Salient Pixels and Dimensionality Reduction for Display of Multi/Hyperspectral Images

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Abstract. Dimensionality Reduction (DR) of spectral images is a common approach to different purposes such as visualization, noise removal or compression. Most methods such as PCA or band selection use either the entire population of pixels or a uniformly sampled subset in order to compute a projection matrix. By doing so, spatial information is not accurately handled and all the objects contained in the scene are given the same emphasis. Nonetheless, it is possible to focus the DR on the separation of specific Objects of Interest (OoI), simply by neglecting all the others. In PCA for instance, instead of using the variance of the scene in each spectral channel, we show that it is more efficient to consider the variance of a small group of pixels representing several OoI, which must be separated by the projection. We propose an efficient method based on saliency to automatically identify OoI and extract only a few relevant pixels to enhance the separation foreground/background in the DR process.

1 Introduction

Dimensionality Reduction (DR) is a very common process in multi/hyperspectral imagery to project pixels to a space with a small number of attributes such as a three-dimensional color space (sRGB, HSV). To do so, many techniques were proposed, which are roughly divided into two categories: the ones which *transform* and the ones which *select* spectral channels. Even though Band Selection (BS) can be thought of as a generalization of transformation, they are based on two very different philosophies. Indeed, BS aims to preserve the physical meaning of spectral channels during the DR [1,2,3], whereas band transformation techniques such as Principal Components Analysis (PCA) [4,5], Independent Components Analysis [6] or true color [7,8], can mix channels to better fuse information along the spectrum. Evidently, the choice between these two approaches is application-driven.

The major drawback of most methods in the literature is that they are based on the assumption that all the pixels are part of the same population, i.e. performing a global mapping. Some approaches such as the Orthogonal Subspace Projection (OSP) [3] require a regular subsampling of the pixel population (down

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to 1% without noticeable change, according to the authors) in order to alleviate their respective complexity. Scheunders [9] proposed to spatially divide the image into square blocks in order to achieve local mappings by means of PCA and Neural Network-based techniques. However, natural scenes are rich and complex, showing large contrasts among their constituents, therefore a more dedicated spatial partitioning would better take care of these properties.

In this paper, we propose to use a non-visual saliency detection [10] to extract relevant pixels, so that to respect the properties of the scene. Three sets of pixels are extracted: the salient ones, the surrounders and the background. Only a few pixels are then extracted, by means of PCA, so that to represent each of the first two sets aforementioned in the dimensionality reduction process.

The remainder of this paper is structured as follows: We first tackle the extraction of the representing set of pixels and present the results obtained, before conclusion.

2 Pixel Selection

As explained earlier, we aim to perform DR by means of a minimum-sized set of pixels to speed up the process, but not only. One of the tasks of DR is to convey, nay, enhance the relative discrepancies between the various Objects of Interest (OoI), contained in the input data. When it comes to images, it is generally equally weighted over the spatial dimensions, despite the rich and complex properties of natural scenes.

To obtain saliency maps from high dimensional images, we used the model that was previously introduced by Le Moan *et al.* [10]. It is inspired by the famous *Itti* model [11] and uses euclidean distance, spectral angle and Gabor filtering to compute low-resolution saliency maps. Figure 3 shows the results obtained on 4 images of the database introduced and used in the results section. It is important to note that these maps depict non-visual saliency, which can be seen as a measure of informative content, as they are computed regardless of the human visual system.

By thresholding these maps into three parts, we isolate different sets of pixels according to their respective contribution to the scene:

- The **salient pixels**, Ω_1, are the pixels whose level of saliency is higher than a threshold T_{up}.
- The **surrounders**, Ω_2, are the pixels whose level of saliency is lower than T_{up} and higher than T_{down}.
- The **background pixels**, Ω_3, are all the rest.

Figure 1 shows an example of such segmentation on a natural scene, using different threshold values. The values of the optimal threshold are of course scene-dependent. We recommend to define them according to the separation of objects present in Ω_1 and Ω_2. For example, the segmentation in Figure 1b would be a more relevant choice than the one in 1c, where the flower petals spread out

(a) (b) (c)

Fig. 1. Examples of saliency-based thresholding. Left: *true color* composite, Middle: $T_{up} = 0.3$ and $T_{down} = 0.1$, Right: $T_{up} = 0.5$ and $T_{down} = 0.3$. Saturated areas represent the salient pixels while surrounders are shown in grey and background in black.

on both Ω_1 and Ω_2, which is undesirable. In this study, the optimal thresholds were defined manually for each scene.

In order to extract a set of representative pixels from each segment, we used PCA [12], over the spatial dimensions. During our experiments, we assessed that no more than five principal components are necessary to explain most of the data's energy (more than 95%) and therefore to represent each Ω_1 and Ω_2 (as we disregard the background). Eventually, only 10 pixels are considered to compute the projection matrix.

Moreover, by mastering the number and type of objects present in the input data, one allows the latter algorithm to be more dedicated to conveying the discrepancies between, in our case, objects in Ω_1 and Ω_2. Considering the relatively high computational complexity of PCA, we performed a random subsampling of 50 pixels in both groups. Moreover, resulting components are then normalized so that to fit the range [0..1]. Figure 2 shows an example of the principal components obtained.

3 Experiments and Results

3.1 Datasets

In this study, we used 4 natural scenes from the multispectral image database used in [13]. They contain 31 spectral channels each, covering the visible range of wavelengths (400-700nm). For more information about the acquisition system, calibration and processings, please refer to the database webpage[1].

3.2 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.

[1] `http://personalpages.manchester.ac.uk/staff/david.foster/Hyperspectral_images_of_natural_scenes_02.html`

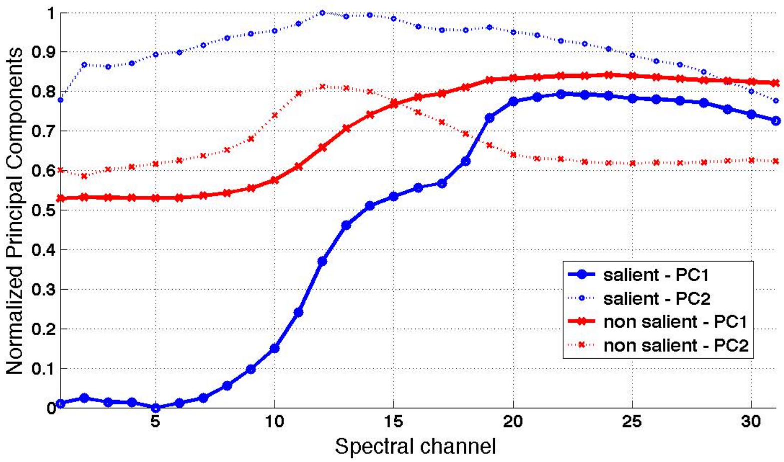

Fig. 2. Examples of (first and second) principal components obtained. Disks: representing Ω_1 and Crosses: representing Ω_2. We can observe for instance that the first PCs (plain lines) are discriminable mostly in the first half of the image's spectrum.

The result was divided by its maximal value so that it fits in the range [0..1]. Moreover, bands with average reflectance value below 2% and those with low correlation (below 0.8) with their neighboring bands have been removed, as suggested in [14].

3.3 Dimensionality Reduction Techniques

We selected three dimensionality reduction techniques to illustrate the proposed approach.

- Information-based Band Selection (**IBS**). We used the band selection approach that was used in [15] without the spectrum segmentation. It is based on a progressive research of dissimilar channels from single to third order.

- Orthogonal Subspace Projection-based Band Selection **OSPBS** [3] is a state-of-the-art band selection approache which consists of progressively selecting bands by maximizing their respective orthogonality.

- $\mathbf{PCA}_{hsv}$ is the traditional Principal Components Analysis of which components are mapped to the HSV color space, according to the normalization used in [5], without shifting the origin of the HSV cone.

Band selection approaches have been implemented in such a way that the band are eventually sorted by descending wavelength before mapping to sRGB.

3.4 Results

Figure 3 shows the *true color* composites of the images used in this study, as well as the corresponding saliency maps. Figures 4 to 6 show the results obtained by means of the different dimensionality reduction techniques, both by considering all the pixels in the image (or a uniform subsampling for **OSPBS**) and only a reduced set of pixels.

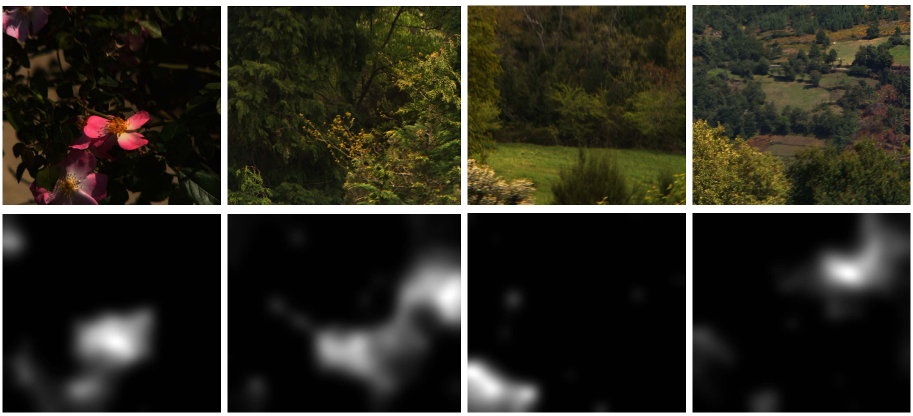

Fig. 3. *True color* composites (first row) and the corresponding saliency maps (computed from the high-dimensional datasets)

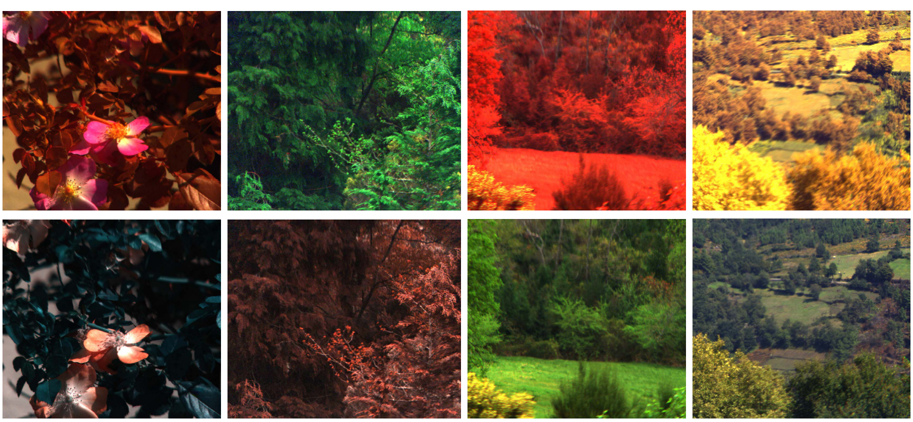

Fig. 4. **IBS** approach. First row: using all the pixels in the image. Second row: using a reduced set.

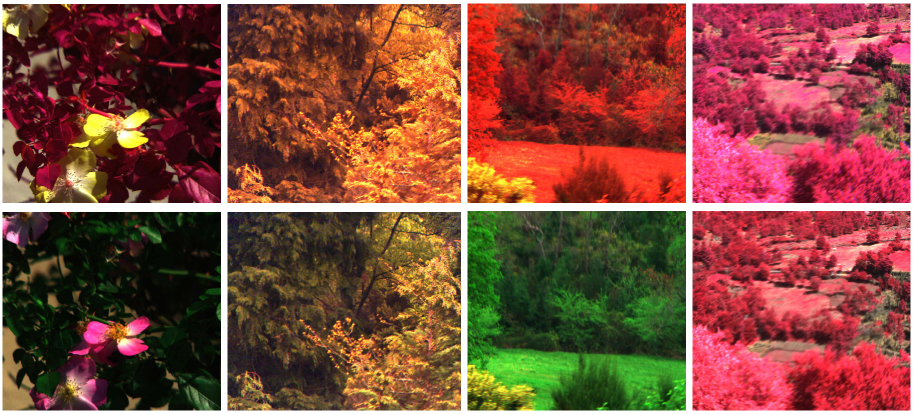

Fig. 5. **OSPBS** approach. First row: using a uniform subsampling of 1% of the image's pixels. Second row: using a reduced set.

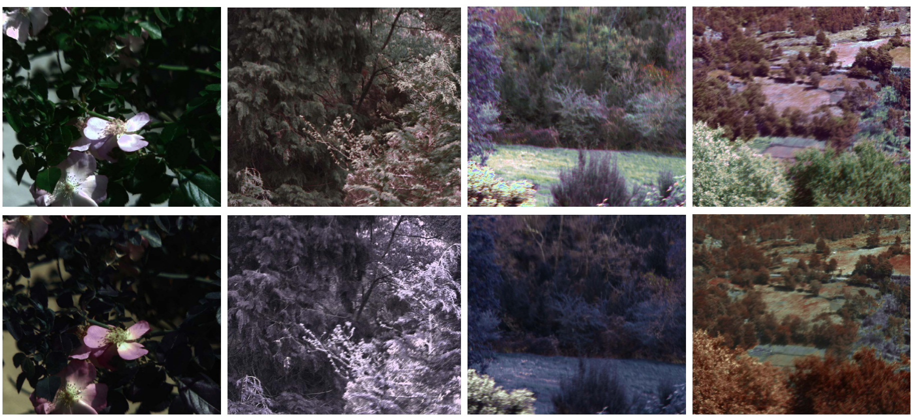

Fig. 6. $\mathbf{PCA}_{hsv}$ approach. First row: using all the pixels in the image. Second row: using a reduced set.

The optimal thresholds for each scene are given in table 1. **OSPBS** obtains their best results with a quite low upper threshold (0.3), while **IBS** and $\mathbf{PCA}_{hsv}$ perform better with a very reduced set of pixels. Overall, we observe that the most salient objects are emphasized, mostly because of a darkening or a diminution of contrast of their surroundings. Note that the natural rendering of these composites is considered outside the scope of this study, although it is very tempting to subjectively judge them according to this single feature.

In order to objectively evaluate the results, we used the color difference metric ΔE^*, which measures the Euclidean distance in the perceptually uniform color space CIELAB. Let ω_1 and ω_2 be two sets of 20 randomly selected pixels from

Ω_1 and Ω_2, respectively. Now let $\bar{\Delta}_{12}$ be the average color difference between ω_1 and ω_2, on a composite obtained with considering all pixels or a uniform subsampling and let $\bar{\Delta}_{12}{}'$ have the same definition but on a composite obtained by the proposed approach. We define the improvement of saliency $\delta_s = \bar{\Delta}_{12}{}' - \bar{\Delta}_{12}$. Table 2 shows the values obtained in this experiment.

Table 1. Optimal thresholds

	scene 1	**scene 2**	**scene 3**	**scene 4**
T_{up}	0.3	0.7	0.5	0.9
T_{down}	0.1	0.5	0.3	0.8

Table 2. Improvements of saliency δ_s. Difference of average Euclidean distance in CIELAB between Ω_1 and Ω_2, using all the pixels versus using only a subset.

	scene 1	**scene 2**	**scene 3**	**scene 4**
IBS	18.8	4.0	44.9	**23.7**
OSPBS	13.9	26.1	32.5	2.1
PCA$_{hsv}$	**20.5**	**42.8**	**47.3**	9.0

Results show that there is an overall increase of conspicuity for the top salient objects. It is not surprising to see that the PCA is more sensitive to the pixel selection as it is more adaptive to the data and has more degrees of freedom than the BS techniques. However, it also shows less contrast in the background areas, due to the fact that these pixels are disregarded during the computation of the projection matrix. Scene 3 shows the best results, mainly because of the well-defined salient region on the bottom left side.

4 Conclusions

We introduced a new approach to perform dimensionality reduction in spectral images over a limited number of relevant pixels. By thresholding the saliency map of the high-dimensional image, we classify pixels according to their conspicuity in the scene, that we assume to be related to their overall relevance in a visualization task. Dimensionality reduction is then performed so that to focus on emphasizing these most important areas. Results show an increased conspicuity of the selected objects of interest, both objectively and subjectively. Yet, several challenges remain such as the efficient finding of optimal parameters for thresholding and the number of principal components to represent each set of pixels.

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