing functions over the spectrum to linearly combine channels.
- **BS-based *True Color* (TCBS)**. Another method which is referred to as *true color*, but this time it is based on a selection of three channels at specific wavelengths roughly corresponding to the respective centers of the red, green and blue ranges.
- **PCA_{hsv}**. Principal Components Analysis (PCA) is one of the most used approaches for dimensionality reduction. It is also known as Principal Components Transform (PCT) or Karhunen-Loève Transform (KLT). It is based on an eigendecomposition of the correlation matrix of the data. For the readers who are unfamiliar with this technique, we suggest the very good tutorial by Smith [29]. We have used the following mapping to the HSV colorspace (PC_i being the i -th principal component): $PC_1 \rightarrow V$, $PC_2 \rightarrow H$, $PC_3 \rightarrow S$.
- **PCA_{Lab}**. We have used the following mapping to the CIELAB colorspace: $PC_1 \rightarrow L$, $PC_2 \rightarrow a$, $PC_3 \rightarrow b$.
- **sPCA**. Segmented PCA, as first suggested by Jia *et al.* [9]. RGB-based segmentation has been used, then PCA has been applied in each of the 3 resulting segments, allowing for the creation of an RGB composite (of course, the extracted PCs have been ranked by descending wavelength of their corresponding segments before mapping to RGB).
- **ICA_{hsv}** (Independent Components Analysis). We have applied the FastICA [30] algorithm to the spectral images and sorted them by decreasing entropy before mapping to the HSV colorspace.
- **LP-based band selection (LPBS)** [21] performs Linear Projections to measure dissimilarity between spectral channels. A progressive algorithm allows to avoid an exhaustive search over all the possible band combinations.
- **1BT-based band selection (1BTBS)** [22] makes use of the One-Bit-Transform, which can be seen as a measure of the edge density of an image. The technique proposed by Demir *et al.* aims at being implemented in an embedded system and is therefore focused on computational efficiency. It involves a preprocessing step aiming at coarsely removing correlated channels.

Note that for both the *True Color* techniques, the reflectance data has been converted into radiance by multiplying the spectral data by the D65 illuminant.

IV. METRICS

In order to compare the benchmarking methods, we propose to study their properties in terms of both perceptual appealing (naturalness) and informative content. At this aim, we propose to use the following metrics:

- **Similarity with the *True Color* composite (TCCMF)**. The latter is used as a ground truth for naturalness. We used the mutual information computed independently over the

three components of the CIELAB color space and then fused as follows: $NR = MI_L + \frac{MI_a + MI_b}{2}$ with MI_L being the mutual information in the L dimension and **NR** standing for Natural Rendering.

- Preservation of saliency. In [31], we have introduced a metric referred to as Saliency Discrepancy (**SD**) which allows to assess how much saliency is conveyed by the dimensionality reduction process. It uses the normalized Mutual Information between the saliency maps in the original high-dimensional image and from the corresponding color composite.
- Preservation of Classification Performances (**PCP**). We have used the K-means classifier in both the original and the reduced spaces and computed their discrepancy in percentage. The same starting point has been used to initialize both classifications to allow comparison.

V. RESULTS

A. Datasets

In this study, we have used the 8 images from the online database available at [32] and used in [33]. Images contain 31 spectral channels covering the visible range of wavelengths (400-720nm). For more information about the acquisition system, calibration and processings, please refer to the database webpage.

B. Pre-processing and normalization

In the raw reflectance data R_{raw} , all pixels above a threshold $\omega = \bar{R} + 3 * std(R)$ has been clipped to ω , to remove the influence of outliers and noisy pixels. The result has been divided by its maximal value so that it fits in the range [0..1].

C. Results

Table I gives, for each aforementioned metrics and dimensionality reduction techniques, the average and standard deviation values over the database. Figure 1 depicts the resulting composites obtained for 4 images from the database.

	NR		SD		PCP	
	mean	std	mean	std	mean	std
TCCMF	/	/	3.0011	0.1663	84.91%	10.59%
TCBS	0.4670	0.0621	4.5749	2.0093	80.22%	12.27%
PCA_{hsv}	0.3936	0.0691	3.9868	0.4381	78.70%	7.83%
PCA_{lab}	0.4181	0.0394	6.3068	3.2765	82.19%	9.04%
sPCA	0.5608	0.0407	2.9893	0.3452	88.43%	13.14%
ICA_{hsv}	0.3442	0.0518	11.5661	8.4652	74.15%	11.56%
LPBS	0.3651	0.0512	4.8280	2.3273	80.27%	10.41%
1BTBS	0.3560	0.1375	4.5175	2.2140	74.93%	15.39%

Table I
RESULTS

In terms of naturalness, the worst results are achieved by **ICA_{hsv}**. This is due to the simplicity of the normalization process used to convert ICs to reflectance data (that is, fitting in the range [0..1]). Indeed, the ICA transformation matrix can drastically change the range of the initial pixels values and even produce negative values, hence the need to map them back to the initial range. By doing so, one must particularly

take care of hue shifts which can indeed decrease naturalness. The same remark applies on PCA-based transformations [4].

Surprisingly, it is not the **TCBS** method that gives the best NR rates (even though it ranks second), but the segmented PCA approach. Indeed, the spectrum segmentation allows for a local analysis over the spectral dimension and is hence better suited for energy-based dimensionality reduction techniques such as PCA. By seeking the maximum energy independently in the Red, Green and Blue ranges of wavelengths, one then obtains better naturalness than with a global approach.

If we now look at the saliency discrepancies, we observe a certain correlation with NR. Indeed, **sPCA** and **TCCMF**, which obtain the best NR rates also outperform the other benchmarking techniques in terms of preservation of saliency. On the other hand, **ICA_{hsv}** once again gives the worst results. However, we believe that this observation is due to the fact that, by stretching the hue as in ICA or PCA-based approaches, one drastically modifies the visual attention properties of the composite, resulting in high saliency discrepancies.

Finally, in terms of **PCP**, once again naturalness influences the results. The segmented PCA achieves the best result (88.43%). Even though the ICA-based approach allows for maximizing the informative content of the resulting composite, the colorspace transformation applied (HSV to RGB) affects this property, hence a bad result (74.15%).

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VII. CONCLUSIONS

We have presented a general comparison of several state-of-the-art dimensionality reduction techniques for the visualization of spectral images. Both appealing and informative content have been objectively measured via five different metrics. Results show that naturalness is a prevalent feature that allows to better the visual informative content of a given composite. Moreover, among the 8 dimensionality reduction techniques applied on the database, we came to the conclusion that the segmented PCA outperforms the others in terms of each metric. However, the variety of normalization processes which are specific to each technique makes it quite challenging to maintain the comparison on a generic level. Further investigation will focus on the influence of normalization as well as other kind of data to be able to draw more general conclusions.

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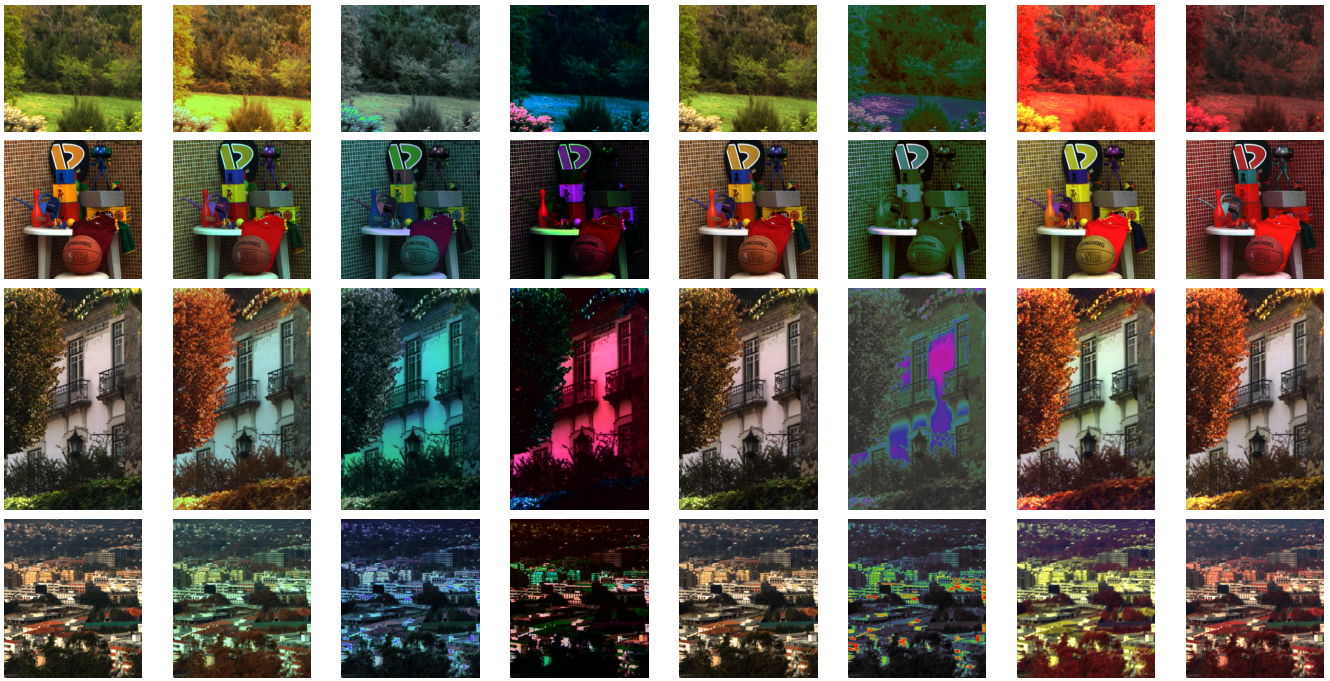


Figure 1. Examples of composites for 4 images of the database. From left to right: TCCMF, TCBS, PCA_{hsv} , PCA_{Lab} , sPCA, ICA_{hsv} , LPBS, 1BTBS.

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