# MULTISPECTRAL IMAGE COMPRESSION BY CLUSTER-ADAPTIVE SUBSPACE REPRESENTATION

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## ABSTRACT

Multispectral imaging has attracted much interest in color science area, for its ability in providing much more spectral information than 3-channel color images. Due to the huge data volume, it is necessary to compress multispectral images for efficient transmission. This paper proposes a framework for spectral compression of multispectral image by using cluster-adaptive subspaces representation. In the framework, multispectral image is initially segmented by hierarchical analysis of the transform coefficients in the global subspace, and then ambiguous pixels are identified and classified into proper clusters based on linear discriminant analysis. The dimensionality of each adaptive subspace is determined by specified reconstruction error level, followed by further cluster splitting if necessary. The efficiency of the proposed method is verified by experiments on real multispectral images.

***Index Terms***— Multispectral image, compression, clustering, PCA, LDA

## 1. INTRODUCTION

In color science area, multispectral imaging has been extensively studied recently due to its ability in high-fidelity color reproduction, which is of wide applications in textile, medicine, digital archives, etc. While multispectral image makes it possible to reproduce accurate colors under various illuminations, its huge data volume needs to be compressed for efficient transmission via internet/intranet.

The compression of multispectral image is possible as the spectral reflectances of object surfaces are highly correlated, and hence can be represented by the linear combination of a few eigenvectors [1]. These eigenvectors, which can be obtained by principal component analysis (PCA) [2], span a subspace with dimensionality lower than that of reflectance. The spectral reduction with this low-dimensional subspace is actually the essence of multispectral image compression. Straightforwardly, eigenvectors are computed in a global manner from the whole multispectral image. When there is a need to balance spectral and colorimetric accuracy, eigenvectors can be calculated by proper weighting [3].

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An image usually consists of clusters (or equivalently, regions), in which pixels have similar reflectance characteristics. Due to this similarity, the subspace dimensionality of a cluster can be lower than that of the whole image. In this regard, Kaarana *et al* [4] and Cagnazzo *et al* [5] classified pixels into regions according to spectral similarity, and compressed the regional-spectrum individually. Chang [6] divided multispectral satellite image into eigenregions. As eigenregions are obtained by analyzing the similarity of eigenvectors of adjacent image blocks, the computation is quite expensive.

This paper proposes an efficient framework for adaptive spectral compression of multispectral images. In the framework, the global subspace of the image is first calculated, based on which initial segmentation is conducted. The ambiguous pixels, which are identified by posterior probability, are then classified into proper clusters by linear discriminant analysis (LDA) [2]. The dimensionality of each cluster-adaptive PCA subspace are determined under the specified spectral error level, with further cluster splitting if necessary. Experiment was conducted to evaluate the performance of spectral compression. The encoding of cluster map and transform coefficients is not considered in this paper.

## 2. BASICS OF MULTISPECTRAL IMAGE

In this study, the multispectral images are acquired by a monochrome digital camera, accompanied by 16 narrow-band filters covering the visual spectrum. The camera response is the product of reflectance and spectral responsivity of the imaging system, with additive imaging noise. The reflectance of the imaged object is reconstructed from camera responses by Wiener estimation [7].

Hereafter, we refer multispectral image as the image containing spectral reflectance data, not the original camera responses. Reflectance is denoted by column vector $\mathbf{r} \in \mathcal{R}^{N\times 1}$, with $N = 31$. To keep data precision, $2N$ bytes are used to store a float-format reflectance. Hence, for a multispectral image with $L$ pixels, the overhead storage in bytes is

$$Q_0 = 2NL. \tag{1}$$

## 3. GLOBAL PCA-BASED COMPRESSION

For global PCA-based multispectral compression, PCA is applied on the whole image to obtain the global subspace. Let $\mathbf{r}_l$ be the reflectance of the $l$th ($1 \leq l \leq L$) pixel, the covariance matrix is

$$\mathbf{C} = \frac{1}{L}\sum_{l=1}^{L}(\mathbf{r}_l - \bar{\mathbf{r}})(\mathbf{r}_l - \bar{\mathbf{r}})^{\mathsf{T}}. \tag{2}$$

where $\bar{\mathbf{r}} \in \mathcal{R}^{N\times 1}$ is the mean reflectance of the image. It is clear that matrix $\mathbf{C} \in \mathcal{R}^{N\times N}$ is semi-definite. By singular value decomposition,

$$\mathbf{U}\mathbf{\Lambda}\mathbf{U}^{\mathsf{T}} = \mathbf{C}, \tag{3}$$

where matrix $\mathbf{U} \in \mathcal{R}^{N\times N}$ consists of eigenvectors $\mathbf{u}_j \in \mathcal{R}^{N\times 1}$, $(1 \leq j \leq N)$, and diagonal matrix $\mathbf{\Lambda} \in \mathcal{R}^{N\times N}$ contains the corresponding eigenvalues $\lambda_j$. Due to the high correlation, reflectance can be represented by a subspace spanned by a small number, $D_0(1 \leq D_0 \leq N)$, of eigenvectors,

$$\mathbf{r} = \sum_{j=1}^{D_0} a_j\mathbf{u}_j + \bar{\mathbf{r}}. \tag{4}$$

Accordingly, the overhead storage of the global PCA-based compression method is

$$Q_{\mathrm{G}} = 2D_0L + 2D_0N. \tag{5}$$

The first and second terms on the right hand side represent the overheads for coefficients and eigenvectors, respectively. Accordingly, the compression ratio (CR) is computed as

$$\eta_{\mathrm{G}} = Q_0/Q_{\mathrm{G}}. \tag{6}$$

## 4. PROPOSED FRAMEWORK

The basic idea of the proposed framework is to separate multispectral image into $K$ clusters which contain similar reflectances, and then compress these reflectances by the cluster-adaptive subspaces. As $K$ is less than 255 for the multispectral image in this study, the cluster label of a pixel can be represented by one byte. If the $k$th cluster contains $L^{(k)}$ pixels and the dimensionality of the corresponding subspace is $D^{(k)}$, the overhead storage is

$$Q^{(k)} = 2D^{(k)}L^{(k)} + 2D^{(k)}N + L^{(k)}, \tag{7}$$

where the first and second terms on the right hand side are similar to those in Eq. 5, and the storage of pixel labeling is equal to $L^{(k)}$. Then the total overhead storage for all clusters is

$$Q_{\mathrm{A}} = \sum_{k=1}^{K} Q^{(k)} = L + 2\sum_{k=1}^{K} D^{(k)}(L^{(k)} + N), \tag{8}$$

and the CR is calculated as $\eta_{\mathrm{A}} = Q_0/Q_{\mathrm{A}}$.

### 4.1. Initial segmentation

The fundamental issue of cluster-adaptive image compression is to separate the image into different non-overlapping regions. However, the direct segmentation of a high-dimensional image is a difficult problem, especially when the number of regions are not known a priori. The initial segmentation is inspired by hierarchical histogram analysis, which is originally used for color image segmentation [8].

By projecting the reflectance data to the global PCA subspace, as shown in Eq. 4, transform coefficient $a_j$ is obtained for each pixel. Then $a_j$ is scaled into the range $[0, S_j]$, with $S_j$ being determined as

$$S_j = \left\lfloor \frac{100}{\log_{10}(\frac{\lambda_1}{\lambda_j})} \right\rfloor, \tag{9}$$

where the operator $\lfloor\cdot\rfloor$ rounds variable to the nearest lower integer.

By this manipulation, the coefficients form a $N$ dimensional byte-type image. It is known that, for an 1-dimensional image, its histogram approaches probability distribution when pixel number is large and noise can be neglected. However, it is not the case in hierarchical histogram analysis as some regions may contain only a few pixels. In this regard, the hierarchical histograms are constructed by using kernel density estimator [9]. In this work the Gaussian kernel is used.

The procedure of image segmentation based on hierarchical kernel histogram is listed as follows:

(1) Set dimension index $j = 1$, region number $K = 1$, and regard the image as one region;
(2) On the $j$th dimension, construct the kernel histogram for each of the $K$ regions and further separated it into proper regions by peak-valley searching;
(3) Update $K$ and set $j = j + 1$;
(4) Repeat (2) and (3) if regions can be further separated; otherwise stop iteration, and set segmentation dimensionality $d = j$.

### 4.2. LDA-based ambiguous pixel classification

It is known that PCA is powerful in representing data, but is not optimal in discriminating data [2]. This means that the initial image segmentation may classify some ambiguous pixels, i.e., those in region boundaries, into wrong regions. To solve this problem, we first identify ambiguous pixels and then perform classification by LDA.

The ambiguous pixels are identified by the comparison of posterior probability. Let $\mathbf{a} \in \mathcal{R}^{d\times 1}$ be scaled coefficient of a pixel, $\mu_k \in \mathcal{R}^{d\times 1}$ and $\mathbf{\Sigma}_k \in \mathcal{R}^{d\times d}$ be the mean vector and covariance matrix for the $k$th region, respectively, then the posterior probability that the pixel belongs to the $k$th region is calculated as

$$p(k|\mathbf{a}) \propto p(\mathbf{a}|k)p(k) = \frac{L^{(k)}}{L}g(\mathbf{a}|\mu_k, \mathbf{\Sigma}_k) \tag{10}$$

where $g(\cdot)$ is multivariate normal density, and $L^{(k)}$ is the number of pixels in the $k$th region.

Suppose that, for a pixel, $k_0$ is the region with maximum posterior probability. This pixel is judged to be unambiguous only if the following inequality is satisfied:

$$p(k_0|\mathbf{a}) > \beta \cdot p(k|\mathbf{a}), \quad \forall \quad k \neq k_0, \tag{11}$$

where parameter $\beta$ controls the ambiguous level. Our investigation indicates that $\beta = 2$ is appropriate.

In LDA, the unambiguous pixels are employed for training and the ambiguous pixels are for classifying. Let $\mathbf{S}_\mathrm{B} \in \mathcal{R}^{N\times N}$ and $\mathbf{S}_\mathrm{W} \in \mathcal{R}^{N\times N}$ be the between-class and within scatter matrices of the reflectance data, respectively, the optimal discriminant matrix $\mathbf{\Phi} \in \mathcal{R}^{N\times(K-1)}$ is calculated by minimizing

$$J(\mathbf{\Phi}) = \frac{\mathbf{\Phi}^\mathsf{T}\mathbf{S}_\mathrm{B}\mathbf{\Phi}}{\mathbf{\Phi}^\mathsf{T}\mathbf{S}_\mathrm{W}\mathbf{\Phi}}, \tag{12}$$

which is actually a generalized eigenvalue problem [2]. By projecting reflectances on to the subspace spanned by the column vectors of $\mathbf{\Phi}$ and then applying 1-NN algorithm, the ambiguous pixels are properly classified.


**Fig. 1**. Four of the multispectral images used in the experiments, illustrated in color for visualization.

### 4.3. Dimensionality

In color science, the difference between reflectance $\mathbf{r}$ and its reconstructed counterpart $\hat{\mathbf{r}}$ is usually evaluated by the spectral root-mean-square (rms) error defined as

$$\varepsilon = \left[\frac{(\mathbf{r}-\hat{\mathbf{r}})^\mathsf{T}(\mathbf{r}-\hat{\mathbf{r}})}{N}\right]^{\frac{1}{2}}. \tag{13}$$

In cluster-adaptive compression, we need to determine the dimensionality $D^{(k)}$ of each subspace under the required image quality that specified by rms error level. In practice, this is reached in a reversed manner, by calculating rms errors under various dimensionality for each cluster [1]. It is noted that this procedure actually involves the decompression procedure under different dimensionality, and is computational expensive. Fortunately, our investigation indicates using only $20\%$ uniformly sampled pixels are adequate to get the reliable distribution between rms error and dimensionality.

### 4.4. Cluster splitting

It is possible that, under specified rms error level, the needed dimensionality for a certain cluster may be much larger than other clusters. To improve compression efficiency, we further check if further cluster splitting is necessary.

Suppose that region $k$ is divided into two regions, i.e., $k_1$ and $k_2$, then the storage overhead after splitting is

$$Q^{(k_1,k_2)} = L^{(k)} + 2(D^{(k_1)} + D^{(k_2)})(L^{(k)} + N). \tag{14}$$

It is expected that the needed coefficient overhead after splitting may be less than the original one, but the cost of eigenvector overhead will increase. Hence we apply cluster splitting only when $Q^{(k)} > Q^{(k_1,k_2)}$.

## 5. EXPERIMENTS

In the experiment we used about 20 multispectral images of knitting and printing textile fabrics, each with $512 \times 512$ pixels. Four of these images, namely A, B, C, and D, are illustrated in Fig. 1. The compression efficiency of the global compression method and adaptive compression method (including initial segmentation and LDA clustering) are evaluated. In the adaptive method, the average dimensionality is calculated as $\overline{D}_A = \sum_{k=1}^{K} \frac{L^{(k)}}{L} D^{(k)}$.

The distributions of peak signal-noise ratio (PSNR) and spectral rms error with respect to subspace dimensionality are shown in Fig. 2. When the dimensionality of subspaces becomes large, more variance in reflectance data can be represented by PCA. This results in the increase of PSNR and decrease of rms error when the dimensionality becomes high. It is obvious that the the adaptive method performs significantly better than the global one, in terms of both PSNR and rms error metrics. The improvement of LDA-clustering in the adaptive method over initial segmentation is also obvious. This improvement is obtained by the ability of LDA in classifying ambiguous pixels.

CR, which is related to number of clusters and dimensionality of subspaces, is an important metric for a compression method. Table 1 shows CRs of the two compression methods under different spectral rms error levels. The magnitude of CR is related to the spectral characteristics of the multispectral image. For example, as the colors in image B are not as distinct as in image A, more clusters and higher subspace dimensionality are needed in compression, which results in a lower CR for image B. It is clear that the CRs of the adaptive

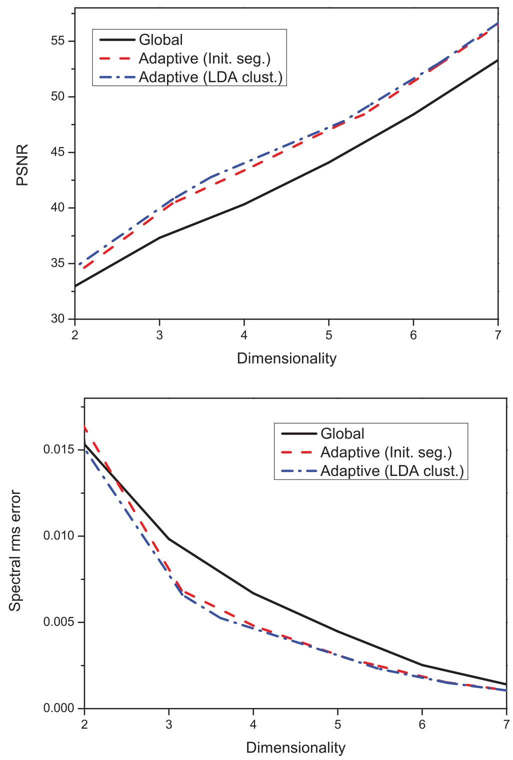


**Fig. 2**. Distributions of PSNR (top) and spectral rms error (bottom) with respect to subspace dimensionality for image A.

**Table 1**. CRs of global and adaptive compression methods under various spectral rms error levels

| Image | Method | Spectral rms error level | | |
|---|---|---|---|---|
| | | 0.01 | 0.005 | 0.002 |
| A | Global | 10.37 | 7.48 | 5.44 |
| | Adapt. (init. seg.) | 19.33 | 11.23 | 6.37 |
| | Adapt. (LDA clust.) | 19.65 | 11.40 | 6.42 |
| B | Global | 6.24 | 4.04 | 3.04 |
| | Adapt. (init. seg.) | 8.98 | 4.98 | 3.27 |
| | Adapt. (LDA clust.) | 9.21 | 5.06 | 3.30 |
| C | Global PCA | 8.69 | 6.49 | 5.07 |
| | Adapt. (init. seg.) | 11.99 | 7.80 | 5.30 |
| | Adapt. (LDA clust.) | 12.24 | 7.95 | 5.33 |
| D | Global PCA | 10.49 | 6.57 | 4.82 |
| | Adapt. (init. seg.) | 11.40 | 7.46 | 5.08 |
| | Adapt. (LDA clust.) | 11.83 | 7.78 | 5.15 |

method are higher than that of the global method. Under rms error level 0.01, the improvement of LDA clustering over initial segmentation is about 0.2 to 0.4; while under level 0.002, the improvement is not so large.

## 6. CONCLUSIONS

This paper proposes a cluster-adaptive method for the compression of multispectral images. The image is first initially segmented into regions by global PCA, and then ambiguous pixels are classify into proper clusters via LDA. Experimental results indicate that the cluster-adaptive method outperforms global method in terms of both PSNR and spectral rms error metrics. The improvement by LDA classification is obvious when compared with initial segmentation. To further improve compression efficiency, our future work will be investigating new algorithms for both region-separation and encoding of subspace-transform coefficients.

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